

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 Velaz, J and Lynch, D A and Myers, J and Steele, M and Martone, P and Panhariz, D G and Walsh, P S and Huang, J and 24 Barth, N M and Raghu, G and Kennedy, G C	American Journal of Respiratory and Critical Care Medicine	2015	USA	Meeting abstract	354 TBB samples	Prospective validation of a genomic classifier for usual interstitial pneumonia in transbronchial biopsies	Case-control study	AUC (training / test set split)	training + test set	<p>https://www.ajrccm.org/lookup/suppl/doi:10.1164/rccm.201501-0111a1/-/DC1</p> <p>This paper, we propose a flexible network feature selection framework that combines metabolomics data with the genome-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.</p> <p>"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 ADC, SQCC and SCLC. 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."</p> <p>"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."</p>		
25 Cai, Q and Alvarez, J and An Kang, J and Yu, T	Network Marker Selection for Untargeted LC-MS Metabolomics Data Res	16	3	1261-1269	2017	USA	Article	<p>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)</p>	Cases only (BMI analysis)	AUC (5-fold CV)	cross-validation	
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	<p>More than 100 samples available for the main sample groups LADC and SCLC in both training and test set</p>	Case-control study	accuracy, precision, recall, F score (LOOCV)	cross-validation
Casanova, R and Varma, S and Simpson, B and Kim, M and An, Y and Saklana, S and Rivero, 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 Lagan, S and 27 Thornsbury, 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	<p>two cohorts of n=93 and n=100 subjects</p>	Case-control study	AUC, sensitivity, specificity (6-fold CV)	cross-validation
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)				
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	<p>787 human cancer cell lines and structural profiles of 244 drugs were considered</p>	Cases only (drug response)	Required, AUC (training/test split)	training + test set
30 Chao, S M and Connolly, J and Ng, Y H and Ganesan, J and Bennett, L	Can urinary proteomes be used as non-invasive markers for renal involvement in childhood febrile urinary tract infection (UTI)?	Pediatric Nephrology	31	10	1746-1746	2016		Meeting abstract	<p>121 patients (68 males, 53 females)</p>	Case-control study	sensitivity, PPV (10-fold CV)	cross-validation
31 Chauthury, 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	<p>360 patients included</p>	Cases only (survival prediction)	<p>"We validated this multi-omic model on five external datasets of various omics types: UPR cohort (n = 236, 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)."</p> <p>"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."</p> <p>"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 Electrospray Ionization Mass Spectrometry (PESI-MS) and Machine Learning to the diagnosis of PDAC. The sensitivity of the machine learning algorithm using PESI-MS profiles to identify PDAC is 90.8% with specificity of 91.7% (95% CI 89.9-97.4% and 82.8%-97.7% respectively). Combined PESI-MS profiles with age and CA19.9 predicted the accuracy for stage 1 or 2 of PDAC is 92.3% and for stage 3 or 4 is 93% (95% CI 86.3-98.2, 97.8-97.4 respectively). The accuracy and simplicity of the PESI-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."</p> <p>"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, TIG6, and SLC6D4 are significantly associated with AZD2644, lapatinib, erlotinib, and paxitaxel, respectively."</p> <p>"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."</p>	external cohort validation
Chong, S and Shihaghi-Rostamizadeh, S and Lu, J and Marzetta, F and van Driel, 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 Complex as Biomarkers for Diagnosing Gastroenter and Monitoring Celiac Disease	Gastroenterology	156	3	582-591.e1	2019	USA	Article	<p>serum samples from 91 patients with biopsy-proven Celiac disease and 79 healthy-proven (controls)</p>	Case-control study	AUC, accuracy, specificity ("well validated out findings in 82 patients with newly diagnosed CD and 217 controls")	external cohort validation
Chung, W Y and Correa, S and Yoshimura, K and Chae, M C and Dennison, A and Takeda, S and 33 Chang, Y T	Using probe electrospray 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	<p>322 PDAC patients and 265 controls</p>	Case-control study	accuracy, sensitivity, specificity (1000 independent repetitions of a bootstrap cross-validation process)	cross-validation
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	<p>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</p>	Cases only (drug response prediction in vitro)	AUC, accuracy (validation in independent breast cancer data and different pharmacological assay)	external cohort validation
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	<p>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</p>	Case-control study	sensitivity, specificity, PPV, NPV (10-fold CV + training / test set split)	validation + test 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 and Computational Intelligence in Bioinformatics	2		59-77	2006	Greece	Article	<p>Review (not applicable)</p>	Case-control study		
Cugliari, G and Benvenuti, S and Guarera, S and Saccone, C and Panico, S and Krog, V and 37 Tumino, A and Vainai, P and Fariello, P and Malatino, G	Improving the prediction of cardiovascular risk with machine-learning and DNA methylation data	BMJ Open	5		39-42	2019	USA	Article	<p>584 subjects (292 M cases and 292 matched controls)</p>	Case-control study	AUC, sensitivity, specificity (nested cross-validation)	cross-validation

"Classically, the cardiovascular risk of individual is evaluated using phenomenological variables (PV) such as blood pressure, body mass, smoker status, gender, age etc. Here we show that, on prospective study (after 10-15 years) these PV display a poor agreement with case-control samples. We were able to obtain more accurate predictions using both DNA methylation data and PV as input features of a Random Forest model, achieving a ROC-AUC of 0.74."

Author(s)	Year	Country	Journal	Article Title	Study Design	Key Findings/Methods	Classification	Outcome
38 Deo, D, Ito, J, and Kadawaki, T and Tsuda, K	2019	Japan	PeerJ	An interpretable machine learning model for diagnosis of Alzheimer's disease	Case-control study	97 AD subjects + 54 controls	AUC, accuracy, sensitivity, specificity (cross-validation + test set)	cross-validation + test set
39 and Colla, M, L and Alonso, L, and Alarcón, P and Martín-Antón, I.A and Pineda, S and Piro, M.	2019	Spain	Genes	Challenges in the integration of omics and non-omics data	Review	(not applicable)	Review	review (not applicable)
40 de Ronda, J J and Border, M J and Usp, E H and Rodenhuis, S and Wessels, L F	2014	Netherlands	PLoS One	Breast cancer subtype specific classifiers trained on all subtypes	Cases only (treatment response predictor)	374 samples were analyzed	AUC (nested cross-validation)	cross-validation
41 M and Furlanello, C and Toffoli, G and Ceccati, C	2012	Italy	PLoS One	Effect of size and heterogeneity of samples on biomarker discovery: synthetic and real data assessment	Case-control study	3 different datasets (more than 50 samples per group in total)	AUC, sensitivity, specificity (cross validation + Monte Carlo bootstrap resampling)	cross-validation
42 Diaz-Cano, S and Sutherland, R and Moorhead, J and Blanes, A and Dobson, R	2016	UK	Laboratory Investigation	Growth pattern analysis in low grade clear cell renal cell carcinoma: Prognostic value and biological significance	Subtype comparison	Low FG (1-2, 174 cases) vs. High FG (3-4, 139 cases) grade	AUC (5-fold cross-validation)	cross-validation
43 and Kim, B and Saravia, T and Martin, M and Lerman, G and Samson, F and Karta, A and de Squillerni, M and Furlanello, C and Toffoli, G and Ceccati, C	2015	USA	Bioinformatics	MACHINE LEARNING FROM CONCEPT TO CLINIC: RELIABLE DETECTION OF BIOMARKER CANDIDATES IN HIGH-THROUGHPUT RNA SEQUENCING DATA	Case-control study	training (n=181) and independent test (n=533) sets	AUC (10-fold CV + external test set)	cross-validation + test set
44 Ding, M Q and Chen, L and Cooper, G F and Young, J D and Lu, X	2018	USA	Mol Cancer Therapeutics	Precision Oncology beyond Targeted Therapy: Combining Omics Data with Machine Learning to Match the Majority of Cancer Cells to Effective Therapeutics	Case only (cancer cell line drug response predictor)	Transcriptomic data from 727 cell lines was used	accuracy, sensitivity, specificity (25-fold cross-validation)	cross-validation
45 Djybari, A and Labbe, A	2009	Canada	BMC Bioinformatics	Refining gene signatures: a Bayesian approach	Case-control study	the approach was applied to multiple Cancer microarray datasets with > 50 samples per group in total	AUC, sensitivity, specificity (nested 10-fold CV + external test set)	cross-validation + test set
46 Dougherty, E R and Hua, J and Blitzer, M L	2007	USA	Current Genomics	Validation of computational methods in genomics	Review	(not applicable)	Review	review (not applicable)
47 A M and Lovelace, J and Corbett, J	2016	Canada	BMC Genomics	Predictive computational phenotyping and biomarker discovery using reference-free genome comparisons	Antibiotic resistance prediction	17 datasets in which the number of examples ranged from 111 to 556	error rate (5-fold CV, test evaluation)	cross-validation + test set
48 Drosou, P and Kildis, M and Moflin, I	2016	Greece	Neuroendocrinology	Graph-theoretic definition of neuroendocrine disease: a tumor specific mathematical toolbox for assessing neoplastic behavior	Case-control study	130 blood samples (NEN: n = 63)	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
49 and Al-Ali, R	2015	Iran	Journal of Computational Science	Large-scale machine learning based on functional networks for biomarker big data with high performance computing platforms	Case-control study	130 blood samples (NEN: n = 63)	AUC, sensitivity, specificity (training/test set split)	training + test set
50 X and Wu, P and Lu, Q and Wang, L and Wang, J	2012	China	PLoS One	Epithelial-mesenchymal transition biomarkers and support vector machine guided model in preoperative metastasis prediction of lymph node metastasis for rectal cancer	Cases only (predicting lymph node metastasis)	1893 patients	accuracy, sensitivity, specificity (training/test set split)	training + test set
51 Fang, Y and Xu, P and Yang, J and Qin, Y	2018	China	PLoS One	A quantile regression forest based method to predict drug response and assess prediction reliability	Cases only (drug response predictor)	data from 947 cell lines (CCLE dataset)	Parson correlation of observed and predicted drug response (out-of-bag error)	out/bag
52 and Michal, R and Filippatos, G	2016	Germany	Eur J Heart Fail	Urine proteome analysis in heart failure with reduced ejection fraction complicated by chronic kidney disease: identification of clinical and pathogenetic correlates	Case-control study	126 Individuals, 59 HFEF patients and 67 Controls	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 (SHMR). A decision tree explains to a patient the diagnosis with a long rule (i.e., conjunction of many intervals), while SHMR employs a weighted sum of short rules. Using proteomics data of 151 subjects in the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset, SHMR 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)."

"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."

"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."

"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."

"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 FG (1-2, 174 cases) vs. high FG (3-4, 139 cases) grade. The age, gender, protein and variant model performed with an AUC of 0.80. Here we report the development, clinical validation, and diagnostic accuracy of a pre-operative molecular test (ARMA BRAF) 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 82% (consistent with published performance of BRAF V600E in this neoplasm) and specificity was 100%, identical to qPCR on the same samples."

"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."

"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."

The manuscript covers several commonly used approaches to evaluate classification and clustering methods (e.g., cross-validation and bootstrap resampling)."

"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 *C. difficile*, *M. tuberculosis*, *P. aeruginosa*, and *S. pneumoniae* 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."

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 (NENs: n = 63) and to differentiate healthy controls and GEP NENs. Gene-based classifiers detected NENs in independent sets with high sensitivity (ES-NENs: specificity (ES-PTN), PPV (ES-NEN) and NPV (ES-NEN)). Additionally, multivariate logistic regression analysis showed that SVM model was indeed an independent predictor of RUMN status (odds ratio, 11.536; 95% confidence interval, 4.113-33.361; P<0.0001).

"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 have 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, 4.113-33.361; P<0.0001).

"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."

"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 (REF) 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 HFrEF patients and 33 controls, achieving 84% sensitivity and 91% specificity."

<p>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 Ewertz, D and Muehleisen, C and Preuser, K and Tomasek, C and 53 De Moor, B and D'Hooghe, T</p>	<p>Biomarkers in plasma or serum: Pitfalls in data processing</p>	<p>Reproductiv S Sciences</p>	<p>18</p>	<p>3</p>	<p>191A-191A</p>	<p>2011</p>	<p>India</p>	<p>http://dx.doi.org/10.1177/1740774510371340 meeting abstract</p>	<p>254 plasma samples from women with (n=165) and without (n=89) endometriosis</p>	<p>Case-control study</p>	<p>accuracy (data were divided randomly (500 times) into training set (70%) and test set (30%)</p>	<p>training + test set</p>	<p>The goal of the study was to test the hypothesis that specific proteins/peptides are differentially expressed in plasma of women with & without endometriosis at specific stages of the disease, during follicular, luteal & menstrual phases. Using the standard practices in the field, a highly correct classification could be reached on both training and test set, however good machine learning practice dictates the use of robust testing by randomizing the data. Using this method, the high classification attained on the training set could not be confirmed. The classification performance increased by separating the different phases, especially the menstrual phase, compared to combining the different phases together. Randomization of the data set should become an integral part of this type of analyses in the future.</p>	<p>254 plasma samples from women with (n=165) and without (n=89) endometriosis</p>	<p>accuracy (data were divided randomly (500 times) into training set (70%) and test set (30%)</p>	<p>training + test set</p>	<p>The goal of the study was to test the hypothesis that specific proteins/peptides are differentially expressed in plasma of women with & without endometriosis at specific stages of the disease, during follicular, luteal & menstrual phases. Using the standard practices in the field, a highly correct classification could be reached on both training and test set, however good machine learning practice dictates the use of robust testing by randomizing the data. Using this method, the high classification attained on the training set could not be confirmed. The classification performance increased by separating the different phases, especially the menstrual phase, compared to combining the different phases together. Randomization of the data set should become an integral part of this type of analyses in the future.</p>
<p>Filimon, R and Ramoa-Cejudo, J and Cheng, D and Turk, D and Panth Shikhi, A and Chen, D and Elber, S and Turner, K S and Johnson, L and Gagnier, C and Gagnier, C and Bodemann, S and 54 C and Schiller, S and Aljarous, S and Hall, M and Ayurvedh, S and Meng, F and Brophy, M and Du, N</p>	<p>An integrative Approach for Identifying Network Biomarkers of Breast Cancer Subtypes Using Genomics, Proteomics, and Transcriptomic Data</p>	<p>Comput. Biol</p>	<p>24</p>	<p>8</p>	<p>756-766</p>	<p>2017</p>	<p>Canada</p>	<p>http://dx.doi.org/10.1186/s12859-017-1454-1 meeting abstract</p>	<p>156 VA patients newly diagnosed with NSCLC</p>	<p>Case-control study</p>	<p>Precision, recall, and area under the ROC curve (AUC) (5-fold CV)</p>	<p>cross-validation</p>	<p>"We have used the METABRIC data set [Curtis et al., 2012], which contains the gene number values and GE value of 2000 primary breast tumors with long-term clinical follow-up."</p>	<p>156 VA patients newly diagnosed with NSCLC</p>	<p>Precision, recall, and area under the ROC curve (AUC) (5-fold CV)</p>	<p>cross-validation</p>	<p>"We have used the METABRIC data set [Curtis et al., 2012], which contains the gene number values and GE value of 2000 primary breast tumors with long-term clinical follow-up."</p>
<p>Firoozbakh, F and Rezaei, L and Daghini, M and Porter, L and Land Rueda, J and Land Ngem, A</p>	<p>Epi-genetic profiling of primary CLL reveals novel DNA methylation-based clusters and novel mechanisms of leukemogenesis</p>	<p>Blood</p>	<p>120</p>	<p>21</p>	<p></p>	<p>2012</p>	<p></p>	<p>http://dx.doi.org/10.1182/blood-2012-07-247130 meeting abstract</p>	<p>"DNA methylation of over 2400 points with CLL"</p>	<p>Case-control study</p>	<p>AUC (10-fold CV)</p>	<p>cross-validation</p>	<p>"Recent cancer is a complex disease that can be classified into at least 10 different molecular subtypes. Appropriate diagnosis of specific subtypes is critical for ensuring the best possible patient treatment and response to therapy. Cancer network biomarkers are subnetworks of functionally related genes that "work in concert" to perform functions associated with a tumorigenic. We propose a machine learning framework that can be used to identify network biomarkers and driver genes for each specific breast cancer subtype. Our results show that the resulting network biomarkers can separate one subtype from the others with very high accuracy."</p>	<p>"DNA methylation of over 2400 points with CLL"</p>	<p>AUC (10-fold CV)</p>	<p>cross-validation</p>	<p>"Recent cancer is a complex disease that can be classified into at least 10 different molecular subtypes. Appropriate diagnosis of specific subtypes is critical for ensuring the best possible patient treatment and response to therapy. Cancer network biomarkers are subnetworks of functionally related genes that "work in concert" to perform functions associated with a tumorigenic. We propose a machine learning framework that can be used to identify network biomarkers and driver genes for each specific breast cancer subtype. Our results show that the resulting network biomarkers can separate one subtype from the others with very high accuracy."</p>
<p>Fong, F and Bar, H Y and Sheldes, K and Sava-Cork, K and Oullette, P and Campagne, F and Melnick, S and 56 A and Makk, S and Shalwinski, R</p>	<p>Predicting Complete Remission of Acute Myeloid Leukemia: Machine Learning Applied to Gene Expression</p>	<p>Cancer Informatics</p>	<p>18</p>	<p>2019</p>	<p>USA</p>	<p></p>	<p></p>	<p>http://dx.doi.org/10.1177/1533315719851111 article</p>	<p>473 bone marrow specimens from 473 patients</p>	<p>Case-control study</p>	<p>AUC (5-fold CV + test set)</p>	<p>training + test set</p>	<p>"The aim of this study is to construct a simple yet robust logic-based classifier amenable to direct expert interpretation. On two well-known, publicly available gene expression classification problems, the paper shows the feasibility of this approach, employing a recently developed supervised discovery methodology. Some of the discovered classifiers allow for novel biological interpretations."</p>	<p>473 bone marrow specimens from 473 patients</p>	<p>AUC (5-fold CV + test set)</p>	<p>training + test set</p>	<p>"The aim of this study is to construct a simple yet robust logic-based classifier amenable to direct expert interpretation. On two well-known, publicly available gene expression classification problems, the paper shows the feasibility of this approach, employing a recently developed supervised discovery methodology. Some of the discovered classifiers allow for novel biological interpretations."</p>
<p>Gamborg, D and Lariva, N and Zakary, F and Totar, J</p>	<p>Induction of comprehensible models for gene expression datasets by subgroup discovery methodology</p>	<p>Biom Inform</p>	<p>37</p>	<p>4</p>	<p>269-284</p>	<p>2004</p>	<p>Croatia</p>	<p>http://dx.doi.org/10.1093/bio/bti011 article</p>	<p>The approach was applied to multiple cancer microarray datasets with >50 samples per group in total</p>	<p>Case-control study</p>	<p>sensitivity, specificity, precision (training/test set split)</p>	<p>training + test set</p>	<p>"The aim of this study is to discover potential biomarkers for pancreatic cancer (PC) using surface-enhanced laser desorption/ionization time-of-flight mass spectrometry (SELDI-TOF-MS). Support vector machine (SVM) analysis of the spectra was used to generate a predictive algorithm based on proteins that were maximally differentially expressed between patients with PC and the HCs in the training cohort. This algorithm was tested using leave-one-out cross-validation in the test cohort. The classifier was challenged with all samples achieving 96.67% sensitivity and 100% specificity in the training cohort and 95.1% sensitivity and 78.57% specificity in the test cohort."</p>	<p>The approach was applied to multiple cancer microarray datasets with >50 samples per group in total</p>	<p>sensitivity, specificity, precision (training/test set split)</p>	<p>training + test set</p>	<p>"The aim of this study is to discover potential biomarkers for pancreatic cancer (PC) using surface-enhanced laser desorption/ionization time-of-flight mass spectrometry (SELDI-TOF-MS). Support vector machine (SVM) analysis of the spectra was used to generate a predictive algorithm based on proteins that were maximally differentially expressed between patients with PC and the HCs in the training cohort. This algorithm was tested using leave-one-out cross-validation in the test cohort. The classifier was challenged with all samples achieving 96.67% sensitivity and 100% specificity in the training cohort and 95.1% sensitivity and 78.57% specificity in the test cohort."</p>
<p>Gao, H and Zheng, Z and Yue, Z and Liu, F and Zhou, L and Zhao, X</p>	<p>Evaluation of serum diagnosis of pancreatic cancer by using surface-enhanced laser desorption/ionization time-of-flight mass spectrometry</p>	<p>Int J Mol Med</p>	<p>30</p>	<p>5</p>	<p>1061-1068</p>	<p>2012</p>	<p>China</p>	<p>http://dx.doi.org/10.3892/ijmm.2012.111 article</p>	<p>serum samples from 123 patients with PCs and 87 healthy controls</p>	<p>Case-control study</p>	<p>sensitivity, specificity (leave-out cross-validation)</p>	<p>cross-validation</p>	<p>"We aimed at predicting different measures of obesity based on the plasma lipoprotein in a large population cohort using advanced machine learning models. Multiple machine intelligence models were trained to predict obesity estimates, i.e., body mass index (BMI), waist circumference (WC), waist:hip ratio (WHR), and body fat percentage (BFP), and validated in 200 randomly chosen participants of the Mainz Diet and Cancer Cardiovascular Cohort (MDC-CC). Comparison of the different models revealed that the lipoprotein predicted BFP the best (0.73), based on a leave-one-out cross-validation. In this model, the strongest positive and the strongest negative predictor were sphingomyelin molecules, which differ by only 1 double bond, implying the involvement of an unknown desaturase in obesity-related alterations of lipid metabolism. Moreover, we used this regression to probe the clinically relevant information contained in the plasma lipoprotein and found that the plasma lipoprotein also contains information about body fat distribution, because WHR (R² = 0.53) predicted more accurately than BMI (R² = 0.47)."</p>	<p>serum samples from 123 patients with PCs and 87 healthy controls</p>	<p>sensitivity, specificity (leave-out cross-validation)</p>	<p>cross-validation</p>	<p>"We aimed at predicting different measures of obesity based on the plasma lipoprotein in a large population cohort using advanced machine learning models. Multiple machine intelligence models were trained to predict obesity estimates, i.e., body mass index (BMI), waist circumference (WC), waist:hip ratio (WHR), and body fat percentage (BFP), and validated in 200 randomly chosen participants of the Mainz Diet and Cancer Cardiovascular Cohort (MDC-CC). Comparison of the different models revealed that the lipoprotein predicted BFP the best (0.73), based on a leave-one-out cross-validation. In this model, the strongest positive and the strongest negative predictor were sphingomyelin molecules, which differ by only 1 double bond, implying the involvement of an unknown desaturase in obesity-related alterations of lipid metabolism. Moreover, we used this regression to probe the clinically relevant information contained in the plasma lipoprotein and found that the plasma lipoprotein also contains information about body fat distribution, because WHR (R² = 0.53) predicted more accurately than BMI (R² = 0.47)."</p>
<p>Gel, M J and Klose, C and Surina, M A and Fernandez, C and Melander, O and Mannisto, S and 60 Borodina, K and Havulinna, A and Salonen, A and Ronnen, E and Canistraci, V and Simons, K</p>	<p>Machine learning of human plasma lipoprotein obesity-related variables in a large population cohort</p>	<p>PLoS Biology</p>	<p>17</p>	<p>10</p>	<p>25-25</p>	<p>2019</p>	<p>China</p>	<p>http://dx.doi.org/10.1371/journal.pbio.1006443 article</p>	<p>Samples of the FINRISK 2012 underwent lipoproteins measurements (1,141 randomly selected individuals) of which 1,061 were used</p>	<p>Case-control study</p>	<p>R-squared of obesity indicator variables (K repeated 10-fold CV)</p>	<p>cross-validation</p>	<p>"We stratified breast cancer patients into either low-risk or high-risk groups based on four published hypoxia signatures (Buffy, Winter, Hu, and Screaming), using 24 different preprocessing approaches for microarray normalization. The 24 binary risk profiles determined for each hypoxia signature were combined using a random forest to evaluate the efficacy of a preprocessing ensemble classifier. We demonstrate that the best way of merging preprocessing methods varies from signature to signature, and that there is likely no "best" preprocessing pipeline that is universal across datasets, highlighting the need to evaluate ensembles of preprocessing algorithms. Further, we developed novel signatures for each preprocessing method and the risk classifications from each were incorporated in a meta-random forest model. Interestingly, the classification of these biomarkers and its ensemble show striking consistency, demonstrating that similar intrinsic biological information are being faithfully represented. As such, these classification patients further confirm that there is a subset of patients whose prognosis is consistently challenging to predict."</p>	<p>Samples of the FINRISK 2012 underwent lipoproteins measurements (1,141 randomly selected individuals) of which 1,061 were used</p>	<p>R-squared of obesity indicator variables (K repeated 10-fold CV)</p>	<p>cross-validation</p>	<p>"We stratified breast cancer patients into either low-risk or high-risk groups based on four published hypoxia signatures (Buffy, Winter, Hu, and Screaming), using 24 different preprocessing approaches for microarray normalization. The 24 binary risk profiles determined for each hypoxia signature were combined using a random forest to evaluate the efficacy of a preprocessing ensemble classifier. We demonstrate that the best way of merging preprocessing methods varies from signature to signature, and that there is likely no "best" preprocessing pipeline that is universal across datasets, highlighting the need to evaluate ensembles of preprocessing algorithms. Further, we developed novel signatures for each preprocessing method and the risk classifications from each were incorporated in a meta-random forest model. Interestingly, the classification of these biomarkers and its ensemble show striking consistency, demonstrating that similar intrinsic biological information are being faithfully represented. As such, these classification patients further confirm that there is a subset of patients whose prognosis is consistently challenging to predict."</p>
<p>Gong, Y and Fox, N S and Huang, Y and Boutros, P C</p>	<p>Prediction of early breast cancer patient survival using ensembles of hypoxia signatures</p>	<p>PLoS One</p>	<p>13</p>	<p>9</p>	<p>40204123-40204123</p>	<p>2018</p>	<p>Canada</p>	<p>http://dx.doi.org/10.1371/journal.pone.0204123 article</p>	<p>1,564 early breast cancer patients</p>	<p>Case only (survival prediction)</p>	<p>AUC, accuracy, sensitivity, specificity (10-fold cross-validation + test set)</p>	<p>cross-validation + test set</p>	<p>"We introduce a multi-view machine-learning strategy called PLATYPUS that builds "views" from multiple data sources that are all used as features for predictive patient outcomes. We show that a learning strategy that finds agreement across the views on unlabeled data increases the performance of the learning methods over any single view."</p>	<p>1,564 early breast cancer patients</p>	<p>AUC, accuracy, sensitivity, specificity (10-fold cross-validation + test set)</p>	<p>cross-validation + test set</p>	<p>"We introduce a multi-view machine-learning strategy called PLATYPUS that builds "views" from multiple data sources that are all used as features for predictive patient outcomes. We show that a learning strategy that finds agreement across the views on unlabeled data increases the performance of the learning methods over any single view."</p>
<p>Grain, K and Friedl, Y and Houshban, K E and Stuart, J M</p>	<p>PLATYPUS: A Multiple-View Learning Predictive Framework for Cancer Drug Sensitivity Prediction</p>	<p>Bioinform</p>	<p>24</p>	<p></p>	<p>136-147</p>	<p>2019</p>	<p>USA</p>	<p>http://www.ncbi.nlm.nih.gov/pmc/articles/PMC6741110/ article</p>	<p>All the time of download the Cancer Cell Line Encyclopedia (CCLE) contained genomic, phenotypic, clinical, and other annotation data for 1,037 cancer cell lines."</p>	<p>Cases only (drug sensitivity prediction)</p>	<p>AUC (cross-validation + external test set)</p>	<p>validation</p>	<p>"Despite considerable sample size limitations, ML techniques have already been successfully applied to ALS datasets and a number of promising prognostic models have been proposed. Prognostic models have been tested using core clinical variables, biological, and neuroimaging data. These models also offer patient stratification opportunities for future clinical trials. Despite the enormous potential of ML, in ALS research, statistical assumptions are often violated, the choice of specific statistical models is seldom justified, and the constraints of ML models are rarely elucidated. From a mathematical perspective, the main barrier to the development of validated diagnostic, prognostic, and monitoring indicators stem from limited sample sizes. The combination of multiple clinical, biofluid, and imaging biomarkers is likely to increase the accuracy of mathematical modeling and contribute to optimized clinical trial designs."</p>	<p>All the time of download the Cancer Cell Line Encyclopedia (CCLE) contained genomic, phenotypic, clinical, and other annotation data for 1,037 cancer cell lines."</p>	<p>AUC (cross-validation + external test set)</p>	<p>validation</p>	<p>"Despite considerable sample size limitations, ML techniques have already been successfully applied to ALS datasets and a number of promising prognostic models have been proposed. Prognostic models have been tested using core clinical variables, biological, and neuroimaging data. These models also offer patient stratification opportunities for future clinical trials. Despite the enormous potential of ML, in ALS research, statistical assumptions are often violated, the choice of specific statistical models is seldom justified, and the constraints of ML models are rarely elucidated. From a mathematical perspective, the main barrier to the development of validated diagnostic, prognostic, and monitoring indicators stem from limited sample sizes. The combination of multiple clinical, biofluid, and imaging biomarkers is likely to increase the accuracy of mathematical modeling and contribute to optimized clinical trial designs."</p>
<p>Grohmann, V and Prasad, P and Queris, G and Delbot, F and Le Chat, G and Pradat, Pevy, J and 63 Bede, P</p>	<p>Machine learning in amyotrophic lateral sclerosis: achievements, pitfalls, and future directions</p>	<p>Frontiers in Neurosc</p>	<p>13</p>	<p></p>	<p></p>	<p>2019</p>	<p>France</p>	<p>http://dx.doi.org/10.3389/fnins.2019.01161 article</p>	<p>review (not applicable)</p>	<p>review</p>	<p>review</p>	<p>"This first dataset we used was collected from Genomes of Drug Sensitivity in Cancer project (release 5.0, http://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 (http://portals.broadinstitute.org/CCLE), which contains 218 drugs and 493 cell lines with 120,870 known responses"</p>	<p>review (not applicable)</p>	<p>review</p>	<p>review</p>	<p>"This first dataset we used was collected from Genomes of Drug Sensitivity in Cancer project (release 5.0, http://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 (http://portals.broadinstitute.org/CCLE), which contains 218 drugs and 493 cell lines with 120,870 known responses"</p>	
<p>Guan, N and Zhao, Y and Wang, C and Li, Q and Chen, X and Piao, X</p>	<p>Anticancer Drug Response Prediction in Cell Lines Using Weighted Graph Regularized Matrix Factorization</p>	<p>Molecular Therapy - Nucleic Acids</p>	<p>17</p>	<p></p>	<p>164-174</p>	<p>2019</p>	<p>China</p>	<p>http://dx.doi.org/10.1016/j.mthe.2019.05.017 article</p>	<p>Multiple microarray datasets for different cancers with >50 samples per group in total were used</p>	<p>Case-control study</p>	<p>accuracy + standard deviation (repeated 5-fold CV)</p>	<p>cross-validation</p>	<p>"In this paper, a new gene selection method is proposed to choose the best subset of features for microarray data with the irrelevant and redundant features removed. We formulate the selection problem as a L1-regularized optimization problem, based on a newly defined linear discriminant analysis criterion. The experimental results on test publicly available microarray datasets demonstrate that the proposed method performs effectively and competently compared with state-of-the-art methods."</p>	<p>Multiple microarray datasets for different cancers with >50 samples per group in total were used</p>	<p>accuracy + standard deviation (repeated 5-fold CV)</p>	<p>cross-validation</p>	<p>"In this paper, a new gene selection method is proposed to choose the best subset of features for microarray data with the irrelevant and redundant features removed. We formulate the selection problem as a L1-regularized optimization problem, based on a newly defined linear discriminant analysis criterion. The experimental results on test publicly available microarray datasets demonstrate that the proposed method performs effectively and competently compared with state-of-the-art methods."</p>
<p>Grohmann, V and Prasad, P and Queris, G and Delbot, F and Le Chat, G and Pradat, Pevy, J and 63 Bede, P</p>	<p>Machine learning in amyotrophic lateral sclerosis: achievements, pitfalls, and future directions</p>	<p>Frontiers in Neurosc</p>	<p>13</p>	<p></p>	<p></p>	<p>2019</p>	<p>France</p>	<p>http://dx.doi.org/10.3389/fnins.2019.01161 article</p>	<p>review (not applicable)</p>	<p>review</p>	<p>review</p>	<p>"This first dataset we used was collected from Genomes of Drug Sensitivity in Cancer project (release 5.0, http://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 (http://portals.broadinstitute.org/CCLE), which contains 218 drugs and 493 cell lines with 120,870 known responses"</p>	<p>review (not applicable)</p>	<p>review</p>	<p>review</p>	<p>"This first dataset we used was collected from Genomes of Drug Sensitivity in Cancer project (release 5.0, http://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 (http://portals.broadinstitute.org/CCLE), which contains 218 drugs and 493 cell lines with 120,870 known responses"</p>	
<p>Guan, N and Zhao, Y and Wang, C and Li, Q and Chen, X and Piao, X</p>	<p>Anticancer Drug Response Prediction in Cell Lines Using Weighted Graph Regularized Matrix Factorization</p>	<p>Molecular Therapy - Nucleic Acids</p>															

Ihii, H and Sahoh, M and Sakamoto, K and Sakamoto, K and Saigusa, D and Kasai, H and Aihwaka, S and Miyawaki, K and Takahashi, S and Maeyama, K and Yoshimura, K	Lipidase-based rapid diagnosis with machine learning for detection of TGF- β signaling activated area in head and neck cancer	British Journal of Cancer	10-10	Japan	https://doi.org/10.1136/bjco-2020-002426	article	A total of 240 and 90 mass spectra were obtained from TGF- β stimulated and unstimulated HNSCC cells, respectively	Case-control study	accuracy (LOOCV)	cross-validation	"We established a rapid diagnostic system based on the combination of probe electrospray ionisation mass spectrometry (PEI-MS) and machine learning without the aid of immunohistological and biochemical procedures to identify tumour areas with heterogeneous TGF- β signalling status in head and neck squamous cell carcinoma (HNSCC). This discriminant algorithm achieved 98.79% accuracy in discrimination of TGF- β stimulated cells from unstimulated cells." "A major roadblock to reducing the mortality of colorectal cancer (CRC) is prompt detection and treatment, and a simple blood test is likely to have higher compliance than all of the current methods. The purpose of this report is to examine the utility of a mass spectrometry-based blood serum protein biomarker test for detection of CRC. A five-marker panel consisting of leucine-rich alpha-2-glycoprotein 1, epidermal growth factor receptor, inter-alpha-trypsin inhibitor heavy chain family member 4, hemopexin, and superoxide dismutase 3 performed the best with 70% specificity at over 80% sensitivity (area under the curve = 0.86) in the validation set."
Ivanic, M M and Maghs, B W and Swerdlow, J and Craven, M and Reichelderfer, M and Pichler, R and Luzzo, S and M, R and Kennedy, G D	Noninvasive Detection of Colorectal Cancers Using Serum Protein Biomarkers	Surg Res	246	United States	https://doi.org/10.1097/MSR.0000000000000202	article	"Blood was drawn from individuals (n = 213) before colonoscopy from patients with nonmetastatic CRC (n = 507). AMI dataset: "194 samples contain methylation data and we use the part of the data measured by HMU-LUC. HumanMethylation450 arrays. 173 samples contain mRNA data measured by HTS-U133 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"."	Case-control study	AUC, sensitivity, specificity (training / test set split)	training + test set	"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." "Early colon cancer detection in patient populations ineligible for testing, such as the elderly or those with significant comorbidities, could have clinical benefit. A multiple assay was developed for 187 candidate marker proteins, using 337 peptides monitored through 674 simultaneously measured MRM transitions in a 30-minute liquid chromatography-mass spectrometry analysis of immunoprecipitated blood plasma. To evaluate the combined candidate marker performance, the present study used 274 individual patient blood plasma samples, 137 with biopsy-confirmed colorectal cancer and 137 age- and gender-matched controls. Using one-half of the data as a discovery set (60 disease cases and 60 control cases), the elastic net feature selection and random forest classifier assembly were used in cross-validation to identify a 15-transition classifier. The mean training receiver operating characteristic area under the curve was 0.82. After final classifier assembly using the entire discovery set, the 136-sample (68 disease cases and 68 control cases) validation set was evaluated. The validation area under the curve was 0.81." "Head and neck squamous cell carcinoma (HNSCC) patients are at risk of suffering from both pulmonary metastases or a second squamous cell carcinoma of the lung (LUSC). Differentiating pulmonary metastases from primary lung cancers is of high clinical importance, but not possible in most cases with current diagnostics. To address this, we performed DNA methylation profiling of primary tumors and trained three different machine learning methods to distinguish metastatic HNSC from primary LUSC. We developed an artificial neural network that correctly classifies 96.4% of the cases in a validation cohort of 279 patients with HNSC and LUSC as well as normal lung controls, outperforming support vector machines (95.7%) and random forests (87.8%)."
Jada, A and Pfeifer, N	Interpretable per case weighted ensemble method for cancer associations	BMC Genomics	17	Germany	https://doi.org/10.1186/s12854-016-0424-6	article	Cases only risk & severity stratification	AUC (training / test set split)	training + test set	"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." "Early colon cancer detection in patient populations ineligible for testing, such as the elderly or those with significant comorbidities, could have clinical benefit. A multiple assay was developed for 187 candidate marker proteins, using 337 peptides monitored through 674 simultaneously measured MRM transitions in a 30-minute liquid chromatography-mass spectrometry analysis of immunoprecipitated blood plasma. To evaluate the combined candidate marker performance, the present study used 274 individual patient blood plasma samples, 137 with biopsy-confirmed colorectal cancer and 137 age- and gender-matched controls. Using one-half of the data as a discovery set (60 disease cases and 60 control cases), the elastic net feature selection and random forest classifier assembly were used in cross-validation to identify a 15-transition classifier. The mean training receiver operating characteristic area under the curve was 0.82. After final classifier assembly using the entire discovery set, the 136-sample (68 disease cases and 68 control cases) validation set was evaluated. The validation area under the curve was 0.81." "Head and neck squamous cell carcinoma (HNSCC) patients are at risk of suffering from both pulmonary metastases or a second squamous cell carcinoma of the lung (LUSC). Differentiating pulmonary metastases from primary lung cancers is of high clinical importance, but not possible in most cases with current diagnostics. To address this, we performed DNA methylation profiling of primary tumors and trained three different machine learning methods to distinguish metastatic HNSC from primary LUSC. We developed an artificial neural network that correctly classifies 96.4% of the cases in a validation cohort of 279 patients with HNSC and LUSC as well as normal lung controls, outperforming support vector machines (95.7%) and random forests (87.8%)."	
Jones, J and Wilcox, B E and Benz, R and Bobbar, N and Borajegla, G and Barrill, J and Christie, E B for Fibroblast Cancer Marker Panel and Croner, L and Liu, C and Pan, D and Dillon, R and Kato, S and Kao, A and Preston, R and Schreckengost, C and Smith, W and Smith, W D and Hillis, W D and Agui, B and Williams, J E	A Fibroblast Cancer Marker Panel Identified by Multiplex Targeted Mass Spectrometry	Clin Colorectal Cancer	186	United States	https://doi.org/10.1158/1538-8514.2016-0128	article	The present study used 274 individual patient blood plasma samples, 137 with biopsy-confirmed colorectal cancer and 137 age- and gender-matched controls.	Case-control study	AUC, sensitivity, specificity (cross-validation + external test set)	cross-validation + external control validation	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."
Jumruttie, P and Beckman, M and Seppeler, F and Beckman, J and Treuss, D and Montson, G and Volbrecht, C and Arnold, A and Teichmann, D and Bressan, K and Schuller, U and von Lurfler, J and Muller, K K and Capper, D and Trautwein, F	Machine learning analysis of DNA methylation profiles distinguishes primary lung squamous cell carcinomas from head and neck metastases	Science Translational Medicine	11	Germany	https://doi.org/10.1126/scitranslmed.aba0511	article	408 patients with a history of primary HNSC and a synchronous or metachronous squamous lung tumor	Case-control study	AUC, accuracy (5-fold CV + external test set)	cross-validation + external control validation	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."
Karnipour-Fard, A and Epperson, L E and Hunter, L E	A survey of computational tools for downstream analysis of proteomic and other omic datasets	Human Genomics	9	USA	https://doi.org/10.1186/s12915-016-0303-2	article	review (not applicable)	review	review	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."	
Khan, S R and Mohan, H and Liu, Y and Batubwala, B and Ghali, H and Al Rajid, A D and Maminlaya, Y	The discovery of novel predictive biomarkers and early-stage pathophysiology for the transition from gestational diabetes to type 2 diabetes	Diabetologia	62	Canada	https://doi.org/10.1007/s00125-016-3822-4	article	55 incident cases matched to 85 non-case control participants	Case-control study	AUC, accuracy, sensitivity, specificity (45-fold cross-validation)	cross-validation	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."
Khalifa, D and Cluff, C E and Callahan, S A and Krasinski, A M and Alzahrani, A and Knight-Scott, J and Cloutier, R and Castillo-Leon, E and Jones, P and Pierpont, B and Caplin, S and Santoro, T and Ali, A and Vogt, M B	Development of a Plasma Screening Panel for Pediatric Nonalcoholic Fatty Liver Disease Using Metabolomics	Hepatology Communications	3	United States	https://doi.org/10.1093/hcp/cax114	article	subjects with NAFLD (n = 222) and without NAFLD (n = 317)	Case-control study	AUC (training set; 2/3 of data, test set 1/3 of data)	training + test set	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."
Kim, J and Du Rosa, J and Lee, J and Tomalia, L and Lowes, M A and Fitz, L and Bernstein, G and Wada, H and Wang, W and Kraus, G G and Soley-Bertram, M	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.	Experiment Dermatology	25	United States	https://doi.org/10.1093/ibd/ibz006	meeting abstract	259 serum samples from a phase 3 study in adults with moderate-to-severe psoriasis	Case-control study	AUC, accuracy (training / test set split; 80%/20%)	training + test set	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."
Kim, M and Oh, J and Ahn, J	An improved method for prediction of cancer prognosis by network learning	Genes	9	Switzerland	https://doi.org/10.3389/fgene.2016.00024	article	"First, we downloaded gene mRNA data, CNV data, DNA methylation data, SNP data, and clinical data for PAAD, BRCA, HNSC, 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). 300 samples of estrogen receptor binary outcome (i.e., ER+ and ER-)." "We demonstrate application of MetaTSP methods to three real omics examples of breast cancer expression profiles (1658 samples in seven studies), IPF expression profiles (IPF; 221 samples in four studies) and The Cancer Genome Atlas multi-cancer methylation profiles (http://cancergenome.nih.gov). 1785 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."	Case-control study	AUC, accuracy (10-fold CV)	cross-validation	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."
Kim, S and Song, J H and Lee, J and Koo, J Y	Meta-analytic support vector machine for integrating multiple omic data	BioData Mining	10	South Korea	https://doi.org/10.1186/1745-6215-10-17	article	300 samples of estrogen receptor binary outcome (i.e., ER+ and ER-)." "We demonstrate application of MetaTSP methods to three real omics examples of breast cancer expression profiles (1658 samples in seven studies), IPF expression profiles (IPF; 221 samples in four studies) and The Cancer Genome Atlas multi-cancer methylation profiles (http://cancergenome.nih.gov). 1785 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."	Case-control study	sensitivity, specificity (cross-validation)	cross-validation	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."
Kim, S and Lin, C W and Tang, C Y	MetaTSP: meta-analytic top scoring pair method for robust cross-validation of omics prediction analysis	Bioinformatics	12	South Korea	https://doi.org/10.1093/bioinformatics/btu113	article	1785 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."	Case-control study	Youden index (5-fold cross-validation)	cross-validation	"This paper, we review the well-known and ready-to-use tools for classification, clustering and validation, interpretation, and generation of biological information from experimental data. We suggest some rules of thumb for the reader on choosing the best suitable learning method for a particular dataset and conclude with pathway and functional analysis and then provide information about submitting final results to a repository." "Gestational diabetes mellitus (GDM) affects up to 20% of pregnancies, and almost half of the women affected progress to type 2 diabetes later in life, making GDM the most self-reported risk factor for the development of future type 2 diabetes. We used a well-characterized prospective cohort of women with a history of GDM pregnancy, all of whom were enrolled at 6-8 weeks postpartum (baseline), were confirmed not to have diabetes via 7.5 g/dL OGTT and tested annually for type 2 diabetes on an ongoing basis (12 years of follow-up). A large-scale targeted lipidomic study was implemented to analyze ~1100 lipid metabolites in plasma plasma samples (1). Machine learning optimization in a decision tree format revealed a seven-lipid metabolite type 2 diabetes predictive signature with a discriminating power (AUC) of 0.92 (95% sensitivity, 93% specificity and 91% specificity). "Nonalcoholic fatty liver disease (NAFLD) is the most common chronic liver disease in children, but diagnosis is challenging due to limited availability of noninvasive biomarkers. Machine learning applied to high-resolution metabolomics and clinical phenotype data offers a novel framework for developing a NAFLD screening panel in youth. Here, untargeted metabolomics by liquid chromatography-mass spectrometry was performed on plasma samples from a combined cross-sectional sample of children and adolescents ages 2-25 years old with NAFLD (n = 222) and without NAFLD (n = 237). The highest performing classification model was random forest, which had an area under the receiver operating characteristic curve (AUROC) of 0.94, sensitivity of 73%, and specificity of 97% for detecting NAFLD cases. A second classification model was developed based on the homocysteine methylase assessment of insulin resistance substituted for the WBIS. Similarly, the highest performing classification model was random forest, which had an AUROC of 0.92, sensitivity of 73%, and specificity of 96%."
Kim, S and Higgins, J and Parkhata, D and Hwang, J and Pagan, M and Sridhar, V and Tom, E and Anderson, J and Choi, Y and Lynch, D A and Steele, M and Fisher, K R and Brown, K K and Farah, and Bukstein, M J and Parada, A and Selman, M and Wotzka, P J and Nathan, S and Cobby, T V and Myers, L N and Kuznetsov, I A and Bagchi, G and Wilensky, G C	Classification of usual interstitial pneumonia in potential interstitial lung disease assessment of a machine Learning approach using high-dimensional transcriptional data	Respiratory Medicine									

Author(s)	Year	Journal	Volume	Issue	Page(s)	DOI	Article Type	Abstract Summary	Keywords	Study Design	Accuracy	Validation
93 Kim, Y and Bionzeri, T and Zwart, M and Wessels, L F A and van, D J	2019	Netherlands	10	1	5034-5034	10.1093/bioinformatics/bty222	Article	Genomic data integration by WOV-PARAFAC for predicting drug sensitivity in vivo	Nat Commun	Case only (drug sensitivity prediction)	AUC (10-fold CV)	cross-validation
94 Kim, Y R and Kim, D and Kim, S Y	2019	Korea	51	2	672-684	10.1093/bioinformatics/bty111	Article	Prediction of Acquired Tazane Resistance Using Personalized Pathway-based Machine Learning Method	Cancer Res Treat	Case only (drug response prediction in vitro)	AUC (LOOCV)	cross-validation
95 Kirgizov, T and Kiliç, S and Abal, Z Y and Yaman, A and Kaygusu, S B and Ertan, M and Turan, S and 95 Hahiro, S and Sağiroğlu, M S and Benzer, A and Guran, T	2019	Turkey	91		128-128	10.1093/bioinformatics/bty168	Article	Simplifying the interpretation of steroid metabolome data by a machine-learning approach	Hormone Research in Pediatrics	Case-control study	sensitivity, specificity (10-fold cross-validation)	cross-validation
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	Japan	Blood	134		10.1182/blood-2019-07-377072	Meeting abstract	Genome-wide methylation analysis using the digital restriction enzyme enzyme MspI and MspII for stratification of patients with juvenile myelomonocytic leukemia	Blood	Case-control study	accuracy (training / test set split)	training + test set
97 Kong, A and Asencio, R	2017	Germany	16	1	13-30	10.1093/bioinformatics/btx016	Article	Binary Markov Random Fields and interpretable mass spectra discrimination	Statistical Applications in Genetics and Molecular Biology	Case-control study	accuracy (LOOCV)	cross-validation
98 Krwaczuk, J and Lukaszuk, T	2016	Poland	66		63-71	10.1093/bioinformatics/btw007	Article	The feature selection bias problem in relation to high-dimensional gene data	Artif Intell Med	Case-control study	accuracy (double LOOCV)	cross-validation
99 Krittawong, C and Bomboka, A S and Baber, J and Bangkoro, S and Messeri, F H and Wilson Tang, W H	2018	Poland	20	9	75-75	10.1093/bioinformatics/bty015	Article	Future Direction for Using Artificial Intelligence to Predict and Manage Hypertension	Curr Hypertens Rep	review (not applicable)	review	
100 Kus, C H S and Pavlidis, S and Liza, M and Barbaud, F and Rowe, A and Pandis, I and Rossio, C and 100 Hahiro, S and Ekiokawa, S and Dotsi, P and Chung, L F A and Akocak, M and Kim, Y	2015	American Journal of Respiratory and Critical Care Medicine	191			10.1164/rccm.2014.04.0714	Meeting abstract	Adhms phenotypes from semi-supervised machine-learning analysis of bronchial biopsy and brush transcripts in 10 biopsied	American Journal of Respiratory and Critical Care Medicine	Case-control study	accuracy (cross-validation)	cross-validation
101 Kurus, M B	2014	Poland	15		8-8	10.1093/bioinformatics/btu131	Article	Robustness of Random Forest-based gene selection methods	BMC Bioinformatics	Case-control study	error-rate (training / test set split)	training + test set
102 Kuzubara, H and Izubuchi, A and Sova, R and Inomoto, M and Ishizaki, T and Tsuchida, A and 102 Nagakawa, Y and Katsumata, K and Sugimoto, M	2019	Annals of Oncology	30		v46-v46	10.1093/annonc/mdz006	Article	Salivary metabolomics for colorectal cancer detection	Annals of Oncology	Case-control study	AUC (training / test set split)	training + test set
103 Lacroix-Trék, M and Kempowski-Hamon, J and Van Valle, C and Hodajzi, 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	Investigative Oncology	93		51A-51A	10.1093/invonc/otg010	Meeting abstract	Fuzzy logic selection as a new reliable tool to identify gene signatures in breast cancer - the INNOCODE Study n	Investigative Oncology	Case-control study	sensitivity, specificity, error rate (training / test set split)	training + test set
104 Li, A and Panos, R and Marjanović, 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	Meeting abstract	A gene expression profile test that distinguishes ovarian from endometrial cancers	Journal of Clinical Oncology	Differential diagnosis prediction	AUC (training / test set split)	training + test set
105 Li, A and Panos, R and Marjanović, 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	Meeting abstract	A gene expression profile test that distinguishes ovarian from endometrial cancers	Journal of Clinical Oncology	Differential diagnosis prediction	AUC (training / test set split)	training + test set

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 Bower, S and Cuddeback, M 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	Large scale automatic feature selection for biomarker discovery in high-dimensional omics data	Case-control + treatment response	balanced accuracy cross-validation + 20% hold-out test set	cross-validation + test set	
Ledrick, M and Vittart, S and Marti-Magneiros, M and Scott Bover, M P and Perin, O and Bergeron, A and Fradet, Y and Dixon, A	2019	Canada	Frontiers in Genetics	10	2019	Canada	article	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, Root Mean Squared Error (RMSE), Correlation Coefficient (CC) (10-fold CV)	cross-validation		
Lee, S S and Atwood, K and Roder, H and Amelrich, 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	An independent validation of a screening test using mass spectrometry for detection of hepatocellular carcinoma	Case-control study	AUC (training and validation cohort)	external cohort validation	
Lin, 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	The ordering of expression among a few genes can provide simple cancer biomarkers and signal BRCA1 mutations	Case-control study	accuracy, sensitivity, specificity (LOOCV, cross-study validation)	cross-validation	
Liu, F and Xing, L and Zhang, X and Zhang, X	2019	China	Genes (Basel)	10	6	2019	China	article	A Four Pseudogene Classifier Identified by Machine Learning Serves as a Novel Prognostic Marker for Survival of Osteosarcoma	Cases only (survival prediction)	AUC (10-fold CV)	cross-validation	
Liu, Y and Wang, L and Zhang, J and Ye, F and Hui, X and Li, B and He, Q Y	2016	China	Mol Med Rep	14	4	3052-3058	2016	China	article	Analysis of gene expression profile identifies potential biomarkers for atherosclerosis	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 Brodie, 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 Arakawa, A and Seiden, M	2019	USA	Journal of Clinical Oncology	37	2019	USA	meeting abstract	Genome-wide cell-free DNA (ctDNA) of methylation signatures and effect on stage of origin (TDO) performance	Case-control study	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	A novel strategy of integrated microarray analysis identifies CEPNA, CDK1 and CCND3 as a cluster of prognostic biomarkers in late adenocarcinoma	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	Metabolomic biosignature and differentiating melancholic depressive patients from healthy controls	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 Nigh, T D and Kang, Y F and Yan, H and Han M M	2016	Vietnam	Oncotarget	8	65	109456	2016	Vietnam	article	Systematic assessment of cervical cancer detection and progression uncovering genetic panels for deep learning-based early diagnosis and prognosis novel diagnostic and prognostic biomarkers	Case-control study	accuracy, sensitivity, specificity (10-fold CV, external test set)	cross-validation + external cohort validation
Long, N P and Nigh, T D and Kang, Y F and Yan, H and Han, M M and Park, S K and Kwon, S W	2020	USA	Metabolites	10	2	2020	USA	article	Toward a standardized strategy of clinical metabolomic approaches for advancement of precision medicine	review (not applicable)	review		
Long, N P and Park, S and Ahn, N H and Nigh, T D and Yoon, S J and Park, J H and Lim, J and Han, K W and S W	2019	Vietnam	Int J Mol Sci	20	2	2019	Vietnam	article	High-Throughput Omics and Statistical Learning Integration for the Discovery and Validation of Novel Diagnostic Signatures in Colorectal Cancer	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 Nigh, T D and Lim, D and Hong, Y J and Hong, S S and Kwon, S W	2018	South Korea	Metabolites	10	8	109-109	2018	South Korea	article	A systematic review on metabolomics-based diagnostic biomarker discovery and validation in pancreatic cancer	review (not applicable)	review	

"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 all 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 CDD2, CDD2 and CDD3 gene abundance. Utilizing carefully aggregated secondary data and leveraging a priori hypotheses, I made robust 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 BioMxM. From a collection of samples and their associated characteristics, i.e., the biomarkers (e.g., gene expression, protein levels, clinical-pathological data), BioMxM exploits various feature selection procedures to produce signatures associated to machine learning models that will predict efficiently a specified outcome. To this purpose, BioMxM 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 set (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 ERCC1 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 RNFL4."

"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 ctDNA, TDO demonstrates 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 TDO 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 hepatobiliary (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 CEPNA, CDK1 and CCND3 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 breast-BMC metabolomics data set, consisting of 97 healthy control and 90 MDO 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 MDO patients are easier to predict from healthy controls than the entire MDO 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% (95.01% 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 translate 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.2017.07.001	article	191 multiple sclerosis patient	Cases only (sub-group stratification)	Rand 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-based 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 (n = 338) and (n = 158). First, the survival-related seed genes were selected from the cohort 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. In 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 10 Genes to Predict Ovarian Cancer Patients by a Machine Learning Model	Cancers	11	2	13-13	2019	Switzerland	https://doi.org/10.3390/cancers11020133	3 different datasets with > 50 samples per group	Cases only (prognosis study)	accuracy, log-rank test p-value (LODCV)	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 (n = 338) and (n = 158). First, the survival-related seed genes were selected from the cohort 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. In 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>
Identification of a sixteen-gene prognostic signature for lung adenocarcinoma using a machine learning method	Journal of Cancer	11	5	1288-1298	2020	China	https://doi.org/10.7150/jco.4456	TCGA cohort (n = 338) and (n = 148) 14,470 microarray samples of 6 lung phenotypes from 26 independent experimental studies and 709 RNA-seq samples of 2 lung phenotypes from 4 independent studies"	Cases only (prognosis)	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 that is transferable 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	USA	https://doi.org/10.1371/journal.pone.0110840	TCGA cohort (n = 338) and (n = 148) 14,470 microarray samples of 6 lung phenotypes from 26 independent studies and 709 RNA-seq samples of 2 lung phenotypes from 4 independent studies"	Case-control study	"here we quantify the impact of these combined "study effects" on a disease signature's predictive performance by comparing two types of validation methods: ordinary randomized cross-validation (OCV), which extracts random subsets of samples for testing, and inter-study validation (ISV), which 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 that is transferable 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	review	review	<p>"Deep neural networks (DNN) 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 bioinformatics 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>
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	review	review	<p>"Deep neural networks (DNN) 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 bioinformatics 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>
Machine learning workflows to estimate class probabilities for precision cancer diagnostics on DNA methylation microarray data	Protocols	15	2	479-512	2020	Germany	https://doi.org/10.1002/prot.416	brain tumor 452k DNA methylation cohort of 2,001 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 (DNN) 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 bioinformatics 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>
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/s13036-019-0162-6	article	review (not applicable)	review	review	review	<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 metabolomics characterization of several NAFD 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 NAFD 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 NAFD stages and evolution by mean of machine-learning automated algorithms	Digestive and Liver Disease	52		e4-e9	2020	Italy	https://doi.org/10.1016/j.dld.2020.07.021	two cohorts of a total of 319 subjects: The first cohort, coming from the main recruitment center (University of Salento), was composed by 169 healthy subjects (CTR) and 84 NAFD patients (F1 NAFD, 21 NAFD, 43 NASH cirrhosis) and the second, coming from the other centers, was composed by 106 subjects (40 CTRL, 34 NAFD, 10 NASH, 18 NASH cirrhosis)"	Case-control study	accuracy (training / test set split)	training + test set	<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 metabolomics characterization of several NAFD 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 NAFD 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	Methods	Results	Conclusions
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/s12859-018-1926-z	Investigation of model stacking for drug sensitivity prediction	Case only (drug sensitivity prediction)	normalized AUC (training, test and validation set)	training + test set	"A significant problem in precision medicine is the prediction of drug sensitivity for individual cancer cell lines. [...] We explore the predictive performance of model stacking and the effect of stacking on the predictive bias and squared error. In addition we discuss the analytical underpinnings supporting the advantages of stacking in reducing squared error and inherent bias of random forests in prediction of cell lines. The performance of individual and stacked models are compared. We note that stacking models built on two heterogeneous datasets provide superior performance to stacking different models built on the same dataset. It is also noted that stacking provides a noticeable reduction in the bias of our prediction when the dominant eigenvalue of the principal axis of variation in the residuals is significantly higher than the remaining eigenvalues." "Peripheral artery disease (PAD) is a global health problem associated with significant morbidity and mortality. Patients with diabetes mellitus (DM) are at substantial risk of developing PAD, however its diagnosis is often delayed until advanced stages when complications arise. Using proteomics and machine learning, a sub-set of artificial intelligence, we recently described a biomarker clinical/proteomic panel to predict prevalent obstructive PAD (HART PAD) in patients undergoing diagnostic peripheral angiography and/or coronary angiography. In this study, we sought to compare the accuracy of the clinical/proteomic panel for the diagnosis of PAD in patients with and without DM. [...] In patients with DM, the HART PAD panel had excellent performance or prediction of peripheral stenosis >50%. The model had an area under the receiver operating characteristic curve of 0.85 for obstructive PAD. Higher scores were associated with greater severity of angiographic stenosis." "In this review, we present examples of current practices for biomarker discovery from complex omics datasets and the challenges that have been encountered in deriving valid and useful signatures of disease. We will then present a high-level review of data-driven (statistical) and knowledge-based methods applied to biomarker discovery, highlighting some current efforts to combine the two distinct approaches. [...] Effective, reproducible and objective tools for combining data-driven and knowledge-based approaches to identify predictive signatures of disease are key approaches to the biomarker field. We will describe our recommendations for possible approaches to this problem including metrics for the evaluation of biomarkers."
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 Januzzi, J L	2018	Netherlands	European Heart Journal	39		117-117	10.1093/eurheartj/ehy124	Performance of a clinical/proteomic 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	"154 patients undergoing peripheral and/or coronary angiography. Performance of this diagnostic panel was assessed in patients with (n=84) and without DM (n=70) using Monte Carlo 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	10.1080/17513758.2012.723029	Challenges in biomarker discovery: Combining expert insights with statistical analysis of complex omics	review (not applicable)	review	"While some small children display early life wheeze, fewer have diagnosable asthma. We aimed to identify a metabolomic signature of early life asthma, which could be used as a diagnostic test or which would provide insight into the biochemical basis of asthma in young children. [...] The BN methodology identified a Bayesian Network predictive of Year 3 asthma with 21 metabolites achieving an Area Under the Receiver Operator Characteristic Curve (AUC) of 86.5%." "Currently there is no means to predict plaque instability in coronary artery disease (CAD). Modified ceramide and modified phospholipid species were shown to distinguish stable and unstable CAD. These newly identified biomarkers were measured together with known plasma lipids, including sphingolipids, sphingomyelin, and phospholipids, to establish a plasma lipid profile using electrospray ionization tandem mass spectrometry. [...] Multivariate analysis using a statistical machine learning approach combined with recursive feature elimination and multiple cross-validation iterations was applied for the creation of prediction models. Comparison of models with varying number of features showed that models with only 8 lipids were sufficient to provide optimal discrimination between stable and unstable cohorts (AUC = 0.73) while 16 lipids were sufficient to discriminate control from CAD patients (AUC = 0.94)."	
132 McGeehan, M and Kelly, R S and Ljotijaca, A A and Weiss, S T and Lasky, J A	2018	USA	Network of Year 3 asthma with 21 metabolites achieving an Area Under the Receiver Operator Characteristic Curve (AUC) of 86.5%				10.1093/eurheartj/ehy124	Network of year 3 asthma with 21 metabolites indicating of early life asthma	Case-control study	AUC (five-fold cross-validation)	cross-validation	"Currently there is no means to predict plaque instability in coronary artery disease (CAD). Modified ceramide and modified phospholipid species were shown to distinguish stable and unstable CAD. These newly identified biomarkers were measured together with known plasma lipids, including sphingolipids, sphingomyelin, and phospholipids, to establish a plasma lipid profile using electrospray ionization tandem mass spectrometry. [...] Multivariate analysis using a statistical machine learning approach combined with recursive feature elimination and multiple cross-validation iterations was applied for the creation of prediction models. Comparison of models with varying number of features showed that models with only 8 lipids were sufficient to provide optimal discrimination between stable and unstable cohorts (AUC = 0.73) while 16 lipids were sufficient to discriminate control from CAD patients (AUC = 0.94)."
133 McKillop, P and Tsoukas, 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	"202 participants (control, n = 60; stable CAD, n = 61; unstable CAD, n = 81) We used the data from the Genomes of Drug Sensitivity in Cancer project [3], which contains 639 cancer cell lines, each of them characterised by a set of genomic features (details in the next section). The characterisation is not complete for every cell line, and therefore we filtered out cell lines with more than 15 missing genomic features, which reduced the set of selected cell lines from 639 to 508. The dataset contains 118 drugs."
134 Monden, M P and Soria, F and Garnett, M and McDermott, U and Barnes, C H and Balasoor, P J and Saiz-Rodriguez, J	2013	United Kingdom	Plos One	8	4	7-7	10.1371/journal.pone.0071971	Machine Learning Prediction of Cancer Cell Sensitivity to Drugs Based on Genomic and Chemical Properties	Case only (drug sensitivity prediction)	R-squared (8-fold cross-validation, hold-out test set)	cross-validation + test set	"Predicting the response of a specific cancer to a therapy is a major goal in modern oncology that should ultimately lead to a personalised treatment. We developed machine learning models to predict the response of cancer cell lines to drug treatment, quantified through IC50 values, based on both the genomic features of the cell lines and the chemical properties of the considered drugs. Models predicted IC50 values in a 8-fold cross-validation an independent blind test with coefficient of determination R ² of 0.72 and 0.64 respectively."
135 Midoorikawa, Y and Tsuji, J and Takayama, T and Aburatani, H	2012	Japan	Pharmacogenomics	13	2	191-199	10.1186/1745-0174-13-202	Genomic approach towards personalized anticancer drug therapy	review (not applicable)	review	"Here, we review recent advances in the development of classification algorithms using microarray technology for prediction of anticancer sensitivity, discuss the availability of ensemble methods for prediction models, and present data regarding the identification of potential responders to FOLFOX therapy using random forest algorithm."	
136 Mobsberry, P and Yousef, S and Angadi, 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	62979	10.1073/pnas.1711111115	Predicting cancer outcomes from histology and genomics using convolutional networks	Case 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	"We developed a computational approach based on deep learning to predict the overall survival of patients diagnosed with brain tumors from microscopic images of tissue biopsies and genomic biomarkers. This method uses adaptive feedback to simultaneously learn the visual patterns and molecular biomarkers associated with patient outcomes. Our approach surpasses the prognostic accuracy of human experts using the current clinical standard for classifying brain tumors and presents an innovative approach for objective, accurate, and integrated prediction of patient outcomes."
137 Modin, Ian Kidd, M and Drosow, I and Bode, J and Mizukawa, A and Matar, S	2019	NETs and controls	Neuroendocrinology	108		132-132	10.1159/000496966	Automated finger prick blood genomic diagnosis of neuroendocrine tumors	Case-control study	sensitivity, specificity (training/test set split)	training + test set	"A sensitive, noninvasive technology that is safely repeatable and provides real-time information is required for neuroendocrine tumors (NET) diagnosis/management."
138 Mohammed, A and Biegler, G and Adams, J and Halkitar, T	2018	USA	Oncotarget	8	49	8562-	10.18632/oncotarget.2122	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	"Machine learning techniques for cancer prediction and biomarker discovery can hasten cancer detection and significantly improve prognosis. Recent "OMICS" studies which include a variety of cancer and normal tissue samples along with machine learning approaches have the potential to further accelerate such discovery. To demonstrate this potential, 2,175 gene expression samples from nine tissue types were obtained to identify gene sets whose expression is characteristic of each cancer class. Using random forests classification and ten-fold cross-validation, we developed nine single-tissue classifiers, two multi-tissue cancer-versus-normal classifiers, and one multi-tissue normal classifier. Given a sample of a specified tissue type, the single-tissue models classified samples as cancer or normal with a testing accuracy between 85.29% and 100%. Given a sample of non-specific tissue type, the multi-tissue bi-class model classified the sample as cancer versus normal with a testing accuracy of 97.89%. Given a sample of non-specific tissue type, the multi-tissue multi-class model classified the sample as cancer versus normal and as a specific tissue type with a testing accuracy of 97.48%. Given a normal sample of any of the nine tissue types, the multi-tissue normal model classified the sample as a particular tissue type with a testing accuracy of 97.35%."
139 Mourikis, T P and Benardis, L and Fokali, A and Tseloukaki, D and Nalson, J and Pinner, J and Corvini, M and Laggren, J and Howell, M and Tau, C and Fitzgerald, R and Scaccia, P and Ciccarini, F	2019	Italy	Net Commun	10	1	3101-3101	10.1105/ncn.1487.19.0008	Automated finger prick blood genomic diagnosis of neuroendocrine tumors	Case only (survival prediction)	log-rank test p-value (cross-validation)	cross-validation	"The identification of cancer-promoting genetic alterations is challenging particularly in highly unstable and heterogeneous cancers, such as esophageal adenocarcinoma (EAC). Here we describe a machine learning approach to identify cancer genes in individual patients considering all types of damaging alterations simultaneously. [...] Experimentally mimicking the alterations of predicted higher genes in cancer and precursor cells validates their contribution to disease progression."
140 Munigan, K and Javel, B 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	"The identification of cancer-promoting genetic alterations is challenging particularly in highly unstable and heterogeneous cancers, such as esophageal adenocarcinoma (EAC). Here we describe a machine learning approach to identify cancer genes in individual patients considering all types of damaging alterations simultaneously. [...] Experimentally mimicking the alterations of predicted higher genes in cancer and precursor cells validates their contribution to disease progression."
141 Nakamura, M and Bai, H and I 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 Spicar, J F and Van Hemelrijck, D and Joseph, H and Li, Y and Rice, K E and Torka, S and Karamitsos, S N	2019	Sweden	Oncotarget	8	6		10.18632/oncotarget.2122	Immune mediator expression (ICEP) in metastasizing cholangiocarcinomas (CHCC/CCA)	Case only (survival prediction)	accuracy, recall, sensitivity, Matthews' correlation coefficient, F1 score (5 times 10 fold cross-validation)	cross-validation	"The identification of cancer-promoting genetic alterations is challenging particularly in highly unstable and heterogeneous cancers, such as esophageal adenocarcinoma (EAC). Here we describe a machine learning approach to identify cancer genes in individual patients considering all types of damaging alterations simultaneously. [...] Experimentally mimicking the alterations of predicted higher genes in cancer and precursor cells validates their contribution to disease progression."

<p>Considerations for automated machine learning in clinical metabolic profiling: Altered homeostatic plasma concentrations associated with metformin exposure</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>Pacific Symposium on Biocomputing 2018</p>	<p>460-471</p> <p>2018</p> <p>USA</p> <p>https://doi.org/10.1145/3186611</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 demonstrably 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." "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 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." "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>A Nasal Brush-based Classifier of Asthma Identified by Machine Learning Analysis of Nasal RNA Sequence Data</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 Schärer, E E and Boryowayak, S</p>	<p>Scientific Reports 8</p>	<p>15-15</p> <p>2018</p> <p>USA</p> <p>https://doi.org/10.1038/s41598-018-21264-2</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 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." "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>Stratification bias in low signal microarray studies</p> <p>154 Parker, B and Guntur, S and Bedo, J</p>	<p>BMC Bioinformatics 8</p>	<p>326-326</p> <p>2007</p> <p>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>review</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 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." "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 head and neck cancer: a systematic review</p> <p>155 Patel, S and Asari, K H and Arakeri, C and Senaviratna, C J and Mudher, N and Mathi, S and Ferraro, M and 155 Rahimi, S and Brennan, P A</p>	<p>Journal of Oral Pathology & Medicine 48</p>	<p>9</p> <p>773-779</p> <p>2019</p> <p>India</p> <p>https://doi.org/10.1111/jor.12855</p>	<p>article</p>	<p>review (not applicable)</p>	<p>review</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>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>156 Porter, D and Gooday, C S and Nijjar, J S and Missow, M and Siebert, S and Mudular, A and 156 McInnes, I B</p>	<p>Arthritis and Rheumatism 68</p>	<p>4130-4131</p> <p>2016</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 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>A transcriptional profile present in CD4 T cells of patients with undifferentiated arthritis predicts the future development of seronegative rheumatoid arthritis and implicates IL-6 in disease evolution</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>Arthritis and Rheumatism 63</p>	<p>10</p> <p>2011</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 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>Case-control study</p> <p>sensitivity, specificity (training and validation cohort)</p>	<p>external cohort validation</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>Targeted bisulfite sequencing identified a panel of DNA methylation-based biomarkers for esophageal squamous cell carcinoma (ESCC)</p> <p>158 Zou, W and Wang, C and Chen, S and Zhao, D and Zhou, Y and Ma, Y and Yang, J and Li, C and Huang, 158 Zou, W and Wang, C and Chen, S and Zhao, D and Zhou, Y and Ma, Y and Yang, J and Wang, M</p>	<p>Clin Epigenetics 9</p>	<p>2</p> <p>129-129</p> <p>2017</p> <p>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 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>Case-control study</p> <p>AUC, accuracy, sensitivity, specificity (5-fold cross-validation + test set)</p>	<p>cross-validation + test set</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>Contribution of an integrative multi-omic approach in the metabolic syndrome prediction: a nested case-control study</p> <p>159 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>Drug Metabolism and Personalized Therapy 31</p>	<p>4</p> <p>6433-6434</p> <p>2016</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. Metabonomic 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(s)	Journal	Year	DOI	Article Type	Study Design	Primary Outcome	Validation Method		
160 Puzatzi, L and Hess, K R	Ann Oncol	15	12	1731-1737	2004	USA	review (not applicable)	review	
161 Rao, R and Dean, K and Migasawa, B and Somvarshi, P and Doyle, F	Biological Psychiatry	85	10	596-596	2019		meeting abstract	Case-control study	
162 Rappoport, N and Shmilir, R	Research	46	20	10562	2018	Israel	article	review (not applicable)	review
163 Reeve, J and Madill-Thomson, K S and Halloran, P F	American Journal of Transplantation	19		452-453	2019		meeting abstract	Case-control study	
164 Reeve, J and Sellares, J and De Freitas, D and Enecke, G and Bromberg, J and Matsa, A and Halloran, P	American Journal of Transplantation	13		109-109	2013		meeting abstract	Case-control study	
165 Pomeroy, Y G	Hum Genet	134	1	3-11	2015	USA	article	review (not applicable)	review
166 Rescon, H W and Varghesa, R S and Abdel-Hamid, M and Elissa, S A and Saha, B and Goldman, R	Analyses of mass spectral serum profiles for biomarker selection	21	21	4039-4045	2005	USA	article	Case-control study	
167 Ritari, J and Hyvärinen, K and Koskela, S and Itälä-Rames, M and Nittynyo, P and Nihminen, L and 167 Salmenniemi, U and Pulkkinen, M and Vaini, L and Kwan, T and Postinen, T and Partanen, J	Leukemia	33	1	240-248	2019	Canada	article	Cases only (relapse prediction)	
168 Roder, J and Oliveira, C and Nui, L and Tsybin, M and Linsted, B and Roder, H	BMC Bioinformatics	20		14-14	2019	USA	article	Case-control study	

"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 is 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 differences 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), R5 (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 TabA."

"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 of 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-TOF/MS profiles of serum."

"Abigenex[®] 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), R5 (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 TabA."

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"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-TOF/MS profiles of serum."

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"For the GSE5081 cohort expression profiling was performed on RNA from frozen, resected tumor tissue from 181 subjects with stage I or II NSCLC. [...] Expression profiling for the GSE5217 cohort was performed for 176 subjects with stage IV NSCLC."

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 microarray (Immunoarray) and factors using multiplexed immunosorbent microarray (Immunoarray) 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 Khatri, P and Zamanian, R T	2019	United Kingdom	Circulation Research	124	6	904-919	10.1161/ATVBAHA.119.319111	article	"Discovery of Distinct Immune Phenotypes Using Machine Learning in Pulmonary Arterial Hypertension ... 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 Saales, S I and Lofkowitz, 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 Bioinformatics	2	3	575-81	10.1093/bioinformatics/btg044	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	Bioinformatics	21	20	3896-3904	10.1093/bioinformatics/bti100	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 Bioinformatics	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 unknown"	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/ijms17090166	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 Mavroudis, S and Cowerthorpe, M C and Shpak, M	2019	Greece	BMC Med Genomics	11	1	118-118	10.1186/s12916-019-0056-6	article	"Blood samples from 81 stroke patients and 68 controls"	Case-control study	accuracy (5-fold cross validation)	cross-validation
196 Toh, T S and Dondelinger, F and Wang, D	2019	UK	Eurobiomed	4	607-615	2019	10.1007/s10260-019-0001-2	article	"Review (not applicable)"	review (not applicable)	review	
197 Tong, D I and Boocock, D I and Covey, C and Saff, J and Gomez, S and Quares, S and Reed, R and Ball, G A	2011	UK	Clinical Proteomics	8	1	2011	10.1007/s12026-011-9111-4	article	"Melanoma data set: 101 patients: analysed yielding mass spectral data for 99 samples. Core blood data set: 158 samples, 70 samples were categorized as containing a 'high' number of core cells and the remaining 88 samples with a 'low' number of core cells"	Case-control study	AUC, accuracy (Monte Carlo cross-validation + external validation set)	cross-validation + external cohort validation

"Three large-scale pharmacogenomic studies have screened anticancer compounds in greater than 1000 distinct human cancer cell lines. We combined these datasets to generate and validate multi-omic predictors of drug response. We compared drug response signatures built using a penalized linear regression model and two non-linear machine learning techniques, random forest and support vector machine. [...] Multi-omic predictors of drug response can be generated and validated for many drugs. Specifically, the random forest algorithm generated more precise and robust prediction signatures when compared to support vector machines and the more commonly used elastic net regression. The resulting drug response signatures can be used to stratify patients into treatment groups based on their individual tumor biology."

"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 microarray (Immunoarray) 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."

"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."

"In this paper, we focus on three different supervised machine learning techniques in cancer classification, namely CA1 decision tree, and bagged and boosted decision trees. We have performed classification tasks on seven publicly available canceromic microarray data and compared the classification/prediction performance of these methods. We have observed that ensemble learning (bagged and boosted decision trees) often performs better than single decision tree classification task."

"Various studies have shown that cancer tissue samples can be successfully detected and classified by their gene expression patterns using machine learning approaches. One of the challenges in applying these techniques for classifying gene expression data is to extract accurate, readily interpretable rules providing biological insight as to how classification is performed. [...] In this study, we have compared our approach to other machine learning techniques for class prediction in 19 binary and multi-class gene expression datasets involving human cancers. The k-NSP classifier performs as efficiently as Prediction Analysis of Microarray and support vector machine, and outperforms other learning methods (decision trees, k-nearest neighbour and naive Bayes). Our approach is easy to interpret as the classifier involves only a small number of informative genes."

"Recent advances in proteomic technologies such as SELDI-TOF mass spectrometry has shown promise in the detection of early stage cancers. However, dimensionality reduction and classification are considerable challenges in statistical machine learning. We therefore propose a novel approach for dimensionality reduction and tested it using published high-resolution SELDI-TOF data for ovarian cancer. [...] The method achieved average sensitivity of 0.9950, specificity of 0.9916, accuracy of 0.9933 and a correlation coefficient of 0.9889 for 100-fold cross validation. Furthermore, only one control was misclassified in leave-one-out cross validation."

"It is very significant to explore the intrinsic differences in breast cancer subtypes. These intrinsic differences are closely related to clinical diagnosis and designation of treatment plans. [...] In this article, we use estrogen receptor (ER), progesterone receptor (PR), human epidermal growth factor receptor 2 (HER2) to define breast cancer subtypes and classify any two breast cancer subtypes using SMO-MMS algorithm. We collected mRNA data, methylation data and copy number variation (CNV) data from TCGA to classify breast cancer subtypes. Multiple Kernel Learning (MKL) is employed to use these omics data distinctly. The result of using three omics data with multiple kernels is better than that of using single omics data with multiple kernels."

"The small number of multi-omics datasets in the field of fibromyofasciitis 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-organ data, thus enabling a real investigation 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 EM by moving from a reactive, targeted, and reductionist approach to a more proactive, global, and integrative one."

"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."

"There are general non-technical issues that are required to be addressed before mainstream application of ML within translational medicine takes place. Oftentimes, sensitive data is required to train ML algorithms. Access to data should be carefully regulated to ensure privacy without stifling innovation and technological advancement to improve outcomes [37]. A proposed scheme called privacy-preserving clinical decision with data support (PPCD) is an encouraging step in this direction [58]. Basics within the training datasets of ML algorithms need to be avoided to reduce the risk of failure of ML methods to generalise. Rethinking responsibility and accountability of individuals or organisations selecting datasets used to train ML algorithms are key to address this. Ethical frameworks should be developed by scientific committees and regulatory bodies to recognize and minimize the effect of models while guiding design choices to introduce systems that build trust, understanding, and maintaining individual privacy [37,59]. Reproducibility is another aspect that needs to be managed to ensure widespread adoption of ML in translational medicine. Caution should be exercised when drawing conclusions solely from large repositories of clinical data as it is often fraught with heterogeneity in quality [60]. Respectively sharing data and code should be made requirements for authors alongside their publications to ensure trust in research findings. Reproducibility of results requires the software environment, source code, and raw data used during experiments [61]. Lastly, there is also a need to explain and easily interpret predictions of ML systems to implement them in clinical settings. Black box algorithms may have good predictive accuracy but their predictions are difficult to interpret and are not actionable, hence limiting their clinical application [62]. Fortunately, new methods have been devised to allow researchers to interpret black-box algorithms to ensure their predictions are sensible [63, 64, 65]."

"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."

"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	Country	Journal	Category	Abstract Summary	Methodology	Validation
198 Trakladis, J and Saribar, S and Chen, A and Fajuljanti, V and Krishniah, A	2019	Canada	American Journal of Medical Genetics Part B: Neuropsychiatry	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	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 (leave k 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	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 Zhang, Y and Chang, J	2017	Norway	Am J Med Genet B Neuropsychiatr	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	Spain	BMC Syst Biol	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	PLoS One	Case-control study	"This compendium contains data from various cancer types 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 Holter, R and Arul, E A and Dhalake, D and Kannan, A and Whitehead, R and Berry, M and Berry, M and Berry, D and Cheng, J and Ding, Y and Eskin, D and Frank, S and Gatto, E and Hansen, L and Liu, Y and Ouyang, G and Land, P and Li, R and Li, C and Robinson, G and Sharma, A and Shih, J and Tang, C and Tsou, A and Young, L and Puthi, C and Heagun, I E	2019	USA	BMC Cancer	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	China	Osteoporosis Int	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 case (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 Spodickovich, A and Liu, M and Yang, X and Vargheese, R S and Taddei, M G and Resconi, H W	2015	USA	Journal of Cancer	review (not applicable)	review	review	review
207 Wang, L and Liu, Z P	2019	China	Frontiers in Genetics	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	States	IEEE J Biomed Health Inform	Case-control study	"In this study, we investigate integrative analysis of proteins, lipids, and metabolites to take advantage of complementary information to improve the ability to distinguish cancer cases from controls..."	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 Zhang, Y and Chang, J	2017	Norway	Am J Med Genet B Neuropsychiatr	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	Spain	BMC Syst Biol	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	PLoS One	Case-control study	"This compendium contains data from various cancer types 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 Holter, R and Arul, E A and Dhalake, D and Kannan, A and Whitehead, R and Berry, M and Berry, M and Berry, D and Cheng, J and Ding, Y and Eskin, D and Frank, S and Gatto, E and Hansen, L and Liu, Y and Ouyang, G and Land, P and Li, R and Li, C and Robinson, G and Sharma, A and Shih, J and Tang, C and Tsou, A and Young, L and Puthi, C and Heagun, I E	2019	USA	BMC Cancer	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	China	Osteoporosis Int	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 case (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 Spodickovich, A and Liu, M and Yang, X and Vargheese, R S and Taddei, M G and Resconi, H W	2015	USA	Journal of Cancer	review (not applicable)	review	review	review
215 Wang, L and Liu, Z P	2019	China	Frontiers in Genetics	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	States	IEEE J Biomed Health Inform	Case-control study	"In this study, we investigate integrative analysis of proteins, lipids, and metabolites to take advantage of complementary information to improve the ability to distinguish cancer cases from controls..."	AUC, accuracy, sensitivity, specificity (10-fold cross-validation + test set)	cross-validation + test set

Author(s)	Year	Journal	Volume	Issue	Pages	Year	Country	URL	Article Type	Abstract Summary	Keywords	DOI	
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	https://doi.org/10.1016/j.gtc.2019.05.006	Case-control study	80 HCC and 67 LC patients. Serum peptide pattern that differentially diagnoses hepatitis B virus-related hepatocellular carcinoma from liver cirrhosis. AUC, accuracy, sensitivity, specificity (10-fold cross-validation + test set)	cross-validation + test set	10.1016/j.gtc.2019.05.006	
Wang, S and Li, M and C	2016	Statistics in Biosciences	8	1	129-158	2016		https://doi.org/10.1007/s12561-016-9161-9	Case-control study	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 1,608 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 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). Drug 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. [...] 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.	accuracy, sensitivity, specificity, PPI, NPI, permutation p-values cross-validation + external validation	cross-validation + external validation	10.1007/s12561-016-9161-9
Wei, Z and Wang, K and Qu, H and Zhang, H and Bradford, J, and Kim, C and Fackler, J and Hou, C and Gleason, J T and Chivukuri, R and Stanley, C and Ramos, D and Grant, S F and Polythronakos, C and Hakonarson, H	2019	PLoS Genet	5	10	e1006978	2009	United States	https://doi.org/10.1371/journal.pgen.1006978	Case-control study	Genome-wide association studies on type 1 diabetes. AUC, accuracy, sensitivity, specificity (5-fold cross-validation + test set)	cross-validation + test set	10.1371/journal.pgen.1006978	
White, B and Khan, S 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		https://doi.org/10.1158/1538-7443.ctr18-0301	Case-control study	correlation, p-value (10-fold CV)	cross-validation	10.1158/1538-7443.ctr18-0301	
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	https://doi.org/10.1155/2018/2392257	Case-control study	AUC, F1-score (5-fold CV)	cross-validation	10.1155/2018/2392257	
Xie, G and Dong, C and Kong, Y and Zhong, J F and Li, M and Wang, K	2019	Genes	10	3		2019	USA	https://doi.org/10.3390/genes10030267	Case-control study			10.3390/genes10030267	
Yang, J and Shi, Z and Xie, Z and He, S and Li, Z and Luo	2013	Bioinformatics			246-251	2013	USA	https://doi.org/10.1093/bioinformatics/btt114	Case-control study	accuracy (10 runs of 10-fold CV)	cross-validation	10.1093/bioinformatics/btt114	
Yang, S and Naiman, D Q	2014	Stat Appl Biom Biol	13	4	477-496	2014	States	https://doi.org/10.1093/biostat/btt004	Case-control study	accuracy (LOOC + test set)	cross-validation + test set	10.1093/biostat/btt004	
Yang, T and Huang, N and Hao, L and Kong, W	2017	BMC Genomics	18		210-210	2017	China	https://doi.org/10.1186/s12864-017-0456-4	Case-control study	accuracy, sensitivity, specificity (5-fold cross-validation)	cross-validation	10.1186/s12864-017-0456-4	

"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 investigate 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 misspecification 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 1,608 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 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). Drug 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 multibial 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."

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218	Yu, H and Samuels, C, C Zhou, Y* and Guo, Y	Architectures and accuracy of artificial neural network for disease classification from omics data	BMC Genomics	20	12-12	2019	China	https://doi.org/10.1186/s12859-019-2444-4	37 omics datasets, including datasets with more than 50 samples per group	Case-control study	Accuracy, Kohn'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, and Xu, Y, and Wang, J, and Kiang, J, and Zhang, W, and Shao, J, and Guo, D, and Wang, Y	LUAOpp: an effective prediction model for lung adenocarcinomas based on somatic mutational features	BMC Cancer	19	1	263-263	2019	China	https://doi.org/10.1186/s12859-019-2443-3	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 genome and clinic information (n=371) from TCGA (The Cancer Genome Atlas) (http://cancergenome.nih.gov), analyzed the somatic mutation difference between the two groups categorized 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 Fan GTPase binding."
220	Yu, H, and Lavoie, D, A and Zhang, H, and Chan, D, W and Zhang, Z, and Snyder, M	Predicting Ovarian Cancer Patients' Clinical Response to Platinum-Based Chemotherapy by Their Tumor Proteomic Signatures	J Proteome Res	15	8	2455-2465	2016	United States	https://doi.org/10.1021/acs.jproteome.5b01129	"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 (ROC), hold-out test set	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, lipophospholipids, and bile acids provided further insights into the metabolic alterations associated with the disease."
221	Zang, X and Jones, C, M and Long, T, Q and Monea, M, E and Zhou, M, and Walker, L, D and Meanecke, B	Feasibility of detecting prostate cancer by ultraperformance liquid chromatography mass spectrometry serum metabolomics	J Proteome Res	13	7	3444-3454	2014	USA	https://doi.org/10.1021/pr400449g	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-SNE about 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	Zhang, L, H 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, S	Deep learning based multi-omics data integration reveals two prognostic subtypes in high-risk neuroblastoma	Frontiers in Genetics	9	2018	China	https://doi.org/10.3389/fgenet.2018.00072	"The TARGET cohort is comprised of 407 high-risk neuroblastoma samples, including 217 samples with gene expression data and 300 samples with copy number alterations (CNA). Among these obtained samples, 130 had both gene expression and CNA data. The SEQC cohort 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 prognosis 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 ~73%, 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	Improvement in prediction of prostate cancer prognosis with somatic mutational signatures	Journal of Cancer	8	16	3261-3267	2017	China	https://doi.org/10.7150/jco.17411	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 (GSE51375, GSE43888) and one validation dataset (TCGA). Univariate and multivariate analyses with logistic regression were performed to evaluate the predictive value 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 (GSE49893, GSE32062). AGO1 and MAFK were found highly expressed in patients with platinum-resistant SOC and independent prognostic 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	High expression levels of AGO1 and MAFK associated with adverse ovarian cancer prognosis	Journal of Cancer	10	2	397-407	2019	China	https://doi.org/10.7150/jco.18121	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	Machine Learning With K-Means Dimensional Reduction for Predicting Survival Outcomes in Patients With Breast Cancer	Cancer Informatics	7	2018	USA	https://doi.org/10.1002/cinb.1101	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 Cox-Ph. 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	The application of deep learning in cancer prognosis prediction	Cancers	12	3	2020	China	https://doi.org/10.3390/cancers12030300	review (not applicable)	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 Cox-Ph. 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)	Journal	Year	Country	Study Type	Findings	Validation		
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 Ankiti, F and Mazi, M and Wolf, J and Gajdosy, J and Hadjiagapiou, G and Davies, R and Al Khatib, R and Bonnet, C and Casone, S and Bakker, E and Hart, D and Mangin, M and Mirza, J and Linnemann, J and Lind, W and Fard, O and Dobbins, J M and Gardner, D and de Bonting, L M and Chau, A T and Keane, H and Rees, P W and de Coster, 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	4031629-4031829	2020	India	cross-validation + test set	
248 Bigelow, G and Baria, A and Farhan, 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 Youssou, Z	Journal of Hepatology	73	5	1049-1410	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 Aheri, A and Carboni, C and Temko, 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	2020	Italy	article	cross-validation + external cohort validation
Catalina, M D and Bachli, P and Yao, E A 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 Kutler, 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	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 Cook, R and Kuebler, J and Saranam, M and Wilmes, P and Colemaro-Morfi, A and Ross, P S and 258 Hilger, C and Bindsig-Jensen, C and Olfert, M and Kuehn, A	Front Immunol	11	594550	2020	Germany	article	Review	
259 Oliveira Lima, E and Navarro, L C and Morikita, N and Kawakami, C M and Rodrigues, R G M and 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 Zarrispar, A	Curr Opin Organ Transplant	25	4	420-425	2020	USA	article	Review
262 Gao, R and Vich Vila, A and Fung, J and Imhann, F and Vlietinck, E and Wehrens, R	Netherlands Journal of Microbiology	7	8	166-167	2019	Netherlands	Meeting abstract	cross-validation
263 Gupta, R	JNCI Cancer Spectrum	4	3	2020	Denmark	Meeting abstract	cross-validation + external cohort validation	

Author(s)	Year	Journal	Volume	Issue	Page(s)	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 P 264 Youniss, Z M and Harrison, S A and Anzoe, Q M and Loomis, R	2020	Hepatology	72	1	43A-44A	100200	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 and Jayasinha and 265 Gupta, R and Anuja, G and Sengupta, D	2020	Genomics	21	1	744-744	100200	Molecular signature comprising 11 placental genes enables accurate blood-based diagnosis of NSCLC	Case-control study	AUC (LCOVC)	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, Y and Kim, H C and Depp, C A	2020	Psychiatry Research	284			100200	Artificial intelligence approaches to predicting and detecting cognitive decline in older adults: A conceptual review	Review		Review
Gumral, A and Sammoura, R and Al-Rahimi, M and AlSalman, H and El-Gaart, A	2021	Health Informatics Journal	27	1		100200	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		100200	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	100200	Precision medicine and artificial intelligence: overview and relevance to reproductive medicine	Review		Review
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	100200	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			100200	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%))	cross-validation
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 272 S and Cheng, L and Qian, L and Liu, R and Xiao, H	2020	Annals of Oncology	31		5132-5132	100200	Development of circulating free DNA methylation markers for thyroid nodule diagnosis	Case-control study	accuracy, sensitivity, specificity (training/test)	training + test set + external cohort
Hosino, A and Kim, H S and Banjar, L and Gyos, K E and Cliff, M and Hernandez, J and Zambonis, C P and Rodrigues, G and Molina, H and Heist, S and Mark, M T and Gohari, I and Benito-Martín, A and Lucero, S and D Gianmatteo, 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 Fretts, D and Kavits, C M and Arano, Y and Buchling, W and Lautzbars, P and Qigian, Y and Sugitara, K and Takahashi, N and Alkhalaf, M and Bailey, K A and Jossland, T and Wang, H and Harris, A M and Garcia-Santos, G and Ponsar, Z and Blichardier, V F and Bhawani, G P and Scher, J and Saji, I and Scher-Shoval, R and Yarden, Y and Oren, M and Maladi, M and Petriccione, M and De Biase, C C and Donelli, M and Fischer, C and Vizzato, S and Wright, G P and Ganahaw, I and Marano, M and Ahmed, A and DeFranco, J and Donceel, J and Bozler, M F A and Lacroix, N and Viscor, 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 Miodini, S and Roberts, S S and Basu, E M and Dulcan, D and Krantz, B A and Carobon, F and Simpson, A L and Benigay, M and Bouch, C M and Smeone, D M and Jain, M and Ghahri, 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 Kromer, K and Sheth, S and Banich, 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 Liu, 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 Johnson, D R and Matzi, I R and Jarnagin, W R and Lyden, D	2020	Cell	182	4	1044-1061	100200	Extracellular Vesicle and Particle Biomarkers Define Multiple Human Cancers	Case-control study	sensitivity, specificity (10-fold CV + external test set)	cross-validation + external cohort
Huang, J and Kuth, C and Covic, M and Trull, M and Adams, J and Zukorff, S and Probst, C and Wang, and Nanno, J and Scherer, M F and Nesch, S and Kastelmann, G and Suhr, K and Lang, M and 274 Schless, J and Geiger, C and Adams, J and Hildebrand, A and Poter, A and Wang Sattler, R	2020	Diabetes	69		2776-2785	100200	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 275 M and Yu, C Y and Chang, J and Xiang, S and Zhang, X and Huang, R	2020	BMC Med Genomics	13		41-41	100200	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 Kim, 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	100200	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			100200	Proteome predicts progression and prognosis of hepatitis B virus-related acute-on-chronic liver failure	Review		Review

Author(s)	Title	Journal	Year	Country	Link	Abstract	Study Design	Key Findings	External Validation
Kandimalla, R and Xu, J and Liu, A and Matsuyama, T and Yamamura, K and Perfori, J and Metzler, S and Hernandez-Ilizaliturri, F and Lozano, J and Borazjani, E and Tsai, S and Evans, D and Laitinen, S and 278 Baha, H and Brand, R and Von Hoff, D and Batgeary, F and Li, W and Gao, A	Epigenetic DNA methylation fingerprint for the early detection of gastrointestinal cancers	Cancer Research	80	16	2020	USA	Meeting abstract	Using this approach, we sequenced 300 plasma specimens from all GI cancers, as well as age-matched healthy controls. Eight datasets containing a total of 10,000 samples, including 1000 colorectal, 1000 cholangiocarcinoma and 1000 gastroesophageal junction cancer patients.	External cohort validation
279 Kaur, H and Bhatta, R and Garg, D and Mehta, N and Raghava, P S	Unravelling the molecular heterogeneity in type 2 diabetes: a potential subtype discovery followed by metabolic modeling	BMC Med Genomics	13	1	2020	India	Article	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 and Kavousi, K and Baniasi-Moghaddam, A M and Movassavi-Moushfar, A A	Network-based machine learning in colorectal bladder organoids models predicts anti-cancer drug efficacy in patients	Nat Commun	11	1	5485-5485	2020	Korea	Article	Training + test set
281 Kong, J and Lee, H and Kim, S and Han, S and Kim, S and Ha, D and Shin, K and Kim, S	Feature selection strategies for drug sensitivity prediction	Sci Rep	10	1	9377-9377	2020	Poland	Article	Training + test set
282 Koras, K and Jurava, D and Kivi, J and Mazar, J and Staub, E and Szarek, E	Target analysis of volatile organic compounds in exhaled breath for lung cancer discrimination from other pulmonary diseases and healthy persons	Metabolites	10	8	1-18	2020	Greece	Article	Cross-validation
283 Koureas, M and Kirgou, P and Amoutzas, G and Hadjichristodoulou, C and Gourogoulani, K and Tsolomidou, A	Overall survival prediction of non-small cell lung cancer by integrating machine learning and clinical data with deep learning	Sci Rep	10	1	4679-4679	2020	Taiwan	Article	Training + test set
284 Lai, H and Chen, W and Han Hsu, T and Chi, C and Tsao, Y and Wu, S	Prediction of breast cancer treatment-induced fatigue by machine learning using genome-wide association data	JNCI Cancer Spectrum	4	5	2020	USA	Article	Training + test set	
285 Lay, S and Deary, J O and Oh, D and Di Maggio, A and Dunbar, A and Marvella, G and Charles, C and Boyatzis, E and Bouziane, M and Bressa, C and Thomas, E and Cottu, P and Trudel, L and Levy, C and Martin, A and Everhard, S and Gati, P and Partridge, A H and Michals, S and 285 Delouis, F and Ardhi, F and Yaa-Luu, I	Multiparameter analysis of early-stage cancer signatures in blood	Clinical Cancer Research	26	11	2020	China	Meeting abstract	Training + test set	
286 Liu, H and Wang, C and Xu, J and Fang, S and Qiu, F and Si, J and Chu, H and Han-Zhang, H and Mao, M and Liu, H and Zhang, W and Zhang, W and Zhang, Z and Zhang, Y and Zhang, H	Prediction of antidepressant treatment response and remission using an ensemble machine learning framework	Pharmacol Sci Experiment	13	10	1-12	2020	USA	Article	Cross-validation
287 Lin, L and Koh, P and Liu, Y and Yu, Y and Yang, A and Tai, S J	Microenvironment characterization and multi-omics signatures related to prognosis and immunotherapy response of hepatocellular carcinoma	Hepatology	9	1	2020	China	Article	External cohort validation	
288 Liu, F and Qin, L and Zhao, S and Yuan, C and Liu, Y and Wang, Y and Xu, H and Zhang, Q and He, Y and Zhang, H and Pan, Y and Chen, Y and Zhang, Z and Zhang, W and Zhang, H	Identification of DNA methylation patterns and biomarkers for clear cell renal cell carcinoma by multi-omics data analysis	PeerJ	8	2020	China	Article	Cross-validation + external cohort validation		
289 Liu, P and Tian, W	LogSum +12J penalized logistic regression model for biomarker selection and cancer classification	Sci Rep	10	1	22125-	2020	China	Cross-validation + test set	
290 Liu, Y and Yang, W, S and Zeng, W Q and Yuan, Z and Xu, H B	Combining Genetic Mutation and Expression Profiles Identifies Novel Prognostic Biomarkers of Lung Adenocarcinoma	Clinical Medicine Insights: Oncology	14	2020	China	Article	Cross-validation + test set		
291 Liu, Y and Liu, F and Hu, X and Hu, J and Jiang, Y	Gene expression along with genomic copy number variation and mutational analysis were used to develop a 9-gene signature for estimating prognosis of esoph	OncoTarget and Therapy	13	2020	China	Article	Prognostic study	External cohort validation	
292 Liu, Y and Wu, S and Cui, C and Yu, M and Wang, S and Yue, Y and Liu, M and Sun, Z	A novel stratification framework for predicting outcomes in patients with prostate cancer	BJ Cancer	122	10	1467-1476	2020	United Kingdom	Article	Training + test set
293 Lucca, B A and Ewings, M and Ellis, C and Edwards, D R and Campbell, C and Cooper, R A and Clark, L and Brewer, D S and Cooper, C S	Identifying CpG methylation signature as a promising biomarker for recurrent and relapse-free survival in non-small cell lung carcinoma	Aging (Albany NY)	12	14	14676	2020	China	Article	External cohort validation
294 Luo, S and Song, J and Xiao, X and Xu, Z and Zhao, Z and Zhang, W and Miao, S and Tang, Y and Ran, R	Machine learning in parkinson's disease using machine learning on public multi-omic datasets: A pilot study	Movement Disorders	35	2020	USA	Meeting abstract	Training + test set		
295 Makarios, M and Neaki, H and Blaudravatz, C and Leonard, A and Hashebi, S and Kim, J and Van Kuren-Jensen, A and Craig, D and Appelman, L and Bookman, M and Sington, T and Fagin, F and Hsieh, M	Machine learning for prediction of cancer-associated venous thromboembolism	Blood	136	37-37	2020	USA	Meeting abstract	Cross-validation	
296 Mancini, M and Palazzo, M and Knott, M E and Beauséjour, P and Vankylevich, P and Grómez, M J and 297 Mangan, M E	Coupled Mass Spectrometry-Based Lipidomics Machine Learning Approach for Early Detection of Clear Cell Renal Cell Carcinoma	J Proteome Res	20	1	841-857	2021	Argentina	Article	Training + test set
298 McCarthy, C P and Neumann, J and Mitchellhugh, S A and Ibrahim, N E and Gagnin, H K and Sørensen, N A and Schäfer, S and Zeller, F and Magaret, C A and Barnes, G and Rhyne, R F and 298 Westermann, D and Januzzi Jr., J L	Derivation and External Validation of a High-Sensitivity Cardiac Troponin Assay for Early Detection of the Presence of Obstructive Coronary Artery Disease	J Am Heart Assoc	9	16	e017221-	2020	USA	Article	External cohort validation

Author(s)	Year	Country	Journal	Volume	Issue	Page	DOI	Article Type	Keywords	Abstract Summary	Methodology	Validation Type	Notes	
299 Miao, R and Chen, H and Han Dang, Q and Xia, L* and Yang, Z and Yi, H and Hao, F and Liang, Z and Liang, Y	2020	China	Pharmacol Res	159		104932	104932	article	Drug response prediction	"The GDS3 dataset contains 140 drug sensitivity experiments results in 624 cell lines" "Targeted DNA sequencing for more than 500 cancer-associated genes and whole-genome RNA sequencing was carried out in more than 25,000 fresh frozen or paraffin embedded tumor samples, including both primary and metastatic samples" "We divided 741 ADN participants with blood microarray data into three groups based on their most recent CDR assessment: cognitive normal (CDR-0), mild cognitive impairment (CDR = 0.5), and probable Alzheimer's disease (CDR ≤ 1.0)" "Here, we investigate whether 25,000 genes from the brush of 296 patients can distinguish those with no liver disease (n = 54), cirrhosis (n = 38), HCC (n = 12), pulmonary hypertension (n = 49), or colorectal cancer liver metastases (n = 51)"	AUC, sensitivity, specificity (5-fold CV)	cross-validation	"The proposed model of this paper used statistical methods and Machine Learning methods combined with genomics data to accurately predict the performance of oncology drugs on cancer cell lines."	"The proposed model of this paper used statistical methods and Machine Learning methods combined with genomics data to accurately predict the performance of oncology drugs on cancer cell lines."
Michuda, J and Lelbowitz, B and Amar-Farhik, S and Beni, C and Breschi, A and Kapilivsky, J and Ighuta, C and Bell, J S and Beaschamps, K A and White, K and Stumpa, M and Beauder, J and Taster, T	2020	USA	Cancer	80	16		11111111	meeting abstract	Differential diagnosis prediction	"Multimodal prediction of diagnosis for cancer of unknown primary"	accuracy (training/test set)	training + test set	"The incorporation of multiple modes of omics data can improve the interpretability and robustness of machine learning models to predict cancer diagnosis"	"The incorporation of multiple modes of omics data can improve the interpretability and robustness of machine learning models to predict cancer diagnosis"
300 T														
301 Miller, J B and Kawe, J S X	2020	USA	Genes (Basel)	11	6		104932	article	Differential diagnosis prediction	"Predicting Clinical Dementia Rating Using Blood RNA Levels"	AUC (10-fold CV)	cross-validation	"Our analyses indicate that machine learning may be able to predict cognitive decline in individuals using RNA levels from a blood microarray by taking into account small differences in expression that are individually nonsignificant. A support vector machine was able to increase predictive accuracy of AD from a 50% baseline to almost 90%."	"Our analyses indicate that machine learning may be able to predict cognitive decline in individuals using RNA levels from a blood microarray by taking into account small differences in expression that are individually nonsignificant. A support vector machine was able to increase predictive accuracy of AD from a 50% baseline to almost 90%."
302 Miller Atkins, G and Azevedo-Moreno, L A and Grove, D and Dweik, R A and Tonelli, A R and Brown, M and Alkhalaf, D S and Azevedo, F and Rotstein, D M	2020	USA	Hepatology Communications	4	7	1041-1055	1041-1055	article	Differential diagnosis prediction	"Breath Metabolomics Provides an Accurate and Noninvasive Approach for Screening Cirrhosis, Primary, and Secondary Liver Tumors"	balanced accuracy (cross-validation)	cross-validation	"The use of machine learning and breath VOCs [Volatile organic compounds] shows promise as an approach to develop improved, noninvasive screening tools for chronic liver disease and primary and secondary liver tumors"	"The use of machine learning and breath VOCs [Volatile organic compounds] shows promise as an approach to develop improved, noninvasive screening tools for chronic liver disease and primary and secondary liver tumors"
303 Morgan, D and Pooking, K and Healy, C and Sisti, S and Cahney, C and Cannon, J and Zampieri, S and Nelson, B and McKoy, P and Nordstrom, M O and Fischer, R and Auer, B and Baranates-Vidal, N and Borgwardt, S and Ruffmann, S and Sachs, G and Van Der Graag, M and Ruten, B and Fontana, C and de Haan, L and Vilmaguy, L and Kempton, M and McGuire, P and Cotter, D	2020	Ireland	Schizophrenia Bulletin	46		528-539	528-539	meeting abstract	Case-control study	"Development of prognostic prediction models for outcomes in the clinical high-risk state and psychotic experiences in adolescence: Machine Learning analysis of two nested case-control studies"	AUC, PPV, NPV (training + test set)	training + test set	"With external validation, models incorporating proteomic data may contribute to improved prediction of clinical outcomes in individuals at risk of psychosis"	"With external validation, models incorporating proteomic data may contribute to improved prediction of clinical outcomes in individuals at risk of psychosis"
304 Mostafaei, M and Chi, Y and Huang, Y and Chen, Y	2020	USA	BMC Med Genomics	13		44-44	11111111	article	Differential diagnosis prediction	"Convolutional neural network models for cancer type prediction based on gene expression"	accuracy (6-fold CV, 80-20% splitting for training and validation)	cross-validation	"Pharmacogenic biomarkers including gene variants for cancer susceptibility genes (CAC1C1) and important MTX pathway enzymes (ATIC) combined with baseline DA28 (CAC1C1) and important MTX pathway enzymes (ATIC) combined with baseline DA28 score predicted MTX response in patients with early RA more reliably than demographics and baseline DA28 alone, with replication in an independent cohort"	"Pharmacogenic biomarkers including gene variants for cancer susceptibility genes (CAC1C1) and important MTX pathway enzymes (ATIC) combined with baseline DA28 score predicted MTX response in patients with early RA more reliably than demographics and baseline DA28 alone, with replication in an independent cohort"
305 Miyasodava, E and Athreya, A and Crowson, C and Weinstock, R and Wang, L and Matreanu, E	2020	USA	Arthritis and Rheumatology	72		4014-4015	4014-4015	meeting abstract	Drug response prediction	"Individualized Prediction of Response to Methotrexate Treatment in Patients with Rheumatoid Arthritis: A Pharmacogenomics-driven Machine Learning Approach"	AUC (5x 10-fold CV + external validation)	cross-validation + external cohort validation	"The outcome of the study confirms that DL provides the best results with the most promising extracted features. DL achieves the accuracy of 87.9% which can be used for further development of the automatic prognosis tool"	"The outcome of the study confirms that DL provides the best results with the most promising extracted features. DL achieves the accuracy of 87.9% which can be used for further development of the automatic prognosis tool"
306 Naz, H and Ahuja, S	2020	India	Diabetes and Metabolic Disorders	19	1	391-403	391-403	article	Case-control study	"Deep learning approach for diabetes prediction using FIMA Indian dataset"	accuracy ("plits in an 80/20% ratio into the training and validation set")	training + test set	"Genomic biomarkers can identify, with high accuracy, approximately one third of patients with MDS who will not respond to HMAA. This study highlights the importance of machine learning technologies such as the recommender system algorithm in stratifying genomic data into useful clinical tools"	"Genomic biomarkers can identify, with high accuracy, approximately one third of patients with MDS who will not respond to HMAA. This study highlights the importance of machine learning technologies such as the recommender system algorithm in stratifying genomic data into useful clinical tools"
307 Natha, A and Sekeres, M A and Bejar, R and Raaf, M J and Komrokji, J S and Barnard, G and Wilson, C B and Kerr, L M and Stearns, D P and Daborn, A and Robo, G and Garcia-Manero, G and Erki, H and Ebert, B L and Maciejewski, J P	2019	USA	ICD Precision Oncology	3			11111111	article	Drug response prediction	"resistant to hypomethylating agents in patients with myelodysplastic syndromes using artificial intelligence"	accuracy (training/test set)	training + test set	"Here, we classify weight loss responders (N = 106) and non-responders (N = 97) of overweight non-diabetic middle-aged Danes to two earlier reported dietary trials over 8 weeks"	"Here, we classify weight loss responders (N = 106) and non-responders (N = 97) of overweight non-diabetic middle-aged Danes to two earlier reported dietary trials over 8 weeks"
308 Nilsen, R and Lohrman, M and Garcia, S L and Roager, H M and Arvan-Adang, D and Hansen, L B S and Lind, M V and Vagt, L and Diggard, M D and Raaf, J and Arnesen, C B and Mikkelsen, B and Warmer, J and Aaslov, V and Gebel, R and Kristensen, M and Frøking, H and Sparholt, M H and Christensen, A F and Vestergaard, V and Hansen, T and Kristensen, S and Brøn, S and Petersen, T N and Lauritzen, L and Lütke, T R and Pedersen, O and Gupta, R	2020	Denmark	Sci Rep	10	1	20103	20103	article	Treatment response prediction	"Data integration for prediction of weight loss in randomized controlled dietary trials"	AUC ("50-shuffle-split fivefold cross-validation was used")	cross-validation	"Overall, this genome-phenome machine-learning integration tool, PhenMap identifies functional and phenotype-integrated discrete or continuous subtypes with clinical translational potential"	"Overall, this genome-phenome machine-learning integration tool, PhenMap identifies functional and phenotype-integrated discrete or continuous subtypes with clinical translational potential"
309 Nyamundanda, G and Eason, K and Gundry, J and Lord, C J and Satsanandana, A	2020	United Kingdom	Cancers	12	10	1-14	11111111	article	Subgroup stratification	"A machine-learning tool concurrently models single omics and phenome data for functional subtyping and personalized cancer medicine"	Silhouette width, cohenetic correlation (external test datasets)	external cohort validation	"This expert review describes and examines, first, the SVM models employed to forecast breast cancer subtypes using diverse systems science data, including transcriptomics, epigenetics, proteomics, and radiomics, as well as biological pathway, clinical, pathological, and biochemical data. Then, we compare the performance of the present SVM and other diagnostic and therapeutic prediction models across the data types. We conclude by emphasizing that data integration is a critical bottleneck in systems science, cancer research and development, and health care innovation and that SVM and machine learning approaches offer new solutions and ways forward in biomedical, bioengineering, and clinical applications"	"This expert review describes and examines, first, the SVM models employed to forecast breast cancer subtypes using diverse systems science data, including transcriptomics, epigenetics, proteomics, and radiomics, as well as biological pathway, clinical, pathological, and biochemical data. Then, we compare the performance of the present SVM and other diagnostic and therapeutic prediction models across the data types. We conclude by emphasizing that data integration is a critical bottleneck in systems science, cancer research and development, and health care innovation and that SVM and machine learning approaches offer new solutions and ways forward in biomedical, bioengineering, and clinical applications"
310 Ozer, M and Sarica, P and Arga, Y	2020	Turkey	Omics	24	5	241-246	241-246	article	Review	"New Machine Learning Applications to Accelerate Personalized Medicine in Breast Cancer: Role of the Support Vector Machines"	review (not applicable)	Review	"The netBc Bioconductor package provides a novel workflow for pathway-based patient classification from sparse genetic data"	"The netBc Bioconductor package provides a novel workflow for pathway-based patient classification from sparse genetic data"
311 Pai, S and Weber, P and Isertler, R and Kaka, H and Hui, S and Shah, M A and Giudice, L and Giugno, G and Nahr, A K and Baumback, J and Bader, G D	2020	Canada	F1000Res	9		1239-1239	1239-1239	article	Case-control study	"Interpretable patient classifiers by multi-omic data integration using patient similarity networks"	AUROC, AUPR, and accuracy (in approximately 70:30 split of samples was used for cross validation)	cross-validation	"The netBc Bioconductor package provides a novel workflow for pathway-based patient classification from sparse genetic data"	"The netBc Bioconductor package provides a novel workflow for pathway-based patient classification from sparse genetic data"
312 A Radich, Z and S. Kenes, C and Bejthout, J and Chiu, W and Wilson, L and Zhang, H H and Lussler, J	2020	USA	BMC Bioinformatics	21	1	374-374	374-374	article	Case-control study	"biomarker interpretability combinatoric efficiency of random forests to identify biomarkers"	Precision, recall, test error (training and test set)	training + test set	"We developed and externally validated a highly accurate and interpretable model that can distinguish MDS from other myeloid malignancies using clinical and mutational data from a large international cohort. The model can provide personalized interpretations of its outcome and can aid physicians and hematopathologists in recognizing MDS with high accuracy when encountering pts with panopneumonia and with a suspected diagnosis of MDS"	"We developed and externally validated a highly accurate and interpretable model that can distinguish MDS from other myeloid malignancies using clinical and mutational data from a large international cohort. The model can provide personalized interpretations of its outcome and can aid physicians and hematopathologists in recognizing MDS with high accuracy when encountering pts with panopneumonia and with a suspected diagnosis of MDS"
313 Radulovic, N and Magagnoli, F and Al Maloufi, L and Serrano, M A and Sireva, I and Bezu Hilton, C and Roushdy, Y and Walter, W and Hutter, S and Mulheiser, S and Kerr, C M and Bha, B K and Gatti, A and Pozzi, S and Gerd, A T and Hafferlach, C and Maciejewski, J P and Hafferlach, T and Nahta, A	2020	USA	Blood	136		33-35	11111111	meeting abstract	Case-control study	"Personalized clinical decision tool to improve the diagnostic accuracy of myelodysplastic syndromes"	AUC (training + external validation)	external cohort validation	"In this article, we compare the usefulness and limitations of traditional statistical methods and ML, when applied to the medical field. Traditional statistical methods seem to be more useful when the number of cases largely exceeds the number of variables under study and a priori knowledge on the topic under study is substantial such as in public health. ML could be more suited in highly innovative fields with a huge bulk of data, such as omics, radiogenomics, drug development, and personalized treatment. Integration of the two approaches should be preferred over a unilateral choice of either approach"	"In this article, we compare the usefulness and limitations of traditional statistical methods and ML, when applied to the medical field. Traditional statistical methods seem to be more useful when the number of cases largely exceeds the number of variables under study and a priori knowledge on the topic under study is substantial such as in public health. ML could be more suited in highly innovative fields with a huge bulk of data, such as omics, radiogenomics, drug development, and personalized treatment. Integration of the two approaches should be preferred over a unilateral choice of either approach"
314 Rajulu, H S R and Veritas, G and Marchia, M and Antonucci, N and Fano, V	2020	Italy	Uthmanya	56	9		11111111	article	Review	"Comparison of Conventional Statistical Methods with Machine Learning in Medicine: Diagnosis, Drug Development, and Treatment"	review (not applicable)	Review	"We have developed a DNA methylation score for exposure to maternal smoking during pregnancy, outperforming the three previously developed scores. One possible application of the current score could be for model adjustment purposes or to assess its association with distal health outcomes where part of the effect can be attributed to maternal smoking. Further, it may provide a biomarker for fetal exposure to maternal smoking"	"We have developed a DNA methylation score for exposure to maternal smoking during pregnancy, outperforming the three previously developed scores. One possible application of the current score could be for model adjustment purposes or to assess its association with distal health outcomes where part of the effect can be attributed to maternal smoking. Further, it may provide a biomarker for fetal exposure to maternal smoking"
315 Rauscher, S and Milton, P E and Hasekawa, A and Kihara, Y and Burgoyne, G and Craig, I M and Godfrey, M M and Elberts, K and Mori, T and Butts, L and Oddy, W H and Pennell, C and Ziviani, M R and Seaton, S and Huang, B C	2020	Australia	Perspect	128	9	9703	9703	article	Case-control study	"Machine Learning Based DNA Methylation Score for Fetal Exposure to Maternal Smoking: Development and Validation in Similes Collected from Adolescents and Adults"	Sensitivity, specificity (10-fold CV)	cross-validation	"Studies are limited in their evaluation of biomarkers by comparisons of patients with ASD and healthy controls, without considering the clarity and specific characteristics of the pathology. Often, the sample cohort is also highly limited. From the point of view of omics data, the biggest limit is that all of the data from the omics are not considered and the data are not integrated with collected clinical data"	"Studies are limited in their evaluation of biomarkers by comparisons of patients with ASD and healthy controls, without considering the clarity and specific characteristics of the pathology. Often, the sample cohort is also highly limited. From the point of view of omics data, the biggest limit is that all of the data from the omics are not considered and the data are not integrated with collected clinical data"
316 Rizzor, M V and Montara, S L and Marzano, V and Guarrera, S and Vennocchi, P and Ianni, G and Gordin, S and Torri, G and Kiani, G and Ricca, S and Guarnieri, A and Pringoli, L	2020	Italy	Int J Mol Sci	21	17		11111111	article	Review	"Insight into AUTISM Spectrum Disorders: Phenotype Stratification and Biomarker Discovery"	review (not applicable)	Review	"In this research, we compared three machine learning methods that have been proven to construct powerful predictive models (genetic algorithms, LASSO, and stepwise) and propose the inclusion of markers from misclassified samples to improve overall prediction accuracy. Our results show that the addition of markers from an initial model plus the markers of the model fitted to misclassified samples improves the area under the receiving operative curve by around 5%, reaching "0.84, which is highly competitive using any genetic information"	"In this research, we compared three machine learning methods that have been proven to construct powerful predictive models (genetic algorithms, LASSO, and stepwise) and propose the inclusion of markers from misclassified samples to improve overall prediction accuracy. Our results show that the addition of markers from an initial model plus the markers of the model fitted to misclassified samples improves the area under the receiving operative curve by around 5%, reaching "0.84, which is highly competitive using any genetic information"
317 Romero-Rozas, B and Tame-Pena, J G and Nociotti, H and Moreno-Treviño, M G and Treviño, V	2020	Mexico	PLoS One	15	4	e0232103	e0232103	article	Case-control study	"Improving predictive models for Alzheimer's disease using Omics data by incorporating misclassified samples modeling"	AUC (20 rounds of internal cross-validation (CV) to 80% of the dataset for training and 20% for testing)	cross-validation	"This novel list of biomarkers, identified through a robust feature selection procedure on public data and validated using independent data sets, coupled with the RAScore may be useful in the early diagnosis and disease and treatment monitoring of RA."	"This novel list of biomarkers, identified through a robust feature selection procedure on public data and validated using independent data sets, coupled with the RAScore may be useful in the early diagnosis and disease and treatment monitoring of RA."
318 Rytikov, D and Neely, J and Sirota, M	2020	USA	Arthritis and Rheumatology	72		1503-1504	1503-1504	meeting abstract	Case-control study	"Uncovering Novel Biomarkers for Rheumatoid Arthritis from Feature Selection and Machine Learning Approaches on Synovium and Blood Gene Expression Data"	AUC (training + test set)	training + test set		

Author(s)	Year	Country	Journal	Volume	Issue	Page(s)	DOI	Article Type	Review Status	Abstract Summary	Keywords
319 Saorin, A and Di Gregorio, E and Miotto, G and Staffan, A and Corona, G	2020	Italy	Metabolites	10	10	1-15	https://doi.org/10.1093/metab/taaa041	article	review (not applicable)	Emerging role of metabolomics in ovarian cancer diagnosis	Metabolites
320 Schack, D and Brenner, T and Weigand, M and Uhlir, F	2019	Germany	Care Medicine Experiment al	7			https://doi.org/10.1093/cmb/taaa041	meeting abstract	Case-control study	Deep-learning neural networks for accurate diagnosis of sepsis using microarray gene expression data	Intensive Care Medicine Experiment al
321 Scherberg, A V and Boickard, A and Tsigelny, I F and Richard, S B and Kurusz, R	2020	USA	Int J Cancer	147	9	2537-2549	https://doi.org/10.1002/ijc.32429	article	Treatment response prediction	Machine learning model to predict oncologic outcomes for drugs in randomized clinical trials	Int J Cancer
322 Senturk, M and Tunali, G and Koseoglu, S and Dogan, B and Sag, S and Mocan, G and Tuncel, S G and Dundar, M and Ergonen, M C	2020	Turkey	Gazi Medical Journal	31	3	P44-P44	https://doi.org/10.15013/1303-2745.2020.01003	article	Case-control study	Developing evidence-based conceptual diagnostic tools for breast cancer early prediction	Gazi Medical Journal
323 Singh, M and Singh, S P and Dubey, P K and Rajhans, R and Mittal, S and Yadav, D and Agarwal, M and Agarwal, S	2020	India	Pept Sci	21		10 965-977	https://doi.org/10.1007/s12013-020-01173-4	article	Review	Advent of Proteomic Tools for Diagnostic Biomarker Analysis in Alzheimer's Disease	Curr Proteom Pept Sci
324 Singh, N and Vinod, P K	2020	India	Mol Genet Genomics	295	3	807-824	https://doi.org/10.1007/s00438-020-01616-6	article	Tumor stage prediction	Integrative analysis of DNA methylation and gene expression in papillary renal cell carcinoma	Mol Genet Genomics
325 Yi and Ho, Q and Zuo, R N	2020	China	Proc Natl Acad Sci U S A	117		28 16173	https://doi.org/10.1073/pnas.2001911117	article	Differential diagnosis prediction	Oral diagnosis of oral carcinoma diagnosed from saliva metabolic profiling	Proc Natl Acad Sci U S A
326 Kapoor, S and Maricci, G	2020	USA	Blood	136	9	10	https://doi.org/10.1182/blood.2020.124414	meeting abstract	Therapy response prediction	Superior therapy response predictions based on an independent, externally validated, retrospective cohort of 144 MDS patients*	Blood
327 Tabares-Soto, R and Ordoñez-Arias, S and Romero-Cano, V and Buchel, V and Rodríguez-Sotelo, J L and Jiménez-Yares, F	2020	Colombia	PeerJ Computer Science				https://doi.org/10.2196/19040	article	Case-control study	A comparative study of machine learning and deep learning algorithms to classify cancer types based on microarray gene expression data	PeerJ Computer Science
328 Talhouk, A and George, J and Wang, C and Goode, I and Ramus, S and Doherty, J and Bowtell, D and Anglesio, M	2020	Canada	Clinical Cancer Research	26	13		https://doi.org/10.1158/1078-0432.CCR.20.0741	meeting abstract	Differential diagnosis prediction	Validation of a clinical-grade consensus classifier for the molecular subtypes of high-grade serous tubo-ovarian cancer	Clinical Cancer Research
329 Taher, J and Carter, H	2020	Canada	Cancer Research	80	16		https://doi.org/10.1158/1538-7443.2020.0201	meeting abstract	Drug response prediction	Assessing cancer drug response/generation from gene expression	Cancer Research
330 Tang, B and Wang, Y and Chen, Y and Li, M and Tao, Y	2020	China	Frontiers in Cell and Developmental Biology	8			https://doi.org/10.3389/fcell.2020.00041	article	Case-control study	A Novel Early-Stage Lung Adenocarcinoma Prognostic Model Based on Feature Selection With Orthogonal Regression	Frontiers in Cell and Developmental Biology
331 Tang, W and Cao, Y and Ma, X	2020	China	Biosci Rep	40	7		https://doi.org/10.1093/bioadv/abaa041	article	Prognostic study	Novel prognostic prediction model constructed through machine learning on the basis of methylation-driven genes in kidney renal clear cell carcinoma	Biosci Rep
332 Tawk, B and Winkler, U and Schweiger, C and Herpel, E and Thiehofer, J and Butsch, T and Van Krause, M and Stoschke, M and Balmann, P and Roedel, C and Grotzer, A and Zipp, D and Combs, S E and Wittmann, C and Baumann, M and Herold-Mende, C and Diebig, T and Adolph, A	2020	Germany	Journal of Radiation Oncology Group (DTRX-ROG) and Multicenter Trial	108	3	e552-e553	https://doi.org/10.1016/j.ijro.2020.01.013	article	Differential diagnosis and survival prediction correlation (training + validation cohort)	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 (DTRX-ROG) and Multicenter Trial	Journal of Radiation Oncology Group (DTRX-ROG) and Multicenter Trial
333 Thiel, S and Brandmaier, S and Düring, M and An, K and Klein, M and Liebig, T and Hohl, L and Teusler, D and Wang-Sattler, B and Schwab, E and Gräber, C and Dörmagel, M	2020	Germany	Journal of Stroke	15	1	77-78	https://doi.org/10.1177/1524280220942000	meeting abstract	Case-control study	Circulating metabolites differentiate acute ischemic stroke from stroke mimics	Journal of Stroke
334 Tran, A and Walsh, C J and Batt, J and Dos Santos, C and Hu, P	2020	Canada	Frontiers in Molecular and Cellular Oncology	18	1	454-464	https://doi.org/10.3389/fmol.2020.00038	article	Differential diagnosis prediction	A machine learning-based clinical tool for diagnosing epilepsy using multi-cohort microarray expression profiles	Frontiers in Molecular and Cellular Oncology
335 Tran, P M H and Tran, L K H and Nechtman, J and Dos Santos, J and Purohit, S and Satter, K B and Durr, D and Kohle, R and Sharma, S and Bollag, B and Li, X	2020	USA	Sci Rep	10	1	20651	https://doi.org/10.1038/s41598-020-77727-2	article	Differential diagnosis and survival prediction accuracy, log rank test p-value (cross-validation)	Comparative analysis of transcriptomic, proteomic, and IDH mutation for classification of gliomas	Sci Rep
336 Brekel, M W M and Vens, C	2020	Netherlands	Radiother Oncol	147		186-194	https://doi.org/10.1016/j.radonc.2020.02.011	article	cross-validation + external cohort validation	Epithelial-to-mesenchymal transition is a prognostic marker for patient outcome in advanced stage HNSCC patients treated with chemoradiotherapy	Radiother Oncol
337 Vitrain, B and Lederer, M and Martin-Magniette, M L and Collin, C and Bergeron, A and Fradet, Y and Droz, A	2020	Canada	Frontiers in Genetics	11			https://doi.org/10.3389/fgen.2020.00041	article	Prognostic study	Comparative analysis of transcriptomic, proteomic, and IDH mutation for classification of gliomas	Frontiers in Genetics

