Article

Ensemble technique to predict heart disease using machine learning classifiers

Aparna Chaurasia[1]**,Vikas Chaurasia**[2]
[1]Research Enthusiastic, India
[2]Department of Computer Applications, MHPGC, VBS Purvanchal University, India
E-mail: aparna3c@gmail.com, chaurasia.vikas@gmail.com

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Abstract
The exact forecast of heart disease is necessary to proficiently treat cardiovascular patients before a heart failure happens. Assuming we talk about AI techniques can be accomplished utilizing an ideal AI model with rich medical services information on heart diseases. To begin with, the feature extraction technique, gradient boosting-based sequential feature selection (GBSFS) is applied to separate the significant number of features (5, 7, 9, and 11) from coronary illness dataset to create important medical services information. The stacking model is prepared for coronary illness forecast. A comparison model is made between datasets with prominent features (5, 7, 9, and 11) as well as all features. The proposed framework is assessed with coronary illness information and contrasted and customary classifiers in view of feature elimination include determination strategies. The proposed framework acquires test accuracy of 98.78%, which is most noteworthy in marking model with 11-featuers and higher than existing frameworks. This outcome shows that our framework is more powerful for the expectation of coronary illness, in contrast with other cutting edge strategies.

Keywords heart disease; feature selection; SFS; stacking model; comparison model; classifiers.

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1 Introduction

Powerful findings and conclusion of coronary illness (HD) are mandatory to forestall human losses (Bowles and Laughlin, 2011). It represents 17,900,000 individuals death from HD in 2019, addressing 32% of every single worldwide demise (Filgueira et al., 2021). In which 85% deaths were because of cardiovascular failure and stroke. The variables that increment an individual's death can be predominantly way of life related components, i.e., age, sex, smoking, family ancestry, cholesterol, horrible eating routine, hypertension, corpulence, actual latency, and liquor. Additionally, it creates with practically no death factors as referenced above, which might prompt a cardiovascular failure without causing any earlier obvious side effects. Subsequently, HD is one of the main diseases with a high death rate, making it one of the confounded reasons to treat. To inspect the dubious indication of HD, specific tests may be expected by a doctor, for example, angiogram, blood test, circulatory strain checking, chest X-rays, electrocardiogram, echocardiogram, and stress tests (Kerkhof et al., 2019). There are different sorts of heart disease, for example, coronary illness, angina pectoris, congestive cardiovascular breakdown, cardiomyopathy, innate coronary illness, arrhythmias, and myocarditis. It is difficult to physically decide the chances of getting coronary illness in view of hazard factors. Thus, numerous scientists these days are requesting more prudent and effective methodologies utilizing AI for diagnosing HD (Smith and Eckroth, 2017). Astute frameworks have been conveyed in clinical-based choice emotionally supportive networks, helping doctors in giving a moment assessment on the identification and analysis of specific sicknesses. Because of the way that HD may be trying to address, mistaken location or postponements in clinical treatment could prompt an unfortunate result or expanded mortality. HD location is reliant upon bunches of factors like family ancestry, age, and orientation, to give some examples by Harris et al. (2011). Besides, it shifts on the discovery strategies utilized and the factors picked. Computerized reasoning and AI strategies have carried another extent to HD recognition and analysis. They have been utilized for finding and uncovering important example from the clinical datasets with a couple of client information sources and endeavors. By its inclination, clinical datasets are questionable and unpredictable; along these lines, it isn't clear to apply AI procedures without a sufficient preprocessing task. Besides, information abnormalities in a clinical dataset are considered to affect the last exhibition of the arrangement model. Consequently, to accomplish the most extreme ability of AI calculations, it is crucial to think about an appropriate information planning strategy (Clark and Toribio, 2012). Besides, a few superfluous elements could debase the presentation of calculations; along these lines, having an information arrangement and component choices are obligatory to acquire the most ideal precision in foreseeing HD. Despite the way that a component determination method is similarly pivotal with the decision of an appropriate strategy, it is as yet not clear on the best way to consolidate AI procedures with a reasonable list of capabilities. The issue portrays us that there exists an open exploration issue in recognizing the value of the list of capabilities and in picking a proper order calculation. Numerous analysts have considered various types of classifiers for anticipating HD, either as individual classifiers or meta classifiers (Korolev et al., 2016). On account of a singular classifier that can't give a beneficial presentation, a meta (e.g., stacking) classifier ought to be obliged to give a huge improvement over individual classifiers. In contrast to single classifiers, meta classifiers train different classifiers to foresee the last expectation result, making them strong and adequate for disease forecast. The decision of joining various classifiers can be either homogeneous or heterogeneous (Korolev et al., 2010). Albeit in numerous other application areas, meta classifiers have shown astounding execution over individual classifiers; picking an assortment of mix strategies and base classifiers stays neglected. In any case, AI methods are helpful to anticipate the result from existing information (Rahman et al., 2022). Subsequently, this paper applies one such AI procedure called SFS with various blends of features as well as stacking model for anticipating coronary illness risk factors (Rahmani et al., 2021). It additionally attempts to work on the exactness of foreseeing coronary illness risk utilizing a stacking model.

2 Related Works

In present, HD expectation strategies have been fabricated and approved on many machine learning repository datasets, which are made out of variables barring angiography. These procedures are less complex, more affordable, replicable, and impartial judgments and can identify naturally and can play out a primer assessment of patients in light of clinical information in medical clinics (Iniesta et al., 2016). In this segment, we sum up AI that utilizations risk factors for training and testing the arrangement models, especially on the datasets accessible on the UCI site. The two-level stacking introduced in this paper is likewise approved on those datasets. Be that as it may, different kinds of techniques, risk factors, and datasets have been proposed for HD analysis.

A notable ensemble learning, to be specific, turn forest with various base classifiers was evaluated (Ozcift and Gulten, 2011). In view of the presentation approval on the Cleveland dataset, turn forest with RBF network as base classifier was the top-performing classifier (Zhang and Bai, 2006). To foster a coronary illness classifier, an information digging calculation was worked for information gathering and for prescient displaying. Thousands of CHD patient records were mined, and the creators utilized a SVM, ANN, and DT for the parallel classification work. The models separately delivered exactnesses of 92.1%, 91%, and 89.6%. Besides, K-folds approval and confusion matrix were utilized to assess the consistency, awareness, and specificity of the information (Lv et al., 2007). Crafted by Muthukaruppan and Er (2012), they introduced a PSO based fuzzy framework for the analysis of CHD. Rules were separated from DT, and they were changed over into fuzzy standards. Having PSO to tune the fuzzy participation work, the fuzzy framework yielded 93.27% precision on the Cleveland dataset. Another information researcher utilized ensemble to increment information consistency and increment information precision. The creator utilized bagging and boosting on Naive Bayes and Multilayer Perceptron Neural Networks. These ensemble procedures expanded the precision by a normal of 7.26% in foreseeing coronary illness. The utilization of SVMs in illness expectation has likewise demonstrated accommodating. Majid Feshki utilized Particle Swarm Optimization (Zhang, 2022) and Feed-Forward Back Propagation brain organizations to streamline highlights. The strategies yielded an exactness of 91.94% (Khazaee, 2013). The capability of a specialist judgment-based highlight determination was investigated in Nahar et al. (2013). Utilizing 10-fold cross validation for assessment, SMO was the best entertainer on the Cleveland dataset. The *k*-means clustering was utilized for highlight extraction from the regular examples that were mined utilizing the MAFIA. Finally, Muhammad et al. (2020) led an exhaustive examination of base classifiers for the forecast for coronary illness. The Extra-Tree Classifier (ETC) demonstrated the best with a precision of 92.09% and AUC of 97.92%. This was trailed by GBC, which had a precision of 91.34%. The concentrate additionally featured the impact of element determination calculations like Lasso and Relief. A work of Alizadehsani et al. (2013) adopted into account a gathering strategy, specifically, Bagging-C4.5, for CHD forecast. The proposed classifier arrived at precision paces of 79.54%, 61.46%, and 68.96% for the determination of the stenoses of the LAD, LCX, and RCA, separately. A basic and dependable FS strategy was proposed to decide the heartbeat case utilizing the WPCA technique. The proposed technique amplified the ECG sign's sufficiency and dispensed with clamors, yielding a precision of 93.19% (Yeh et al., 2016). A dataset gathered from Rajaie Cardiovascular Medical and Research Center, having 54 information highlights and 303 examples, was utilized in the examination. Comparative creators in Alizadehsani et al. (2013) utilized a few AI calculations like Bagging, SMO, NN, and Bayes. The best exactness was accomplished by SMO at 94.08%. A data gain-based include determination was likewise engaged with picking an appropriate list of capabilities. Additionally, Alizadehsani et al. (2016) pointed toward working on the precision in the analysis of the stenosis of each significant coronary supply route. To accomplish this, the creators proposed a component determination to pick more discriminative element subsets for every supply route. In light of their trial, the proposed classifier, e.g., SVM acquired exactness rates at 86.14%, 83.17%, and 83.50% for LAD, LCX, and RCA, individually. Backpropagation strategies (Al-Milli, 2013) assist with contrasting classification correctnesses. The creator conveyed high precision yield from his models. A hybrid approach for CHD analysis in view of the mix of CFS, PSO, and *k*-means clustering was started in Verma et al. (2016). The proposed model is tried on Cleveland and IGMC datasets, having 83.5% and 90.28% exactness, individually. A near investigation (Srinivasaraghavan and Joseph, 2016) of correctness's on coronary illness expectation utilized the NB classifier, SVM, and LR. The most noteworthy exactness, 80%, was yielded by the SVM, portraying its extension in expectation. A review introduced by Qin et al. (2017) integrated different feature selection into the ensemble calculation to check the significance of element determination in the Z-Alizadeh Sani CHD dataset. Besides, Nilashi et al. (2020) displayed that fuzzy SVMs with PCA can accomplish higher correctness at foreseeing coronary illness at a lower componential time, utilizing gradual learning. Weight enhancement of NN by means of the hereditary calculation utilized for coronary illness location was presented in Arabasadi et al. (2017). The proposed classifier was tried on the Z-Alizadeh Sani dataset, getting 93.85%, 97%, and 92% concerning exactness, awareness, and explicitness, individually. ANNs have been utilized in past examination connected with coronary illness forecast. Olaniyi at el. (2015) proposed a three-venture model in view of an ANN to analyze angina, which accomplished a precision of 88.89%. An exploration of Haq et al. (2018) proposed a hybrid FS and LR to coronary illness, while Dwivedi (2018) assessed the presentation of a few AI calculations for coronary illness expectation. LR was accounted for as the best classifier, giving 85% exactness on the Statlog dataset. Das et al. (2009) delivered an ANN ensemble based prescient model, utilizing a factual examination framework. This accomplished a classification exactness of 89.01% and a specificity of 95.91%. Dutta et al. (2020) displayed that their proposed CNN engineering arrived at an exactness of 77% to anticipate coronary illness and anticipated negative cases with higher precision in contrast with conventional strategies, for example, SVMs and RF. Besides, the presentation of supported C5.0 and NN were contrasted with foresee CHD for the Cleveland dataset (Ahmadi at el., 2018). In view of the trial, the creators inferred that there was no massive contrast among C5.0 and NN. Finally, Jabbar et al. (2013) made a multi-facet perceptron ANN-driven back propagation learning calculation and element choice calculation for coronary illness.

All the more as of late, Abdar et al. (2019) laid out another improvement strategy called N2 Genetic analyzer. The nuSVM was then used to group the patients having CHD or not. The proposed location technique was looked at against existing works, yielding exactness at 93.08% on the Z-Alizadeh Sani dataset. To analyze coronary illness, an incorporated decision support clinical framework in view of ANN and Fuzzy Analytical Hierarchical handling was planned by the creators (Samuel et al., 2017). Ensemble engineering utilizing voting was recommended by (Raza, 2019). It consolidated LR, multi-facet perceptron, and innocent Bayes to foresee coronary illness in a patient. Arrangement exactness of 88.88% was accomplished, where it was superior to any singular base classifiers. Ensemble strategies have likewise been identified as accommodating in diagnosing coronary illness (Pandey et al., 2013). Information researchers cross-thought about different clustering strategies like EM, Cobweb, *k*-means, Farthest First, and so on. The best ended up being a thickness based way to deal with diagnosing coronary illness. Additionally, Amin et al. (2019) endeavored to look for the best suitable highlights for CHD analysis. A voting based ensemble of NB and LR was used for preparing the selected highlight subset of 9 elements of the Cleveland dataset. The last prescient exhibition was accomplished by 87.41% concerning 10-CV methodology. The clustering (Ng et al., 2001) has additionally been utilized in a CBIR of cardiovascular models (Bergamasco et al., 2015) to assist with diagnosing congestive heart values. The original model yielded a precision of 83%. Most as of late, Mohan et al. (2019) proposed a hybrid technique for coronary illness forecast in light of the mix of RF with a HRFLM. The proposed technique upgraded the exhibition level with an exactness of 88.7% on the Cleveland dataset.

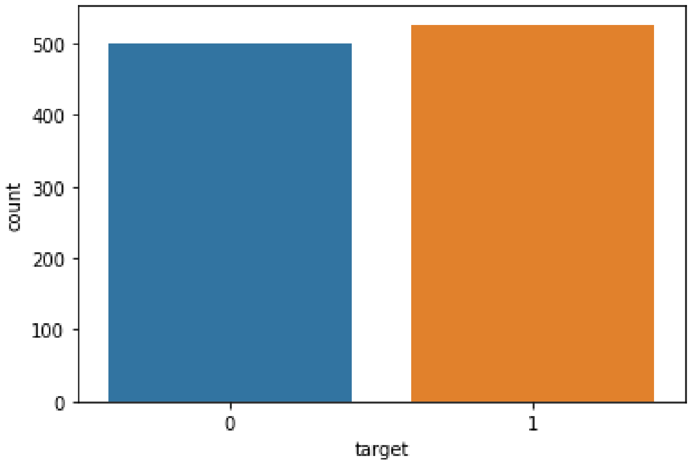
3 Materials and Methodology

This section gives the information about dataset and strategies utilized in our examination. It comprises of insights regarding dataset, a calculated work process of heart disease, include sequential feature selection (Gradient Boosting Classifier), and the classification procedures, i.e., decision tree, random forest, multi-layer perceptron, support vector machine, extra tree, gradient boosting, logistic regression, *k*-nearest neighbor and stacking as a combined decision (Chaurasia and Pal, 2022; Habib et al., 2020; Rahman et al., 2022).

3.1 Heart disease dataset

Dataset considered for heart disease forecast is gotten from commonly available kaggle archive (Kaggle Dataset, Accessed on 2022). The dataset are picked on the grounds that different researchers in this field often use them. This dataset contain 1025 instances and 13 independent features along with 1 dependent feature. It is blend of four data sets: Cleveland, Hungary, Switzerland, and Long Beach V., while Table 1 summarizes dataset's properties.

Table 1 Summary of heart disease dataset.

<table>
<tr><th>Features</th><th>Description</th><th>Range</th><th>Diagnosis</th></tr>
<tr><td>age</td><td>age in years</td><td>29-77</td><td rowspan="14">1 526 (disease)
0 499 (no disease)

</td></tr>
<tr><td>sex</td><td>(1 = male; 0 = female)</td><td>0-1</td></tr>
<tr><td>cp</td><td>chest pain type</td><td>0-3</td></tr>
<tr><td>trestbps</td><td>resting blood pressure (in mm Hg on admission to the hospital)</td><td>94-200</td></tr>
<tr><td>chol</td><td>serum cholestoral in mg/dl</td><td>126-564</td></tr>
<tr><td>fbs</td><td>(fasting blood sugar > 120 mg/dl) (1 = true; 0 = false)</td><td>0-1</td></tr>
<tr><td>restecg</td><td>resting electrocardiographic results</td><td>0-2</td></tr>
<tr><td>thalach</td><td>maximum heart rate achieved</td><td>71-202</td></tr>
<tr><td>exang</td><td>exercise induced angina (1 = yes; 0 = no)</td><td>0-1</td></tr>
<tr><td>oldpeak</td><td>ST depression induced by exercise relative to rest</td><td>0-6.2</td></tr>
<tr><td>slope</td><td>the slope of the peak exercise ST segment</td><td>0-2</td></tr>
<tr><td>ca</td><td>number of major vessels</td><td>0-4</td></tr>
<tr><td>thal</td><td>thal: 0 = normal; 1 = fixed defect; 2 = reversable defect</td><td>0-3</td></tr>
<tr><td>target</td><td>0 = no disease and 1 = disease</td><td>0-1</td></tr>
</table>

3.2 Heart disease detection framework

A calculated system of HD recognition is imagined in Fig. 1. The work process is comprised of three stages, i.e., highlight determination (GBSFS), decreased include features, and classification, stackining model, validation. The primary stage manages the method of definitively deciding a bunch of highlights as the most important for HD discovery within reach (Alfiero et al., 2021). It is completed by utilizing an gradient boosting based highlight determination (GBSFS), where its inquiry technique is streamlined utilizing 5 ('cp', 'trestbps', 'chol', 'oldpeak', 'ca'), 7 ('age', 'sex', 'cp', 'trestbps', 'chol', 'oldpeak', 'ca'), 9 ('age', 'sex', 'cp', 'trestbps', 'chol', 'restecg', 'exang', 'oldpeak', 'ca') and 11 ('age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'exang', 'oldpeak', 'slope', 'ca') noticeable features. The method for include determination is completed in next segment.

In the accompanying stage, model assessment and endorsement is outlined. This stage is answerable for building a model i.e., the variety of a couple of classifiers like DT, RF, MLP, SVM, ET, GBC, LR and K-NN (Chaurasia and Pal, 2021). These classifiers build a stacked model to produce a assumption. According to this development, other individual classifiers can in like manner be considered. We want to benchmark our proposed classifier and the base classifiers that structure the model. Moreover, the point is to find out wheather the particular classifier execution as well as stacking model of classifiers performed well on datasets with 5, 7, 9, 11 or all features. The request assessment and execution relationships presented in section 4 rely upon the gathering computations as referred to already (Theodorakopoulos and Baras, 2006).

At long last, in the last stage, the proposed classification and it is evaluated to stack model. The assessment method is based upon *k*-fold cross validation, where *k* is set to 10. This strategy is otherwise called 10-fold cross validation. Moreover, five execution measures are ordinarily utilized in the imbalanced information issue (Forman and Scholz, 2010). These are accuracy, precision, recall, F1, and area under ROC (AUC). Section 4 presents the trial aftereffects of the article.

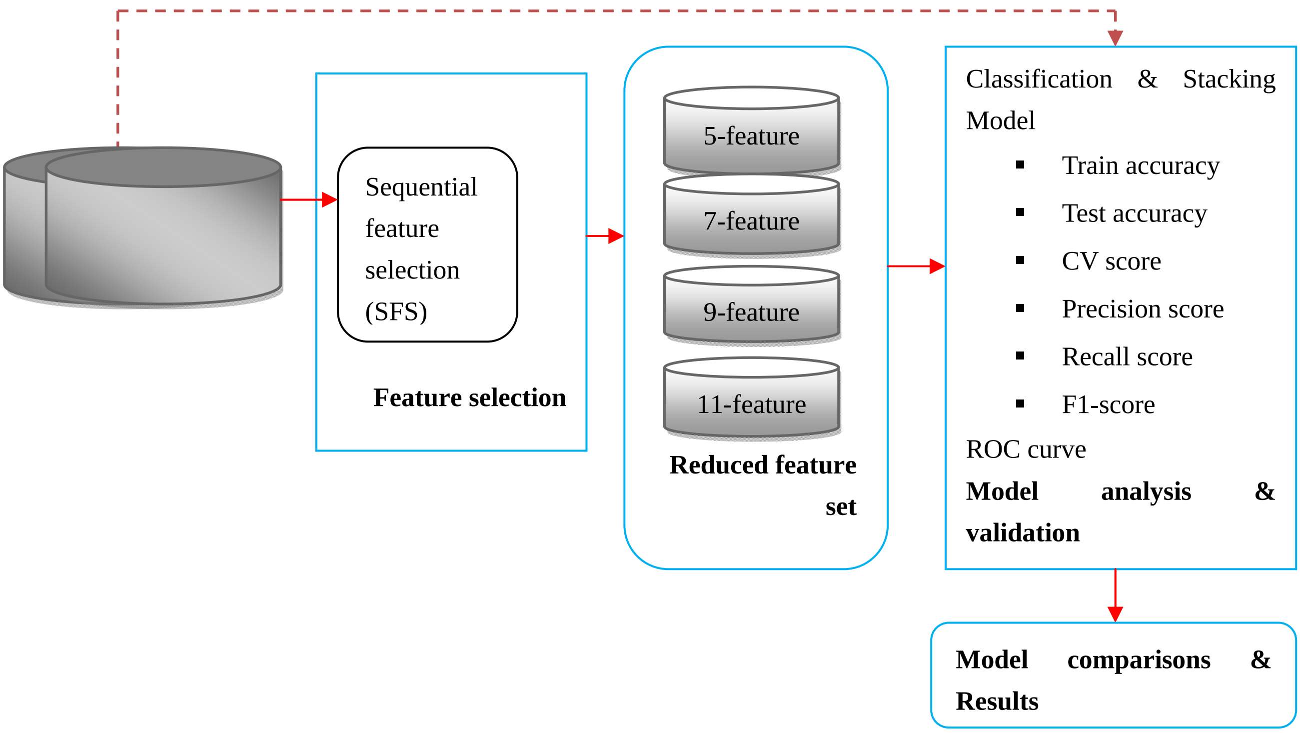


Fig. 1 Theoretical framework of heart disease prediction.

3.3 Feature selection

As we have referenced over, a few immaterial information elements could bring down the classifier's presentation. Henceforth, picking an exact and thorough subset of highlights from a specific arrangement of elements for the forecast task is exceptionally difficult. In this paper, we exploit a slope helping based consecutive component choice (GBSFS) as it is a well known characteristic evaluator for AI. Moreover, much of the time, GBSFS gave tantamount execution to the covering strategy and, as a general rule, outflanked the covering technique on little datasets. It assesses the pertinence of an element subset utilizing data gain and entropy (Li et al., 2019). All the more explicitly, irrelevant and pointless highlights are excluded in this stage. Moreover, we influence (GBSFS) for choosing conspicuous number of elements as 5, 7, 9 and 11. The best list of capabilities is then picked by the most extreme precision of the classifier.

3.4 Classification techniques

The proposed stacking model is based upon a few different classifier, i.e., DT, RF, MLP, SVM, ET, GBC, LR and K-NN. Contrasted with stacking that generally exploit frail individual learners, in this work, we consider stacking of base classifiers. The best learning hyperparameters of each base classifier are acquired utilizing grid search by evaluating every single imaginable worth (Mendez et al., 2019). We momentarily make sense of these base classifiers utilized in this concentrate as follows.

3.4.1 Decision tree (DT)

The design of the DT is like a flowchart, in which each inward focus point tests the quality, each branch estimates the experimental outcomes, and each leaf community estimates the cycle class mark (Lombardo et al., 2021). The way from root to leaf is connected with portrayal rules.

In dynamic examinations, DT and firmly related impact frames are utilized as visual and logical determination help apparatuses to decide the typical advantages of contending decisions. Furthermore, we can utilize the Gini list as a model to part the dataset.

$$Entropy = \sum_{i=1}^{c} -p_i \times log_2(p_i)$$

where, c→No. of classes

$$Gini = 1 - \sum_{i=1}^{c} (p_i)^2$$

3.4.2 Random forest (RF)

RF is a group learning method for requested, recursive, and various undertakings. It works by fostering countless DT in planning time and producing classes as a technique for organizing or recursively anticipating a solitary tree. Erratic choice trees are reasonable for DT and tend to overfit their arrangements (Patro et al., 2021). RF comprises of huge parallel choice trees, yet its exactness is lower than that of angle support trees. By and by, the idea of the data will influence its showcase

$$RFfi_i = \frac{\sum_{j \in all\ trees} normfi_{ij}}{T}$$

where,

$RFfi_i$ = i calculated from all trees in the Random Forest model
$normfi_{ij}$ = normalized feature importance for i in tree j, T= number of trees.

3.4.3 Multilayer perceptron (MLP)

Not at all like polynomials and other fixed pieces, every unit of a brain network has inward boundaries that can be tuned to give it an adaptable shape. A MLP is an organization of straightforward neurons called perceptrons (De Almeida et al., 2015). The perceptron processes a solitary result from numerous genuine esteemed inputs by shaping a direct mix as per its feedback loads and afterward potentially putting the result through some nonlinear actuation work. Numerically this can be composed as

$$y = \varphi(\sum_{i=1}^{n} w_i x_i + b) = \varphi(w^T x + b)$$

where *w* means the vector of loads, *x* is the vector of sources of info, *b* is the inclination and φ is the initiation work.

3.4.4 Support vector machine (SVM)

SVM is a facilitated learning model with related learning computations for examining data for portrayal and repeat checking (Goh et al., 2017). In a gigantic layered space a hyperplane is created by SVM. These hyperplanes or hyperplane sets can be utilized to orchestrate, rehash, or track down peculiarities and other various errands. Instinctually, a good division is finished by a hyperplane, which has the biggest separation from the most as of late pre-arranged data objective of any classification, on the grounds that by and large, the bigger the edge, the lower the classifier's forecast blunder.

The speculative capacity is characterized as

$$\mathrm{h}(\mathrm{x_i}) = \{ \begin{matrix} +1 \text{ if } \mathrm{w.x+b} \geq 0 \\ -1 \text{ if } \mathrm{w.x+b} < 0 \end{matrix}$$

Here, The point above or on the hyperplane will be assigned class +1, and the point under the hyperplane will be named class - 1. Handling the (sensitive edge) SVM classifier amounts to restricting an outpouring of the design

$$[\frac{1}{\mathrm{n}} \sum_{\mathrm{i=1}}^{\mathrm{n}} \max(0, 1 - \mathrm{y_i}(\mathrm{w.x_i} - \mathrm{b}))] + \lambda \, ||\mathrm{w}||^2$$

3.4.5 Extra tree (ET)

ET is an outfit AI calculation that joins the forecasts from numerous DT (Indra, 2021). It is connected with the generally utilized RF calculation. It can frequently accomplish as-great or preferred execution over the RF calculation, despite the fact that it utilizes a less difficult calculation to build the DT utilized as individuals from the gathering. It is likewise simple to utilize given that it has not many key hyperparameters and reasonable heuristics for arranging these hyperparameters.

3.4.6 Gradient boosting (GBC)

GBC helping is an AI program for overt repetitiveness and change issues. It fills in as a bunch of earlier models and DT to frame a speculative model. Like other trend setting innovations, it fosters the model in a staged, unmistakable style and sums up the model by permitting improvements on discretionary works (Ramakrishnan, 2018).

For the time being, let us consider a slope helping computation with M stages. The incline of each stage is expanded by m (1 <= m <= M), it is flawed to expect that the model Fm. To further develop Fm, some new assessor's hm(x) ought to be added to our computations. In this manner,

$$F_{m+1}(x) = F_m(x) + h_m(x) = y$$

or,

$$h_m(x) = y - F_m(x)$$

3.4.7 Logistic regression (LR)

LR or logit models are utilized to demonstrate the chance of a specific class or capacity (Greene and Hensher, 2003). A few useful classes can be extended to show. The likelihood of each article recognized in the image will be diminished to a worth somewhere in the range of 0 and 1, and the number will be 1.

Consider a model with two markers x_1 and x_2 and an equal reaction variable Y, we mean p = P (Y = 1). We acknowledge the immediate connection between the file factor and the log opportunity of the capacity Y = 1.

This immediate relationship can be written in the going with advanced structure.

Among them, l is the logarithmic opportunity, b is the foundation of the logarithm, and β_i is the limit of the model

$$l = \log_b \frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \beta_2 x_2$$

3.4.8 K-nearest neighbour (K-NN)

K-NN is a non-parametric technique for succession and repeat. In the two cases, the data incorporates the k-nearest neighbour models in the creation space. K-NN is a sort of event based learning or slow execution, in which the capacity is just approximated locally, and all estimations are held until the work assessment (Haworth and Cheng, 2012). Since this computation relies upon the partition of ensemble, normalizing arrangement data can incredibly further develop its exactness.

Whether it is portrayal or repeat, a helpful strategy can be to disseminate the heap to neighbors' guarantees so the nearer neighbors offer more ordinary types of assistance than the more difficult to reach neighbors.

Following distance work are utilized to assess K-NN

$$\sqrt{\sum_{i=1}^{k} (x_i - y_i)^2} \quad \text{Euclidean function}$$

$$\sum_{i=1}^{k} |x_i - y_i| \quad \text{Manhattan Function}$$

$$\left(\sum_{i=1}^{k} (|x_i - y_i|)^q \right)^{1/q} \quad \text{Minkowski Function}$$

3.5 Stacking of classifiers

For working on the presentation of the classifiers it is utilized to stack or stacked speculation. It is an ensemble AI calculation. It utilizes a meta-learning calculation to figure out how to best join the expectations from at least two base AI calculations (Jiang et al., 2021). The advantage of stacking is that it can bridle the capacities of a scope of well-performing models on an order or relapse undertaking and cause forecasts that to have preferable execution over any single model in the ensemble.

4 Results

In this part, the aftereffects of all trials are talked about. We first and foremost present the consequences of component choice, trailed by a characterization investigation of GBSFS discovery. Eventually, this segment benchmarks the proposed approach with existing ones. All examinations were performed on a Window machine, 64 GB memory, and Intel processor. We utilized an open-source information mining device, Python, for arrangement process for the HD detection model was carried out.

4.1 Results based on feature selection

We, most importantly, talk about the examination of picking the best list of features by utilizing gradient boosting based sequential feature selection. Different conspicuous elements selcted by GBSFS are portrayed in Table 2. The outcomes for the prescient accuracy of the classifiers are introduced in Fig. 2. Obviously in the vast majority of cases the test accuracy of the classifiers (RF, MLP, SVC, ET, GBC, LR and K-NN) have the most noteworthy accuracy with all elements while in only one case with DT classifier, the test accuracy is higher with 5-features. All of all the stacking classifier is best with every number of features for example 5, 7, 9, 11 all. It likewise has been seen from Table 2 and Fig. 2, the general accuracy of the stacking classifier is high with 11-features i.e. 98.78%.

Table 2 Number of selected features for HD dataset w.r.t. different number of features.

Model	No. of Features	Train_accuracy	Test_accuracy	CV_score	Precision_score	Recall_score	F1_score
DT	5	0.9036	0.8804	0.8621	0.7614	0.8829	0.8177
	7	0.9207	0.878	0.8658	0.7941	0.8617	0.8265
	9	0.9195	0.8719	0.8682	0.8018	0.9042	0.85
	11	0.9195	0.8695	0.8707	0.8018	0.9042	0.85
	All	0.9292	0.878	0.8731	0.7203	0.9042	0.8018
RF	5	0.9951	0.9597	0.9609	0.9019	0.9787	0.9387
	7	0.9987	0.9743	0.9609	0.9791	100	0.9894
	9	0.9975	0.9634	0.9658	0.9494	100	0.974
	11	0.9987	0.967	0.9707	100	0.968	0.9837
	All	100	0.9804	0.9743	0.969	100	0.9842
MLP	5	0.4731	0.5268	0.5268	0.54	100	0.7
	7	0.5268	0.5268	0.5268	0.4585	100	0.6287
	9	0.5268	0.5268	0.5268	0.4585	100	0.6287
	11	0.5268	0.5268	0.5268	0.4585	100	0.6287
	All	0.5268	0.5268	0.5268	0.4585	100	0.6287
SVC	5	100	0.9743	0.9768	0.9845	0.9864	0.9852
	7	100	0.9768	0.9768	0.9845	0.9864	0.9852
	9	100	0.9768	0.9768	0.9845	0.9864	0.9852
	11	100	0.9768	0.9768	0.9845	0.9864	0.9852
	All	100	0.9768	0.9768	0.9845	0.9864	0.9852
ET	5	0.8487	0.839	0.8426	0.7043	0.8617	0.7751
	7	0.828	0.8219	0.8256	0.7192	0.8723	0.7884
	9	0.8646	0.8536	0.8621	0.7391	0.9042	0.8133

	11	0.8573	0.8426	0.839	0.7272	0.9361	0.8186
	All	0.8756	0.8719	0.8719	0.7798	0.9042	0.8374
GBC	5	0.8792	0.8634	0.8658	0.7407	0.851	0.792
	7	0.8987	0.8817	0.8804	0.75	0.8617	0.8019
	9	0.9024	0.8804	0.8829	0.7543	0.9148	0.8269
	11	0.9048	0.8817	0.889	0.787	0.9042	0.8415
	All	0.917	0.8902	0.8963	0.7876	0.9468	0.8599
LR	5	0.8414	0.8256	0.8365	0.7102	0.8085	0.7562
	7	0.8414	0.8304	0.8365	0.6991	0.8404	0.7632
	9	0.8451	0.8524	0.8475	0.79	0.8404	0.8144
	11	0.8414	0.8341	0.8414	0.7452	0.8404	0.79
	All	0.8719	0.8621	0.8646	0.7456	0.9042	0.8173
KNN	5	0.767	0.7012	0.6987	0.663	0.6489	0.6559
	7	0.7378	0.6634	0.6597	0.6804	0.7021	0.691
	9	0.7414	0.6646	0.6621	0.66	0.7021	0.6804
	11	0.7475	0.667	0.6658	0.6666	0.7021	0.7021
	All	0.7804	0.7134	0.7036	0.6956	0.6808	0.6881
Stacking	5	100	0.9804	0.9817	0.969	100	0.9842
	7	100	0.9804	0.9865	0.969	100	0.9842
	9	100	0.9841	0.9865	0.969	100	0.9842
	11	100	0.9878	0.9853	0.969	100	0.9842
	All	100	0.9829	0.9878	0.969	100	0.9842

Here, different measurements like cv-score, precision, recall and f1-measure have their significance. The higher worth of these measurements are with the stacking classifier with 11-features. Fig. 2 address the test accuracy of the classifiers. The few classifiers with 5, 7, 9, 11 and all features shows their test accuacy. Generally speaking stacking classifier has the accuracy 98.04% with 5 and 7-features , 98.41% with 9-features, 98.78% with 11-features and 98.29% accuracy with all features.

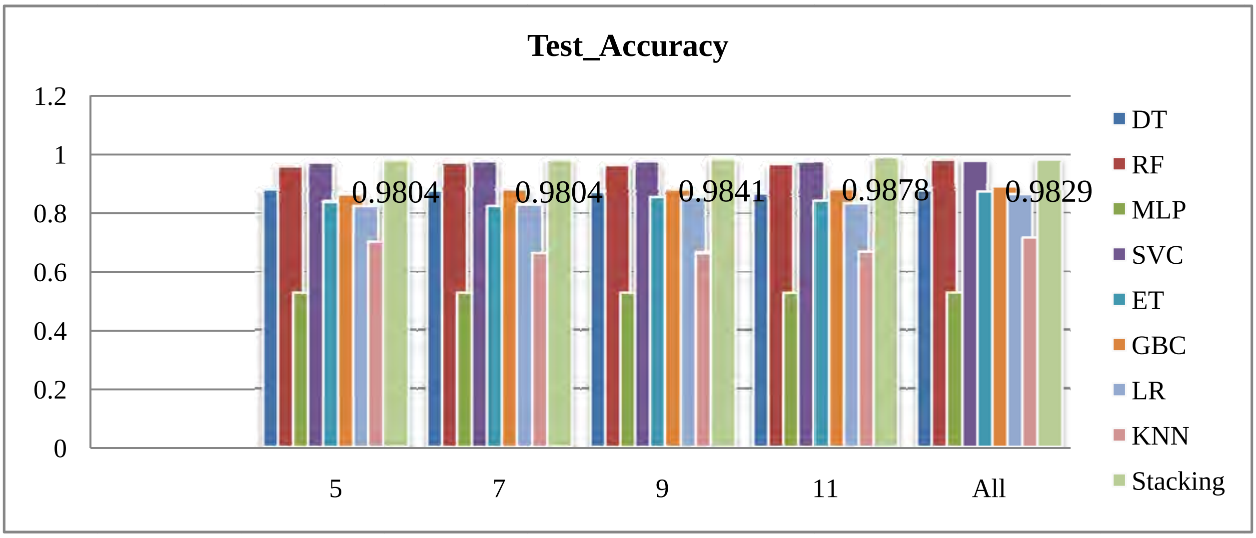


Fig. 2 Comparision of test accuracy of the classifiers.

4.2 ROC (AUC) curve

AUC-ROC curve is a presentation estimation for the grouping issues at different edge settings. ROC is a likelihood curve and AUC addresses the degree or proportion of distinctness. It tells how much the model is equipped for recognizing classes. The higher the AUC, the better the model is at recognizing patients with the sickness and no illness (Fig. 3). The ROC curve is plotted with TPR against the FPR where TPR is on the y-pivot and FPR is on the x-pivot. An astounding model has AUC close to the 1 which implies it has a decent proportion of distinctness. An unfortunate model has an AUC close to 0 which implies it has the most obviously terrible proportion of detachability. It implies it is responding the outcome, as a matter of fact. It is foreseeing 0s as 1s and 1s as 0s. What's more, when AUC is 0.5, it implies the model has no class detachment limit at all. In Fig. 3, DT, RF, SVC, ET, GBC, LR and stacking classifier has the 1 which implies that it has great proportion of distinctness in comparision to MLP and K-NN.

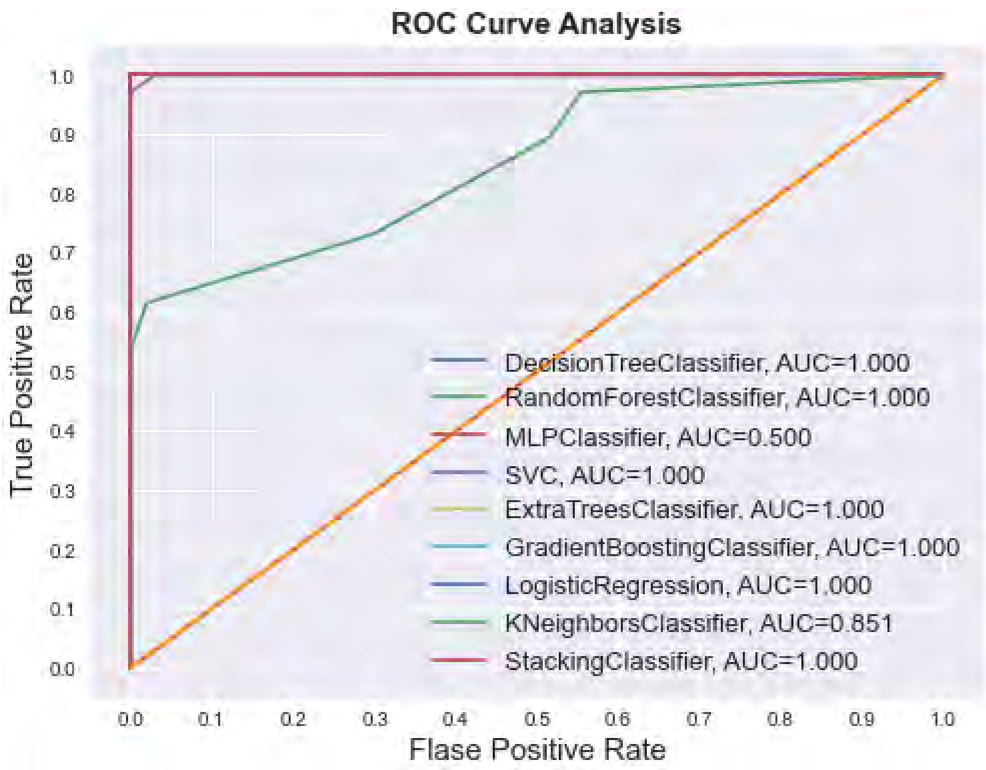


Fig. 3 ROC (AUC) curve of different classifiers.

5 Discussion

Momentum research primarily centers upon customary classifiers. This review helps exhibit how stacking and GBCSFS are powerful and more solid techniques than the ones at present being tried. On a concentrate on the HD dataset, the stacking classifier with 11-features was viewed as the most effective. As displayed in Table 2, the stacking classifier with 11-features ended up being the best in our concentrate also with exactness of 98.78%. Past examinations have likewise displayed how stacking models are more compelling to their conventional partners, which is obviously displayed in the outcomes yielded by this concentrate also. A few investigations that involved stacking methods for expectation of coronary illness support the way that stacking model with 11-features beats base classifiers altogether. The stacked model utilized beat the base classifiers for every measurement assessed in this concentrate too. This included support vector machine and random forest. This study investigates stacking as customary techniques for the expectation of coronary illness in patients. As displayed in the outcomes, stacking of models demonstrated to have the most elevated accuracy when contrasted with base-classifiers. This strategy for feature selection (GBSFS) with stacking model has not been investigated broadly in past writing connected with anticipating coronary illness. Albeit past examinations furnish models with more prominent exactnesses, their datasets are fundamentally more modest than the one investigated in this review. This renders most past models unreasonable with genuine information. In any case, the proposed model arranges with a huge dataset, making the proposed model more reasonable, effective, and strong.

6 Conclusions

In this review, we proposed a better location model of heart disease (HD) in light of an angle supporting based successive component determination and stacking model with a few base learning classifiers. The proposed technique was worked by the stacking model considering on various capabilities, like the 5, 7, 9, 11 and all elements. The proposed location model was tried on openly accessible dataset to give a fair benchmark against existing examinations. We additionally directed CV-score, accuracy, review and f1-score to assess the presentation importance among benchmarked classifiers, where it right now needs the ongoing writing. In light of the exploratory outcomes, our proposed model had the option to outflank cutting edge HD recognition techniques as for exactness and AUC esteem. The outcomes mirrored the most elevated outcome got so far applied to those previously mentioned datasets.

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References

Abdar M, Książek W, Acharya UR, Tan RS, Makarenkov V, Pławiak P. 2019. A new machine learning technique for an accurate diagnosis of coronary artery disease. Computer Methods and Programs in Biomedicine, 179: 104992

Ahmadi E, Weckman GR, Masel DT. 2018. Decision making model to predict presence of coronary artery disease using neural network and C5.0 decision tree. Journal of Ambient Intelligence and Humanized Computing, 9(4): 999-1011

Alfiero S, Brescia V, Bert F. 2021. Intellectual capital-based performance improvement: a study in healthcare sector. BMC Health Services Research, 21(1): 1-15

Alizadehsani R, Habibi J, Hosseini MJ, Mashayekhi H, Boghrati R, Ghandeharioun A, Sani ZA. 2013. A data mining approach for diagnosis of coronary artery disease. Computer Methods and Programs in Biomedicine, 111(1): 52-61

Alizadehsani R, Habibi J, Sani ZA, Mashayekhi H, Boghrati R, Ghandeharioun A, ..., Alizadeh-Sani F. 2013. Diagnosing coronary artery disease via data mining algorithms by considering laboratory and echocardiography features. Research in Cardiovascular Medicine, 2(3): 133

Alizadehsani R, Zangooei MH, Hosseini MJ, Habibi J, Khosravi A, Roshanzamir M, ..., Nahavandi S. 2016. Coronary artery disease detection using computational intelligence methods. Knowledge-Based Systems, 109: 187-197

Al-Milli N. 2013. Backpropogation neural network for prediction of heart disease. Journal of theoretical and applied information Technology, 56(1): 131-135

Amin MS, Chiam YK, Varathan KD. 2019. Identification of significant features and data mining techniques in predicting heart disease. Telematics and Informatics, 36: 82-93

Arabasadi, Z, Alizadehsani R, Roshanzamir M, Moosaei H, Yarifard AA. 2017. Computer aided decision making for heart disease detection using hybrid neural network-Genetic algorithm. Computer Methods and Programs in Biomedicine, 141, 19-26

Bergamasco LC, Oliveira, R A, Wechsler H, Dajuda C, Delamaro M, Nunes FL. 2015. Content-based image retrieval of 3d cardiac models to aid the diagnosis of congestive heart failure by using spectral clustering. In 2015 IEEE 28th International Symposium on Computer-Based Medical Systems. 183-186, IEEE

Bhaskaran S, Paramananda S, Ramnarayan M. 2010. Per-pixel and object-orented classification methods for mapping urban features using Ikonos satellite data. Applied Geography, 30(4): 650-665

Bowles DK, Laughlin MH. 2011. Mechanism of beneficial effects of physical activity on atherosclerosis and coronary heart disease. Journal of applied physiology, 111(1): 308-310

Chaurasia V, Pal S. 2021. Ensemble technique to predict breast cancer on multiple datasets. Computer Journal https://doi.org/10.1093/comjnl/bxab110

Chaurasia, V, Pal S. 2022. An ensemble framework-stacking and feature selection technique for detection of breast cancer. International Journal of Medical Engineering and Informatics, 14(3): 240-251

Clark A, Toribio J. 2012. Magic words: how language augments hum an computation. In: Language and Meaning in Cognitive Science. 33-51, Routledge, USA

Das R, Turkoglu I, Sengur A. 2009. Effective diagnosis of heart disease through neural networks ensembles. Expert systems with applications, 36(4): 7675-7680

De Almeida LF, Bizarria JW, Bizarria FC, Mathias MH. 2015. Condition-based monitoring system for rolling element bearing using a generic multi-layer perceptron. Journal of Vibration and Control, 21(16): 3456-3464

Dutta A, Batabyal T, Basu M, Acton ST. 2020. An efficient convolutional neural network for coronary heart disease prediction. Expert Systems with Applications, 159: 113408

Dwivedi AK. 2018. Performance evaluation of different machine learning techniques for prediction of heart disease. Neural Computing and Applications, 29(10): 685-693

Filgueira TO, Castoldi A, Santos LER, de Amorim GJ, de Sousa Fernandes MS, Anastácio WDL, ..., Souto FO. 2021. The relevance of a physical active lifestyle and physical fitness on immune defense: mitigating disease burden, with focus on COVID-19 consequences. Frontiers in Immunology, 12: 150

Forman G, Scholz M. 2010. Apples-to-apples in cross-validation studies: pitfalls in classifier performance measurement. ACM Sigkdd Explorations Newsletter, 12(1): 49-57

Goh GB, Hodas NO, Vishnu A. 2017. Deep learning for computational chemistry. Journal of computational chemistry, 38(16): 1291-1307

Greene WH, Hensher DA. 2003. A latent class model for discrete choice analysis: contrasts with mixed logit. Transportation Research Part B: Methodological, 37(8): 681-698

Habib N, Hasan M, Rahman MM. 2020. Fusion of Deep Convolutional Neural Network with PCA and Logistic Regression for diagnosis of pediatric pneumonia on chest X-Rays. Network Biology, 10(3): 62-76

Haq AU, Li JP, Memon MH, Nazir S, Sun R. 2018. A hybrid intelligent system framework for the prediction of heart disease using machine learning algorithms. Mobile Information Systems, 2018

Harris JC, Hrmova M, Lopato S, Langridge P. 2011. Modulation of plant growth by HD-Zip class I and II transcription factors in response to environmental stimuli. New Phytologist, 190(4): 823-837

Haworth J, Cheng T. 2012. Non-parametric regression for space–time forecasting under missing data. Computers, Environment and Urban Systems, 36(6): 538-550

https://www.kaggle.com/datasets/johnsmith88/heart-disease-dataset?select=heart.csv (Access on 13/05/2022)

Indra G. 2021. Applicability of svmnarx for prediction alayis of flood in humid and semi-humid regions. Annals of the Romanian Society for Cell Biology, 25(6): 6282-6293

Iniesta R, Stahl D, McGuffin P. 2016. Machine learning, statistical learning and the future of biological research in psychiatry. Psychological medicine, 46(12): 2455-2465

Jabbar M. A, Deekshatulu BL, Chandra P. 2013. Classification of heart disease using artificial neural network and feature subset selection. Global Journal of Computer Science and Technology Neural Artificial Intelligence, 13(3): 4-8

Jiang T, Li JP, Haq AU, Saboor A, Ali A. 2021. A novel stacking approach for accurate detection of fake news. IEEE Access, 9: 22626-22639

Kerkhof PL, Peace RA, Handly, N. 2019. Ratiology and a complementary class of metrics for cardiovascular investigations. Physiology, 34(4): 250-263

Khazaee A. 2013. Heart beat classification using particle swarm optimization. International Journal of Intelligent Systems and Applications, 5(6): 25

Korolev IO, Symonds LL, Bozoki AC, Alzheimer's Disease Neuroimaging Initiative. 2016. Predicting progression from mild cognitive impairment to Alzheimer's dementia using clinical, MRI, and plasma biomarkers via probabilistic pattern classification. PloS one, 11(2): e0138866

Li Y, Lin S, Zhang B, Liu J, Doermann D, Wu Y, ..., Ji R. 2019. Exploiting kernel sparsity and entropy for interpretable CNN compression. In: Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2800-2809

Lombardo T, Duquesnoy M, El-Bouysidy H, Årén F, Gallo-Bueno A, Jørgensen PB, ..., Franco AA. 2021. Artificial intelligence applied to battery research: hype or reality? Chemical Reviews, 2021

Lv J, Zhang X, Han X, Fu Y. 2007. A novel adaptively dynamic tuning of the contention window (CW) for distributed coordination function in IEEE 802.11 ad hoc networks. In: 2007 International Conference on Convergence Information Technology (ICCIT 2007). 290-294, IEEE

Mendez, KM, Reinke SN, Broadhurst DI. 2019. A comparative evaluation of the generalised predictive ability of eight machine learning algorithms across ten clinical metabolomics data sets for binary classification. Metabolomics, 15(12): 1-15

Mohan S, Thirumalai C, Srivastava G. 2019. Effective heart disease prediction using hybrid machine learning techniques. IEEE Access, 7: 81542-81554

Muhammad Y, Tahir M, Hayat M, Chong KT. 2020. Early and accurate detection and diagnosis of heart disease using intelligent computational model. Scientific Reports, 10(1): 1-17

Muthukaruppan S, Er MJ. 2012. A hybrid particle swarm optimization based fuzzy expert system for the diagnosis of coronary artery disease. Expert Systems with Applications, 39(14): 11657-11665

Nahar J, Imam T, Tickle KS, Chen YPP. 2013. Computational intelligence for heart disease diagnosis: A medical knowledge driven approach. Expert systems with applications, 40(1): 96-104

Ng A, Jordan M, Weis, Y. 2001. On spectral clustering: Analysis and an algorithm. Advances in Neural Information Processing Systems, 14

Nilashi M, Ahmadi H, Manaf AA, Rashid TA, Samad S, Shahmoradi L, ..., Akbari E. 2020. Coronary heart disease diagnosis through self-organizing map and fuzzy support vector machine with incremental updates. International Journal of Fuzzy Systems, 22(4): 1376-1388

Olaniyi EO, Oyedotun OK, Adnan,K. 2015. Heart diseases diagnosis using neural networks arbitration. International Journal of Intelligent Systems Applications, 7(12)

Ozcift A, Gulten A. 2011. Classifier ensemble construction with rotation forest to improve medical diagnosis performance of machine learning algorithms. Computer methods and programs in biomedicine, 104(3): 443-451

Pandey AK, Pandey P, Jaiswal KL, Sen AK. 2013. Datamining clustering techniques in the prediction of heart disease using attribute selection method. International Journal of Science, Engineering and Technology Research, 2013

Patro SP, Padhy N, Chiranjevi D. 2021. Ambient assisted living predictive model for cardiovascular disease prediction using supervised learning. Evolutionary Intelligence, 14(2): 941-969

Qin CJ, Guan Q, Wang XP. 2017. Application of ensemble algorithm integrating multiple criteria feature selection in coronary heart disease detection. Biomedical Engineering: Applications, Basis and Communications, 29(6): 1750043

Rahmani AM, Yousefpoor E, Yousefpoor MS, Mehmood Z, Haider A, Hosseinzadeh M, Ali Naqvi R. 2021. Machine Learning (ML) in medicine: Review, applications, and challenges. Mathematics, 9(22): 2970

Rahman M, Rana MR, et al. 2022. A web-based heart disease prediction system using machine learning algorithms. Network Biology, 12(2): 64-81

Ramakrishnan S. 2018. Cryptographic and Information Security Approaches for Images and Videos. CRC Press, USA

Raza K. 2019. Improving the prediction accuracy of heart disease with ensemble learning and majority voting rule. In: U-Healthcare Monitoring Systems. 179-196, Academic Press, USA

Samuel OW, Asogbon GM, Sangaiah AK, Fang P, Li G. 2017. An integrated decision support system based on ANN and Fuzzy_AHP for heart failure risk prediction. Expert Systems with Applications, 68: 163-172

Smith RG, Eckroth, J. 2017. Building AI applications: Yesterday, today, and tomorrow. AI Magazine, 38(1): 6-22

Srinivasaraghavan Anuradha, Joseph Vincy. 2016. Comparative analysis of accuracy on heart disease prediction using classifcation methods. International Journal of Applied Information Systems, 11: 22-25

Theodorakopoulos G, Baras JS. 2006. On trust models and trust evaluation metrics for ad hoc networks. IEEE Journal on Selected Areas in Communications, 24(2): 318-328

Verma L, Srivastava S, Negi PC. 2016. A hybrid data mining model to predict coronary artery disease cases using non-invasive clinical data. Journal of Medical Systems, 40(7): 1-7

Yeh YC, Chen CW, Chiou CW, Chu TY. 2016. A reliable feature selection algorithm for determining heartbeat case using weighted principal component analysis. In: 2016 International Conference on System Science and Engineering (ICSSE). 1-4, IEEE

Zhang WJ. 2022. Particle swarm optimization: A Matlab algorithm. Selforganizology, 9(3-4): 35-41

Zhang WJ, Barrion AT. 2006. Function approximation and documentation of sampling data using artificial neural networks. Environmental Monitoring and Assessment, 122: 185-201