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Heart Disease Classification/Prediction: A Review

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ABSTRACT

Heart disease is the biggest cause of death worldwide; it cannot be seen with the bare eyes and occurs suddenly when its limits are reached. It requires a correct diagnosis at the right moment. Every day, the health care sector generates a massive amount of data about patients and diseases. However, scholars and practitioners do not make effective use of this data. The healthcare sector is currently data-rich but knowledge-poor. To effectively extract information from databases and apply that knowledge for diagnosis that is even more precise and decision-making, a variety of data mining and machine learning approaches and technologies are available. As research on algorithms for predicting heart disease expands, it is critical to assess the findings, which are now unclear. The primary purpose of this research paper is to present a summary of current research on the use of datasets, classifiers, data preprocessing methods, and the efficiency of integrating both to predict heart disease, with comparison findings and analytical conclusions. According to the study, the performance of the heart disease prediction system is improved in many scenarios by the use of KNN, ANN, RF, PCA, χ 2 and GA algorithms.

1. INTRODUCTION

Heart disease (HD) refers to a wide range of heart-related medical problems. These medical diseases explain abnormalities that have a direct impact on the heart and all of its parts. Heart disease is currently a serious public health concern. HD or cardiovascular disease (CVD) is that the leading reason for a death worldwide. In line with world statistics, 17.9 million people die every year from HDs. HD causes more than 32% of global deaths each year. It is estimated that more than 130 million adults will have HD by 2035 [1]. HD is a group of heart and vascular diseases, including ischemic HD, cerebrovascular disease, rheumatic HD, and other conditions. The main behavioral risk factors for HD and stroke are poor diet, sedentary lifestyle and tobacco use, and harmful effects [2]. Quitting smoking, reducing the salt content in your diet, eating more fruits and vegetables, exercising regularly, and avoiding harmful drinks have been shown to reduce your risk of HD. It is crucial to identify HD as early as possible. Possible for people at increased risk for HD and ensuring adequate treatment can prevent premature deaths [3]. However, accurate diagnosis is difficult to achieve and is frequently delayed due to the numerous factors that complicate disease diagnosis [4].

The Heart Disease Data Prediction is made to help doctors make accurate diagnoses of heart disease. They usually do their work using a knowledge foundation of clinical competence and a study of medical data. Improvements to these Predicting algorithms can raise the calibre of medical diagnoses for heart disease [5]. A method for extracting the information buried in the data is data mining [6]. Data mining is a process of data processing used to find hidden patterns in massive amounts of data. It's been successfully applied to information retrieval in a variety of fields [7]. According to Giudici, it is a process of exploration, collecting, and analysis of enormous amounts of data to reveal patterns and interconnections that are initially unknown with the purpose of finding obvious and useful information for the authorities of database. Various data mining techniques have been utilized and developed in the modern era [8]. In recent years, we have seen growth in all fields and in almost all data types. In recent years, the growth of biomedical data has been particularly rapid due to the exponential growth in knowledge in the biomedical field [9]. With the help of knowledge discovery or data mining (DM) methods based on different machine learning (ML) and deep learning (DL) methods, it is possible to determine predictive models from different sources of medical data as well as the predictive accuracy of the resulting smart data [10]. The system can even be very precise. It is a process of finding the correlation or pattern between different regions in a large medical database. Affected by the annual increase in the global death rate of patients with heart disease (HD) and the large amount of patient data available. Researchers use data mining to help healthcare providers manage their conditions by providing them with vital information [11]. This motivates us to conduct this review of studies examining classifiers and classifiers using data preprocessing techniques in predicting HD. Figure 1 shows the Simple experimental workflow of heart disease prediction.

The goal of this review is therefore to empirically examine the effectiveness of classifiers and classifiers with data preprocessing in the prediction / classification of HDs. The evaluation recognized applicable research published between 2007 and 2020, leading to a complete of 55 researches. From this research, we recall the most effective ones that could be associated with practicing HD data for the purpose of classification. Highlight the fact that, the primary research have been recognized the use of the subsequent search string: (TITLE-ABS-KEY ("heart disease" OR "cardiovascular disease") AND TITLE-ABS-KEY ("prediction" OR “classification”) AND TITLE-ABS-KEY ("machine learning" OR "deep learning").This search string became utilized in 3 virtual databases namely: Scopus database, IEEE Xplore virtual library and Google Scholar. Figure 2 shows the study selection of the outcomes of the choice manner of this review. General primary research from 1949 published between 2007 and 2020 was recognized using virtual searchable databases. Of the 1,949 articles, 55 articles were selected that focused on the use of classifiers in predicting / classifying HD.

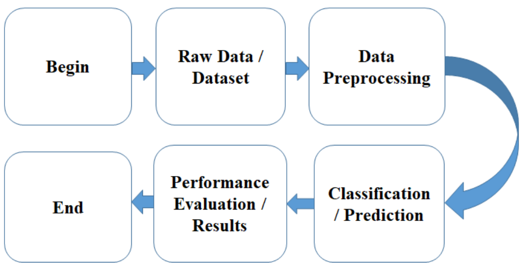

Figure 1. Simple experimental workflow of heart disease prediction

The reason for this review has been changed to compile and summarise the empirical proof regarding the applying of classifiers and classifiers with data preprocessing strategies in predicting / classifying HD by answering five questions: (1) Identify the datasets used for prediction of HD, (2) Identify the classifiers used for prediction of HD, (3) Identify the classifiers which provide the higher overall performance in HD classification, (4) Identify the data pre-processing techniques in combination with classifiers utilized in HD classification, and (5) Identify which combinations of classifiers with data pre-processing techniques are good on the utility of HD prediction.

The paper follows the following structure: The datasets used for HD prediction are described in Section 2. Most commonly used performance metrics to evalute the efficiency of the system are given in Section 3. Several classifiers utilised in HD prediction are then given in section 4. The data pre-processing techniques are described in Section 5. The combination of classifier with data preprocessing techniques are described in section 6. Section 7 includes conclusion & future scope.

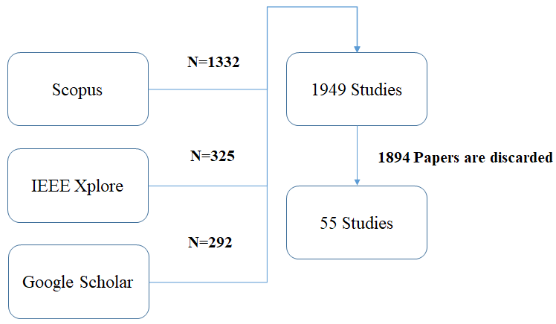

Figure 2. Result of study selection process

2. DATASETS USED FOR PREDICTION/CLASSIFICATION OF HEART DISEASE

A dataset is a group of observations saved in a tabular layout wherein every row is one observation and wherein every column incorporates a data factor that relates to a feature of an observation. Data units can maintain facts consisting of scientific data or insurance data, to be utilized by a application running at the machine. Data units also are used to keep information wanted through programs or the working machine itself, consisting of source programs, macro libraries, or machine variables or parameters. Datasets are essential to foster the improvement of numerous computational fields, giving scope, robustness, and self-assurance to results. Datasets have become famous with the evolution of artificial intelligence, machine learning, and deep learning. In Machine Learning, you can divide your data into training, testing, and validation datasets. A dataset is frequently utilised for purposes other than educational. A training dataset that has been processed is commonly cut up into multiple pieces in order to test how well the model's training went [12].

In the early prediction/classificatin of HD 42 plus datasets are used and those datasets are tabulated in Table 1 and corresponding charts are shown in Figure 3. In Table 1, name of the dataset, number of instances, number of attributes, presence of HD, absence of HD and missing values are arranged as contents of the columns. Among these 42 plus datasets 3 datasets are mostly used. They are, Statlog HD dataset (270), Cleveland HD dataset (297) and Cleveland HD dataset (303).

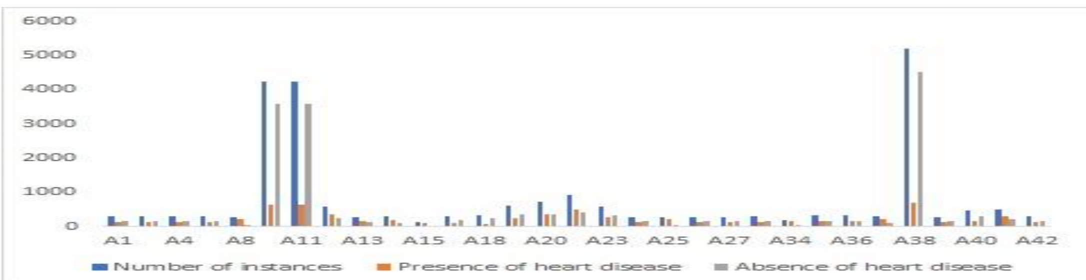

Figure 3. Representation for dataset corresponding to number of instances, presence of heart disease and absence of heart disease

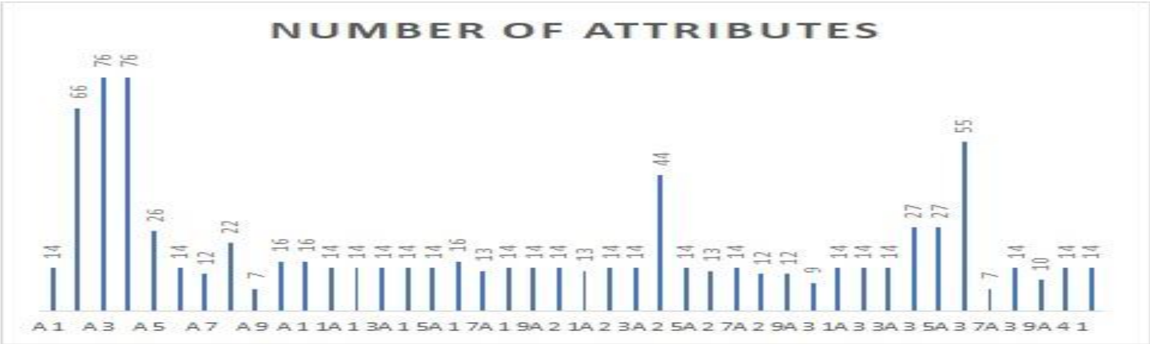

Figure 4. Representation of dataset corresponding to number of attributes

Table 1. Datasets used for heart disease prediction/ classification

Dataset code	Name of the data set	Number of instances	Number of attributes	Presence of heart disease	Absence of heart disease	Missing values	Reference
A1	Cleveland heart disease dataset	297	14	137	160	No	[2, 5, 13 -18]
A2	Cardiovascular disease dataset	3000	66	-	-	No	[4]
A3	Cleveland heart disease dataset (unprocessed)	303	76	139	164	Yes	[6]
A4	Heart Disease Data.arff	303	76	120	150	No	[6]
A5	Indira Gandhi Medical College (IGMC), Shimla CAD dataset	335	26	-	-	Yes	[7]
A6	Cleveland heart disease dataset	303	14	139	164	Yes	[8, 10, 19-33]
A7	Heart disease 2 dataset	23	12	-	-	No	[10]
A8	SPECT dataset	267	22	223	49	No	[24]
A9	Eric dataset	209	7	-	-	No	[24]
A10	Framingham dataset	4238	16	643	3595	Yes	[33]
A11	Heart Disease dataset	4238	16	643	3595	Yes	[33]
A12	Cleveland and Hungarian heart disease dataset	577	14	345	232	No	[34]
A13	Cleveland heart disease dataset	283	14	157	126	No	[34-35]
A14	Hungarian heart disease dataset	294	14	188	106	No	[35]
A15	Switzerland heart disease dataset	123	14	115	8	Yes	[35]
A16	Hungarian heart disease dataset	294	14	106	188	Yes	[34-36]
A17	Kita Hospital Jakarta (HKH) dataset	450	16	-	-	No	[36]
A18	Health insurance research database of Taiwan nation (NHI database)	317	13	84	233	No	[36]
A19	Cleveland, Hungarian heart disease dataset	597	14	245	352	Yes	[36]
A20	Cleveland, Hungary, and Switzerland datasets	720	14	360	360	Yes	[36]
A21	Cleveland, Long Beach VA, Switzerland, and Hingarian dataset	920	14	509	411	Yes	[36]
A22	Rajaie cardiovascular medical dataset	303	13	-	-	No	[36]
A23	Cleveland and Statlog heart disease dataset	573	14	259	314	Yes	[36]
A24	Cleveland heart disease dataset	270	14	120	150	No	[37, 38]
A25	SPECTF dataset	267	44	223	49	No	[38]
A26	Heart disease dataset (catalog)	270	14	120	150	No	[38]
A27	Statlog heart disease dataset	270	13	120	150	No	[39-45]
A28	Cleveland heart disease dataset	296	14	136	160	No	[41]
A29	Heart disease 1 dataset	40	12	-	-	No	[42]
A30	Heart disease Andhra Pradesh	23	12	-	-	No	[43]
A31	Heart disease Andhra Pradesh	768	9	-	-	No	[43]
A32	Heart Disease dataset	10082	14	-	-	Yes	[46]
A33	Heart Disease dataset	81	14	-	-	No	[46]
A34	Long Beach VA heart disease dataset	200	14	149	51	Yes	[47]
A35	SDS data set	335	27	164	171	Yes	[48]
A36	CDS data set	335	27	164	171	Yes	[48]
A37	Z-Alizadeh Sani CHD dataset	303	55	216	87	No	[49]
A38	Cardiovascular disease dataset	5209	7	689	4520	No	[50]
A39	Heart disease (angina) dataset	270	14	120	150	No	[51]
A40	South Africa HD dataset	462	10	160	302	No	[52]
A41	Cleveland and VA Long Beach heart disease dataset	503	14	288	215	Yes	[53]
A42	Heart disease dataset	300	14	140	160	Yes	[54]

Cleveland HD dataset (303) contains 14 attributes, 303 instances with 139 presence and 164 absences [55]. The "goal" field indicates whether the patient has HD or not. Integer values range from 0 to 4. While experimenting with the Cleveland database, the focus has been on attempting to differentiate between presence of HD (values 1,2,3,4) and absence of HD (value 0) [13, 19]. Statlog HD dataset (270) is multivariate and this database contains 13 attributes, 270 instances with 120 presence and 150 absences [34]. Cleveland HD dataset (297) contains 14 attributes, 297 instances with 137 presence and 160 absences. The "goal" field indicates whether the patient has HD or not. Integer values range from 0 to 4. While experimenting with the Cleveland database, the focus has been on attempting to differentiate between presence of HD (values 1,2,3,4) and absence of HD (value 0) [37]. These 3 datasets are gathered from the UCI machine learning repository. Generally, most of the datasets can be download from Kaggle and GitHub. The datasets corresponding attributes are shown in Figure 4.

3. PERFORMANCE PARAMETERS

Usually, performance of any physical quantity/matter can be considered as productive based on different parameters. The most used Performance metrics for classification problems are Accuracy, Sensitivity, Specificity, Precision, F1-Score, Area under the receiver operator curve [20]. The listed variables are subjected to different algorithm techniques to compare and analyse the efficiency.

3.1 Accuracy (ACC)

Accuracy is described as the percentage of correct predictions of the experimental data. It is easy to calculate by splitting the number of correct guesses by the total number of guesses. More formally, it is described as the number of true positive and true negative results divided by the number of true positive, true negative, false and false negative results. If you are solving a classification problem, the best result is 100% accuracy. If you are solving a regression problem, the best result is an error of 0.0%. These estimates are unattainable upper / lower limits. All predictive modelling problems contain forecast errors [56].

$$Accuracy = \frac{correctly\ predicted\ class}{total\ testing\ class} \times 100\% \quad (1)$$

(OR)

As the proportion of effectively categorized instances

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

where, TP, FN, FP and TN represent the number of true positives, false negatives, false positives and true negatives, respectively.

3.2 Sensitivity, hit rate, recall, or True Positive Rate (TPR)

Sensitivity could be a live of the proportion of actual positive cases that got foreseen as positive (or true positive). Sensitivity is outlined as the true-positive recognition rate: number of true positives / (number of true positives + number of false negatives). This means, what percentage subjects with a sickness are literally known as having the disease by the test [56].

$$Sensitivity = \frac{TP}{(TP + FN)} \quad (3)$$

3.3 Specificity, selectivity or True Negative Rate (TNR)

Specificity is outlined because the proportion of actual negatives, that got foreseen as the negative (or true negative). This means that there'll be another proportion of actual negative, which got predicted as positive and will be termed as false positives. This proportion could even be referred to as a false positive rate. In different words, it represents the proportion of individuals while not the disease, that may have a negative result [56].

$$Specificity = \frac{TN}{(TN + FP)} \quad (4)$$

3.4 Precision or Positive Predictive Value (PPV)

Precision (also referred to as positive predictive value) is that the fraction of relevant instances among the retrieved instances. preciseness may be a live that tells us out of all expected cases, what number are actual cases potential values vary from zero to one [19].

$$Precision = \frac{TP}{(TP + FP)} \quad (5)$$

3.5 F1-Score

The F1 Score is additionally referred to as the F Score or the F Measure. place another way, the F1 score conveys the balance between the exactitude and therefore the recall. The F1-score is the mean between precision and recall. during this case, we aim for each high recall and high precision, that means we wish to be able to determine an oversized variety of cases and that we also want to make sure that the bulk of foreseen cases are actual cases. The F1-score ranges from zero to one, wherever 0 is the worst performance [56].

$$F_1\_Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)} \quad (6)$$

(OR)

$$F_\beta\_Score = (1 + \beta^2) \frac{Precision * Recall}{(\beta^2 * Precision) + Recall} \quad (7)$$

3.6 Area under the receiver operator curve (AUROC)

AUROC curve may be a performance measure for the classification issues at numerous threshold settings. ROC is a probability curve and AUC represents the degree or measure of separability. It tells what proportion the model is capable of distinctive between categories. Higher the AUC, the higher the model is at predicting zero classes as 0 and one classes as 1. By analogy, the upper the AUC, the better the model is at distinguishing between patients with the illness and no disease. The AUC for the roc will be calculated by using the roc_auc_score(). Just like the roc_curve() function, the AUC function takes both the true outcomes (0,1) from the check set and therefore the foreseen chances for the one class. It returns the AUC score between zero and one for no ability and excellent skill respectively [56].

Some of the other parameters used to measure the performance of a classification model are Negative Predictive Value (NPV), Miss Rate or False Negative Rate (FNR), Fall-Out or False Positive Rate (FPR), False Discovery Rate (FDR), False Omission Rate (FOR), Positive Likelihood Ratio (LR+), Negative Likelihood Ratio (LR-) and Diagnostic Odds Ratio (DOR). The corresponding formulas are given below.

$$NPV = \frac{TN}{(TN + FN)} \tag{8}$$

$$FNR = \frac{FN}{(FN + TP)} \tag{9}$$

$$FPR = \frac{FP}{(FP + FN)} \tag{10}$$

$$FDR = \frac{FP}{(FP + TP)} \tag{11}$$

$$FOR = \frac{FN}{(FN + TN)} \tag{12}$$

$$LR+= \frac{TPR}{FPR} \tag{13}$$

$$LR-= \frac{FNR}{TNR} \tag{14}$$

$$DOR = \frac{LR+}{LR-} \tag{15}$$

For precise classifiers, TPR and TNR each need to be closer to 100%. Similar is the case with precision and accuracy parameters. On the contrary, FPR and FNR each need to be as near 0% as possible [56].

4. CLASSIFIERS USED FOR HEART DISEASE PREDICTION/CLASSIFICATION

A classifier in machine learning is an algorithm that automatically sorts or classifies data into one or more sets of "classes". A classifier is the algorithm itself, the rules that the machine uses to classify data. On the other hand, the classification model is the end result of your classifier's machine learning [3].

In case of HD prediction the classifiers used are AdaBoost Boosting Method (ABBM), AdaBoost (AB), Artificial Neural Network (ANN), Back-Propagation (BP), Binary Discriminant (BD), Back-Propagation Neural Network (BNN), Bat Based Back-Propagation (BAT-BP), Boosted Tree (BT), Bagging, Bootstrap Aggregation (Bagging) with multi-objective optimized weighted vote (BagMOOV), C4.5, Classification And Regression Tree (CART), Classification Tree (CT), Chaos firefly (CF), Decision Tree (DT), Decision Tree Bagging Method (DTBM), Deep Trained Neocognitron Neural Network (DTNNN), Differential Evolution (DE), Deep Neural Network (DNN), Decision Support System with Improved Multilayer Perceptron (DSS-IMP), Ensemble Classifier (EC), Extreme Learning Machine (ELM), Feed Forward Neural Network (FFNN), Forward Sequential Search (FSS), Fuzzy Logic-Based Clinical Decision Support System (FLBCDSS), Fuzzy Naive Bayesian (FNB), Fuzzy unordered rule induction algorithm (FURIA), Framingham Risk Score (FRS), Genetic Algorithm Fuzzy Logic System (GAFL), Genetic Algorithm Optimization of a Convolutional Neural Network (GA-CNN), Genetic Algorithm (GA), Global Classifier (GC), Gradient Boosting (GB), Gradient Boosting Boosting Method (GBBM), Gradient-boosted decision tree (GBDT), Generalized Linear Model (GLM), Gradient Boosted Trees (GBT), Hybrid Random Forest with a Linear Model (HRFLM), Hybridized Ruzzo–Tompa memetic (HRM), Improved multilayer perceptron algorithm (IMPA), J48, K-Nearest Neighbors (KNN), K-Nearest Neighbors Bagging Method (KNNBM), Logistic Regression (LR), Linear Discriminant Analysis (LDA), Linear Regression (LR), Levenberg–Marquardt Artificial Neural Network (LMANN), Least Square Support Vector Machine (LS-SVM), Multilayer perceptron (MLP), Multinomial Logistic Regression model (MLR), Naïve Bayes (NB), Neural Network Ensembles (NNE), Neural Network (NN), Probabilistic Principal Component Analysis (PPCA), Quadratic Discriminant Analysis (QDA), Quantum neural network (QNN), Radial Basis Function (RBF), Rules Based Classifier (RBC), Random Forest Bagging Method (RFBM), Random Forest (RF), Recursion enhanced random forest with an Improved Linear Model (RFRF-ILM), Single Conjunctive Rule Learner (SCRL), Support Vector Machine (SVM), Tree Augmented Naive Bayesian (TAN), Vote. Different classifiers with different datasets and their performances interms of Accuracy, Sensitivity, Specificity, AUROC, F1-measure and Precision are shown in Table 2. The analysis shows that Decision Tree, K-Nearest Neighbors, Logistic regression, Multilayer perceptron, Naive Bayes, Random Forest and Support Vector Machine are mostly used for the prediction/ classification of HD.

Table 2. Performance metric values of classifiers

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C1	A6	Logistic Regression (5 Fold)	Regression Algorithms	13	83.83	-	-	-	-	-	[20, 33]
C2	A24	Logistic regression	Regression Algorithms	13	96.29	96	96.67	97.29	-	97	[24, 38]
C3	A25	Logistic regression	Regression Algorithms	44	78.28	9.09	96.23	-	-	16.61	[8, 21]
C4	A6	Linear Regression (3 Fold)	Regression Algorithms	13	83.5	-	-	-	-	-	[17, 20]
C5	A38	Framingham risk score	Regression Algorithms	7	19.22	-	-	-	-	-	[17, 49]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C6	A6	Logistic regression	Regression Algorithms	13	86	-	-	-	-	-	[23, 25]
C7	A27	Logistic regression	Regression Algorithms	13	82.59	87.33	76.67	-	-	81.65	[23, 30]
C8	A6	Linear Regression (10 Fold)	Regression Algorithms	13	83.83	-	-	-	-	-	[14-15]
C9	A38	Logistic regression	Regression Algorithms	7	77	-	-	-	-	-	[15, 18]
C10	A37	Logistic regression	Regression Algorithms	54	85.71	-	-	-	-	86.5	[37]
C11	A6	Logistic Regression (3 Fold)	Regression Algorithms	13	83.83	-	-	-	-	-	[20,45]
C12	A6	Linear Regression (5 Fold)	Regression Algorithms	13	83.5	-	-	-	-	-	[20, 26]
C13	A6	Logistic Regression (10 Fold)	Regression Algorithms	13	83.17	-	-	-	-	-	[20, 23, 26, 36]
C14	A1	Logistic regression (C = 10)	Regression Algorithms	13	84	83	85	-	84	-	[14, 18]
C15	A27	Logistic regression	Regression Algorithms	13	85	89	81	85	-	-	[13, 56]
C16	A6	Logistic regression	Regression Algorithms	9	85.86	-	-	-	-	-	[27]
C17	A6	Logistic regression	Regression Algorithms	13	84.85	-	-	86.12	-	-	[27]
C18	A27	Logistic regression	Regression Algorithms	13	84.81	-	-	85.49	-	-	[27]
C19	A6	Logistic regression	Regression Algorithms	13	83.5	88.41	77.7	-	-	82.71	[27]
C20	A21	Logistic regression	Regression Algorithms	13	91.61	-	-	-	-	-	[24, 36]
C21	A8	Logistic regression	Regression Algorithms	22	83.15	38.18	94.81	-	-	54.44	[10, 32,39, 42]
C22	A9	Logistic regression	Regression Algorithms	7	77.99	88.89	64.13	-	-	74.51	[8, 10, 21, 23]
C23	A41	Logistic regression	Regression Algorithms	13	92.12	-	-	-	-	-	[4]
C24	A6	Logistic regression	Regression Algorithms	13	78	78	-	79	-	78	[4]
C25	A10	Logistic regression	Regression Algorithms	13	83	83	-	84	-	84	[4]
C26	A27	Logistic regression	Regression Algorithms	13	95.93	98.67	92.5	94.27	-	96	[4]
C27	A1	Logistic regression	Regression Algorithms	13	82.9	91.1	25	89.6	-	90.2	[39, 44, 45]
C28	A34	LS-SVM	Instance-based Algorithms	13	80	77.96	81.57	-	79.6	-	[31]
C29	A4	KNN	Instance-based Algorithms	13	75.18	-	-	-	-	-	[31]
C30	A30	KNN (K=1)	Instance-based Algorithms	12	95	-	-	-	-	-	[31]
C31	A37	Support Vector Machine	Instance-based Algorithms	54	92.74	95.8	85.1	-	90.4	95	[44]
C32	A6	KNN	Instance-based Algorithms	7	82.49	-	-	-	-	-	[44]
C33	A6	Support Vector Machine	Instance-based Algorithms	9	86.87	-	-	-	-	-	[44]
C34	A27	Support Vector Machine	Instance-based Algorithms	13	82.22	-	-	-	-	-	[44]
C35	A27	Support Vector Machine	Instance-based Algorithms	9	86.76	-	-	-	-	-	[44]
C36	A27	KNN (K=1)	Instance-based Algorithms	13	100	-	-	-	-	-	[14]
C37	A37	KNN	Instance-based Algorithms	54	82.42	-	-	-	-	82.48	[14]
C38	A37	Support Vector Machine	Instance-based Algorithms	54	84.62	-	-	-	-	83.57	[14]
C39	A1	Support Vector Machine	Instance-based Algorithms	13	86.1	100	0	86.1	-	92.5	[14]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C40	A1	KNN (K=15)	Instance-based Algorithms	13	82.83	83	80.3	-	87.9	84	[14]
C41	A37	KNN (K=20)	Instance-based Algorithms	54	78.87	81.9	61.4	-	78.5	84.7	[14]
C42	A6	KNNBM	Instance-based Algorithms	13	84.07	-	-	-	-	-	[45]
C43	A6	KNNBM	Instance-based Algorithms	13	89.63	-	-	-	-	-	[45]
C44	A6	KNNBM	Instance-based Algorithms	13	85.48	-	-	-	-	-	[45]
C45	A33	Support Vector Machine	Instance-based Algorithms	13	85.18	81.4	89.5	89.7	85.4	85.4	[53]
C46	A6	KNN	Instance-based Algorithms	13	87	-	-	-	-	-	[53]
C47	A6	SVM (10 Fold)	Instance-based Algorithms	13	82.84	-	-	-	-	-	[53]
C48	A6	SVM (3 Fold)	Instance-based Algorithms	13	83.17	-	-	-	-	-	[53]
C49	A27	KNN	Instance-based Algorithms	13	65.56	68.67	61.67	-	-	64.98	[13]
C50	A6	Support Vector Machine	Instance-based Algorithms	13	80.86	93.9	65.47	-	-	77.15	[13]
C51	A9	Support Vector Machine	Instance-based Algorithms	7	78.47	89.74	64.13	-	-	74.81	[13]
C52	A8	Support Vector Machine	Instance-based Algorithms	22	67.04	85.45	62.26	-	-	72.04	[13]
C53	A27	Support Vector Machine	Instance-based Algorithms	13	81.85	94.67	65.83	-	-	77.66	[13]
C54	A6	KNN (K=1)	Instance-based Algorithms	13	76.23	-	-	-	75.2	78.2	[13]
C55	A6	Support Vector Machine	Instance-based Algorithms	13	84.15	-	-	-	83.6	86	[13]
C56	A40	KNN	Instance-based Algorithms	22	79.4	7.27	98.11	-	-	13.54	[23]
C57	A25	KNN	Instance-based Algorithms	44	71.91	36.36	81.13	-	-	50.22	[23]
C58	A1	SVM (kernel = RBF, C = 100, g = 0.0001)	Instance-based Algorithms	13	86	78	88	-	86	-	[33]
C59	A27	KNN	Instance-based Algorithms	13	80	84	76	81	-	-	[33]
C60	A27	Support Vector Machine	Instance-based Algorithms	13	82	77	89	90	-	-	[33]
C61	A21	Support Vector Machine	Instance-based Algorithms	13	88.26	-	-	-	-	-	[33]
C62	A27	Support Vector Machine	Instance-based Algorithms	13	82	76	89	90	-	83	[33]
C63	A6	Support Vector Machine	Instance-based Algorithms	13	53	-	-	-	-	-	[33]
C64	A1	KNN (K=2)	Instance-based Algorithms	13	58	-	-	-	-	-	[33]
C65	A1	KNN (K=3)	Instance-based Algorithms	13	59	-	-	-	-	-	[33]
C66	A1	KNN (K=4)	Instance-based Algorithms	13	69	-	-	-	-	-	[33]
C67	A1	KNN (K=5)	Instance-based Algorithms	13	68	-	-	-	-	-	[33]
C68	A1	KNN (K=6)	Instance-based Algorithms	13	67	-	-	-	-	-	[33]
C69	A1	KNN (K=7)	Instance-based Algorithms	13	67	-	-	-	-	-	[33]
C70	A1	KNN (K=8)	Instance-based Algorithms	13	66	-	-	-	-	-	[33]
C71	A41	Support Vector Machine	Instance-based Algorithms	13	91.95	-	-	-	-	-	[37]
C72	A6	KNN	Instance-based Algorithms	13	60	59	-	61	-	58	[37]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C73	A10	KNN	Instance-based Algorithms	13	81	81	-	75	-	77	[37]
C74	A6	Support Vector Machine	Instance-based Algorithms	13	79	79	-	80	-	79	[37]
C75	A10	Support Vector Machine	Instance-based Algorithms	13	82	82	-	78	-	80	[37]
C76	A27	KNN	Instance-based Algorithms	13	94.25	93.31	95.46	95.89	-	95	[37]
C77	A24	KNN	Instance-based Algorithms	13	96.42	94.57	96.82	97.11	-	96	[37]
C78	A27	Support Vector Machine	Instance-based Algorithms	13	97.04	95.33	96.67	97.28	-	96	[37]
C79	A24	Support Vector Machine	Instance-based Algorithms	13	97.41	97.33	97.5	97.99	-	98	[37]
C80	A1	KNN (K=1)	Instance-based Algorithms	13	52	-	-	-	-	-	[37]
C81	A6	KNN	Instance-based Algorithms	13	64.36	68.9	58.99	-	-	63.56	[37]
C82	A2	Support Vector Machine	Instance-based Algorithms	66	84.31	-	-	-	-	-	[37]
C83	A25	Support Vector Machine	Instance-based Algorithms	44	79.7	100	0	-	-	-	[37]
C84	A6	SVM (5 Fold)	Instance-based Algorithms	13	82.51	-	-	-	-	-	[34]
C85	A1	KNN (K= 9)	Instance-based Algorithms	13	76	73	74	-	73	-	[34]
C86	A1	SVM (kernel = linear)	Instance-based Algorithms	13	75	75	78	-	74	-	[34]
C87	A26	Support Vector Machine	Instance-based Algorithms	13	75.9	78.3	74.2	-	-	-	[54]
C88	A9	KNN	Instance-based Algorithms	7	65.55	68.38	61.96	-	-	65.01	[54]
C89	A1	HRFLM	Hybrid Algorithm	13	88.4	92.8	82.6	90.1	-	90	[31]
C90	A27	Extreme Learning Machine	Hybrid Algorithm	9	86.5	-	-	-	-	-	[31]
C91	A6	HRFLM	Hybrid Algorithm	13	88.7	92.8	82.6	-	-	-	[31]
C92	A39	FNB	Fuzzy -based Algorithms	8	83.7	-	-	-	-	-	[31]
C93	A16	FLBCDSS	Fuzzy -based Algorithms	13	79.5	80	59.09	-	-	-	[31]
C94	A15	FLBCDSS	Fuzzy -based Algorithms	13	56.47	62.5	53.76	-	-	-	[31]
C95	A13	FLBCDSS	Fuzzy -based Algorithms	13	55.99	72.47	30.58	-	-	-	[31]
C96	A26	type-2 fuzzy logic system	Fuzzy -based Algorithms	13	86	87.1	90	-	-	-	[31]
C97	A25	type-2 fuzzy logic system	Fuzzy -based Algorithms	44	79.1	85.5	63.4	-	-	-	[31]
C98	A5	FURIA	Fuzzy -based Algorithms	26	77.9	-	-	-	-	-	[31]
C99	A38	Fuzzy-evidential based theories	Fuzzy -based Algorithms	7	91.58	-	-	-	-	-	[31]
C100	A27	Random Forest	Ensemble Algorithms	13	78	85	69	77	-	80	[8]
C101	A21	Random Forest	Ensemble Algorithms	13	89.53	-	-	-	-	-	[46]
C102	A6	Random Forest	Ensemble Algorithms	13	58	-	-	-	-	-	[46]
C103	A41	Random Forest	Ensemble Algorithms	13	94.9	-	-	-	-	-	[46]
C104	A6	Gradient Boosting	Ensemble Algorithms	13	81	84	-	79	-	81	[46]
C105	A10	Gradient Boosting	Ensemble Algorithms	13	83	78	-	88	-	83	[46]
C106	A10	Random Forest	Ensemble Algorithms	13	83	81	-	87	-	84	[46]
C107	A27	Random Forest	Ensemble Algorithms	13	89.48	90.39	88.78	89.33	-	90	[46]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C108	A24	Random Forest	Ensemble Algorithms	13	90.46	89.19	89.85	92.38	-	91	[46]
C109	A37	GBDT	Ensemble Algorithms	54	74.73	-	-	-	-	74.66	[25]
C110	A37	Random Forest	Ensemble Algorithms	54	84.62	-	-	-	-	85.16	[25]
C111	A1	Generalized Linear Model	Ensemble Algorithms	13	85.1	94.9	20	88.8	-	91.6	[25]
C112	A1	Gradient Boosted Trees	Ensemble Algorithms	13	78.3	80.7	60	94.1	-	86.8	[25]
C113	A6	Random Forest	Ensemble Algorithms	13	83	87	-	81	-	84	[25]
C114	A1	Random Forest	Ensemble Algorithms	12	86.1	98.8	10	87.1	-	92.4	[22]
C115	A1	Vote	Ensemble Algorithms	13	87.41	-	-	90.2	-	84.4	[22]
C116	A1	Random Forest	Ensemble Algorithms	13	83.16	85.5	82.2	-	90.1	84.7	[22]
C117	A37	Random Forest	Ensemble Algorithms	54	86.46	94.9	86.3	-	92.3	90.9	[22]
C118	A6	Vote	Ensemble Algorithms	8	86.2	-	-	-	-	-	[22]
C119	A27	Vote	Ensemble Algorithms	13	86.3	-	-	-	-	-	[22]
C120	A6	GBBM	Ensemble Algorithms	13	78.88	-	-	-	-	-	[22]
C121	A18	GBBM	Ensemble Algorithms	13	82.5	-	-	-	-	-	[22]
C122	A21	Gradient Boosting	Ensemble Algorithms	13	84.27	-	-	-	-	-	[22]
C123	A27	Gradient Boosting	Ensemble Algorithms	13	95.19	-	-	-	-	-	[22]
C124	A21	Random Forest	Ensemble Algorithms	13	80.89	-	-	-	-	-	[22]
C125	A6	RFBM	Ensemble Algorithms	13	80.53	-	-	-	-	-	[22]
C126	A20	RFBM	Ensemble Algorithms	13	88.4	-	-	-	-	-	[22]
C127	A20	RFBM	Ensemble Algorithms	13	92.65	-	-	-	-	-	[22]
C128	A33	Random Forest	Ensemble Algorithms	13	81.48	74.4	89.5	88.9	92.2	81	[22]
C129	A6	Random Forest (10 Fold)	Ensemble Algorithms	13	85.81	-	-	-	-	-	[22]
C130	A6	Random Forest (3 Fold)	Ensemble Algorithms	13	82.84	-	-	-	-	-	[22]
C131	A6	Random Forest (5 Fold)	Ensemble Algorithms	13	82.18	-	-	-	-	-	[22]
C132	A1	Random Forest (100)	Ensemble Algorithms	13	83	94	70	-	83	-	[22]
C133	A21	Gradient Boosting	Ensemble Algorithms	13	90.7	-	-	-	-	-	[22]
C134	A37	AdaBoost	Ensemble Algorithms	54	87.91	-	-	-	-	87.6	[29]
C135	A1	Bagging	Ensemble Algorithms	13	82.83	87.3	83.6	-	89.1	84.7	[29]
C136	A37	Bagging	Ensemble Algorithms	54	86.46	90.7	76.7	-	87.1	90.5	[7]
C137	A37	Ensemble Classifier	Ensemble Algorithms	54	92.07	94	87.4	-	95.3	94.4	[7]
C138	A6	ABBM	Ensemble Algorithms	13	75.9	-	-	-	-	-	[7]
C139	A27	ABBM	Ensemble Algorithms	13	89.07	-	-	-	-	-	[7]
C140	A6	AdaBoost	Ensemble Algorithms	13	54.13	-	-	-	-	-	[50]
C141	A17	AdaBoost	Ensemble Algorithms	16	46	-	-	-	-	-	[50]
C142	A16	DTBM	Ensemble Algorithms	75	85.03	-	-	-	-	-	[50]
C143	A22	DTBM	Ensemble Algorithms	13	87.97	-	-	-	-	-	[50]
C144	A33	AdaBoost	Ensemble Algorithms	13	86.21	85.7	86.4	89.7	92.7	85.4	[50]
C145	A33	Boosted tree	Ensemble Algorithms	13	85.75	83.1	84.9	89.5	94.5	98.2	[25]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C146	A13	AdaBoost	Ensemble Algorithms	29	80.14	-	-	81.5	71	-	[25]
C147	A1	GAFL	Distribution Algorithm	7	86	-	-	-	-	-	[24]
C148	A6	GA-CNN	Distribution Algorithm	13	98.53	-	-	98.34	-	-	[5]
C149	A6	PPCA	Dimensionality Reduction Algorithms	13	82.18	75	90.57	-	-	-	[24]
C150	A6	QDA	Dimensionality Reduction Algorithms	13	65.68	68.29	62.59	-	-	65.32	[24]
C151	A9	QDA	Dimensionality Reduction Algorithms	7	46.41	10.26	92.39	-	-	18.46	[24]
C152	A8	QDA	Dimensionality Reduction Algorithms	22	83.52	36.36	95.75	-	-	52.71	[24]
C153	A25	QDA	Dimensionality Reduction Algorithms	44	20.6	100	0	-	-	0	[24]
C154	A27	QDA	Dimensionality Reduction Algorithms	13	68.15	64	73.33	-	-	68.35	[24]
C155	A33	Binary discriminant	Dimensionality Reduction Algorithms	13	84.26	97.2	96.3	95.8	93.1	96.5	[24]
C156	A6	LDA	Dimensionality Reduction Algorithms	13	78	79	-	80	-	79	[24]
C157	A10	LDA	Dimensionality Reduction Algorithms	13	83	83	-	81	-	82	[24]
C158	A6	Neural Network	Deep Learning Algorithms	11	84.85	-	-	-	-	-	[24]
C159	A1	NNE	Deep Learning Algorithms	13	89.01	-	-	-	-	-	[24]
C160	A1	Neural Network	Deep Learning Algorithms	13	94.17	-	-	-	-	-	[24]
C161	A38	Neural Network	Deep Learning Algorithms	7	84	-	-	-	-	-	[24]
C162	A38	Quantum neural network	Deep Learning Algorithms	7	98.57	-	-	-	-	-	[24]
C163	A27	DNN	Deep Learning Algorithms	13	97.41	98	96.67	97.35	-	98	[24]
C164	A24	DNN	Deep Learning Algorithms	13	98.15	98.67	97.5	98.01	-	98	[24]
C165	A27	CART	Decision Tree Algorithms	9	83.49	-	-	-	-	-	[35]
C166	A6	Decision Tree	Decision Tree Algorithms	7	82.49	-	-	-	-	-	[35]
C167	A27	Decision Tree	Decision Tree Algorithms	9	80.68	-	-	-	-	-	[2]
C168	A27	Decision Tree	Decision Tree Algorithms	13	74.81	-	-	74.28	-	-	[16]
C169	A27	Decision Tree	Decision Tree Algorithms	13	77	79	74	78	-	78	[24]
C170	A42	Decision Tree	Decision Tree Algorithms	13	91	-	-	-	-	-	[24]
C171	A41	Decision Tree	Decision Tree Algorithms	13	89.88	-	-	-	-	-	[24]
C172	A13	CART	Decision Tree Algorithms	20	92.6	-	-	92.6	90.4	-	[24]
C173	A6	CART	Decision Tree Algorithms	13	68	68	-	69	-	68	[24]
C174	A10	CART	Decision Tree Algorithms	13	75	75	-	74	-	74	[24]
C175	A27	Decision Tree	Decision Tree Algorithms	11	95.37	95.45	96.11	96.85	-	96	[24]
C176	A24	Decision Tree	Decision Tree Algorithms	13	96.42	95.76	97.05	97.4	-	97	[24]
C177	A1	Decision Tree	Decision Tree Algorithms	13	74	68	76	-	76	-	[24]
C178	A6	Decision Tree	Decision Tree Algorithms	13	76.09	-	-	74.21	-	-	[24]
C179	A2	Decision Tree	Decision Tree Algorithms	66	72.69	-	-	-	-	-	[24]
C180	A1	Decision Tree	Decision Tree Algorithms	13	70	-	-	-	-	-	[38]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C181	A6	Decision Tree	Decision Tree Algorithms	13	77.55	-	-	-	80	80.1	[38]
C182	A6	SCRL	Decision Tree Algorithms	13	69.96	-	-	-	70.7	71.8	[38]
C183	A6	Decision Tree (10 Fold)	Decision Tree Algorithms	13	79.21	-	-	-	-	-	[38]
C184	A6	Decision Tree (3 Fold)	Decision Tree Algorithms	13	77.56	-	-	-	-	-	[38]
C185	A6	Decision Tree (5 Fold)	Decision Tree Algorithms	13	79.54	-	-	-	-	-	[38]
C186	A27	Classification tree	Decision Tree Algorithms	13	77	79	73	79	-	-	[38]
C187	A6	J48	Classification Algorithms	13	78.9	-	-	-	-	-	[35]
C188	A4	J48	Classification Algorithms	13	76.66	-	-	-	-	-	[36]
C189	A29	J48	Classification Algorithms	12	95	-	-	-	-	-	[36]
C190	A7	J48	Classification Algorithms	12	82.6	-	-	-	-	-	[36]
C191	A30	J48	Classification Algorithms	12	95	-	-	-	-	-	[36]
C192	A27	J48	Classification Algorithms	13	91.48	-	-	-	-	-	[36]
C193	A36	C4.5	Classification Algorithms	27	97.6	97.5	97.6	-	-	-	[36]
C194	A35	C4.5	Classification Algorithms	27	80.8	-	-	-	-	-	[36]
C195	A6	BagMOOV	Classification Algorithms	13	84.16	93.29	73.38	-	-	82.15	[36]
C196	A9	BagMOOV	Classification Algorithms	7	80.86	86.32	73.91	-	-	79.64	[36]
C197	A8	BagMOOV	Classification Algorithms	22	82.02	27.27	96.2	-	-	42.5	[36]
C198	A25	BagMOOV	Classification Algorithms	44	78.28	7.27	96.7	-	-	13.53	[36]
C199	A27	BagMOOV	Classification Algorithms	13	84.07	92	74.17	-	-	82.13	[36]
C200	A5	C4.5	Classification Algorithms	26	77.3	-	-	-	-	-	[36]
C201	A33	J48	Classification Algorithms	13	77.78	62.8	94.7	93.1	78.9	75	[36]
C202	A1	FFNN	Biologically inspired classification Algorithm	13	90.54	-	-	-	-	-	[36]
C203	A4	Naive Bayes	Bayesian Algorithms	13	83.7	-	-	-	-	-	[17]
C204	A29	Naive Bayes	Bayesian Algorithms	12	72.5	-	-	-	-	-	[17]
C205	A7	Naive Bayes	Bayesian Algorithms	12	95.65	-	-	-	-	-	[32]
C206	A30	Naive Bayes	Bayesian Algorithms	12	72.5	-	-	-	-	-	[32]
C207	A39	Naive Bayes	Bayesian Algorithms	8	72.51	-	-	-	-	-	[32]
C208	A39	TAN	Bayesian Algorithms	8	73.52	-	-	-	-	-	[32]
C209	A36	Naive Bayes	Bayesian Algorithms	27	97.01	96.9	97	-	-	-	[32]
C210	A3	Naive Bayes	Bayesian Algorithms	27	78.5	-	-	-	-	-	[32]
C211	A1	Naive Bayes	Bayesian Algorithms	13	75.8	79.8	60	90.5	-	84.5	[32]
C212	A37	Naive Bayes	Bayesian Algorithms	54	80.85	81.5	63.3	-	88.3	85.9	[32]
C213	A37	Naive Bayes	Bayesian Algorithms	54	85.47	87.5	72.2	-	90.8	89.6	[32]
C214	A6	Naive Bayes	Bayesian Algorithms	6	85.86	-	-	-	-	-	[32]
C215	A27	Naive Bayes	Bayesian Algorithms	9	69.11	-	-	-	-	-	[32]
C216	A27	Naive Bayes	Bayesian Algorithms	13	84.07	-	-	84.36	-	-	[32]
C217	A26	Naive Bayes	Bayesian Algorithms	13	83.3	82.6	83.9	-	-	-	[32]
C218	A39	Naive Bayes	Bayesian Algorithms	44	77.5	85.2	47.4	-	-	-	[32]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C219	A27	Naive Bayes	Bayesian Algorithms	13	82	84	79	83	-	83	[26]
C220	A42	Naive Bayes	Bayesian Algorithms	13	87	-	-	-	-	-	[26]
C221	A6	Naive Bayes	Bayesian Algorithms	13	77.23	81.71	71.94	-	-	76.51	[20]
C222	A9	Naive Bayes	Bayesian Algorithms	7	68.9	77.78	57.61	-	-	66.19	[20]
C223	A8	Naive Bayes	Bayesian Algorithms	22	80.52	76.36	81.6	-	-	78.9	[20]
C224	A25	Naive Bayes	Bayesian Algorithms	44	78.28	23.64	92.45	-	-	37.65	[20]
C225	A27	Naive Bayes	Bayesian Algorithms	13	78.52	82	74.17	-	-	77.89	[20]
C226	A6	Naive Bayes	Bayesian Algorithms	13	83.49	-	-	-	90.4	85.1	[20]
C227	A33	Naive Bayes	Bayesian Algorithms	13	86.42	83.7	89.5	90	93	86.7	[20]
C228	A27	Naive Bayes	Bayesian Algorithms	13	83	85	80	84	-	-	[20]
C229	A21	Naive Bayes	Bayesian Algorithms	13	90.95	-	-	-	-	-	[20]
C230	A27	Naive Bayes	Bayesian Algorithms	13	91.38	90.86	92.42	93.39	-	92	[18]
C231	A24	Naive Bayes	Bayesian Algorithms	13	90.47	90.25	92.19	92.75	-	92	[18]
C232	A6	Naive Bayes	Bayesian Algorithms	13	81.48	-	-	-	-	-	[18]
C233	A27	Naive Bayes	Bayesian Algorithms	13	85.18	-	-	-	-	-	[18]
C234	A1	Naive Bayes	Bayesian Algorithms	13	83.49	86.7	83.3	84.18	90.4	85.1	[18]
C235	A1	Naive Bayes	Bayesian Algorithms	13	83	78	87	-	84	-	[36]
C236	A6	BNN (10 neurons)	Backpropagation Neural Network Algorithms	13	86.67	-	-	80.95	-	-	[48]
C237	A6	BNN (10 neurons)	Backpropagation Neural Network Algorithms	13	91.11	-	-	85.19	-	-	[48]
C238	A6	BNN (11 neurons)	Backpropagation Neural Network Algorithms	13	77.78	-	-	73.91	-	-	[48]
C239	A6	BNN (11 neurons)	Backpropagation Neural Network Algorithms	13	95.56	-	-	91.67	-	-	[48]
C240	A6	BNN (12 neurons)	Backpropagation Neural Network Algorithms	13	84.44	-	-	83.33	-	-	[48]
C241	A6	BNN (12 neurons)	Backpropagation Neural Network Algorithms	13	91.11	-	-	88	-	-	[48]
C242	A6	BNN (6 neurons)	Backpropagation Neural Network Algorithms	13	86.67	-	-	90.95	-	-	[17]
C243	A6	BNN (7 neurons)	Backpropagation Neural Network Algorithms	13	82.22	-	-	84	-	-	[17]
C244	A6	BNN (7 neurons)	Backpropagation Neural Network Algorithms	13	93.33	-	-	89.29	-	-	[17]
C245	A6	BNN (8 neurons)	Backpropagation Neural Network Algorithms	13	86.67	-	-	86.96	-	-	[17]
C246	A6	BNN (8 neurons)	Backpropagation Neural Network Algorithms	13	95.56	-	-	95.45	-	-	[17]
C247	A6	BNN (9 neurons)	Backpropagation Neural Network Algorithms	13	71.11	-	-	70.83	-	-	[17]
C248	A6	BNN (9 neurons)	Backpropagation Neural Network Algorithms	13	91.11	-	-	88.46	-	-	[17]
C249	A6	BAT-BP	Backpropagation Neural Network Algorithms	13	97.46	-	-	97.04	-	-	[17]
C250	A2	BNN	Backpropagation Neural Network Algorithms	66	78.95	-	-	-	-	-	[17]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C251	A6	BNN (3 neurons)	Backpropagation Neural Network Algorithms	13	82.22	-	-	78.26	-	-	[15]
C252	A6	BNN (3 neurons)	Backpropagation Neural Network Algorithms	13	91.11	-	-	100	-	-	[15]
C253	A6	BNN (4 neurons)	Backpropagation Neural Network Algorithms	13	75.56	-	-	66.67	-	-	[15]
C254	A6	BNN (4 neurons)	Backpropagation Neural Network Algorithms	13	88.89	-	-	84	-	-	[15]
C255	A6	BNN (5 neurons)	Backpropagation Neural Network Algorithms	13	84.44	-	-	89.29	-	-	[15]
C256	A6	BNN (5 neurons)	Backpropagation Neural Network Algorithms	13	88.89	-	-	92.31	-	-	[15]
C257	A6	BNN (6 neurons)	Backpropagation Neural Network Algorithms	13	75.56	-	-	76.67	-	-	[15]
C258	A6	back-propagation (20 Neurons)	Backpropagation Neural Network Algorithms	13	98.58	-	-	-	-	-	[39]
C259	A6	back-propagation (5 Neurons)	Backpropagation Neural Network Algorithms	13	97.5	-	-	-	-	-	[39]
C260	A6	Rules based Classifier	Association Rule Learning Algorithms	13	86.7	-	-	-	-	-	[49]
C261	A28	RBF	Artificial Neural Network Algorithms	13	83.82	-	-	-	-	-	[6]
C262	A27	RBF	Artificial Neural Network Algorithms	13	84.44	-	-	-	-	-	[6]
C263	A30	ANN	Artificial Neural Network Algorithms	12	92.5	-	-	-	-	-	[6]
C264	A6	RBF	Artificial Neural Network Algorithms	13	83.83	-	-	-	-	-	[6]
C265	A1	ANN	Artificial Neural Network Algorithms	13	88.12	-	-	-	-	-	[41]
C266	A26	ANN	Artificial Neural Network Algorithms	13	77.8	82.6	74.2	-	-	-	[41]
C267	A36	MLP	Artificial Neural Network Algorithms	27	96.1	95.7	96.4	-	-	-	[42]
C268	A35	MLP	Artificial Neural Network Algorithms	27	75.5	-	-	-	-	-	[42]
C269	A1	MLP	Artificial Neural Network Algorithms	13	82.5	83.6	80.6	-	88.3	83.9	[42]
C270	A6	MLP	Artificial Neural Network Algorithms	13	84.15	-	-	85.01	-	-	[42]
C271	A27	MLP	Artificial Neural Network Algorithms	13	85.56	-	-	86.12	-	-	[42]
C272	A5	MLR	Artificial Neural Network Algorithms	26	83.5	-	-	-	-	-	[43]
C273	A6	RBF	Artificial Neural Network Algorithms	13	83.82	-	-	-	89.2	85.3	[43]
C274	A33	MLP	Artificial Neural Network Algorithms	13	83.95	83.7	84.2	85.7	92.5	84.7	[51]
C275	A1	ANN (13, 16, 2)	Artificial Neural Network Algorithms	3	74	74	73	-	69	-	[51]
C276	A13	ANN	Artificial Neural Network Algorithms	20	90.4	-	-	97.1	80.8	-	[51]

Classifier Code	Dataset	Classifier	Algorithm	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref.
C277	A6	DTNNN	Artificial Neural Network Algorithms	13	99.85	-	-	99.83	-	-	[21], [47]
C278	A37	MLP	Artificial Neural Network Algorithms	54	83.52	-	-	-	-	86.12	[47]
C279	A2	ANN	Artificial Neural Network Algorithms	66	80.82	-	-	-	-	-	[47]
C280	A6	MLP	Artificial Neural Network Algorithms	13	82.83	-	-	-	89.4	82.4	[47]
C281	A27	ANN	Artificial Neural Network Algorithms	13	84	87	79	84	-	86	[47]
C282	A25	ANN	Artificial Neural Network Algorithms	44	73.3	76.5	60.5	-	-	-	[22]
C283	A5	MLP	Artificial Neural Network Algorithms	26	77	-	-	-	-	-	[22]
C284	A34	LMANN	Artificial Neural Network Algorithms	13	71.11	67.11	74.32	-	70.8	-	[35]
C285	A4	Multilayer	Artificial Neural Network Algorithms	13	78.148	-	-	-	-	-	[35]

Accuracy is the measurement utilised to decide the best among the selected classifier. Based on the accuracy as shown in Figure 5, KNN (K=1) classifier using Statlog HD dataset (A27) having 100% as the highest accuracy [14] is concluded to be most efficient. Succeeding to the KNN (K=1) classifier, Deep Trained Neocognitron Neural Network (DTNNN) using Cleveland HD dataset (A6) regarded as the next high yielding classifier with 99.85% accuracy [21]. Followed by back-propagation (20 Neurons) using Cleveland HD dataset (A6) having 98.58% accuracy [39] and so on.

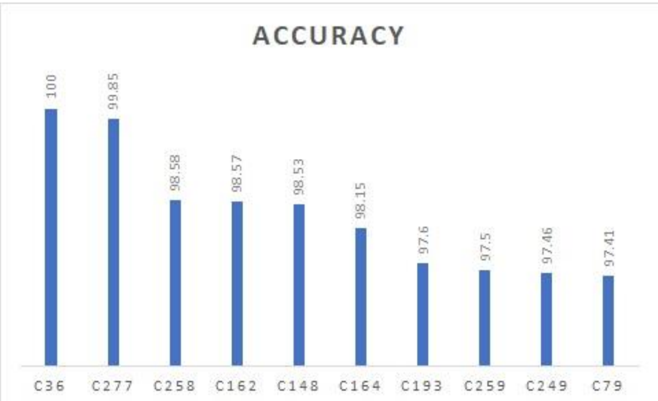

Figure 5. Accuracy of top 10 classifiers

Sensitivity is the criteria that is used to examine the impact of each feature on classifier. From Figure 6, on comparing sensitivity of different classifiers, it is observed that Support Vector Machine (SVM) using Cleveland HD dataset (A1) [14] is the finest classifier with 100% sensitivity along with the SVM classifier, Quadratic Discriminant Analysis (QDA) using SPECTF dataset (A25) [37] having the same sensitivity of 100%. Followed by Random Forest using Cleveland HD dataset (A1) having 98.8% sensitivity [22] and so on.

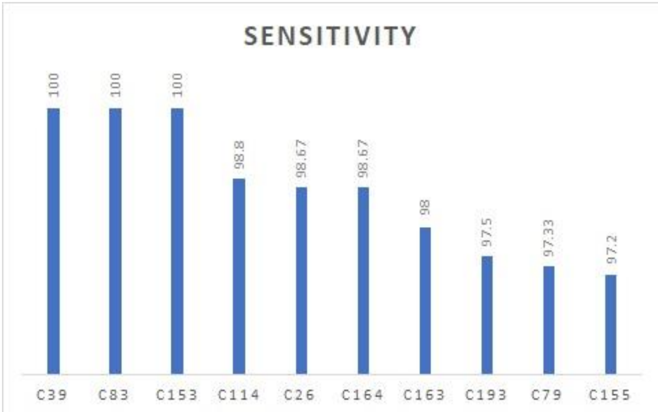

Figure 6. Sensitivity of top 10 classifiers

Specificity is the extent to which a diagnostic test is specific for a particular condition, trait, etc. Based on the Specificity, KNN classifier using SPECT dataset (A8) having 98.11% as the highest Specificity [36] is concluded to be most efficient. Succeeding to the KNN classifier, C4.5 using CDS dataset (A36) regarded as the next high yielding classifier with 97.6% Specificity [36]. Followed by Deep Neural Network (DNN) using Cleveland HD dataset (A24) having 97.5% Specificity [24] is shown in Figure 7, and so on.

Precision is the quality of being exact. Based on the Precision, BNN (3 neurons) [15] using Cleveland HD dataset (A6) having 100% as the highest Precision is concluded to be most efficient. Succeeding to the BNN (3 neurons) Classifier, Deep Trained Neocognitron Neural Network (DTNNN) using Cleveland HD dataset (A6) regarded as the next high yielding classifier with 99.83% Precision [21]. Followed by Genetic Algorithm Optimization of a Convolutional Neural Network (GA-CNN) using Cleveland HD dataset (A6) having 98.34% Precision [5] is shown in Figure 8, and so on.

Figure 7. Specificity of top 10 classifiers

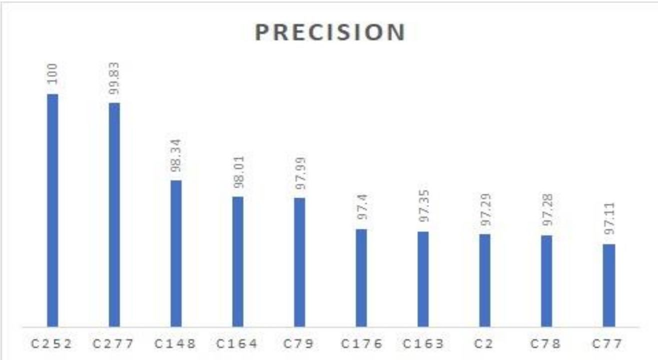

Figure 8. Precision of top 10 classifiers

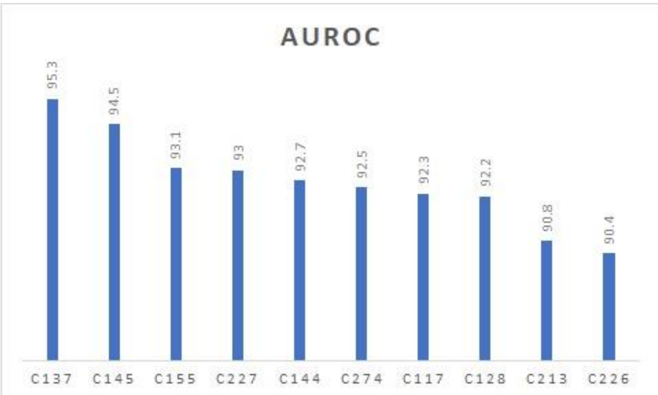

Figure 9. Auroc of top 10 classifiers

At various threshold levels, the AUROC curve is a performance measurement for classification issues. Based on the AUROC, Ensemble Classifier using Z-Alizadeh Sani CHD dataset (A37) having 95.3% as the highest AUROC [7] is concluded to be most efficient. Succeeding to the Ensemble Classifier, boosted tree using HD dataset (A33) regarded as the next high yielding classifier with 94.5% AUROC [25]. Followed by Binary discriminant using HD dataset (A33) having 93.1% AUROC [24] is shown in Figure 9, and so on.

The F1-measure combines precision and recall into a single measure that captures both attributes while giving them equal importance. Based on the F1-measure, boosted tree Classifier using HD dataset (A33) having 98.2% as the highest F1-measure [25] is concluded to be most efficient. Succeeding to the Deep Neural Network (DNN) Classifier, boosted tree using Cleveland HD dataset (A24) regarded as the next high yielding classifier with 98% F1-measure [24] along with it, Support Vector Machine (SVM) using Cleveland HD dataset (A24) having 98% F1-measure [37] is shown in Figure 10, and so on.

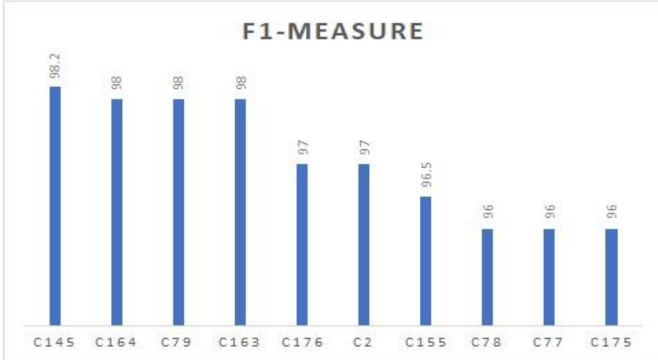

Figure 10. F1-Measure of top 10 classifiers

5. DATA PRE-PROCESSING TECHNIQUES USED IN HEART DISEASE PREDICTION/CLASSIFICATION

Data preprocessing is a data mining approach for converting unstructured data into a suitable format. Real-world data is frequently partial, inconsistent, and/or lacking in specific behaviours or trends, as well as including numerous errors [7]. Data preprocessing is a data mining technique used to convert raw data into a useful and efficient format. The steps involved in data preprocessing are Data Cleaning (D.C), Data Transformation (D.T) and Data Reduction (D.R). Data Cleaning involves handling of missing data and noisy data. Missing data can be handled by Ignore the tuples or Fill the Missing values. Noisy data can be handled by Binning Method or Regression or by using Clustering. Data Transformation involves Normalization, Attribute Construction, Discretization, Generalisation, Integration, Manipulation, Normalisation and Smoothing. Data Reduction involves Data Cube Aggregation, Attribute Selection (or) Feature Selection (F.S), Numerosity Reduction, Dimensionality Reduction (or) Feature Extraction (F.E) [57].

In case of HD prediction, the data preprocessing techniques used are Accuracy Based Weighted Aging Classifier Ensemble (AB-WAE), Adaptive-Weighted-Fuzzy-System-Ensemble (AWFSE), Analysis Of Variance (ANOVA), ANN-Fuzzy-AHP (AFP), Ant Colony Optimization (ACO), Ant Colony Optimization Neural Networks (ACONN), Bacterial Foraging Optimization (BFO), Binary Particle Swarm Optimization (BPSO), Binary Particle Swarm Optimization And Rough Sets Based Attribute Reduction (BPSORS-AR), Bootstrap Aggregation (Bagging) With Multi-Objective Optimized Weighted Vote (Bagmoov), CFS (Correlation Based Feature Selection), Chaos Firefly Algorithm And Rough Sets Based Attribute Reduction (CFARS-AR), Chi-Squared (CS), Chi-With-In-Sum-Of-Squares (WSS), Clinical Decision Support System (CDSS), Conditional Mutual Information Maximization (CMIM), Correlation Feature Subset (CFS), Density-Based Spatial Clustering Of Applications With Noise (DBSCAN), Effective HD Prediction System (EHDPS), Ensemble Algorithm Based On Multiple Feature Selection (EA-MFS), Exponentiated Estimate Of The Coefficient Exp(B), Factor Analysis Of Mixed Data (FAMD), Fast Conditional Mutual Information (FCMIM), Fast Correlation-Based Filter (FCBF), Feature Selection (FS), Forward Sequential Search (FSS), Fruit Fly Optimization (FFO), Fuzzy Logic-Based Clinical Decision Support System (FLBCDSS), Gain Ratio (GR), Half Selection(HS), HD Clinical Decision Support System

(HDCDSS), Hybrid Ant Colony Optimization Approach (HACO), Hybrid Genetic Algorithm With A New Local Search Algorithm (HGLSA), Hybrid Particle Swarm Optimization With Wrapper Filter (HPSOWF), Information Gain (IG), Instance Based Learner (Ibk), Kernel F-Score Feature Selection (KFFS), Learning Vector Quantization (LVQ), Least Square Twin Support Vector Machine (LSTSVM), Least-Absolute-Shrinkage-Selection-Operator (LASSO), Leave-One-Subject-Out Cross-Validation (LOSO), Local-Learning-Based Features- Selection (LLBFS), Local-Learning-Based-Features-Selection (LLBFS), Mean Fisher Score Feature Selection Algorithm (MFSFSA), Mean Selection(MS), Minimum Redundancy Maximum Relevance (mRMR), Mutual Information-Based Feature Selection (MIFS), Neural Network For Threshold Selection (NNTS), Normalized Mutual Information Feature Selection (NMIFS), Particle Swarm Optimization (PSO), Principal Component Analysis (PCA), Relief-F (RF), Rough Set Based Attribute Reduction (RSBAR), Rough Sets-Based Attributes Selection And Backpropagation Neural Network (RS-BPNN), Standard Scalar (SS), Symmetrical Uncertainty (SU), Synthetic Minority Over-Sampling Technique-Edited Nearest Neighbor (SMOTE-ENN), Weighted Aging Classifier Ensemble (WAE). From the Table 3 it is clear that, most of the data preprocessing techniques used are related to data reduction specifically feature selection.

6. CLASSIFIERS WITH DATA PRE-PROCESSING (CWD) TECHNIQUES USED IN HEART DISEASE PREDICTION

This section examines the performance parameters of each classifier in combination with various data preprocessing approaches in order to determine the optimum combinations for HD prediction and classification. Table 3 shows the performance measure values of several classifiers with data preparation/preprocessing. A vast number of combinations were investigated, as can be seen in Table 3.

Table 3. Performance metric values of classifier with data preprocessing

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D1	2007	A6	Chi-WSS (F.S)+NB	4	84.48	-	-	-	88.46	-	[10]
D2	2007	A6	FSS (F.S)+LR	8	84.81	-	-	-	86.43	-	[10]
D3	2007	A6	FSS (F.S)+SVM	8	84.81	-	-	-	84.44	-	[10]
D4	2007	A27	Chi-WSS (F.S)+NB	4	84.81	-	-	-	87.99	-	[10]
D5	2007	A27	FSS (F.S)+LR	5	85.18	-	-	-	86.01	-	[10]
D6	2007	A27	FSS (F.S)+SVM	4	84.44	-	-	-	83.92	-	[10]
D7	2009	A34	F-score (F.E)+ ANN	6	77.61	77.61	88.23	-	82.1	-	[47]
D8	2009	A34	F-score (F.E)+ LS-SVM	6	77.78	76.78	78.48	-	77.1	-	[47]
D9	2009	A34	Linear kernel F-score (F.E)+ ANN	13	80.74	78.95	85.5	-	81.1	-	[47]
D10	2009	A34	linear kernel F-score (F.E)+ LS-SVM	13	80	86.67	76.67	-	78.5	-	[47]
D11	2009	A34	RBF kernel F-score (F.E)+ ANN	13	76.3	71.21	81.15	-	76.5	-	[47]
D12	2009	A34	RBF kernel F-score (F.E)+ LS-SVM	13	83.7	83.92	83.54	-	83.1	-	[47]
D13	2012	A4	CFS (F.S)+Bayes theorem (F.S)+ J48	3	85.18	-	-	-	-	-	[6]
D14	2012	A4	CFS (F.S)+Bayes theorem (F.S)+ KNN	3	85.55	-	-	-	-	-	[6]
D15	2012	A4	CFS (F.S)+Bayes theorem (F.S)+ Multi layer perceptron	3	85.18	-	-	-	-	-	[6]
D16	2012	A4	CFS (F.S)+Bayes theorem (F.S)+ NB	3	80.37	-	-	-	-	-	[6]
D17	2012	A4	CFS (F.S)+FilteredSubsetEval (F.S)+ KNN	6	80.74	-	-	-	-	-	[6]
D18	2012	A4	CFS (F.S)+FilteredSubsetEval (F.S)+J48	6	79.62	-	-	-	-	-	[6]
D19	2012	A4	CFS (F.S)+FilteredSubsetEval (F.S)+Multi layer Perceptron	6	78.88	-	-	-	-	-	[6]
D20	2012	A4	CFS (F.S)+FilteredSubsetEval (F.S)+NB	6	85.18	-	-	-	-	-	[6]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D21	2012	A4	CFS subset eval (F.S)+ Multi layer Perceptron	7	82.22	-	-	-	-	-	[6]
D22	2012	A4	CFS subset eval (F.S)+J48	7	81.11	-	-	-	-	-	[6]
D23	2012	A4	CFS subset eval (F.S)+NB	7	85.5	-	-	-	-	-	[6]
D24	2012	A4	CFS subset eval(F.S)+KNN	7	78.14	-	-	-	-	-	[6]
D25	2012	A4	Chi-squared attribute eval (F.S)+ Multi layer Perceptron	13	80.37	-	-	-	-	-	[6]
D26	2012	A4	Chi-squared attribute eval (F.S)+ J48	13	76.66	-	-	-	-	-	[6]
D27	2012	A4	Chi-squared attribute eval (F.S)+ KNN	13	75.18	-	-	-	-	-	[6]
D28	2012	A4	Chi-squared attribute eval (F.S)+NB	13	83.7	-	-	-	-	-	[6]
D29	2012	A4	Consistency subset evaluation (F.S) + J48	10	78.88	-	-	-	-	-	[6]
D30	2012	A4	Consistency subset evaluation (F.S)+ KNN	10	78.14	-	-	-	-	-	[6]
D31	2012	A4	Consistency subset evaluation (F.S)+ Multi layer Perceptron	10	81.11	-	-	-	-	-	[6]
D32	2012	A4	Consistency subset evaluation (F.S)+ NB	10	84.07	-	-	-	-	-	[6]
D33	2012	A4	Filtered attribute Evaluation (F.S)+ J48	13	76.66	-	-	-	-	-	[6]
D34	2012	A4	Filtered attribute Evaluation (F.S)+ KNN	13	75.18	-	-	-	-	-	[6]
D35	2012	A4	Filtered attribute Evaluation (F.S)+ Multi layer Perceptron	13	80.37	-	-	-	-	-	[6]
D36	2012	A4	Filtered attribute Evaluation (F.S)+ NB	13	83.7	-	-	-	-	-	[6]
D37	2012	A4	Filteredsubset eval (F.S)+ J48	6	79.6	-	-	-	-	-	[6]
D38	2012	A4	Filteredsubset eval (F.S)+ Multi layer Perceptron	6	78.88	-	-	-	-	-	[6]
D39	2012	A4	Filteredsubset eval (F.S)+ NB	6	85.18	-	-	-	-	-	[6]
D40	2012	A4	Gain ratio attribute Evaluation (F.S)+ Multi layer Perceptron	13	78.88	-	-	-	-	-	[6]
D41	2012	A4	Gain ratio attribute Evaluation (F.S)+ NB	13	83.7	-	-	-	-	-	[6]
D42	2012	A4	Gain ratio attribute Evaluation (F.S)+ J48	13	76.66	-	-	-	-	-	[6]
D43	2012	A4	Gain ratio attribute Evaluation (F.S)+ KNN	13	75.18	-	-	-	-	-	[6]
D44	2012	A4	Info gain attribute Evaluation (F.S)+ Multi layer Perceptron	13	80.37	-	-	-	-	-	[6]
D45	2012	A4	Info gain attribute Evaluation (F.S) + J48	13	76.66	-	-	-	-	-	[6]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D46	2012	A4	Info gain attribute Evaluation (F.S)+ KNN	13	75.18	-	-	-	-	-	[6]
D47	2012	A4	Info gain attribute Evaluation (F.S)+ NB	13	83.7	-	-	-	-	-	[6]
D48	2012	A4	Latent semantic analysis (F.S)+ Multi layer Perceptron	1	52.96	-	-	-	-	-	[6]
D49	2012	A4	Latent semantic analysis (F.S)+ J48	1	55.55	-	-	-	-	-	[6]
D50	2012	A4	Latent semantic analysis (F.S)+ KNN	1	51.11	-	-	-	-	-	[6]
D51	2012	A4	Latent semantic analysis (F.S)+ NB	1	54.07	-	-	-	-	-	[6]
D52	2012	A4	One attribute eval (F.S)+ J48	13	76.66	-	-	-	-	-	[6]
D53	2012	A4	One attribute eval (F.S)+ KNN	13	75.18	-	-	-	-	-	[6]
D54	2012	A4	One attribute eval (F.S)+ Multi layer Perceptron	13	79.25	-	-	-	-	-	[6]
D55	2012	A4	One attribute eval (F.S)+ NB	13	83.7	-	-	-	-	-	[6]
D56	2012	A4	Relief attribute evaluation (F.S)+ J48	13	76.66	-	-	-	-	-	[6]
D57	2012	A4	Relief attribute evaluation (F.S)+ KNN	13	75.18	-	-	-	-	-	[6]
D58	2012	A4	Relief attribute evaluation (F.S)+ Multi layer Perceptron	13	78.14	-	-	-	-	-	[6]
D59	2012	A4	Relief attribute evaluation (F.S)+ NB	13	83.7	-	-	-	-	-	[6]
D60	2013	A29	ANN+PCA (F.E)	4	100	-	-	-	-	-	[42]
D61	2013	A29	ANN+χ 2 (F.S)	4	100	-	-	-	-	-	[42]
D62	2013	A29	KNN+SU (F.S+D.T)	4	97.5	-	-	-	-	-	[42]
D63	2013	A7	ANN+GA (F.S+.D.T)	5	100	-	-	-	-	-	[42]
D64	2013	A7	ANN+PCA (F.E)	5	100	-	-	-	-	-	[42]
D65	2013	A7	ANN+χ 2 (F.S)	5	100	-	-	-	-	-	[42]
D66	2013	A7	KNN+SU (F.S+D.T)	5	100	-	-	-	-	-	[42]
D67	2013	A27	ANN+GA (F.S+.D.T)	7	99.62	-	-	-	-	-	[42]
D68	2013	A27	ANN+PCA (F.E)	7	98.14	-	-	-	-	-	[42]
D69	2013	A27	ANN+χ 2 (F.S)	7	97.7	-	-	-	-	-	[42]
D70	2013	A27	KNN+SU (F.S+D.T)	7	100	-	-	-	-	-	[42]
D71	2013	A28	HS (F.S) + RBF	7	83.44	84	83	-	-	-	[41]
D72	2013	A28	MS (F.S) + RBF	6	81.75	82	82	-	-	-	[41]
D73	2013	A28	NNTS (F.S)+ RBF	3	84.46	82	82	-	-	-	[41]
D74	2013	A28	RBF + CMIM (F.S)	3	83.78	-	-	-	-	-	[41]
D75	2013	A28	RBF + FCBF (F.S)	4	80.74	-	-	-	-	-	[41]
D76	2013	A28	RBF + Fuzzyentropy-NNTS (F.S)	4	84.46	-	-	-	-	-	[41]
D77	2013	A28	RBF + IG (F.S)	5	82.43	-	-	-	-	-	[41]
D78	2013	A28	RBF + MIFS (F.S)	5	76.35	-	-	-	-	-	[41]
D79	2013	A28	RBF + mRMR (F.S)	4	83.78	-	-	-	-	-	[41]
D80	2013	A28	RBF + NMIFS (F.S)	4	84.12	-	-	-	-	-	[41]
D81	2013	A27	HS (F.S) + RBF	7	84.81	85	84	-	89	-	[41]
D82	2013	A27	MS (F.S) + RBF	6	84.44	85	84	-	89	-	[41]
D83	2013	A27	NNTS (F.S)+ RBF	4	85.19	85	86	-	89	-	[41]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D84	2013	A27	RBF + CMIM (F.S)	3	83.33	-	-	-	-	-	[41]
D85	2013	A27	RBF + FCBF (F.S)	4	82.96	-	-	-	-	-	[41]
D86	2013	A27	RBF + Fuzzyentropy-NNTS (F.S)	4	85.18	-	-	-	-	-	[41]
D87	2013	A27	RBF + IG (F.S)	5	84.81	-	-	-	-	-	[41]
D88	2013	A27	RBF + MIFS (F.S)	5	83.7	-	-	-	-	-	[41]
D89	2013	A27	RBF + mRMR (F.S)	4	84.44	-	-	-	-	-	[41]
D90	2013	A27	RBF + NMIFS (F.S)	4	84.81	-	-	-	-	-	[41]
D91	2013	A30	Chi square (F.S) + ANN	5	100	-	-	-	-	-	[39]
D92	2013	A30	GA(F.S+.D.T)+ ANN	5	100	-	-	-	-	-	[39]
D93	2013	A30	PCA (F.E)+ ANN	5	100	-	-	-	-	-	[39]
D94	2013	A2	Chi square (F.S) + ANN	5	97.7	-	-	-	-	-	[39]
D95	2013	A2	GA(F.S+.D.T)+ ANN	5	99.62	-	-	-	-	-	[39]
D96	2013	A2	PCA (F.E) + ANN	5	98.14	-	-	-	-	-	[39]
D97	2013	A30	GA(F.S+.D.T)+A NN	12	100	-	-	-	-	-	[43]
D98	2013	A30	KNN (K=1)	12	95	-	-	-	-	-	[43]
D99	2013	A30	KNN+GA (F.S+.D.T)	12	100	-	-	-	-	-	[43]
D100	2013	A30	NN+PCA (F.E)	12	100	-	-	-	-	-	[43]
D101	2013	A30	NN+χ 2 (F.S)	2	100	-	-	-	-	-	[43]
D102	2013	A27	GA(F.S+.D.T)+A NN	13	99.6	-	-	-	-	-	[43]
D103	2013	A27	KNN (K=1)	13	100	-	-	-	-	-	[43]
D104	2013	A27	KNN+GA (F.S+.D.T)	13	100	-	-	-	-	-	[43]
D105	2013	A27	NN+PCA (F.E)	13	98.14	-	-	-	-	-	[43]
D106	2013	A27	NN+χ 2 (F.S)	13	97.7	-	-	-	-	-	[43]
D107	2015	A6	GA (F.S+.D.T)+ Naïve Bayes	8	84.16	-	-	-	-	-	[21]
D108	2015	A6	GA(F.S+.D.T) + J48	8	77.56	-	-	-	-	-	[21]
D109	2015	A6	GA(F.S+.D.T) + RBF	8	85.48	-	-	-	-	-	[21]
D110	2017	A6	BPSO(F.S+D.T) + RSBAR (F.S) + SVM	9	75.9	-	-	-	-	-	[30]
D111	2017	A6	BPSO(F.S+D.T) + RSBAR (F.S) + Naive Bayes	9	79.6	-	-	-	-	-	[30]
D112	2017	A6	CF + RSBAR (F.S)+ ANN	9	81.5	-	-	-	-	-	[30]
D113	2017	A6	modified DE (F.S) + fuzzy AHP + feed-forward NN	9	83	-	-	-	-	-	[30]
D114	2017	A37	Adaboost + ANOVA F(F.S)	29	90.11	-	-	-	-	91.35	[49]
D115	2017	A37	Adaboost + CHI(F.S)	34	91.21	-	-	-	-	93.22	[49]
D116	2017	A37	Adaboost + LR.coef (F.S)(Embedded+SVM)	12	89.01	-	-	-	-	89.74	[49]
D117	2017	A37	Adaboost + MutualInfo (F.S)	10	90.01	-	-	-	-	91.02	[49]
D118	2017	A37	Adaboost + RF.coef (F.S) (Embedded+SVM)	28	89.01	-	-	-	-	89.74	[49]
D119	2017	A37	Adaboost + SVM.coef (F.S)(Embedded+SVM)	16	90.11	-	-	-	-	91.07	[49]
D120	2017	A37	GBDT + ANOVA F(F.S) (Filter+Adaboost)	29	86.81	-	-	-	-	90.1	[49]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D121	2017	A37	GBDT + CHI (F.S) (Filter+Adaboost)	34	86.81	-	-	-	-	87.05	[49]
D122	2017	A37	GBDT + LR.coef (F.S) (Embedded+SVM)	12	84.62	-	-	-	-	88.18	[49]
D123	2017	A37	GBDT + MutualInfo (F.S) (Filter+Adaboost)	10	83.52	-	-	-	-	88.3	[49]
D124	2017	A37	GBDT + RF.coef (F.S)(Embedded+SVM)	28	86.81	-	-	-	-	90.1	[49]
D125	2017	A37	GBDT + SVM.coef (F.S) (Embedded+SVM)	16	83.52	-	-	-	-	85.37	[49]
D126	2017	A37	KNN + ANOVA F (F.S)(Filter+Adaboost)	29	85.71	-	-	-	-	88.03	[49]
D127	2017	A37	KNN + CHI (F.S)(Filter+Adaboost)	34	89.01	-	-	-	-	85.83	[49]
D128	2017	A37	KNN + LR.coef (F.S)(Embedded+SVM)	12	85.71	-	-	-	-	88.18	[49]
D129	2017	A37	KNN + MutualInfo (F.S) (Filter+Adaboost)	10	86.81	-	-	-	-	87.84	[49]
D130	2017	A37	KNN + RF.coef (F.S)(Embedded+SVM)	28	85.71	-	-	-	-	88.03	[49]
D131	2017	A37	KNN + SVM.coef (F.S) (Embedded+SVM)	16	89.01	-	-	-	-	90.51	[49]
D132	2017	A37	LR + ANOVA F (F.S)(Filter+Adaboost)	29	89.01	-	-	-	-	90.51	[49]
D133	2017	A37	LR + CHI (F.S)(Filter+Adaboost)	34	87.91	-	-	-	-	89.18	[49]
D134	2017	A37	LR + LR.coef (F.S)(Embedded+SVM)	12	91.21	-	-	-	-	90.84	[49]
D135	2017	A37	LR + MutualInfo (F.S) (Filter+Adaboost)	10	89.01	-	-	-	-	89.74	[49]
D136	2017	A37	LR + RF.coef (F.S)(Embedded+SVM)	28	89.01	-	-	-	-	90.51	[49]
D137	2017	A37	LR + SVM.coef (F.S)(Embedded+SVM)	16	92.31	-	-	-	-	92.18	[49]
D138	2017	A37	MLP + ANOVA F(F.S) (Filter+Adaboost)	29	90.11	-	-	-	-	91.07	[49]
D139	2017	A37	MLP + CHI(F.S) (Filter+Adaboost)	34	90.11	-	-	-	-	89.51	[49]
D140	2017	A37	MLP + LR.coef(F.S) (Embedded+SVM)	12	90.11	-	-	-	-	91.07	[49]
D141	2017	A37	MLP + MutualInfo(F.S) (Filter+Adaboost)	10	85.71	-	-	-	-	88.77	[49]
D142	2017	A37	MLP + RF.coef (F.S)(Embedded+SVM)	28	89.01	-	-	-	-	89.74	[49]
D143	2017	A37	MLP + SVM.coef (F.S)(Embedded+SVM)	16	91.21	-	-	-	-	91.63	[49]
D144	2017	A37	RF + RF.coef (F.S)(Embedded+SVM)	28	85.71	-	-	-	-	90.22	[49]
D145	2017	A37	RF + SVM.coef (F.S)(Embedded+SVM)	16	87.91	-	-	-	-	89.18	[49]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D146	2017	A37	RF + ANOVA F (F.S) (Filter+Adaboost)	29	86.81	-	-	-	-	90.1	[49]
D147	2017	A37	RF + CHI (F.S)(Filter+Adaboost)	34	85.52	-	-	-	-	85.84	[49]
D148	2017	A37	RF + LR.coef (F.S)(Embedded+SVM)	12	86.81	-	-	-	-	88.61	[49]
D149	2017	A37	RF + MutualInfo(F.S) (Filter+Adaboost)	10	87.91	-	-	-	-	89.18	[49]
D150	2017	A37	SVM + RF.coef (F.S)(Embedded+SVM)	28	90.11	-	-	-	-	91.07	[49]
D151	2017	A37	SVM + ANOVA F (F.S)(Filter+Adaboost)	29	86.81	-	-	-	-	89.36	[49]
D152	2017	A37	SVM + CHI (F.S) (Filter+Adaboost)	34	87.91	-	-	-	-	89.94	[49]
D153	2017	A37	SVM + LR.coef (F.S) (Embedded+SVM)	12	90.11	-	-	-	-	91.07	[49]
D154	2017	A37	SVM + MutualInfo (F.S)(Filter+Adaboost)	10	89.01	-	-	-	-	90.51	[49]
D155	2017	A37	SVM + SVM.coef (F.S)(Embedded+SVM)	16	91.21	-	-	-	-	91.63	[49]
D156	2018	A27	Decision Tree + Gain Ratio (F.S)	9	84.1	-	-	-	-	-	[32]
D157	2018	A27	Neural Network with Fuzzy	9	80	-	-	-	-	-	[32]
D158	2018	A27	Neural Network with Genetic Algorithm (F.S+.D.T)	9	80.99	-	-	-	-	-	[32]
D159	2018	A27	Support Vector Machine	13	82.22	-	-	-	-	-	[32]
D160	2018	A27	Vote + Naïve Bayes and Logistic Regression (F.S)	9	87.41	-	-	-	-	-	[32]
D161	2018	A27	Vote + Naïve Bayes and Logistic Regression (F.S)	9	87.41	-	-	-	-	-	[32]
D162	2020	A6	CFS (F.S)+ PSO (F.S)+K-means (D.T)+ MLP	13	90.28	-	-	-	-	-	[20]
D163	2020	A6	DBSCAN + SMOTE-ENN (D.B- D.T)+ XGBOOST	8	98.4	-	-	-	-	-	[20]
D164	2020	A6	FAMD (F.S)+ RF	13	93.44	-	-	-	-	-	[20]
D165	2020	A6	HDPM	13	98.4	-	-	98.57	-	-	[20]
D166	2020	A6	Majority Vote with NB, BN, RF and MP	13	85.48	-	-	-	-	-	[20]
D167	2020	A6	MFSFSA (F.S)+ SVM	13	81.19	-	-	-	-	-	[20]
D168	2020	A6	Relief (F.S) +LR	13	89	-	-	-	-	-	[20]
D169	2020	A27	CFARS-AR (F.S)	13	88.3	-	-	-	-	-	[20]
D170	2020	A27	DBSCAN + SMOTE-ENN (D.B- D.T)+ XGBOOST	9	95.9	-	-	-	-	-	[20]
D171	2020	A27	HDPM	13	95.9	-	-	97.14	-	-	[20]
D172	2020	A27	RS-BPNN (F.S)	13	90.4	-	-	-	-	-	[20]
D173	2020	A27	Vote with NB and LR (F.S)	13	87.41	-	-	-	-	-	[20]
D174	2020	A6	FAMD (F.S) + DT	13	81.96	71.42	90.9	-	81.16	78.43	[32]
D175	2020	A6	FAMD (F.S)+ KNN	13	90.16	92.85	87.87	-	90.36	89.65	[5]
D176	2020	A6	FAMD (F.S)+ LR	13	91.8	92.85	90.9	-	91.88	91.22	[5]
D177	2020	A6	FAMD (F.S)+ RF	13	93.44	89.28	96.96	-	93.12	92.59	[5]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D178	2020	A6	FAMD (F.S)+ SVM	13	91.8	100	84.84	-	92.42	91.8	[5]
D179	2020	A6	L1 Linear SVM + L2 Linear SVM & RBF SVM	13	92.22	82.92	100	-	-	-	[5]
D180	2020	A6	LASSO (F.S)+ SVM	13	88	75	96	-	-	-	[5]
D181	2020	A6	mRMR (F.S)+ NB	13	84	77	90	-	-	-	[5]
D182	2020	A6	PSO (F.S) + SVM	13	84.36	-	-	-	-	-	[5]
D183	2020	A6	RBF kernal - based SVM	13	81.19	72.92	88.68	-	-	-	[5]
D184	2020	A6	Relief (F.S)+ LR	13	89	77	98	-	-	-	[5]
D185	2020	A1	ANN - FUZZY-AHP	13	91.1	-	-	-	-	-	[18]
D186	2020	A1	ANN+Fuzzy Logic	13	87.4	-	-	-	-	-	[18]
D187	2020	A1	FCMIM (DISC) + ANN	6	75.23	-	-	-	-	-	[18]
D188	2020	A1	FCMIM (DISC) + DT	6	79.12	-	-	-	-	-	[18]
D189	2020	A1	FCMIM (DISC) + KNN	6	82.11	-	-	-	-	-	[18]
D190	2020	A1	FCMIM (DISC) + LR	6	88.67	-	-	-	-	-	[18]
D191	2020	A1	FCMIM (DISC)+ NB	6	86.01	-	-	-	-	-	[18]
D192	2020	A1	FCMIM (DISC)+ SVM(Linear)	6	92.37	-	-	-	-	-	[18]
D193	2020	A1	LASSO (F.S) + ANN	6	79	-	-	-	-	-	[18]
D194	2020	A1	LASSO (F.S)+ DT	6	78	-	-	-	-	-	[18]
D195	2020	A1	LASSO (F.S)+ KNN	6	79	-	-	-	-	-	[18]
D196	2020	A1	LASSO (F.S)+ LR	6	85	-	-	-	-	-	[18]
D197	2020	A1	LASSO (F.S)+ NB	6	79	-	-	-	-	-	[18]
D198	2020	A1	LASSO(F.S) + SVM(Linear)	6	86	-	-	-	-	-	[18]
D199	2020	A1	LASSO(F.S) + SVM(RBF)	6	85	-	-	-	-	-	[18]
D200	2020	A1	LLBFS (F.S) + SVM (Linear)	6	87	-	-	-	-	-	[18]
D201	2020	A1	LLBFS (F.S)+ ANN	6	80	-	-	-	-	-	[18]
D202	2020	A1	LLBFS (F.S)+ DT	6	74	-	-	-	-	-	[18]
D203	2020	A1	LLBFS (F.S)+ KNN	6	77	-	-	-	-	-	[18]
D204	2020	A1	LLBFS (F.S)+ LR	6	88	-	-	-	-	-	[18]
D205	2020	A1	LLBFS (F.S)+ NB	6	76	-	-	-	-	-	[18]
D206	2020	A1	LLBFS (F.S)+ SVM(RBF)	6	82	-	-	-	-	-	[18]
D207	2020	A1	MLP + SVM	13	80.41	-	-	-	-	-	[18]
D208	2020	A1	mRMR (F.S) + ANN	6	78	-	-	-	-	-	[18]
D209	2020	A1	mRMR (F.S) + DT	6	78	-	-	-	-	-	[18]
D210	2020	A1	mRMR (F.S) + KNN	6	78	-	-	-	-	-	[18]
D211	2020	A1	mRMR (F.S) + LR	6	83	-	-	-	-	-	[18]
D212	2020	A1	mRMR (F.S) + SVM(RBF)	6	83	-	-	-	-	-	[18]
D213	2020	A1	mRMR (F.S)+ NB	6	77	-	-	-	-	-	[18]
D214	2020	A1	mRMR (F.S)+ SVM(Linear)	6	87	-	-	-	-	-	[18]
D215	2020	A1	Relief (F.S)+ ANN	6	75	-	-	-	-	-	[18]
D216	2020	A1	Relief (F.S)+ DT	6	73	-	-	-	-	-	[18]
D217	2020	A1	Relief (F.S)+ KNN	6	74	-	-	-	-	-	[18]
D218	2020	A1	Relief (F.S)+ LR	6	85	-	-	-	-	-	[18]
D219	2020	A1	Relief (F.S)+ NB	6	76	-	-	-	-	-	[18]
D220	2020	A1	Relief (F.S)+ SVM(Linear)	6	86	-	-	-	-	-	[18]
D221	2020	A1	Relief (F.S)+ SVM(RBF)	6	81	-	-	-	-	-	[18]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D222	2020	A1	Three phase technique based on ANN	13	88.89	-	-	-	-	-	[18]
D223	2020	A6	ABBM + LASSO (F.S)	8	90.75	-	-	-	-	-	[26]
D224	2020	A6	ABBM + Relief (F.S)	7	95.38	-	-	-	-	-	[26]
D225	2020	A6	Adaboost + LASSO (F.S)	8	90.75	-	-	-	-	-	[26]
D226	2020	A6	Adaboost + Relief (F.S)	7	92.85	-	-	-	-	-	[26]
D227	2020	A6	DT + LASSO (F.S)	13	88.6	-	-	-	-	-	[26]
D228	2020	A6	DT + Relief (F.S)	13	89.12	-	-	-	-	-	[26]
D229	2020	A6	GBBM + LASSO (F.S)	8	97.85	-	-	-	-	-	[26]
D230	2020	A6	GBBM + Relief (F.S)	7	98.32	-	-	-	-	-	[26]
D231	2020	A6	KNN + LASSO (F.S)	13	93	-	-	-	-	-	[26]
D232	2020	A6	KNN + LASSO (F.S)	8	93	-	-	-	-	-	[26]
D233	2020	A6	KNN + Relief (F.S)	13	94.11	-	-	-	-	-	[26]
D234	2020	A6	KNN + Relief (F.S)	7	94.11	-	-	-	-	-	[26]
D235	2020	A6	KNNBM + LASSO (F.S)	13	96.6	-	-	-	-	-	[26]
D236	2020	A6	KNNBM + LASSO (F.S)	8	96.6	-	-	-	-	-	[26]
D237	2020	A6	KNNBM + Relief (F.S)	13	90.75	-	-	-	-	-	[26]
D238	2020	A6	KNNBM + Relief (F.S)	7	98.05	-	-	-	-	-	[26]
D239	2020	A6	RFBM + LASSO (F.S)	8	97.65	-	-	-	-	-	[26]
D240	2020	A6	RFBM + Relief (F.S)	7	99.05	-	-	-	-	-	[26]
D241	2020	A20	RFBM + LASSO (F.S)	13	97.65	-	-	-	-	-	[26]
D242	2020	A20	RFBM + Relief (F.S)	13	96.6	-	-	-	-	-	[26]
D243	2020	A21	GB + LASSO (F.S)	13	92.85	-	-	-	-	-	[26]
D244	2020	A21	GB + Relief (F.S)	13	88.65	-	-	-	-	-	[26]
D245	2020	A21	RF + LASSO (F.S)	13	86.97	-	-	-	-	-	[26]
D246	2020	A21	RF + Relief (F.S)	13	97.89	-	-	-	-	-	[26]
D247	2020	A18	GBBM + LASSO (F.S)	13	97.85	-	-	-	-	-	[26]
D248	2020	A18	GBBM + Relief (F.S)	13	98.32	-	-	-	-	-	[26]
D249	2020	A16	DTBM + LASSO (F.S)	8	88.65	-	-	-	-	-	[26]
D250	2020	A16	DTBM + Relief (F.S)	7	90.22	-	-	-	-	-	[26]
D251	2020	A17	Adaboost + LASSO (F.S)	16	90.75	-	-	-	-	-	[26]
D252	2020	A17	Adaboost + Relief (F.S)	16	92.85	-	-	-	-	-	[26]
D253	2020	A47	DTBM + LASSO (F.S)	13	88.65	-	-	-	-	-	[26]
D254	2020	A47	DTBM + Relief (F.S)	13	97.65	-	-	-	-	-	[26]
D255	2020	A40	ABBM + LASSO (F.S)	13	90.75	-	-	-	-	-	[26]
D256	2020	A27	ABBM + Relief (F.S)	13	97.85	-	-	-	-	-	[26]
D257	2020	A27	GB + LASSO (F.S)	8	92.85	-	-	-	-	-	[26]
D258	2020	A27	GB + Relief (F.S)	7	96.22	-	-	-	-	-	[26]
D259	2011	A16	FLBCDSS	13	79.5	80	59.09	-	-	-	[35]
D260	2011	A15	FLBCDSS	13	56.47	62.5	53.76	-	-	-	[35]
D261	2011	A13	FLBCDSS	13	55.99	72.47	30.58	-	-	-	[35]
D262	2013	A1	FFNN + EXP(B)	8	85.2	-	-	-	-	-	[8]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D263	2013	A1	FFNN + PCA (F.E)	8	87.6	-	-	-	-	-	[8]
D264	2013	A1	FFNN +PCA1 (F.E)	7	95.2	-	-	-	-	-	[8]
D265	2013	A1	FFNN +PCA2 (F.E)	10	82.5	-	-	-	-	-	[8]
D266	2013	A1	FFNN +PCA3 (F.E)	7	86.5	-	-	-	-	-	[8]
D267	2013	A1	FFNN +PCA4 (F.E)	7	88.2	-	-	-	-	-	[8]
D268	2014	A6	ANN + IMPA	13	82.8	-	-	-	-	-	[37]
D269	2014	A6	ANN + LVQ	13	85.55	-	-	-	-	-	[37]
D270	2015	A26	ANN + BPSORS-AR (F.S+D.T)	4	74.1	78.3	71	-	-	-	[14]
D271	2015	A26	ANN + CFARS-AR (F.S)	4	81.5	82.6	80.6	-	-	-	[14]
D272	2015	A26	Naive Bayes + BPSORS-AR (F.S+D.T)	4	79.6	87	74.2	-	-	-	[14]
D273	2015	A26	Naive Bayes + CFARS-AR (F.S)	4	85.2	82.6	87.1	-	-	-	[14]
D274	2015	A26	SVM + BPSORS-AR (F.S+D.T)	4	75.9	78.3	74.2	-	-	-	[14]
D275	2015	A26	SVM + CFARS-AR (F.S)	4	81.5	82.6	80.6	-	-	-	[14]
D276	2015	A26	type-2 fuzzy logic system + BPSORS-AR (F.S+D.T)	4	87	93.3	79.2	-	-	-	[14]
D277	2015	A26	type-2 fuzzy logic system + CFARS-AR (F.S)	4	88.3	84.9	93.3	-	-	-	[14]
D278	2015	A25	ANN + BPSORS-AR (F.S+D.T)	4	77	91.3	21.1	-	-	-	[14]
D279	2015	A25	ANN + CFARS-AR (F.S)	3	77	89.3	28.9	-	-	-	[14]
D280	2015	A25	Naive Bayes + BPSORS-AR (F.S+D.T)	4	79.7	100	0	-	-	-	[14]
D281	2015	A25	Naive Bayes + CFARS-AR (F.S)	3	79.7	100	0	-	-	-	[14]
D282	2015	A25	SVM + BPSORS-AR (F.S+D.T)	4	79.7	100	0	-	-	-	[14]
D283	2015	A25	SVM + CFARS-AR (F.S)	3	79.7	100	0	-	-	-	[14]
D284	2015	A25	type-2 fuzzy logic system + BPSORS-AR (F.S+D.T)	4	81.8	84.3	53.3	-	-	-	[14]
D285	2015	A25	type-2 fuzzy logic system + CFARS-AR (F.S)	3	87.2	94.2	68.9	-	-	-	[14]
D286	2015	A1	NNTS (F.S)	3	84.46	-	-	-	-	-	[12]
D287	2016	A5	C4.5 + CFS (F.S) + PSO (F.S)	5	77.9	-	-	-	-	-	[3]
D288	2016	A5	FURIA + CFS (F.S) + PSO (F.S)	5	80.29	-	-	-	-	-	[3]
D289	2016	A5	MLP + CFS (F.S) + PSO (F.S)	5	79.7	-	-	-	-	-	[3]
D290	2016	A5	MLR + CFS (F.S) + PSO (F.S)	5	84.17	-	-	-	-	-	[3]
D291	2017	A32	Ensembled model (Naïve Bayes, AdaBoost, and boosted tree)	13	92.14	92.3	92.15	92.5	97.7	92.4	[34]
D292	2017	A33	Ensembled model (Naïve Bayes, AdaBoost, and boosted tree)	13	87.91	100	90	53.9	96.5	98.9	[34]
D293	2016	A6	IBk with Aprior Algorithm	13	99.19	-	-	-	-	-	[24]
D294	2017	A27	PSO (F.S) + AdaBoost	7	88.89	-	-	-	-	-	[16]
D295	2017	A27	PSO (F.S) + Bagged Tree	7	100	-	-	-	-	-	[16]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D296	2017	A27	PSO (F.S) + Random Forrest	7	90.37	-	-	-	-	-	[16]
D297	2019	A6	Bayes Net + Bagging	13	84.16	-	-	-	-	-	[20]
D298	2019	A6	Bayes Net + Bagging	7	84.82	-	-	-	-	-	[20]
D299	2019	A6	C4.5 + Bagging	13	79.87	-	-	-	-	-	[20]
D300	2019	A6	C4.5 + Bagging	7	82.18	-	-	-	-	-	[20]
D301	2019	A6	C4.5 + Boosting	13	75.9	-	-	-	-	-	[20]
D302	2019	A6	C4.5 + Boosting	13	75.9	-	-	-	-	-	[20]
D303	2019	A6	C4.5 + Boosting	13	75.9	-	-	-	-	-	[20]
D304	2019	A6	C4.5 + Boosting	13	75.9	-	-	-	-	-	[20]
D305	2019	A6	C4.5 + Boosting	13	75.9	-	-	-	-	-	[20]
D306	2019	A6	C4.5 + Boosting	11	79.87	-	-	-	-	-	[20]
D307	2019	A6	C4.5 + Boosting	8	79.21	-	-	-	-	-	[20]
D308	2019	A6	C4.5 + Boosting	9	78.22	-	-	-	-	-	[20]
D309	2019	A6	C4.5 + Boosting	9	77.23	-	-	-	-	-	[20]
D310	2019	A6	C4.5 + Boosting	6	76.57	-	-	-	-	-	[20]
D311	2019	A6	Multilayer Perceptron + Bagging	13	81.52	-	-	-	-	-	[20]
D312	2019	A6	Multilayer Perceptron + Bagging	13	81.52	-	-	-	-	-	[20]
D313	2019	A6	Multilayer Perceptron + Bagging	13	81.52	-	-	-	-	-	[20]
D314	2019	A6	Multilayer Perceptron + Bagging	11	82.18	-	-	-	-	-	[20]
D315	2019	A6	Multilayer Perceptron + Bagging	6	82.18	-	-	-	-	-	[20]
D316	2019	A6	Multilayer Perceptron + Bagging	8	81.85	-	-	-	-	-	[20]
D317	2019	A6	Multilayer Perceptron + Bagging	13	79.54	-	-	-	-	-	[20]
D318	2019	A6	Multilayer Perceptron + Bagging	13	79.54	-	-	-	-	-	[20]
D319	2019	A6	Multilayer Perceptron + Bagging	6	80.86	-	-	-	-	-	[20]
D320	2019	A6	Multilayer Perceptron + Bagging	9	80.53	-	-	-	-	-	[20]
D321	2019	A6	Naïve Bayes + Bagging	13	84.16	-	-	-	-	-	[20]
D322	2019	A6	Naïve Bayes + Bagging	11	84.49	-	-	-	-	-	[20]
D323	2019	A6	Naïve Bayes + Bagging	13	84.16	-	-	-	-	-	[20]
D324	2019	A6	Naïve Bayes + Bagging	11	84.49	-	-	-	-	-	[20]
D325	2019	A6	Random Forest + Bagging	13	80.53	-	-	-	-	-	[20]
D326	2019	A6	Random Forest + Bagging	13	80.53	-	-	-	-	-	[20]
D327	2019	A6	Random Forest + Bagging	11	82.18	-	-	-	-	-	[20]
D328	2019	A6	Random Forest + Bagging	9	81.52	-	-	-	-	-	[20]
D329	2019	A6	Random Forest + Boosting	13	78.88	-	-	-	-	-	[20]
D330	2019	A6	Random Forest + Boosting	13	78.88	-	-	-	-	-	[20]
D331	2019	A6	Random Forest + Boosting	13	78.88	-	-	-	-	-	[20]
D332	2019	A6	Random Forest + Boosting	13	78.88	-	-	-	-	-	[20]
D333	2019	A6	Random Forest + Boosting	11	82.18	-	-	-	-	-	[20]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D334	2019	A6	Random Forest + Boosting	9	80.86	-	-	-	-	-	[20]
D335	2019	A6	Random Forest + Boosting	8	80.86	-	-	-	-	-	[20]
D336	2019	A6	Random Forest + Boosting	9	79.87	-	-	-	-	-	[20]
D337	2019	A6	Decision Tree + PCA (F.E)	13	70	-	-	-	-	-	[4]
D338	2019	A6	Logistic Regression + PCA (F.E)	13	68	-	-	-	-	-	[4]
D339	2019	A6	MLP Classifier + PCA (F.E)	13	69	-	-	-	-	-	[4]
D340	2019	A6	Naïve Bayes + PCA (F.E)	13	68	-	-	-	-	-	[4]
D341	2019	A6	Random Forest + PCA (F.E)	13	84	-	-	-	-	-	[4]
D342	2019	A6	Support Vector Machines + PCA (F.E)	13	55	-	-	-	-	-	[4]
D343	2020	A16	DT + CHI-PCA (F.E)	4	95.5	-	-	90.3	-	93.3	[21]
D344	2020	A16	DT + PCA (F.E)	4	88.8	-	-	88	-	83	[21]
D345	2020	A16	GBT + CHI-PCA (F.E)	4	98.8	-	-	97	-	98.5	[21]
D346	2020	A16	GBT + PCA (F.E)	4	89.7	-	-	87	-	83.3	[21]
D347	2020	A16	LOG + CHI-PCA (F.E)	4	98.8	-	-	100	-	98.2	[21]
D348	2020	A16	LOG + PCA (F.E)	4	94.9	-	-	91.4	-	92.8	[21]
D349	2020	A16	MPC + CHI-PCA (F.E)	4	94	-	-	88.9	-	91.4	[21]
D350	2020	A16	MPC + PCA (F.E)	4	95.5	-	-	92.6	-	92.6	[21]
D351	2020	A16	NB + CHI-PCA (F.E)	4	82.8	-	-	84.4	-	77.1	[21]
D352	2020	A16	NB + PCA (F.E)	4	78	-	-	63.6	-	67.7	[21]
D353	2020	A16	RF + CHI-PCA (F.E)	4	99	-	-	100	-	98.4	[21]
D354	2020	A16	RF + PCA (F.E)	4	93.2	-	-	93.1	-	90	[21]
D355	2020	A12	DT + CHI-PCA (F.E)	5	98.4	-	-	100	-	98.1	[21]
D356	2020	A12	DT + PCA (F.E)	5	73.7	-	-	70.8	-	60.2	[21]
D357	2020	A12	GBT + CHI-PCA (F.E)	5	98.9	-	-	97.3	-	98.6	[21]
D358	2020	A12	GBT + PCA (F.E)	5	74.3	-	-	63.6	-	61.9	[21]
D359	2020	A12	LOG + CHI-PCA (F.E)	5	99.4	-	-	100	-	99.3	[21]
D360	2020	A12	LOG + PCA (F.E)	5	78.6	-	-	71.4	-	70.9	[21]
D361	2020	A12	MPC + CHI-PCA (F.E)	5	88.6	-	-	87.1	-	85.3	[21]
D362	2020	A12	MPC + PCA (F.E)	5	80.5	-	-	74.6	-	73.4	[21]
D363	2020	A12	NB + CHI-PCA (F.E)	5	68.8	-	-	70.8	-	62.1	[21]
D364	2020	A12	NB + PCA (F.E)	5	71.5	-	-	62.7	-	73.2	[21]
D365	2020	A12	RF + CHI-PCA (F.E)	5	99.4	-	-	100	-	99.3	[21]
D366	2020	A12	RF + PCA (F.E)	5	75.1	-	-	66.2	-	68.5	[21]
D367	2020	A13	ChiSqSelector (F.S) + PCA (F.E) and RF	13	98.7	-	-	100	97.1	-	[21]
D368	2020	A13	DT + CHI-PCA (F.E)	4	97.3	-	-	100	-	96	[21]
D369	2020	A13	DT + PCA (F.E)	4	62.8	-	-	57.1	-	61.5	[21]
D370	2020	A13	GBT + CHI-PCA (F.E)	4	96.1	-	-	97.1	-	95.7	[21]
D371	2020	A13	GBT + PCA (F.E)	4	74.7	-	-	59.5	-	65.7	[21]
D372	2020	A13	LOG + CHI-PCA (F.E)	4	97.6	-	-	100	-	97	[21]
D373	2020	A13	LOG + PCA (F.E)	4	73.3	-	-	60	-	67.7	[21]
D374	2020	A13	MPC + CHI-PCA (F.E)	4	92.1	-	-	95.2	-	92	[21]
D375	2020	A13	MPC + PCA (F.E)	4	74	-	-	74.2	-	69.7	[21]
D376	2020	A13	NB + CHI-PCA (F.E)	4	68.4	-	-	65	-	75.7	[21]

CWD Code	Year	Dataset	Classifier with Data pre-processing (CWD)	Number of features used	Accuracy	Sensitivity	Specificity	Precision	AUROC	F1-measure	Ref
D377	2020	A13	RF + CHI-PCA (F.E)	4	98.7	-	-	100	-	98.6	[21]
D378	2020	A13	RF + PCA (F.E)	4	67.9	-	-	77.1	-	66.7	[21]
D379	2020	A6	CART + AB-WAE	13	93	91	-	96	-	93	[33]
D380	2020	A10	CART + AB-WAE	13	91	90	-	92	-	91	[33]
D381	2020	A6	ACONN (F.S)	13	98.79	-	-	98.67	-	-	[27]
D382	2020	A6	BAT-BP	13	97.46	-	-	97.04	-	-	[27]
D383	2020	A6	GA(F.S+.D.T)+CNN	13	98.53	-	-	98.34	-	-	[27]

Accuracy is the quantity intended to be measured, From the Figure 11, we can say that the combinations of classifier with data preprocessing of ANN+PCA (F.E), ANN+χ 2 (F.S), ANN+GA (F.S+.D.T) [39, 42], KNN+SU (F.S+D.T), KNN+GA (F.S+.D.T), NN+PCA (F.E), NN+χ 2 (F.S) [43], PSO (F.S) + Bagged Tree gives [40] the 100% accuracy for different number of features selected in different datasets (A7, A27, A29, and A30). Succeeding to these combinations of classifiers with data preprocessing for A15 dataset ANN+GA (F.S+.D.T), GA(F.S+.D.T)+ ANN gives 99.62% accuracy and LOG + CHI-PCA (F.E), RF + CHI-PCA (F.E) [34] gives the 99.4% accuracy and so on.

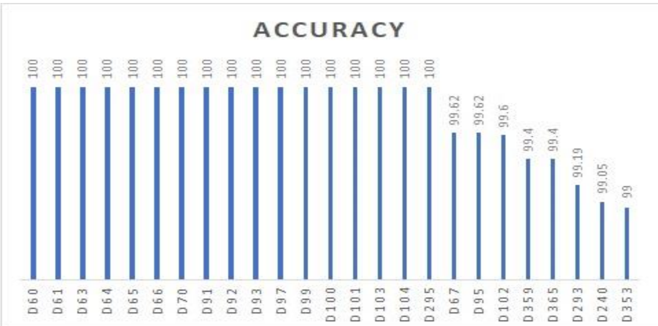

Figure 11. Accuracy of top 25 CWD

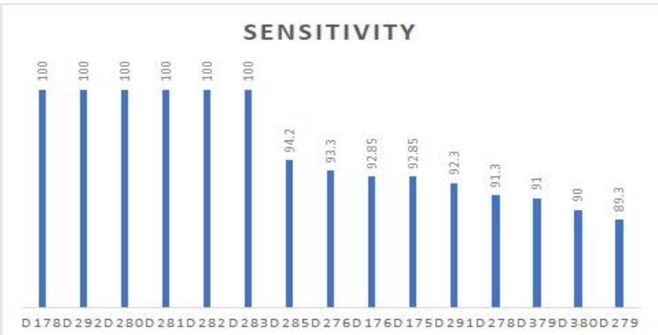

Figure 12. Sensitivity of top 15 CWD

Sensitivity values of different combinations of Classifiers plus Data preprocessing with datasets are shown in Figure 12, From the Figure 12, we can say that the combinations of classifier with data preprocessing of FAMD (F.S) + SVM [26], Ensembled model (Naïve Bayes, AdaBoost, and boosted tree), Naive Bayes + BPSORS-AR (F.S+D.T), Naive Bayes + CFARS-AR (F.S), SVM + BPSORS-AR (F.S+D.T), SVM + CFARS-AR (F.S) gives the 100% sensitivity for different number of features selected in different datasets (A6, A25 and A33). Succeeding to these combinations of classifiers with data preprocessing for A25 dataset type-2 fuzzy logic system + CFARS-AR (F.S) gives the 94.2% sensitivity and followed by type-2 fuzzy logic system + BPSORS-AR (F.S + D.T) [38] gives the 93.3% sensitivity and so on.

In this analysis for the Figure 13, we know that which of the combinations of Classifiers plus Data preprocessing with A6 datasets has good specificity. From the Figure 13, L1 Linear SVM + L2 Linear SVM & RBF SVM gives the 100% specificity. Succeeding to this, Relief (F.S) + LR [26] gives 98% specificity followed by FAMD (F.S) + RF gives 96.96% specificity.

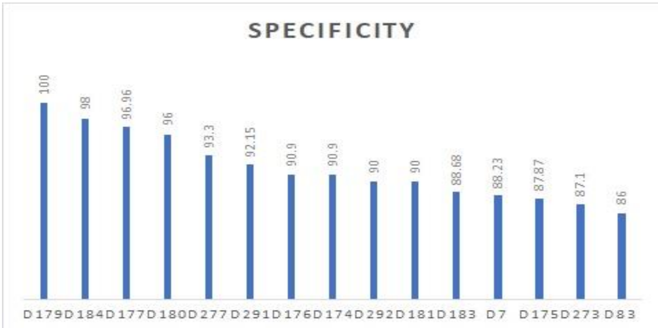

Figure 13. Specificity of top 15 CWD

Precision is the quantity of being exactness, From the Figure 14, we can say that the combinations of classifier with data preprocessing of ChiSqSelector (F.S) + PCA (F.E), RF LOG + CHI-PCA (F.E), RF + CHI-PCA (F.E) and DT + CHI-PCA (F.E) [15] gives the 100% accuracy for different number of features selected in different datasets (A12, A13 and A16). Succeeding to these combinations of classifiers with data preprocessing for A6 dataset ACONN (F.S) [20] gives 98.67% and HDPM gives 98.57% accuracy. For A6 dataset GA(F.S + D.T)+CNN gives the 98.34% followed by GBT + CHI-PCA (F.E) [27] gives 97.3% precision and so on. Figure 14 shows Precision of top 15 CWDs.

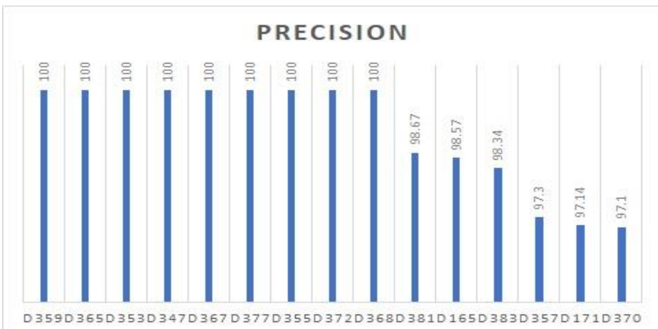

Figure 14. Precision of top 15 CWDs

AUROC values of different combinations of Classifiers plus Data preprocessing with datasets are shown in Figure 15, From the Figure 15, we can say that the combinations of classifier with data preprocessing of Ensembled model (Naïve Bayes, AdaBoost, and boosted tree) [46] gives the highest value of 97.7% for A32 dataset. Succeeding to this combination of classifiers with data preprocessing for A9 dataset ChiSqSelector (F.S) + PCA (F.E) and RF [34] gives the 97.1% AUROC and followed by Ensembled model (Naïve Bayes, AdaBoost, and boosted tree) [46] gives the 96.5% AUROC for A6 dataset and so on.

F1-measure of different combinations of Classifiers plus Data preprocessing with datasets are shown in Figure 16, From the Figure 16, we can say that the combinations of classifier with data preprocessing of LOG + CHI-PCA (F.E) and RF + CHI-PCA (F.E) [34] gives the 99.3% F1-measure for A12 dataset. Succeeding to these combinations of classifiers with data preprocessing for A29 dataset Ensembled model (Naïve Bayes, AdaBoost, and boosted tree) gives 98.9% followed by GBT + CHI-PCA (F.E) and RF + CHI-PCA (F.E) [34] gives the 98.6% F1-measure for A12 and A13 datasets and so on.

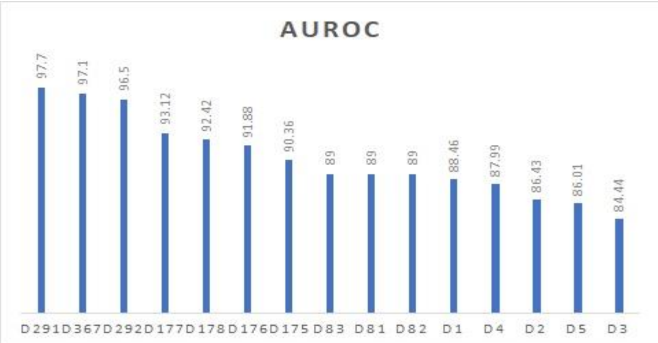

Figure 15. AUROC of top 15 CWDs

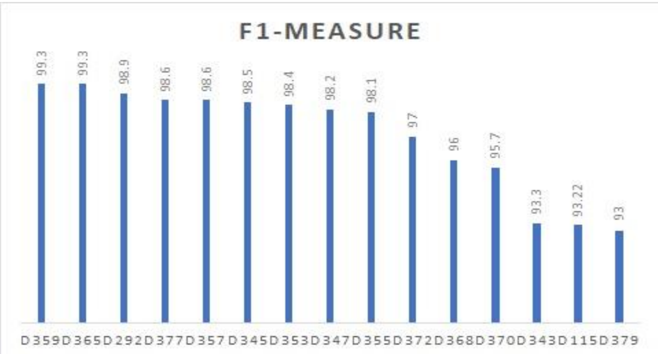

Figure 16. F1-Measure of top 15 CWDs

7. CONCLUSION & FUTURE SCOPE

In this review, we analysed the performance of classifiers and classifier with data preprocessing techniques in HD prediction. A complete of 55 researches published in the period of 2007 and 2020 were pick out through a study investigation. We analysed the picked out researches from five perspectives: the datasets used, the classifiers used, the impact of classifiers on the prediction of HD, the general performance of classifiers when it is utilised with data Preprocessing methods, and the comparison of combos of classifier and data preprocessing in terms of Accuracy, Sensitivity, Specificity, AUROC, F1-measure and Precision.

The following is a summary of the review's principal findings:

What are the datasets largly used for heart disease prediction/classification?

within the prediction of HD several datasets are used. From those datasets two datasets are mostly used those are Cleveland HD dataset and Statlog HD datasets from UCI machine learning respiratory.

Which classifiers were mostly used for heart disease prediction/classification?

When it comes to HD prediction, from the selected studies K-Nearest Neighbors algorithm, Support vector machines, random forest, Logistic Regression and Naive Bayes are the most used Classifiers.

What are the most used prediction methods (classifiers) which gives better performance when combined with data preprocessing methods?

A range of classifiers were utilised to explore the impact of preprocessing procedures on classification performance in HD prediction. The most commonly utilised classification approaches were ANN, KNN, NN, RF, and SVM, which performed well when paired with preprocessing techniques.

Are there any promising combinations of classifier and data preprocessing to properly forecast heart disease?

As a result of the studies, a significant number of combinations were evaluated. ANN+PCA (F.E), ANN+χ 2 (F.S), ANN+GA (F.S + D.T), KNN+SU (F.S + D.T), KNN+GA (F.S + D.T), NN+PCA (F.E), NN+χ 2 (F.S) and PSO (F.S) + Bagged Tree are promising in terms of most of the performance parameters.

Researchers have generally worked to improve models in terms of their accuracy, sensitivity, specificity, precision, F1-Score and area under the receiver operator curve.

We draw the following conclusions from this study that should be considered in future research for high performance and more accurate diagnosis of heart disease utilising smart prediction systems.

Most trials employed a small and identical dataset to train prediction models. As a result, we must collect real data from a big number of heart disease patients from reputable medical organizations in our country and utilise it to train and evaluate our prediction algorithms. The accuracy of our prediction models must next be tested on huge datasets.

It is necessary to create more intricate hybrid models for precise prediction by combining various data mining and machine learning approaches, as well as text mining of the unstructured medical data that is readily available in huge amounts at healthcare centers.

Therefore, Future studies will study hybrid classifier models and ensemble data preparation strategies to better forecast HD.

CONTRIBUTIONS FROM THE AUTHORS

The manuscript was written by all of the authors.

Bala Srinivas Peteti: Concept, design, data collecting and interpretation, evaluation of classifiers and data mining techniques, paper drafting and revision.

Dr. Durgesh Nandan: concept, design, statistical support, data interpretation, and critical revision.

The final manuscript was read and approved by all writers.

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