

Computational Comparative Review-Driven Analysis on Machine Learning Classifiers for Heart Disease Detection

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Abstract

The accurate prediction of heart disease is essential for timely diagnosis and effective clinical intervention. Advances in machine learning have facilitated the development of predictive models that employ both conventional classifiers and advanced hybrid or deep learning frameworks. This study selects a total of 39 research papers published between 1 January 2008 and 31 December 2025 for the computational comparative review of machine learning models for myocardial infarction and heart disease through their classifiers, feature selection methods, data preprocessing techniques, and optimization strategies. Support Vector Machines, Random Forests, and Artificial Neural Networks have emerged as the most effective individual classifiers, whereas hybrid and ensemble approaches consistently deliver superior accuracy, sensitivity, and robustness. Feature selection techniques, including Particle Swarm Optimization, Genetic Algorithms, Recursive Feature Elimination, and Relief, in conjunction with data balancing methods such as Synthetic Minority Over-sampling Technique, are critical for enhancing predictive performance, albeit with increased computational demands. Deep learning architectures, notably Convolutional Neural Networks (CNN) and Multiple Feature Branch CNN, demonstrate exceptional predictive capability, frequently achieving accuracies above 98%, particularly on real-world clinical datasets. Integrating optimized feature selection, balanced data handling, and advanced classifiers represents the most effective strategy for constructing reliable, high-performance heart disease prediction systems, underscoring future directions in precision healthcare and clinical decision support.

Categories: Machine Learning (ML), Medical Expert systems, Medical recommender system

Keywords: heart disease prediction, machine learning, hybrid models, ensemble learning, deep learning, feature selection, data balancing, support vector machine, neural networks, clinical datasets

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Introduction And Background

In modern society, people are often preoccupied with their personal and professional commitments, leading to insufficient time to prioritize their health. Individuals experience anxiety, depression, unhappiness, and various other disorders due to neglecting their health amid hectic lifestyles. This oversight results in numerous health issues and hazardous conditions. Cancer, heart disease, and tuberculosis significantly impact annual mortality rates. Heart disease represents the primary cause of mortality within the medical field [1,2].

The heart is a vital organ of the human body that functions continuously throughout an individual's lifetime. It plays a critical role in sustaining physiological activities by circulating blood, oxygen, and essential nutrients to various organs and tissues. The body's other organs may also cease to function efficiently if the heart is not working properly. Thus, maintaining overall organ function depends on heart health. Furthermore, the incidence of cardiovascular diseases increases among individuals as a result of hectic lifestyles and unhealthy dietary practices [2,3]. Figure 1 shows the characteristics and structure of the human heart [4].

Machine learning (ML) represents a systematic approach for identifying patterns in extensive datasets and deriving significant information or insights. The application of ML primarily involves forecasting future trends and behaviors by examining existing results and patterns. ML methodologies can be utilized to create a decision support system aimed at detecting heart disease through the efficient and cost-effective use of clinical data. This decision-making framework can assist medical professionals in achieving an early diagnosis [5]. ML is an increasingly essential field for the early detection of diseases. It underscores the importance of decision-making informed by new information through the identification of latent patterns within observations [6,7].

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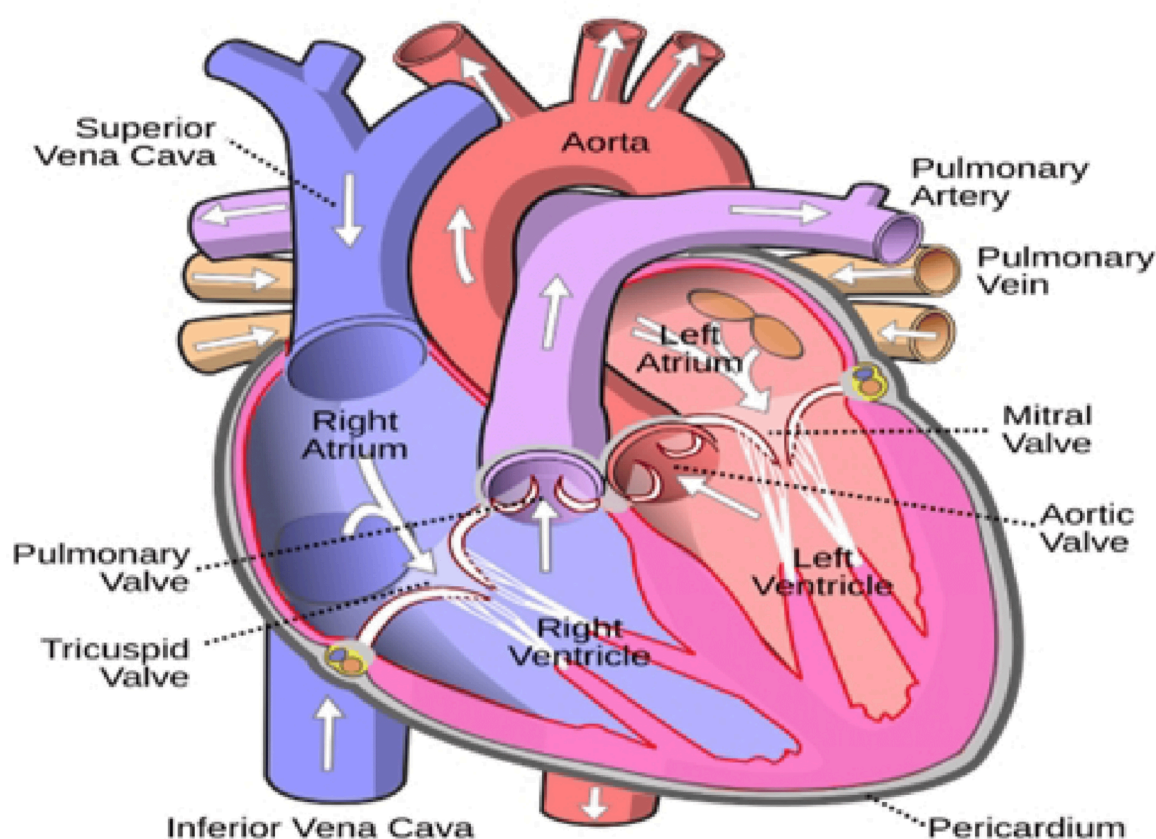


FIGURE 1: Structure of the human cardiac system

Source: Gupta et al. [4]

Researchers have suggested multiple decision-support frameworks for the prediction and diagnosis of myocardial infarction, employing diverse ML classifiers. Each contribution introduces a novel model that depends on multiple aspects, including the classification algorithm, data preprocessing, statistical methodologies, feature selection techniques, optimization strategies, and performance indicators. The literature evaluation offers a framework and computational assessment of prior research to inform and guide the development of the new methodology. This article analyzes the literature pertaining to various studies and classification methods for predicting myocardial infarction.

Review methodology

Objective

This study adopts a systematic review methodology to analyze the computational efficiency of ML classifiers with respect to heart disease detection. The objective of this study is to identify, evaluate, and compare the computational performance of existing ML-based diagnostic approaches, classification algorithms, feature selection techniques, evaluation metrics, and datasets used for cardiovascular disease prediction. The methodology follows a structured review framework through literature identification, screening, eligibility assessment, data extraction, and comparative analysis.

Review Questions

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State-of-the-art literature surveys systematically map the evolution of ML-driven heart disease detection approaches. The literature covers a wide range of ML-driven heart disease detection approaches. This review is guided by the following research questions:

1. Which ML classifiers are most frequently employed for heart disease detection?
2. What datasets, feature engineering techniques, and preprocessing methods are utilized in existing studies?
3. How do ML classifiers compare in terms of predictive performance, computational complexity, and diagnostic effectiveness?

Literature Search Strategy

This study used a comprehensive literature search approach across major scientific databases, including IEEE Xplore, ScienceDirect, SpringerLink, Wiley Online Library, ACM Digital Library, Scopus, Web of Science, PubMed, and Google Scholar. The search strategy used the following combinations of keywords with the Boolean operators (AND, OR, NOT). The literature search covered publications from database inception, 1 January 2008, through 31 December 2025, and selected a total of 39 research papers on ML models for myocardial infarction for the computational comparative review to identify the key insights of the study.

- "Heart Disease Detection"
- "Heart Disease Prediction"
- "Cardiovascular Disease Diagnosis"
- "Machine Learning for Heart Disease"
- "Machine Learning for Cardiovascular Disease Diagnosis"
- "Classification Algorithms for Cardiovascular Disease Diagnosis"
- "Data Preprocessing Techniques for Cardiovascular Disease Diagnosis"
- "Feature Extraction Techniques for Cardiovascular Disease Diagnosis"
- "Data for Cardiovascular Disease Diagnosis"
- "Artificial Intelligence in Healthcare"
- "Deep Learning for Heart Disease"
- "Medical Decision Support Systems"

Inclusion Criteria:

- ML-driven literature on heart disease detection.
- Literature involving comparative analyses of heart disease detection.
- Literature reporting quantitative performance metrics.
- Literature using clinical cardiovascular datasets.

Exclusion Criteria:

- Did not involve heart disease prediction or classification.
- Lacked experimental validation.
- Studies that were editorials, short communications, theses, or non-peer-reviewed articles.
- Contained incomplete methodological information.
- Focused exclusively on non-computational clinical analyses.

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Review

State-of-the-art heart disease prediction model

This section examines the diverse predictive models grounded in data mining processes, including feature extraction, model validation, classification algorithms, experimental outcomes, problems, advantages, and disadvantages. According to the literature review, each ML model relies on a feature selection algorithm and a classifier.

Palaniappan et al. [8] developed an Intelligent Heart Disease Prediction System that predicts heart disease using a historical heart disease database. The model selects relevant risk attributes and uses artificial neural networks, naive Bayes, and decision trees for classification. The Intelligent Heart Disease Prediction System effectively identifies disease patterns and relationships for real-time prediction and diagnosis, reducing classification costs. However, implementing the neural network classifier is challenging due to its complex structure and the difficulty of attribute selection and computation.

Shao et al. [9] developed a hybrid intelligent model to identify and classify heart-related disease using 13 risk factors. In the first phase, logistic regression, multivariate adaptive regression splines, and a rough set classifier identify explanatory variables. The second phase uses an artificial neural network to extract the remaining variables. Using these classifiers with feature selection, the model achieves high accuracy, with the combination of multivariate adaptive regression splines and the artificial neural network proving to be the most accurate.

Bashir et al. [10] proposed the MV5 ensemble classifier framework for predicting heart disease. The framework uses a vote-based scheme with an ensemble of classifiers, including naive Bayes, Gini index- and information gain-based decision trees, support vector machines (SVM), and memory-based classifiers. The process includes data preprocessing steps such as feature selection (using backward and forward elimination), missing value imputation (using statistical techniques such as the mean and mode), and outlier detection (using the interquartile range). After preprocessing, the model is trained and validated using cross-validation. The final results are based on the classifiers that perform best across metrics such as accuracy, F-measure, specificity, and sensitivity. The MV5 framework achieved impressive results, including 88.52% accuracy and an 88.85% F-measure.

Gandhi and Singh [11] evaluated the predictive performance of naive Bayes, neural networks, and decision trees for myocardial infarction. The study used these classifiers to extract hidden information and knowledge from medical data and analyzed their individual strengths and weaknesses based on their predictive performance for different heart diseases.

Quantin et al. [12] proposed a heart disease prediction model using symbolic data analysis on real-world data. Symbolic data analysis identifies relationships between risk and non-risk attributes without affecting the data's hierarchical structure. The framework, which uses regression tree analysis and statistical methodologies, predicts patient survival during myocardial infarction. The statistical methods validate patient data aggregation and allow for the extraction of complete patient information to improve the accuracy of traditional regression trees.

Parthiban and Srivatsa [13] developed a heart disease prediction model for diabetic patients. The model uses correlation to select diabetes-related attributes and then employs SVM and naive Bayes classifiers to predict myocardial infarction. The experimental results show that SVM significantly improves prediction accuracy. The key attributes for the prediction are age, sex, blood pressure, and blood sugar.

Sun et al. [14] developed an automated heart disease prediction model using a multiple-instance learning approach. The model analyzes patient records, specifically ECG data from the PTB diagnostic database, using supervised data mining techniques. The experimental results show that the k-nearest neighbors (KNN) multiple-instance learning algorithm improves the classification quality, sensitivity, specificity, and accuracy of the model.

Helmy et al. [15] proposed a hybrid and ensemble classifier-based data mining model to predict heart disease. This model, referred to as a hybrid computational intelligence data mining model, addresses the shortcomings of traditional classification algorithms by automatically selecting the most accurate classifier. It uses SVM, neural networks, function

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networks, and fuzzy logic. The experimental results show that the hybrid and ensemble approach improves model accuracy on various bioinformatics datasets compared to using individual classifiers. The model can automatically select risk-based attributes based on the ensemble. However, this feature-based selection increases computational time and cost.

Shilaskar and Ghatol [16] developed a hybrid forward selection method for cardiovascular disease detection. This feature reduction technique enhances model accuracy by combining forward and backward feature elimination. The forward approach ranks features by distance measurement, while the backward approach selects the final feature subset for classification. The model uses an SVM classifier for classification, as its performance is not dependent on the number of dataset attributes. The combined technique improves prediction and diagnosis accuracy more than either approach used alone.

Amin et al. [17] developed a hybrid model for heart disease prediction that combines neural networks and genetic algorithms. The model first extracts major risk factors from a dataset. It then uses a variety of classifiers, including neural networks, naive Bayes, SVM, and decision trees with bagging trees. The genetic algorithms handle global optimization, while the neural networks manage link weight optimization. This hybrid approach, combined with an effective feature extraction technique, stabilizes results and improves prediction efficiency and accuracy by up to 89%. The study also found that the back propagation technique significantly impacts the neural network's performance.

Safdari et al. [18] proposed a heart disease detection model using seven classification data mining and association rule learning algorithms on a real-world dataset from an Iranian hospital. Association rule learning identifies critical risk attributes for the classifiers, which then predict the disease. The neural network showed high sensitivity. However, it failed to satisfy other validation metrics in real-world clinical trials. The CHAID decision tree was the most accurate predictor, outperforming other techniques across metrics like accuracy, sensitivity, specificity, and precision.

Otoom et al. [19] developed a mobile-based real-time application for the prediction, diagnosis, and monitoring of myocardial infarction. The application uses naive Bayes, SVM, and decision trees for classification. The model first extracts sensor data from patients, which is then preprocessed. The authors used 10-fold cross-validation to determine the significance of risk factors and cost ratios. The study found that using feature selection, hold-out, and cross-validation tests improved prediction results, with the feature selection method alone increasing accuracy by up to 3% compared to classical data mining models.

Vembandasamy et al. [20] developed a heart disease prediction model that uses a naive Bayes classifier. The model follows a standard data mining process, which includes data preprocessing, risk feature selection, and data normalization. The study found that naive Bayes is computationally efficient and can handle various types of medical data. The model's accuracy, which is heavily dependent on the selected risk features, reached up to 86.42%.

Verma et al. [21] proposed a hybrid model for heart disease prediction and coronary artery disease diagnosis. The model first uses correlation analysis to identify risk attributes. These attributes are then reduced using particle swarm optimization (PSO). A clustering algorithm validates the data and approves the selected attributes for classification. The model then uses several classifiers, including the C4.5 decision tree, multilayer perceptron, fuzzy unordered rule induction, and multinomial logistic regression, to predict myocardial infarction. The study found that this approach, which relies heavily on feature selection via correlation and PSO, improved the accuracy of each classifier by 8.3% to 11.4%.

Seenivasagam and Chitra [22] developed an intelligent data mining model for heart disease detection using SVM and neural networks. The model uses a multi-step process: first, it extracts risk factors and then normalizes them with the min-max normalization method. Next, it classifies the data using cascade correlation, SVM, and feed-forward neural networks. A genetic algorithm and PSO are used to optimize the neural networks, which improves the model's accuracy and performance. Experimental results showed that PSO enhanced the model's accuracy more, and the neural network classifier performed better with larger datasets. However, using these neural networks and optimization algorithms increases computational time and cost.

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Hamidi and Daraei [23] proposed a hybrid feature selection model for heart disease prediction. The model combines an SVM and a genetic algorithm; the SVM assigns weights to features, and the genetic algorithm uses these weights to select the most predictive features. The selected features are then used by a classification set containing sequential minimal optimization, KNN, REPTree, random forest, Bayesian network, and multilayer perceptron. The study found that multilayer perceptron and sequential minimal optimization achieved superior precision and accuracy. The model's performance, however, is affected by data volume, as a large amount of data increases the time and space required for training.

Nidhyananthan et al. [24] developed a heart disease prediction model using a wavelet-related method and an SVM classifier. The method first converts ECG signals into subbands and then uses frame-based segmentation and multiscale factor analysis to extract risk data. This data is validated using statistical analysis. The SVM classifier then classifies the ECGs as either normal or abnormal, achieving 90.42% accuracy on a small set of samples. A notable drawback is the high computational time and space required to analyze the ECG signals.

Daraei and Hamidi [25] proposed a hybrid feature selection model for heart disease prediction using a two-step process. First, the Relief and Genetic classifiers identify risk-based features. Second, these two methods work to balance the data and determine cost ratios for classification. The Relief method assigns a weight to each feature, and the genetic classifier extracts the optimal risk-based features to determine these ratios. A cost-sensitive J48 metacost classifier then uses these ratios to predict heart disease on unlabeled data. The model can balance unbalanced data and uses a genetic algorithm to improve accuracy. However, a significant drawback is the increased time required for weight assignment, feature extraction, and cost ratio determination.

Sonet et al. [26] utilized association rule data mining to uncover hidden patterns and information related to heart disorders such as myocardial infarction, unstable angina, and coronary heart disease. Their method identifies these patterns based on attributes such as age, gender, region, and socioeconomic level. The analysis revealed that heart disease patterns are indeed dependent on these factors. This approach enhances execution time by creating rules tailored to specific heart disease patterns and attributes. The model demonstrated superior accuracy compared to other rule-learning methods. However, the prediction process is highly complex due to its reliance on both primary rules and the careful selection of attributes.

Mokeddem [27] developed a clinical decision support system for predicting heart disease and diagnosing coronary artery diseases. The system uses a combination of three classifiers: random forest, C5.0 decision tree, and a fuzzy classifier. The random forest first ranks and extracts relevant features. The C5.0 decision tree generates, analyzes, and validates crisp rules. Finally, the fuzzy classifier uses these crisp rules to predict the disease. This clinical decision support system can handle missing and noisy data and achieved a classification accuracy of up to 90.50%, with optimized processing time.

Dwivedi [28] developed a heart disease prediction framework using multiple data mining classification algorithms, including artificial neural networks, SVM, naive Bayes, logistic regression, KNN, and decision trees. The model selects risk-based features and then applies a classifier, with a tenfold cross-validation used to ensure accuracy and optimal model selection. The study found that the logistic regression algorithm outperformed the others, achieving an 85% accuracy, 89% sensitivity, and 81% specificity.

Haq et al. [29] proposed a noninvasive, accurate, and timely predictive framework for heart disease diagnosis that does not rely on medical history. The framework involves several key steps: data preprocessing (handling missing values and normalizing data using standard and min-max scalars), feature selection (using methods like minimal redundancy, maximal relevance, relief, and least absolute shrinkage), and classification. The model uses a range of classifiers, including logistic regression, artificial neural networks, naive Bayes, decision trees, KNN, and SVM. The performance of each classifier is validated using metrics like accuracy, sensitivity, precision, specificity, correlation coefficient, and computation time. The study found that an effective feature selection approach significantly enhances classifier accuracy, speed, and efficiency without compromising results.

Verma et al. [30] developed a hybrid noninvasive model to address the need for technical expertise in cardiovascular disease diagnosis by proposing a non-invasive alternative to angiography. The model uses a two-step approach: first, a K-means clustering algorithm handles missing value imputation and feature extraction. Then, a classification set, consisting

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of decision trees, naive Bayes, and a multilayer perceptron, predicts the disease. The study found that this model reduces the cost of angiography and improves screening, accuracy, and severity assessment. The K-means clustering and feature extraction enhance prediction accuracy but are computationally expensive due to their iterative, centroid-based nature. Additionally, the model can use a fuzzy optimizer to improve the performance of the decision tree through rule extraction, but the rule attribution process can negatively impact the model's overall performance.

Liu et al. [31] proposed a Multiple Feature Branch Convolutional Neural Network (MFB-CNN) for heart disease prediction using 12-lead ECG data. This deep learning model automatically diagnoses the condition by processing physiological data, with each lead analyzed individually before being integrated by a SoftMax layer. The MFB-CNN effectively manages inter-patient variability and achieved exceptionally high performance on a universal PTB diagnostic database, with an accuracy of up to 99.95% for ECG classification data and 98.79% for patient data. While its high accuracy and ability to act as a computer-aided diagnosis platform are notable, its complex structure results in high computational time.

Anitha and Sridevi [32] implemented a heart disease prediction framework using a standard data mining model. They compared KNN, naive Bayes, and SVM, and found that naive Bayes was the most suitable for detecting the disease, achieving an accuracy of 86.6%.

Beulah Christalin Latha and Carolin Jeeva [33] developed a heart disease prediction model using ensemble classifiers to improve accuracy by merging multiple classifiers. The study implemented ensemble techniques as stacking, bagging, majority voting, and boosting-using classifiers such as Bayes net, naive Bayes, random forest, PART, multilayer perceptron, and C4.5. The model's accuracy and performance are highly dependent on effective feature selection. The experiment found that majority voting was the most effective ensemble technique, boosting accuracy by 7.26%, followed by stacking (6.93%), bagging (6.92%), and boosting (5.94%).

Mohan et al. [34] developed a hybrid random forest with a linear model for heart disease prediction. The model first preprocesses clinical data and selects risk features. It then integrates random forest and linear models to enhance prediction accuracy. The study found that this hybrid approach improved accuracy by up to 88.7%.

Garate-Escamila et al. [35] proposed a dimensionality reduction and feature selection approach that uses principal component analysis (PCA) for feature extraction and chi-square (CHI) selector to analyze and select relevant risk factors. The extracted features were validated using various classifiers, including decision trees, gradient-boosted trees, logistic regression, multilayer perceptrons, naive Bayes, and random forest. The study found that the CHI-PCA algorithm combined with the random forest classifier achieved the highest accuracy on the Cleveland and Cleveland-Hungarian datasets, demonstrating its effectiveness in improving the performance of data mining models, especially with high-dimensional datasets.

Ibrahim et al. [36] proposed a heart disease prediction framework to address class imbalance issues using the Synthetic Minority Over-sampling Technique (SMOTE). Their framework employs recurrent neural networks, decision trees, CNN, and XGBoost classifiers. The study found that SMOTE effectively handles both data preparation and class imbalance. The XGBoost classifier was particularly good at feature extraction, and the overall framework, especially when paired with XGBoost and supplementary data, achieved a high accuracy of 97.5%, outperforming the CNN (89.9%) and recurrent neural network (84.6%) classifiers.

Shah et al. [37] proposed a data mining model for heart disease prediction, including myocardial infarction, which first preprocesses the data and then selects attributes based on risk factors from the Cleveland heart dataset. The model uses various classifiers - KNN, naive Bayes, decision tree, and random forest - and selects the most accurate one for prediction. The study found that KNN was the most accurate classifier and performed best across other validation metrics and that feature selection improved both the model's time efficiency and accuracy.

Mandair et al. [38] developed a data mining model for heart disease prediction using logistic regression, boosted gradient machines, random forest, and deep neural network classifiers. To address dataset imbalance, they used a sampling technique and 10-fold cross-validation. The model was trained on harmonized electronic health record data

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and a deep neural network with seven layers. While logistic regression excelled at analyzing large-scale risk factors, the study found that a hybrid model combining a deep neural network with random sampling produced the most superior results, achieving 73.3% specificity, 82% sensitivity, 82% recall, and 05% accuracy.

Reddy et al. [39] developed a heart disease prediction model for patients with type 1 and type 2 diabetes using various regression models. Their analysis identified the Thallium heart scan as a key attribute for prediction. The study found that the lasso regression model outperformed both multiple linear regression and ridge regression, achieving a superior R-squared value of 0.2278 and a lower Root Mean Squared Error of 0.418. The authors note that, while effective, this model is best suited for small datasets due to the high computational time and space required for larger-scale analysis.

Tozlu et al. [40] developed a data mining model for heart disease prediction using a real-world dataset. The model preprocesses data and extracts relevant information using statistical techniques such as mean, mode, median, variance, kurtosis, and derivative. The data is then split into a 66% training set and a 34% testing set for classification. The study found that SVMs achieved higher accuracy compared to KNN and neural networks. The model avoids the use of an electronic nose for patient health record observation and provides information on both heart disease and coronary artery diseases.

Patro et al. [41] developed a heart disease prediction model using Salp Swarm Optimized Neural Networks, naive Bayes, KNN, and a Bayesian Optimized SVM. The model uses risk attributes from a heart disease dataset and optimizes each classifier using a kernel function. Experimental results showed that the Bayesian Optimized SVM performed best in terms of accuracy, precision, and sensitivity, while the overall framework helps avoid overlearning issues and is effective for healthcare monitoring systems.

Reddy and Gopichand [42] proposed a heart disease prediction model using a variety of classifiers, including KNN, decision trees, neural networks, naive Bayes, random forest, and SVM. The model first preprocesses data and selects suitable features before applying the classifiers. The study, implemented on the UCI heart disease dataset, found that random forest achieved the highest accuracy when evaluated using metrics such as precision, recall, F1-score, and accuracy.

Rani et al. [5] proposed a hybrid decision support system for heart disease prediction based on a patient's clinical data. Their model uses a series of data mining steps: multivariate imputation to handle missing values, a two-step feature selection process (a genetic algorithm for identification and recursive feature elimination to select risk attributes), and SMOTE to balance the data and ensure a mean of zero and a standard deviation of one for each attribute. The preprocessed data is then used by a set of classifiers, including logistic regression, naive Bayes, random forests, SVM, and AdaBoost. The system selects the most accurate classifier for prediction. While the model achieved an accuracy of up to 86.6%, the comprehensive preprocessing steps resulted in a longer computational time than existing algorithms.

Liu et al. [43] proposed a two-layer model for heart disease risk prediction. The top layer handles data preparation, which includes preprocessing and feature identification. The study found that a down-sampling approach was the most effective for dataset construction. The bottom layer focuses on model building using gradient boosting decision trees, random forests, SVM, and logistic regression. The gradient boosting decision tree algorithm achieved the highest F1-score and accuracy. The overall goal of the model is to improve patient cure rates and prognosis.

Pathan et al. [44] addressed the complexity of feature extraction and disease prediction in large medical datasets by using a hybrid filter- and wrapper-based feature selection approach. This method combines border analysis to evaluate interdependent features with statistical validation and a filtering approach to optimize the feature subset for classification. Applied to the Cardiovascular Disease and Framingham datasets, the optimized feature subset significantly reduced training and testing time. The proposed algorithm achieved accuracies of 75% and 71% on the respective datasets, demonstrating the effectiveness of feature optimization in improving the performance of the classification algorithms.

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Ozcan and Peker [45] proposed a heart disease detection model using the Classification and Regression Tree algorithm. This supervised classification model uses a decision tree to extract features and establish decision rules for determining relationships. It works with both numerical and categorical data types. To improve accuracy, the model uses an 80% training and 20% testing data split. The Classification and Regression Tree algorithm achieved an accuracy of 87%, sensitivity of 85%, specificity of 90%, and precision of 88%, while also optimizing computational time and cost compared to other models.

Comparative analysis of state-of-the-art heart disease prediction model

This section analyzes the extensive literature review, employing essential parameters to improve the existing heart disease prediction model. The selected data mining classifier, feature selection method, experimental dataset, and validation metric are critical components. This section delineates the trajectory of the research, which seeks to construct a predictive model for heart disease utilizing empirical data. The comparative analysis is based on the computational attributes [1,2,4,6,22,28,32,35,37,46].

Table 1 shows the comparative analysis of various ML models for heart disease prediction. This table demonstrates a consistent improvement in predictive accuracy across various datasets and combinations of classifiers. The examination of current heart disease prediction models indicates notable advancements from conventional classifiers such as artificial neural networks, naive Bayes, and decision trees to more sophisticated hybrid and deep learning frameworks. Initial models concentrated on fundamental risk factor analysis, whereas contemporary research highlights the significance of ensemble learning, optimization algorithms, and CNN-based architectures in enhancing precision and reliability.

Author(s)	Model	Classifiers	Dataset/Data Source	Key Findings
Rani et al. [5]	Hybrid Decision Support System	LR, NB, RF, SVM, AdaBoost	Clinical Data	The integration of GA, RFE, and SMOTE enhanced classification performance by improving feature selection and class balancing; however, the framework incurred higher computational overhead.
Palaniappan et al. [8]	IHDPS	ANN, NB, DT	Historical Heart Disease DB	ANN effectively captured complex relationships among clinical attributes and improved disease prediction, although model implementation and training remained computationally demanding.
Shao et al. [9]	Hybrid Intelligent Model	LR, MARS, Rough Set, ANN	13 Risk Factors	The hybrid MARS-ANN framework achieved superior predictive accuracy, demonstrating the effectiveness of combining statistical and neural learning approaches.
Bashir et al. [10]	MV5 Ensemble	NB, DT, SVM, Memory-based	Real Dataset	The MV5 ensemble model improved classification robustness and accuracy through the integration of multiple learning algorithms and comprehensive preprocessing.
Gandhi and Singh [11]	Comparative Study	NB, ANN, DT	Myocardial Infarction Data	Comparative evaluation revealed significant variations in classifier performance, emphasizing the

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				importance of model selection for heart disease prediction.
Quantin et al. [12]	SDA Framework	Regression Tree, Statistical Methods	Real-world Data	The SDA framework preserved hierarchical data structures and improved regression performance for complex clinical datasets.
Parthiban and Srivatsa [13]	Heart Disease Model (Diabetic)	SVM, NB	Diabetes Dataset	SVM achieved higher predictive accuracy than NB in diabetic patient datasets, indicating its suitability for cardiovascular risk assessment.
Sun et al. [14]	MIL Model	KNN (MIL)	PTB Diagnostic ECG Data	The MIL-based KNN approach improved sensitivity and classification accuracy for ECG-based heart disease diagnosis.
Helmy et al. [15]	Hybrid Ensemble Model	SVM, NN, Fuzzy Logic	Bioinformatics Data	The hybrid ensemble framework enhanced predictive reliability and diagnostic accuracy, albeit at the expense of increased computational complexity.
Shilaskar and Ghatol [16]	Hybrid Forward Selection	SVM	Cardiovascular Dataset	Forward-backward feature elimination reduced feature redundancy and improved SVM classification performance.

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Amin et al. [17]	Hybrid NN + GA	ANN, NB, SVM, DT	Heart Disease Dataset	GA optimization enhanced ANN learning capability and prediction stability, resulting in improved diagnostic performance.
Safdari et al. [18]	Association Rule + Classifiers	NN, CHAID DT	Iranian Hospital Dataset	CHAID DTs outperformed neural network models and demonstrated superior classification accuracy on hospital datasets.
Otoom et al. [19]	Mobile-based Real-Time Model	NB, SVM, DT	Sensor Data	Feature selection techniques improved classification accuracy and enabled efficient real-time heart disease prediction in mobile environments.
Vembandasamy et al. [20]	NB Classifier Model	NB	Medical Data	NB provided efficient and reliable classification performance while effectively handling heterogeneous medical data.
Verma et al. [21]	PSO-based Hybrid Model	C4.5, MLP, FURIA, LR	Coronary Dataset	PSO-based optimization improved feature relevance and classification accuracy across multiple predictive models.
Seenivasagam and Chitra [22]	Intelligent Data Mining Model	SVM, NN, GA, PSO	–	PSO enhanced predictive performance and optimization capability; however, increased computational requirements limited scalability.
Hamidi and Daraei [23]	Hybrid Feature Selection	SVM, GA, SMO, MLP, RF	Heart Dataset	MLP and SMO classifiers achieved superior precision, while model

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				training efficiency declined with increasing dataset size.
Nidhyananthan et al. [24]	Wavelet + SVM	SVM	ECG Signals	The wavelet–SVM framework provided accurate ECG-based diagnosis, although computational complexity remained a significant challenge.
Daraei and Hamidi [25]	Relief + Genetic + J48	Relief, GA, Metacost J48	Heart Data	The integration of relief, GAs, and MetaCost J48 improved class balancing and predictive performance but increased processing time.
Sonet et al. [26]	Association Rule Mining	Rule-based	Myocardial, Angina, CHD	Association rule mining identified clinically relevant disease patterns and risk factors, although rule management became increasingly complex with larger datasets.
Mokeddem [27]	CDSS System	RF, C5.0, Fuzzy Classifier	Clinical Data	The CDSS framework effectively handled noisy and incomplete clinical records while maintaining reliable diagnostic performance.
Dwivedi [28]	Comparative Framework	ANN, SVM, NB, LR, KNN, DT	–	LR achieved the highest overall performance among the evaluated classifiers, demonstrating strong predictive capability and interpretability.
Haq et al. [29]	Noninvasive Framework	LR, ANN, NB, SVM, DT, KNN	–	Feature selection significantly improved classification accuracy, sensitivity, and specificity across

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				multiple machine learning models.
Verma et al. [30]	Noninvasive Hybrid Model	K-means, DT, NB, MLP	–	The hybrid non-invasive framework reduced dependence on angiographic procedures while maintaining competitive prediction performance.
Liu et al. [31]	MFB-CNN	CNN (12-lead ECG)	PTB ECG Data	The MFB-CNN model achieved exceptionally high diagnostic accuracy from ECG signals, although substantial computational resources were required.
Anitha and Sridevi [32]	Standard Data Mining	KNN, NB, SVM	Heart Dataset	NB demonstrated superior classification accuracy compared with KNN and SVM for the evaluated heart disease dataset.
Beulah Christalin Latha and Carolin Jeeva [33]	Ensemble (Stacking, Bagging, etc.)	NB, RF, MLP, C4.5	–	Ensemble learning, particularly majority voting strategies, improved prediction robustness and overall classification performance.
Mohan et al. [34]	HRFLM	RF + Linear Model	Clinical Data	The HRFLM framework enhanced predictive accuracy through the integration of RF and linear modeling techniques.

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Garate-Escamila et al. [35]	CHI-PCA	PCA, Chi-Square, RF	Cleveland Dataset	The CHI-PCA-RF framework effectively addressed high-dimensional data challenges and improved classification efficiency and accuracy.
Ibrahim et al. [36]	SMOTE-based Framework	RNN, CNN, XGBoost, DT	Clinical Data	SMOTE-based data balancing improved model generalization, with XGBoost achieving the highest predictive performance among evaluated classifiers.
Shah et al. [37]	Data Mining Model	KNN, NB, DT, RF	Cleveland Dataset	KNN produced the best classification accuracy, while feature selection reduced computational complexity and improved efficiency.
Mandair et al. [38]	Hybrid DNN Framework	LR, BGM, RF, DNN	EHR Data	DNNs combined with sampling strategies achieved superior predictive performance on electronic health record datasets.
Reddy et al. [39]	Regression Models	Lasso, Ridge, MLR	Diabetes Data	Lasso regression demonstrated robust predictive capability and effective feature regularization, particularly for small-scale datasets.
Tozlu et al. [40]	Statistical Preprocessing Model	SVM, KNN, NN	Real-world Dataset	SVM consistently outperformed KNN and NN models, demonstrating strong generalization capability on real-world data.
Patro et al. [41]	Salp Swarm + BO-SVM	NN, NB, KNN, BO-SVM	Heart Dataset	The BO-SVM framework achieved the highest accuracy and sensitivity through optimized

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				feature selection and parameter tuning.
Reddy and Gopichand [42]	Comparative Classifier Model	KNN, DT, NN, NB, RF, SVM	UCI Dataset	RF outperformed alternative classifiers and demonstrated strong robustness and predictive accuracy on the UCI dataset.
Liu et al. [43]	Two-layer Model	GBDT, RF, SVM, LR	Clinical Data	The GBDT-based framework achieved the highest F1-score and classification accuracy, indicating superior predictive capability.
Pathan et al. [44]	Hybrid Feature Optimization	Filter + Wrapper	CVD & Framingham Data	The hybrid filter–wrapper feature optimization framework reduced training time while maintaining competitive classification performance.
Ozcan and Peker [45]	CART Model	DT (CART)	Clinical Data	The CART model achieved high sensitivity and specificity, offering a computationally efficient solution for heart disease prediction.

TABLE 1: Summary of Heart Disease Prediction Models

ANN, Artificial Neural Network; BGM, Bayesian Gaussian Mixture; BO, Bayesian Optimization; CART, Classification and Regression Tree; CDSS, Clinical Decision Support System; CHI-PCA, Chi-Square-Principal Component Analysis; DNN, Deep Neural Network; DT, Decision Tree; GA, Genetic Algorithm; GBDT, Gradient Boosting Decision Tree; HRFLM, Hybrid Random Forest with a Linear Model; IHGPS, Intelligent Heart Disease Prediction System; KNN, k-Nearest Neighbors; LR, Logistic Regression; MARS, Multivariate Adaptive Regression Splines; MFB-CNN, Multi-Feature Fusion-Based Convolutional Neural Network; MIL, Multiple Instance Learning; MLP, Multilayer Perceptron; NB, Naïve Bayes; NN, Neural Network; PSO, Particle Swarm Optimization; RF, Random Forest; RNN, Recurrent Neural Network; SDA, Symbolic Data Analysis; SMO, Sequential Minimal Optimization; SMOTE, Synthetic Minority Over-sampling Technique; SVM, Support Vector Machine; XGBoost, Extreme Gradient Boosting.

Table 2 shows that the analysis of feature selection and preprocessing techniques demonstrates that hybrid and optimization-based approaches play a vital role in enhancing model performance for heart disease prediction. The studies employing genetic algorithms, PSO, and SMOTE achieved better accuracy, precision, and class balance, while

methods such as minimal-redundancy-maximal-relevance, PCA, and chi-square improved dimensionality reduction and feature relevance. Additionally, data preprocessing methods like imputation and normalization further stabilized classification outcomes. Overall, the integration of feature optimization and balancing techniques significantly contributes to improved predictive reliability.

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Authors	Feature Selection Techniques	Data Preprocessing Methods	Optimization/Balancing	Remarks
Bashir et al. [10]	Backward & Forward Elimination	Missing Value Imputation, Outlier Detection	–	Improves classifier consistency
Parthiban and Srivatsa [13]	Correlation Analysis	Attribute Selection	–	Diabetes-related attributes
Amin et al. [17]	GA-based Optimization	Risk Factor Extraction	GA	Stabilizes model performance
Verma et al. [21]	Correlation + PSO	Attribute Validation via Clustering	PSO	Boosts accuracy
Hamidi and Daraei [23]	SVM Weight + GA	Feature Weight Assignment	GA	High precision but time-costly
Daraei and Hamidi [25]	Relief + GA	Cost Ratio Determination	GA	Time-consuming
Mokeddem [27]	RF-based Ranking	–	–	Effective rule generation
Haq et al. [29]	mRMR, Relief, LASSO	Normalization (Min-Max)	–	Boosts accuracy & efficiency
Verma et al. [30]	K-means	Missing Value Imputation	Fuzzy Optimizer	High cost
Beulah Christalin Latha and Carolin Jeeva [33]	Feature Subset Selection	–	–	Key for ensemble accuracy
Garate-Escamila et al. [35]	Chi Square + PCA	Dimensionality Reduction	–	Effective in high-dimensional data
Ibrahim et al. [36]	SMOTE + FS	Data Balancing	SMOTE	Handles imbalance
Rani et al. [5]	GA + RFE + SMOTE	Multivariate Imputation	SMOTE	Time-consuming but accurate
Pathan et al. [44]	Hybrid Filter + Wrapper	Statistical Validation	–	Reduces time and improves performance

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TABLE 2: Feature Selection and Preprocessing Approaches
FS, Feature Selection; GA, Genetic Algorithm; PCA, Principal Component Analysis; PSO, Particle Swarm Optimization; RFE, Recursive Feature Elimination; SMOTE, Synthetic Minority Over-sampling Technique; SVM, Support Vector Machine

Table 3 shows that the comparative analyses indicate that SVM, artificial neural networks, and ensemble or hybrid models are the most frequently employed approaches for heart disease prediction, achieving accuracies ranging from 85% to 99%. Classical classifiers such as naive Bayes, decision trees, and logistic regression offer simplicity and interpretability but struggle with correlated or nonlinear data. In contrast, advanced methods such as random forests, CNNs, and hybrid frameworks demonstrate superior robustness and generalization capabilities at the cost of higher computational demands. Overall, ensemble and deep learning techniques provide the best predictive reliability among existing models. The frequency of use was calculated based on the 39 included research articles. Most of the studies employed multiple ML classifiers to compare their predictive performance. Therefore, each classifier was counted once for every study in which it was used. As a result, the total frequency of classifiers exceeds the number of included articles (39).

Classifier	Frequency of Use	Typical Accuracy Range	Common Pairings	Strengths	Weaknesses
SVM	18	85–97%	GA, PSO, NB	Handles nonlinear data	Sensitive to tuning
NB	15	83–89%	SVM, DT	Fast, low computation	Limited on correlated features
DT	17	80–90%	RF, NB	Interpretability	Overfitting
RF	10	85–90%	PCA, Linear Model	Robust and stable	Computationally heavy
NN/ANN	16	85–99%	GA, PSO, CNN	High performance	High complexity
KNN	9	80–87%	NB, DT	Simple, non-parametric	Memory intensive
LR	7	80–85%	FS, EHR Data	Transparent	Poor with nonlinear data
CNN/DNN	4	90–99%	RNN, XGBoost	Excellent feature learning	High computation
Ensemble/Hybrid	11	85–99%	Multiple	Highest accuracy	Costly training

TABLE 3: Classifier Comparison Analysis

ANN, Artificial Neural Network; CNN, Convolutional Neural Network; DNN, Deep Neural Network; DT, Decision Tree; FS, Feature Selection; GA, Genetic Algorithm; KNN, k-Nearest Neighbors; LR, Logistic Regression; NB, Naïve Bayes; NN, Neural Network; PCA, Principal Component Analysis; PSO, Particle Swarm Optimization; RF, Random Forest; RNN, Recurrent Neural Network; SVM, Support Vector Machine; XGBoost, Extreme Gradient Boosting

Table 4 shows that recent research trends in heart disease prediction reveal a strong shift toward hybrid and ensemble models, which consistently deliver higher accuracy than individual classifiers. Deep learning architectures such as CNN and MFB-CNN further enhance predictive performance, often surpassing 98% accuracy. Feature selection and data balancing techniques like PSO, genetic algorithms, recursive feature elimination, Relief, and SMOTE remain essential for optimizing model outcomes, though they increase computational demands. Additionally, there is a growing focus on utilizing real-world clinical datasets instead of traditional benchmark datasets.

Aspect	Observation	Examples
Hybrid & Ensemble Dominance	Most recent studies use hybrid or ensemble models for superior accuracy.	[15,33,34,36]
Deep Learning Growth	CNN and MFB-CNN models achieving >98% accuracy.	[31,36]
Feature Selection Crucial	Correlation, PSO, GA, RFE, Relief key for performance.	[5,21,23,25]
Data Imbalance Handling	SMOTE widely used for balanced learning.	[5,36]
Computational Complexity	High accuracy models often have high computation time.	[8,15,22,24,30]
Best Single Classifier	Random Forest and Support Vector Machine consistently outperform others.	[36,42]
Use of Real-world Clinical Data	Growing preference over benchmark datasets (e.g., Cleveland).	[5,27,36]

TABLE 4: Observed Trends and Challenges

CNN, Convolutional Neural Network; GA, Genetic Algorithm; MFB, Multiple Feature Branch; PSO, Particle Swarm Optimization; RFE, Recursive Feature Elimination; SMOTE, Synthetic Minority Over-sampling Technique

Table 5 provides a comparative study of chosen classifiers to assess their computational capabilities. This table explores a comprehensive analysis of excellent classifiers based on the comparative analysis of the above tables. The analysis of the above section and tables demonstrates that random forest, SVM, naive Bayes, KNN, decision tree, and neural networks outperform other classifiers in heart disease prediction models. It examines the computing capacity, advantages, and disadvantages of the classifiers. The classifier's efficiency is determined by its accuracy, memory usage, computing speed, and cost. The reliability of the assessment is contingent upon an exhaustive examination of pertinent literature.

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Algorithms	Advantages	Disadvantages	References
RF	Excellent accuracy	Slow computational speed in high-dimensional and large datasets	[1,2,4,6,22,28,32,35,37]
SVM	Excellent accuracy	Slow computational speed in high-dimensional and large datasets	[1,2,4,6,22,28,32,35,37]
NB	Low computation speed and less memory computation	Less effective accuracy	[1,2,4,6,22,28,32,35,37]
DT	Excellent accuracy	Slow for large datasets, high computation power	[1,2,4,6,22,28,32,35,37]
KNN	Computational speed	Less accurate for unlabeled data	[1,2,4,6,22,28,32,35,37]
NN	Excellent accuracy	Slow computational speed in high-dimensional and large datasets	[1,2,4,6,22,28,32,35,37]

TABLE 5: Comparative Analysis of Classifiers Based on Computational Performance

DT, Decision Tree; KNN, k-Nearest Neighbors; NB, Naïve Bayes; NN, Neural Network; RF, Random Forest; SVM, Support Vector Machine

Limitations of the review

This review has several limitations. First, it focuses predominantly on ML-based techniques for heart disease prediction and does not comprehensively examine newer approaches, such as deep learning models, multimodal data fusion frameworks, and explainable artificial intelligence methods. Second, the comparative analysis is restricted to the selected studies included in this review. Consequently, variations in datasets, feature selection techniques, data preprocessing strategies, evaluation metrics, validation protocols, and experimental settings across the reviewed studies may influence the reported comparative findings. Third, although feature selection was recognized as a major contributor to prediction performance, this review does not present or validate a unified predictive framework for heart disease detection.

Future research should focus on the development and validation of a comprehensive ML framework for heart disease prediction by integrating advanced dataset analysis, data preprocessing, feature engineering, feature selection, data transformation, data partitioning, classification, model optimization, explainability, and performance evaluation. Such an integrated framework has the potential to improve the accuracy, robustness, interpretability, generalizability, and clinical applicability of intelligent heart disease prediction systems.

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Conclusions

This study establishes a foundation for creating an innovative framework aimed at forecasting cardiovascular conditions. The selection of features is a crucial factor in the prediction of heart disease. The enhancement of feature selection significantly elevates the performance metrics of the ML model. The Cleveland Heart Disease Dataset functions as the foundational dataset for this research endeavor. The review of heart disease prediction models demonstrates a clear progression from traditional classifiers to advanced hybrid, ensemble, and deep learning approaches. The models incorporating feature selection techniques (e.g., PSO, genetic algorithms, recursive feature elimination, Relief), data preprocessing, and balancing methods (e.g., SMOTE) consistently achieve higher accuracy, precision, and robustness across diverse datasets. The support vector machines, random forests, and neural network-based models remain the most effective individual classifiers, while hybrid and ensemble frameworks offer superior predictive performance, albeit with increased computational cost. Furthermore, the shift toward real-world clinical datasets highlights the growing focus on practical applicability and reliability. Integrating optimized feature selection, advanced classifiers, and balanced data handling emerges as the key strategy for improving the efficiency and accuracy of heart disease prediction systems.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Satish K. Tewalker

Acquisition, analysis, or interpretation of data: Satish K. Tewalker

Drafting of the manuscript: Satish K. Tewalker

Critical review of the manuscript for important intellectual content: Satish K. Tewalker

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Data Availability Statements

The data (and/or code) supporting this study are openly available in UCI Machine Learning Repository at <https://archive.ics.uci.edu/dataset/45/heart+disease>

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