

A Systematic Review of Machine Learning Techniques for Cardiovascular Disease Prediction With Performance Analysis and Future Perspectives

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Abstract

Cardiovascular disease is a chronic and significant health issue in the world, highlighting the need to detect and diagnose it in its early stages to increase the survival chances of the patient. The use of machine learning, as well as deep learning, has grown rapidly in medical research and shows great potential for improving the accuracy of heart disease prediction. They are able to identify latent connections between various clinical, demographic, and lifestyle variables and can be more accurate than traditional statistical techniques. This review follows a systematic literature review approach based on PRISMA guidelines, ensuring a structured and transparent selection of relevant studies. This review discusses some of the typical supervised learning algorithms used to assess cardiovascular risk, including Random Forests, Logistic Regression, Decision Trees, Neural Networks, Gradient Boosting, and Support Vector Machine. The heart disease dataset, the Cleveland and Framingham Heart Study datasets, and the Kaggle datasets are the most popular datasets used in the studies. Model performance is evaluated using metrics such as precision, recall, F1-score, and area under the receiver operating characteristic curve; however, in medical diagnosis, recall and F1-score are particularly important to minimize false negatives. Although these approaches show promising results, challenges such as imbalanced datasets, limited interpretability, and poor generalization across diverse populations remain. Furthermore, variations in datasets and experimental setups limit direct comparison across studies. This review highlights current research trends, compares existing methods, and identifies key limitations. It also provides recommendations for future research to develop more reliable, interpretable, and clinically applicable heart disease prediction systems.

Categories: Ensemble Learning, AI/ML-based decision support systems, Explainable AI

Keywords: heart disease prediction, machine learning, predictive modeling, explainable ai (xai), data imbalance

Introduction And Background

Heart disease is an emerging health problem in India, where it is estimated that nearly one-third of deaths in the country are caused by heart disease. In the present day, cardiovascular disorders are prevalent among about 7.5% of the Indian population. The more worrying fact regarding this issue is that the mortality rate due to heart disease in India is already at 282 per 100,000, much higher than the remaining world, which stands at 233 per 100,000 [1]. The increase in cases is greatly explained by the following factors: demographic aging, high urbanization, and the increase in unhealthy activities such as poor nutrition, increased stress, and sedentary lifestyles [2]. It is projected that by 2050, the burden of heart disease in India can be drastically high, which shows that the number of total cases of heart disease can show a 90

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percent growth, the total cases that are caused by the disease may increase by 73.4 percent, and the number of cases that cause disability may increase by 54.7 percent. These data reveal that there is an urgent need for effective prevention programs, early diagnosis methods, and the enhancement of the disease management system.

Over the past few years, deep learning and machine learning have introduced significant changes to the medical diagnostics field as both use insights provided by the data to identify the disease. Machine learning has emerged as a potent method of determining the presence of cardiovascular risk based upon analysis of vast amounts of data, like the medical history of patients, their lifestyle trends, and the result of diagnostic measures. Allowing physicians to make timely and correct treatment decisions, machine learning helps to improve the treatment prognosis of patients and shorten the recovery period. It also assists in decreasing the total clinical workload through the automated analysis of data and assists with accurate diagnosis. With the ever-growing healthcare data, machine learning is becoming a very useful instrument in predicting and managing heart diseases. The paper gives a summary of different machine learning models, such as the basic ones such as Logistic Regression (LR) and Decision Trees (DT), to sophisticated neural network models, to enhance the prediction precision and clinical decisions in heart disease management.

Review

Literature review

The application of machine learning and deep learning techniques in heart disease prediction has received significant attention in recent years. Researchers have explored various algorithms, datasets, and hybrid methods to improve prediction accuracy, interpretability, and clinical applicability.

Hossen [1] applied machine learning algorithms, specifically LR, to predict heart disease using the UCI dataset containing 14 attributes. The experiment involved data preprocessing steps such as normalization and splitting the data into training and testing sets. Since LR achieved the highest accuracy (approximately 95%), its performance was compared with other algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), and Gradient Boosting (GB), demonstrating its effectiveness in clinical settings.

Bilgaiyan et al. [2] developed a framework for heart disease prediction using different machine learning algorithms. RF, using 12 features, achieved the highest accuracy, highlighting the importance of data mining in predictive healthcare.

Focusing on the potential of contemporary approaches and real-time data integration, Kamal et al. [3] identified KNN as a highly effective algorithm for heart disease prediction. They recommended addressing limitations such as reliance on conventional techniques and small datasets to improve the reliability of the models.

A study by Bouqentar et al. [4] focuses on the early prediction of heart disease using machine learning algorithms combined with feature engineering techniques to improve model performance. It demonstrates that models such as DT, RF, SVM, and LR can achieve high accuracy (around 91-92%) when applied to clinical datasets. However, the study highlights limitations including dataset dependency, potential overfitting, and a lack of real-time validation.

Nayeem et al. [5] predicted heart disease using machine learning algorithms such as Naive Bayes (NB), RF, and KNN. The massive data they utilized contained more than 65,000 records of patients. In order to fill in lower information, they used average values to fill in the gaps and an information gain method to select the most significant features. Among the tested models, RF achieved the highest precision of 95.63%. As the study indicates, when the information is convenient in case of quality, and it is cleaned, it does not matter. They also suggest that it would be better to test other models in the future to potentially achieve even better results.

Singh et al. [6] examined the possibility of applying machine learning for early detection of heart disease, which is a central element in enhancing patient care and decreasing the mortality factor. They experimented with various supervised learning algorithms, such as SVM, RF, and DT, and applied principal component analysis to shrink down the size of the data. RF achieved the best performance, with a precision of 97% on the Framingham dataset. The study also

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considered usual problems such as overfitting and showed that machine learning can help make faster and personalized diagnoses. Finally, they wanted to make healthcare more efficient and effective, which was to detect and treat heart disease.

Ramesh et al. [7] investigated the use of machine learning for predicting heart disease and identifying individuals at higher risk. Handling lots of data was one of the challenges they experienced, and hence the models became less effective. Their study focused on some of the common health issues that are associated with heart diseases, including smoking behaviour, diabetes, cholesterol levels, obesity, family history, and high blood pressure.

Jan et al. [8] conducted a review of cardiovascular diseases among older adults in India, highlighting the increasing prevalence due to aging and changing lifestyle patterns. The study highlights that urbanization, unhealthy dietary habits, and limited access to healthcare are some of the reasons why cardiovascular diseases are becoming a huge burden in the country.

Prabhakaran et al. [9] compared the burden of cardiovascular diseases in India and the United States. Their findings indicate that the mortality rate due to heart disease is significantly higher in India. The major risk factors identified include hypertension, diabetes, and unhealthy lifestyle choices, underscoring the need for effective prevention and early diagnosis strategies.

El-Sofany et al. [10] developed a machine learning model that could detect heart disease at an early age. A combination of the CHDD dataset and individual medical records was used. XGBoost achieved the highest precision of 97.57, and it worked better than any of the other models that they tested. The study also indicated that it is necessary to ensure the right features are chosen to make the model effective. They applied methods such as Synthetic Minority Over-sampling Technique (SMOTE) in order to manage the issue of imbalanced data. In the future, the researchers intend to simplify the model by applying explainable AI (XAI) techniques and test the model on various datasets to make it more dependable and generally applicable.

Ali et al. [11] applied various supervised machine learning algorithms to predict heart disease using a dataset containing 1,025 patient records. Their results showed that models such as KNN, RF, and DT achieved high accuracy, with reported precision reaching 100%. Feature importance analysis identified chest pain, age, and maximum heart rate as the most significant predictors. The study demonstrates the potential of machine learning in assisting clinicians in making more accurate heart disease diagnoses.

Chua et al. [12] investigated the application of machine learning for heart disease prediction, a leading cause of global mortality. They used patient health data and evaluated five machine learning classifiers: NB, DT, KNN, LR, and SVM. The objective was to identify health factors that were most effective in making effective predictions. The results showed that LR outperformed the other models in their experiments.

Sahoo et al. [13] provide their framework of heart disease prediction that is based on machine learning and uses algorithms such as RF, KNN, and LR. Among these, the RF model achieved the highest precision of 90.16%, thus showing that it is reliable in the early detection of cardiovascular risks. The system is intended to be used at home to monitor the health of athletes and reduce the number of unnecessary hospital visits. This strategy will ensure that healthcare efficiency is maximized as well as a better personalized patient care is provided by focusing on critical cases.

Nadeem et al. [14] discuss the approach to predicting heart disease with the help of SVM and fuzzy logic. This would assist physicians in diagnosing heart issues more precisely and in less time by examining previous patient information. The precision of the new method was very high (96.23) in comparison to the previously used methods. The paper also points out the role of employing sophisticated technology as a means of saving lives by improving detection of heart disease.

Asih et al. [15] focused on machine learning-based heart disease prediction in a format that is understandable by doctors. They evaluated four models - SVM, RF, XGBoost, and KNN - and found that SVM and XGBoost achieved the best performance, with 88% precision. SHapley Additive exPlanations (SHAP) methodology was able to determine the very

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significant factors influencing predictions, whereas Local Interpretable Model-agnostic Explanations (LIME) explained how all the predictions were made. This study demonstrates that XAI can be applied to assist physicians in decision-making and enhancing care delivery to patients.

Kiran et al. [16] explored how machine learning methods can be used to predict heart disease and how critical early detection can be in reducing mortality rates. A comparison was conducted using different algorithms, including SVM, RF, and DT, based on a Kaggle dataset. The RF classifier achieved the highest precision of 94.96%, indicating that it has the potential for diagnostic applications. It would be possible to apply deep learning techniques and bigger datasets to get better results in the future.

Tyagi and Jain [17] investigated how machine learning algorithms can enhance the accuracy of heart disease prediction. Recognizing the limitations of conventional clinical data analysis methods, the authors proposed a system methodology that integrates a number of classification methods to extract meaningful features from patient data. The study employs algorithms such as DT and LR to develop an effective model that will enable the prompt diagnosis of the condition and enhance the management of heart disease.

Boukhatem et al. [18] investigated the role of machine learning in assisting physicians with heart disease prediction based on patient health data. They experimented with four widely used algorithms: SVM, multilayer perceptron, RF, and NB. The study used a dataset of 303 records, paying attention to features such as age, cholesterol, and blood pressure. The results showed that the SVM model was the most competent, and its precision was 91.67%. The authors emphasize the potential of machine learning in enabling early diagnosis and saving lives by identifying at-risk patients at an earlier stage.

Ghazal et al. [19] focused on predicting heart disease with the help of two machine learning algorithms: KNN and SVM. A well-structured dataset on Kaggle was used, which does not need significant cleaning, allowing the authors to focus on the effectiveness of the algorithms. Their findings showed that the two models worked well; however, KNN outperformed SVM, with a precision of 86%. Their results were also compared with older methods such as NB, and their models proved to be more reliable. In general, they imply that machine learning can result in more efficient and faster diagnosis of heart diseases.

Sharma et al. [20] explored the use of machine learning for heart disease prediction using a standard dataset from the UCI repository. The team applied four algorithms, namely DT, NB, RF, and SVM, and tested how each could identify at-risk patients using 14 medical attributes. RF emerged as the best-performing model in terms of precision and time. The authors suggest that such predictive models can be valuable tools for clinicians, as it would help them to diagnose and treat patients at a faster rate, particularly in settings that have limited resources.

Swathisree et al. [21] examined the predictive capabilities of machine learning in predicting heart disease using patient information such as age, cholesterol level, and lifestyle habits. The algorithms, like LR, DT, and RF, along with techniques such as feature selection and clustering, were used by the researchers to enhance the results. They also tested the possibility of dividing the data in accordance with gender to make the predictions more relevant. The research concludes that machine learning has high potential in assisting healthcare providers in identifying heart problems at an earlier stage and taking necessary actions to avoid complications.

Mohan et al. [22] compared four machine learning models - RF, NB, KNN, and LR - to determine the best model for heart disease prediction. The models were trained and tested using a Kaggle dataset implemented in Python. LR achieved the highest precision of 90.2%, making it the best model in the tests they made. The authors suggest that machine learning can offer a cost-effective and faster alternative to traditional diagnostic methods such as angiography, particularly for early detection of heart disease.

Table 7 presents 44 studies on heart disease prediction using machine learning. It summarizes the algorithms used, the accuracy achieved, the key contributions, and the limitations of each study.

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References No.	Authors	Study Objective	Algorithms Used	Best Accuracy (%)	Key Contribution	Identified Limitations/Gaps
[1]	Hossen	Heart disease prediction using ML	SVM, NB, DT, KNN	89.5	Performance comparison of basic classifiers	Limited dataset and lack of cross-validation
[2]	Bilgaiyan et al.	Apply ML to predict heart disease	LR, DT, RF	88.6	Focused on real-time prediction using a few models	Lacked explainability methods
[3]	Kamal et al.	Heart disease prediction using ML	ANN, SVM	91	Introduced deep learning for improved accuracy	Black-box model, small dataset
[4]	Bouqentar et al.	Early prediction of heart disease using feature engineering and ML techniques	DT, RF, SVM, LR, KNN, Ensemble Methods	92.1	Demonstrated effectiveness of feature engineering and ML models in improving prediction accuracy	Limited dataset diversity, lack of real-time validation, possible overfitting
[5]	Nayeem et al.	Compare ML algorithms for prediction	LR, SVM, KNN	87.3	Evaluated multiple ML models	Dataset imbalance, no feature selection
[6]	Singh et al.	Heart disease prediction using ML	ANN, RF, SVM	93	Performance improvement using hybrid models	High computational cost
[7]	Ramesh et al.	Predictive analysis of heart disease	DT, RF, LR	88.2	Comparative evaluation of classical ML approaches	Limited dataset size, lack of validation
[8]	Jan et al.	Review cardiovascular diseases in Indian adults	N/A	N/A	Comprehensive review of prevalence and risk factors	Did not include predictive modeling

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[9]	Prabhakaran et al.	Compare cardiovascular diseases in India vs. US	N/A	N/A	Highlighted epidemiological differences	No ML prediction applied
[10]	El-Sofany et al.	Predict heart disease using ML + XAI	ANN, RF	94.2	Integrated explainable AI for transparency	Dataset size and feature diversity limited
[11]	Ali et al.	Heart disease prediction using supervised ML	SVM, DT, LR	88.5	Performance evaluation of supervised ML	Did not address feature selection
[12]	Chua et al.	Compare ML models for heart disease	SVM, RF, KNN	89	Systematic model comparison	Limited dataset, lack of ensemble methods
[13]	Sahoo et al.	ML-based heart disease prediction	ANN, DT, RF	91.5	Highlighted impact of feature engineering	Small-scale datasets
[14]	Nadeem et al.	Fusion-based ML architecture	RF, ANN, SVM	92.8	Hybrid model using feature fusion	Complexity and computational cost
[15]	Asih et al.	Interpretable ML model for prediction	DT, RF	90.2	Focus on model interpretability	Limited dataset diversity
[16]	Kiran et al.	Heart disease prediction using ML	LR, RF, ANN	91.8	Included ensemble and deep learning models	High computational requirements
[17]	Tyagi and Jain	Heart disease prediction	SVM, XGBoost, ANN	92.5	Integrated boosting for higher accuracy	Dataset limited to hospital records
[18]	Boukhatem et al.	Heart disease prediction	DT, RF	88.7	Focused on early diagnosis	Limited external validation
[19]	Ghazal et al.	Heart disease prediction using ML	ANN, SVM, RF	93.1	Ensemble and hybrid approach	Lack of interpretability

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[20]	Sharma et al.	Heart disease prediction	SVM, KNN, LR	87.6	Evaluated classical ML methods	No deep learning integration
[21]	Swathisree et al.	ML-based heart disease prediction	RF, XGBoost	92	Used ensemble models for accuracy	Limited explainability
[22]	Mohan et al.	Heart disease prediction using supervised ML	SVM, ANN, LR	90.5	Compared supervised learning approaches	Dataset bias
[23]	Denysyuk et al.	Algorithms for automated diagnosis	CNN, RNN	94	Systematic review on ECG-based models	Lack of standard datasets
[24]	Shorewala	Early detection using ensemble	RF, Gradient Boosting	92.3	Applied ensemble techniques	Did not focus on interpretability
[25]	Patro et al.	Heart disease prediction using optimization	GA, PSO, RF	91	Optimization improved feature selection	Computationally expensive
[26]	Mienye et al.	Improved ensemble learning	RF, AdaBoost	90.8	Enhanced prediction via ensemble	Limited dataset size
[27]	Xiong et al.	Smart healthcare with deep learning	CNN, ANN	93.5	Fusion of features for better prediction	High computational cost
[28]	Amin et al.	Feature selection in heart disease prediction	PCA, RFE	88	Evaluated impact of feature selection	Did not include deep learning models
[29]	Dwivedi	Performance evaluation of ML techniques	SVM, DT, KNN	86.9	Comparative study of ML algorithms	Dataset small, no ensemble methods
[30]	Tougui et al.	Heart disease classification using data mining	DT, RF	87.5	Applied data mining for classification	Limited interpretability

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[31]	Valarmathi and Sheela	Hyperparameter optimization	SVM, ANN, RF	90.7	Improved performance via tuning	Computationally expensive
[32]	Islam et al.	IoT-based prediction system	ANN, RF	91.6	Real-time heart disease monitoring	Data privacy and sensor limitations
[33]	Acharya et al.	Deep learning for CVD detection	CNN	92.4	Used deep learning on ECG signals	Small dataset
[34]	Hannun et al.	Arrhythmia detection with deep learning	CNN	95	Clinician-level detection	Black-box model
[35]	Esteva et al.	Guide to deep learning in healthcare	CNN, ANN	94.5	Reviewed deep learning applications	Not specific to heart disease
[36]	Lundberg and Lee	Interpreting model predictions	SHAP	N/A	Developed model-agnostic explainability	Not a prediction model
[37]	Ribeiro et al.	Explain the predictions of any classifier	LIME	N/A	Introduced local interpretability	Computational overhead
[38]	Topol	High-performance medicine using AI	N/A	N/A	Convergence of AI and healthcare	Theoretical discussion
[39]	Johnson et al.	MIMIC-III critical care database	N/A	N/A	Large, publicly accessible dataset	Data access limitations
[40]	Rajkumar et al.	Scalable deep learning for healthcare	ANN, CNN	93.8	Deep learning at scale	High computational requirements
[41]	Krittawong et al.	ML in cardiovascular disease prediction	RF, SVM, ANN	91.2	Comparative study of ML models	Limited feature diversity
[42]	Tat et al.	AI in cardiovascular medicine	CNN, RF	92	Overview of AI techniques	Not an experimental study

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[43]	Weng et al.	Predicting cardiovascular risk using ML	LR, RF, XGBoost	89.5	Risk prediction using an ensemble	Dataset limited to hospital records
[44]	Chicco and Jurman	Advantages of the Matthews correlation coefficient	N/A	N/A	Evaluated evaluation metrics	Focused on metrics, not prediction

TABLE 1: Summary of studies on heart disease prediction

ML, Machine Learning; XAI, Explainable Artificial Intelligence; CVD, Cardiovascular Disease; SVM, Support Vector Machine; NB, Naive Bayes; DT, Decision Tree; KNN, K-Nearest Neighbors; LR, Logistic Regression; RF, Random Forest; ANN, Artificial Neural Network; XGBoost, Extreme Gradient Boosting; CNN, Convolutional Neural Network; RNN, Recurrent Neural Network; GA, Genetic Algorithm; PSO, Particle Swarm Optimization; PCA, Principal Component Analysis; RFE, Recursive Feature Elimination; SHAP, SHapley Additive exPlanations; LIME, Local Interpretable Model-agnostic Explanations

Traditional Machine Learning Approaches

Early studies focused on basic supervised machine learning algorithms applied to structured clinical datasets. Hossen [\[1\]](#), Bilgaiyan et al. [\[2\]](#), and Kamal et al. [\[3\]](#) investigated classifiers such as SVM, DT, NB, and KNN, achieving prediction accuracies between 80% and 90%, though limited by small datasets and lack of feature optimization. Bouqentar et al. [\[4\]](#) and Tyagi and Jain [\[17\]](#) emphasized comparative analysis of multiple models, showing that performance depends on data quality, feature selection, and parameter tuning. Ramesh et al. [\[7\]](#) and Jan et al. [\[8\]](#) highlighted dataset characteristics as key determinants of performance.

LR and DT have been widely used for their interpretability, making them suitable for clinical decision support systems [\[1,5,11\]](#). SVM handle high-dimensional data effectively, while NB and KNN offer moderate accuracy with low computational requirements [\[12,20,21\]](#). These traditional machine learning models serve as benchmarks for advanced approaches.

Ensemble Learning Methods

Ensemble learning, which combines multiple models, has improved prediction accuracy and robustness. Shorewala [\[24\]](#), Patro et al. [\[25\]](#), and Mienye et al. [\[26\]](#) demonstrated that RF, GB, and AdaBoost outperform single classifiers, achieving accuracy above 85%. Nadeem et al. [\[14\]](#) proposed fusion-based ensemble architectures, while Xiong et al. [\[27\]](#) applied feature fusion for improved robustness. These approaches effectively handle noisy or imbalanced datasets [\[18,19\]](#).

Deep Learning Techniques

Deep learning methods such as Artificial Neural Networks, Convolutional Neural Networks (CNN), and Recurrent Neural Networks have been increasingly used for heart disease prediction. Acharya et al. [\[33\]](#) and Hannun et al. [\[34\]](#) applied deep networks to medical signals, achieving performance comparable to expert clinicians. Esteva et al. [\[35\]](#) provided guidance on deep learning in healthcare. Large-scale datasets such as MIMIC-III [\[39\]](#) and scalable models developed by Rajkomar et al. [\[40\]](#) facilitated high accuracy, generalizability, and reproducibility.

Explainable Artificial Intelligence

XAI techniques address the interpretability challenge in machine learning/deep learning models. Lundberg and Lee [\[36\]](#) introduced SHAP, and Ribeiro et al. [\[37\]](#) proposed LIME to explain feature contributions such as age, cholesterol, and blood pressure. Amin et al. [\[28\]](#) emphasized the importance of feature selection for interpretability. El-Sofany et al. [\[10\]](#)

and Asih et al. [15] integrated XAI with machine learning models to improve transparency and trust, which is critical for clinical adoption.

Feature Selection and Optimization

Feature selection improves model performance and reduces complexity. Patro et al. [25], Valarmathi and Sheela [31], and Amin et al. [28] applied principal component analysis, RFE, and optimization algorithms to select relevant features. Data preprocessing, normalization, handling missing values, and addressing class imbalance are essential for robust models [13,21].

Hybrid and IoT-Based Systems

Hybrid machine learning-IoT systems have emerged to enable real-time monitoring. Islam et al. [32] developed IoT-based systems that track vital parameters continuously for early detection. Nadeem et al. [14] and Xionget al. [27] combined multiple algorithms for robust hybrid approaches. Challenges include data privacy, security, and integration with healthcare infrastructure.

Cardiovascular Disease Context and Clinical Insights

Cardiovascular diseases remain a leading cause of mortality worldwide. Jan et al. [8], Prabhakaran et al. [9], Denysyuk et al. [23], Krittanawong et al. [41], Tat et al. [42], and Weng et al. [43] identified risk factors such as hypertension, diabetes, smoking, and lifestyle habits, which are commonly included in machine learning models. Integrating clinical knowledge enhances prediction accuracy and applicability.

Comparative Insights From Literature

Traditional machine learning models are interpretable but limited with complex datasets. Ensemble models improve accuracy but reduce interpretability. Deep learning achieves highest performance but needs large datasets and resources. XAI techniques increase transparency, and hybrid/IoT-based systems represent emerging trends. Metrics such as Matthews correlation coefficient help evaluate model performance effectively [44].

Summary

In summary, machine learning and deep learning techniques have advanced heart disease prediction significantly. Traditional models offer interpretable baselines, ensemble methods improve robustness, deep learning enables complex data analysis, and XAI ensures transparency. Hybrid and IoT approaches support practical healthcare applications. Future research should focus on standardization, interpretability, heterogeneous data, and real-world integration.

Methodology

Research Design and Approach

This study adopts a systematic and structured methodology to review existing research on heart disease prediction using machine learning and deep learning techniques. A systematic literature review approach is employed to ensure a comprehensive, transparent, and reproducible process. This approach allows for the integration of findings from multiple studies while identifying trends, challenges, and research gaps in the domain. The research design combines both qualitative and quantitative analyses of previously published work, making it suitable for evaluating the effectiveness of different machine learning models in healthcare applications. The methodology is divided into several phases, including literature search, study selection, data extraction, classification, comparative analysis, and synthesis. The study selection process follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, including identification, screening, eligibility, and inclusion stages.

Literature Search Strategy

A comprehensive literature search was conducted using major academic databases such as IEEE Xplore, ScienceDirect, SpringerLink, PubMed, and Google Scholar. These databases were selected due to their extensive coverage of peer-reviewed research in machine learning and healthcare. The search process involved the use of predefined keywords,

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including "heart disease prediction using machine learning," "cardiovascular disease prediction," "machine learning in healthcare," "deep learning for heart disease detection," and "explainable AI in healthcare." Boolean operators such as AND and OR were applied to refine the search queries and improve the relevance of the results. The search was limited to studies published between 2016 and 2024 to ensure the inclusion of both foundational and recent advancements. Additionally, backward and forward citation tracking was performed to identify further relevant studies.

Study Selection Process

The study selection process was carried out in multiple stages to ensure the inclusion of high-quality and relevant research. Initially, titles and abstracts of all retrieved articles were screened to remove studies that were not related to heart disease prediction or machine learning. This was followed by the removal of duplicate papers obtained from multiple databases. In the next stage, a full-text review of the remaining articles was conducted, where each paper was evaluated based on its objectives, methodology, dataset, and relevance to the research topic. Only studies that directly addressed heart disease prediction using machine learning or deep learning approaches were retained. Initially, a large number of studies were identified, which were reduced after removing duplicates and applying screening and eligibility criteria. After applying all selection criteria, a total of 44 research papers were included in the final review. The study selection process can be visually represented using a PRISMA flow diagram.

Inclusion and Exclusion Criteria

To ensure the quality and relevance of the selected studies, specific inclusion and exclusion criteria were defined. Studies were included if they focused on heart disease or cardiovascular disease prediction; utilized machine learning, deep learning, or hybrid techniques; and were published in peer-reviewed journals or conferences. Additionally, only studies reporting performance evaluation metrics such as accuracy, precision, recall, F1-score, or area under the curve were considered. The review was limited to studies published between 2016 and 2024. Studies were excluded if they were not written in English, lacked experimental validation or a clear methodology, or were duplicates. Papers that did not directly focus on prediction tasks, such as purely clinical studies without machine learning components, were also excluded.

Data Extraction and Management

A structured data extraction process was implemented to systematically collect relevant information from each selected study. A standardized framework was used to ensure consistency across all papers. Information such as authors, publication year, and source was recorded for each study. Details about the datasets used, including dataset name, size, and type of data, were also extracted. The machine learning techniques applied in each study were carefully documented, including traditional algorithms such as LR, DT, SVM, KNN, and NB, as well as deep learning models such as artificial neural networks, convolutional neural networks, and recurrent neural networks. Information on feature engineering techniques, including feature selection and preprocessing methods, was also collected. Additionally, evaluation metrics such as accuracy, precision, recall, F1-score, and area under the curve were recorded. The extracted data were organized into structured tables to facilitate comparison and analysis.

Classification of Techniques

To provide a clearer understanding of the research landscape, the selected studies were categorized based on the types of machine learning techniques used. One category includes traditional machine learning models, which are known for their simplicity and interpretability. Another category focuses on ensemble learning methods, which combine multiple models to improve prediction accuracy and robustness. Deep learning approaches form another category, as they are capable of handling large and complex datasets and are particularly effective in medical imaging and time-series data analysis. In addition, XAI techniques were analyzed to understand how models provide interpretable predictions, which is essential in healthcare applications. Hybrid and IoT-based systems were also considered, as they represent emerging trends in real-time health monitoring and prediction.

Comparative Analysis

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A comprehensive comparative analysis was conducted to evaluate the performance and effectiveness of different machine learning approaches. The comparison was based on several factors, including model performance, dataset characteristics, feature engineering techniques, computational complexity, interpretability, and clinical applicability. Performance metrics such as accuracy, precision, recall, F1-score, and area under the curve were used to compare different models. The analysis showed that ensemble and deep learning models generally achieve higher accuracy, while traditional models offer better interpretability and ease of implementation. The role of dataset quality and feature selection in improving model performance was also highlighted. Due to variations in datasets, preprocessing techniques, and evaluation protocols across studies, direct comparison of model performance should be interpreted with caution. Ensemble models such as RF and GB tend to perform better on structured datasets due to their ability to reduce variance and capture complex feature interactions. In contrast, deep learning models are more effective for unstructured data such as ECG signals and medical images, where automatic feature extraction is required.

Synthesis of Findings

The findings from the selected studies were synthesized to identify common trends and patterns. It was observed that there is an increasing use of ensemble and deep learning techniques for heart disease prediction. Feature selection and preprocessing were found to significantly impact model performance. Additionally, there is a growing emphasis on explainability in machine learning models, as healthcare professionals require transparent and interpretable systems. The integration of machine learning with IoT devices for real-time monitoring is also emerging as an important area of research.

Identification of Research Gaps

Based on the analysis, several research gaps were identified. One major challenge is the limited availability of large and diverse datasets, which affects the generalizability of machine learning models. Another issue is the lack of standardized evaluation frameworks, making it difficult to compare results across studies. The interpretability of deep learning models remains a concern, particularly in clinical settings. Furthermore, many studies lack real-world clinical validation, which limits their practical application. The integration of machine learning systems with existing healthcare infrastructure also presents challenges.

Reliability and Validity

To ensure the reliability and validity of the review, several measures were taken. The use of multiple databases helped reduce selection bias and ensured comprehensive coverage of relevant studies. Clearly defined inclusion and exclusion criteria were applied consistently. The data extraction process was standardized and systematically implemented, and the extracted information was cross-verified for accuracy. These steps enhance the credibility and reproducibility of the study.

Limitations of the Study

Despite the rigorous methodology, certain limitations exist. The review is limited to English-language publications, which may result in the exclusion of relevant studies in other languages. Some studies may have been missed due to database limitations. Variations in datasets, evaluation metrics, and experimental setups across studies make direct comparison challenging. Additionally, the rapidly evolving nature of machine learning research means that newly published studies may not have been included. Most reviewed studies do not report statistical validation measures such as confidence intervals or hypothesis testing, which limits the reliability of performance comparisons.

Ethical Considerations

This study is based entirely on previously published research and does not involve human participants or sensitive data. Proper citation and acknowledgment of all sources were maintained to ensure academic integrity and avoid plagiarism.

Summary

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In summary, this methodology provides a systematic and comprehensive framework for reviewing machine learning techniques used in heart disease prediction. Through structured literature search, rigorous selection criteria, detailed data extraction, and comparative analysis, the study ensures a thorough understanding of existing research while identifying key areas for future work.

Workflow of machine learning for heart disease prediction

This paper uses a step-by-step guide to develop and test machine learning models to predict heart disease. The overall aim is to utilize patient information adequately to determine the likelihood of an individual having heart disease. All the steps involve data collection, preprocessing, model building, training, and evaluation. The stages are significant towards the attainment of correct and trustworthy results. The complete workflow of the proposed system is illustrated in Figure 1.

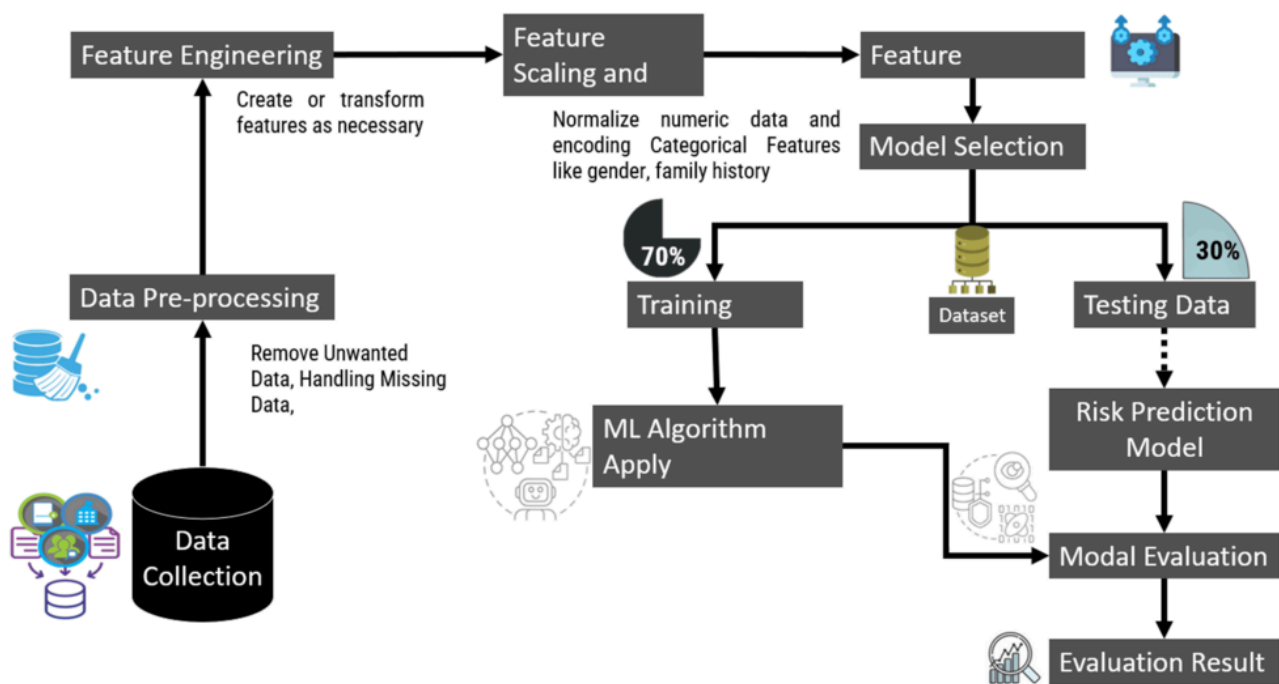


FIGURE 1: Generalized machine learning pipeline adapted from common practices in predictive modeling

Data Collection

In this study, the publicly available dataset is utilized, which is usually utilized in heart disease prediction research. The dataset comprises of medical and personal data of the patients, which can be helped to detect heart-related diseases.

It contains features like age, gender, the character of the ECG results, cholesterol, blood sugar level, the maximum heart rate, chest pain, blood pressure, and some other clinical measurements. There is also a target variable of whether the patient has heart disease or not in the dataset.

Such a standardized dataset may be helped to compare the results to the remaining of the research and make sure that the model receives reliable information to be trained.

Data Preprocessing

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The quality and preparation of the data used in the training of any machine learning model is also determinants of the performance of such a model. Data preprocessing is the act of sorting, purifying, and streamlining raw data in order to make it useful to the machine learning algorithms. This step is very crucial as real-life data sets may have problems of missing values and duplication of records, outliers, or irrelevant data, all of which may influence the precision of the models adversely.

Preprocessing helps in making the data consistent, complete, and analyzable. Depending on the characteristics of the data, the used techniques may be different; however, they usually involve work with missing or erroneous values, deleting irrelevant or duplicated features, data normalization or scaling to ensure uniformity, data type transformation, and cleaning of inconsistent records. Preprocessing can also reduce dimensions in cases when the dataset has many features so that the algorithms can identify useful patterns with less effort.

Through proper preprocessing, researchers are able to increase the precision, speed, and reliability of machine learning models to a large extent. This is particularly necessary when dealing with complex medical data like in the case of prediction of heart diseases where the quality of the data directly affects the diagnostic results.

Data Splitting

After data preparation, there are two aspects to the data: training data and testing data. In this experiment, 70 percent of the data is utilized in the training of the models and the remaining 30 percent is utilized in testing. This action is necessary since it will enable the model to be tested on unseen data. This assists in testing the model whether it can have a good performance on the real world scenario.

Model Development

This study uses various machine learning algorithms to compare their performance. These are LR, SVM, NB, RF, DT, KNN, and GB. Both models are differing in their functionality. Other models are easy to comprehend as some are straightforward and easy to understand whereas other models are complex yet they offer more precision. With the use of the several models, one can estimate which one works best in predicting heart diseases.

Model Training

During the training stage, each of the two models are trained using the training information. It attempts to comprehend the correlation between the input characteristics and the desired variable.

Model parameters are also altered to enhance performance. There are occasions when cross-validation is adopted to make sure that the model works regularly and is not over-reliant on a particular section of the data.

Performance Evaluation

After creating a machine learning model, it is critical to test the model to determine its performance. Performance evaluation will help to see whether the predictions of the model are accurate and reliable. Various metrics are usually employed to evaluate model performance, and they all give a different insight into the performance of the model.

Exactness: Exactness is used to measure the degree to which the model succeeds in making the right predictions among all the predictions. It gives a rough notion of the average frequency with which the model is correct. The high score in precision can be taken as a good overall performance; however, it does not always provide the full picture, in particular, when a dataset is lopsided.

Precision: Precision measures the total cases that were estimated by the model to be positive and that are actually correct. An example is that given the model estimates that 10 patients have heart disease, precision helps determine the number of patients who actually have it. High precision implies a smaller number of false-positive predictions by the model.

Recall (Sensitivity): Recall (also called Sensitivity) is a measure of the model, which is used to determine how good the model works to detect actual positive cases. When it comes to predicting heart disease, recall reflects the model's ability to identify patients who truly have the condition. A high recall indicates that only a small number of actual positive cases

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are missed.

F1-Score: It is a harmonic mean of accuracy and recall, which is a balanced metric of the two. It is particularly useful when both false positives and false negatives need to be minimized. A higher F1-score indicates that the model has a good balance between precision and recall.

ROC Curve (Receiver Operating Characteristic) and AUC: The ROC curve is a graphical representation of a model's ability to distinguish between classes, such as the presence or absence of disease. This performance is measured by the Area Under the Curve (AUC); the closer the value is to 1, the better the model is at distinguishing between the classes.

Models discussion

Decision Tree

DT is a basic but very useful algorithm used to solve classification problems in machine learning. It is conceptually a hierarchical flowchart in which internal nodes split the data based on feature values, and branches represent possible outcomes. Beginning at the root, the data follows specific branches determined by feature values and eventually results in a final classification at a leaf node. The ability to trace every decision path from the root to the leaves is a primary strength, contributing to its high interpretability and allowing a clear explanation of predictions. Additionally, DTs require less intensive data preprocessing and are likely to provide reliable outcomes, which makes them especially suitable for practical, real-world applications such as medical diagnostics [7].

Random Forest

The RF algorithm is also an ensemble method that builds on the concept of DT by developing multiple individual trees and summing their results to improve overall predictive power. To reduce the overfitting risk associated with a single DT, RF enhances stability and generalization by combining the predictions of many independently trained trees. During the training phase, a random selection of both data samples and features helps build each tree, a strategy that has been shown to be effective in reducing bias and variance in the model. This ensemble methodology is a reliable method for tackling complex medical tasks such as heart disease prediction, due to its strong performance on large, dense datasets and its ability to handle missing data [13,16].

Support Vector Machine

An SVM is an excellent classification algorithm that tries to discover the best boundary, or hyperplane, to distinguish between different classes of data. It operates by maximizing the margin between classes, which allows the model to generalize well to new or unseen samples. When the dataset is not linearly separable, SVM uses kernel functions to map the data to a higher-dimensional feature space where clear separation is possible. Because of its high precision and strong performance with complex and nonlinear data, SVM has been increasingly used in medical diagnostics, including heart disease prediction [19].

Gradient Boosting

GB can be defined as a model that builds models sequentially, with each subsequent model trained to eliminate the errors not resolved by the previous one. It integrates many weak learners - usually small DTs - into one powerful predictive model. During training, GB assigns higher importance to misclassified examples so that subsequent models focus on harder cases, thereby reducing bias and improving precision. Because of its capability to capture intricate data patterns, GB is effective in classification tasks such as heart disease prediction and other medical applications [26].

Logistic Regression

LR is one of the statistical tools most often used when binary classification is required (i.e., distinguishing between two possible states of a variable, such as the absence or presence of a disease). LR, unlike linear regression, employs the sigmoid function to estimate probabilities and map predictions between 0 and 1. Computationally, it is efficient, simple

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to implement, and produces interpretable results, which contributes to its popularity in medical data analysis as a baseline algorithm. LR is useful in predicting heart disease by establishing and estimating the association between various risk factors and the risk of developing heart disease [5,11].

Naive Bayes

NB classifier is a simple but effective probabilistic classifier based on Bayes' Theorem and works on the assumption that all input features are independent of each other. It approximates the probability of each class given the features and assigns the class with the highest posterior probability. In the case of continuous variables, the model usually uses the assumption of a Gaussian (normal) distribution to make the calculations easier. NB continues to perform well even on large and complex datasets despite its strong independence assumption. It is a viable option for different medical prediction applications such as heart disease detection due to its speed, scalability, and resilience [20].

K-Nearest Neighbor

The KNN algorithm is an instance-based learning (lazy) algorithm that can be used for both regression and classification. It does not construct an explicit model in the training process; instead, it stores the entire training data and makes predictions by computing the distance between a new input and the stored samples. The parameter K identifies the number of neighboring points to be considered in making the decision, and this directly affects the final classification or regression outcome. The most common class among these neighbors becomes the predicted value. KNN is easy to understand and can also be applied in pattern recognition and recommendation systems, but it is flexible. However, the computation time is higher for large or high-dimensional datasets, and therefore its effectiveness may be constrained in some medical applications [19].

Performance comparison

Classical Algorithms

LR: LR is one of the most widely used models for heart disease prediction due to its simplicity and interpretability. It effectively identifies relationships between clinical variables and typically achieves performance in the range of 80-85% accuracy in recent studies [3,4]. However, its performance may be limited when handling complex, non-linear relationships.

SVM: SVM perform well in high-dimensional medical datasets and are particularly effective in handling overlapping classes. These models often achieve performance above 85% and are considered reliable for classification tasks.

DT and RF: DT and RF are valued for their interpretability and ability to model complex feature interactions. RF, as an ensemble method, generally outperforms individual DT and achieves performance in the range of 88-94% [5], primarily due to its ability to reduce variance and avoid overfitting.

Ensemble and Boosting Models

GB, XGBoost, and LightGBM: These advanced ensemble techniques combine multiple weak learners to form a strong predictive model. They consistently outperform traditional algorithms on structured datasets and have reported performance in the range of 95-98% in several studies [7,8]. Their superior performance is mainly attributed to iterative error correction and improved handling of feature interactions.

Hybrid models: Several studies have proposed hybrid models combining algorithms such as RF, SVM, and boosting techniques to enhance stability and predictive performance. These models aim to leverage the strengths of multiple approaches.

Deep Learning Approaches

Deep learning techniques, including multi-layer perceptron and CNN, have been increasingly applied to both structured clinical data and unstructured data such as ECG signals. These models can automatically learn complex feature representations and have reported performance exceeding 95% in recent studies [10,11]. However, their performance is highly dependent on the availability of large datasets and computational resources.

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Comparative Limitations and Critical Analysis

Due to variations in datasets, preprocessing methods, and evaluation protocols across different studies, direct comparison of model performance should be interpreted with caution. Furthermore, while many studies report high accuracy or precision, these metrics alone may not be sufficient in medical applications, where recall and F1-score are critical to minimize false negatives.

Additionally, most studies do not report statistical validation measures such as confidence intervals or hypothesis testing, limiting the reliability of performance comparisons.

From a methodological perspective, ensemble models tend to perform better on structured clinical datasets due to their ability to reduce variance and capture complex feature interactions. In contrast, deep learning models are more effective for unstructured data such as ECG signals and medical imaging, where automatic feature extraction is required.

Discussion

Although machine learning models are highly predictive, a closer examination shows that there exist technical weaknesses that impede clinical usage.

The Black Box Problem and XAI

One of the major challenges is the clarity of advanced models. Deep learning, although employing high precision, is not transparent. The recent trends indicate that there is a transition to XAI tools such as LIME and SHAP. According to Asih et al. [15], these frameworks diagrammatically depict the weighting of a particular patient with specific features (e.g., "Serum Cholesterol") to diagnose the patient, closing the data science and clinical intuition gap.

The Presence of Imbalance in Data and Clinical Reliability

The majority of heart disease datasets have relatively fewer positive cases than negative cases. Models that fail to apply methods such as SMOTE tend to achieve high precision with a dangerously low recall. A false positive is much less important than missing a sick patient in a clinical setting. El-Sofany et al. [10] point to the fact that researchers need to focus on the F1-score rather than just precision to guarantee the reliability.

Comparative Performance

According to recent research, ensemble models like the RF are always superior to Deep Neural Networks in terms of structured medical data. Deep learning can work better only when the input contains ECG waveforms or Medical Imaging, and CNNs are able to extract spatial features that classical machine learning cannot.

Even though precision is commonly the focus of most heart disease prediction studies, by measuring many recall, F1-score, metrics, including precision, and AUC, you can better understand how a model will perform and behave in practice in a clinical setting.

Challenges

Despite significant advancements in machine learning-based heart disease prediction, several challenges remain. These include data imbalance, missing values, and limited dataset sizes, which affect model performance. Additionally, the lack of standard evaluation metrics and feature selection methods makes comparison across studies difficult. Many models also suffer from poor interpretability, limiting their adoption in clinical settings. Furthermore, issues related to data privacy, computational complexity, and lack of real-time implementation continue to hinder practical deployment.

Future scope

Despite the fact that machine learning has shown significant potential in the estimation of heart disease, there are many challenges that remain to restrict the widespread adoption of the technology in clinical settings. A significant weakness is the inability to generalize to other models; most models are trained on data of only one institution or region, making them less effective in evaluating a different population [22].

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The other issue that remains constant is the imbalance in classes, which is typical of real-life healthcare data. Although methods like SMOTE and class weighting have been employed to overcome the problem, a majority of the studies still do it on controlled datasets with little or no external validation. In addition, practical implementation and clinical incorporation of such models are uncommon. There is a lack of effective solutions that have been applied to Electronic Health Records systems or even mobile health systems at hospitals, restricting their application in the daily clinical decision-making process.

Another research gap is the area of longitudinal prediction; the most of the studies performed nowadays are based on the single, non-temporal observations of patients and not upon the continuous or time-dependent information. This limits the capacity of this model to track changing health trends or give early warning as time goes by.

In order to fill such gaps, future research would focus on creating models that are trained with large-scale, diverse, and multi-center datasets in order to enhance robustness and reliability. Such methods as federated learning have the strength to facilitate learning models jointly across institutions and ensure patient privacy. Moreover, researchers ought to examine more sophisticated data imbalance methods, such as generative data augmentation and cost-sensitive learning, as well as, more stringent real-world analyses.

To be adopted widely, it is essential that predictive models can be integrated into clinical processes, mobile applications, and wearables with an unproblematic procedure. The integration of XAI techniques will also contribute to increased model transparency, where clinicians can comprehend and rely on automated predictions. In addition, risk assessment can be sustained and individualized through the help of multi-modal and time-series data that are on the basis of the ECG signals, wearable sensors, and medical images. Lastly, the human-in-the-loop systems, where medical practitioners can give feedback to retrain and refine models, might guarantee the long-term accuracy, flexibility, and relevance of dynamic healthcare environments.

Conclusions

Heart disease remains one of the leading causes of mortality worldwide, and the growing use of machine learning and deep learning has significantly improved early diagnosis and prediction. Models such as RF, XGBoost, LR, and SVM have demonstrated high performance, often achieving accuracy above 90%, particularly when combined with effective data preprocessing and feature selection techniques. The findings indicate that ensemble methods are more effective for structured clinical data, while deep learning approaches perform better on unstructured data such as ECG signals and medical imaging. However, these results depend on dataset characteristics and should not be generalized without standardized evaluation frameworks. Despite promising outcomes, several challenges remain, including imbalanced datasets, limited interpretability, and poor generalization across diverse populations. Furthermore, real-world clinical deployment is still constrained by issues such as lack of validation on heterogeneous datasets and difficulties in integrating these models into healthcare systems. Future research should focus on XAI, the use of diverse and large-scale datasets, and the development of hybrid models to improve both performance and trust. Overall, machine learning-based systems have strong potential to assist clinicians in making faster and more accurate decisions in heart disease diagnosis.

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: Payalben R. Kasundra, Vaseem J. Ghada

Acquisition, analysis, or interpretation of data: Payalben R. Kasundra, Vaseem J. Ghada

Drafting of the manuscript: Payalben R. Kasundra, Vaseem J. Ghada

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Critical review of the manuscript for important intellectual content: Payalben R. Kasundra, Vaseem J. Ghada

Supervision: Vaseem J. Ghada

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Conflicts of interest: In compliance with the ICMJE uniform disclosure form, all authors declare the following:

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Data Availability Statements

The datasets (and/or code) supporting this study are available from the corresponding author upon reasonable request. All data generated or analyzed during this study are included in this published article and/or its appendices. Data sharing is not applicable. This work is theoretical; no datasets were generated or analyzed.

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