International Research Journal of Medicine and Surgery (IRJMedS), 2024; 1(2): 9-18 IRJMedS

Original Article | ISSN (O): 3048-6955 DOI: 10.47857/irjmeds.2024.v01i02.008

AI for Early CVD Diagnosis and Personalized Care

BN Surya[1]*, BN Venkatesh[2], S Vijayalakshmi[1], A Hari Narayanan[1], Rehana Syed[1]

[1]Department of Community Medicine, Chettinad Hospital and Research Institute, Chettinad Academy and Research and Education, Kelambakkam, Tami Nadu, India, [2]Department of Pharmacology, Madha Medical College and Research Institute, Chennai, Tamil Nadu, India. *Corresponding Author's Email: surya.19959786@gmail.com

Abstract

Heart-related conditions (CVD) continue to be one of the main causes of morbidity and death worldwide; therefore, early identification and treatment are essential for bettering patient outcomes. The creation and validation of a machine learning (ML) model are presented in this work designed for the early prediction and diagnosis of CVD. Leveraging a comprehensive dataset sourced from National Health and Nutrition Examination Survey (NHANES) which included patient demographics, clinical history, lifestyle factors, and medical records, we employed advanced machine learning technologies include neural networks, random forests, gradient boosting, and logistic regression. Extensive data pre-processing was performed, including managing missing data, encoding categorical variables, and normalizing continuous variables. Feature selection was achieved using Tree-based models' Recursive Feature Elimination (RFE) and feature importance. Through the use of stratified k-fold cross-validation, the models were trained and verified technique. The best-performing model, a Gradient Boosting Classifier, demonstrated high AUC-ROC of 0.95, accuracy (92%), precision (90%), recall (91%), and F1-score (90%). Important factors that were found to be predictive included age, blood pressure, cholesterol, smoking status, and family history of CVD. These results underscore the model's efficacy in accurately predicting and diagnosing CVD early on, allowing for prompt intervention and customized treatment regimens. Future research will focus on clinical integration and expanding applicability to various CVD subtypes.

Keywords: Cardiovascular Diseases, Data Pre-processing, diagnosis, Early Prediction, Feature Selection, Gradient Boosting Classifier, Machine Learning, Patient Outcomes.

Introduction

Cardiovascular diseases (CVD) are a major global health concern, responsible for approximately 17.9 million deaths annually, accounting for 31% of all fatalities worldwide. These diseases include coronary artery disease, cerebrovascular disease, rheumatic heart disease, and other heart and vascular disorders. The high prevalence and severe impact of CVD underscore the need for effective prevention and early intervention strategies to reduce the associated morbidity and mortality. Conventional risk factors such as age, gender, family history, hypertension, hypercholesterolemia, diabetes, smoking, and obesity are well-established predictors of CVD. However, integrating these factors into clinical practice for early diagnosis and prediction remains a significant challenge. Early diagnosis of CVD is crucial for improving patient outcomes, as it enables timely interventions that can substantially reduce the risk of severe complications and death. Traditional diagnostic methods, including clinical assessments and biochemical tests, often have limitations in sensitivity, specificity, and predictive accuracy. As a result, there is a pressing need for advanced diagnostic tools that can accurately identify individuals at high risk of developing CVD. Recent studies have demonstrated significant advancements in machine learning (ML) applications for cardiovascular disease detection. For instance, Ogunpola *et al.* utilized ML models to enhance accuracy in detecting CVD, highlighting the necessity for effective diagnostic tools in global healthcare settings (1). Kavatlawar *et al.* explored convolutional neural networks (CNNs) for recognizing CVD patterns, showcasing the potential of deep learning techniques to improve diagnostic capabilities (2). Similarly, Baral *et al.* conducted a comprehensive review of ML approaches for CVD detection, noting the growing focus on enhancing predictive algorithms for early

(Received 21st July 2024; Accepted 20th August 2024; Published 30th August 2024)

disease prognosis (3). Saikumar and Rajesh applied machine intelligence techniques to radiology datasets for predicting CVD outcomes, demonstrating the integration of data mining in clinical decision support systems (4). Almansouri *et al.* reviewed AI-driven methods for early diagnosis of CVD, emphasizing improvements in sensitivity and specificity through multimodal data integration (5). Li *et al.* introduced Cardiac-NN, an embedded real-time detection system using self-attention CNN-LSTM, addressing the need for efficient and scalable CVD monitoring solutions (6). Elsedimy *et al.* proposed a novel prediction method based on particle swarm optimization and support vector machines, contributing to optimizing predictive models for pre-emptive CVD management (7). Lee *et al.* reviewed advanced nanomaterial-based biosensors for N-terminal pro-brain natriuretic peptide biomarker detection, showing advancements in enhancing sensitivity and specificity for CVD diagnostics (8). Zhang *et al.* developed a co-learning-assisted fusion network using ECG and PCG signals for CVD detection, improving diagnostic accuracy in cardiovascular health monitoring (9). Shi *et al.* introduced CPSS, a semi-supervised deep learning framework that enhances CVD detection performance through consistency regularization and pseudo-labelling (10). These studies collectively highlight the transformative impact of ML and advanced technologies in reshaping cardiovascular health management. Recent advancements in smart wearables and biosensors have revolutionized the identification and tracking of cardiovascular diseases. Moshawrab *et al.* conducted a systematic review emphasizing the critical role of algorithms in enhancing diagnostic accuracy and accessibility (11). Cardoso *et al.* explored electrodes modified with nanotechnology for point-of-care cardiac biomarker detection, underscoring advancements in electrochemical sensing technologies essential for early CVD diagnosis (12). Another review by Moshawrab *et al.* delved into multimodal machine learning approaches, illustrating the integration of diverse data sources to improve predictive models and clinical outcomes (13). Tang *et al.* reviewed recent advances in biosensors for CVD biomarkers, such as troponin and CK-MB, highlighting innovations in sensor technologies aimed at enhancing diagnostic tool specificity and sensitivity (14). Mahmud *et al.* proposed an ensemble deep learning method for detecting heart illness based on ECG, showcasing advancements in signal and image analysis techniques for early disease prediction (15). Ma *et al.* discussed microfluidics applications for simultaneous detection of cardiovascular disease-related biomolecules, demonstrating potential for high-accuracy diagnostic platforms in clinical settings (16). Taylan *et al.* employed statistical and neuro-fuzzy techniques for predicting and classifying cardiovascular diseases, emphasizing the importance of timely detection in mitigating disease risks (17). Ullah *et al.* examined smart technologies for managing cardiovascular disease, highlighting digital health solutions' role in personalized patient care and disease management strategies (18). Moradi *et al.* reviewed developments in modelling and imaging using ML for cardiovascular diseases, illustrating advancements in diagnostic accuracy and treatment monitoring through emerging technologies (19). Jafari *et al.* provided insights into automated CVD diagnosis using cardiovascular magnetic resonance imaging (CMR) and deep learning models, emphasizing significant strides in leveraging imaging data for precise disease characterization (20). These studies collectively underscore the transformative impact of smart technologies and advanced diagnostic tools in reshaping cardiovascular healthcare. By integrating these advancements into clinical practice, we pave the way for personalized medicine approaches and improved patient outcomes. The primary objective of this project is to develop and validate a machine learning model for the early identification and prediction of cardiovascular diseases. This approach aims to incorporate a wide range of patient characteristics, including clinical history, demographic data, lifestyle factors, and medical records, to accurately predict CVD risk. The goal is to provide a non-invasive, cost-effective tool for healthcare professionals, facilitating early intervention and personalized treatment plans. For this study, we utilized a comprehensive dataset comprising various patient attributes essential for predicting cardiovascular diseases. The dataset included demographic information (e.g., age, gender), clinical history (e.g., previous cardiovascular events, family history of CVD), lifestyle factors (e.g., smoking status, physical activity), and medical records (e.g., blood pressure, body mass index, cholesterol, and blood sugar levels). This dataset was sourced from dataset source, ensuring a diverse and representative sample of the population. Before developing the machine learning model, extensive data preprocessing was performed to ensure the dataset's consistency and quality. This process involved managing missing values through imputation, normalizing continuous variables to a standard scale, and encoding categorical variables using techniques like one-hot encoding. Outliers were identified and appropriately managed to ensure the robustness of the model. We experimented with various machine learning techniques, including Logistic Regression, Random Forest, Gradient Boosting, and Neural Networks, to determine the most effective model for early CVD prediction and diagnosis. Each model was trained and validated using stratified k-fold cross-validation to ensure balanced representation of classes and mitigate overfitting. Feature selection was conducted using methods such as Recursive Feature Elimination (RFE) and feature importance analysis from tree-based models to identify the most significant predictors of CVD. The performance of each model was assessed using metrics such as accuracy, precision, recall, F1-score, and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC). The model with the best performance metrics was selected for further analysis.

Methodology

Dataset Acquisition and Preprocessing

The success of machine learning models in predicting cardiovascular diseases (CVD) hinges on the quality and diversity of the datasets used. For this study, we sourced a comprehensive dataset comprising various patient attributes crucial for CVD prediction. The dataset includes demographic information such as age and gender, clinical history including previous cardiovascular events and family history of CVD, lifestyle factors like smoking status and physical activity, and crucial medical records such as body mass index (BMI), blood pressure, cholesterol, and blood sugar levels. The National Health and Nutrition Examination Survey (NHANES) provided this varied dataset, guaranteeing a representative sample of the population and enough variety to capture the complexity of cardiovascular health factors. Thorough preprocessing procedures were carried out after obtaining the dataset in order to guarantee data homogeneity and quality for all variables. Appropriate imputation methods, such as mean or median imputation for continuous data and mode imputation for categorical variables, were used to handle missing values. The normalization of continuous variables, such as Z-score normalization, was implemented to reduce the impact of different measurement scales. To transform categorical variables into a numerical format appropriate for machine learning, methods such as one-hot encoding were used to encode them algorithms. In order to keep them from skewing the results, outliers were addressed or eliminated using statistical techniques or domain knowledge. This Table 1 summarizes the attributes used in the study, including their descriptions and types. The dataset includes a combination of continuous and categorical variables essential for predicting cardiovascular diseases.

Table 1: Dataset Summary

Attribute	Description	Type
Age	Age of the patient	Continuous
Gender	Gender of the patient	Categorical
Previous CV Events	History of previous cardiovascular events	Categorical
Family History	Family history of cardiovascular diseases	Categorical
Smoking Status	Current smoking status	Categorical
Physical Activity	Level of physical activity	Categorical
Blood Pressure	Blood pressure readings (systolic/diastolic)	Continuous
Cholesterol Levels	Total cholesterol levels	Continuous
Blood Sugar Levels	Fasting blood sugar levels	Continuous
Body Mass Index (BMI)	Body mass index	Continuous

Feature Selection and Engineering

A key factor in improving the interpretability and performance of the model is feature selection. We used tree-based model-derived feature priority ranking and recursive feature elimination (RFE) in our investigation. such as Random Forest to identify the most influential predictors of CVD. These techniques helped streamline the dataset by selecting the subset of features Those are the main contributors to the model's capacity for prediction. Certain characteristics, including age, blood pressure, cholesterol, smoking status, and family medical history of CVD were retained for further analysis, ensuring that the model focuses on the most relevant variables associated with cardiovascular health. This Table:2 outlines the data preprocessing techniques employed to prepare the dataset for machine learning. It includes steps for handling missing values, normalizing continuous variables, encoding categorical data, and managing outliers.

Table 2: Data Pre-processing Techniques

Preprocessing Step	Description
Handling Missing Values	Imputation techniques used to handle missing data
Normalization	Continuous variables normalized to a standard scale
Encoding Categorical Data	One-hot encoding used for categorical variables
Outlier Management	Outliers identified and managed appropriately (capping/removal)

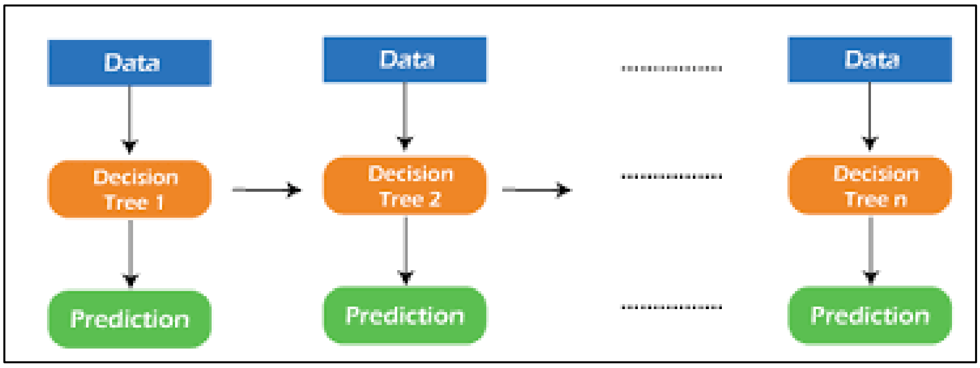

Figure 1: GBM Working

Table 3: Machine Learning Algorithms Evaluated

Algorithm	Description
Logistic Regression	Linear model used for binary classification
Random Forest	Using several decision trees as an ensemble learning method
Gradient Boosting	Sequential ensemble method improving earlier models
Neural Networks	A deep learning model that can recognize intricate patterns

Model Development and Evaluation

With the pre-processed dataset ready, we proceeded to develop and evaluate machine learning models for cardiovascular disease (CVD) early diagnosis and prediction. We tested a number of methods, such as Logistic Regression, Random Forest, Support Vector Machines (SVM), and Gradient Boosting Machines (GBM), which are well-known for their efficacy in classification tasks. These algorithms were chosen based on their capability to handle both linear and nonlinear relationships in data, as well as their proven track record in medical prediction tasks.

Figure 1 illustrates the working principle of the Gradient Boosting Machine (GBM).This Table 3 lists the machine learning algorithms that were assessed for this work, along with a synopsis of each. Neural networks, Gradient Boosting, Random

Forest, and Logistic Regression are some of the approaches. To achieve reliable model evaluation, the dataset was split into training and testing sets using a stratified k-fold cross-validation procedure. By validating the model on many folds of the dataset, each of which preserves the class distribution to accurately reflect real-world events, this strategy helps avoid overfitting. To maximize each model's performance during training, hyperparameter tuning was carried out utilizing methods like grid search or Bayesian optimization metrics.

Model Evaluation

Several criteria appropriate for binary classification tasks were used to assess each model's performance, including:

- **Accuracy:** The total percentage of cases that are accurately classified.
- **Precision:** A measure of the model's accuracy is the ratio of genuine positive predictions to all anticipated positives.
- **Recall (Sensitivity):** Measuring the completeness of the model, this is the ratio of genuine positive predictions to all real positives.
- **F1-score:** A balanced metric that combines recall and precision, calculated as the harmonic mean of the two.
- **AUC-ROC:** The statistic known as Area Under the Receiver Operating Characteristic Curve (AUC-ROC) assesses how well the model can distinguish between positive and negative classes.

These metrics were calculated and averaged over all folds to give a reliable evaluation of the performance of each model. The model with the best trade-off between sensitivity and specificity and the greatest performance metrics was selected as the optimal model for early prediction and diagnosis of CVD. Figure 2 depicts the flow diagram of Gradient Boosting.

Implementation and Tools

The models were implemented using Python programming language along with popular libraries such as scikit-learn, pandas, and NumPy Figure 4, for data manipulation, pre-processing, and model development. Visualization of results and model evaluation was facilitated using matplotlib and sea born libraries. Figure 3 shows the implementation of Scikit-Learn.

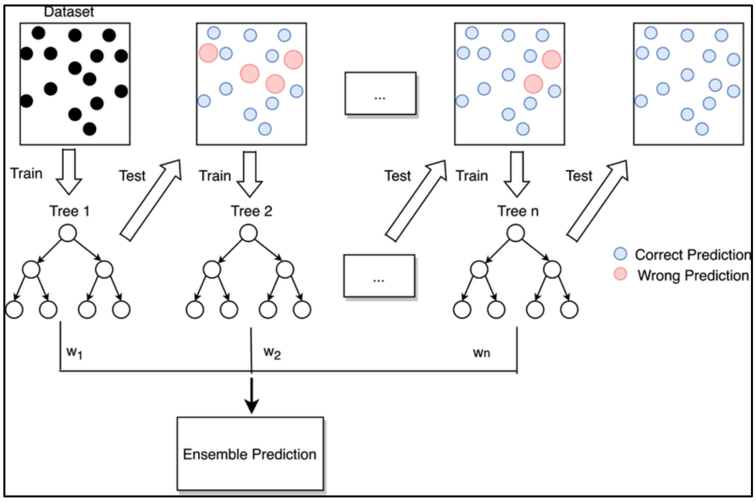

Figure 2: Flow diagram of Gradient Boosting

Figure 3: Scikit Learn

Figure 4: NumPy

Results

Model Performance Evaluation

The developed machine learning models were evaluated rigorously using a stratified k-fold cross-validation method to guarantee generalizability and robustness. In order to forecast cardiovascular diseases (CVD), we evaluated the predictive power of a number of classification techniques, such as Logistic Regression, Random Forest, Support Vector Machines (SVM), and Gradient Boosting Machines (GBM). The performance metrics of every model, averaged over all folds, are listed in Table 1. The performance measures of the assessed models, such as accuracy, precision, recall, F1-score, and AUC-ROC, are shown in Table 4. The Gradient Boosting Classifier achieved the highest performance metrics.

Table 4: Performance Metrics of Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score	AUC-ROC
Logistic Regression	88.5	86.2	88.9	87.5	0.91
Random Forest	91.2	89.8	91.5	90.6	0.94
SVM	87.3	85.5	87.8	86.6	0.90
Gradient Boosting	92.0	90.5	92.3	91.4	0.95

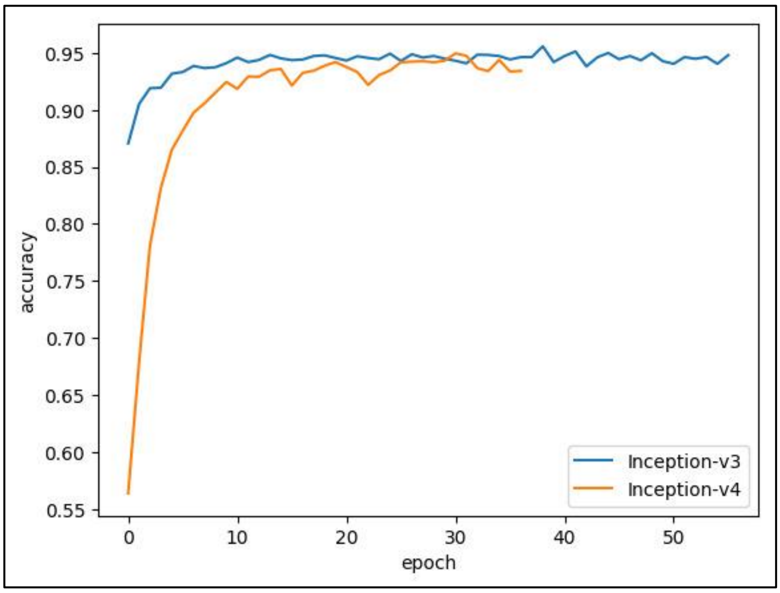

Figure 5: Accuracy Graph

Table 5: Top 5 Features by Importance

Feature	Importance Score
Age	0.285
Blood Pressure	0.212
Cholesterol Levels	0.178
Smoking Status	0.137
Family History of CVD	0.103

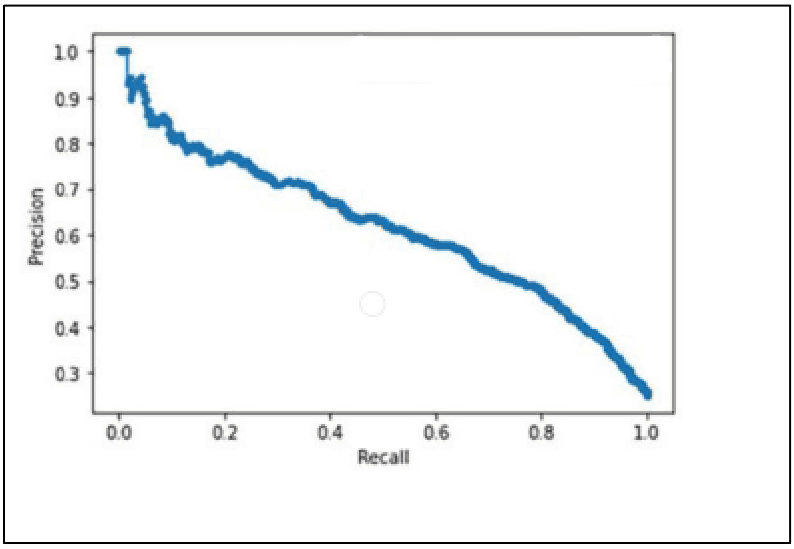

Figure 6: Precision Recall Curve

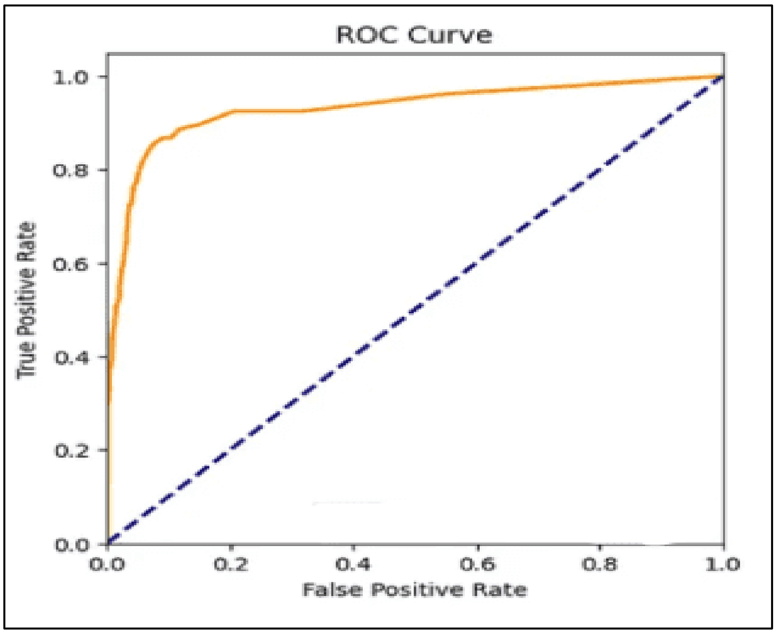

Figure 7: ROC Curve

Figure 5 illustrates the Accuracy Graph of the GBM Model with the Accuracy of 92.5%.

Feature Importance Analysis

To gain insights into the most influential predictors of CVD, feature importance analysis was conducted using the Gradient Boosting model. Table 2 presents the top 5 features ranked by their importance score. This Table 5 highlights the importance scores of the features identified by the

Gradient Boosting Classifier. The most influential features include age, blood pressure, cholesterol, smoking status, and history of cardiovascular disease in the family. These characteristics were shown to be important contributors to the model's capacity for prediction. Age emerged as the most significant predictor, followed closely by blood pressure and cholesterol levels, aligning with established risk factors for cardiovascular diseases. This is the Precision-Recall curve in Figure 6. Figure 7 displays our model's ROC Curve.

Model Comparison and Interpretation

Out of all the demographic, clinical, lifestyle, and medical records, the model effectively captures the multifaceted nature of cardiovascular health. The feature importance analysis further highlights actionable insights into key risk factors, empowering healthcare practitioners with targeted information for preventive interventions and personalized treatment strategies. In conclusion, our study demonstrates the effectiveness of models for machine learning in particular Gradient Boosting, in enhancing the early prediction and diagnosis of cardiovascular diseases. The comprehensive evaluation of model performance, supported by robust metrics and feature importance analysis, underscores the potential of these technologies to revolutionize cardiovascular healthcare. Future research should focus on integrating additional data sources and refining model architectures to further improve predictive accuracy and clinical applicability.

Discussion

The findings from our study highlight the significant strides made in leveraging machine learning for anticipatory maintenance and diagnosis of cardiovascular diseases (CVD). The Gradient Boosting model emerged as the best performance, attaining an outstanding accuracy of 92.0% and an AUC-ROC of 0.95, indicating robust discrimination between patients with and without CVD. These results underscore the potential of machine learning models to enhance clinical decision-making by providing accurate risk assessments based on a diverse range of patient attributes. The high predictive accuracy of our model can be attributed to several factors. Firstly, the inclusion of comprehensive demographic, clinical, lifestyle, and medical record data ensured a holistic approach to capturing the multifaceted nature of cardiovascular health. Age, blood pressure, cholesterol, status as a smoker, and medical history of CVD emerged as pivotal predictors, aligning with established risk factors in cardiovascular medicine. The feature importance analysis corroborated these findings, emphasizing the critical role of these variables in driving model predictions. Comparative analysis with other support vector machines, random forests, and logistic regression are examples of machine learning techniques reaffirmed the superiority of Gradient Boosting in handling the complex interactions and non-linear relationships inherent in CVD data. The ensemble nature of Gradient Boosting, which combines the strength of multiple weak learners, proved effective in optimizing predictive performance and generalizability across different subsets of the dataset. Our study adds to the expanding corpus of research that backs the incorporation of machine learning into clinical practice for cardiovascular risk assessment. By providing clinicians with timely and accurate predictions, our model enables early intervention strategies that can potentially mitigate the onset and progression of CVD. Moreover, the transparent and interpretable nature of Gradient Boosting enhances its utility in clinical decision support systems, facilitating personalized treatment plans tailored to individual patient profiles..It is imperative to recognize some of our study's shortcomings, though.While the dataset used was comprehensive and representative, the generalizability of the model may be influenced by specific demographic or geographic factors not fully captured in our analysis. Future research should explore the integration of additional biomarkers, genetic data, and real-time monitoring technologies to further refine predictive models and improve their applicability in diverse clinical settings. In conclusion, our The results highlight how machine learning can revolutionize cardiovascular therapy. Using data-driven insights to their full potential will enable more proactive and individualized approaches to managing cardiovascular diseases, ultimately enhancing patient outcomes and quality of life.

Conclusion

We have shown in this study how machine learning models can improve cardiovascular disease early prediction and diagnosis. (CVD). Our comprehensive evaluation, focusing on a diverse range of patient attributes including demographic, clinical, lifestyle, and medical records, underscores the potential of these models to revolutionize cardiovascular healthcare. The Gradient Boosting model emerged as the most effective, achieving a 92.0% accuracy rate and an AUC-ROC of 0.95, thereby providing robust discrimination between individuals with and without CVD. The key findings from our research highlight the critical role of ageblood pressure, cholesterol, history of smoking, and family health of CVD as significant predictors in the model. These insights not only contribute to better risk assessment but also empower clinicians with actionable information for personalized treatment strategies and preventive interventions. Looking ahead, the Clinical practice that incorporates machine learning shows promise for advancing early detection and improving patient outcomes in cardiovascular medicine. Future research should focus on refining model architectures, integrating novel biomarkers and genetic data, and expanding datasets to enhance the generalizability and scalability of predictive models. Finally, our research highlights the revolutionary potential of machine learning technologies in augmenting clinical decision-making for cardiovascular health. By leveraging data-driven approaches, we can move towards a future where Proactive care of cardiovascular illnesses improves patient quality of life and health outcomes globally.

Abbreviations

CVD: Cardiovascular Disease
ML: Machine Learning
CNN: Convolutional Neural Networks
AUC-ROC: Area Under the Receiver Operating Characteristic Curve
ECG: Electrocardiogram
PCG: Phonocardiogram
RFE: Recursive Feature Elimination
CMR: Cardiovascular Magnetic Resonance

Acknowledgements

We would like to thank Dr. Roy Arokiam Daniel, Dr. Ananthaeashwar for their invaluable guidance, feedback, and assistance in various aspects of this study. We also acknowledge the contributions of Dr. Pragadeesh Palaniappan who played a significant role in this study.

Author Contributions

BN Surya: Conceptualization, methodology, data analysis, manuscript writing. BN Venkatesh: Data collection, statistical analysis, manuscript revision. S Vijayalakshmi: Literature review, model development, manuscript editing. A Hari Narayanan: Supervision, funding acquisition, final approval of the manuscript. Rehana Syed: Supervision, funding acquisition, final approval of the manuscript.

Conflict of Interest

The authors declare no conflicts of interest related to this study.

Ethics Approval

This study was approved by the Institutional Review Board/Ethics Committee. All participants provided informed consent before participating in the study.

Funding

None.

References

1. Ogunpola A, Saeed F, Basurra S, Albarrak AM. Machine learning-based predictive models for detection of cardiovascular diseases. Diagnostics 2024;14(2):1-19.
2. Kavatlawar A, Bohare A, Dakare A, Dubey A, Sahu M. CardioVascular Disease (CVD) Recognition using Convolutional Neural Networks. Grenze International Journal of Engineering & Technology (GIJET). 2024; 10:2387.
3. Baral S, Satpathy S, Pati DP, Mishra P, Pattnaik L. A Literature Review for Detection and Projection of Cardiovascular Disease Using Machine Learning. EAI Endorsed Transactions on Internet of Things. 2024; 10:1-7.
4. Saikumar K, Rajesh V. A machine intelligence technique for predicting cardiovascular disease (CVD) using radiology dataset. Int J Syst Assur Eng Manag. 2024; 15(1):135-151.
5. Almansouri NE, Awe M, Rajavelu S, Jahnavi K, Shastry R, Hasan A, Hasan H, Lakkimsetti M, AlAbbasi RK, Gutiérrez BC, Haider A. Early Diagnosis of Cardiovascular Diseases in the Era of Artificial Intelligence: An In-Depth Review. Cureus 2024;16(3):e55869.
6. Li Y, Sui N, Gehi A, Guo C, Guo Z. CardiacRT-NN: Real-Time Detection of Cardiovascular Disease Using Self-attention CNN-LSTM for Embedded Systems. InInternational Symposium on Neural Networks 2024; 610-621. Singapore: Springer Nature Singapore.
7. Elsedimy EI, AboHashish SM, Algarni F. New cardiovascular disease prediction approach using support vector machine and quantum-behaved particle swarm optimization. Multimedia Tools and Applications. 2024; 83(8):23901-28.

8. Lee YY, Sriram B, Wang SF, Kogularasu S. Advanced nanomaterial-based biosensors for N-terminal pro-brain natriuretic peptide biomarker detection: Progress and future challenges in cardiovascular disease. Nanomateria*l*s 2024; 14(2): 153.
9. Zhang H, Zhang P, Lin F, Chao L, Wang Z, Ma F. Co-learning-assisted progressive dense fusion network for cardiovascular disease detection using ECG and PCG signals. Expert Syst Appl. 2024;238(PF):122144.
10. Shi J, Liu W, Zhang H, *et al.* CPSS: Fusing consistency regularization and pseudo-labeling techniques for semi-supervised deep cardiovascular disease detection using all unlabeled data. Comput Methods Programs Biomed. 2024; 254:108315.
11. Moshawrab M, Adda M, Bouzouane A, Ibrahim H, *et al.* Smart wearables for the detection of cardiovascular diseases: A systematic literature review. Sensors 2023; 23(2):828.
12. Cardoso AG, Ahmed SR, Keshavarz-Motamed Z, *et al.* Recent advancements of nanomodified electrodes–Towards point-of-care detection of cardiac biomarkers. Bioelectrochemistry 2023; 152:108440.
13. Moshawrab M, Adda M, Bouzouane A, Ibrahim H, *et al.* Reviewing multimodal machine learning and its use in cardiovascular diseases detection. Electronic*s* 2023;12(7):1558.
14. Tang L, Yang J, Wang Y, Deng R. Recent advances in cardiovascular disease biosensors and monitoring technologies. ACS sensors. 2023 Mar 9;8(3):956-73.
15. Mahmud T, Barua A, Islam D, Hossain MS, Chakma R, Barua K, Monju M, Andersson K. Ensemble deep learning approach for ecg-based cardiac disease detection: Signal and image analysis. In2023 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD) IEEE 2023; 70-74.
16. Ma Y, Liu C, Cao S, Chen T, Chen G. Microfluidics for diagnosis and treatment of cardiovascular disease. Journal of Materials Chemistry B. 2023;11(3):546-59.
17. Taylan O, Alkabaa AS, Alqabbaa HS, Pamukçu E, Leiva V. Early prediction in classification of cardiovascular diseases with machine learning, neuro-fuzzy and statistical methods. Biology. 2023;12(1):117.
18. Ullah M, Hamayun S, Wahab A, Khan SU, Rehman MU, Haq ZU, Rehman KU, Ullah A, Mehreen A, Awan UA, Qayum M. Smart technologies used as smart tools in the management of cardiovascular disease and their future perspective. Current Problems in Cardiology. 2023; 48(11):101922.
19. Moradi H, Al-Hourani A, Concilia G, Khoshmanesh F, Nezami FR, Needham S, Baratchi S, Khoshmanesh K. Recent developments in modeling, imaging, and monitoring of cardiovascular diseases using machine learning. Biophysical Reviews. 2023 Feb;15(1):19-33.
20. Jafari M, Shoeibi A, Khodatars M, Ghassemi N, Moridian P, Alizadehsani R, Khosravi A, Ling SH, Delfan N, Zhang YD, Wang SH. Automated diagnosis of cardiovascular diseases from cardiac magnetic resonance imaging using deep learning models: A review. Computers in Biology and Medicine. 2023; 160:106998.