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Number	Authors	Title	Journal	Volume	Issue	Pages	Year	Location	URL / DOI	Type of publication	Study population and sample size if applicable	Methodology Study design	Outcome measures, if applicable	Validation type	Main results	Key findings that relate to the review question
1	Agarwal, D and Fernandes-Reyes, D and Papatopoulou, M C and Rojas, S A and Herbstler, M and Loosmore, A and Tarell, C and Sheldon, J and Schenk, A and Pollok, R and Rayner, C F and Krishna, R	Identification of diagnostic markers for tuberculous by proteomic fingerprinting of sputum	Lancet	368	9540	1012-1021	2006	UK	https://doi.org/10.1016/S0140-6736(06)28424-2	article	179 serum samples from patients, 170 serum samples from controls	Case-control study	accuracy, sensitivity, specificity (in k-fold cross-validation + validation set test)	cross-validation + test set	SOM classifier discriminated the proteomic profile of patients with active tuberculosis from that of controls with overlapping clinical features. Diagnostic accuracy was 88% (sensitivity 93.3%, specificity 84.6%) for patients with tuberculous disease. Technical variability and frequent misspellings in input "big data" require the application of dedicated data preprocessing pipelines that often lead to some loss of information and compressed view of the biological signal. Most of the variability in the drug response levels across the cell lines can be explained by the genome-wide gene expression data, whereas the other omics profiles only marginally improve the prediction performance (Jiang et al. 2014, Costello et al. 2014). However, the use of multiple omics profiles from various biological levels can still improve the prediction results.	Patients with active tuberculosis can be distinguished from controls with overlapping clinical features using machine learning and proteomic data. Technical variability and frequent misspellings in input "big data" require the application of dedicated data preprocessing pipelines that often lead to some loss of information and compressed view of the biological signal. Most of the variability in the drug response levels across the cell lines can be explained by the genome-wide gene expression data, whereas the other omics profiles only marginally improve the prediction performance (Jiang et al. 2014, Costello et al. 2014). However, the use of multiple omics profiles from various biological levels can still improve the prediction results.
2	Ali, M and Altmokkilt, T	Machine learning and feature selection for drug response prediction in precision oncology applications: Ovarian Cancer Classification Using Serum Proteomic Profiling and Wavelength Features as Comparison of Machine Learning and Feature Selection Algorithms	Biophysical Reviews	11	1	31-39	2019	Finland	https://doi.org/10.1007/s12541-019-00040-4	article	review (not applicable)	Review			Results show that the presented ML algorithms performed well for Ovarian Cancer Classification, with different feature selection algorithms all exceeding 90% accuracy. Machine learning analysis revealed that a standard MS proteomic panel that is able to predict NAB in a cognitively normal cohort at an accuracy of 86.6%. Pathway analysis highlights the convergence of pathways involved in coagulation, APP processing, neuronal transcription factors, and several injury to be important in predicting NAB. Current machine learning approaches are either too complex or perform poorly. The proposed two-step Bayes classification framework was equal to and, in some cases, outperformed other classification methods in terms of prediction accuracy, minimum number of classification markers, and computational time.	Results show that the presented ML algorithms performed well for Ovarian Cancer Classification, with different feature selection algorithms all exceeding 90% accuracy. Machine learning analysis revealed that a standard MS proteomic panel that is able to predict NAB in a cognitively normal cohort at an accuracy of 86.6%. Pathway analysis highlights the convergence of pathways involved in coagulation, APP processing, neuronal transcription factors, and several injury to be important in predicting NAB. Current machine learning approaches are either too complex or perform poorly. The proposed two-step Bayes classification framework was equal to and, in some cases, outperformed other classification methods in terms of prediction accuracy, minimum number of classification markers, and computational time.
3	Alquodbi, A M	Machine learning analysis reveals that a subset of MS proteomic panel that is able to predict NAB in a cognitively normal cohort at an accuracy of 86.6%	Journal of Clinical Engineering	44	4	165-173	2019		https://doi.org/10.1007/s12541-019-00040-4	article	262 cancer patients, 191 controls	Case-control study	accuracy, sensitivity, and precision (70% training set, 30% test set split)	training + test set	Results show that all the presented ML algorithms performed well for Ovarian Cancer Classification, with different feature selection algorithms all exceeding 90% accuracy. Machine learning analysis revealed that a standard MS proteomic panel that is able to predict NAB in a cognitively normal cohort at an accuracy of 86.6%. Pathway analysis highlights the convergence of pathways involved in coagulation, APP processing, neuronal transcription factors, and several injury to be important in predicting NAB. Current machine learning approaches are either too complex or perform poorly. The proposed two-step Bayes classification framework was equal to and, in some cases, outperformed other classification methods in terms of prediction accuracy, minimum number of classification markers, and computational time.	Results show that the presented ML algorithms performed well for Ovarian Cancer Classification, with different feature selection algorithms all exceeding 90% accuracy. Machine learning analysis revealed that a standard MS proteomic panel that is able to predict NAB in a cognitively normal cohort at an accuracy of 86.6%. Pathway analysis highlights the convergence of pathways involved in coagulation, APP processing, neuronal transcription factors, and several injury to be important in predicting NAB. Current machine learning approaches are either too complex or perform poorly. The proposed two-step Bayes classification framework was equal to and, in some cases, outperformed other classification methods in terms of prediction accuracy, minimum number of classification markers, and computational time.
4	Ashton, N J and Novgado-Holvas, A J and Lynham, S and Ward, M and Gupta, V B and Chatterjee, P and Goswami, K and Hone, E and Pedrin, S and Bui, A and Ross, C C and Villanueva, V L L and Ames, D and Mousnier, C C and Aird, D and Lovett, S and Martens, R N and Aye, A	Biomarker selection and classification of "omics" data using a two-step robust classification framework	Biomed Res Int	2013	14804	14804	2013	Thailand	https://doi.org/10.1155/2013/14804	article	more than 45 microarray and proteomics datasets of different used size	Case-control study	AUC, accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	Low-complexity machine learning models using few features can achieve similar performance as more complex models.	
5	Aswawami, A and Prakashan, S and Kulwanamunshi, S and Shaw, P J and Varavithya, V and Ruangsakpapakorn, T and Tongtong, S	Prostate cancer recognition based on mass spectrometry sensing data and data fingerprint recovery	Signal Processing and Control	33	392-399	2017	USA	https://doi.org/10.1016/j.spro.2016.12.004	article	237 blood samples from subjects with different PSA levels	Case-control study (case with different PSA levels)	accuracy, sensitivity, specificity, PPV, NPV (10-fold CV)	cross-validation	The study highlights the benefits of compressed sensing for dimensionality reduction in high-dimensional omics classification analysis.		
6	Awadot, A and Abdel-Qader, I and Springstead, J R	Molecular classification of AML/MRC reveals a distinct profile and identifies MRC-like patients with poor overall survival	Blood	134			2019		https://doi.org/10.1182/blood-2019-03-810000	meeting abstract	619 patients with survival data	Case-control study	accuracy (10-fold CV)	cross-validation	AML with myelodysplasia related changes (AML-MRC) can be diagnosed using patients' history and NGS-derived genetic information instead of morphology, allowing to identify 96.99% of AML-MRC as defined in WHO today.	Using patients' history and genetic information instead of morphology allow to identify 96.99% of AML-MRC as defined in WHO today
7	Baei, C and Walter, W and Stengel, A and Hutter, S and Maggendorfer, M and Kern, W and Hafterlach, T	MALDI-TOF analysis of blood serum proteome can predict the presence of mononuclear gammopathy of undetermined significance	PLoS One	13			2018	Spain	https://doi.org/10.1371/journal.pone.0201793	article	103 patients clinically diagnosed with MGUS, 108 healthy volunteer donors	Case-control study	accuracy, sensitivity, specificity (20-fold cross-validation)	cross-validation	MALDI-TOF analysis of blood serum proteome using support vector machines can predict the presence of mononuclear gammopathy of undetermined significance. The aim of this review is to explain how to build a general purpose design analysis protocol (DAP) for predictive proteomic profiling, we show how to limit baggage due to parameter tuning and how to organize classification and ranking into large numbers of replicate versions of the original data to avoid selection bias. A procedure for assessing stability and predictive value of the resulting biomarker list is also provided.	MALDI-TOF analysis of blood serum proteome using support vector machines can predict the presence of mononuclear gammopathy of undetermined significance.
8	Barcelo, F and Gomez, R and del Puai, J and Gil, X and Perez-Montaña, A and Jimenez-Monzo, T and Sampol, A and Fonteguit, J	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Brief Bioinform	9	2	119-128	2008	Italy	https://doi.org/10.1093/bib/bbn011	article	review (not applicable)	Review			The review presents common techniques for avoiding selection bias and assessing the stability and predictive value of biomarkers for proteomic machine learning studies.	
9	Barta, A and Juran, G and Riccardoni, S and Merler, S and Chierici, M and Furlanetto, C	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Transplantation	15			2015		https://doi.org/10.1093/txso/tjv014	article	96 samples with tolerance to renal allograft	Case-control study	accuracy, sensitivity, specificity (6-fold cross-validation + external validation)	cross-validation + test set	A gene signature derived from blood cell transcriptional data predicts tolerance to renal allograft correctly in 92% of cases.	A gene signature derived from blood cell transcriptional data predicts tolerance to renal allograft correctly in 92% of cases.
10	Baron, D and Ramstein, G and Choussat, M and Elchassoui, Y and Pallier, A and Paul, C and Dagueau, N and Hernandez Fuentes, M and Sanchez-Fayos, A and Newell, K and Gray, M and Soutouli, J P and Hougluette, R and Bourauel, S	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We determined the diagnostic potential of TTPs by mRNA sequencing of 283 placental samples. We distinguished 229 placental samples with localized and metastasized tumors from 55 healthy individuals with 96% accuracy.	We determined the diagnostic potential of TTPs by mRNA sequencing of 283 placental samples. We distinguished 229 placental samples with localized and metastasized tumors from 55 healthy individuals with 96% accuracy.
11	Bashiri, A and Ghazizadeh, M and Sadati, R and Shahmoradi, L and Eltahan, H	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
12	Baumback, J	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
13	Baumgartner, C and Bohn, C and Baumgartner, D	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
14	Beck, M and Sand, S and Kooi, J and Taniuchi, I and Westerman, B A and Rutenber, F and Scheller, P and Vercharen, N and Post, E and Koster, J and Vistra, B and Amesz, N and Dorst, J, J and Sim, F and Verhulst, H and Nieuwe, D and Reijnders, J C and Nijssen, R J A and Tanoussi, E A and Wesseling, P and Wurdinger, T	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
15	Bhik, Y and Jeong, H and Cho, Y S and Ison, S and Choi, J and Gim, J and Ison, Y and Bazyko, A and Park, S G and Kim, H M and Shin, E S and Park, J W and Lee, H W and Kang, W and Kim, A and Kim, S and Lee, S and Kim, S and Lee, S	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
16	Bhaskar, S and Bellinger, C and Bernheim, M and Drost, J and Fether-Kramer, D and Lee, H and Choi, Y and Park, J and Lee, S and Park, J W and Lee, H W and Kang, W and Kim, A and Kim, S and Lee, S and Kim, S and Lee, S	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
17	Bhattacharya, S and Singh, Y and Ray, D	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
18	Bhattacharya, S and Singh, Y and Ray, D	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
19	Bhattacharya, S and Singh, Y and Ray, D	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
20	Bhattacharya, S and Singh, Y and Ray, D	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
21	Bhattacharya, S and Singh, Y and Ray, D	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
22	Bhattacharya, S and Singh, Y and Ray, D	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.
23	Bhattacharya, S and Singh, Y and Ray, D	Machine learning methods for predictive proteomics: A common gene signature across multiple studies identifies biomarkers and functional regulation in tolerance to renal allograft	Journal of Public Health	46	2	165-172	2017	Iran	https://doi.org/10.1093/ajph/111.11.1100	article	review (not applicable)	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.	We developed machine learning models to predict depression and suicide risk using blood methylation and transcriptome data. Our random forest classifiers showed accuracies of 92.6% in distinguishing SAs from MDD patients, 87.3% in distinguishing MDD patients from controls, and 86.7% in distinguishing SAs from controls.

Author(s)	Journal	Year	Country	Article Type	Study Design	Key Findings/Abstract	Classification	Methodology	Validation		
Brown, K K and Choi, Y and Colby, T V and Flaherty, R R and Groshong, S and Venz, J A and Lynch, D A and Myers, J and Steele, M P and Martinez, P S and Panikar, D G and Walsh, P S and Huang, J and 24 Barth, N M and Ragh, G and Kennedy, G C	American Journal of Respiratory and Critical Care Medicine	2017	USA	Meeting abstract	354 T88 samples	Prospective validation of a genomic classifier for viral interstitial pneumonia in transbronchial biopsies	Case-control study	AUC (training / test set split)	training + test set	A definitive diagnosis of idiopathic pulmonary fibrosis (IPF) requires the presence of a usual interstitial pneumonia (UIP) pattern on chest imaging or surgical lung biopsy (SLB). A genomic classifier based on the gene expression pattern found in tissue obtained by less-invasive transbronchial biopsy (TBB) was evaluated and distinguished UIP from non-UIP in the training set with a receiver operator characteristic area under the curve (AUC) of 0.81 (specificity = 91% (CI 85-95), sensitivity = 71% (CI 65-77)). In validation, the test achieved an AUC of 0.85 (CI 0.73-0.97), with specificity = 88% (CI 80-97) and sensitivity = 67% (CI 45-84). In this paper, we propose a flexible network feature selection framework that combines metabolomics data with the genomic-scale metabolic network. The method adopts a sequential feature screening procedure and machine learning based criteria to select important subnetworks and identify the optimal feature matching simultaneously. Simulation studies show that the proposed method has a much higher sensitivity than the commonly used maximal matching approach. For demonstration, we apply the method on a cohort of healthy subject to detect subnetworks associated with the body mass index (BMI). The method identifies several subnetworks that are supported by the current literature, as well as detects some subnetworks with plausible new functional implications. "There are three major types of lung cancers, non-small cell lung cancer (NSCLC), small cell lung cancer (SCLC) and carcinoma. NSCLC is further classified into lung adenocarcinoma (ADC), squamous cell lung cancer (SQC) as well as large cell lung cancer. In the present study, ROC (Receiving Operating Curve), RFs (Random Forests) and mRMR (Maximum Relevancy and Minimum Redundancy) were proposed to capture the unbiased, informative as well as compact molecular signatures followed by machine learning methods to classify AUC, SDCI and SCCC. As a result, a panel of 16 DNA methylation markers exhibits an ideal classification power with an accuracy of 86.5%, 84.6% and a recall 84.37%, 85.3% in the leave-one-out cross-validation (LOOCV) and independent data set test experiments, respectively. "Recently, quantitative metabolomics identified a panel of 10 plasma lipids that were highly pre-diagnostic of conversion to Alzheimer's disease (AD) in cognitively normal/older individuals. We failed to replicate these findings in a substantially larger study from two independent cohorts. These findings underscore the importance of large-scale independent validation of index findings from biomarker studies with relatively small sample sizes."	
25 Cai, Q and Alvarez, J A and Kang, J and Yu, T	Network Marker Selection for Untargeted LC-MS Metabolomics Data Res	16	3	1261-1269	2017	USA	Article	Cases only (BMI analysis)	AUC (5-fold CV)	cross-validation	subjects with available high-resolution plasma metabolomics from the Emory-Georgia Tech Predictive Health Initiative Cohort of the Center for Health Discovery and Well Being (n = 371)
26 Cai, Z and Xu, D and Zhang, Q and Zhang, J and Ngai, S M and Shao, J	Classification of lung cancer using ensemble-based feature selection and machine learning methods	Mol Biolyt	11	3	791-800	2015	China	Article	accuracy, precision, recall, F1 score (LOOCV)	cross-validation	More than 100 samples available for the main sample groups LADC and SCLC in both training and test set
Casanova, R and Varma, S and Simpson, B and Kim, M and An, Y and Saklana, S and Rveros, C and Moscatto, P and Grissold, M and Song, D and Wirthner, J and Kivimäki, A and Jonsson, P V and Eriksson, G and Appelkvist, T and Sauer, J I and Gustavson, V and Lapidus Quilley, C and 27 Thornhill, M	Blood metabolite markers of preclinical Alzheimer's disease in two longitudinal followed cohorts of older individuals	Alzheimers Dement	12	7	815-822	2016	Australia	Article	AUC, sensitivity, specificity (6-fold CV)	cross-validation	Two cohorts of n=93 and n=100 subjects
28 Chaoibonchoe, A and Samarasinghe, S and Kulsiri, O	Machine Learning for Childhood Acute Lymphoblastic Leukemia Gene Expression Data Analysis: A Review	Current Bioinforma	5	2	118-133	2010	Review (not applicable)	Review (not applicable)	Review (not applicable)	Review (not applicable)	787 human cancer cell lines and structural profiles of 244 drugs were considered
29 Chang, Y and Park, H and Yang, H J and Lee, S and Lee, K Y and Kim, T S and Jung, J and Shin, M J	Cancer Drug Response Profile scan (CDRscan): A Deep Learning Model That Predicts Drug Effectiveness from Cancer Genomic Signature	Sci Rep	8	1	8857-8857	2018	Australia	Article	Required, AUC (training/test split)	training + test set	"We present a comprehensive review of machine learning approaches that have been used on (acute lymphoblastic leukemia) ALL) microarray data. These methods have been used in four major areas of microarray data analysis: gene selection, clustering, classification and pathway analysis. Each machine learning algorithm has its own advantages and drawbacks. "We report Cancer Drug Response profile scan (CDRscan) a novel deep learning model that predicts anticancer drug responsiveness based on a large-scale drug screening assay data encompassing genomic profiles of 787 human cancer cell lines and structural profiles of 244 drugs. We applied CDRscan to 1,487 approved drugs and identified 14 oncology and 23 non-oncology drugs having new potential cancer indications. "To investigate if urinary proteomics be used as non-invasive markers for renal involvement in childhood fibrinolytic urinary tract infection (UTI), decision trees as classifiers were constructed and were able to predict correctly after 10 fold cross-validation, 69.23% patients' status as no renal scarring, 81.82% sensitivity, 78.6% PPV. However only 53.8% patients' status as acute pyelonephritis (APN) were correctly predicted (47.1% sensitivity, 49.0% PPV). Larger cohort studies are needed to test the validity and reproducibility of these biomarkers. "Identifying robust survival subgroups of hepatocellular carcinoma (HCC) will significantly improve patient care. We built the DL-based, survival sensitive model on 360 HCC patients' data using RNA sequencing (RNA-Seq), miRNA sequencing (miRNA-Seq), and methylation data from The Cancer Genome Atlas (TCGA). This DL-based model provides two optimal subgroups of patients with significant survival differences (P = 7.13e-6) and good model fitness (concordance index (C-index) = 0.68). "We aimed to discover biomarkers of Cd derived from neoplasms of deamidated gliadin peptides (DGP) and TG fragments and to determine if immune reactivity against these epitopes can identify patients with Cd with mucosal healing. A fluorescent peptide microarray platform was used to estimate the antibody binding intensity of each synthesized TIG-DGP epitope. In the 101 training cohort, the set of neoplasms derived from the TIG-DGP 101 complex identified patients with Cd with 99% sensitivity and 103 100% specificity. The assay identified patients with mucosa healing status 110 with 84% sensitivity and 95% specificity. "A rapid blood-based diagnostic modality to detect pancreatic duct adenocarcinoma (PDAC) with high accuracy is an unmet medical need. The study aimed to validate a unique diagnosis system using Probe Electrophoretic Ionization Mass Spectrometry (PEI-MS) and Machine Learning to the diagnosis of PDAC. The sensitivity of the machine learning algorithm using PEI-MS profiles to identify PDAC is 90.8% with specificity of 91.7% (95% CI 89.97-97.4% and 82.8% 97.7% respectively). Combined PEI-MS profiles with age and CA19.9 predicted the accuracy for stage 1 or 2 of PDAC is 92.9% and for stage 3 or 4 is 93% (95% CI 86.3-98.2, 97.9-97.4 respectively). The accuracy and simplicity of the PEI-MS profiles combined with machine learning provide an opportunity to detect PDAC at an early stage and must be applicable to the examination of at-risk populations. "To identify robust transcriptional biomarkers for drug response across studies, we develop a meta-analytical framework combining the pharmacological data from two large-scale drug screening datasets. We use an independent pan-cancer pharmacogenomic dataset to test the robustness of our candidate biomarkers across multiple cancer types. We further analyze two independent breast cancer datasets and find that specific isoforms of G23P2, NECTN4, TIGB, and SLC6D4 are significantly associated with AZD2644, lapatinib, erlotinib, and paclitaxel, respectively. "The objective was to develop a blood-based colorectal cancer (CRC) test with clinically useful performance in patients with CRC symptoms. Machine learning was used to build and test candidate classifiers. The final classifier was a logistic regression using 10 predictors: eight proteins, age, and gender. In validation, the intermediate rate was 23.2%, sensitivity/specificity was 0.80/0.83, the PPV was 35.5%, and the NPV was 97.1%. This performance compares favorably to that from other CRC blood tests."
30 Chao, S M and Connolly, J and Ng, H Y and Ganesan, J and Bennett, L	Can urinary proteomes be used as non-invasive markers for renal involvement in childhood fibrinolytic urinary tract infection (UTI)?	Pediatric Nephrology	31	10	1746-1746	2016	Meeting abstract	Case-control study	sensitivity, PPV (10-fold CV)	cross-validation	121 patients (68 males, 53 females)
31 Chauthary, K and Porion, O B and Lu, L and Garmire, L X	Deep Learning-Based Multi-Omic Integration Robustly Predicts Survival in Liver Cancer	Clin Cancer Res	24	6	1248-1259	2018	USA	Article	"We validated this multi-omic model on five external datasets of various omics types: LRP1 cohort (n = 238, C-index = 0.75), NCI cohort (n = 221, C-index = 0.67), Chinese cohort (n = 166, C-index = 0.69), ETABM-35 cohort (n = 40, C-index = 0.71), and Hawaiian cohort (n = 27, index = 0.82). "We aimed to discover biomarkers of Cd derived from neoplasms of deamidated gliadin peptides (DGP) and TG fragments and to determine if immune reactivity against these epitopes can identify patients with Cd with mucosal healing. A fluorescent peptide microarray platform was used to estimate the antibody binding intensity of each synthesized TIG-DGP epitope. In the 101 training cohort, the set of neoplasms derived from the TIG-DGP 101 complex identified patients with Cd with 99% sensitivity and 103 100% specificity. The assay identified patients with mucosa healing status 110 with 84% sensitivity and 95% specificity. "A rapid blood-based diagnostic modality to detect pancreatic duct adenocarcinoma (PDAC) with high accuracy is an unmet medical need. The study aimed to validate a unique diagnosis system using Probe Electrophoretic Ionization Mass Spectrometry (PEI-MS) and Machine Learning to the diagnosis of PDAC. The sensitivity of the machine learning algorithm using PEI-MS profiles to identify PDAC is 90.8% with specificity of 91.7% (95% CI 89.97-97.4% and 82.8% 97.7% respectively). Combined PEI-MS profiles with age and CA19.9 predicted the accuracy for stage 1 or 2 of PDAC is 92.9% and for stage 3 or 4 is 93% (95% CI 86.3-98.2, 97.9-97.4 respectively). The accuracy and simplicity of the PEI-MS profiles combined with machine learning provide an opportunity to detect PDAC at an early stage and must be applicable to the examination of at-risk populations. "To identify robust transcriptional biomarkers for drug response across studies, we develop a meta-analytical framework combining the pharmacological data from two large-scale drug screening datasets. We use an independent pan-cancer pharmacogenomic dataset to test the robustness of our candidate biomarkers across multiple cancer types. We further analyze two independent breast cancer datasets and find that specific isoforms of G23P2, NECTN4, TIGB, and SLC6D4 are significantly associated with AZD2644, lapatinib, erlotinib, and paclitaxel, respectively. "The objective was to develop a blood-based colorectal cancer (CRC) test with clinically useful performance in patients with CRC symptoms. Machine learning was used to build and test candidate classifiers. The final classifier was a logistic regression using 10 predictors: eight proteins, age, and gender. In validation, the intermediate rate was 23.2%, sensitivity/specificity was 0.80/0.83, the PPV was 35.5%, and the NPV was 97.1%. This performance compares favorably to that from other CRC blood tests."		
Chong, S and Shihaghi-Rostomelski, S and Lu, J and Marzetta, F and von Döbeln, C T and Rajasekaran, J and Jayaraman, V and Wang, T and Bai, K and Rajasekaran, K and Krishna, K and Krishnamurthy, H K and Murray, J A	Synthetic Neopeptides of the Transglutaminase-Oxidized Gliadin Antigen as Biomarkers for Diagnosing Gastroenter and Monitoring Celiac Disease	Gastroenterology	156	3	582-591.e1	2019	USA	Article	AUC, accuracy, specificity ("well validated out findings in 82 patients with newly diagnosed CD and 217 controls")	external cohort validation	serum samples from 90 patients with biopsy-proven Celiac disease and 79 healthy-proven Celiac disease
Chung, W Y and Correa, J and Yoshimura, K and Chae, M C and Dennison, A and Takeda, S and 33 Chang, Y T	Using probe electrophoretic ionization mass spectrometry and machine learning for detecting pancreatic cancer with high performance	American Journal of Translational Research	12	1	171-179	2020	Japan	Article	accuracy, sensitivity, specificity (1000 independent repetitions of a bootstrap cross-validation process)	cross-validation	322 PDAC patients and 265 controls
34 Clark, O and Safkham, Z and Seninoy, P and Habu-Kiani, B	Gene isoforms as expression-based biomarkers predictive of drug response in vitro	Irish Journal of Medical Science	187		5348-5348	2018	Canada	Article	Case only (drug response prediction in independent breast cancer data and different vtro)	external cohort validation	The data comprised 79,303 experiments for 140 different drugs tested on a panel of up to 778 unique cell lines from 30 tissue types
35 Crower, L and Ko, A and Beni, R and Blume, J L and Dillon, R and Wilcox, B and Kari, S N	A new blood test for colorectal cancer in high-risk subjects	Clinical Chemistry	63		522-523	2017	Denmark	Meeting abstract	sensitivity, specificity, PPV, NPV (10-fold CV + training / test set split)	validation + test set	4,835 patient samples (3,066 patients (IAD CRC and 2,769 non-CRC) were randomly assigned to the classifier discovery set. The remaining 1,336 samples (147 CRC and 1,189 non-CRC) were assigned to the validation set
36 Cruz, J A and Wishart, D S	Applications of machine learning in cancer prediction and prognosis	Cancer Informatics 2019 16th IEEE International Conference on Computational Intelligence in Bioinformatics and Computational Intelligence in Bioinformatics	2		59-77	2006	Greece	Article	Review (not applicable)	Review (not applicable)	"In assembling this review we conducted a broad survey of the different types of machine learning methods being used, the types of data being integrated and the performance of these methods in cancer prediction and prognosis. A number of trends are noted, including a growing dependence on protein biomarkers and microarray data, a strong bias towards applications in prostate and breast cancer, and a heavy reliance on "older" technologies such artificial neural networks (ANNs) instead of more recently developed or more easily interpretable machine learning methods. A number of published methods also appear to lack an appropriate level of validation or testing. Among the better designed and validated studies it is clear that machine learning methods can be used to substantially (15-25%) improve the accuracy of predicting cancer susceptibility, recurrence and mortality."
Cugliari, G and Benvenuti, S and Guarera, S and Saccone, C and Panico, S and Krog, V and 37 Tumino, A and Vaini, P and Farielli, P and Malatino, G	Improving the prediction of cardiovascular risk with machine-learning and DNA methylation data	BMJ Open	3		39-42	2019	USA	Article	AUC, sensitivity, specificity (nested cross-validation)	cross-validation	584 subjects (292 M cases and 292 matched controls)

Author(s)	Year	Country	Journal	Article Title	Study Design	Key Findings/Methods	Classification	Outcome Measures	Notes
38 Das, D, Imoto, J, and Kadawaki, T and Tsuda, K	2019	3	2019 Japan	https://doi.org/10.1186/s12864-019-0641-1 article	97 AD subjects + 54 controls	Case-control study	AUC, accuracy, sensitivity, specificity (cross-validation + test set)	cross-validation + test set	"We present an interpretable machine learning model for medical diagnosis called sparse high-order interaction model with rejection option (SHMRO). A decision tree explains to a patient the diagnosis with a long rule (i.e., conjunction of many intervals), while SHMRO employs a weighted sum of short rules. Using proteomics data of 151 subjects in the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, SHMRO is shown to be as accurate as other non-interpretability methods (Sensitivity, SN = 0.84 ± 0.1, Specificity, SP = 0.69 ± 0.15 and Area Under the Curve, AUC = 0.86 ± 0.09)."
39 de Maturana, L and Alonso, L, And Narcon, P and Martín-Antón, I A and Pineda, S and Piro, M and Celi, M, L and Mátiz, N	2019	3	2019 Spain	https://doi.org/10.1186/s12864-019-0642-2 article	review (not applicable)	Review			"Only a small number of published studies performed a 'real' integration of omics and non-omics (OHO) data, mainly to predict cancer outcomes. Challenges in OHO data integration regard the nature and heterogeneity of non-omics data, the possibility of integrating large-scale non-omics data with high-throughput omics data, the relationship between OHO data (i.e., ascertainment bias), the presence of interactions, the fairness of the models, and the presence of subphenotypes. These challenges demand the development and application of new analysis strategies to integrate OHO data. In this contribution we discuss different attempts of OHO data integration in clinical and epidemiological studies. The integrative strategies used in the identified papers adopted three modeling methods: independent, conditional, and joint modeling."
40 de Ronde, J J and Border, M J and Upp, E H and Rodenhuis, S and Wessels, L F	2014	2	2014	https://doi.org/10.1186/s12864-014-0065-1 article	374 samples were analyzed	Cases only (treatment response predictor)	AUC (nested cross-validation)	cross-validation	"We set out to study if gene expression based predictors of chemotherapy resistance that are specific for breast cancer subtypes can improve upon the performance of generic predictors. For HER2-, ER+ breast cancer, subtype specific predictors based on clinical features outperformed the generic, non-specific predictor. This can be explained by the fact that the generic predictor included HER2 and ER status, features that are predictive over the whole set, but not within this subtype. In all other scenarios the generic predictors outperformed the subtype specific predictors or showed equal performance."
41 Camilli, B and Saravia, T and Martini, M and Iurman, G and Samon, F and Faria, A and Scavallari, M and Furlanello, C and Toffoni, G and Ceccelli, C	2012	7	2012 Italy	https://doi.org/10.1186/s12864-012-0020-2 article	3 different datasets (more than 50 samples per group in total)	Case-control study	AUC, sensitivity, specificity (cross validation + Monte Carlo bootstrap resampling)	cross-validation	"The identification of robust lists of molecular biomarkers related to a disease is a fundamental step for early diagnosis and treatment. However, methodologies for the discovery of biomarkers using microarray data often provide results with limited overlap. These differences are imputable to 1) dataset size (few subjects with respect to the number of features); 2) heterogeneity of the disease; 3) heterogeneity of experimental protocols and computational pipelines employed in the analysis. In this paper, we focus on the first two issues and assess, both on simulated (through an in silico regulation network model) and real clinical datasets, the consistency of candidate biomarkers provided by a number of different methods. The simulated data allowed us to outline advantages and drawbacks of different methods across multiple studies and varying number of samples and to evaluate precision of feature selection on a benchmark with known biomarkers. Although comparable classification accuracy was reached by different methods, the use of external cross-validation loops is helpful in finding features with a higher degree of precision and stability."
42 Diaz-Cano, S and Sutherland, R and Moorhead, J and Blanes, A and Dobson, R	2016	26A-126A	2016	https://doi.org/10.1186/s12864-016-0111-1 meeting abstract	low FGI (1-2, 174 cases) vs. high FGI (3-4, 139 cases) grade	Subtype comparison	AUC (5-fold cross-validation)	cross-validation	"The Pan-Cancer Analysis Project aimed to identify the genomic changes in cancer types from the Cancer Genome Atlas (TCGA). The mapping of architectural features in clear cell renal cell carcinoma (ccRCC) by Fuhrman grade (FG) has not been investigated at clinic-pathologic or genetic levels in this set. Clinical data were also collected (gender, age, and stage). We used a Random Forest machine learning approach comparing low FGI (1-2, 174 cases) vs. high FGI (3-4, 139 cases) grade. The age, gender, protein and variant models performed with an AUC of 0.80. Here we report the development, clinical validation, and diagnostic accuracy of a pre-operative molecular test (Affra BMF) to identify BRAF V600E mutations using mRNA expression in thyroid fine needle aspirate biopsies (FNABs). The resulting 128 gene linear support vector machine was compared to qPCR in the independent test set. Clinical sensitivity and specificity for malignancy were evaluated in a subset of test set samples (n=213) with expert-derived histopathology. We observed high positive (PPA, 90.4%) and negative (PPN, 95.0%) percent agreement with qPCR on the test set. Clinical sensitivity for malignancy was 93% (consistent with published performance of BRAF V600E in this neoplasm) and specificity was 100%, identical to qPCR on the same samples."
43 Ogilvie, A and Kim, S Y and Ho, Z Z and Parkin, D and Lee, M and Howland, J, Tom, C, and Wain, M and Monroe, R and Rossi, J and Lovell, V and Larman, R B and Kloss, R T and Walter, P A and Kennedy, C C	2015	371-382	2015 USA	https://doi.org/10.1186/s12864-015-0207-7 article	training (n=181) and independent test (n=533) sets	Case-control study	AUC (10-fold CV + external test set)	cross-validation + test set	"In this study, machine learning methods (e.g., deep learning) were used to identify informative features from genome-scale omics data and to train classifiers for predicting the effectiveness of drugs in cancer cell lines. The methodology introduced here can accurately predict the efficacy of drugs, regardless of whether they are molecularly targeted or non-specific chemotherapy drugs. This approach, on a per-drug basis, can identify sensitive cancer cells with an average sensitivity of 0.82 and specificity of 0.82; on a per-cell line basis, it can identify effective drugs with an average sensitivity of 0.80 and specificity of 0.82."
44 Ding, M Q and Chen, L and Cooper, G F and Young, J D and Lu, X	2018	269-278	2018 States	https://doi.org/10.1186/s12864-018-0210-1 article	Transcriptomic data from 777 cell lines was used	Cases only (cancer cell line drug response predictor)	accuracy, sensitivity, specificity (25-fold cross-validation)	cross-validation	"In this paper, we are interested in the question of how many and which genes should be selected for a disease class prediction. Our work consists of a Bayesian supervised statistical learning approach to refine gene signatures with a regularization which penalizes for the correlation between the variables selected. Our novel Bayesian approach includes a prior which penalizes highly correlated features in model selection and is able to extract key genes in the highly correlated context of microarray data. On real microarray datasets, we show that our approach can refine gene signatures to obtain either the same or better predictive performance than other existing methods with a smaller number of genes."
45 Djebbari, A and Labbe, A	2009	410-410	2009 Canada	https://doi.org/10.1186/1471-2166-9-241 article	the approach was applied to multiple Cancer microarray datasets with > 50 samples per group in total	Case-control study	AUC, sensitivity, specificity (nested 10-fold CV + external test set)	cross-validation + test set	"The manuscript covers several commonly used approaches to evaluate classification and clustering methods (e.g., cross-validation and bootstrap resampling)."
46 Dougherty, E R and Hua, J and Blattner, M L	2007	1-19	2007 USA	https://doi.org/10.1186/1471-2166-7-121 article	review (not applicable)	review			"The identification of genomic biomarkers is a key step towards improving diagnostic tests and therapies. We present a reference-free method for this task that relies on a linear representation of genomes and a machine learning algorithm that produces intelligible models. The method was validated by generating models that predict the antibiotic resistance of <i>C. difficile</i> , <i>M. tuberculosis</i> , <i>P. aeruginosa</i> , and <i>S. pneumoniae</i> for 17 antibiotics. The obtained models are accurate, faithful to the biological pathways targeted by the antibiotics, and they provide insight into the process of resistance acquisition. The method is not limited to predicting antibiotic resistance in bacteria and is applicable to a variety of organisms and phenotypes."
47 A M and Lovell, L E and Corbett, J	2016	1	2016 Canada	https://doi.org/10.1186/s12864-016-0064-6 article	17 datasets in which the number of examples ranged from 111 to 556	Antibiotic resistance prediction	error rate (5-fold CV, test evaluation)	cross-validation + test set	"The identification of genomic biomarkers is a key step towards improving diagnostic tests and therapies. We present a reference-free method for this task that relies on a linear representation of genomes and a machine learning algorithm that produces intelligible models. The method was validated by generating models that predict the antibiotic resistance of <i>C. difficile</i> , <i>M. tuberculosis</i> , <i>P. aeruginosa</i> , and <i>S. pneumoniae</i> for 17 antibiotics. The obtained models are accurate, faithful to the biological pathways targeted by the antibiotics, and they provide insight into the process of resistance acquisition. The method is not limited to predicting antibiotic resistance in bacteria and is applicable to a variety of organisms and phenotypes."
48 Drosow, B and Kildé, M and Moldán, I	2016	45-46	2016	https://doi.org/10.1186/s12864-016-0247-2 abstract	130 blood samples (NEN: n = 63)	Case-control study	AUC, sensitivity, specificity, PPV, NPV (The model was validated in two independent sets (Set 1: n = 115, NEN: n = 73; Set 2: n = 120, NEN: n = 58))	training + test set	GEP NENs (gastric-pancreatic neuroendocrine neoplasm) were investigated by reverse engineering intracellular signaling networks and identifying hub genes using degree (number of interactions) and betweenness (number of shortest paths) statistics. A random forest algorithm was used to assess hub gene expression in 130 blood samples (NEN: n = 63) and to differentiate healthy controls and GEP NENs. Gene-based classifiers detected NENs in independent sets with high sensitivity (85-98%), specificity (93-97%), PPV (95-98%) and NPV (97-98%). Additionally, multivariate logistic regression analysis showed that SVM model was indeed an independent predictor of RUMN status (odds ratio, 11.536; 95% confidence interval, 4.113-33.163; P<0.0001)."
49 and Al-Ali, R	2015	69-81	2015	https://doi.org/10.1186/s12864-015-0207-7 article	130 blood samples (NEN: n = 63)	Case-control study	AUC, sensitivity, specificity (training/test set split)	training + test set	"The goal of the study was to identify severe asthma exacerbation children using phenotypic and SNP Data. We concluded that the new classifier with the Newton-Raphson iterative process and propensity scores has reliable performance with the increase in AUC values in all cases: (i) phenotypic data only; (ii) phenotypic data with the top ten significant SNPs; and (iii) phenotypic data with the top 160 to 302 significant SNPs. Current imaging modalities are inadequate in preoperatively predicting regional lymph node metastasis (RNM) status in rectal cancer (RC). Here, we designed support vector machine (SVM) model to address this issue by integrating epithelial-mesenchymal-transition (EMT) related biomarkers along with clinicopathological variables. The sensitivity, specificity and overall accuracy of SVM in predicting RNM were 88.3%, 81.3% and 72.3%, respectively. Importantly, multivariate logistic regression analysis showed that SVM model was indeed an independent predictor of RNM status (odds ratio, 11.536; 95% confidence interval, 4.113-33.163; P<0.0001)."
50 X and Wu, P H and Lu, Q and Wang, L and Wang, J	2012	1735-1741	2012 China	https://doi.org/10.1186/s12864-012-0174-1 article	1893 patients	Cases only (predicting lymph node metastasis)	accuracy, sensitivity, specificity (training/test set split)	training + test set	"Drug response prediction is a critical step for personalized treatment of cancer patients and ultimately leads to precision medicine. In this paper, we propose a method based on quantile regression forest and applied it to the CCLE dataset. Through the out-of-bag validation, our method achieved much higher prediction accuracy of drug response than other available tools."
51 Fang, Y and Xu, P and Yang, J and Qin, Y	2018	40205-155	2018 China	https://doi.org/10.1186/s12864-018-0207-7 article	data from 947 cell lines (CCLE dataset)	Cases only (drug response predictor)	Pairson correlation of observed and predicted drug response (out-of-bag validation)	out/bag	"Urine proteome analysis (UPA) has already provided accurate discriminatory patterns of urinary peptides for renal disease, coronary artery disease, and asymptomatic LV diastolic dysfunction. UPA has now been used to characterize a discriminatory peptide biomarker pattern and establish a diagnostic classifier for heart failure patients with reduced ejection fraction (HEF) in the presence of chronic kidney disease (CKD). In total, 107 significant discriminatory peptides were identified and used to establish a support vector machine-based classifier that was successfully applied to a test set of 25 HEF patients and 33 controls, achieving 84% sensitivity and 91% specificity."
52 Farnhills, D and Kooze, T and Mulvaney, W and Parslow, J and Goggin, B D and Nikolaou, M and Lohakis, P and Mischak, H and Filippatos, G	2016	822-829	2016 Germany	https://doi.org/10.1186/s12864-016-0111-1 article	126 Individuals, 59 HEF patients and 67 Controls	Case-control study	AUC, accuracy, sensitivity, specificity (cross-validation + test set)	cross-validation + test set	"Urine proteome analysis (UPA) has already provided accurate discriminatory patterns of urinary peptides for renal disease, coronary artery disease, and asymptomatic LV diastolic dysfunction. UPA has now been used to characterize a discriminatory peptide biomarker pattern and establish a diagnostic classifier for heart failure patients with reduced ejection fraction (HEF) in the presence of chronic kidney disease (CKD). In total, 107 significant discriminatory peptides were identified and used to establish a support vector machine-based classifier that was successfully applied to a test set of 25 HEF patients and 33 controls, achieving 84% sensitivity and 91% specificity."

Author(s)	Journal	Year	Country	Study Type	Abstract	Goal of the study	Methods	Results		
Fausbinder, A and Walters, E and Nyama, C and Bokor, A and Vozobakova, A and Verbeek, W and Van De Plas, R and Gupta, F and Eswart, D and Muehlenberg, C and Prewer, K and Tomaszewski, C and De Moor, B and D'Hooghe, T	Biomarkers in plasma or serum: Pitfalls in data processing	18	3	191A-191A	2011	India	254 plasma samples from women with (n=163) and without (n=91) endometriosis	Case-control study	accuracy (data were divided randomly (500 times) into training set (70%) and test set (30%)	training + test set
Filimon, R and Ramoa-Cejudo, J and Cheng, D and Turk, D and Panth Shikhi, A and Chen, D and Elbers, C and Turner, K and Johnson, L and Gagnon, C and Hirschman, C and Schiller, S and Aljarous, S and Hall, M and Ayvazian, S and Meng, F and Brophy, M and Du, N	An integrative Approach for Identifying Network Biomarkers of Breast Cancer Subtypes Using Genomic, Proteomic, and Transcriptomic Data	37			2019		156 VA patients newly diagnosed with NSCLC	Case-control study	Precision, recall, and area under the ROC curve (AUC) (5-fold CV)	cross-validation
55 Firoozbakh, F and Rezaeei, L and Daghini, M and Porter, L and Land Rueda, J and Land Ngem, A	Tumour subtyping	24	8	756-766	2017	Canada	"We have used the METABIC data set [Curtis et al., 2012], which contains the gene number values and GE level of 2000 primary breast tumors with long-term clinical follow-up."	Case-control study	AUC, sensitivity, specificity (10-fold CV)	cross-validation
Fong, F and Bar, HY and Sheddin, K and Suya-Cork, K and Oullette, P and Campagne, F and Melnick, S and Al Masak, Sand Shalwani, M	Epigenetic profiling of primary CLL reveals novel DNA methylation-based clusters and novel mechanisms of leukemogenesis	120	21		2012		"DNA methylation of over 2400 genes with CLL"	Case-control study	AUC (10-fold CV)	cross-validation
57 Gal, D and Auslander, N and Fan, Y and Meerman, D	Predicting Complete Remission of Acute Myeloid Leukemia: Machine Learning Applied to Gene Expression	18			2019	USA	473 bone marrow specimens from 473 patients	Case-control study	AUC (5-fold CV + test set)	cross-validation + test set
58 Gamberger, D and Lavaric, N and Zakany, F and Totar, J	Induction of comprehensible models for gene expression datasets by subgroup discovery methodology	37	4	269-284	2004	Croatia	"The approach was applied to multiple cancer microarray datasets with 50 samples per group in total"	Case-control study	sensitivity, specificity, precision (training/test set split)	training + test set
59 Gao, H and Zheng, Z and Yue, Z and Liu, F and Zhou, L and Zhao, X	Evaluation of serum diagnosis of pancreatic cancer by using surface-enhanced laser desorption/ionization time-of-flight mass spectrometry	30	5	1061-1068	2012	China	serum samples from 123 patients with PCs and 87 healthy controls	Case-control study	sensitivity, specificity (leave-out cross-validation)	cross-validation
60 Borodulin, K and Havulinna, A and Salonen, V and Ronnen, E and Canistraci, V and Simons, K	Machine learning of human plasma lipoprotein obesity-related clusters in a large population cohort	17	10	25-25	2019	China	Samples of the FINRISK 2012 underwent lipoprotein measurements (1,141 randomly selected individuals of which 1,061 were used)	Case-control study	R-squared of obesity indicator variables (K repeated 10-fold CV)	cross-validation
61 Gong, Y and Fox, N and Huang, Y and Boutros, P C	Prediction of early breast cancer patient survival using ensembles of hypoxia signatures	13	9	40204123-40204123	2018	Canada	1,564 early breast cancer patients	Case only (survival prediction)	AUC, accuracy, sensitivity, specificity (10-fold cross-validation + test set)	cross-validation + test set
62 Grain, K and Friedl, Y and Houshban, K E and Stuart, J M	PLATYPUS: A Multiple View Learning Predictive Framework for Cancer Drug Sensitivity Prediction	24		136-147	2019	USA	"At the time of download the Cancer Cell Line Encyclopedia (CCLE) contained genomic, phenotypic, clinical, and other annotation data for 1,037 cancer cell lines"	Case only (drug sensitivity prediction)	AUC (cross-validation + external test set)	cross-validation + external test set
63 Bode, P	Machine learning in amyotrophic lateral sclerosis: achievements, pitfalls, and future directions	13			2019	France	review (not applicable) "The first dataset we used was collected from Genomics of Drug Sensitivity in Cancer project (release 5.0, https://www.canceromics.org/downloads), including 652 cancer cell lines, 135 drugs, and 70,676 known response values. The second dataset was collected from the CCLE."	review		
64 Guan, N and Zhao, Y and Wang, C and Li, Q and Chen, X and Piao, X	Anticancer Drug Response Prediction in Cell Lines Using Weighted Graph Regularized Matrix Factorization	17		164-174	2019	China	"Sursum samples were collected from all participants, including 587 CDD patients (which contains 216 drugs and 493 cell lines with 10,870 known responses)"	Case only (drug response prediction)	Pearson correlation coefficient (PCC), root-mean-square error (RMSE), PCCor, and RMSEr averaged over all drugs (10-fold CV)	cross-validation
65 Guo, S and Guo, D and Chen, L and Tang, Q	A centroid based gene selection method for microarray data classification	400		32-41	2016	China	"Multiple microarray datasets for different cancers with > 50 samples per group in total were used"	Case-control study	accuracy + standard deviation (repeated 5-fold CV)	cross-validation
66 Guo, Y and Yu, H and Chen, D and Zhao, Y Y	Machine learning distilled metabolite biomarkers for early stage renal injury	16	1	10-10	2019	China	"Serum samples were collected from all participants, including 107 CKD patients (CKD1 = 126, CKD2 = 104, CKD3 = 110, CKD4 = 135, CKD5 = 134) and 116 age-matched normal healthy controls."	Case-control study	AUC (10-fold CV)	cross-validation

<p>Ihii, H and Sahoh, M and Sakamoto, K and Sakamoto, K and Saigusa, D and Kasai, H and Aihwaka, R and Miyawaki, K and Takahashi, T and Maeyama, K and Yoshimura, K.</p>	<p>Lipidase-based rapid diagnosis with machine learning for detection of TGF-β1 signaling activated area in head and neck cancer</p>	<p>British Journal of Cancer</p>	<p>10-10</p>	<p>Japan</p>	<p>https://doi.org/10.1136/bjco-2020-024242</p>	<p>article</p>	<p>A total of 240 and 90 mass spectra were obtained from TGF-β1-stimulated and unstimulated HNSCC cells, respectively</p>	<p>Case-control study</p>	<p>accuracy (LOOCV)</p>	<p>cross-validation</p>
<p>Ivanic, M M and Maghs, B W and Swerlow, J and Craven, M and Reichelderfer, M and Pichler, R and Luzzo, M and Krenkel, G D</p>	<p>Noninvasive Detection of Colorectal Cancers Using Serum Protein Biomarkers</p>	<p>Surg Res</p>	<p>246</p>	<p>United States</p>	<p>https://doi.org/10.1097/SLA.0000000000000201</p>	<p>article</p>	<p>"Blood was drawn from individuals (n = 211) before colonoscopy from patients with nonmetastatic CRC (n = 60) AMI dataset: "194 samples contain methylation data and we use the part of the data measured by HMU-LUC HumanMethylat450 arrays. 173 samples contain mRNA data measured by HT-1133 arrays." "BRCA dataset: This data set includes 993 samples with clinical data. Only very few samples in this data set are indicated as having metastasized (8 samples). Hence the data are analyzed according to "tumor size", "affected nearby lymph nodes", "stage", and "estrogen receptor"."</p>	<p>Case-control study</p>	<p>AUC, sensitivity, specificity (training / test set split)</p>	<p>training + test set</p>
<p>Jada, A and Pfeifer, N</p>	<p>Interpretable per case weighted ensemble method for cancer associations</p>	<p>BMC Genomics</p>	<p>17</p>	<p>Germany</p>	<p>https://doi.org/10.1186/s12854-016-0424-7</p>	<p>article</p>	<p>"Molecular measurements from cancer patients such as gene expression and DNA methylation can be influenced by several external factors. If a model does not take potential biases in the data into account, this can lead to problems when trying to predict the stage of a certain cancer type. This is especially true when these biases differ between the training and test set. We introduce a method that can estimate this bias on a per-feature level and incorporate calculated feature confounders into a weighted combination of classifiers with disjoint feature sets. Moreover, we show how to visualize the learned classifiers to display interesting associations with the target label."</p>	<p>Cases only risk & severity stratification</p>	<p>AUC (training / test set split)</p>	<p>training + test set</p>
<p>Jones, J and Wilcox, B E and Benz, R and Bobbar, N and Borajegla, G and Barrill, J and Christie, E B for Colorectal Cancer Detection and Croner, L and Liu, C and Pan, D and Dillon, R and Kato, S and Kato, A and Preston, R and Schreckengost, G S S R and Shi, and Smith, W J and Tilly, W D and Agui, D and Wu, J and...</p>	<p>A Fluorescent-Based Protein Marker Panel for Colorectal Cancer Detection Identified by Multiplex Targeted Mass Spectrometry</p>	<p>Clin Colorectal Cancer</p>	<p>186</p>	<p>United States</p>	<p>https://doi.org/10.1016/j.clcc.2016.07.001</p>	<p>article</p>	<p>The present study used 274 individual patient blood plasma samples, 137 with biopsy-confirmed colorectal cancer and 137 age- and gender-matched controls.</p>	<p>Case-control study</p>	<p>AUC, sensitivity, specificity (cross-validation + external test set)</p>	<p>cross-validation + external control validation</p>
<p>Jurmette, P and Beckmann, M and Seppner, F and Beckmann, T and Treuss, D and Montson, G and Volbrecht, C and Arnold, A and Teichmann, D and Bressan, K and Schuller, U and von Lurff, F and Muller, K K and Capper, D and Traussnigg, F</p>	<p>Machine learning analysis of DNA methylation profiles distinguishes primary lung squamous cell carcinomas from head and neck metastases</p>	<p>Science Translational Medicine</p>	<p>11</p>	<p>Germany</p>	<p>https://doi.org/10.1126/scitranslmed.aag0511</p>	<p>article</p>	<p>408 patients with a history of primary HNSCC and a synchronous or metachronous squamous lung tumor</p>	<p>Case-control study</p>	<p>AUC, accuracy (5-fold CV + external test set)</p>	<p>cross-validation + external control validation</p>
<p>Karimpoor-Fard, A and Epperson, L E and Hunter, L E</p>	<p>A survey of computational tools for downstream analysis of proteomic and other omic datasets</p>	<p>Human Genomics</p>	<p>9</p>	<p>USA</p>	<p>https://doi.org/10.1186/s12918-016-0205-2</p>	<p>article</p>	<p>review (not applicable)</p>	<p>review</p>	<p>review</p>	<p>review</p>
<p>Khan, S R and Mohan, H and Liu, Y and Batschauer, B and Ghali, H and Al Rijjal, A D and Malmaluy, Y</p>	<p>The discovery of novel predictive biomarkers and early-stage pathophysiology for the transition from gestational diabetes to type 2 diabetes</p>	<p>Diabetologia</p>	<p>62</p>	<p>Canada</p>	<p>https://doi.org/10.1007/s00125-016-3824-4</p>	<p>article</p>	<p>55 incident cases matched to 85 non-case control participants</p>	<p>Case-control study</p>	<p>AUC, accuracy, sensitivity, specificity (45-fold cross-validation)</p>	<p>cross-validation</p>
<p>Khalifa, D and Cluff, C E and Callahan, S A and Krasinski, A M and Alzarak, A and Knight-Scott, J and Clifton, R and Castillo-Leon, E and Jones, P and Pierson, B and Caprio, S and Santoro, T and Abi, A and Vogt, M B</p>	<p>Development of a Plasma Screening Panel for Fatty Liver Disease Using Metabolomics</p>	<p>Hepatology Communications</p>	<p>3</p>	<p>United States</p>	<p>https://doi.org/10.1016/j.hc.2019.08.014</p>	<p>article</p>	<p>subjects with NAFLD (n = 222) and without NAFLD (n = 317)</p>	<p>Case-control study</p>	<p>AUC (training set: 2/3 of data, test set: 1/3 of data)</p>	<p>training + test set</p>
<p>Kim, J and Du Rosa, J C and Lee, J and Tomalia, L and Lowes, M A and Fitz, L and Bernstein, G and Weng, H and Wang, W and Kraus, G G and Soley-Bertram, M</p>	<p>Precision medicine in psoriasis: Machine learning and proteomics join forces to develop a blood-based test to predict response to tofacitinib or Etanercept in psoriasis patients</p>	<p>Experimental Dermatology</p>	<p>25</p>	<p>United States</p>	<p>https://doi.org/10.1111/exd.12926</p>	<p>meeting abstract</p>	<p>259 serum samples from a phase 1 study in adults with moderate-to-severe psoriasis</p>	<p>Case-control study</p>	<p>AUC, accuracy (training / test set split: 80%/20%)</p>	<p>training + test set</p>
<p>Kim, M and Oh, J and Ahn, J</p>	<p>An improved method for prediction of cancer prognosis by network learning</p>	<p>Genes</p>	<p>9</p>	<p>Switzerland</p>	<p>https://doi.org/10.3389/genes.2019.01604</p>	<p>article</p>	<p>"First, we downloaded gene mRNA data, CNV data, DNA methylation data, SNP data, and clinical data for HNSCC, BRCA, HCC, LGG, and STAD from The Cancer Genome Atlas (TCGA) (more than 50 samples per gene for multiple datasets) "We apply the Meta-SVM methods to two real samples of idiopathic pulmonary fibrosis expression profiles (IPF: 221 samples in four studies of binary outcome [i.e., case and control]) and breast cancer expression profiles provided by The Cancer Genome Atlas (TCGA) including mRNA, copy number variation (CNV) and epigenetic DNA methylation. (http://cancergenome.nih.gov/). "We demonstrate application of MetaSTP methods to three real omics examples of breast cancer expression profiles (1658 samples in seven studies), IPF expression profiles (IPF: 229 samples in six studies) and The Cancer Genome Atlas multi-cancer methylation profiles (http://cancergenome.nih.gov/). "1795 samples in six studies" "125 surgical lung biopsies from 86 patients. 58 samples were identified by the expert panel as usual interstitial pneumonia, 23 as non-specific interstitial pneumonia, 16 as hypersensitivity pneumonia, four as sarcoidosis, four as respiratory bronchiolitis, two as cryptogenic organizing pneumonia, and 18 as subtypes other than usual interstitial pneumonia"</p>	<p>Case-control study</p>	<p>AUC, accuracy (10-fold CV)</p>	<p>cross-validation</p>
<p>Kim, S and Song, J H and Lee, J and Koo, J Y</p>	<p>Meta-analytic support vector machine for integrating multi-omic data</p>	<p>BioData Mining</p>	<p>10</p>	<p>South Korea</p>	<p>https://doi.org/10.1186/s13047-017-0018-7</p>	<p>article</p>	<p>300 samples of estrogen receptor binary outcome (i.e., ER+ and ER-)" "We demonstrate application of MetaSTP methods to three real omics examples of breast cancer expression profiles (1658 samples in seven studies), IPF expression profiles (IPF: 229 samples in six studies) and The Cancer Genome Atlas multi-cancer methylation profiles (http://cancergenome.nih.gov/). "1795 samples in six studies" "125 surgical lung biopsies from 86 patients. 58 samples were identified by the expert panel as usual interstitial pneumonia, 23 as non-specific interstitial pneumonia, 16 as hypersensitivity pneumonia, four as sarcoidosis, four as respiratory bronchiolitis, two as cryptogenic organizing pneumonia, and 18 as subtypes other than usual interstitial pneumonia"</p>	<p>Case-control study</p>	<p>sensitivity, specificity (cross-validation)</p>	<p>cross-validation</p>
<p>Kim, S and Lin, C W and Tseng, C C</p>	<p>MetaSTP: meta-analytic top scoring pair method for robust cross-validation of omics prediction analysis</p>	<p>Bioinformatics</p>	<p>32</p>	<p>South Korea</p>	<p>https://doi.org/10.1093/bioinformatics/bty113</p>	<p>article</p>	<p>"We propose a meta-analytic support vector machine (Meta-SVM) that can accommodate multiple omics data, making it possible to detect consensus genes associated with diseases across studies. Experimental studies show that the Meta-SVM is superior to the existing meta-analysis method in detecting true signal genes. In real data applications, diverse omics data of breast cancer (TCGA) and mRNA expression data of lung disease (Idiopathic pulmonary Fibrosis, IPF) were applied. As a result, we identified gene sets consistently associated with the diseases across studies."</p>	<p>Case-control study</p>	<p>Youden index (5-fold cross-validation)</p>	<p>cross-validation</p>
<p>Kim, S and Higgins, J and Park, D and Hong, J and Pagan, M and Sridhar, V and Tom, E and Anderson, J and Choi, Y and Lynch, D A and Steele, M J and Faherty, K R and Brown, K K and Farah, F and Bakstein, M J and Parola, A and Selman, M and Wotzka, P J and Nathan, S and O'Conor, T V and Myers, L M and Kozminski, A L and Bagchi, G and Wilensky, G C</p>	<p>Classification of usual interstitial pneumonia in patients with interstitial lung disease: assessment of a machine learning approach using high-dimensional transcriptional data</p>	<p>Respiratory Medicine</p>	<p>6</p>	<p>Mexico</p>	<p>https://doi.org/10.1016/j.rmed.2020.07.004</p>	<p>article</p>	<p>"Idiopathic pulmonary fibrosis is a progressive fibrotic lung disease that distorts pulmonary architecture, leading to hypoxia, respiratory failure, and death. Diagnosis is difficult because other interstitial lung diseases have similar radiological and histopathological characteristics. We aimed to develop a molecular test that distinguishes usual interstitial pneumonia from other interstitial lung diseases in surgical lung biopsy samples. [...] The meta-analytic classifier was trained on 77 samples and was assessed in a test set of 48 samples, for which it had a specificity of 92% (95% CI: 81-100) and a sensitivity of 82% (64-95)."</p>	<p>Case-control study</p>	<p>sensitivity, specificity (training/test set split)</p>	<p>training + test set</p>

Author(s)	Year	Journal	Volume	Issue	Page(s)	DOI	Article Type	Abstract Summary	Case(s) only (Sng sensitivity prediction)	AUC (10-fold CV)	Cross-validation	
93 Kim, Y and Bionzer, T and Zwart, M and Wessels, L F A and van, D J	2019	Netherlands	10	1	5034-5034	10.1093/bioinformatics/btz222	Genomic data integration by WOV-PARAFAC for predicting drug sensitivity in vivo	1813 genes by 955 cell lines	1813 genes by 955 cell lines	1813 genes by 955 cell lines	1813 genes by 955 cell lines	1813 genes by 955 cell lines
94 Kim, Y R and Kim, D and Kim, S Y	2019	Korea	51	2	672-684	10.1093/bioinformatics/btz111	Prediction of Acquired Tazane Resistance Using Personalized Pathway-based Machine Learning Method	more than 50 samples per group for most human cancer cell line datasets considered	more than 50 samples per group for most human cancer cell line datasets considered	more than 50 samples per group for most human cancer cell line datasets considered	more than 50 samples per group for most human cancer cell line datasets considered	more than 50 samples per group for most human cancer cell line datasets considered
95 Kirgizov, T and Kilic, S and Abal, Z Y and Yaman, A and Kaygusu, S B and Ertan, M and Turan, S and Hahiro, S and Sagiroglu, M S and Beneket, A and Gunar, T	2019	Hormone Research in Pediatrics	91		128-128	10.1093/erj/erj184	Simplifying the interpretation of steroid metabolome data by a machine-learning approach	500 healthy controls and 427 treatment-naive children with a disorder of adrenal steroidogenesis	500 healthy controls and 427 treatment-naive children with a disorder of adrenal steroidogenesis	500 healthy controls and 427 treatment-naive children with a disorder of adrenal steroidogenesis	500 healthy controls and 427 treatment-naive children with a disorder of adrenal steroidogenesis	500 healthy controls and 427 treatment-naive children with a disorder of adrenal steroidogenesis
96 Kitazawa, H and Muramatsu, H and Murakami, N and Okino, Y and Wakamatsu, M and Yoshida, T and Yamada, M and Yamamoto, K and Taniguchi, R and Kawashima, N and Nishikawa, A and Nurtia, A and Nishi, N and Kojima, S and Takahashi, Y	2019	Blood	134			10.1182/blood-2019-07-877072	Genome-wide methylation analysis using the digital restriction enzyme enzyme M and methylase M for stratification of patients with juvenile myelomonocytic leukemia	99 children (67 boys and 32 girls) with JMML	99 children (67 boys and 32 girls) with JMML	99 children (67 boys and 32 girls) with JMML	99 children (67 boys and 32 girls) with JMML	99 children (67 boys and 32 girls) with JMML
97 Kong, A and Asencio, R	2017	Statistical Applications in Genetics and Molecular Biology	16	1	13-30	10.1093/bioinformatics/btt116	Binary Markov Random Fields and interpretable mass spectra discrimination	"A dataset of 238 MALDI-colonial mass spectra and two datasets of 236 and 233 SELDI-ovarian mass spectra respectively were used to test our approach."	"A dataset of 238 MALDI-colonial mass spectra and two datasets of 236 and 233 SELDI-ovarian mass spectra respectively were used to test our approach."	"A dataset of 238 MALDI-colonial mass spectra and two datasets of 236 and 233 SELDI-ovarian mass spectra respectively were used to test our approach."	"A dataset of 238 MALDI-colonial mass spectra and two datasets of 236 and 233 SELDI-ovarian mass spectra respectively were used to test our approach."	"A dataset of 238 MALDI-colonial mass spectra and two datasets of 236 and 233 SELDI-ovarian mass spectra respectively were used to test our approach."
98 Krwaczuk, J and Lukaszuk, T	2016	Artif Intell Med	66		63-71	10.1016/j.artmed.2016.07.001	The feature selection bias problem in relation to high-dimensional gene data	seven microarray datasets with > 50 samples/group for multiple datasets were used	seven microarray datasets with > 50 samples/group for multiple datasets were used	seven microarray datasets with > 50 samples/group for multiple datasets were used	seven microarray datasets with > 50 samples/group for multiple datasets were used	seven microarray datasets with > 50 samples/group for multiple datasets were used
99 Wittenberg, C and Bockmuhl, A S and Baber, J and Bangalore, S and Messeri, F H and Wilson Tang, W H	2018	Curr Hypertens Rep	20	9	75-75	10.1093/cthr/cpy014	Future Direction for Using Artificial Intelligence to Predict and Manage Hypertension	review (not applicable)	review (not applicable)	review (not applicable)	review (not applicable)	review (not applicable)
100 Kus, C H S and Pavlidis, S and Laza, M and Barbaud, F and Rowe, A and Pandis, I and Rossio, C and Hahiro, S and Sakaguchi, M and Daux, P and Chung, L F A and Akocak, M and Kim, G Y	2015	American Journal of Respiratory and Critical Care Medicine	191			10.1164/rccm.2014.04.0814	Adhms phenotypes from semi-supervised machine-learning analysis of bronchial biopsy and brush transcripts in 10 biopsied	"Subjects with moderate-to-severe asthma recruited in the IL13OPRD study underwent fiberoptic bronchoscopy for bronchial biopsy (9) and brush (10) samples"	"Subjects with moderate-to-severe asthma recruited in the IL13OPRD study underwent fiberoptic bronchoscopy for bronchial biopsy (9) and brush (10) samples"	"Subjects with moderate-to-severe asthma recruited in the IL13OPRD study underwent fiberoptic bronchoscopy for bronchial biopsy (9) and brush (10) samples"	"Subjects with moderate-to-severe asthma recruited in the IL13OPRD study underwent fiberoptic bronchoscopy for bronchial biopsy (9) and brush (10) samples"	"Subjects with moderate-to-severe asthma recruited in the IL13OPRD study underwent fiberoptic bronchoscopy for bronchial biopsy (9) and brush (10) samples"
101 Kurus, M B	2014	BMC Bioinformatics	15		8-8	10.1186/s12859-014-0234-3	Robustness of Random Forest-based gene selection methods	4 microarray datasets were used, one contained > 50 samples per group	4 microarray datasets were used, one contained > 50 samples per group	4 microarray datasets were used, one contained > 50 samples per group	4 microarray datasets were used, one contained > 50 samples per group	4 microarray datasets were used, one contained > 50 samples per group
102 Kowabara, H and Iwabuchi, A and Sova, R and Inomoto, M and Ishizaki, T and Tsuchida, A and Nagakawa, Y and Katsumata, K and Sugimoto, M	2019	Annals of Oncology	30		446-446	10.1093/annonc/mdz066	Salivary metabolomics for colorectal cancer detection	"231 subjects with CRC, 99 subjects with polyps, and 2272 subjects with healthy controls"	"231 subjects with CRC, 99 subjects with polyps, and 2272 subjects with healthy controls"	"231 subjects with CRC, 99 subjects with polyps, and 2272 subjects with healthy controls"	"231 subjects with CRC, 99 subjects with polyps, and 2272 subjects with healthy controls"	"231 subjects with CRC, 99 subjects with polyps, and 2272 subjects with healthy controls"
103 Lacroix-Trék, M and Kempowski-Hamon, J and Van Valle, C and Hodajaj, L and Larnane, S and Trouill, L and Puythouin, L and Mhamdi, L and Dalem, F and Fillard, T and Favre, C and de Launay, M and Van Le Bern-Arson, A	2013	Laboratory Investigation	93		51A-51A	10.1093/bioinformatics/btz111	Fuzzy logic selection as a new reliable tool to identify gene signatures in breast cancer	7 breast cancer microarray datasets + 151 consecutive invasive breast carcinomas	7 breast cancer microarray datasets + 151 consecutive invasive breast carcinomas	7 breast cancer microarray datasets + 151 consecutive invasive breast carcinomas	7 breast cancer microarray datasets + 151 consecutive invasive breast carcinomas	7 breast cancer microarray datasets + 151 consecutive invasive breast carcinomas
104 Li, A and Panos, R and Marjanovic, M and Walker, M and Fuentes, L and Kap, D and San Hender, W D and Buturovic, J and Miller, M H	2012	Journal of Clinical Oncology	30	15		10.1200/JCO.2011.20011	A gene expression profile test that distinguishes ovarian from endometrial cancers	75 metastatic, poorly differentiated or undifferentiated primary FIFR tumor specimens	75 metastatic, poorly differentiated or undifferentiated primary FIFR tumor specimens	75 metastatic, poorly differentiated or undifferentiated primary FIFR tumor specimens	75 metastatic, poorly differentiated or undifferentiated primary FIFR tumor specimens	75 metastatic, poorly differentiated or undifferentiated primary FIFR tumor specimens

Author(s)	Year	Country	Journal	Article Type	Abstract Summary	Case-control Study	Accuracy	Methodology	Validation				
Lawton, K A and Brown, M V and Alexander, D and Li, Z and Wulff, E and Lawson, R and Jaffe, M and Mitsuru, M and Ayoub, J and Al-Bowzer, F and Cuddebois, M E and Henry, D	2014	England	Oral Degener	15	5	362-370	2014	England	article	Plasma metabolomic biomarker panel to distinguish patients with asymptomatic latent sarcosis from disease-free controls. Integrated machine learning pipeline for aberrant biomarker enrichment (n=160) samples, treatment-naïve SLE (n=1,200) samples, and SLE samples exposed to various treatments (n=1,200)	Case-control study	AUC, sensitivity, specificity (training / test set split)	training + test set
Lu, T T and Blackwood, N O and Taroni, J and Fu, W and Breitenstein, M K	2018	USA	AMA Assoc Symp Proc	2018	1358-1367	2018	USA	article	Review (not applicable)	Case-control + treatment response	balanced accuracy cross-validation + 20% hold-out test set	cross-validation + test set	
Ledrick, M and Vittart, S and Martini-Magnietti, M and Scott Boyer, M P and Perin, O and Bergeron, A and Fradet, Y and Dixon, A	2019	Canada	Frontiers in Genetics	10	2019	Canada	article	Review (not applicable)	Five microarray datasets were used, including datasets with >50 samples per group	Case-control study	accuracy (ACC), balanced error rate (BER), Matthews' correlation coefficient (MCC), area under the curve (AUC), sensitivity, specificity, Receiver Mean Squared Error (RMSE), Correlation Coefficient (CC) (10-fold CV)	cross-validation	
Lee, S S and Atwood, K and Roder, H and Ameliaz, S and Meyer, C and Kakolyris, S and Oliveira, C and Roder, J and Grigoriou, J and Chelis, L and Lee, Y and Al Mahalingam, D	2019	USA	Cancer Research	79	13	2019	USA	meeting abstract	156 pts (97 HCC, 59 non-HCC healthy controls)	Case-control study	AUC (training and validation cohort)	external cohort validation	
Liu, X and Affari, B and Marchionni, L and Cope, L and Parmigiani, G and Naiman, D and Gemma, D	2009	USA	BMC Bioinformatics	10	256-266	2009	USA	article	118 samples for BRCA1 breast cancer + three datasets used for the ER Lasso cross-study validation, including a dataset with ~50 samples per group	Case-control study	accuracy, sensitivity, specificity (LOOCV, cross-study validation)	cross-validation	
Liu, Y and Xing, L and Zhang, X and Zhang, X	2019	China	Genes (Basel)	10	6	2019	China	article	94 osteosarcoma patients. A total of 188 samples from the peripheral blood of females, including 47 osteosarcoma and 7 non-osteosarcoma patients, were used for expression profiling.	Cases only (survival)	AUC (10-fold CV)	cross-validation	
Liu, M C and Jamshidi, A and Vero, O and Fields, A and Maher, M C and Cam, G and Amin, H and Gross, S and Breslow, J and Miller, M and Schellerger, J and Kurtzman, K N and Fung, T and Madala, T and Onouf, O R and Kishi, E A and Spigel, D R and Hartman, A R and Aravani, A and Seiden, M	2016	China	Mol Med Rep	14	4	3052-3058	2016	China	article	Analysis of gene expression profile identifies potential biomarkers for attherosclerosis	Case-control study	AUC (5-fold CV)	cross-validation
Liu, M C and Jamshidi, A and Vero, O and Fields, A and Maher, M C and Cam, G and Amin, H and Gross, S and Breslow, J and Miller, M and Schellerger, J and Kurtzman, K N and Fung, T and Madala, T and Onouf, O R and Kishi, E A and Spigel, D R and Hartman, A R and Aravani, A and Seiden, M	2019	China	Journal of Clinical Oncology	37	2019	China	meeting abstract	811 cancer cell methylomes representing 21 tumor types	811 cancer cell methylomes representing 21 tumor types	Tissue-of-origin prediction	accuracy (training / test set split)	training + test set	
Liu, W T and Wang, L and Zhang, J and Ye, F and Hui, X and Li, B and He, Q Y	2018	China	Cancer Lett	425	483-5	2018	China	article	5 different microarray datasets that included 330 samples	Case-control study	accuracy (LOOCV, external test set)	cross-validation + external cohort validation	
Liu, Y and Yue, L and Yang, T and Drinkenburg, W and Peeters, P and Stekler, T and Narayan, V A and Wittenberg, G and J	2016	Belgium	BMC Genomics	17	669-669	2016	Belgium	article	The data set consists of 97 healthy controls and 90 MDD subjects	Case-control study	accuracy, sensitivity, specificity (10-fold CV)	cross-validation	
Long, N P and Jung, H and Yoon, S J and Ahn, N H and Ngi, T D and Kang, Y P and Yan, H and Kim, M M	2016	Vietnam	Oncotarget	8	65	109456	2016	Vietnam	article	202 cancer, 115 cervical intraepithelial neoplasia (CIN), and 105 normal samples	Case-control study	accuracy, sensitivity, specificity (10-fold CV, external test set)	cross-validation + external cohort validation
Long, N P and Ngi, T D and Kang, Y P and Yan, H and Kim, M M and Park, S K and Kwon, S W	2020	USA	Metabolites	10	2	2020	USA	article	Review (not applicable)	review	review		
Long, N P and Park, S and Ahn, N H and Ngi, T D and Yoon, S J and Park, J H and Lim, J and Kwon, S W	2019	Vietnam	Int J Mol Sci	20	2	2019	Vietnam	article	202 cancer, 115 cervical intraepithelial neoplasia (CIN), and 105 normal samples	Case-control study	AUC, sensitivity, specificity (5-times repeated 10-fold CV, test set)	cross-validation + test set	
Long, N P and Yoon, S J and Ahn, N H and Ngi, T D and Lim, J and Hong, Y J and Hong, S S and Kwon, S W	2018	South Korea	Metabolites	10	8	109-109	2018	South Korea	article	Review (not applicable)	review	AUC, sensitivity, specificity (25 discovery studies + different validation strategies across 9 validation studies)	

"Our objective was to identify plasma biomarkers of ALS that can aid in distinguishing patients with ALS from those with disease mimics. Using all identified biochemicals detected in >50% of samples in the metabolomics analysis, samples were classified as ALS or mimic with 65% sensitivity and 81% specificity by LASSO analysis (AUC of 0.76). A subset panel of 32 candidate biomarkers classified these diagnosis groups with a specificity of 90% sensitivity 58% (AUC of 0.81)."

"Within a compendium of systemic lupus erythematosus (SLE) patients, we applied the integrated machine learning pipeline for aberrant biomarker enrichment (n=160) to profile de novo gene expression features affecting C22D, C22E and C23D gene abundance. Utilizing carefully aggregated secondary data and leveraging a priori hypotheses, we made robust biomarker profiling among interdependent biological features."

"The identification of biomarker signatures in omics molecular profiling is usually performed to predict outcomes in a precision medicine context, such as patient disease susceptibility, diagnosis, prognosis, and treatment response. To identify these signatures, we have developed a biomarker discovery tool, called BioBioML. From a collection of samples and their associated characteristics, i.e., the biomarkers (e.g., gene expression, protein levels, clinical-pathological data), BioBioML exploits various feature selection procedures to produce signatures associated to machine learning models that will predict efficiently a specified outcome. To this purpose, BioBioML uses a large variety of machine learning algorithms to select the best combination of biomarkers for predicting categorical or continuous outcomes from highly unbalanced datasets."

"Early detection is critical to improve outcome in hepatocellular carcinoma (HCC). A test to detect HCC in a high-risk population from 30.5 us, combining MALDI mass spectrometry and AFP data was developed using a dropout-regularized hierarchical machine learning approach designed to minimize overfitting in small development sets. It was previously validated in 293 high risk pts (158 HCC, 135 non-HCC) with S2/P of 83%/84% in development and 81%/79% in validation across various etiologies and Child-Pugh classification [...]. In independent validation, AUC for the test output prior to thresholding was 0.975, significantly better than AFP AUC 0.915 (P=0.001)."

"We present a three-gene version of 'relative expression analysis' (REA), a rigorous and systematic comparison with earlier approaches in a variety of cancer studies, a clinically relevant application to predicting germline BRCA1 mutations in breast cancer and a cross-study validation for predicting ER status in the BRCA1 study. REA yields high accuracy with a simple decision rule: in tumors carrying mutations, the expression of a 'reference gene' falls between the expression of two differentially expressed genes, PPF1CB and RNFLF4."

"Osteosarcoma is a common malignancy with high mortality and poor prognosis due to lack of predictive markers. The aim of this study was to identify a prognostic pseudogene signature of osteosarcoma by machine learning. A sample of 94 osteosarcoma patients' RNA-seq data with clinical follow-up information was involved in the study. The survival-related pseudogenes were screened and related signature model was constructed by co-expression analysis (Levenstein, Isaac, and Shifman). In total, 125 survival-related pseudogenes were identified and a four-pseudogene (RP11-55114.1, HR, 0.65 (95% CI: 0.44-0.95); RP17AP2, HR, 0.32 (95% CI: 0.14-0.76); WTA816.3, HR, 1.89 (95% CI: 1.35-2.63); RP132A3.3, HR, 0.5295% (CI: 0.37-0.74)) signature effectively distinguished the high- and low-risk patients, and predicted prognosis with high sensitivity and specificity (AUC: 0.878)."

"The present study aimed to identify potential biomarkers for atherosclerosis via analysis of gene expression profiles [...]. The RF algorithm was used to identify 11 biomarkers, whose receiver operating characteristic curves had an area under curve of 0.92, indicating that the identified 11 biomarkers were representative."

"For multi-cancer detection using DNA, TCGO demonstrated a critical role in a safe and efficient diagnostic follow-up. Previous array-based studies captured ~2% of genomic CpGs. Here, we report genome-wide fragment level methylation patterns across 811 cancer cell methylomes representing 21 tumor types (97% of SEER cancer incidence), and define effects of this methylation database on TCGO prediction within a machine learning framework. Improvement was observed across all cancer types and was consistent in early-stage cancers (Stage I-III). Respective performances in breast cancer (n = 23) were 70% vs 90%, in lung cancer (n = 32) were 85% vs 88%, in hepatocellular (n = 10) were 70% vs 90%, and in pancreatic cancer (n = 17) were 94% vs 100%."

"Lung adenocarcinoma (LAC) is the most lethal cancer and the leading cause of cancer-related death worldwide. To determine potential indicators of LAC, we performed genome-wide relative significance (GWRS), genome-wide global significance (GWGS) and support vector machine (SVM) analyses progressively to identify robust gene biomarker signatures from 5 different microarray datasets that included 330 samples. In conclusion, our integrated microarray analysis demonstrated that CNPA, CD1 and CCDC1 might serve as a novel cluster of prognostic biomarkers for LAC, and the cooperative use of these genes provides a technically simple approach for identification of LAC patients."

"Here we report results on the Incan-BMC metabolomics data set, consisting of 97 healthy control and 90 MDD subjects, of which 21 suffer melancholic depression and 58 from anxious depression. In this work, our goals are three-fold. First, we test the hypothesis that more clinically homogeneous groups of MDD patients are easier to predict from healthy controls than the entire MDD group using blood metabolomics data. Second, we develop a novel method for building maximally predictive and robust machine-learning classifiers that retain information on the correlation structure of the metabolomics data to ease biological interpretation. Third, we use this framework to describe the metabolomics biosignature of melancholic depression."

"In this study, eight different gene expression data sets containing 202 cancer, 115 cervical intraepithelial neoplasia (CIN), and 105 normal samples were utilized for an integrative systems biology assessment in a multi-stage carcinogenesis manner. Deep learning-based diagnostic models were established based on the genetic panels of intrinsic genes of cervical carcinogenesis as well as on the unbiased variable selection approach [...]. The 168 gene deep learning model for the differentiation of cancer from normally achieved an externally validated accuracy of 97.96% (95.02% sensitivity and 95.65% specificity). Survival analysis revealed that 2NF281 and EPHB6 were the two most promising prognostic genetic markers for Cx6 among others."

"Despite the tremendous success, pitfalls have been observed in every step of a clinical metabolomics workflow, which impedes the internal validity of the study. In this conceptual review, we will cover inclusive barriers of a metabolomics-based clinical study and suggest potential solutions in the hopes of enhancing study robustness, usability, and transferability. The importance of quality assurance and quality control procedures is discussed, followed by a practical rule containing three phases, including two additional 'pre-pre' and 'post-post' analytical steps. Besides, we will elucidate the potential involvement of machine learning and demonstrate that the need for automated data mining algorithms to improve the quality of future research is undeniable. Consequently, we propose a comprehensive metabolomics framework, along with an appropriate checklist refined from current guidelines and our previously published assessments, in the attempt to accurately track achievements in metabolomics into clinical and epidemiological research."

"This study employed a novel approach combining multi-platform transcriptomic and cutting-edge algorithms to introduce novel signatures for accurate diagnosis of colorectal cancer (CRC). All models showed satisfactory performance in which RF appeared to be the best. For instance, regarding the RF model, the following were observed: mean accuracy 0.998 (standard deviation (SD) < 0.003), mean specificity 0.999 (SD < 0.003), and mean sensitivity 0.998 (SD < 0.004). Moreover, proposed biomarker signatures were highly associated with multifactorial hallmarks in cancer."

"In this study, we conducted a systematic review to examine recent advancements in the oncometabolomics-based diagnostic biomarker discovery and validation in pancreatic cancer. The included 25 studies primarily focused on the identification rather than the validation of predictive capacity of potential biomarkers. The sample size ranged from 10 to 8760. External validation of the biomarker panels was observed in nine studies. The diagnostic area under the curve ranged from 0.88 to 1.00 (sensitivity 0.4-1.0, specificity 0.7-1.0). The effects of patient's bio-parameters on metabolome alterations in a context-dependent manner have not been thoroughly elucidated."

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An unsupervised machine learning method for discovering patient clusters based on genetic signatures	J Biomed Inform	85	30-39	2018	USA	https://doi.org/10.1016/j.jbi.2018.07.017	article	191 multiple sclerosis patient	Clases only (sub-group stratification)	Random index on benchmark clusters (10-fold CV)	cross-validation	<p>"This work presents an unsupervised machine learning method to cluster patients based on their genomic makeup without providing input parameters a priori. The method implements internal validity metrics to algorithmically identify the number of clusters, as well as statistical analyses to test for the significance of the results. Furthermore, the method takes advantage of the high degree of linkage disequilibrium between single nucleotide polymorphisms. Firstly, a gene pathway analysis is performed to identify potential relationships between the clusters in the context of known biological knowledge. Benchmark results indicate that the proposed method provides the greatest performance out of the methods tested."</p> <p>"Based on increasing evidence suggesting that MS pathology involves alterations in bioactive lipid metabolism, the present analysis was aimed at generating a complex serum lipid biomarker. Using unsupervised machine learning, implemented as an emergent self-organizing maps of neuronal networks, swarm intelligence and Minimum Curvature Embedding, a cluster structure was found in the input data space comprising serum concentrations of 4-43 different lipid markers of various classes. This was subsequently assessed using supervised machine learning, implemented as random forests and composed AUC analysis feature selection. Bayesian statistics-based biomarker creation was used to map the diagnostic classes of either MS patients (n = 102) or healthy subjects (n = 301). A complex classifier or biomarker was developed that predicted MS at a sensitivity, specificity and accuracy of approximately 95% in training and test data sets, respectively."</p>
Machine-learning based lipid mediator serum concentration patterns allow identification of multiple sclerosis patients with high accuracy	Sci Rep	8	1	14884	2018	Germany	https://doi.org/10.1038/s41598-018-33072-z	MS patients (n = 102) and healthy subjects (n = 301)	Case-control study	accuracy, sensitivity, specificity (10-fold nested CV)	cross-validation	<p>"Epithelial ovarian cancer patients usually relapse after primary management. We utilized the support vector machine algorithm to develop a model for the chemorecurrence using the Cancer Cell Line Encyclopedia (CCLE) and validated the model in The Cancer Genome Atlas (TCGA) and the GSE8983 dataset. The 10-gene predictive model demonstrated that the high response group had a longer recurrence-free survival (RFS) (log-rank test, p = 0.015 for TCGA, p = 0.013 for GSE8983 and p = 0.039 for NTH) and overall survival (OS) (log-rank test, p = 0.002 for TCGA and p = 0.016 for NTH). In a multivariate Cox hazard regression model, the predictive model (HR: 0.644, 95% CI: 0.436-0.952, p = 0.027) and residual tumor size <1 cm (HR: 0.312, 95% CI: 0.170-0.573, p < 0.001) were significant factors for recurrence. The predictive model (HR: 0.511, 95% CI: 0.334-0.783, p < 0.002) and residual tumor size <1 cm (HR: 0.252, 95% CI: 0.128-0.496, p < 0.001) were significant factors for death."</p> <p>"Lung adenocarcinoma (LUAD) accounts for a majority of cancer-related deaths worldwide annually. The identification of prognostic biomarkers and prediction prognosis for LUAD patients is necessary. In this study, LUAD RNA-Seq data and clinical data from The Cancer Genome Atlas (TCGA) were divided into TCGA cohort 1 (n = 338) and (n = 158). First, the survival-related seed genes were selected from the cohort 1 using the machine learning model (random survival forest, RSF), and then in order to improve prediction accuracy, the forward selection model was utilized to identify the prognosis-related key genes among the seed genes using the clinically-integrated RNA-Seq data. Second, the survival risk score system was constructed by using these key genes in the cohort 1, the GSE27094 cohort and the GSE11969 cohort, and the evaluation metrics such as HR, p value and C-index were calculated to validate the proposed method. Based on the RSF model and clinically-integrated RNA-Seq data, we identified seven key genes that formed the prognostic gene expression signature. These seven key genes could achieve a strong power for prognostic prediction of LUAD patients in cohort 1 (HR = 3.80, p = 1.6e-06, C-index = 0.656), and were further validated in the GSE27094 cohort (HR = 4.12, p = 1.34e-10, C-index = 0.672) and GSE11969 cohort (HR = 3.87, p = 6.81e-07, C-index = 0.670)."</p>
Developing a Prognostic Gene Panel of Lung and Ovarian Cancer Patients by a Machine Learning Model	Cancers	11	2	11313	2019	Switzerland	https://doi.org/10.3390/cancers110911313	3 different datasets with > 50 samples per group	Cases only (prognosis study)	accuracy, log-rank test p-value (LODCV)	cross-validation	<p>"We show that by examining how fast DV performance approaches RCV as the number of studies is increased, one can estimate when "sufficient" diversity has been achieved for learning a molecular signature likely to translate without significant loss of accuracy to new clinical settings."</p> <p>"In this chapter, we review common bioinformatic approaches that aim to use sequencing data to predict sample-specific drug susceptibility. First, we explain the importance of customized drug regimens to the future of medical care. Second, we discuss the different public databases and community efforts that can be leveraged to develop new methods for identifying new predictive biomarkers. Third, we cover the basic methods that are currently used to identify markers or signatures of drug response, without any prior knowledge of the drug's mechanism of action. We further discuss how one can integrate knowledge about drug targets, mechanisms, and predictive markers to better estimate drug response in a diverse set of samples. We begin this section with a primer on popular methods to identify targets and mechanism of action for new small molecules. This discussion also includes a set of computational methods that incorporate other drug features, which do not relate to drug-induced genetic changes or sequencing data such as drug structures, side-effects, and efficacy profiles."</p>
Identification of a sixteen-gene prognostic biomarker for lung adenocarcinoma using a machine learning method	Journal of Cancer	11	5	1288-1298	2020	China	https://doi.org/10.7150/jco.4455	TCGA cohort (n = 338) and (n = 148) 11,470 microarray samples of lung phenotypes from 26 independent experimental studies and 209 RNA-seq samples of lung phenotypes from 4 independent studies	Cases only (prognosis study)	hazard ratio, p-value and C-index (training / test set split)	training + test set	<p>"We show that by examining how fast DV performance approaches RCV as the number of studies is increased, one can estimate when "sufficient" diversity has been achieved for learning a molecular signature likely to translate without significant loss of accuracy to new clinical settings."</p> <p>"In this chapter, we review common bioinformatic approaches that aim to use sequencing data to predict sample-specific drug susceptibility. First, we explain the importance of customized drug regimens to the future of medical care. Second, we discuss the different public databases and community efforts that can be leveraged to develop new methods for identifying new predictive biomarkers. Third, we cover the basic methods that are currently used to identify markers or signatures of drug response, without any prior knowledge of the drug's mechanism of action. We further discuss how one can integrate knowledge about drug targets, mechanisms, and predictive markers to better estimate drug response in a diverse set of samples. We begin this section with a primer on popular methods to identify targets and mechanism of action for new small molecules. This discussion also includes a set of computational methods that incorporate other drug features, which do not relate to drug-induced genetic changes or sequencing data such as drug structures, side-effects, and efficacy profiles."</p>
Measuring the effect of inter-study variability on estimating prediction error	PLoS One	9	10	e110840	2014	America	https://doi.org/10.1371/journal.pone.0110840		Case-control study	excludes an entire study for testing"	cross-validation + external cohort validation	<p>"We show that by examining how fast DV performance approaches RCV as the number of studies is increased, one can estimate when "sufficient" diversity has been achieved for learning a molecular signature likely to translate without significant loss of accuracy to new clinical settings."</p> <p>"In this chapter, we review common bioinformatic approaches that aim to use sequencing data to predict sample-specific drug susceptibility. First, we explain the importance of customized drug regimens to the future of medical care. Second, we discuss the different public databases and community efforts that can be leveraged to develop new methods for identifying new predictive biomarkers. Third, we cover the basic methods that are currently used to identify markers or signatures of drug response, without any prior knowledge of the drug's mechanism of action. We further discuss how one can integrate knowledge about drug targets, mechanisms, and predictive markers to better estimate drug response in a diverse set of samples. We begin this section with a primer on popular methods to identify targets and mechanism of action for new small molecules. This discussion also includes a set of computational methods that incorporate other drug features, which do not relate to drug-induced genetic changes or sequencing data such as drug structures, side-effects, and efficacy profiles."</p>
Bioinformatics Approaches to Predict Drug Responses from Genomic Sequencing	Methods Mol Biol	1711		277-296	2018	USA	https://doi.org/10.1007/978-1-4939-9746-1_11		review (not applicable)	review		<p>"Deep neural networks (DNNs) are efficient algorithms based on the use of compositional layers of neurons, with advantages well matched to the challenges - omics data presents. While achieving state-of-the-art results and even surpassing human accuracy in many challenging tasks, the adoption of deep learning to biomedicine has been comparatively slow. Here, we discuss key features of deep learning that may give this approach an edge over other machine learning methods. We then consider limitations and review a number of applications of deep learning in biomedical studies demonstrating proof of concept and practical utility."</p> <p>"DNA methylation data based precision cancer diagnostics is emerging as the state of the art for molecular tumor classification. Standards for choosing statistical methods with regard to well-calibrated probability estimates for these typically highly multiclass classification tasks are still lacking. To support this choice, we evaluated well-established machine learning (ML) classifiers including random forests (RF), elastic net (ENET), support vector machines (SVM) and boosted trees in combination with post-processing algorithms and developed ML workflows that allow for unbiased class probability (CP) estimation. ENET was the top stand-alone classifier with the best calibration profiles. The best overall two-stage workflow was MR-calibrated SVM with linear kernels closely followed by ridge-calibrated tuned RF. For calibration, SVM was the most effective regardless of the primary classifier. The protocols developed as a result of these comparisons provide valuable guidance on choosing ML workflows and their tuning to generate well-calibrated CP estimates for precision diagnostics using DNA methylation data."</p> <p>"Traumatic brain injury (TBI) affects 1.7 million people in the United States each year, causing lifelong functional deficits in cognition and behavior. The complex pathophysiology of neural injury is a primary barrier to developing sensitive and specific diagnostic tools, which consequently has a detrimental effect on treatment regimens. Biomarkers of other diseases (e.g. cancer) have provided critical insight into disease emergence and progression that lend to developing powerful clinical tools for intervention. Therefore, the biomarker discovery field has recently focused on TBI and made substantial advancements to characterize markers with promise of transforming TBI patient diagnostics and care. This review focuses on these key advances in neural injury biomarkers discovery, including novel approaches spanning from omics-based approaches to imaging and machine learning as well as the evolution of established techniques. [...] Several biomarkers of TBI have been identified but they carry the disadvantage of either not being sensitive or specific to TBI, which diminishes their clinical utility. Biomarkers have the potential for improving diagnostic accuracy, predicting the severity of injury progression, and conveying information to clinicians about injury progression for individual patients. Advancements in biomarker discovery range from improving upon already established techniques to applying novel methods to elucidate mechanisms of the neural injury environment."</p> <p>"Non-Alcoholic Fatty Liver Disease encompasses a spectrum of diseases ranging from simple steatosis to NASH and cirrhosis/HCC. The challenge in this field is to recognize the more severe and/or progressive pathology. A reliable non-invasive method based on biomarkers does not exist at the moment. Metabonomics technique has a great potential for this task, because it can non-invasively perform a complete "metabolic fingerprint" of a disease and, in turn, potentially detect all its evolution steps. With this aim, we performed a serum metabonomics characterization of several NAFLD forms and then tested its accuracy confirming it with an independent cohort by means of machine-learning model" approach. [...] Blind analysis using the described test showed a global accuracy for NAFLD identification of 96.8% ± 2.1, 94.0% ± 4.2 for NASH and 81.2% ± 12.2 for NASH cirrhosis identification."</p>
Applications of Deep Learning in Biomedicine	Mol Pharm	13	5	1445-1454	2016	China	https://doi.org/10.1021/acs.molpharmaceut.6b00024		review (not applicable)	review		<p>"Deep neural networks (DNNs) are efficient algorithms based on the use of compositional layers of neurons, with advantages well matched to the challenges - omics data presents. While achieving state-of-the-art results and even surpassing human accuracy in many challenging tasks, the adoption of deep learning to biomedicine has been comparatively slow. Here, we discuss key features of deep learning that may give this approach an edge over other machine learning methods. We then consider limitations and review a number of applications of deep learning in biomedical studies demonstrating proof of concept and practical utility."</p> <p>"DNA methylation data based precision cancer diagnostics is emerging as the state of the art for molecular tumor classification. Standards for choosing statistical methods with regard to well-calibrated probability estimates for these typically highly multiclass classification tasks are still lacking. To support this choice, we evaluated well-established machine learning (ML) classifiers including random forests (RF), elastic net (ENET), support vector machines (SVM) and boosted trees in combination with post-processing algorithms and developed ML workflows that allow for unbiased class probability (CP) estimation. ENET was the top stand-alone classifier with the best calibration profiles. The best overall two-stage workflow was MR-calibrated SVM with linear kernels closely followed by ridge-calibrated tuned RF. For calibration, SVM was the most effective regardless of the primary classifier. The protocols developed as a result of these comparisons provide valuable guidance on choosing ML workflows and their tuning to generate well-calibrated CP estimates for precision diagnostics using DNA methylation data."</p> <p>"Traumatic brain injury (TBI) affects 1.7 million people in the United States each year, causing lifelong functional deficits in cognition and behavior. The complex pathophysiology of neural injury is a primary barrier to developing sensitive and specific diagnostic tools, which consequently has a detrimental effect on treatment regimens. Biomarkers of other diseases (e.g. cancer) have provided critical insight into disease emergence and progression that lend to developing powerful clinical tools for intervention. Therefore, the biomarker discovery field has recently focused on TBI and made substantial advancements to characterize markers with promise of transforming TBI patient diagnostics and care. This review focuses on these key advances in neural injury biomarkers discovery, including novel approaches spanning from omics-based approaches to imaging and machine learning as well as the evolution of established techniques. [...] Several biomarkers of TBI have been identified but they carry the disadvantage of either not being sensitive or specific to TBI, which diminishes their clinical utility. Biomarkers have the potential for improving diagnostic accuracy, predicting the severity of injury progression, and conveying information to clinicians about injury progression for individual patients. Advancements in biomarker discovery range from improving upon already established techniques to applying novel methods to elucidate mechanisms of the neural injury environment."</p> <p>"Non-Alcoholic Fatty Liver Disease encompasses a spectrum of diseases ranging from simple steatosis to NASH and cirrhosis/HCC. The challenge in this field is to recognize the more severe and/or progressive pathology. A reliable non-invasive method based on biomarkers does not exist at the moment. Metabonomics technique has a great potential for this task, because it can non-invasively perform a complete "metabolic fingerprint" of a disease and, in turn, potentially detect all its evolution steps. With this aim, we performed a serum metabonomics characterization of several NAFLD forms and then tested its accuracy confirming it with an independent cohort by means of machine-learning model" approach. [...] Blind analysis using the described test showed a global accuracy for NAFLD identification of 96.8% ± 2.1, 94.0% ± 4.2 for NASH and 81.2% ± 12.2 for NASH cirrhosis identification."</p>
Machine learning workflows to estimate case probabilities for precision cancer diagnostics on DNA methylation microarray data	Protocols	15	2	479-512	2020	Germany	https://doi.org/10.1002/prot.1418	brain tumor 452k DNA methylation cohort of 2,801 samples with 91 diagnostic categories (multiple groups with ~50 samples per group)	Cases only (sub-group stratification)	accuracy (5 × 5-fold nested cross-validation scheme)	cross-validation	<p>"Deep neural networks (DNNs) are efficient algorithms based on the use of compositional layers of neurons, with advantages well matched to the challenges - omics data presents. While achieving state-of-the-art results and even surpassing human accuracy in many challenging tasks, the adoption of deep learning to biomedicine has been comparatively slow. Here, we discuss key features of deep learning that may give this approach an edge over other machine learning methods. We then consider limitations and review a number of applications of deep learning in biomedical studies demonstrating proof of concept and practical utility."</p> <p>"DNA methylation data based precision cancer diagnostics is emerging as the state of the art for molecular tumor classification. Standards for choosing statistical methods with regard to well-calibrated probability estimates for these typically highly multiclass classification tasks are still lacking. To support this choice, we evaluated well-established machine learning (ML) classifiers including random forests (RF), elastic net (ENET), support vector machines (SVM) and boosted trees in combination with post-processing algorithms and developed ML workflows that allow for unbiased class probability (CP) estimation. ENET was the top stand-alone classifier with the best calibration profiles. The best overall two-stage workflow was MR-calibrated SVM with linear kernels closely followed by ridge-calibrated tuned RF. For calibration, SVM was the most effective regardless of the primary classifier. The protocols developed as a result of these comparisons provide valuable guidance on choosing ML workflows and their tuning to generate well-calibrated CP estimates for precision diagnostics using DNA methylation data."</p> <p>"Traumatic brain injury (TBI) affects 1.7 million people in the United States each year, causing lifelong functional deficits in cognition and behavior. The complex pathophysiology of neural injury is a primary barrier to developing sensitive and specific diagnostic tools, which consequently has a detrimental effect on treatment regimens. Biomarkers of other diseases (e.g. cancer) have provided critical insight into disease emergence and progression that lend to developing powerful clinical tools for intervention. Therefore, the biomarker discovery field has recently focused on TBI and made substantial advancements to characterize markers with promise of transforming TBI patient diagnostics and care. This review focuses on these key advances in neural injury biomarkers discovery, including novel approaches spanning from omics-based approaches to imaging and machine learning as well as the evolution of established techniques. [...] Several biomarkers of TBI have been identified but they carry the disadvantage of either not being sensitive or specific to TBI, which diminishes their clinical utility. Biomarkers have the potential for improving diagnostic accuracy, predicting the severity of injury progression, and conveying information to clinicians about injury progression for individual patients. Advancements in biomarker discovery range from improving upon already established techniques to applying novel methods to elucidate mechanisms of the neural injury environment."</p> <p>"Non-Alcoholic Fatty Liver Disease encompasses a spectrum of diseases ranging from simple steatosis to NASH and cirrhosis/HCC. The challenge in this field is to recognize the more severe and/or progressive pathology. A reliable non-invasive method based on biomarkers does not exist at the moment. Metabonomics technique has a great potential for this task, because it can non-invasively perform a complete "metabolic fingerprint" of a disease and, in turn, potentially detect all its evolution steps. With this aim, we performed a serum metabonomics characterization of several NAFLD forms and then tested its accuracy confirming it with an independent cohort by means of machine-learning model" approach. [...] Blind analysis using the described test showed a global accuracy for NAFLD identification of 96.8% ± 2.1, 94.0% ± 4.2 for NASH and 81.2% ± 12.2 for NASH cirrhosis identification."</p>
Current trends in biomarker discovery and analysis tools for traumatic brain injury	Journal of Biological Engineering	13	1		2019	USA	https://doi.org/10.1186/s13039-019-0161-z		review (not applicable)	review		<p>"Deep neural networks (DNNs) are efficient algorithms based on the use of compositional layers of neurons, with advantages well matched to the challenges - omics data presents. While achieving state-of-the-art results and even surpassing human accuracy in many challenging tasks, the adoption of deep learning to biomedicine has been comparatively slow. Here, we discuss key features of deep learning that may give this approach an edge over other machine learning methods. We then consider limitations and review a number of applications of deep learning in biomedical studies demonstrating proof of concept and practical utility."</p> <p>"DNA methylation data based precision cancer diagnostics is emerging as the state of the art for molecular tumor classification. Standards for choosing statistical methods with regard to well-calibrated probability estimates for these typically highly multiclass classification tasks are still lacking. To support this choice, we evaluated well-established machine learning (ML) classifiers including random forests (RF), elastic net (ENET), support vector machines (SVM) and boosted trees in combination with post-processing algorithms and developed ML workflows that allow for unbiased class probability (CP) estimation. ENET was the top stand-alone classifier with the best calibration profiles. The best overall two-stage workflow was MR-calibrated SVM with linear kernels closely followed by ridge-calibrated tuned RF. For calibration, SVM was the most effective regardless of the primary classifier. The protocols developed as a result of these comparisons provide valuable guidance on choosing ML workflows and their tuning to generate well-calibrated CP estimates for precision diagnostics using DNA methylation data."</p> <p>"Traumatic brain injury (TBI) affects 1.7 million people in the United States each year, causing lifelong functional deficits in cognition and behavior. The complex pathophysiology of neural injury is a primary barrier to developing sensitive and specific diagnostic tools, which consequently has a detrimental effect on treatment regimens. Biomarkers of other diseases (e.g. cancer) have provided critical insight into disease emergence and progression that lend to developing powerful clinical tools for intervention. Therefore, the biomarker discovery field has recently focused on TBI and made substantial advancements to characterize markers with promise of transforming TBI patient diagnostics and care. This review focuses on these key advances in neural injury biomarkers discovery, including novel approaches spanning from omics-based approaches to imaging and machine learning as well as the evolution of established techniques. [...] Several biomarkers of TBI have been identified but they carry the disadvantage of either not being sensitive or specific to TBI, which diminishes their clinical utility. Biomarkers have the potential for improving diagnostic accuracy, predicting the severity of injury progression, and conveying information to clinicians about injury progression for individual patients. Advancements in biomarker discovery range from improving upon already established techniques to applying novel methods to elucidate mechanisms of the neural injury environment."</p> <p>"Non-Alcoholic Fatty Liver Disease encompasses a spectrum of diseases ranging from simple steatosis to NASH and cirrhosis/HCC. The challenge in this field is to recognize the more severe and/or progressive pathology. A reliable non-invasive method based on biomarkers does not exist at the moment. Metabonomics technique has a great potential for this task, because it can non-invasively perform a complete "metabolic fingerprint" of a disease and, in turn, potentially detect all its evolution steps. With this aim, we performed a serum metabonomics characterization of several NAFLD forms and then tested its accuracy confirming it with an independent cohort by means of machine-learning model" approach. [...] Blind analysis using the described test showed a global accuracy for NAFLD identification of 96.8% ± 2.1, 94.0% ± 4.2 for NASH and 81.2% ± 12.2 for NASH cirrhosis identification."</p>
Accuracy of metabolomics profiles to non-invasively diagnose NAFLD stages and evolution by mean of machine-learning automated algorithms	Digestive and Liver Disease	52		49-49	2020		https://doi.org/10.1155/2020/2020	Maszone, M and Troisi, J and Aglitti, A and Cavasina, G and Torri, F and Caruso, R and Colucci, A and Dalila, M and Fedecola, A and Balsano, C and Perisio, M	Case-control study	accuracy (training / test set split)	training + test set	<p>"Deep neural networks (DNNs) are efficient algorithms based on the use of compositional layers of neurons, with advantages well matched to the challenges - omics data presents. While achieving state-of-the-art results and even surpassing human accuracy in many challenging tasks, the adoption of deep learning to biomedicine has been comparatively slow. Here, we discuss key features of deep learning that may give this approach an edge over other machine learning methods. We then consider limitations and review a number of applications of deep learning in biomedical studies demonstrating proof of concept and practical utility."</p> <p>"DNA methylation data based precision cancer diagnostics is emerging as the state of the art for molecular tumor classification. Standards for choosing statistical methods with regard to well-calibrated probability estimates for these typically highly multiclass classification tasks are still lacking. To support this choice, we evaluated well-established machine learning (ML) classifiers including random forests (RF), elastic net (ENET), support vector machines (SVM) and boosted trees in combination with post-processing algorithms and developed ML workflows that allow for unbiased class probability (CP) estimation. ENET was the top stand-alone classifier with the best calibration profiles. The best overall two-stage workflow was MR-calibrated SVM with linear kernels closely followed by ridge-calibrated tuned RF. For calibration, SVM was the most effective regardless of the primary classifier. The protocols developed as a result of these comparisons provide valuable guidance on choosing ML workflows and their tuning to generate well-calibrated CP estimates for precision diagnostics using DNA methylation data."</p> <p>"Traumatic brain injury (TBI) affects 1.7 million people in the United States each year, causing lifelong functional deficits in cognition and behavior. The complex pathophysiology of neural injury is a primary barrier to developing sensitive and specific diagnostic tools, which consequently has a detrimental effect on treatment regimens. Biomarkers of other diseases (e.g. cancer) have provided critical insight into disease emergence and progression that lend to developing powerful clinical tools for intervention. Therefore, the biomarker discovery field has recently focused on TBI and made substantial advancements to characterize markers with promise of transforming TBI patient diagnostics and care. This review focuses on these key advances in neural injury biomarkers discovery, including novel approaches spanning from omics-based approaches to imaging and machine learning as well as the evolution of established techniques. [...] Several biomarkers of TBI have been identified but they carry the disadvantage of either not being sensitive or specific to TBI, which diminishes their clinical utility. Biomarkers have the potential for improving diagnostic accuracy, predicting the severity of injury progression, and conveying information to clinicians about injury progression for individual patients. Advancements in biomarker discovery range from improving upon already established techniques to applying novel methods to elucidate mechanisms of the neural injury environment."</p> <p>"Non-Alcoholic Fatty Liver Disease encompasses a spectrum of diseases ranging from simple steatosis to NASH and cirrhosis/HCC. The challenge in this field is to recognize the more severe and/or progressive pathology. A reliable non-invasive method based on biomarkers does not exist at the moment. Metabonomics technique has a great potential for this task, because it can non-invasively perform a complete "metabolic fingerprint" of a disease and, in turn, potentially detect all its evolution steps. With this aim, we performed a serum metabonomics characterization of several NAFLD forms and then tested its accuracy confirming it with an independent cohort by means of machine-learning model" approach. [...] Blind analysis using the described test showed a global accuracy for NAFLD identification of 96.8% ± 2.1, 94.0% ± 4.2 for NASH and 81.2% ± 12.2 for NASH cirrhosis identification."</p>

Author(s)	Year	Country	Journal	Volume	Issue	Page	DOI	Abstract	Keywords	MeSH	PMID
129 Matlock, K and De Nil, C and Rahman, R and Ghosh, S and Pua, R	2018	USA	BMC Bioinformatics	19		71-71	10.1186/s12859-018-1702-2	"We aggregate 50 training samples into our vertical and horizontal groups, build individual predictive model for each group, build the stacking model using a set of 150 samples, and obtain the prediction MSE of candidate models on a set of 50 testing samples. We then add 2 training samples and reestimate the MSE. We repeat this process until the training set has a total of 150 samples. The entire process is replicated 500 times with randomly selected training, testing, and validation sets in every iteration."	Cases only (drug sensitivity prediction)	normalised AUC (training, test and validation set)	training + test set
130 McCarthy, C and Shrestha, S and Ibrahim, N E and Van Kimmerdale, R and Gagli, H K and Mulaik, R and Magner, C A and Barnes, G and Rhyne, R and Garasic, J M and Janusz, I J	2018	Netherlands	European Heart Journal	39		117-117	10.1093/eurheartj/ehy184	"154 patients undergoing peripheral and/or coronary angiography. Performance of a clinical/probomic panel to predict obstructive peripheral artery disease in patients with and without diabetes mellitus."	Case-control study	sensitivity, specificity, PPV, NPV (Monte Carlo cross-validation)	cross-validation
131 McDermott, J E and Wang, J and Mitchell, H and Webb-Robertson, B J and Hufen, R and Ramsey, J and Rofstad, O D	2013	USA	Expert Opinion on Medical Diagnostics	7	1	37-51	10.1080/17513758.2012.728294	"Challenges in biomarker discovery: Combining expert insights with statistical analysis of complex omics."	review (not applicable)	review	
132 McGeehan, M and Kelly, R S and Ljotijaca, A A and Weiss, T S and Lasky, J A	2018	USA	Network of year 3 asthma	197			10.1093/nci/nkz133	"Network of year 3 asthma with indicators of early life asthma."	Case-control study	AUC (five-fold cross-validation)	cross-validation
133 McKillop, P and Tsontas, D and Barlow, C and Weir, J and Macintosh, G and Barber, M and Gouley, B and Bebo, J and Stern, L and Kowalczyk, A and Hawn, J and White, A and Dart, A and Duffy, S and Kingwell, B	2010	Australia	Atherosclerosis Supplement	11	2	24-24	10.1016/j.athero.2010.11.001	"Plasma lipomic analysis of stable and unstable coronary artery disease."	Case-control study	AUC (multiple cross-validation iterations)	cross-validation
134 Monden, M P and Soria, J and Garnett, M and McDermott, U and Benes, C H and Balasoor, P J and Saiz-Rodriguez, J	2013	United Kingdom	PLoS One	8	4	7-7	10.1371/journal.pone.0061917	"Machine Learning Prediction of Cancer Cell Sensitivity to Drugs Based on Genomic and Chemical Properties."	Cases only (drug sensitivity prediction)	R-squared (8-fold cross-validation, hold-out test set)	cross-validation + test set
135 Midoorika, Y and Tsuji, J and Takayama, T and Aburatani, H	2012	Japan	Pharmacogenomics	13	2	191-199	10.1186/1475-2875-13-202	"Genomic approach towards personalized anticancer drug therapy."	review (not applicable)	review	
136 Mobsberry, P and Yousef, S and Angad, M and Gulman, D A and Barnholtz-Sloan, J S and Velazquez Vega, J and For, D J and Cooper, J A D	2018	USA	Proc Natl Acad Sci U S A	115	13	E2970	10.1073/pnas.1711111115	"Predicting cancer outcomes from histology and genomics using convolutional networks."	Cases only (prognosis prediction)	15 accuracy measurements, including Harrell's C-index for measuring concordance between predicted risk and actual survival (Monte Carlo cross-validation)	cross-validation
137 Modin, Ian Kidd, M and Drosow, I and Bode, J and Mizukawa, A and Matar, S	2019	USA	Neuroendocrinology	108		132-132	10.1159/000504966	"Automated finger prick blood genomic diagnosis of neuroendocrine tumors."	Case-control study	sensitivity, specificity (training/test set split)	training + test set
138 Mohammed, A and Biegler, G and Adams, J and Halkar, T	2015	USA	Oncotarget	8	49	8562	10.1186/s12604-015-0242-2	"Identification of potential tissue-specific cancer biomarkers and development of cancer versus normal genomic classifiers."	Case-control study	accuracy, sensitivity, specificity, precision, F1 score (10-fold cross-validation)	cross-validation
139 Mourikis, T P and Benoit, L and Foxall, J and Tseloukidi, D and Nalson, J and Pinner, J and Corvini, M and Lagoren, J and Howell, M and Tau, C and Fitzgerald, R and Scaccia, P and Ciccarini, F	2019	Italy	Nat Commun	10	1	3101-3101	10.1038/s41467-019-09683-8	"Patient-specific cancer genes: history and genomics using pathway and establish therapeutic pathways and establish therapeutic vulnerabilities in esophageal adenocarcinomas."	Cases only (survival prediction)	log-rank test p-value (cross-validation)	cross-validation
140 Munigan, K and Javel, M and Schrodt, A B and Ngo, N and Fumagalli, C M and Alvarado, B M and Miller, V A and Bekai-Sabb, T and Ablesky, L A and Ross, J S and Al, M S	2019	USA	Annals of Oncology	30		2526-2527	10.1093/annonc/mdz001	"Comprehensive genomic profiling (CGP) of metastasizing cholangiocarcinomas (CHCC/CCA)."	Case-control study	error rate, AUC (Random Forest out-of-bag error)	outbag
141 Nakamura, M and Bai, H and Scotti, D and Sourit, E A and Sofia, S and Harris, R J and Hamann, N and Wallius, G and Winship, A and Ghosh, S and Montes, A and Spoor, J F and Van Hemelrijck, D and Joseph, H and Li, Y and Rice, K E and Torka, S and Karamgani, S N	2019	Sweden	Oncotarget	8	6		10.1186/s12604-019-01911-1	"Immune mediator expression (ICPE) of metastasizing cholangiocarcinomas (CHCC/CCA) with improved outcome in ovarian carcinoma."	Cases only (survival prediction)	accuracy, recall, sensitivity, Matthews' correlation coefficient, F1 score (5 times 10 fold cross-validation)	cross-validation

Author	Title	Journal	Year	Country	Article Type	Abstract Summary	Study Design	Key Findings	Validation Type		
142 Nakariakov, S	A hybrid gene selection algorithm based on interaction information for microarray-based cancer classification	PLoS One	14	2	4021233-3	2019 Thailand	article	ten microarray data sets with > 50 samples per group for multiple datasets	Case-control study	accuracy, precision, recall, F-score (nested cross-validation)	cross-validation
143 Naorem, D, D Mohaiyan, M and Venkatesan, A	Integrated network analysis and machine learning approach for the identification of key genes of triple-negative breast cancer	Journal of Cellular Biochemistry	120	4	6154-6167	2019 India	article	Six microarray data sets consisting of 463 non-TNBC and 405 TNBC samples	Case-control study	AUC (training / test set split)	training + test set
Nazha, A and Komroji, R S and Barnard, J and Al-Isa, K and Padron, E and Madanat, Y F and Kumanov, T and Alshahr, N and Steensma, D P and Dzüden, A E and Roboz, G J and Garcia-144 Munero, G and Liu, A F and Hodgejewski, J P and Sakore, M A	A Personalized Prediction Model to Risk Stratify Patients with Myelodysplastic Syndromes (MDS)	Blood	130			2017	article	"Of 2302 pts, 1471 were included in the training cohort and 831 in the validation cohort"	Cases only (survival prediction)	C-index (training and validation cohort)	external cohort validation
Nazha, A and Sakeres, M A and Bejar, R and Komroji, R S and Barnard, J and Al-Isa, K and Pzyrach, B P and Hirsch, C M and Steensma, D P and Dzüden, A E and Roboz, G J and Garcia-145 Munero, G and Elvert, B I and Maciejewski, J P	Genomic Biomarkers to Predict Responses to Hypomethylating Agents in Patients with Myelodysplastic Syndromes (MDS)	Blood	130			2017	article	483 pts with MDS (per 2008 WHO criteria) who received HMAs (230 at our institution [training cohort], and 203 at multiple other academic institutions [validation cohort])	Cases only (treatment response prediction)	accuracy, sensitivity, specificity (training and validation cohort)	external cohort validation
Nowak, C and Carlson, A C and Östergren, C and Nyström, F H and Alam, M and Fehrknecht, T R and Sundström, J and Carreira-Rodríguez, J J and López-Larrea, J and Herberg, P O and Cordeiro, A C and Lind, L and 146 Ingelsson, A and Fall, T and Ärnlöv, J	Multiple proteomics for prediction of major cardiovascular events in type 2 diabetes	Diabetologia	61		565-565	2018 Brazil	meeting abstract	1,211 adults with type 2 diabetes	Case-control study	accuracy with 95% confidence intervals (training / test set split)	training + test set
O'Reilly, P and Orlund, C and Gerson, G and O'Connell, E and Seigler, C and Boye, S and Serrano, 147 and Szegedi, B	Co-acting gene networks predict TRAIL responsiveness of tumor cells with high accuracy	BMC Genomics	15		1144-1144	2014 Ireland	article	Gene expression microarray data for 109 tumor cell lines with known sensitivity to the death ligand cytosine tumor necrosis factor-related apoptosis-inducing ligand (TRAIL)	Case-control study	AUC, sensitivity, specificity (training and validation cohort)	external cohort validation
148 Oh, J H and Lotan, Y and Gurnani, P and Rosenblatt, P P and Gao, J	Prostate cancer biomarker discovery using high performance mass spectral serum profiling	Comput Methods Programs Biomed	96	1	33-41	2009 USA	article	Serum samples from 179 prostate cancer patients and 74 benign patients	Case-control study	accuracy, sensitivity, specificity, NPV, PPV (20 times 10 fold CV)	cross-validation
149 Oksa, S and Pahlkka, T and Anttila, T	Genetic variants and their interactions in disease risk prediction - Machine learning and network perspectives	BioData Mining	6	1		2013 Finland	article	review (not applicable) "The first cohort (EGAD00001001443, hereafter study cohort) contains HRAseq data and from CLL purified cells of 196 individuals along with clinical data. The cohort was composed of 103 CLL, 22 monoclonal B cell lymphocytosis (MBL), and five small lymphocytic lymphoma (SLL) samples. There were 130 IGHV unmutated cases (6 159 males and 77 females. By staging at diagnosis, there were 22 MBL cases, 153 Binet Stage A cases, 14 Binet Stage B cases, and 8 Binet C stage cases. The second cohort (EGAD00001000258, hereafter validation cohort) is composed of HRAseq data of CLL purified cells from 98 individuals, of which 79 155 males and 24 females) have publicly available phenotypic information. In this cohort there were 72 CLL, 4 SLL, and 3 MBL samples. 45 of these patients had mutated IGHV and 54 had unmutated IGHV. By staging at diagnosis, there were 3 MBL, 72 Binet Stage A, 3 Binet Stage B, and 1 Binet Stage C cases."	review		
Ortega, A M and Rodriguez, B A and Venchi, A M and López, A B and Ariza, J A D and Venchi, N D and 150 Pérez, M S G and Encinas, M M P and López, J B	Time to treatment prediction in chronic lymphocytic leukemia based on new transcriptional patterns	Frontiers in Oncology	9			2019 Spain	article	more than 50 samples per group for both discovery and validation cohort	Case-control study	accuracy, precision, recall, ROC (training and validation cohort)	external cohort validation
151 Oriol, D and Vilhjálmsson, E E and Estrada, K and Peña, J G T and Athléniers DS Neuroimaging, Initia	Benchmarking machine learning models for site-specific Alzheimer's disease prediction from genomic data	BMC Bioinformatics	20	1	17-17	2019 Mexico	article	more than 50 samples per group for both discovery and validation cohort	Case-control study	balanced error, accuracy, sensitivity, specificity, AUC (cross-validation, training + validation cohort)	cross-validation + external cohort validation

"We address gene selection and machine learning methods for cancer classification using microarray gene expression data. Due to the high dimensionality of microarray data, traditional gene selection algorithms are filter-based, focusing on intrinsic properties of the data such as distance, dependency, and correlation. These methods are fast but select too many genes to use for the classification task. In this work, we present a new hybrid filter-wrapper gene subset selection algorithm that is an improved modification of our prior algorithm. Our proposed method employs interaction information to rank candidate genes to add into a gene subset. [...] Experimental results on ten public cancer microarray data sets show that our method consistently outperforms prior gene selection algorithms in terms of classification accuracy, while requiring a small number of selected genes."

"Triple-negative breast cancer (TNBC) has attracted more attention compared with other breast cancer subtypes due to its aggressive nature, poor prognosis, and chemotherapy remains the mainstay of treatment with no other approved targeted therapy. Therefore, the study aimed to discover more promising therapeutic targets and investigating new insights of biological mechanism of TNBC. Six microarray data sets consisting of 463 non-TNBC and 405 TNBC samples were mined from Gene Expression Omnibus. [...] A naive Bayes based classifier built using the expression profiles of 16 features (but gene) accurately and reliably classify TNBC from non-TNBC samples in the validation test data set with a receiver operating curve of 0.93 to 0.98."

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"We built a personalized prediction model based on clinical and genomic data that outperformed IPS3 and IPS4 in predicting OS and AMI transformation. The new model gives survival probabilities at different time points that are unique for a given pt. Incorporating clinical and mutational data outperformed a mutations only model even when cytogenetics and age were added."

"While treatment with the hypomethylating agents (HMAs) azacitidine (AZA) and decitabine (DAC) improves cytopenias and prolongs survival in MDS patients (pts), response is not guaranteed. Identification of non-responders could prevent prolonged exposure to ineffective therapy, avoid toxicities and decrease unnecessary costs. We developed an unbiased framework to study the association of several mutations in predicting response to HMAs, analogous to NetPho or Anova's recommender system in which customers who bought products A and B is likely to buy C. pts who have a mutation in gene A, and B are likely to respond or not respond to HMA. [...] When applying these rules to the validation cohort, the sensitivity of these genomic biomarkers for no response to HMA was 1, specificity for response to HMA was 1, and accuracy was .85."

"Multiple proteomics could improve understanding and risk prediction of major adverse cardiovascular events (MACE) in type 2 diabetes. This study assessed 80 cardiovascular and inflammatory proteins for biomarker discovery and prediction of MACE in type 2 diabetes. [...] Addition of the 80-protein assay to the established risk model improved discrimination in the separate validation sample from 68.4% (95% CI, 68.26-68.9%) to 74.8% (95% CI, 74.66-75.1%)."

"Gene expression microarray data for 109 tumor cell lines with known sensitivity to the death ligand cytosine tumor necrosis factor-related apoptosis-inducing ligand (TRAIL) was used to identify genes with potential functional relationships determining responsiveness to TRAIL-induced apoptosis. The machine learning technique Random Forest in the statistical environment "R" with backward elimination was used to identify the key predictors of TRAIL. [...] Prediction accuracy was assessed by calculating the area under the receiver operator curve using an independent dataset. We show that the gene panel identified could predict TRAIL sensitivity with a very high degree of sensitivity and specificity (AUC = 0.84). The genes in the panel are co-regulated and at least 48% of them functionally interact in signal transduction pathways that regulate cell death and cell survival, cellular differentiation and morphogenesis. Importantly, only 12% of the TRAIL-predictor genes were differentially expressed highlighting the importance of functional interactions in predicting the biological response."

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"Prostate-specific antigen (PSA) is the most widely used serum biomarker for early detection of prostate cancer (PCA). Nevertheless, PSA level can be falsely elevated due to prostatic enlargement, inflammation or infection, which limits the PSA test specificity. The objective of this study is to use a machine learning approach for the analysis of mass spectrometry data to discover more reliable biomarkers that distinguish PCA from benign specimens. [...] From the new marker selection algorithm, a panel of 26 peptides achieved an accuracy of 80.7%, a sensitivity of 83.5%, a specificity of 74.4%, a positive predictive value (PPV) of 87.9%, and a negative predictive value (NPV) of 68.2%. On the other hand, when PSA alone was used (with a cutoff of 4.0 ng/mL), a sensitivity of 66.7%, a specificity of 53.6%, a PPV of 73.5%, and a NPV of 45.4% were obtained."

"A central challenge in systems biology and medical genetics is to understand how interactions among genetic loci contribute to complex phenotypic traits and human diseases. While most studies have so far relied on statistical modeling and association testing procedures, machine learning and predictive modeling approaches are increasingly being applied to mining genotype-phenotype relationships, also among those associations that do not necessarily meet statistical significance at the level of individual variants, yet still contributing to the combined predictive power at the level of variant panels. Network-based analysis of genetic variants and their interaction partners is another emerging trend by which to explore how sub-network level features contribute to complex disease processes and related phenotypes. In this review, we describe the basic concepts and algorithms behind machine learning-based genetic feature selection approaches, their potential benefits and limitations in genome-wide setting, and how physical or genetic interaction networks could be used as a priori information for providing improved predictive power and mechanistic insights into the disease network."

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<p>Considerations for automated machine learning in clinical metabolic profiling: Altered homeostatic plasma concentrations associated with metformin exposure</p>	<p>Pacific Symposium on Biocomputing 2018</p>	<p>Orienko, A and Moore, J H and Orzechowski, P and Olson, R S and Cairns, J and Caraballo, P J and Weinschilow, R M and Wang, L W and Breitenstein, M K</p>	<p>460-471</p>	<p>2018 USA</p>	<p>https://doi.org/10.1146/annals-ats.2018.14.11.2186</p>	<p>article</p>	<p>546 unique patients (Cases (n=273) included patients exposed to metformin therapy with type 2 diabetes having glycemic control; controls consisted of healthy normal patients with no known metformin exposure)</p>	<p>Case-control study</p>	<p>accuracy (training / test set split)</p>	<p>training + test set</p>	<p>"With the maturation of metabolomics science and proliferation of biobanks, clinical metabolic profiling is an increasingly opportunistic frontier for advancing translational clinical research. Automated Machine Learning (AutoML) approaches provide exciting opportunity to guide feature selection in agnostic, metabolic profiling endeavors, where potentially thousands of independent data points must be evaluated. In previous research, AutoML using high-dimensional data of varying types has been demonstrated robust, outperforming traditional approaches. However, considerations for application in clinical metabolic profiling remain to be evaluated. Particularly, regarding the robustness of AutoML, to identify and adjust for common clinical confounders. In this study, we present a focused case study regarding AutoML considerations for using the Tree-Based Optimization Tool (TOOT) in metabolic profiling of exposure to metformin in a Biobank cohort. [...] First, we propose a tandem rank accuracy measure to guide agnostic feature selection and corresponding threshold determination in clinical metabolic profiling endeavors. Second, while AutoML, using default parameters, demonstrated potential to lack sensitivity to low effect confounding clinical covariates, we demonstrated residual training and adjustment of metabolic features as an easily applicable approach to ensure AutoML adjustment for potential confounding characteristics. Finally, we present increased homeostatic with long-term exposure to metformin as a potentially novel, non-replicated metabolic association suggested by TOOT, an association not identified in parallel clinical metabolic profiling endeavors." "Asthma is a common, under-diagnosed disease affecting all ages. We sought to identify a nasal brush-based classifier of mild/moderate asthma. 190 subjects with mild/moderate asthma and controls underwent nasal brushing and RNA sequencing of nasal samples. A machine learning-based pipeline identified an asthma classifier consisting of 90 genes interpreted via an L2-regularized logistic regression classification model. This classifier performed with strong predictive value and sensitivity across eight test sets."</p>		
<p>A Nasal Brush-based Classifier of Asthma Identified by Machine Learning Analysis of Nasal RNA Sequence Data</p>	<p>Scientific Reports</p>	<p>Fanday, C and Fanday, D J and Rogers, A J and Alshari, M E and Hoffman, G E and Kirby, B A and 153 Weinschilow, R M and Schär, E E and Boryowayak, S</p>	<p>8</p>	<p>15-15</p>	<p>2018 USA</p>	<p>https://doi.org/10.1038/s41598-018-27444-2</p>	<p>article</p>	<p>190 subjects with mild/moderate asthma and controls</p>	<p>Case-control study</p>	<p>AUC (5x4-fold CV)</p>	<p>cross-validation</p>	<p>"When analyzing microarray and other small sample size biological datasets, care is needed to avoid various biases. We analyze a form of bias, stratification bias, that can substantially affect analyses using sample-reuse validation techniques and lead to inaccurate results. This bias is due to imperfect stratification of samples in the training and test sets and the dependency between these stratification errors, i.e. the variations in class proportions in the training and test sets are negatively correlated. We show that when estimating the performance of classifiers on low signal datasets (i.e. those which are difficult to classify), which are typical of many prognostic microarray studies, commonly used performance measures can suffer from a substantial negative bias. For error rates this is only severe in quite restricted situations, but can be much larger and more frequent when using ranking measures such as the receiver operating characteristic (ROC) curve and area under the ROC (AUC). [...] The classification error rate can have large negative biases for balanced datasets, whereas the AUC shows substantial pessimistic biases even for imbalanced datasets. [...] Stratification bias can substantially affect several performance measures. In computing the AUC, the strategy of pooling the test samples from the various folds of cross-validation can lead to large biases; computing it as the average of per-fold estimates avoids this bias and is thus the recommended approach. As a more general solution applicable to other performance measures, we show that stratified repeated holdout and a modified version of a fold cross-validation, balanced, stratified cross-validation and balanced leave-one-out cross-validation, avoids the bias. Therefore for model selection and evaluation of microarray and other small biological datasets, these methods should be used and unstratified versions avoided. In particular, the commonly used (unbalanced) leave-one-out cross-validation should not be used to estimate AUC for small datasets."</p>	
<p>Stratification bias in low signal microarray studies</p>	<p>BMC Bioinformatics</p>	<p>154 Parker, B and Gurrin, S and Bello, J</p>	<p>8</p>	<p>326-326</p>	<p>2007 Australia</p>	<p>https://doi.org/10.1186/1471-2108-8-326</p>	<p>article</p>	<p>review (not applicable)</p>	<p>review</p>	<p>"The aim of this systematic review was to evaluate the existing literature and assess the application of machine learning of genomic data in head and neck cancer (HNC). [...] Two studies each evaluated oral cancer and laryngeal cancer, while other one study each evaluated nasopharyngeal cancer and oropharyngeal cancer. The majority of studies employed support vector machine (SVM) as a ML technique. Among the included studies, the accuracy rates for ML techniques ranged from 56.7% to 99.4%. Our findings showed that ML techniques for the analysis of genomic data can play a role in the prognostic prediction of HNC."</p>			
<p>Machine learning and its potential application to the genomic study of Oral Pathology & Medicine</p>	<p>Journal of Oral Pathology & Medicine</p>	<p>Patil, S and Asava, K H and Arakeri, C and Senaviratna, C J and Mudde, N and Malhi, S and Ferraro, M and 155 and Rahim, S and Brennan, P A</p>	<p>48</p>	<p>9</p>	<p>773-779</p>	<p>2019 India</p>	<p>https://doi.org/10.1111/j.1365-2256.2019.03742.x</p>	<p>article</p>	<p>review (not applicable)</p>	<p>"The OBIIT study demonstrated that rituximab is non-inferior to a TNF-α first strategy in biologic naive, sero-positive patients with active rheumatoid arthritis (RA) over 12 months (Lancet doi.org/10.1016/S0140-6736(19)30389-9). However, a significant proportion of patients failed to respond to their first biologic drug and switched to an alternative. The ability to identify and stratify these patients prior to treatment would improve patient care and optimize the use of scarce financial resources. The aim of this study was to identify peripheral blood transcriptional biomarkers in the OBIIT cohort that can predict subsequent response/non-response to biologic therapy. Three gene sets were identified using support vector machine (SVM) recursive feature elimination. These predicted general responsiveness to both TNFα and rituximab therapy (8 genes), response to TNF therapy (23 genes) or rituximab (23 genes) respectively. When tested on the validation set, these models resulted in ROC plots with an AUC of 0.816 for general responsiveness, 83.7% for TNF response, and 85.7% for rituximab response."</p>			
<p>Predicting the response to TNF inhibition or B cell depletion therapy from peripheral whole blood gene expression profiles in patients with rheumatoid arthritis</p>	<p>Arthritis and Rheumatism</p>	<p>Porter, D and Goodbyear, C S and Nijjar, J S and Missow, M and Siebert, S and Mukuldar, A and 156 McInnes, I B</p>	<p>68</p>	<p>4130-4131</p>	<p>2016</p>	<p>https://doi.org/10.1002/art.38072</p>	<p>meeting abstract</p>	<p>70% (n=168) of samples were used to develop response prediction models, and 30% (n=72) were reserved for validation</p>	<p>Cases only (drug response study)</p>	<p>sensitivity, specificity, PPV and NPV (10-fold CV)</p>	<p>cross-validation</p>	<p>"The diagnosis of seronegative rheumatoid arthritis (RA) remains challenging in the early arthritis clinic. Recent GWAS data strongly implicate CD4+ T cells in the pathogenesis of seropositive RA. Our objectives were to identify biomarkers present in CD4+ T cells, or in serum, that identified patients with undifferentiated arthritis (UA) destined to develop seronegative RA. [...] Machine learning approaches were used to test the utility of a classification model amongst an independent validation cohort of 62 patients presenting with UA. [...] A 12-gene expression 'signature' predicted the subsequent development of RA amongst ACPA-negative UA patients in the validation cohort (sensitivity 83%, specificity 79%). The signature had a predictive value equivalent to the Liden score in these patients and provided enhanced predictive power in combination with the Liden score. The 12-gene signature contained an over-representation of STAT3 target genes, and pathway analysis confirmed that genes functionally involved with CD4+ T-cell survival, including STAT pathway components, were downregulated in early RA."</p>	
<p>A transcriptional profile present in CD4+ T cells of patients with undifferentiated arthritis predicts the future development of seronegative rheumatoid arthritis and implicates T-bet in disease evolution</p>	<p>Arthritis and Rheumatism</p>	<p>157 Pratt, A and Swan, D and Richardson, S and Wilson, G and Hilken, C and Young, D and Isaacs, J D</p>	<p>63</p>	<p>10</p>	<p>2011</p>	<p>https://doi.org/10.1002/art.10144</p>	<p>article</p>	<p>"Microarray analysis of 111 RNA samples was performed. [...] Machine learning approaches were used to test the utility of a classification model amongst an independent validation cohort of 62 patients presenting with UA. [...] A high-throughput DNA methylation dataset (100 samples) of ESCC from The Cancer Genome Atlas (TCGA) project was analyzed and validated along with another independent dataset (12 samples) from the Gene Expression Omnibus (GEO) database. [...] The methylation status of peripheral blood mononuclear cells and peripheral blood leukocytes from healthy controls was also utilized for biomarker selection. The candidate CpG sites as well as their adjacent regions were further validated in 94 pairs of ESCC tumor and adjacent normal tissues from the Chinese Han population using the targeted bisulfite sequencing method. [...] Eight statistical models along with five-fold cross-validation were further applied, in which the SVM model reached the best accuracy in both training and test dataset (accuracy = 0.82 and 0.80, respectively)."</p>					
<p>Targeted bisulfite sequencing identified a panel of DNA methylation-based biomarkers for esophageal squamous cell carcinoma (ESCC)</p>	<p>Clin Epigenetics</p>	<p>Pu, W and Wang, C and Chen, S and Zhao, D and Zhou, Y and Ma, Y and Yang, J and Li, C and Huang, X and Jin, J and Guo, S and Wang, J and Wang, M</p>	<p>9</p>	<p>129-129</p>	<p>2017 China</p>	<p>https://doi.org/10.1186/s12874-017-0430-7</p>	<p>article</p>	<p>"Microarray analysis of 111 RNA samples was performed. [...] Machine learning approaches were used to test the utility of a classification model amongst an independent validation cohort of 62 patients presenting with UA. [...] A high-throughput DNA methylation dataset (100 samples) of ESCC from The Cancer Genome Atlas (TCGA) project was analyzed and validated along with another independent dataset (12 samples) from the Gene Expression Omnibus (GEO) database. [...] The methylation status of peripheral blood mononuclear cells and peripheral blood leukocytes from healthy controls was also utilized for biomarker selection. The candidate CpG sites as well as their adjacent regions were further validated in 94 pairs of ESCC tumor and adjacent normal tissues from the Chinese Han population using the targeted bisulfite sequencing method. [...] Eight statistical models along with five-fold cross-validation were further applied, in which the SVM model reached the best accuracy in both training and test dataset (accuracy = 0.82 and 0.80, respectively)."</p>					
<p>Contribution of an integrative multi-omic approach in the metabolic syndrome prediction: a nested case-control study</p>	<p>Drug Metabolism and Personalized Therapy</p>	<p>Fajó-Gutiérrez, C and Barreiro, J and Barreiro, M and Párriz, M and Brandolini, M and Fernandez, A and 159 Val-Martín, I and López-Marín, C and Carmona, S and Casas, B</p>	<p>31</p>	<p>4</p>	<p>6433-6434</p>	<p>2016</p>	<p>https://doi.org/10.1038/s12243-016-0020-2</p>	<p>meeting abstract</p>	<p>n=92 born small vs n=76 born adequate for gestational age</p>	<p>Case-control study</p>	<p>error rate (training/test split + validation set)</p>	<p>cross-validation + test set</p>	<p>"The rising worldwide prevalence of metabolic syndrome (MetS), a cluster of cardiometabolic risk factors of predictive of type 2 diabetes, relates largely to increasing obesity and sedentary but also to early metabolic life events [1]. Objective The objective of the study was to identify predictive biomarkers of evolution toward MetS 8 years later, and to bring new knowledge about this pathological state using a multidisciplinary approach in an at-risk population (subjects with small birth weight). [...] Individual predictive models were first built using linear logistic regressions from the omic datasets. Metabolomic and proteomic data were finally integrated using random forest to determine whether multidimensional models improve prediction. The resulting models based on either 4 metabolites or 4 proteins showed good performance: 22% misclassification on training set, 23% on validation set, 25% on 11% misclassification on training set, 33% on validation set, respectively. Multi-omic data integration improved performance and robustness of the prediction (11% misclassification on training set, 8% on validation set)."</p>

Author	Year	Journal	Volume	Issue	Page	DOI	Article Type	Review Status	Methodology	Validation Type	Validation Cohort
160 Puzat, L and Hess, K R	2004	Ann Oncol	15	12	1731-1737	https://doi.org/10.1093/annonc/ahd480	article	review (not applicable)	review		
161 Rao, R and Dean, K and Migasawa, B and Samvarshi, P and Doyle, F	2019	Biological Psychiatry	85	10	596-596	https://doi.org/10.1016/j.biopsych.2019.07.024	meeting abstract		Case-control study	AUC, accuracy, sensitivity, specificity (training / test set + external validation)	cross-validation + external cohort validation
162 Rappoport, N and Shmil, R	2018	Research	46	20	10562	https://doi.org/10.1093/rch/46.20.10562	article	review (not applicable)	review		
163 Reeve, J and Madill-Thomson, K S and Halloran, P F	2019	American Journal of Transplantation	19		452-453	https://doi.org/10.1111/ajt.15469	meeting abstract		Case-control study	accuracy (training and validation set)	training + test set
164 Reeve, J and Sellares, J and De Freitas, G and Erneck, G and Bromberg, J and Matsa, A and Halloran, P	2013	American Journal of Transplantation	13		109-109	https://doi.org/10.1111/ajt.12429	meeting abstract		Case-control study	accuracy (training / test set split)	training + test set
165 Pomeroy, Y G	2015	Hum Genet	134	1	3-11	https://doi.org/10.1007/s12052-014-0610-4	article	review (not applicable)	review		
166 Petrosin, F F and Conradi, P and Venstra, T and De Lofredo, C A and Goldman, R	2005	Analyses of mass spectral serum profiles for biomarker selection	21	21	4039-4045	https://doi.org/10.1002/ajb.10010	article		Case-control study	accuracy, sensitivity, specificity (k-fold cross-validation and bootstrapping methods)	cross-validation
167 Ritari, J and Hyvärinen, K and Koskela, S and Itälä-Rames, M and Nittynyo, P and Nihminen, L and Sälmenlahti, U and Pukkonen, M and Vain, L and Kwan, T and Postinen, T and Partanen, J	2019	Leukemia	33	1	240-248	https://doi.org/10.1111/leuk.13749	article		Cases only (relapse prediction)	AUC with confidence intervals (LOOCV)	cross-validation
168 Roder, J and Oliveira, C and Noh, L and Taysin, M and Linsted, B and Roder, H	2019	BMC Bioinformatics	20		14-14	https://doi.org/10.1186/s12859-019-2020-2	article		Case-control study	AUC (training and validation cohort)	external cohort validation

"To discover a predictive marker for a given treatment, a single-arm study design may be sufficient. A simple strategy is to base sample size calculations on the number needed to ensure adequate power for the univariate screening of discriminating genes; in other words, how many training samples are needed to identify reliably an individually predictive gene? We can assume that the array data are approximately normally distributed on some scale, then we can use standard two-sample testing methods to perform sample size calculations [...] Once a candidate predictor has been identified and its predictive accuracy was estimated, the goal of an independent validation study is to: (i) define the sensitivity, specificity and the positive (PPV) and negative predictive values (NPV) with greater precision; and (ii) to prove clinical utility of the test. Different trial designs may be needed for different clinical situations, but there are not a single best design for any particular clinical scenario. Several designs could yield complementary information (Figure 2). An important question for a predictive marker validation study is to determine whether the response rate is higher (and how much higher) in the group that is predicted to respond compared with unselected patients that may represent the current standard of care (in the case of chemotherapy for example)."

"In our benchmark, single-omic data alone sometimes gave better results than multi-omic data. This was identified when for each algorithm the 'best' single-omic for each cancer type was chosen. These results question the current assumption that underlying multi-omics analysis in general and multi-omics clustering in particular. [...] We detected large differences between the p-values derived from the χ^2 approximation compared to the P-values derived from the permutation tests in the statistical tests we used. The differences were especially large due to the small sample size, small cluster sizes (in isolation with a high number of clusters) and due to a low number of events (high survival) for the logrank test. These p-values are used by single and multi-omic methods to assess their performance, and the logrank p-value is often the main argument for an algorithm's merit. The large difference between the P-values question the validity of analyses that are based on the χ^2 approximation, at least for TCGA data. [...] The benchmark we performed is not without limitations. Grouping performance using patient survival is somewhat biased to known cancer subtypes, which may have been used in treatment decisions. Additionally, cancer subtypes that are biologically different may have similar survival. This is true for enrichment of clinical and genomic data. However, these measures are widely used for clustering assessment, including in the papers describing some of the benchmarked methods."

"The Molecular Microscope diagnostic system (MMDS), based on microarray gene expression, uses ensembles of machine learning classifiers rather than single genes, gene sets, or classifiers, to maximize the accuracy of rejection diagnosis and injury assessment. We tested its accuracy and stability, and developed an automated system for generating molecular reports on kidney transplant biopsies. [...] Twelve separate machine learning methods and their median were evaluated. In a separate analysis, a random forest classifier was used to predict the report sign-outs of an expert clinician. Results: There was considerable variation between the 12 classifier methods for any given biopsy. The median had a higher accuracy than any of the individual classifiers, and was among the most stable (highest correlation between predictions from separate random training sets-Figure 1C and D). A random forest classifier was used to predict the sign-out of an expert evaluator. Accuracy for the expert's molecular TCMR and ABMR diagnoses were ~88 and 87% respectively. Most disagreements were in biopsies near diagnostic thresholds. [...] We combined an existing dataset with new data from a multi-center international collaboration (INTERCOM), to predict graft loss in a patient population undergoing kidney transplant biopsies for cause. We used a machine learning method: Random Survival Forests - combining histologic, clinical, and microarray data from 562 patients (1 biopsy per patient). [...] In addition, three previously published molecular scores, IRBAT (injury response and repair transcripts), RS (molecular risk score) and ABMR score (probability of ABMR) were used. [...] Inclusion of molecular variables increased accuracy (All vs All except molecular), but the best model used only IRBATs and Tabs."

"The current convergence of molecular and pharmacological data provides unprecedented opportunities to gain insights into the relationships between the two types of data. Multiple forms of large-scale molecular data, including but not limited to gene and microRNA transcript expression, DNA somatic and germline variations from next generation DNA and RNA sequencing, and DNA copy number from array comparative genomic hybridization are all potentially informative when one attempts to recognize the panoply of potentially influential events both for cancer progression and therapeutic outcomes. [...] For cancer cell lines, the National Cancer Institute cell line panel (NCI-60), the Cancer Cell Line Encyclopedia (CCLE), and the Collaborative Genomics of Drug Sensitivity in Cancer (GDSC) databases all provide subsets of these forms of data. For the patient-derived data, The Cancer Genome Atlas (TCGA) provides analogous forms of genomic information along with treatment histories. Integration of these data in turn relies on the fields of statistics and statistical learning. Multiple algorithmic approaches may be chosen, depending on the data being considered, and the nature of the question being asked. [...] A promising new direction for enhancing all these techniques is to leverage prior biological knowledge, such as molecular interactions derived from biological pathways using literature-curated resources, or computationally inferred gene regulatory networks."

"Mass spectrometric profiles of peptides and proteins obtained by current technologies are characterized by complex spectra, high dimensionality and substantial noise. These characteristics generate challenges in the discovery of proteins and protein-profiles that distinguish disease states, e.g. cancer patients from healthy individuals. We present low level methods for the processing of mass spectral data and a machine learning method that combines support vector machines, with particle swarm optimization for biomarker selection. The proposed method identified mass points that achieved high prediction accuracy in distinguishing liver cancer patients from healthy individuals in SELDI-CTOP profiles of serum. [...] "Abgenex" haematopoietic stem cell transplantation currently represents the primary potentially curative treatment for cancers of the blood and bone marrow. While relapse occurs in approximately 30% of patients, few risk-modifying genetic variants have been identified. The present study evaluates the predictive potential of patient genetics on relapse risk in a genome-wide manner. [...] Our results show that germline genetic polymorphisms in patients entail a significant contribution to relapse risk, as judged by the predictive performance of a model (AUC = 0.72 [95% CI: 0.63-0.81])."

"We describe a novel approach to classifier development designed to create clinically useful tests together with reliable estimates of their performance. The method incorporates elements of traditional and modern machine learning to facilitate the use of cohorts where the number of samples is less than the number of measured patient attributes. It is based on a hierarchy of classification and information abstraction and combines boosting, bagging, and strong dropout regularization. [...] We apply this dropout-regularized combination approach to two clinical problems in oncology using mRNA expression and associated clinical data and compare performance with other methods of classifier generation, including Random Forest. Performance of the new method is similar to or better than the Random Forest in the two classification tasks used for comparison. The dropout-regularized combination method also generates an effective classifier in a classification task with a known confounding variable. Most importantly, it provides a reliable estimate of test performance from a relatively small development set of samples."

"This manuscript reviews methodological and statistical issues relevant to clinical trial design to discover and validate gene predictors of response to therapy. [...] Signals associated with PTSD development might emerge across multiple levels of physiological regulation. Diagnostic cases synthesizing signals from several single-layer molecular signatures into a multi-omic panel can improve diagnostic performance compared to any individual molecular signature. [...] Single and multi-omic classifiers were initially identified in a cohort of 83 PTSD positive cases and 83 PTSD negative matched controls, and subsequently refined and validated in a cohort of 29 PTSD cases and 40 controls. A novel longitudinal cohort of 1800 active duty soldiers is used for external validation. [...] We previously found that the multi-omic panel results in a small improvement in diagnostic performance in comparison to individual single-omic panels in the initial training and validation cohorts (AUC=0.80, 77% accuracy, 81% sensitivity, 78% specificity). Preliminary external validation in the longitudinal cohort suggests that single-omic metabolic panels constituting the multi-omic panel are significantly associated with PTSD status."

"Here, we review algorithms for multi-omic clustering, and discuss key issues in applying these algorithms. Our review covers methods developed specifically for omic data as well as generic multi-view methods developed in the machine learning community for joint clustering of multiple data types. In addition, using cancer data from TCGA, we perform an extensive benchmark spanning ten different cancer types, providing the first systematic comparison of leading multi-omic and multi-view clustering algorithms. The results highlight key issues regarding the use of single- versus multi-omics, the choice of clustering strategy, the choice of multi-view methods and the use of approximated p-values for gauging solution quality."

"The Molecular Microscope diagnostic system (MMDS), based on microarray gene expression, uses ensembles of machine learning classifiers rather than single genes, gene sets, or classifiers, to maximize the accuracy of rejection diagnosis and injury assessment. We tested its accuracy and stability, and developed an automated system for generating molecular reports on kidney transplant biopsies. [...] Twelve separate machine learning methods and their median were evaluated. In a separate analysis, a random forest classifier was used to predict the report sign-outs of an expert clinician. Results: There was considerable variation between the 12 classifier methods for any given biopsy. The median had a higher accuracy than any of the individual classifiers, and was among the most stable (highest correlation between predictions from separate random training sets-Figure 1C and D). A random forest classifier was used to predict the sign-out of an expert evaluator. Accuracy for the expert's molecular TCMR and ABMR diagnoses were ~88 and 87% respectively. Most disagreements were in biopsies near diagnostic thresholds. [...] We combined an existing dataset with new data from a multi-center international collaboration (INTERCOM), to predict graft loss in a patient population undergoing kidney transplant biopsies for cause. We used a machine learning method: Random Survival Forests - combining histologic, clinical, and microarray data from 562 patients (1 biopsy per patient). [...] In addition, three previously published molecular scores, IRBAT (injury response and repair transcripts), RS (molecular risk score) and ABMR score (probability of ABMR) were used. [...] Inclusion of molecular variables increased accuracy (All vs All except molecular), but the best model used only IRBATs and Tabs."

"The current convergence of molecular and pharmacological data provides unprecedented opportunities to gain insights into the relationships between the two types of data. Multiple forms of large-scale molecular data, including but not limited to gene and microRNA transcript expression, DNA somatic and germline variations from next generation DNA and RNA sequencing, and DNA copy number from array comparative genomic hybridization are all potentially informative when one attempts to recognize the panoply of potentially influential events both for cancer progression and therapeutic outcomes. [...] For cancer cell lines, the National Cancer Institute cell line panel (NCI-60), the Cancer Cell Line Encyclopedia (CCLE), and the Collaborative Genomics of Drug Sensitivity in Cancer (GDSC) databases all provide subsets of these forms of data. For the patient-derived data, The Cancer Genome Atlas (TCGA) provides analogous forms of genomic information along with treatment histories. Integration of these data in turn relies on the fields of statistics and statistical learning. Multiple algorithmic approaches may be chosen, depending on the data being considered, and the nature of the question being asked. [...] A promising new direction for enhancing all these techniques is to leverage prior biological knowledge, such as molecular interactions derived from biological pathways using literature-curated resources, or computationally inferred gene regulatory networks."

"Mass spectrometric profiles of peptides and proteins obtained by current technologies are characterized by complex spectra, high dimensionality and substantial noise. These characteristics generate challenges in the discovery of proteins and protein-profiles that distinguish disease states, e.g. cancer patients from healthy individuals. We present low level methods for the processing of mass spectral data and a machine learning method that combines support vector machines, with particle swarm optimization for biomarker selection. The proposed method identified mass points that achieved high prediction accuracy in distinguishing liver cancer patients from healthy individuals in SELDI-CTOP profiles of serum. [...] "Abgenex" haematopoietic stem cell transplantation currently represents the primary potentially curative treatment for cancers of the blood and bone marrow. While relapse occurs in approximately 30% of patients, few risk-modifying genetic variants have been identified. The present study evaluates the predictive potential of patient genetics on relapse risk in a genome-wide manner. [...] Our results show that germline genetic polymorphisms in patients entail a significant contribution to relapse risk, as judged by the predictive performance of a model (AUC = 0.72 [95% CI: 0.63-0.81])."

"We describe a novel approach to classifier development designed to create clinically useful tests together with reliable estimates of their performance. The method incorporates elements of traditional and modern machine learning to facilitate the use of cohorts where the number of samples is less than the number of measured patient attributes. It is based on a hierarchy of classification and information abstraction and combines boosting, bagging, and strong dropout regularization. [...] We apply this dropout-regularized combination approach to two clinical problems in oncology using mRNA expression and associated clinical data and compare performance with other methods of classifier generation, including Random Forest. Performance of the new method is similar to or better than the Random Forest in the two classification tasks used for comparison. The dropout-regularized combination method also generates an effective classifier in a classification task with a known confounding variable. Most importantly, it provides a reliable estimate of test performance from a relatively small development set of samples."

Author(s)	Year	Country	Journal	Volume	Issue	Page	DOI	Article Type	Study Design	Key Findings / Methods	Validation Status
169 Rodriguez-Oviri, M et al	2018	Germany	Sci Rep	8	1	15940	https://doi.org/10.1038/s41598-018-24186-2	article	Case-control study	Novel Urinary Biomarkers for Improved Prediction Of Progressive Egr Loss In Early Chronic Kidney Disease Stages And In High Risk Individuals Without Chronic Kidney Disease. CKD2/3 subclassifiers specific for CKD stages to allow the early identification of patients at high risk of CKD progression. In individuals with eGFR < 60 ml/min/1.73 m2 and albuminuria < 30 mg/day, CKD2/3 subclassifiers predicted rapid eGFR loss with AUC ranging from 0.797 (0.743-0.844) to 0.736 (0.687-0.780). The association between CKD2/3 subclassifiers and rapid progression remained significant after adjustment for age, sex, albuminuria, DM, baseline eGFR, and systolic blood pressure.	cross-validation + external cohort validation
170 Rodriguez-Oviri, M et al	2018	France	Oncologist	23	12	1550-1510	https://doi.org/10.1200/JCO.2018.16415	article	Cases only (prognosis study)	91 patients with asymptomatic oligodendroglioma. For the prognostic, we collected 13 datasets with 312 biopsy samples. Among them, there were 278 BA samples and 36 healthy tissue biopsies. For whole blood data, we collected 11 datasets with 2,153 samples, 1,286 BA and 79 healthy controls (sufficient samples for whole blood). Machine Learning for Better Prognostic Stratification and Driver Gene Identification Using Semantic Copy Number Variations in Anaplastic Oligodendroglioma. AUC, sensitivity, specificity, PPV, NPV (LOOCV + external validation cohort)	cross-validation + external cohort validation
171 Rytchkov, D and Sirota, M and Liu, C	2018		meeting abstract			2206-2206	https://doi.org/10.1136/annrheumdis-2018-216016	meeting abstract	Case-control study	Leveraging publicly available gene expression data and applying machine learning to identify novel biomarkers for rheumatoid arthritis. Cohen's kappa, sensitivity, specificity (5-fold CV)	cross-validation
172 Saini, G and Mittal, A and Rida, F and Janssen, F A M and Gagnier, J and Anjia, R	2019	USA	article	11	9		https://doi.org/10.1136/bmjopen-2018-021221	article	review (not applicable)	Panelistic view of prognostic models for personalized breast cancer management. review	
173 Scheubert, L and Lutzrak, M and Schmidt, R and Repplert, D and Fruellen, G	2012	Germany	BMC Bioinform	13		266-266	https://doi.org/10.1186/1471-2108-13-266	article	Case-control study	Tissue-based Alzheimer gene expression marker comparison of multiple machine learning approaches and investigation of redundancy in small biomarker sets. PLURI and AD dataset contain > 50 samples per group. accuracy (3-fold CV)	cross-validation
174 Shah, A and Nguyen, T and Pevayandor, A and Nguyen, H and Draghici, S	2019	United States	Frontiers in Genetics	10			https://doi.org/10.3389/fgen.2019.00169	article	Cases only (prognosis study)	A multi-cohort and multi-omics meta-analysis for identifying network-based gene signatures. 622 samples, 533 samples from GBM patients and 89 from healthy (non-tumor) individuals. Cox + p-value (training + validation cohort)	external cohort validation
175 Shai, K L and Acharya, C and Smetzer, S and Lyyer, H and Acharya, K S	2019		Fertility and Sterility	112	3	e80-840	https://doi.org/10.1016/j.fertnstert.2019.04.044	article	Case-control study	Non-invasive diagnosis of endometriosis using machine learning inside of the operating room. We trained Random Forest classifiers on ten gene-expression based modules, derived from spectral decomposition of the discovery dataset of 1,414 cases to predict the presence of endometriosis. AUC, accuracy, NPV, PPV (10-fold CV + external test set)	cross-validation + external cohort validation
Shan, L and Chen, Y L and Davis, L and Fan, G and Li, W and Holton, A and Arango, H and LaPlante, J P and Hoffmann, M S and Sellers, T and Khrty, T and Nicolas, S and Sponheim, R	2012	USA	PLoS One	7	10	e46846	https://doi.org/10.1371/journal.pone.0046846	article	Case-control study	Measurement of phospholipids may improve diagnostic accuracy in ovarian cancer. To total of 1057 women with suspected ovarian cancer were enrolled. Only patients who underwent surgery based on clinical suspicion of ovarian cancer were eligible and if a patient was diagnosed with EOC, surgical staging was documented including 213 in whom EOC was confirmed. A total of 211 cases and 212 benigns was included in the analysis. error rate, sensitivity, specificity (5-fold CV)	cross-validation
Shao, C and Chen, C L and Liu, Y P and Chen, F and Fu, S H and Chen, Y T and Chang, Y S and Yu, J S and Jiang, K H and Jiao, G and Wang, J F	2017	China	Oncotarget	8	24	38820	https://doi.org/10.1186/s12943-017-0553-3	article	Case-control study	Metabolite marker discovery for the separation of bladder cancer by comparative metabolomics. T metabolite profiles of 87 samples from bladder cancer patients and 85 samples from benign patients. AUC, accuracy, sensitivity, specificity (5-fold cross-validation + test set)	cross-validation + test set
"Chronic kidney disease is associated with increased risk of CKD progression and death. Therapeutic approaches to limit progression are limited. Developing tools for the early identification of those individuals most likely to progress will allow enriching clinical trials in high risk early CKD patients. The CKD2/3 classifier is a panel of 273 urinary peptides that enables early detection of CKD and prognosis of progression. We have generated urine capillary electrophoresis mass spectrometry-based peptidomics CKD2/3 subclassifiers specific for CKD stages to allow the early identification of patients at high risk of CKD progression. [...] In individuals with eGFR < 60 ml/min/1.73 m2 and albuminuria < 30 mg/day, CKD2/3 subclassifiers predicted rapid eGFR loss with AUC ranging from 0.797 (0.743-0.844) to 0.736 (0.687-0.780). The association between CKD2/3 subclassifiers and rapid progression remained significant after adjustment for age, sex, albuminuria, DM, baseline eGFR, and systolic blood pressure."											
"[13]3p codetated anaplastic gliomas have variable clinical behavior. We have recently shown that the common 19p21.3 allelic loss is an independent prognostic factor in this tumor type. The aim of this study is to identify less frequent genomic copy number variations (CNVs) with clinical importance that may shed light on molecular oncogenesis in this tumor type. [...] Computational biology and feature selection based on the random forest method were used to identify CNV events associated with overall survival and other clinical-pathological variables. [...] Several recurrent CNV events, detected in anaplastic oligodendrogliomas, enable better survival prediction. More importantly, they help in identifying potential genes for understanding oncogenesis and prognosis for personalized medicine. [...] Diagnosis and monitoring the disease progression of BA is challenging requiring a combination of imaging techniques and blood tests. There is currently no biochemical test for detection of early-stage disease. In this study, we aimed to define a Rheumatoid Arthritis meta-profile and identify biomarkers by leveraging publicly available gene expression data with machine learning approaches. [...] Finally, we built a Random Forest classification model on the synovium data with these 5 genes. We applied 5-fold cross-validation with 10 repeats technique and used Cohen's Kappa statistic as a metric. We obtained Kappa equals 0.63 with sensitivity 0.86 and specificity 0.59 on the testing set. In the final step, we validated the prediction model on the whole blood data, resulting kappa of 0.57 with sensitivity 0.54 and specificity 0.87."											
"The efforts to personalize treatment for patients with breast cancer have led to a focus on the deeper characterization of genotypic and phenotypic heterogeneity among breast cancers. [...] This review summarizes the prognostic and predictive insights provided by commercially available gene expression-based tests and other multivariate or clinical -omics-based prognostic/predictive models currently under development, and proposes a more inclusive multiplatform approach to tackling the challenging heterogeneity of breast cancer to individualize its management. [...] Alzheimer's disease has been known for more than 100 years and the underlying molecular mechanisms are not yet completely understood. The identification of genes involved in the processes in Alzheimer affected brain is an important step towards such an understanding. [...] Based on microarray data we identify potential biomarkers as well as biomarker combinations using three feature selection methods: information gain, mean decrease accuracy of random forest and a wrapper of genetic algorithm and support vector machine (GA-SVM). [...] Compared to the other methods, GA-SVM has the advantage of finding small, less redundant sets of genes that, in combination, show superior classification characteristics."											
"Although massive amounts of condition-specific molecular profiles are being accumulated in public repositories every day, meaningful interpretation of these data remains a major challenge. In an effort to identify the biomarkers that describe the key biological phenomena for a given condition, several approaches have been developed over the past few years. However, the majority of these approaches either (i) do not consider the known intermolecular interactions, or (ii) do not integrate molecular data of multiple types (e.g., genomics, transcriptomics, proteomics, epigenetics, etc.), and thus potentially fail to capture the true biological changes responsible for complex diseases (e.g., cancer). In addition, these approaches often ignore the heterogeneity and study bias present in independent molecular cohorts. In this manuscript, we propose a novel multi-cohort and multi-omics meta-analysis framework that overcomes all three limitations mentioned above in order to identify robust molecular subnetworks that capture the key dynamic nature of a given biological condition. [...] We demonstrate the proposed framework by constructing subnetworks related to two complex diseases: glioblastoma and low-grade glioma. We validate the identified subnetworks by showing their ability to predict patients' clinical outcome on multiple independent validation cohorts. [...] Endometriosis affects an estimated 1 in 10 women during their reproductive years, and up to 30% to 50% of women with endometriosis may experience infertility. [...] A previous study developed classifiers for prediction of endometriosis in a cycle-phase specific manner by using margin tree classification within one dataset. Our aim was to build on this research by utilizing machine learning to predict and independently validate the presence or absence of endometriosis, regardless of cycle phase and other ovarian pathology, through endometrial biopsy (EMB) samples. [...] We identified a 280 gene predictor of endometriosis using Random Forests that was found to predict the presence of endometriosis, regardless of the endometrial phase and other pathology, with an accuracy of 88% (area under ROC 1.0 0.84, p-value: 6.14e-05), with a negative predictive value of 86% and a positive predictive value of 81%. We reduced model over-fitting by performing 10-fold cross-validation of our discovery data."											
"More than two-thirds of women who undergo surgery for suspected ovarian neoplasm do not have cancer. Our previous results suggest phospholipids as potential biomarkers of ovarian cancer. In this study, we measured the serum levels of multiple phospholipids among women undergoing surgery for suspected ovarian cancer to identify biomarkers that better predict whether an ovarian mass is malignant. [...] The HE-SVM model using the measurements of specific combinations of phospholipids supplements clinical CA125 measurement and improves diagnostic accuracy. Specifically, the measurement of phospholipids improved sensitivity identification of cases with preoperative CA125 levels below 351 among two types of cases in which CA125 performance is historically poor - early stage cases and those of mucinous histology. Measurement of phospholipids improved the identification of early stage cases from 65% (based on CA125) to 82%, and mucinous cases from 49% to 88%. [...] In this study, we applied ultra-performance liquid chromatography time-of-flight mass spectrometry to profile metabolite profiles of 87 samples from bladder cancer patients and 85 samples from benign patients. An OPLS-DA classification revealed that bladder cancer samples can be discriminated from benign samples based on the profiles. A marker discovery pipeline selected six acetate markers from the metabolomic profiles. [...] A machine learning model, decision trees, was built based on the metabolomic profiles and the six marker candidates. The decision tree obtained an accuracy of 76.60%, a sensitivity of 71.86%, and a specificity of 86.67% from an independent test."											

Author(s)	Year	Country	Journal	Volume	Issue	Pages	DOI	Article Type	Abstract Summary	Keywords
178 Sharma, A and Rani, R	2019	India	Biomed	178		219-235	https://doi.org/10.1080/17513758.2019.1630002	article	The proposed machine learning approach tested on 7 microarray datasets, including 4 datasets with > 50 samples per group	Case-control study accuracy (LOOCV + test set)
179 Shen, L and Tan, E C	2005	Singapore	Journal of Computational Biology	2	2	166-175	https://doi.org/10.1089/cmb.2004.2.166	article	The proposed machine learning approach tested on 7 microarray datasets, including 4 datasets with > 50 samples per group	Case-control study mean error + standard deviation (LOOCV, test set)
Sherman, S I and Pagan, M and Huang, J and Liu, B and Duggan, J and Tom, E and Hagan, B and 180 Tuttle, R M and Kennedy, G	2015	USA	Journal of Clinical Oncology	33	15		https://doi.org/10.1200/JCO.2014.28.4292	meeting abstract	"81 Samples preoperatively collected in a previous study and post-surgically diagnosed as PTC. [...] Each patient was categorized as either ATA low risk or ATA intermediate/high risk using established guidelines for recurrence risk stratification." (< 50 samples per group)	Case only (risk of recurrence prediction) AUC (cross-validation)
181 Shi, P and Ray, S and Zhu, Q F and Koh, M A	2011	USA	Bioinformatics	12		15-15	https://doi.org/10.1093/bioinformatics/btt216	article	4 cancer prognosis microarray datasets, including data with > 50 samples per group	Case-control study error rate (LOOCV, test set)
182 Sinner, J A and Cai, T	2013	United States	Biometrics	69	4	861-873	https://doi.org/10.1111/biom.12143	article	"Training set of 454 high node negative breast cancer patients [...] a total of 119 deaths or recurrences were observed"	Case-control study C statistic (training + validation data)
Sosa, J and Anghel, T E and Babiarz, J and Barth, N and Bevilin, T and Duh, Q and Ghossein, R A and 183 Hameer, R M and Huang, J and Hirota, U and Kennedy, G and Kim, S and Koo, K T and Ullrich, V A and Patel, K N and Reddy, G and Sadava, P M and Shank, M H and Trowell, S T and Wang, P S and 183 Whitney, D and Yeh, M and Ladenson, P W	2017	USA	Thyroid	27		AS0-A51	https://doi.org/10.1089/thy.2016.27.450	meeting abstract	476 FNAs+6 parathyroid and 470 thyroid FNAs	Case-control study sensitivity, specificity (training and validation cohort)
184 Srivastava, S and Wang, W and Mammen, G and Ordovas, C and Balasubrahayyan, V	2013	USA	Eur J Hum Genet	2013	1		https://doi.org/10.1038/ejhg.2012.243	article	"GBM data have multiple molecular measurements on over 500 samples that include gene expression, copy number, methylation and miRNA expression"	Case-control study mean square prediction error ("We randomly split the GBM survival data into a training data and a test data with 223 (90%) and 29 (10%) patients, respectively")
Stamatou, D and Kim, M and Protsis, P and Westwood, S and Baird, A and Nevado-Holgado, A and Hye, A and Bos, J and Vos, J B and Vandenberghe, A and Teusissen, C and Koo, K T and Schellen, P and 185 Gaber, S and Moore, K and Bin, Q and Richardson, J and De Rooij, E and Engelborg, S and Sleegers, P and Bortel, R and Balle, D and Kettunen, M and Vermy, J and Alcala, D and Translational Research European Medical Information and Intervention Consortium	2019	Belgium	Alzheimer's and Dementia	5		933-938	https://doi.org/10.1016/j.pneunf.2019.07.001	article	242 cognitively normal (CN) people and 115 with AD type dementia utilizing plasma metabolites	Case-control study AUC (nested cross-validation, external test set)
186 Stanilovic, A and Affric, C F and Tsamardinos, I and Harth, D and Levy, S	2005	USA	Bioinformatics	21	5	611-643	https://doi.org/10.1093/bioinformatics/bti103	article	11 datasets spanning 74 diagnostic categories and 41 cancer types and 12 normal tissue types	Case-control study accuracy, relative classifier information (Design 1: nested stratified 10-fold CV outer loop, 9-fold CV inner loop; Design 2: nested LOOCV outer loop, 10-fold CV inner loop)

"We have proposed framework (C-HMOSHSA) for gene selection using multi-objective spotted hyena optimizer (MOSH) and salp swarm algorithm (SSA). The real life optimization problems with more than one objective usually face the challenge to maintain convergence and diversity. Salp Swarm Algorithm (SSA) maintains diversity but, suffers from the overhead of main-taining the necessary information. On the other hand, the calculation of MOSHO requires low computational efforts hence it is used for maintaining the necessary information. Therefore, the proposed algorithm is a hybrid algorithm that utilizes the features of both SSA and MOSHO to facilitate its exploration and exploitation capabilities. [...] Four different classifiers are trained on seven high-dimensional datasets using a subset of features (genes), which are obtained after applying the proposed hybrid gene selection algorithm. The results show that the proposed technique significantly outperforms existing state-of-the-art techniques."

"The use of penalized logistic regression for cancer classification using microarray expression data is presented. Two dimension reduction methods are respectively combined with the penalized logistic regression to take both the classification accuracy and computational speed as enhanced. Two other machine-learning methods, support vector machines and least-squares regression, have been chosen for comparison. It is shown that our methods have achieved at least equal or better results. They also have the advantage that the output probability can be explicitly given and the regression coefficients are easier to interpret."

"Transcriptional data from FNA of thyroid nodules may improve the pre-operative prediction of risk for post-operative recurrence. If independently validated in a sufficiently large number of patients, such molecular classifiers may augment initial risk stratification and individualization of patient care."

"The widely used top scoring pair (TSP) algorithm is a simple yet powerful parameter-free classifier. It owes its success in many cancer microarray datasets to an effective feature selection algorithm that is based on relative expression ordering of gene pairs. However, its general robustness does not extend to some difficult datasets, such as those involving cancer outcome prediction, which may be due to the relatively simple voting scheme used by the classifier. We believe that the performance can be enhanced by separating its effective feature selection component and combining it with a powerful classifier such as the support vector machine (SVM). [...] We developed an approach integrating the TSP ranking algorithm (TSP) with other machine learning methods, allowing combination of the computationally efficient, multivariate feature ranking of TSP with multivariate classifiers such as SVM. We evaluated this hybrid scheme in TSP+SVM in a range of simulated datasets with known data structures. As compared with other feature selection methods, such as a univariate method similar to Fisher's discriminant criterion (Fisher), or a recursive feature elimination embedded in SVM (RFE), TSP is increasingly more effective than the other two methods as the informative genes become progressively more correlated, which is demonstrated both in terms of the classification performance and the ability to recover the informative gene."

"Integrating genomic information with traditional clinical risk factors to improve the prediction of disease outcomes could profoundly change the practice of medicine. However, the large number of potential markers and possible complexity of the relationship between markers and disease make it difficult to construct accurate risk prediction models. [...] In recent years, much work has been done to group genes into pathways and networks. Integrating such biological knowledge into statistical learning could potentially improve model interpretability and reliability. One effective approach is to employ a kernel machine (KM) framework, which can capture nonlinear effects if nonlinear kernels are used. [...] In this article, we derive testing and prediction methods for KM regression under the accelerated failure time (AFT) model. A useful alternative to the PH model. We approximate the null distribution of our test statistic using resampling procedures. When multiple kernels are of potential interest, it may be unclear in advance which kernel to use for testing and estimation. We propose a robust Omnibus Test that combines information across kernels, and an approach for selecting the best kernel for estimation. The methods are illustrated with an application in breast cancer."

"The parathyroid glands are located adjacent to the thyroid and occasionally within it. Enlarged and iodinated parathyroid glands can be mistaken as thyroid nodules or suspicious lymph nodes. On the needle aspiration biopsy (FNAB) of such lesions, cytology is often indeterminate, failing to identify its parathyroid origin and potentially resulting in an unnecessary thyroid surgery. The AtroGenomics Sequencing Classifier (GSC) identifies genomically benign thyroid nodules among those with indeterminate FNAB to prevent unnecessary diagnostic surgery using RNA sequencing and machine learning algorithms. [...] The first classifier was initially tested on an independent test set of 195 FNAs (118 Bethesda III, 77 Bethesda IV). The classifier had 100% sensitivity (4/4 parathyroid correctly called positive, 0/38-0, 100% and 100% specificity (35/35 thyroid correct called negative, 0/3-0, 100%)."

"For predicting relevant clinical outcomes, we propose a flexible statistical machine learning approach that acknowledges and models the interaction between platform-specific measurements through nonlinear kernel machines and borrows information within and between platforms through a hierarchical Bayesian framework. Our model has parameters with direct interpretations in terms of the effects of platforms and data interactions within and across platforms. The parameter estimation algorithm in our model uses a computationally efficient variational Bayes approach that scales well to large high-throughput datasets. [...] We apply our methods of integrating gene/miRNA expression and microRNA profiles for predicting patient survival times to The Cancer Genome Atlas (TCGA) based glioblastoma multiforme (GBM) dataset. In terms of prediction accuracy, we show that our non-linear and interaction-based integrative methods perform better than linear alternatives and non-integrative methods that do not account for interactions between the platforms. We also find several prognostic miRNAs and microRNAs that are related to tumor invasion and are known to drive tumor metastasis and severe inflammatory response in GBM. [...] Our approach gains its flexibility and power by modeling the non-linear interaction structures between and within the platforms."

"Machine learning (ML) may harbor the potential to capture the metabolic complexity in Alzheimer Disease (AD). Here we set out to test the performance of metabolites in blood to categorize AD when compared to CSF biomarkers. [...] Deep Learning (DL), Extreme Gradient Boosting (XGBoost) and Random Forest (RF) were used to differentiate AD from CN. These models were internally validated using Nested Cross Validation (NCV). [...] On the test data, DL produced an AUC of 0.85 (0.80-0.89), XGBoost produced 0.88 (0.86-0.89) and RF produced 0.85 (0.83-0.87). By comparison, CSF measures of amyloid β and tau (along with age and gender) produced with XGBoost the AUC values of 0.78, 0.83 and 0.87, respectively. [...] This study showed that plasma metabolites have the potential to match the AUC of well-established AD CSF biomarkers in a relatively small cohort."

"[...] we performed a systematic and comprehensive evaluation of several major algorithms for multicategory classification, several gene selection methods, multiple ensemble classifier methods and two cross-validation designs using 11 datasets spanning 74 diagnostic categories and 41 cancer types and 12 normal tissue types. [...] Multicategory support vector machines (MC-SVMs) are the most effective classifiers in performing accurate cancer diagnosis from gene expression data. The MC-SVM techniques by Crummer and Singer, Weston and Watkins and one-versus-rest were found to be the best methods in this domain. MC-SVMs outperform other popular machine learning algorithms, such as k-nearest neighbors, backpropagation and probabilistic neural networks, often to a remarkable degree. Gene selection techniques can significantly improve the classification performance of both MC-SVMs and other non-SVM learning algorithms. Ensemble classifiers do not generally improve performance of the best non-ensemble models. These results guided the construction of a software system (GMS: Gene Expression Model Selector) that automates high-quality model construction and enforces sound optimization and performance estimation procedures."

Author(s)	Year	Country	Journal	Volume	Issue	Page	DOI	Article Type	Abstract Summary	Case only (drug response study)	precision + standard deviation of precision (10-fold CV, external validation data)	cross-validation
187 Stetson, C and Pkari, T and Chen, Y W and Barnholtz-Sloan, J S	2014	USA	BMC Genomics	15	8-8	2014	10.1186/s12854-014-0114-4	article	"To develop multi-omic predictors of anticancer therapeutic response we curated data from the CCLE, COP, and NCI60 databases. The resulting datasets consisted of the gene expression (Affymetrix U133A and Affymetrix U133A plus 2.0), copy number variation (Affymetrix SNP_6), and mutation status (Targeted and whole exome sequencing) of 1299 distinct human cancer cell lines representing 35 cancer types. [...] In a prospective observational study of group 1 PAH patients evaluated at Stanford University (discovery cohort, n=281) and University of Sheffield (validation cohort, n=104) between 2008 and 2014, we measured a circulating proteomic panel of 48 cytokines, chemokines, and factors using multiplexed immunosorbent machine learning (consensus clustering) was applied to both cohorts independently to classify patients into proteomic immune clusters, without guidance from clinical features. [...] Findings were replicated in the validation cohort, where machine learning classified 4 immune clusters with comparable proteomic, clinical, and prognostic features."	Case only (drug response study)	precision + standard deviation of precision (10-fold CV, external validation data)	cross-validation
188 Sweet, A J and Health, M and Bafiqur, R and Hu, A and Blum, L K and Robinson, W J and Haddad, F and Hickley, P M and Cantafium, R and Lawrie, A and Nicolini, M and Rabunovich, M and 188 Khatri, P and Zamanian, R T	2019	United Kingdom	Circulation Research	124	6	904-919	10.1161/ATB.119.032111	article	"Due to the range of biological and molecular heterogeneity in diffuse large B-cell lymphoma (DLBCL), personalized risk stratification and treatment is a promising avenue to improving outcomes. [...] We performed targeted NGS on plasma samples from 310 previously untreated DLBCL pts enrolled in the GOYA study (NCT132741) with a custom DLBCL-specific panel using a workflow optimized for ctDNA. [...] We describe a single NGS-based method, which calls variants, determines CPO, and assesses tumor burden from plasma. Using these results, we show that pre-treatment plasma-based molecular and tumor burden measurements in previously untreated DLBCL pts correlate with PFS."	Case-control study	log-rank test p-value (discovery + validation cohort)	external cohort validation
189 Tabari, F and Lovejoy, A F and Lin, H and Böhlen, C R and Saalek, S I and Lolkowitz, J P and Kurtz, D M and Vitvack, P and Venstrom, J M and Nelson, T G and Paravis, J M and Goss, D M and Lungu, K T	2019			134			10.1158/1078-0432.CCR.19.0242	meeting abstract	"Targeted NGS on plasma samples from 310 previously untreated DLBCL pts enrolled in the GOYA study"	Case only (predicting progression-free survival)	Correlation with progression-free survival (training/test set split)	training + test set
190 Tan, C and Gilbert, D	2003	UK	Appl Bioinform	2	3	575-83	10.1093/bio/btt014	article	"Seven microarray datasets were used, including data with ~50 samples group."	Case-control study	accuracy, sensitivity, specificity, PPV (10-fold CV)	cross-validation
191 Tan, A C and Naiman, D Q and Xu, L and Winslow, R L and Geman, D	2005	USA	Bioinform	21	20	3896-3904	10.1093/bio/bti010	article	"19 publicly available microarray datasets, with sample sizes ranging from 35 to 327 (more than 50 samples per group for multiple datasets)."	Case-control study	accuracy (LOOC, test set)	cross-validation + test set
192 Tang, K L and Li, T and Xiong, W W and Chen, K	2010	China	BMC Bioinform	11	109-109	2010	10.1186/1471-2165-11-109	article	"High-resolution SELDI-TOF ovarian data set for 95 control samples and 121 cancer samples"	Case-control study	accuracy, sensitivity, specificity (cross-validation)	cross-validation
193 Tao, M and Song, T and Du, W and Han, S and Jiao, C and Li, Y and Wang, Y and Yang, Z	2019	China	Genes (Basel)	10	3	2019	10.3390/genes10030202	article	"Our dataset contained 496 distinct patient samples of breast cancer, which was divided into five subtypes: 277 luminal A, 40 luminal B, 70 triple negative breast cancer (TNBC), 11 HER2 (+), and 208 unclear"	Case-control study	accuracy, AUC (10-fold CV)	cross-validation
194 Tebani, A and Alonso, C and Marret, S and Bekri, S	2016	France	Int J Mol Sci	17	9	2016	10.3390/ijms170906466	article	"In this review, we present state-of-the-art multi-omics data analysis strategies in a clinical context. The challenges of omics-based biomarker translation are discussed. Perspectives regarding the use of multi-omics approaches for inborn error of metabolism (IEM) are presented by introducing a new paradigm shift in addressing IEM investigations in the post-genomic era."	review (not applicable)	review	
195 Theofilatos, K and Korfiatis, A and Mavrouli, S and Cowerthorpe, M C and Shpak, M	2019	Greece	BMC Med Genomics	11	1	118-118	10.1186/s12916-019-0056-6	article	"The small number of multi-omics datasets in the field of fibromyofasciitis (FMS) and the lack of standardized and harmonized protocols affect the wide dissemination of these approaches. To overcome these drawbacks, attention should be given to validation strategies at all stages. Moreover, the development of new analytical and machine learning methods will facilitate analysis of multi-tissue and multi-omic data, thus enabling a real integration of systemic effects [95,141,161]. Extended and effective resources for bioinformatics are also essential to ensure consistency. Addressing these challenges will improve healthcare management of IEM by moving from a reactive, targeted, and reductionist approach to a more proactive, global, and integrative one."	Case-control study	accuracy (5-fold cross validation)	cross-validation
196 Toh, T S and Dondelinger, F and Wang, D	2019	UK	Eurobiomed	4	47	607-615	10.1007/s10240-019-00201-2	article	"Identifying molecular biomarkers characteristic of ischemic stroke has the potential to aid in distinguishing stroke cases from stroke mimicking symptoms, as well as advancing the understanding of the physiological changes that underlie the body's response to stroke. This study uses machine learning-based analysis of gene expression to identify transcription patterns characteristic of patients with acute ischemic stroke. [...] A predictive model with 89.0% accuracy was identified using 6 network-central and differentially expressed genes (EG, MERTK, NOS, SPN2, BMS, SLC22A1), characterized by large differences in association network connectivity between stroke and control samples. In contrast, classification models based solely on individual genes identified by significant fold-changes in expression level provided lower predictive accuracies: 71% for any single gene, and even models with larger (10-20) numbers of gene transcript biomarkers gave lower predictive accuracies (5-82%) than the 6-network-based gene signature classification. [...] Network-based models have the potential to identify a more statistically robust pattern of gene expression typical of acute ischemic stroke and to generate hypotheses about possible interactions among functionally relevant genes, leading to the identification of more informative biomarkers."	Case-control study	accuracy (5-fold cross validation)	cross-validation
197 Tong, D I and Boocock, D I and Covey, C and Saff, J and Gomez, S and Quares, S and Reed, R and 197 Ball, G R	2011	UK	Clinical Proteomics	8	1	2011	10.1186/1092-2724-8-22	article	"Both new and old techniques of artificial intelligence (AI) and machine learning (ML) can now help increase the success of translational studies in three areas: drug discovery, imaging, and genomics medicine. However, ML technologies do not come without their limitations and shortcomings. Current technical limitations and other limitations including governance, reproducibility, and interpretation will be discussed in this article."	Case-control study	AUC, accuracy (Monte Carlo cross-validation + external validation set)	cross-validation + external cohort validation
									"Raw spectral data from matrix-assisted laser desorption/ionization time-of-flight (MALDI-TOF) with MS profiling techniques usually contains complex information not readily providing biological insight into disease. The association of identified features within raw data to a known peptide is extremely difficult. Data preprocessing to remove uncertainty characteristics in the data is normally required before performing any further analysis. This study proposes an alternative yet simple solution to preprocess raw MALDI-TOF MS data for identification of candidate marker ions. Two in-house MALDI-TOF MS data sets from two different sample sources (melanoma serum and cord blood plasma) are used in our study. [...] Our model identified 10 candidate marker ions for both data sets. These ion peaks achieved over 90% classification accuracy on blind validation data. Receiver operating characteristics analysis was performed and the area under the curve for melanoma and cord blood classifiers was 0.991 and 0.986, respectively."			

Author(s)	Year	Journal	Study Title	Study Design	Key Findings/Abstract	AI/ML Application	Validation Type
198 Trakladis, J and Saribar, S and Chen, A and Fajuljani, V and Krishnan, A	2019	American Journal of Medical Genetics Part B: Neuropsychiatry	Machine learning in schizophrenia genetics: a case-control study using 5,000 exomes	Case-control study	"This study applies ML to WES data from 2,545 individuals with SZ and 2,545 unaffected individuals..."	AUC, accuracy, sensitivity, specificity, precision, recall, F1-measure training + test set	training + test set
199 D'Alessandro, P and Ciccocioppo, R and Gada, M	2017	Metabolomics	A metabolomics-based approach for genetic case-control study using chromosomal anomalies	Case-control study	"Metabolomic profiles have been obtained on serum of 120 mothers (120 controls) and 108 cases..."	AUC, accuracy, sensitivity, specificity, PPV, NPV, F-measure, G-mean (k=6) cross-validation + external test set	cross-validation + external test set
200 McCowan, M and Pizzano, A and Martinelli, P and Gada, M	2018	Birth Defects Research	Noninvasive screening of fetal anomalies: The serum metabolomic way	Case-control study	"Metabolomic profiles were obtained from serum of 120 mothers (120 controls), with a normal fetus and 334 cases with a malformed fetus..."	accuracy, sensitivity, specificity (training and validation set)	cross-validation + test set
201 Tveit, O and Hest, J and Lund Quinn, T P and Barke, R and Huang, H and Zhang Zang, Y and Chang, J	2017	Am J Med Genet B Neuropsychiatr	Blood transcriptomic comparison of individuals with and without autism spectrum disorder: A combined-sample meta-analysis	Case-control study	"Raw microarray data and clinical meta-data were obtained from seven studies, totalling 826 affected and 447 comparison subjects..."	AUC, sensitivity, specificity (nested 10-fold CV within 5-times bootstrapped (Boot5) samples + test set)	cross-validation + test set
202 Urida, D and Argon, J and Bautista, R and Franco, L and Verdesi, F and Clara, M and Jerez, J M	2018	BMC Syst Biol	BLASSO: integration of biological knowledge into a regularized linear model	Case-control study	"Out of the 1212 samples, 1013 corresponds to controls (or alive patients) and 199 to cases (or patients who died from the disease)"	AUC (10 repetitions of 10-fold nested CV, with 5-fold CV nested for hyper-parameter tuning)	cross-validation
203 van Vliet, M H and Kijp, C N and Wessels, L F and Rand Rindner, M J	2007	Netherlands	Modulo-based outcome prediction using breast cancer genomics	Case-control study	"This compendium contains data from various cancer studies and has a total of 1873 arrays (more than 50 samples per group for combined datasets)"	AUC (double-loop cross-validation + external validation)	cross-validation + external test set
204 Wang, N and Weinberg, D and Liu, T Y and Holroyd, K and Ariazi, E A and Dhalwani, D and Kannan, A and Whitehead, R and Berrin, M and Berry, M and Breen, D and Cress, J and Fung, J and Gao, E and Gao, L and Hanson, L and Liu, Y and Ota, G and Land, P and Jones, R B and Anderson, G E and Sharma, A and St John, J and Tang, C and Tsou, A and Young, L and Puthi, C and Heagerty, P	2019	BMC Cancer	Machine learning enables detection of early-stage colorectal cancer by whole genome sequencing of plasma cell-free DNA	Case-control study	"N = 546 colorectal cancer and 271 non-cancer controls"	AUC, sensitivity, specificity (5-fold CV + confounder-based cross-validation)	cross-validation
205 Wang, J and Yao, D and Zhao, A and Hou, Y and Zheng, X and Chen, P and Bao, Y and Su, W and Hu, C	2019	Osteoporosis Int	Discovery of potential biomarkers for osteoporosis using GC-MEMS metabolic methods	Case-control study	"Our study recruited 320 participants, including 188 males and 132 postmenopausal females"	AUC, accuracy, sensitivity, specificity ("The data sets were randomly split into the train curve AUC of receiver operating characteristic (ROC) curves increased significantly")	training + test set
206 Wang, J and Zuo, Y and Man, Y and Avila, J and Spodickov, A and Liu, M and Yang, X and Vargheese, R S and Taddei, M G and Resconi, H W	2015	Journal of Cancer	Pathway and network approach for identification of cancer signature markers from omics data	review (not applicable)	review	review	review
207 Wang, L and Liu, Z P	2019	Frontiers in Genetics	Detecting diagnostic biomarkers of Alzheimer's disease by integrating gene expression data in six brain regions	Case-control study	gene expression profiles of 161 samples in six brain regions	AUC, sensitivity, specificity (LOOCV)	cross-validation
208 Wang, M and Yu, G and Resconi, H W	2016	United States	Integrative Analysis of Proteomic, Glycomic, and Metabolomic Data for Biomarker Discovery	Case-control study	"In this study, we investigate integrative analysis of proteomic, glycomic, and metabolomic studies in distinguishing liver cancer cases from patients with liver cirrhosis..."	AUC, accuracy, sensitivity, specificity (10-fold cross-validation + test set)	cross-validation + test set
209 Tveit, O and Hest, J and Lund Quinn, T P and Barke, R and Huang, H and Zhang Zang, Y and Chang, J	2017	Am J Med Genet B Neuropsychiatr	Blood transcriptomic comparison of individuals with and without autism spectrum disorder: A combined-sample meta-analysis	Case-control study	"Raw microarray data and clinical meta-data were obtained from seven studies, totalling 826 affected and 447 comparison subjects..."	AUC, sensitivity, specificity (nested 10-fold CV within 5-times bootstrapped (Boot5) samples + test set)	cross-validation + test set
210 Urida, D and Argon, J and Bautista, R and Franco, L and Verdesi, F and Clara, M and Jerez, J M	2018	BMC Syst Biol	BLASSO: integration of biological knowledge into a regularized linear model	Case-control study	"Out of the 1212 samples, 1013 corresponds to controls (or alive patients) and 199 to cases (or patients who died from the disease)"	AUC (10 repetitions of 10-fold nested CV, with 5-fold CV nested for hyper-parameter tuning)	cross-validation
211 van Vliet, M H and Kijp, C N and Wessels, L F and Rand Rindner, M J	2007	Netherlands	Modulo-based outcome prediction using breast cancer genomics	Case-control study	"This compendium contains data from various cancer studies and has a total of 1873 arrays (more than 50 samples per group for combined datasets)"	AUC (double-loop cross-validation + external validation)	cross-validation + external test set
212 Wang, N and Weinberg, D and Liu, T Y and Holroyd, K and Ariazi, E A and Dhalwani, D and Kannan, A and Whitehead, R and Berrin, M and Berry, M and Breen, D and Cress, J and Fung, J and Gao, E and Gao, L and Hanson, L and Liu, Y and Ota, G and Land, P and Jones, R B and Anderson, G E and Sharma, A and St John, J and Tang, C and Tsou, A and Young, L and Puthi, C and Heagerty, P	2019	BMC Cancer	Machine learning enables detection of early-stage colorectal cancer by whole genome sequencing of plasma cell-free DNA	Case-control study	"N = 546 colorectal cancer and 271 non-cancer controls"	AUC, sensitivity, specificity (5-fold CV + confounder-based cross-validation)	cross-validation
213 Wang, J and Yao, D and Zhao, A and Hou, Y and Zheng, X and Chen, P and Bao, Y and Su, W and Hu, C	2019	Osteoporosis Int	Discovery of potential biomarkers for osteoporosis using GC-MEMS metabolic methods	Case-control study	"Our study recruited 320 participants, including 188 males and 132 postmenopausal females"	AUC, accuracy, sensitivity, specificity ("The data sets were randomly split into the train curve AUC of receiver operating characteristic (ROC) curves increased significantly")	training + test set
214 Wang, J and Zuo, Y and Man, Y and Avila, J and Spodickov, A and Liu, M and Yang, X and Vargheese, R S and Taddei, M G and Resconi, H W	2015	Journal of Cancer	Pathway and network approach for identification of cancer signature markers from omics data	review (not applicable)	review	review	review
215 Wang, L and Liu, Z P	2019	Frontiers in Genetics	Detecting diagnostic biomarkers of Alzheimer's disease by integrating gene expression data in six brain regions	Case-control study	gene expression profiles of 161 samples in six brain regions	AUC, sensitivity, specificity (LOOCV)	cross-validation
216 Wang, M and Yu, G and Resconi, H W	2016	United States	Integrative Analysis of Proteomic, Glycomic, and Metabolomic Data for Biomarker Discovery	Case-control study	"In this study, we investigate integrative analysis of proteomic, glycomic, and metabolomic studies in distinguishing liver cancer cases from patients with liver cirrhosis..."	AUC, accuracy, sensitivity, specificity (10-fold cross-validation + test set)	cross-validation + test set

Author(s)	Year	Journal	Volume	Page	DOI	Article Type	Abstract Summary	Keywords						
Wang, N and Cao, Y and Song, W and He, X and Li, T and Wang, J and Xu, B and Shi, H and Yu, H and Guo, J and Li, A L	2019	Gastroenterology and Hepatology	29	7	1544-1550	2014	China	http://dx.doi.org/10.1016/j.gtc.2019.02.001	article	80 HCC and 67 LC patients	Case-control study	AUC, accuracy, sensitivity, specificity (10-fold cross-validation + test set)	cross-validation + test set	
210 Wang, S J and Li, M C	2016	Statistics in Biosciences	8	1	129-158	2016		http://dx.doi.org/10.1007/s12561-016-9161-9	article		Case-control study	accuracy, sensitivity, specificity, PPV, NPV, permutation p-values (cross-validation + external validation)	cross-validation + external validation	
Wei, Z and Wang, K and Qu, H and Zhang, H and Bradford, J, and Kim, C and Fackler, S and How, C and Gleason, J T and Chivukuri, R and Stanley, C and Ramos, D and Grant, S F and Polyzopoulos, A and Hakonarson, H	2019	PLoS Genet	5	10	e1006878	2019	United States of America	http://dx.doi.org/10.1371/journal.pgen.1006878	article		Case-control study	AUC, accuracy, sensitivity, specificity (5-fold cross-validation + test set)	cross-validation + test set	
White, B and Khan, S A and Ahmad-Ullah, O and Al and Pottler, S and Masou, M and Topgan, C and Drake, R and Heckman, C A and Kalloniemi, D P and Kurtz, S E and Pörkka, K and Tyrer, J W and 212 Altshuler, T and Wernberg, K and Guinney, J	2018	Cancer Research	78	13		2018		http://dx.doi.org/10.1158/1538-7443.CCR18-0111	meeting abstract		Case-control study	correlation, p-value (10-fold CV)	cross-validation	
213 Wu, H and Cai, L and Li, D and Wang, X and Zhao, S and Zou, F and Zhou, X	2018	Biomed Res Int			2392257	2392257	2018	China	http://dx.doi.org/10.1155/2018/2392257	article		Case-control study	AUC, F1-score (5-fold CV)	cross-validation
214 Xie, G and Dong, C and Kong, Y and Zhong, J F and Li, M and Wang, K	2019	Genes	10	3		2019	USA	http://dx.doi.org/10.3390/genes10030240	article		Case-control study			
215 Wang, J S and Zhu, Z X and He, S and Ji, Z and Luo	2013	Bioinformatics			246-251	2013	USA	http://dx.doi.org/10.1093/bioinformatics/btt114	article		Case-control study	accuracy (10 runs of 10-fold CV)	cross-validation	
216 Yang, S and Naiman, D Q	2014	Stat Appl Biom Bioinform	13	4	477-496	2014	States	http://www.ncbi.nlm.nih.gov/pmc/articles/PMC4076474/	article		Case-control study	accuracy (LOOCV + test set)	cross-validation + test set	
217 Tang, Y and Huang, N and Hao, L and Kong, W	2017	BMC Genomics	18		210-210	2017	China	http://dx.doi.org/10.1186/s12864-017-0454-6	article		Case-control study	accuracy, sensitivity, specificity (5-fold cross-validation)	cross-validation	

"Although alpha-fetoprotein (AFP) is a useful serologic marker of hepatocellular carcinoma (HCC), it is not sufficiently sensitive to differentiate HCC and liver cirrhosis (LC) caused by hepatitis B virus (HBV) infection. [...] With a highly optimized peptide extraction and matrix-assisted laser desorption/ionization time-of-flight/matrix-assisted laser desorption/ionization time-of-flight mass spectrometry approach, we investigated serum peptide profiles of 80 HCC and 67 LC patients. Three supervised machine learning methods were employed to construct classifiers. [...] We proposed a novel method for distinguishing HCC from cirrhosis, based on a multilayer perceptron (MLP) method. We obtained a sensitivity of 80.0%, specificity of 79.4%, and overall accuracy of 81.1% on an independent test set. The combination of the MLP model and serum AFP level outperformed serum AFP marker alone in distinguishing HCC patients from LC patients. [...] We investigated the classification performance characteristics of a binary genomic composite biomarker (expected to be predictive of treatment effects) including sensitivity, specificity, accuracy, positive predictive value and negative predictive value as a function of true sensitive prevalence. In doing so, we report the finding based on three representative tuning parameter sets with varying degree of rigor in their choices of the parameters ranging from highly rigorous, moderately rigorous to mildly rigorous. We articulate the rationales on the choices of tuning parameter sets. We also study the impacts of misclassification of genomic biomarker classifiers on their assessment of treatment effects in the positive and negative patient subpopulations, and all-cancer patients."

"Genome-wide association studies (GWAS) have been fruitful in identifying disease susceptibility loci for common and complex diseases. A remaining question is whether we can quantify individual disease risk based on genotype data, in order to facilitate personalized prevention and treatment for complex diseases. Previous studies have typically failed to achieve satisfactory performance, primarily due to the use of only a limited number of confirmed susceptibility loci. Here we propose that sophisticated machine-learning approaches with a large ensemble of markers may improve the performance of disease risk assessment. We applied a Support Vector Machine (SVM) algorithm on a GWAS dataset generated on the Affymetrix genotyping platform for type 1 diabetes (T1D) and optimized a risk assessment model with hundreds of markers. We subsequently tested this model on an independent Illumina-genotyped dataset with imputed genotypes (1,608 cases and 1,600 controls), as well as a separate Affymetrix-genotyped dataset (1,529 cases and 1,458 controls), resulting in area under ROC curve (AUC) of ~0.84 in both datasets."

"To evaluate drug sensitivity studies of samples derived from acute myeloid leukemia (AML) patients have been shown to be predictive of in vivo response. These findings are based on a limited number of well-characterized agents for which in vivo patient response data and ex vivo drug sensitivity data—on that same patient—are available. To show the feasibility of scaling such ex vivo studies to large drug screens, we characterized the reproducibility of expression-based models of drug response across two independent data sets. [...] For each of the 94 drugs in common between the two data sets, we trained a Ridge regression model on the OHSU data set, used the model to predict response in the FIMM data set, and calculated the Pearson correlation between the predicted and observed FIMM responses. 41 of the 94 drug models had a positive and statistically significant correlation (false discovery rate (FDR) < 20%; mean $\rho = 0.43$, 95% CI = 0.21–0.77). Drugs corresponding to the top decile of these significant models (mean $\rho = 0.54$, 95% CI = 0.48–0.77) clustered into four primary classes: MEK inhibitors (PD184522, Saracatinib, and Trametinib), EGFR/VEGFR inhibitors (Cabozantinib, Erlotinib, Foretinib, and Sorafenib), and singletons Venetoclax and Sirtinib."

"The dysbiosis of human microbiome has been proposed to be associated with the development of many human diseases. Metagenome sequencing emerges as a powerful tool to investigate the effects of microbiome on diseases. [...] Here, we developed a pipeline to address the challenging characterization of multibale samples. In this study, a total of 300 biomarkers were selected from the microbiome of 85 Chinese individuals (185 controls, 170 with type 2 diabetes, 120 with rheumatoid arthritis, and 123 with liver cirrhosis), and then logistic regression prediction algorithm was applied to those markers as the model intrinsic features. The estimated model produced an AUC score of 0.942, which was better than other popular classification methods, and an average receiver operating characteristic (ROC) of 0.9475 showed a significant correlation between these selected biomarkers from microbiome and corresponding phenotypes."

"To harness the rich information in multi-omics data, we developed GDP (Group lasso regularized Deep learning for cancer Prognosis), a computational tool for survival prediction using both clinical and multi-omics data. GDP integrated a deep learning framework and Cox proportional hazard model (CPH) together, and applied group lasso regularization to incorporate gene-level group prior knowledge into the model training process. We evaluated its performance in both simulated and real data from the Cancer Genome Atlas (TCGA) project."

"This paper studies a minimal-redundancy-maximal-relevance (MRMR) feature selection for omics data classification using three different relevance evaluation measures including mutual information (MI), correlation coefficient (CC), and maximal information coefficient (MIC). A linear forward search method is used to search the optimal feature subset. The experimental results on five real-world omics datasets indicate that MRMR feature selection with CC is more robust to obtain better (or competitive) classification accuracy than the other two measures."

"[...] Multiclass classification problems pose new methodological and computational challenges for developing novel and effective statistical approaches. In this paper, we introduce a new approach for classifying multiple disease states associated with cancer based on gene expression profiles. Our method focuses on detecting small sets of genes in which the relative comparison of their expression values leads to class discrimination. For an m -class problem, the classification rule typically depends on a small number of m gene sets, which provide transparent decision boundaries and allow for potential biological interpretations. We first test our approach on seven common gene expression datasets and compare it with popular classification methods including support vector machines and random forests. We then consider an extremely large cohort of leukemia cancer to further assess its effectiveness. In both experiments, our method yields comparable or even better results to benchmark classifiers. In addition, we demonstrate that our approach can integrate pathway analysis of gene expression to provide accurate and biologically meaningful classification."

"This study aims to select combinatorial miRNA biomarkers, which have higher sensitivity and specificity than single-gene biomarkers. In order to avoid exhaustive search and redundant information, miRNAs are firstly clustered, and the combinations of representative cluster members are assessed as potential biomarkers. [...] Our experimental results demonstrate that the clustering-based method can identify microRNA combinatorial biomarkers with high accuracy and efficiency."

Author(s)	Year	Journal	Volume	Issue	Page(s)	DOI	Article Type	Abstract Summary	Classification	Validation Type			
218 Yu, H and Samuels, C, C Zhou, Y* and Guo, Y	2019	BMC Genomics	20	12-12	2019	https://doi.org/10.1186/s12854-019-0244-4	article	Architectures and accuracy of artificial neural network for disease classification from omics data	37 omics datasets, including datasets with more than 50 samples per group	Case-control study	Accuracy, Kohan's kappa (nested cross-validation)	cross-validation	"Deep learning has made tremendous successes in numerous artificial intelligence applications and it is unsurprisingly penetrating into various biomedical domains. High-throughput omics data in the form of molecular profile matrices, such as transcriptomes and metabolomes, have long existed as a valuable resource for facilitating diagnosis of patient status/stages. It is timely imperative to compare deep learning neural networks against classical machine learning methods in the setting of matrix-formed omics data in terms of classification accuracy and robustness. [...] Using 37 high-throughput omics datasets, covering transcriptomes and metabolomes, we evaluated the classification power of deep learning compared to traditional machine learning methods. Representative deep learning methods, Multi-Layer Perceptron (MLP) and Convolutional Neural Networks (CNN), were deployed and explored in seeking optimal architectures for the best classification performance. Together with five classical supervised classification methods (Linear Discriminant Analysis, Multinomial Logistic Regression, Naïve Bayes, Random Forest, Support Vector Machine), MLP and CNN were comparatively tested on the 37 datasets to predict disease stages or to discriminate diseased samples from normal samples. MLPs achieved the highest overall accuracy among all methods tested. More thorough analyses revealed that single hidden layer MLPs with ample hidden units outperformed deeper MLPs. Furthermore, MLP was one of the most robust methods against imbalanced class composition and inaccurate class labels. [...] Our results concluded that shallow MLPs (of one or two hidden layers) with ample hidden neurons are sufficient to achieve superior and robust classification performance in exploring numerical matrix-formed omics data for diagnosis purpose."
219 Yu, H, Yu, Y, Yao, X, Yu, W, Wang, J, Kang, J, and Zhang, W, Shao, J, Guo, D, and Wang, Y	2019	BMC Cancer	19	1	263-263	https://doi.org/10.1186/s12854-019-0443-7	article	LUAOpp: an effective prediction model for lung adenocarcinomas based on somatic mutational features	more than 50 samples per group for "good" vs. "poor" distinction (Table S3)	Case-control study	ROC, accuracy, sensitivity, specificity (5-fold CV)	cross-validation	"Non-small cell lung cancer (NSCLC) is the most common type of lung cancer while adenocarcinoma (LUAD) is its most common subtype. [...] However, it remains difficult to find the most significant genetic features and build a high-effective predictive model for treatment outcomes. To confront the challenge, we collected the large-scale LUAD case data with both genomic and clinic information (n=371) from TCGA (The Cancer Genome Atlas) [http://cancergenome.nih.gov], analyzed the somatic mutation difference between the two groups stratified based on the 3-year overall survival, and developed a machine learning model to predict prognosis based on the most significant genetic markers. Through the analysis, we identified a list of genes with different mutation frequencies between different prognosis groups and many were involved in cell-cell adhesion and motility. An absolute majority of the genes showed higher mutation frequencies in the poor prognosis group. [...] Our cancer is the deadliest cancer in the United States, with most patients diagnosed in the advanced stage of the disease. Platinum-based anti-metastatic therapeutics is indispensable to treating advanced ovarian serous carcinoma. However, patients have heterogeneous response to platinum drugs, and it is difficult to predict these inter-individual differences before administering medication. In this study, we investigated the tumor proteomic profiles and clinical characteristics of 130 ovarian serous carcinoma patients analyzed by the Clinical Proteomic Tumor Analysis Consortium (CPTAC), predicted the platinum drug response using supervised machine learning methods. [...] Our data-driven feature selection approach indicated that tumor proteomic profiles contain information for predicting binarized platinum response (P<0.0001). We further built a least absolute shrinkage and selection operator (LASSO) Cox proportional hazards model that stratified patients into early relapse and late relapse group (P<0.0001). The top proteomic features indicative of platinum response were involved in ATP synthase pathways and Ran GTPase binding."
220 Yu, H, and Levine, D, A and Zhang, H, and Chan, D, W and Zhang, Z, and Snyder, M	2016	United States	15	8	2455-2465	https://doi.org/10.1158/1078-0432.CCR.1510712	article	Predicting Ovarian Cancer Patients' Clinical Response to Platinum-Based Chemotherapy by Their Tumor Proteomic Signatures	"Proteomic profiles of 130 ovarian serous carcinoma patients were analyzed by The Cancer Genome Atlas (TCGA) Clinical Proteomic Tumor Analysis Consortium (CPTAC)"	Case only (drug response study)	AUC (BDOCV, hold-out test)	training + test set	"Prostate cancer (PCa) is the second leading cause of cancer-related mortality in men. The prevalent diagnosis method is based on the serum Prostate-Specific Antigen (PSA) screening test, which suffers from low specificity, over-diagnosis and over-treatment. In this work, untargeted metabolomic profiling of age-matched serum samples from prostate cancer patients and healthy individuals was performed using ultra performance liquid chromatography coupled to high resolution tandem mass spectrometry (UPLC-MS/MS) and machine learning methods. A metabolite-based in vitro diagnostic multivariate index assay (VDMIA) was developed to predict the presence of PCa in serum samples with high classification sensitivity, specificity and accuracy. A panel of 40 metabolic spectral features was found to be differentiated with 92.1% sensitivity, 94.3% specificity, and AUC of 99.0% accuracy. The performance of the VDMIA was higher than the prevalent PSA test. [...] The identification of fatty acids, amino acids, lipopolysaccharides, and bile acids provided further insights into the metabolic alterations associated with the disease."
221 Zhang, X, and Jones, C, M and Long, T, Q and Monea, M, E and Zhou, M, and Walker, L, D and Meanecke, B	2014	USA	13	7	3444-3454	https://doi.org/10.1158/1078-0432.CCR.1319040	article	Feasibility of detecting prostate cancer by ultraperformance liquid chromatography-mass spectrometry serum metabolomics	Age-matched blood serum samples were obtained from 64 PCa patients (age range 49-65, mean age 59 ± 4 years) and 50 healthy individuals (age range 45-76, mean age 57.7 years).	Case-control study	accuracy, sensitivity, specificity (10-fold cross-validation)	cross-validation	"High-risk neuroblastoma is a very aggressive tumor with excessive tumor growth and poor outcomes. A proper stratification of the high-risk patients by prognostic outcome is important for treatment. However, there is still a lack of survival stratification for the high-risk neuroblastoma. To fit the need, we adopted a deep learning algorithm, Autoencoder, to integrate multi-omics data, and combine it with K-means clustering to identify two subtypes with significant survival difference. By comparing the Autoencoder with PCA, Cluster, and t-Distributed Stochastic Neighbor Embedding (t-SNE), we also validated the classification based on multi-omics data integration. Autoencoder-based classification outperforms the alternative approaches. Furthermore, we also validated the classification in two independent datasets by training machine learning classification models, and confirmed its robustness. Functional analysis revealed that MYCN amplification was more frequently occurred in the ultra-high-risk subtype, in accordance with the overexpression of MYCN/MYCN targets in this subtype."
222 Shi, T, Zhang, L, and Li, C, and Jin, Y, and Cheng, G, and Fu, Y, and Yuan, D, and Tao, Y, and Guo, Y, and Ni, X, and Zhang, L, and Han, Z, and Shi, T, and Li, H	2018	China	9	1	0017	https://doi.org/10.1158/1078-0432.CCR.1710007	article	Deep learning-based multi-omics data integration reveals high prognostic subtypes in high-risk neuroblastoma	"The TARGET cohort is comprised of 407 high-risk neuroblastoma samples, including 217 samples with gene expression data and 200 samples with copy number alterations (CNA). Among these obtained samples, 130 had both gene expression and CNA data. The t-SNE cluster has a total of 498 neuroblastoma samples, including 176 high-risk and 322 low- or intermediate-risk samples."	Cases only (prognostic stratification)	C-index, log-rank p-value, AUC (10-fold CV, external validation set)	cross-validation + external cohort validation	"Prostate cancer is a leading male malignancy worldwide, while the prognosis prediction remains quite inaccurate. The study aimed to observe whether there was an association between the prognosis of prostate cancer and genetic mutation profile, and to build an accurate prognostic predictor based on the genetic signatures. [...] No significant gene with somatic mutation rate difference was found between prognostic groups of prostate cancer. Total 43 physical genes were screened for building a support vector machine model to predict prostate cancer prognosis, with an average accuracy of 66% and 64% for 5-fold cross-validation or training/testing evaluation respectively. When combined with the National Institute for Health and Care Excellence (NICE) features, the model could be further improved, with the 5-fold cross-validation accuracy of 71%, much better than NICE itself (62%)."
223 Zhang, S, and Xu, Y, and Hu, X, and Yang, F, and Hu, Y, and Shao, J, and Liang, H, and Wang, Y	2017	China	8	16	3261-3267	https://doi.org/10.1158/1078-0432.CCR.1710007	article	Improvement in prediction of prostate cancer prognosis with somatic mutational signatures	more than 50 samples per group (both for recurrence status and tumor status)	Cases only (prognosis study)	ROC, accuracy (5-fold CV, training/test split)	training + test set	"Primary platinum-based chemoresistance occurs in approximately one-third of patients with serous ovarian cancer (SOC); however, traditional clinical indicators are poor predictors of chemoresistance. So we aimed to identify novel genes as predictors of primary platinum-based chemoresistance. Gene expression microarray analyses were performed to identify the genes related to primary platinum resistance in SOC on two discovery datasets (GSE1373, GSE43888) and one validation dataset (TCGA). Univariate and multivariate analyses with logistic regression were performed to evaluate the predictive values of the genes for platinum resistance. Machine learning algorithms (linear kernel support vector machine and artificial neural network) were applied to build prediction models. Univariate and multivariate analyses with Cox proportional hazards regression and log-rank tests were used to assess the effects of these gene signatures for platinum resistance on prognosis in two independent datasets (GSE1373, GSE43888). AGO1 and MAFK were found highly expressed in patients with platinum-resistant SOC and independent predictors of platinum resistance. Platinum resistance prediction models based on these targets had robust predictive power (logNest AUC: 0.8056, 95% CI: 0.6388-0.9773; AUC: 0.7245, 95% CI: 0.6022-0.8487)."
224 Zhou, H, and Sun, Q, and Li, L, and Zhou, J, and Zhang, C, and Hu, Y, and Zhou, Y, and Zhang, L, and Wang, B	2019	China	10	2	397-407	https://doi.org/10.1158/1078-0432.CCR.1810012	article	High expression levels of AGO1 and MAFK associated with adverse ovarian cancer prognosis	The used TCGA data covers more than 50 samples per group	Cases only (drug resistance prediction)	log-rank test p-value, AUC (5 times 10-fold CV + external validation)	cross-validation + external cohort validation	"Despite existing prognostic markers, breast cancer prognosis remains a difficult subject due to the complex relationships between many contributing factors and survival. This study seeks to integrate multiple clinicopathological and genomic factors with dimensional reduction across machine learning algorithms to compare survival predictions. [...] ROC and accuracy were not significantly different between models (ROC and accuracy around 0.67 and 0.72 across models, respectively). However, ensemble methods resulted in better fit (CS) with stable measures of variable importance across 10 random training/validation splits. K-means clustering of gene expression profiles on training data points along with KNN classification of validation data points was a robust method of dimensional reduction. Furthermore, the gene expression cluster with the highest mortality risk was an influential factor in model prediction. [...] Using machine learning methods to construct predictive models for 5-year survival in patients with breast cancer, we demonstrated discrimination ability across models with new insight into the stability and utility of dimensional reduction on genomic features in breast cancer survival prediction."
225 Zhao, M, and Tang, Y, and Kim, H, and Hasegawa, K	2018	USA	17	1	110-111	https://doi.org/10.1158/1078-0432.CCR.1710007	article	Machine Learning With K-Means Dimensional Reduction for Predicting Survival Outcomes in Patients With Breast Cancer	TC509 adult female participants with breast cancer in a prospective cohort study	Cases only (survival prediction)	ROC, accuracy (10-fold CV)	cross-validation	"To this review, we reviewed the most recent published works that used deep learning to build models for cancer prognosis prediction. Deep learning has been suggested to be a more generic model, requires less data engineering, and achieves more accurate prediction when working with large amounts of data. The application of deep learning in cancer prognosis has been shown to be equivalent or better than current approaches, such as CoxPH. With the burst of multi-omics data, including genomic data, transcriptomic data and clinical information in cancer studies, we believe that deep learning would potentially improve cancer prognosis."
226 Zhu, W, and Xia, L, and Han, J, and Guo, X	2020	China	12	3	3000	https://doi.org/10.1158/1078-0432.CCR.1910012	article	The application of deep learning in cancer prognosis prediction	review (not applicable)	review	review	review	"To this review, we reviewed the most recent published works that used deep learning to build models for cancer prognosis prediction. Deep learning has been suggested to be a more generic model, requires less data engineering, and achieves more accurate prediction when working with large amounts of data. The application of deep learning in cancer prognosis has been shown to be equivalent or better than current approaches, such as CoxPH. With the burst of multi-omics data, including genomic data, transcriptomic data and clinical information in cancer studies, we believe that deep learning would potentially improve cancer prognosis."

Author(s)	Year	Journal	Volume	Issue	Page(s)	DOI	Article Type	Abstract Summary	Case(s) only (prognosis study)	AIUC (training + validation data)	training + test set	cross-validation + test set	cross-validation + external cohort validation	Review
227 Zou, M and Liu, Z and Zhang, X and Wang, Y	2015	Biomformats	11	20	330-338	1015	China	NCC-AIC: An AIUC optimization method to identify multi-biomarker panel for cancer prognosis from genomic and clinical data	Dataset 1: 1983 patients with 328 basal-like tumors, 238 HER2 tumors, 719 luminal A, 490 luminal B and 200 normal-like tumors. Dataset 2: 444 stage II NSCLC patients	Case(s) only (prognosis study)	AIUC (training + validation data)	training + test set		
228 Zou, M and Zhang, P-J and Chen, L and Tian, Y-P and Wang, Y	2016	Biomark Med	10	6	567-575	2016	China	Identifying joint biomarker panel from multiple level dataset by an optimization method	"101 colorectal cancer and 95 benign samples". "Whole-blood gene expression profiles were collected from a total of 523 individuals. After preprocessing, the data contained 486 gene profiles (n = 205 PD, n = 233 controls, n = 48 other monogenetic diseases) that were partitioned into training, validation, and independent test cohorts to identify and validate a gene signature."	Case-control study	accuracy (DOCV + test set)	cross-validation + test set		
Shamir, Ron and Klein, Christine and Amar, David and Volkov, Eva Juliane and Boren, Michael and Ussakov, Marly and Wong, Yette C. and Mow, Alex and Potts, Sean and Sailer, Herbert and the Covid, Jean Christophe and Lesage, Suzanne and Lavi, Ofer and Deuchin, Gai and Kuhlmann, Gregor and Pevsack, Hella and Ullrich, Yael and Kaplan, Meike and Rees, Ofra and Bick, Alon and Eisenberg, Ron and Kravitz, Omri	2017	Neurology	89	16	1676-1683	2017	Croatia	Analysis of blood-based gene expression in idiopathic Parkinson disease	"101 colorectal cancer and 95 benign samples". "Whole-blood gene expression profiles were collected from a total of 523 individuals. After preprocessing, the data contained 486 gene profiles (n = 205 PD, n = 233 controls, n = 48 other monogenetic diseases) that were partitioned into training, validation, and independent test cohorts to identify and validate a gene signature."	Case-control study	AIUC (cross-validation + external test set)	cross-validation + external cohort validation		
230 Glaab, E	2016	Briefings in Biomaterials	17	3	440-452	2016	England	Using prior knowledge from cellular pathways and molecular networks for diagnostic specimen classification	review (not applicable)	review				
Shreve, J and Maggendorfer, M and Awada, H and Mukherjee, S and Walter, W and Hutter, S and Mahboub, C and Hibon, C and Radokovich, N and Nagas, R and Garcia, A and Tomar, C M and Ghaf, S J and Sambamurti, T and Mackey, T F and Hefarlich, C and Sekeres, M A and Hafarlich, T and Nizha, A	2019	Blood	134			2019	USA	A personalized prediction model to risk stratify patients with acute myeloid leukemia using artificial intelligence	"A total of 792,779 genomic and clinical data points from 3,421 pts were analyzed. The cohort was comprised of five independent datasets: 443 pts from the Basel AML Master Trial (Tyrer et al., Nature, 2018), 855 pts from Cleveland Clinic, 414 pts from Munich Leukemia Laboratory (MALL, 1,509 pts from the German-Austrian Study Group (GAP) and 205 pts from The Cancer Genome Atlas (TCGA, 2013)."	subtype categorization	C-index (training + test cohorts)	external cohort validation		
232 Beer, C and Walter, W and Stengel, A and Hutter, S and Maggendorfer, M and Kern, W and Hafarlich, T	2019	Blood	134			2019	Germany	Molecular classification of AML/MRC reveals a distinct profile and identifies MRC-like patients with poor overall survival	"According to WHO standards, 163,739 (22%) cases fulfilled MRC criteria (96 males (69 female)). The non-MRC cohort (n=576) represents a heterogeneous AML population incl. the WHO defined recurrent cytogenetic abnormalities of t(AM1,10) (n=24), 72% female."	Case-control study	true positive rate, false positive rate (10-fold cross-validation)	cross-validation		
233 Zhu, W and Xia, L and Han, J and Guo, X	2020	Cancers	12	3		2020	China	The application of deep learning in cancer prognosis prediction	review (not applicable)	Review				
234 Urbig, A and Morgenthaler, S and Dolezal, M	2019	Annals of Oncology	30		445-451	2019	Switzerland	Discovery of an immunotranscriptomic signature in blood in early colorectal cancer detection	"The cohort included 189 subjects with CRC, 115 with advanced adenoma (AA), 39 with other types of cancer (OC) as well as 228 individuals without any colorectal lesions (CON)."	Case-control study	AIUC, sensitivity, specificity (independent test validation)	training + test set		
236 Mackey, T F and Hafarlich, T and Nizha, A	2019	Blood	134			2019	USA	Geno-clinical model for the diagnosis of bone marrow myeloid neoplasms	"A total of 2,602 unstimulated saliva samples were collected from 221 subjects with CRC, 99 subjects with polyps, and 2272 subjects with healthy controls."	Case-control study	AIUC (The cohort was randomly divided into learner (80%) and validation (20%) cohorts")	training + test set		
237 and Dai, H and Liang, Z	2019	Annals of Oncology	30		261-262	2019	China	Early detection of pancreatic ductal adenocarcinoma using methylation signatures in circulating tumour DNA	"We have collected freshly frozen clinical PDAC tissues (n=48), pancreatico-pancreas tissues (n=30), PDAC plasma samples (n=120), chronic pancreatitis plasma samples (n=95), and normal plasma samples (n=100)."	Case-control study	AIUC	cross-validation		
238 Adams, D and Rowan, C and Adhinay, T and Tang, L and Paceira, S	2020	Front Immunol	11		673-673	2020	USA	Biomarkers for Allogeneic HCT Outcomes	review (not applicable)	Review				
239 Ahmed, T and Park, S and Jiang, Q and You, Y and Hwang, T and Zhang, W	2020	BMC Med Genomics	13		193-193	2020	USA	Network-based drug sensitivity prediction	"The feature selection methods and prediction models were tested on 144 NSCLC cell lines RNA-seq gene expression dataset [36]. All the 144 cell lines were screened by the same drugs and the AUC and ESSE scores for each drug on each cell line are available in this study."	Case-control study	correlation (70% as the training set, and 30% as the test set)	training + test set		
240 Ahmed, Z and Mohamed, A and Zeeshan, S and Dong, X	2020	Database (Oxford)	2020			2020	USA	Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine	review (not applicable)	Review				
241 Semburi, A and Yu, E and Lin, L and Otero, A and Koch, H and Hedou, J J and Leavy, E B and Sempere, V P and Mignot, E and Taylor, S	2020	Front Immunol	11		11	2020	Qatar	Proteomic biomarkers of sleep apnea	"Serum samples from 713 individuals in the Stanford Sleep Cohort."	Case-control study	AIUC (10-fold CV + validation)	cross-validation + test set		
242 Sun, X and Liu, M and Fan, Y and Miao, M and Song, J and Gu, C	2020	Nano Biomedicine	12	1	1-13	2020	China	SVM based classification and prediction system for gastric cancer using dominant features of saliva	"720 saliva samples were collected from the non-cancerous and gastric cancer patients."	Case-control study	AIUC, accuracy, specificity, sensitivity (10-fold cross-validation). "To avoid the overfitting issue, we used an ES approach. We controlled the error of the network during the training phase and stopped the training if the model undergoes the overfitting."	cross-validation		
243 Awada, H and Duran, A and Gurnal, C and Khatkhaty, A and Maggendorfer, M and Kern, C M and Kuzmanovic, T and Duran, J and Nagata, S and Radokovich, T and Adawi, A S and Ravandi, F and Carraway, H E and Nizha, A and Hafarlich, C and Samartharajah, Y and Scott, S and Vidone, P and Kantipati, H M and Kadia, T M and Sekeres, M A and Hafarlich, T and Mackey, T F	2020	Blood	136		28-28	2020	USA	The application of machine learning to improve the subclassification and prognostication of acute myeloid leukemia	"We collected and analyzed genomic data from a multicenter cohort of 6788 AML patients"	Case-control study	accuracy (cross-validation)	cross-validation		
244 Bader, J M and Geyer, P F and Miller, J B and Strauss, M J and Koch, M and Lippoldt, F and Koertgen, P and Bittner, D and Schipke, C S and Inceoy, E I and Peters, O and Diegelmann, N and Simons, M and Jensen, M and Zetterberg, H and Mann, M	2020	Mol Syst Biol	16	6	49356	2020	Germany	Proteomic profiling in cerebrospinal fluid reveals novel biomarkers of Alzheimer's disease	"From three independent studies (197 individuals), we characterized differences in proteins by A0 status"	Case-control study	AIUC (N-fold CV, k = 6)	cross-validation		

Author(s)	Journal	Year	Country	Study Type	Findings/Conclusions	Validation Type		
Bergamacci, A and Ku, J and Ning, Y and Collin, F and Ellison, C and Phillips, T and McCarthy, E and Wang, W and Antonio, M and Han, D and Scott, A and Lloyd, J and Guler, G and Ashworth, A and 245 Quake, S and Lavy, S	Cancer Research	80	16	2020	USA	Meeting abstract	cross-validation	
Berry, S E and Valdes, A M and Drew, D A and Ankrich, F and Mazi, M and Wolf, J and Gajdos, J and Hadjiagapiou, G and Davies, R and Al Khalil, H and Bonnet, C and Casone, S and Bakker, E and Hart, D and Mangin, M and Mirza, J and Linnemann, J and Lloyd, W and Ford, D and O'Brien, J and M Gardner, D and de Lathauwer, L and Chau, A T and Keegan, H and Frew, J and Woodhead, T S	Nat Med	26	6	964-973	2020	UK	training + test set	
247 Bhatta, S and Kaur, I and Kaur, R and Sharma, S and Raghava, G P S	PLoS One	15	4	4031629-4031629	2020	India	cross-validation + test set	
248 Bigelow, G and Baria, A and Yarbcan, M and Jaffe, E M	Cancer Research	80	16	2020	USA	meeting abstract	training + test set	
Brown, E and Karar, A and Hellings, S and Stepanova, M and Warrick, B and Lam, L and Donato, J and Felix, S and Agfil, A and Jeffers, T and Rajar, B and Charles, E and Nader, F and Luo, Y and Behr, M and Zhao, L and Thompson, C and Goodman, Z and Younus, Z	Journal of Hepatology	73	5	5409-5410	2020	USA	meeting abstract	cross-validation
250 Cai, W and Dong, Z and Fu, X T and Lin, L Y and Wang, L and Ye, G D and Lu, Q C and Chen, Y C	Theranostics	10	19	8633-8647	2020	China	article	external cohort validation
251 Cammarota, G and Inrita, G and Ahern, A and Carboni, C and Tomko, A and Claesson, M J and 251 Gasbarrini, A and Tortora, G	Nat Rev Gastroenterol Hepatol	17	10	655-668	2020	Italy	article	Review
252 Casanelli, S and Molinari, I and Isella, C and Massaroli, M and Medico, E	Sci Rep	10	1	14071-14071	2020	Italy	article	cross-validation + external cohort validation
Catalina, M D and Bachli, P and Yao, A E and Gerard, N S and Petri, M A and Grammer, A C and 253 Lipka, P E	ICJ Height	5	15	2020	USA	article	cross-validation	
254 Kodra, A M and Mawhoo, C and Ko, J and Bottiglieri, T and Wangstein, A and Opatowski, A and 254 Cutler, S	Journal of the American College of Cardiology	75	11	552-562	2020	USA	meeting abstract	cross-validation
255 Chan, S and Reddy, A and Myers, B and Thibodeau, Q and Brownstone, W and Luo, W	Dermatology and Therapy	10	3	365-386	2020	USA	article	Review
256 Chavarriaga, J and Moreno, C	Urologia Colombiana	29	3	158-167	2020	Colombia	article	Review
Cherici, M and Bussola, M and Marchetti, A and Francescato, M and Zambò, A and Trastulla, L and 257 Agostinelli, C and Juman, G and Farfallo, C	Frontiers in Molecular and Cellular Oncology	10	2020	Italy	article	cross-validation + external cohort validation		
258 Ciolek, R and Kuebler, J and Saranen, M and Wilmes, P and Coimbra-Morand, F and Ross, P S and 258 Hilger, C and Bindsig-Jensen, C and Ollert, M and Kuehn, A	Front Immunol	11	594550-594550	2020	Germany	article	Review	
259 Vicentini, A P and Rocha, A and Catharino, R R	mySystems	5	3	2020	Brazil	article	cross-validation	
260 Eddy, S and Mariani, L H and Kretzler, M	Nat Rev Nephrol	16	11	657-668	2020	USA	article	Review
261 Fu, S and Zarrissir, A	Curr Opin Organ Transplant	25	4	420-425	2020	USA	article	Review
262 Kurthioğlu, A and Fu, J and Zhamalov, A and Weerama, R	Netherlands Journal of Medicine	7	8	166-167	2019	Netherlands	meeting abstract	training + test set
263 Gupta, R	JNCI Cancer Spectrum	4	3	2020	Denmark	meeting abstract	cross-validation + external cohort validation	

Author(s)	Year	Journal	Volume	Issue	Page	DOI	Abstract	Study Design	Outcome	Notes
Gindly, Y and Chang, J and Billin, A and Camargo, M and Husa, R and Chung, C and Myers, R and 264 Youniss, Z M and Harrison, S A and Antea, Q M and Loomis, R	2020	Hepatology	72	1	434-44A	100268.11314	The study included 1,120 adults with advanced fibrosis (F3-F4) due to NAFLD enrolled in the international STEAP cohort. The study included 1,120 adults with advanced fibrosis (F3-F4) due to NAFLD enrolled in the international STEAP cohort. The study included 1,120 adults with advanced fibrosis (F3-F4) due to NAFLD enrolled in the international STEAP cohort.	Case-control study	AUC (training + validation cohort)	training + test set
Goswami, C and Chavla, S and Thakral, D and Pant, H and Verma, P and Mallik, P S and Jayasinha and 265 Gupta, R and Anuja, G and Sengupta, D	2020	Genomics	21	1	744-744	10.1016/j.gen.2020.07.024	Molecular signature comprising 11 placental genes enables accurate blood-based diagnosis of NSCLC	Case-control study	AUC (LOOCV)	cross-validation
Grathos, S A and Lee, E E and Josta, D V and Van Patten, R and Twamley, E W and Nebeker, C and 266 Yamada, I and Kim, H C and Depp, C A	2020	Psychiatry Research	284			10.1016/j.psychres.2020.11314	Artificial intelligence approaches to predicting and detecting cognitive decline in older adults: A conceptual review	Review		review (not applicable)
Gumral, A and Sammoura, R and Al-Rakhani, M and AlSalman, H and El-Gaart, A	2021	Health Informatics Journal	27	1		10.1177/1463426920949494	Feature selection with ensemble learning for prostate cancer diagnosis from microarray gene expression	Case-control study	accuracy (10-fold CV)	cross-validation
Guy, L and Wu, A H and Wang, Y X and Zhang, P L and Chai, H and Liang, X F	2020	BioData Mining	13	1		10.1093/bioinformatics/btaa019	Deep learning-based ovarian cancer subtypes identification using multi-omics data	Tumor stratification	silhouette score (external test datasets)	training + test set
Hajjoulou, I and Elemento, O	2020	Fertil Steril	114	5	908-913	10.1016/j.fertnstert.2020.05.016	Precision medicine and artificial intelligence: overview and relevance to reproductive medicine	Review		review (not applicable)
Hao, S and Bai, J and Liu, W and Wang, L and Liu, T and Lin, C and Luo, X and Gao, J and Zhuo, J and 270 H and Tang, H	2020	Regenerative Therapy	15		180-186	10.1016/j.reth.2020.07.001	Comparison of machine learning tools for the prediction of AMD based on genetic, age, and diabetes-related variables in the Chinese population	Case-control study	AUC (4-fold CV)	cross-validation
He, Z and Zhang, J and Yuan, X and Zhang, Y	2020	Frontiers in Genetics	11			10.3389/fgen.2020.00197	Integrating Somatic Mutations for Breast Cancer Survival Prediction Using Machine Learning Methods	Case-control study	AUC (entire datasets were randomly divided into a learning dataset (80% of the entire dataset) and validation dataset (20%))	
Hong, S and Su, Z and Li, L and Yu, S and Liu, B and Gu, Z and Zhang, Q and Guo, Z and Lu, W and Peng and 272 S and Cheng, L and Qian, L and Liu, R and Xiao, H	2020	Annals of Oncology	31		5132-5132	10.1093/annonc/mdz319	Development of circulating free DNA methylation markers for thyroid nodular diagnosis	Case-control study	accuracy, sensitivity, specificity (training/test)	training + test set + external cohort
Hosino, A and Kim, H S and Banjar, L and Gyus, K E and Cluff, M and Hernandez, J and Zambonis, C P and Rodrigues, G and Molina, H and Heist, S and Mark, M T and Oliver, I and Benito-Martín, A and Lucero, S and D Gamaral, A and Oller, J and Nakajima, M and Williams, C and Naguib, I and Peltzer-Vetter, F A and Hashimoto, A and Davoli, E and Fretz, D and Kretz, C M and Arano, Y and Buchling, W and Lautzbars, P and Qigari, Y and Sugitara, K and Takahashi, N and Alkhalaf, M and Bailey, K A and Jossinet, J and Wang, H and Harris, A and Schaffner, L M and Garcia-Santos, G and Ponsor, Z and Blichner, V F and Bhawoo, J P and Bhatt, S and Saji, I and Scherz-Shouval, R and Yarden, Y and Oren, M and Maladi, M and Petriccione, M and De Briceno, K C and Donelli, M and Fischer, C and Vizzato, S and Wright, G P and Ganahay, L and Marano, M and Ahmed, A and DeFranco, J and Donceel, E and Boer, M F A and Lacey, J and Viscusi, T C and Weiser, M R and Brady, M S and Meyers, P A and Winkler, L H and Ambati, S R and Chou, A J and Sliker, E K and Motta, S and Roberts, S S and Basu, E M and Dulani, D and Krantz, B A and Carobon, F and Simpson, A L and Benay, M and Bouch, C M and Smeone, D M and Jain, M and Ghauri, C M and Bato, S K and Stanger, B Z and Bai, J and Brown, K A and Rajagohar, V K and Healy, H J and de Souza, M and Krone, K and Sheth, S and Banaji, J and Facciolo, V and Hamed, T E and Li, Q and Qiu, B and Piscioli, D J and Schwartz, R and Zhang, H and Lu, Y and Shukla, A and Blavier, L and DeClerck, A and LaBerge, M and Bossi, M and Caffrey, T C and Grangirgny, P M and Hollingsworth, M D and Bromberg, J and Costa-Silva, B and Frenkel, H and Kang, W B and Okilly, E M and 273 Kelson, D and Pappert, T W and Jones, D R and Matal, I R and Jarnagin, W R and Lyden, D	2020	Cell	182	4	1044-1061.e18	10.1016/j.cell.2020.07.043	Extracellular Vesicle and Particle Biomarkers Define Multiple Human Cancers	Case-control study	sensitivity, specificity (10-fold CV + external test set)	validation + external cohort
Huang, J and Kuth, C and Covic, M and Trull, M and Adams, J and Zukausk, S and Probst, C and Wang, and Nano, J and Scherer, F F and Nesch, S and Kastlunger, G and Suhr, K and Lang, M and 274 Schless, J and Geiger, C and Adams, J and Hildebrandt, G and Potos, A and Wang Sattler, R	2020	Diabetes	69		2776-2785	10.2337/201765	Machine Learning Approaches Reveal Metabolic Signatures of Incident Chronic Kidney Disease in Individuals With Prediabetes and Type 2 Diabetes	Case-control study	AUC (three-step feature selection with 100 random repeats of 10-fold cross validation)	cross-validation
Huang, Y and Johnson, T S and Han, Z and Helm, B and Cao, S and Zhang, C and Salama, P and Nakata and 275 Ma and Yu, C Y and Chang, J and Xiang, S and Zhang, X and Huang, K	2020	BMC Med Genomics	13		41-41	10.1186/s12920-020-00621-1	Deep learning-based cancer survival prognosis from RNA-seq data: approaches and evaluation	Cancer survival prognosis	C-index, p-value of log-rank test (Each dataset was split into training, validation, and testing sets in a proportion of 80, 20, and 20% respectively)	training + test set
Jiang, J and Yan, H and Yang, L and Li, J and Xin, J and Shi, D and Jiang, X and Cai, Q and Ren, K and 276 Chen, X and Li, J	2019	Hepatology	70		162A-163A	10.1002/hep.24729	Proteome predicts progression and prognosis of hepatitis B virus-related acute-on-chronic liver failure	Cancer progression and prognosis prediction	AUC (training + validation cohort)	external cohort validation
Jovkovic, I	2020	Frontiers in Oncology	10			10.3389/fonc.2020.00197	Painting the Epigenetic Portrait of Glioblastoma	Review		review (not applicable)

Author(s)	Journal	Year	Country	Link	Abstract	Study Type	Methodology	Findings	Conclusion
Kandimalla, R, et al.	Cancer Research	2020	USA	https://doi.org/10.1158/1538-8514.2020-0104	meeting abstract	Case-control study	AUC (training + validation cohort)	"Using this approach, we sequenced 300 plasma specimens from all 61 Cancers, as well as age-matched healthy controls"	external cohort validation
278 Baha, H, et al.	Journal of Hepatology	2020	India	https://doi.org/10.1016/j.jhep.2020.09.016	meeting abstract	Case-control study	AUC, accuracy (training + validation set)	"The dataset contains gene expression data from participants with glucose tolerance ranging from normal to newly diagnosed T2DM, in which 71 and 63 individuals were healthy and diabetic, respectively"	training + test set
280 Khojehchi, M, et al.	BMC Med Genomics	2020	Iran	https://doi.org/10.1186/s12916-020-01614-z	article	Case-control study	AUC, accuracy, F1 score, precision, recall (10-fold CV)	"The final predictive performance was measured by comparing the correlation between the observed and predicted drug response in the test set (92) "left the original dataset into training (80%), validation (10%), and test (8%) sets", 3-fold CV for training"	cross-validation
281 Kong, J, et al.	Commun Nat Commun	2020	Korea	https://doi.org/10.1038/s41467-020-18113-8	article	Case-control study		"We downloaded the PRM-UCI (upper quartile) dataset from TCGA data portal for expression analysis"	training + test set
282 Korac, K, et al.	Sci Rep	2020	Poland	https://doi.org/10.1038/s41598-020-67679-z	article	Drug response prediction	Correlation, RMSE (3-fold CV on training data + test set evaluation)	"The total set of samples consisted of 983 cancer cell lines originating from 13 tissue sites"	training + test set
283 Kouras, M, et al.	Metabolites	2020	Greece	https://doi.org/10.3390/met10050102	article	Case-control study	AUC (10-fold CV + validation)	"The random forest machine learning algorithm achieved a correct classification of patients of 88.5% (area under the curve—AUC 0.94). However, none of the methods used achieved adequate discrimination between LC patients and patients with abnormal computed tomography (CT) findings. Biomarker sets, consisting mainly of the exogenous monomeric compounds and 1- and 2-propanol, adequately discriminated LC patients from healthy controls"	cross-validation + test set
284 Lai, H, et al.	Sci Rep	2020	Taiwan	https://doi.org/10.1038/s41598-020-10910-0	article	Case-control study	AUC, accuracy (10-fold CV + validation set)	"We separated 256 patients as the test set (92) "left the original dataset into training (80%), validation (10%), and test (8%) sets", 3-fold CV for training"	training + test set
285 Le, S, et al.	INCI Cancer Spectrum	2020	USA	https://doi.org/10.1038/s41598-020-18113-8	article	Treatment response prediction	AUC (training + test set)	"We assessed germline genome-wide data of 2778 early-stage breast cancer patients from the Cancer Toxicity study (NCT01993997)"	training + test set
286 Liu, B, et al.	Clinical Cancer Research	2020	China	https://doi.org/10.1158/1078-0432.CCR.20-001	meeting abstract	Case-control study	AUC (training + test set)	"The study was conducted among 412 surgery-resectable patients with lung cancer (N=180), colorectal cancer (N=210), liver cancer (N=42), and 290 age-/sex-/matched non-cancer controls"	training + test set
287 Liu, L, et al.	Pharmacol Sci Experiment	2020	USA	https://doi.org/10.1093/psp/ckaa013	article	Case-control study	AUC (repeated 10-fold CV)	"We retained 42,100 patients for the subsequent analysis"	cross-validation
288 Liu, F, et al.	Hematology Oncology	2020	China	https://doi.org/10.1186/s12916-020-01614-z	article	Prognostic subtype correlation (discovery + validation cohorts)		"We performed unsupervised clustering of total 1000 HC (hepatocellular carcinoma) samples including discovery and validation group from available public datasets"	external cohort validation
289 Liu, P, et al.	PeerJ	2020	China	https://doi.org/10.7717/peerj.9614	article	Case-control study	AUC (10-fold CV + validation cohort)	"The discovery stage involved 150 pairs of cCRCC (clear cell renal cell carcinoma) and matched normal tissues for investigation of DMMs and biomarkers as well as 318 cases of cCRCC including clinical diagnosis"	cross-validation + external cohort validation
290 Liu, Y, et al.	Sci Rep	2020	China	https://doi.org/10.1038/s41598-020-41804-4	article	Case-control study	AUC (10-fold CV + validation)	"This article describes 25,501 genes in 406 different breast cancer samples. We retained only samples with complete information. After that, 85 TMBs and 466 non-TMBs were further divided into two groups: training (n=327, 51 TMB, 276 non-TMB) and testing (n=218, 34 TMB, 184 non-TMB) sets"	cross-validation + test set
291 Liu, Y, et al.	Clinical Medicine Insights: Oncology	2020	China	https://doi.org/10.1177/1076220620960002	article	Prognostic study	AUC (10-fold CV + validation)	"772 samples of the TCGA LIHC cohort were selected according to the overall survival and were partitioned into the training set and testing set (75%/25%)"	cross-validation + test set
292 Liu, Y, et al.	OncoTarget and Therapy	2020	China	https://doi.org/10.1177/1076220620960002	article	Prognostic study	AUC (training + test set + external validation set)	"The TCGA training set contains 226 samples and the test set contains 227 samples. As an external validation set, the GSE17518 data set contains a total of 244 samples, including 6 mouse samples, while among the 238 human samples, 98 samples recorded the survival status of NA, and finally used for follow-up analysis"	external cohort validation
293 Luca, B, et al.	Br J Cancer	2020	United Kingdom	https://doi.org/10.1038/s41325-020-02064-z	article	Prognostic subtype stratification	Correlation, log rank p-value (hold-out validation)	"There were 1785 samples from primary malignant tissue, and 178 from normal tissue"	training + test set
294 Luo, S, et al.	Ageing (Albany NY)	2020	China	https://doi.org/10.1089/aging.2020.0005	article	Tumor recurrence and immunotherapy response prediction	AUC (training + external validation)	"To this study, we initially identified 4 CpG biomarkers associated with recurrence of NSCLC. Based on TCGA NSCLC cohort comprised of lung adenocarcinomas (LIAD) and lung squamous cell carcinomas (LISC), a promising DMM-based risk score model predictive of relapse was constructed and then validated in the other 3 datasets"	external cohort validation
295 Makarios, M, et al.	Movement Disorders	2020	USA	https://doi.org/10.1002/md.2368	meeting abstract	Case-control study	AUC (30% test samples after training on 70% of samples)	"This included 272 samples that had sequenced genomes, clinical data, and 50K normalized transcripts from RNA sequencing"	training + test set
296 Arora, M, et al.	Blood	2020	USA	https://doi.org/10.1182/blood.2020.135070	meeting abstract	Prognostic study	C-index (cross-validation)	"12,049 patients were included in the final analysis. There were 855 CAT events during the observation period"	cross-validation
297 Mancini, M, et al.	J Proteome Res	2021	Argentina	https://doi.org/10.1021/acs.jproteome.1c00003	article	Case-control study	accuracy (training/test set)	"Patients with clear cell renal cell carcinoma (cCRCC) stage I, II, and IV (n = 112) and controls (n = 12)"	training + test set
298 Westermann, D, et al.	J Am Heart Assoc	2020	USA	https://doi.org/10.1161/aha.120.027121	article	Case-control study	AUC (train + test + external validation)	"This a derivation cohort of 636 patients referred for coronary angiography, predictors of 270% coronary stenosis were identified from 6 clinical variables and 109 biomarkers. The final model was first internally validated on a separate cohort (n=75) and then externally validated on a cohort of 243 patients"	external cohort validation
299 McCarthy, C, et al.	J Am Heart Assoc	2020	USA	https://doi.org/10.1161/aha.120.027121	article	Case-control study	AUC (train + test + external validation)	"We have derived and externally validated a clinical/prognostic panel that can predict the presence of obstructive CAD with high accuracy. The score performs similarly well in the evaluation of acute chest pain in the ED (including patients who had MI neither ruled in nor ruled out) and in outpatients presenting for evaluation of stable angina including those with renal injury."	external cohort validation

319	Saorin, A and Di Gregorio, E and Mioio, G and Staffan, A and Corona, G	Emerging role of metabolomics in ovarian cancer diagnosis	Metabolites	10	10	1-15	2020	Italy	https://doi.org/10.1136/bmjopen-2020-025125	article	review (not applicable)	Review	"The most promising circulating signatures of OC [Ovarian Cancer] involve metabolites belonging to lipids and AA pathways. These metabolic fingerprints find agreement in many studies, making them relevant for OC diagnosis. However, their clinical application appears to be limited because a lack of independent, large validation studies prevents their effective use for OC screening and monitoring. Future research should include better designed studies on large homogeneous populations that include proper external validation in order to further improve the translational success of metabolomics for OC diagnosis."	"The most promising circulating signatures of OC [Ovarian Cancer] involve metabolites belonging to lipids and AA pathways. These metabolic fingerprints find agreement in many studies, making them relevant for OC diagnosis. However, their clinical application appears to be limited because a lack of independent, large validation studies prevents their effective use for OC screening and monitoring. Future research should include better designed studies on large homogeneous populations that include proper external validation in order to further improve the translational success of metabolomics for OC diagnosis."			
320	Schack, D and Brenner, D and Weigand, R and Uhlir, F	Deep-learning neural networks for accurate diagnosis of sepsis using microarray gene expression data	Care Medicine Experiment al	7			2019	Germany	https://doi.org/10.1093/bioinformatics/btz426	meeting abstract	"Septic patients (n=1354), trauma patients (n=478), and healthy controls (n=381)"	Case-control study	AUC, sensitivity, specificity (training, validation and test set)	training + test set	"By limiting the number of available genes for development, we can prove that, instead of learning idiopathic features related to specific data series, generalised strategies for sample discrimination have been developed in the trained artificial neural networks. The combination of artificial neural networks and microarray gene expression data is therefore capable of achieving sepsis diagnosis with superior accuracy and thus augments the current diagnostic scope."	"By limiting the number of available genes for development, we can prove that, instead of learning idiopathic features related to specific data series, generalised strategies for sample discrimination have been developed in the trained artificial neural networks. The combination of artificial neural networks and microarray gene expression data is therefore capable of achieving sepsis diagnosis with superior accuracy and thus augments the current diagnostic scope."	
321	Scherberger, A V and Boickard, A and Tigselly, J F and Richard, S B and Kuruzov, R	Machine learning model to predict oncologic outcomes for drugs in randomized clinical trials	Int J Cancer	147	9	2537-2549	2020	USA	https://doi.org/10.1002/ijc.32429	article	"A total of 467 progression-free survival (PFS) and 369 overall survival (OS) data points were used as training sets to build our ML (random forest) model"	Treatment response prediction	Spearman correlation (cross-validation)	cross-validation	"In this study, we determine whether machine learning (ML) can extract meaningful associations between oncologic outcome and clinical trial, drug-related biomarker and molecular profile information. [...] The Spearman correlation [ρ] between predicted and actual outcomes was statistically significant (PFS: $\rho = 0.879$, OS: $\rho = 0.878$, $P < .0001$)"	"In this study, we determine whether machine learning (ML) can extract meaningful associations between oncologic outcome and clinical trial, drug-related biomarker and molecular profile information. [...] The Spearman correlation [ρ] between predicted and actual outcomes was statistically significant (PFS: $\rho = 0.879$, OS: $\rho = 0.878$, $P < .0001$)"	
322	Senurku, M and Tunçel, G and Koseoglu, Sad Dogan, B and Sağ, S and Mocan, G and Tuncel, S G and Dundar, M and Ergonen, M C	Developing evidence based conceptual diagnostic tools for breast cancer early prediction	Casi Medical Journal	31	3	P44-P44	2020	Turkey	https://doi.org/10.21863/medcas.6026	article	"268 different BRCA2 positive breast cancer patients"	Case-control study	accuracy (training/test set)	training + test set	"Overall, our developed models will provide the early prediction for BRCA1/BRCA2 related breast cancer cases and will improve to be beneficial for preventive medicine and a unique example for today's genetic-based personalized medicine software"	"Overall, our developed models will provide the early prediction for BRCA1/BRCA2 related breast cancer cases and will improve to be beneficial for preventive medicine and a unique example for today's genetic-based personalized medicine software"	
323	Singh, M and Singh, S P and Dubey, P K and Rashana, R and Mittal, S and Yadav, D and Agarwal, M and Agarwal, S	Advent of Proteomic Tools for Diagnostic Biomarker Analysis in Alzheimer's Disease	Curr Protein Pept Sci	21	10	965-977	2020	India	https://doi.org/10.2165/00043173400021100903	article	Review (not applicable)	Review	"The pathological stages are known for 200 samples (common across both the platforms) with the following distribution: Stage I=187, Stage II=19, Stage III=50, and Stage IV=14. We divided the dataset containing these 200 samples into training (80%) and test (20%) datasets"	Review			"The pathological stages are known for 200 samples (common across both the platforms) with the following distribution: Stage I=187, Stage II=19, Stage III=50, and Stage IV=14. We divided the dataset containing these 200 samples into training (80%) and test (20%) datasets"
324	Singh, N and Vinod, P K	Integrative analysis of DNA methylation and gene expression in papillary renal cell carcinoma	Mol Genet Genomics	295	3	807-824	2020	India	https://doi.org/10.1007/s00438-020-01616-6	article	"Saliva samples from 373 volunteers, 124 who are healthy, 124 who have pre-malignant lesions, and 125 who are OSCC patients."	Tumor stage prediction	PR, AUC, MCC, Accuracy, Sensitivity and Specificity ("The performance of the models was evaluated on the 20% test dataset")	training + test set	"In this study, we performed an integrative analysis of DNA methylation and gene expression to characterize the patterns of DNA methylation in PRCC. Our analysis showed that most probes are hypomethylated in RCC, and both hyper- and hypomethylated probes can distinguish normal from cancer samples."	"In this study, we performed an integrative analysis of DNA methylation and gene expression to characterize the patterns of DNA methylation in PRCC. Our analysis showed that most probes are hypomethylated in RCC, and both hyper- and hypomethylated probes can distinguish normal from cancer samples."	
325	Xiang, Y and Yang, X and Narayanan, A and Shankar, V and Ehtaj, S and Wang, X and Du, N and Ding, F and He, Q and Zuo, R N	Oral diagnosis of oral carcinoma diagnosed from saliva metabolic profiling	Proc Natl Acad Sci U S A	117	28	16167-16174	2020	China	https://doi.org/10.1073/pnas.2005300117	article	"The performance of Singal™ was validated on an independent, externally selected, retrospective cohort of 144 MOS patients."	Differential diagnosis prediction	Accuracy ("20-fold cross-validation was carried out; external validation samples)	cross-validation + test set	"Saliva metabolic profile can reflect oral cancer development. Most discovered metabolites in saliva were found to be highly linked to their expression levels within the primary oncological site of oral cavity tissues, demonstrating the potential of saliva for in vitro molecular diagnosis of OSCC."	"Saliva metabolic profile can reflect oral cancer development. Most discovered metabolites in saliva were found to be highly linked to their expression levels within the primary oncological site of oral cavity tissues, demonstrating the potential of saliva for in vitro molecular diagnosis of OSCC."	
326	Kapoor, S and Maricci, G	Superior therapy response predictions based on an independent, externally selected, retrospective cohort of 144 MOS patients."	Blood	136	9	1410-1414	2020	USA	https://doi.org/10.1182/blood.2020.124414	meeting abstract	"The performance of Singal™ was validated on an independent, externally selected, retrospective cohort of 144 MOS patients."	Therapy response prediction	Accuracy + confidence intervals (training + external cohort)	external cohort validation	"Calceos Singal™ has high accuracy and sensitivity in predicting CR (complete response) for MDS [Myelodysplastic Syndrome] patient response to physician prescribed therapies. Singal™ also has high specificity in identifying patients who are unlikely to respond to physician prescribed therapies and provides alternative treatment recommendations for these patients."	"Calceos Singal™ has high accuracy and sensitivity in predicting CR (complete response) for MDS [Myelodysplastic Syndrome] patient response to physician prescribed therapies. Singal™ also has high specificity in identifying patients who are unlikely to respond to physician prescribed therapies and provides alternative treatment recommendations for these patients."	
327	Talhouk, A and George, J and Wang, C and Goode, I and Ramus, S and Doherty, J and Bowtell, D and Angioletti, M	A comparative study of machine learning and deep learning algorithms to classify cancer types based on microarray gene expression data: PROTYPY (Predictor of high-grade serous Ovarian carcinoma molecular subtype): The development and validation of a clinical-grade consensus classifier for the molecular subtypes of high-grade serous tubovarian cancer	Clinical Cancer Research	26	13		2020	Canada	https://doi.org/10.1158/1078-0432.CCR.20.1418	meeting abstract	"This database consists of 174 samples with 12,533 genes expressed microarray for 11 different types of cancers."	Case-control study	accuracy, confusion matrix (10-fold CV)	cross-validation	"We validated the Predictor of high-grade serous Ovarian carcinoma molecular subtypes, PROTYPY, following the Institute of Medicine guidelines for the development of omics-based tests. This simple-to-use, cost-effective, fully defined, and locked-down clinical-grade assay will facilitate molecular subtype stratification into clinical trial design."	"We validated the Predictor of high-grade serous Ovarian carcinoma molecular subtypes, PROTYPY, following the Institute of Medicine guidelines for the development of omics-based tests. This simple-to-use, cost-effective, fully defined, and locked-down clinical-grade assay will facilitate molecular subtype stratification into clinical trial design."	
328	Talhouk, A and George, J and Wang, C and Goode, I and Ramus, S and Doherty, J and Bowtell, D and Angioletti, M	Assessing cancer drug response prediction from gene expression	Cancer Research	80	16		2020	Canada	https://doi.org/10.1158/1078-0432.CCR.20.1418	meeting abstract	"Gene expression data for 17,737 genes across 203 human cancer cell lines. K562 concentrations for 251 anti-cancer drugs were obtained from the Genomics of Drug Sensitivity in Cancer Project"	Drug response prediction	accuracy (train/test set)	training + test set	"Overall, our analysis shows that utilizing gene expression profiles independent of other omics data for cancer drug response prediction through machine learning frameworks offers modest predictive capabilities. To increase performance, we suggest augmenting training size through shared pathway cross-training, optimizing feature encoding to maximize neural network predictive capabilities, and incorporating other omics data."	"Overall, our analysis shows that utilizing gene expression profiles independent of other omics data for cancer drug response prediction through machine learning frameworks offers modest predictive capabilities. To increase performance, we suggest augmenting training size through shared pathway cross-training, optimizing feature encoding to maximize neural network predictive capabilities, and incorporating other omics data."	
330	Tang, B and Wang, Y and Chen, Y and Li, M and Tao, Y	A Novel Early Stage Lung Adenocarcinoma Prognostic Model Based on Feature Selection With Orthogonal Regression	Frontiers in Cell and Developmental Biology	8			2020	China	https://doi.org/10.3389/fcell.2020.00055	article	"Normal samples = 160, tumor samples = 323"	Case-control study	AUC (cross-validation + external validation)	cross-validation + external cohort validation	"In conclusion, the proposed FSOR [feature selection with orthogonal regression] method can deliver better prediction performance for the early-stage prognosis and has the potential to improve therapy strategy, but with few predictor consideration and computation burden."	"In conclusion, the proposed FSOR [feature selection with orthogonal regression] method can deliver better prediction performance for the early-stage prognosis and has the potential to improve therapy strategy, but with few predictor consideration and computation burden."	
331	Tang, W and Cao, Y and Mu, X	Novel prognostic prediction model constructed through machine learning on the basis of methylation-driven genes in kidney renal clear cell carcinoma	Bioinf Rep	40	7		2020	China	https://doi.org/10.1093/bioinformatics/btaa292	article	"Normal samples = 160, tumor samples = 323"	Prognostic study	AUC (10-fold, cv, test set)	cross-validation + test set	"We used the machine learning method to establish a multivariate methylation prognostic prediction model and combined with clinical information to build the trans-omics prognostic nomogram. [...] These results can help in the accurate evaluation of the prognosis of RCC patients and provide new clues and data resources for the further study of the pathogenesis and the development of the disease."	"We used the machine learning method to establish a multivariate methylation prognostic prediction model and combined with clinical information to build the trans-omics prognostic nomogram. [...] These results can help in the accurate evaluation of the prognosis of RCC patients and provide new clues and data resources for the further study of the pathogenesis and the development of the disease."	
332	Tieth, S and Brandmair, S and Düring, M and An, K and Klein, M and Liebig, T and Hobel, I and Teusler, D and Wang Sattler, B and Schwab, E and Grager, C and Dolgopiat, M	Hypoxia Methylation Classifier (HMC) Outperforms Gene Signatures in Identifying HPV-Negative HNSCC Patients at Risk for Locoregional Failure Post Primary Radiochemotherapy: A German Cancer Consortium Radiation Oncology Group (DTRK-ROG) Multicenter Trial	International Journal of Radiation Oncology Group (DTRK-ROG) Multicenter Trial	Physics	108	3	e552-e553	2020	Germany	https://doi.org/10.1016/j.ijro.2020.05.023	article	"We defined untagged metabolomics on serum samples obtained from patients with ischemic stroke (N=219) and stroke mimics (N=138; as defined by absence of a DWI positive lesion on MRI)"	Differential diagnosis and survival prediction	correlation (training + validation cohort)	external cohort validation	"A methylation-based classifier of tumor hypoxia is successfully developed and validated to be prognostic for LR [local-regional recurrence], progression and OS [overall survival] in HPV-HNSCC patients treated with primary RCHT."	"A methylation-based classifier of tumor hypoxia is successfully developed and validated to be prognostic for LR [local-regional recurrence], progression and OS [overall survival] in HPV-HNSCC patients treated with primary RCHT."
333	Tieth, S and Brandmair, S and Düring, M and An, K and Klein, M and Liebig, T and Hobel, I and Teusler, D and Wang Sattler, B and Schwab, E and Grager, C and Dolgopiat, M	Circulating metabolites differentiate acute ischemic stroke from stroke mimics	International Journal of Stroke	15	1	77-78	2020	Germany	https://doi.org/10.1016/j.ijstroke.2020.05.023	meeting abstract	"We defined untagged metabolomics on serum samples obtained from patients with ischemic stroke (N=219) and stroke mimics (N=138; as defined by absence of a DWI positive lesion on MRI)"	Case-control study	AUC (training + test set)	training + test set	"We performed untagged metabolomics on serum samples obtained from patients with ischemic stroke (N=219) and stroke mimics (N=138; as defined by absence of a DWI positive lesion on MRI)"	"We performed untagged metabolomics on serum samples obtained from patients with ischemic stroke (N=219) and stroke mimics (N=138; as defined by absence of a DWI positive lesion on MRI)"	
334	Tran, A and Walsh, C J and Batt, J and Dos Santos, C and Hu, P	A machine learning-based clinical tool for diagnosing epilepsy using multi-cohort microarray expression profiles	J Translational Medicine	18	1	454-464	2020	Canada	https://doi.org/10.1093/jtm/taaa026	article	"Muscle tissue samples originating from 1320 patients with muscle weakness"	Differential diagnosis prediction	AUC (training + test set)	training + test set	"Our results present a well-performing machine classification tool with the selected gene markers for muscle disease classification. In practice, this tool addresses an important gap in the literature on myopathies and presents a potentially useful clinical tool for muscle disease subtype diagnosis."	"Our results present a well-performing machine classification tool with the selected gene markers for muscle disease classification. In practice, this tool addresses an important gap in the literature on myopathies and presents a potentially useful clinical tool for muscle disease subtype diagnosis."	
335	Tran, P M H and Tran, L K H and Nechtman, J and Dos Santos, J and Satter, K B and Leung, D	Comparative analysis of transcriptomic, proteomic, and iDH mutation for classification of gliomas	Sci Rep	10	1	20651	2020	USA	https://doi.org/10.1038/s41598-020-77727-7	article	"RNAseq and microarray data were generated for 1023 gliomas from the TCGA and 395 gliomas from MBMRAND"	Differential diagnosis and survival prediction	accuracy, log rank test p-value (cross-validation)	cross-validation	"TNT [TMT + HPV-negative HNSCC co-defines patient outcome after chemoradiotherapy. The generated HNSCC-EMT predictor models can function as strong prognostic biomarkers."	"TMT [TMT + HPV-negative HNSCC co-defines patient outcome after chemoradiotherapy. The generated HNSCC-EMT predictor models can function as strong prognostic biomarkers."	
336	van der Weijden, M and Ezzari, F B and Verhaagen, C V M and Williams, V M and Sander, J and de Rooij, R H and Vossen, D M and Leeman, C B and Verheij, M J and van den Broek, M W M and Vens, C	Epithelial-to-mesenchymal transition is a prognostic marker for patient outcome in advanced stage HNSCC patients treated with chemoradiotherapy	Netherlands Oncol	147		186-194	2020		https://doi.org/10.1007/s12220-020-00111-1	article	"We developed and validated an unbiased, automated pipeline for transcriptomic clustering. Without any domain knowledge, our classifier recapitulated known glioma subtypes from histology and mutation status. Our analytical pipeline avoids the potential of overfitting a supervised model to misclassified or mislabeled samples [...]	Prognostic study	AUC (cross-validation + external validation)	cross-validation	"Without any domain knowledge, our classifier recapitulated known glioma subtypes from histology and mutation status. Our analytical pipeline avoids the potential of overfitting a supervised model to misclassified or mislabeled samples [...]	"Without any domain knowledge, our classifier recapitulated known glioma subtypes from histology and mutation status. Our analytical pipeline avoids the potential of overfitting a supervised model to misclassified or mislabeled samples [...]	
337	Vittrini, B and Lederer, M and Martin-Magniette, M L and Collin, C and Bergron, A and Fridez, V and Droz, A	Machine Learning Using a Combination of Small Cell Clusters of Prostate Cancer	Genetics	111	3	PC3 patients	2020	Canada	https://doi.org/10.1093/genetics/gwaa266	article	"Gene expression data were extracted from three RNA-seq datasets cumulating a total of 373 PC3 patients"	Prognostic study	balanced error rate ("The resampling strategy was run 200 times with a split of 80% for training and 20% for test sets")	stratified resampling training and test sets	"Determining which treatment to provide to men with prostate cancer (PCa) is a major challenge for clinicians. [...] This study demonstrates the feasibility to regroup different small datasets in one larger to identify a predictive genomic signature that would benefit PCa patients."	"Determining which treatment to provide to men with prostate cancer (PCa) is a major challenge for clinicians. [...] This study demonstrates the feasibility to regroup different small datasets in one larger to identify a predictive genomic signature that would benefit PCa patients."	

Author(s)	Journal	Year	Country	DOI	Article Type	Abstract Summary	Study Design	Key Findings	External Validation
Wang, S and Su, W and Zhong, C and Yang, T and Chen, W and Chen, G and Liu, Z and Wu, K and 338 Zhong, W and Li, B and Mao, X and Lu, J	Frontiers in Cell and Developmental Biology	2020	China	https://doi.org/10.3389/fcell.2020.00046	article	"The dataset is from the GEO Database, using a cohort of 144 patients in Canada..."	Prognostic study	AUC (10-fold CV)	cross-validation
Wang, Y and Wang, Y and Huang, A and Jiang, R and Zheng, J and Li, Z and Peng, J and Sun, J and Liu, J and 339 Zhang, G and Yuan, J and Yang, X and Zhou, J and Fan, J	Cancer Research	2020	China	https://doi.org/10.1158/1538-7443.2020.178	meeting abstract	"The training cohort consists of 148 Hepatocellular carcinoma cases (median age of 63) and 84 healthy individuals (median age of 60)..."	Case-control study	AUC (10-fold CV + validation cohort)	cross-validation + external cohort validation
Wang, Y and Zhong, J and Li, Z and Jiang, R and Peng, J and Sun, J and Yang, G and Yang, R and 340 Huang, A and Wang, Y and Jie, Y and Liu, X and Gao, F and Wu, X and Wang, D and Wu, W and Liu, W and 340 and Fan, J	Journal of Clinical Oncology	2020	China	https://doi.org/10.1200/JCO.2020.38.15	meeting abstract	"Based on the metabolomics data from cohort 1 [504 HBV associated liver fibrosis patients and 502 normal controls, we selected a panel of 4 predictive metabolite markers..."	Case-control study	AUC, sensitivity, specificity (10-fold CV, training + validation cohort)	cross-validation + external cohort validation
Xu, G and Wang, X and Wu, R and Wang, J and Zhao, A and Chen, T and Wang, Y and Zhang, J and 341 Xiao, Z and Liu, X and Deng, Y and Wang, L and Rajani, C and Kwee, S and Bian, H and Gao, X and Liu, 341 P and Jia, W	BMC Med	2020	China	https://doi.org/10.1186/s12916-020-01636-6	article	"Our study showed that this 4-metabolite panel has potential usefulness in clinical assessments of CLD progression in patients with chronic hepatitis B virus infection..."	Differential diagnosis prediction	AUC (10-fold CV + validation cohort)	cross-validation + external cohort validation
342 Xu, D and Zhang, J and Xu, H and Zhang, Y and Chen, W and Gao, R and Delmer, M	BMC Genomics	2020	China	https://doi.org/10.1186/s12859-020-01916-6	article	"see Table 1"	Differential diagnosis prediction	accuracy (10-fold CV)	cross-validation
343 Xu, R and Liang, X and Justice, A and So-Armah, K and Krystal, J and Sinha, R	Neurophopth and Alzheimer's Disease	2019	USA	https://doi.org/10.1007/s12073-019-09172-9	meeting abstract	"In this study, we aimed to select DNAm signatures in blood to predict HAD from two demographically and clinically distinct populations: Pheas = 130..."	Surrogate biomarker study	AUC, correlation (training + external cohort)	external cohort validation
344 Yan, Y and Song, D and Zhang, J and Hul, G and Wang, J	Frontiers in Pharmacology	2020	China	https://doi.org/10.3389/fphar.2020.00112	article	"In summary, this study indicates the important role of DNA methylation in prediction of drug response, and reveals methylation sites related to drug effectiveness..."	Case-control study	AUC (bootstrap analysis)	bootstrapping
345 Yuan, R and Chen, S and Wang, Y	Frontiers in Genetics	2020	China	https://doi.org/10.3389/fgen.2020.00011	article	"The results indicated that histopathological image features had potential as significant prognostic biomarkers for overall survival in patients with HNSCC..."	Drug response prediction	AUC (5-fold CV + external validation)	cross-validation + external cohort validation
346 Zeng, H and Chen, L and Huang, Y and Luo, Y and Ma, X	Frontiers in Cell and Developmental Biology	2020	China	https://doi.org/10.3389/fcell.2020.00016	article	"The results indicated that histopathological image features had potential as significant prognostic biomarkers for overall survival in patients with HNSCC..."	Case-control study	AUC (10-fold CV + validation)	cross-validation + test set
347 Zhang, L and Ma, F and Qi, A and Liu, L and Zhang, J and Xu, S and Zhong, Q and Chen, Y and Zhang, 347 and Cai, C	Chem Commun (Camb)	2020	China	https://doi.org/10.1039/c9cc07293a	article	"We develop an optimal model to discriminate ischemic stroke patients from healthy persons with 100% sensitivity and 93.18% specificity..."	Case-control study	AUC (training + test set)	training + test set
Zhang, Y and Nock, W and Woye, M and Weber, Z and Adams, E J and Sarah, A and Stockard, S and 348 Tallman, D and Singh, J and Bao, J and Winer, P and Liu, N U and Jiang, Y and Ma, D and Wang, P and 348 Shi, L and Huang, W and Shao, Z and M and Verhoef, R and C and Chertov, M and Ludberg, M B and 348 Ransmayr, E and Seifried, S and VanDriessche, J and Williams, N and Harbert, R and Lopez, D G	Cancer Research	2020	USA	https://doi.org/10.1158/1538-7443.2020.178	meeting abstract	"We provide a new approach to define TNBC [triple-negative breast cancer] based on timing of release..."	Prognostic study	AUC (train + test + external validation)	external cohort validation
349 Zhang, Y H and Li, H and Zeng, T and Chen, L and Li, Z and Huang, T and Cai, Y D	Frontiers in Cell and Developmental Biology	2020	China	https://doi.org/10.3389/fcell.2020.00016	article	"A total of 89 patients were infected with SARS-CoV-2, 100 patients with other viruses, and 41 patients without viral infection..."	Case-control study	Matthews Correlation Coefficient (10-Fold CV)	cross-validation
350 Zhao, T and Khalka, V S and Deng, Y	Aling (Albany NY)	2020	USA	https://doi.org/10.1089/alin.2020.0004	article	"In this review, we survey current knowledge-guided statistical learning methods, including both supervised learning and unsupervised learning..."	Case-control study	AUC (training + external validation)	external cohort validation
351 Zhao, Y and Chang, C and Long, Q	ICO Precision Oncology	2019	USA	https://doi.org/10.1007/s12014-019-00011-4	article	"In this review, we survey current knowledge-guided statistical learning methods, including both supervised learning and unsupervised learning..."	Review	Review	Review
352 Zhuang, H and Chen, Y and Sheng, X and Hong, L and Gao, R and Zhi, X	PeerJ	2020	China	https://doi.org/10.7717/peerj.9412	article	"Our study examined the expression patterns in AML samples from the GEO and TCGA databases..."	Prognostic study	AUC, log rank p-value (training + external test set)	external cohort validation