Communications on Applied Nonlinear Analysis
ISSN: 1074-133X
Vol 33 No. 1s (2026)

HeartGuard: A Machine Learning-Based Framework for Accurate Heart Disease Prediction and Real-Time Clinical Decision Support

CH.Naresh

Assistant Professor Artificial Intelligence and Data Science

Vignan Institute of Technology and Science

N.Alekya

Artificial Intelligence and Data Science

Vignan Institute of Technology and Science Hyderabad, India

A.Tejasri redddy

Artificial Intelligence and Data Science

Vignan Institute of Technology and Science Hyderabad, India

G.Raymond Wilson

Artificial Intelligence and Data Science

Vignan Institute of Technology and Science Hyderabad, India

Hyderabad, India challanaresh8@gmail.com

alekyanallagonda30@gmail.com addelatejasrireddy@gmail.com
raymondgwilson2005@gmail.com

Article History:
Received: 04-02-2026
Revised: 20-03-2026
Accepted: 10-04-2026

Abstract:
Heart disease remains a leading cause of mortality worldwide, making early risk prediction essential for timely intervention and improved patient outcomes. This paper presents HeartGuard, a machine learning-based heart disease prediction system that analyzes structured clinical data, including age, sex, chest pain type, resting blood pressure, cholesterol, fasting blood sugar, ECG results, maximum heart rate, and related attributes. The proposed framework performs data preprocessing, feature handling, model training, and prediction using a Gradient Boosting Classifier trained on the Cleveland heart disease dataset. The trained model is integrated into a Django-based web application that enables users to enter health parameters and receive instant risk predictions through a simple interface.

Index Terms—Keywords— Heart disease prediction, machine learning, Gradient Boosting Classifier, cardiovascular risk assess-ment, clinical decision support, Cleveland heart disease dataset, Django web application.

I. INTRODUCTION

Heart disease is one of the major causes of death in the world with a major number of deaths being recorded annually. It is necessary to ensure that complications are minimized and patient survival rates are increased through early diagnosis and the ability to reliably predict the risks. Conventional methods of diagnosis are overly dependent on clinical experience, labo-ratory results and manual review of patient information, which may be time-consuming, subjective, and subject to variability. As the access to electronic health records and clinical datasets continues to rise, there is a demand to have intelligent systems capable of analyzing complex medical data efficiently and supporting healthcare professionals in the process of decision-making.

Machine learning algorithms have become powerful tools in modern healthcare analytics, enabling the detection of hidden patterns and relationships among various cardiovascular risk factors, as discussed in the HeartGuard system . The use of publicly available healthcare datasets, particularly those sourced from platforms like Kaggle and similar repositories, has supported extensive research and model development using clinical attributes such as age, blood pressure, cholesterol levels, heart rate, and ECG results. In this project, data preprocessing, feature selection, and supervised learning tech-niques such as Gradient Boosting are utilized to enhance prediction accuracy and reliability. Early research in this domain established that statistical and probabilistic methods are effective in diagnosing coronary artery disease, which has laid the foundation for modern machine learning-based prediction systems. [2].

Further studies have focused on improving prediction ac-curacy using advanced machine learning techniques within healthcare systems . Algorithms such as Logistic Regression, Decision Tree, Support Vector Machine, Random Forest, and Gradient Boosting have been widely applied to classify pa-tients based on their heart disease risk levels. [3]. Neural network-based approaches and advanced machine learning models are used to capture complex nonlinear relationships among clinical features in heart disease prediction . [4]. Also, the use of ensemble methods and hybrid machine learning systems has demonstrated better accuracy and resilience in heart disease forecasting [5]. Recent developments focus on the significance of features selection, dimensionality reduction, and comparison of several algorithms to enhance model effi-ciency and reliability [6], [7]. Other classification and feature selection algorithms have also been studied to maximize prediction and minimize complexity of computation [8].

Although these developments have been made, a number of obstacles still exist, such as low interpretability of models, the unavailability of real-time models, and the inability to fully integrate predictive systems into the real healthcare setting. The majority of solutions available are based on the development of models, but they do not consider usability, scalability, and deployment, which are the key aspects of the real-world clinical implementation.

Novelty of the Proposed Work: The proposed HeartGuard system is designed to provide a comprehensive and practical solution for heart disease prediction by integrating machine learning accuracy with real-time healthcare support . Unlike many existing studies that focus mainly on algorithmic perfor-mance, this project emphasizes a complete end-to-end system that includes data collection, preprocessing, model selection, evaluation, and deployment through a user-friendly web-based platform. The system utilizes a Gradient Boosting Classifier to effectively model complex nonlinear relationships among clinical attributes such as age, blood pressure, cholesterol, and other health indicators. Additionally, the integration of the Django framework enables secure access, real-time prediction, risk visualization, personalized recommendations, chatbot as-sistance, and doctor suggestions, making the system highly accessible, interactive, and practical for real-world healthcare applications.

A. Key Contributions of this Paper

- Creatio of a machine learning-based prediction system of heart diseases using structured clinical data.
- Adoption of a refined predictive model that has the capa-bility of modeling the interaction of features to achieve enhanced accuracy.
- Incorporation of the trained model into a convenient web-based application to acquire real-time risk forecast.
- Architecture The architecture of a scalable and modular system which can be generalized to other disease predic-tion systems.
- Presentation of a viable clinical decision-support system, which helps to close the gap between machine learning models and real-world healthcare applications.

In this regard, the suggested HeartGuard system is ex-pected to offer an efficient, precise, and affordable so-lution to cardiovascular risk prediction to support early diagnostics, enhance clinical decision-making, and help intelligent healthcare systems evolve.

II. RELATED WORK

Recent advancements in machine learning have significantly improved the accuracy and reliability of heart disease pre-diction systems . Ensemble-based techniques such as Ran-dom Forest and Gradient Boosting have gained considerable attention due to their ability to combine multiple models and enhance predictive performance. In this project, various machine learning algorithms were evaluated, and Gradient Boosting was selected for its superior accuracy and ability to handle complex clinical data. [9] showed better diagnostic performance and lower computational cost. Equally, Akella and Akella [10] have discussed different machine learning algorithms in predicting coronary artery diseases with the focus being on open-source frameworks, which are more reproducible and more accessible.

The methods of feature selection and optimization have also received a lot of research to enhance the model performance. Sarra et al. [11] proposed an effective feature selection approach combined with machine learning models to identify the most relevant clinical attributes, leading to improved predic-tion accuracy . In this project, important medical features such as age, blood pressure, cholesterol, and heart rate are carefully selected during preprocessing to enhance model performance.

[13] Additionally, multiple algorithms are evaluated to ensure that the most suitable model is chosen for accurate and reliable heart disease prediction. Such strategies emphasize the necessity of dealing with skewed datasets and feature set optimization in cardiovascular risk prediction.

A number of studies have concentrated on comparative studies and systematic analysis on machine learning methods. In a recent study by Azmi et al. [12], the authors have provided an extensive review of machine learning methods of cardiovascular disease prediction in the context of medical big data, including the following critical issues: the heterogeneity of data, its scalability, and the interpretability of its model. In the same manner, Mao et al. [20] provided a systematic review of machine learning algorithms to diagnose heart diseases, but argued that they should be robust and generalizable to a wide range of datasets. Further development of this analysis was carried out by Liu et al. [19], who conducted a meta-study of electronic health record-based prediction models, demonstrat-ing the increasing significance of large-scale healthcare data in enhancing predictive performance.

Research trends in the recent past have also looked into integrating deep learning and advanced machine learning techniques. Subramani et al. [14] proved that a combination of machine learning and deep learning models could be used to predict cardiovascular disease with better accuracy by using hybrid networks. The study by Baghdadi et al. [15] explored the use of modern machine learning methods in early detection and diagnosis, focusing on the importance of data-based methods to enhance clinical outcomes.

The other direction of recent research that is also significant is the elaboration of explainable and interpretable models. El-Sofany et al. [16] suggested an interpretable artificial intelli-gence (AI)-based prediction system that improves the quality of transparency and trust in clinical decision-making. On the same note, Wang et al. [17] presented an explainable frame-work of coronary artery disease prediction using AutoML that was capable of selecting its own models automatically and at the same time provide the interpretability. A systematic review by Teshale et al. [18] concentrated on time-to-event prediction models and indicated the significance of time-based analysis and survival modeling in cardiovascular risk assessment.

Regardless of these developments, there are still a number of limitations available in existing solutions. Numerous models are mainly concerned with enhancing predictive performance without considering real-time implementation, accessibility to the user, and compatibility with clinical processes. Moreover, interpretability, scalability, and management of heterogeneous healthcare data issues are not yet sorted out. The constraints encourage the creation of a more integrated and useful system like the HeartGuard, which will unite the correct machine

are eliminated. Encoding techniques are used to transform categorical features into numerical ones so that they can be used by machine learning algorithms. To make the feature space standard and to prevent bias attributed to the different scale of a feature, the feature normalization is performed through standardization:

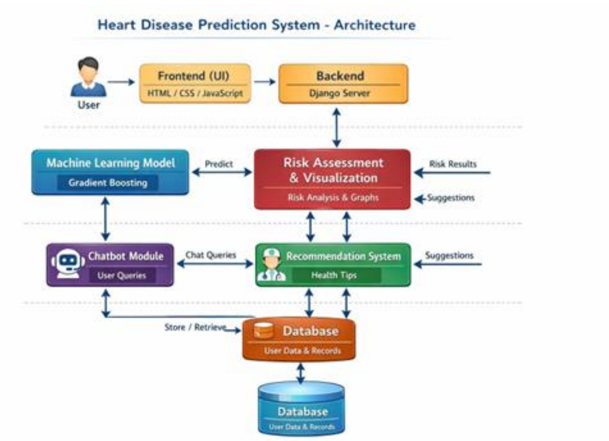

Fig. 1. System Architecture

learning models with the convenience of a user-friendly in-terface and the ability to predict in real time.

III. METHODOLOGY

A. *System Overview*

The proposed HeartGuard system is an intelligent machine learning-based web application designed to predict heart dis-ease using structured clinical data . It follows a systematic pipeline that includes data collection from healthcare datasets, data preprocessing, feature selection, model training, evalua-tion, and deployment through a Django-based platform. The system utilizes advanced algorithms such as Gradient Boosting to analyze patient data and generate accurate risk predictions along with probability-based classification. By integrating pre-diction, visualization, personalized recommendations, chatbot support, and doctor suggestions, the system transforms raw medical data into meaningful insights, ensuring reliable, real-time, and scalable healthcare assistance. The Fig. 1 Illustrates the system architecture

B. *Dataset Description*

The model is trained using the Cleveland Heart Disease dataset obtained from the UCI Machine Learning Repository. This dataset contains patient-level clinical attributes that are commonly used for cardiovascular diagnosis. The input fea-ture vector is defined as $x \in \mathbb{R}^d$, where each dimension represents a clinical parameter such as age, blood pressure, cholesterol, chest pain type, and electrocardiographic results. The corresponding output label is defined as $y \in \{0, 1\}$, where 0 indicates absence and 1 indicates presence of heart disease. Thus, the problem is formulated as a binary classification task where the goal is to learn a mapping function $f(x) \rightarrow y$.

C. *Data Preprocessing*

Preprocessing of data is done to enhance the quality of data and consistency of data across features. The gaps in the dataset and inconsistencies are addressed with the help of appropriate imputation techniques, and redundant and unnecessary records

where μ represents the mean and σ represents the standard deviation of the feature. The dataset is then divided into training and testing subsets to evaluate the generalization capability of the model.

D. *Feature Selection*

Feature selection is carried out to identify the most rele-vant attributes influencing heart disease prediction. Statistical analysis and correlation-based methods are used to evaluate the contribution of each feature to the target variable. By selecting a subset of informative features $X_{\text{selected}} \subseteq X$, the model complexity is reduced, and overfitting is minimized. This step also improves computational efficiency and enhances the interpretability of the model.

E. *Model Development*

The proposed system employs a Gradient Boosting Clas-sifier, which is an ensemble learning technique that builds a strong predictive model by combining multiple weak learners in a sequential manner. The model is constructed iteratively, where each new learner is trained to correct the errors of the previous model. The final prediction function is represented as:

$$F(x) = \sum_{m=1}^{M} \gamma_m h_m(x) \quad (2)$$

where $h_m(x)$ represents the m^{th} weak learner, γ_m is the corresponding weight, and M is the number of iterations. This approach enables the model to capture complex nonlinear relationships among clinical features and improves predictive accuracy.

F. *Model Training*

This model is trained on the preprocessed data learning the relationship between the input features and the target labels. In training the algorithm is minimizing a loss function $L(y, F(x))$ through the update of the model parameters. Hyperparameters including estimators, learning rate and the maximum decision tree depth are optimized to meet the best performance. The correct tuning will make sure that the model generalizes to unseen data and not overfitting.

G. *Model Evaluation*

The performance of the trained model is evaluated using standard classification metrics derived from the confusion ma-trix. Accuracy measures the overall correctness of predictions and is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

where TP , TN , FP , and FN represent true positives, true negatives, false positives, and false negatives, respectively. Precision and recall are used to evaluate the quality of positive predictions, and the F1-score provides a balanced measure of both metrics. These evaluation criteria ensure that the model performs reliably in a medical context, where incorrect predictions can have significant consequences.

H. *System Deployment*

The trained Gradient Boosting model is integrated into a Django-based web application to provide real-time heart disease risk prediction . Users can enter their clinical details through a simple and user-friendly interface, after which the data is preprocessed and passed to the trained model for analysis. The system instantly displays the prediction result along with risk classification, visualization, and personalized health recommendations. This deployment ensures that the system is not only accurate but also practical, interactive, and accessible for real-world healthcare usage. Additionally, the system includes chatbot assistance to guide users with basic health queries and improve user interaction. It also provides doctor recommendations to help users seek timely medical consultation based on their risk level.

IV. RESULTS AND DISCUSSION

A. *Experimental Setup*

The dataset of the HeartGuard system is tested with the Cleveland Heart Disease. Missing values, the categorical fea-tures are coded and the features scaled to guarantee their uniformity amongst all the attributes. To test the ability of the model to be generalized, the processed data is split into the training and testing sets in an 80:20 ratio. Training of the Gradient Boosting Classifier is done on the training dataset and the hyper parameters are adjusted to obtain the best performance. As shown in the Fig.2. the Home Page serves as the primary interface of the Heart Disease Prediction System, providing users with an overview of the application and easy navigation to essential features.

implemented as a web application based on Django, to make real-time prediction. Fig.3 indicates the interface of search logs of the system.

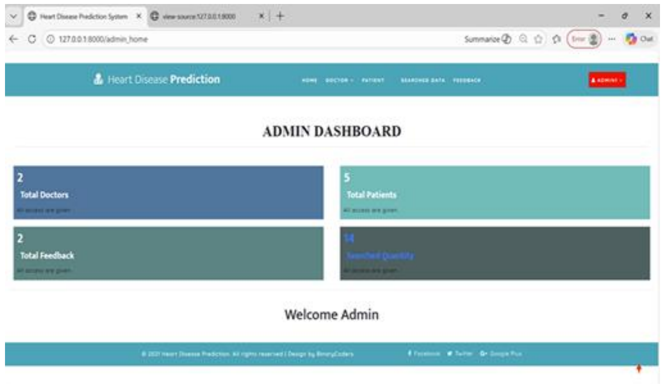

Fig. 3. Admin Dashboard Interface

B. Performance Evaluation Metrics

The model is tested based on the standard classification measures based on the confusion matrix. The confusion matrix comprises of four elements, where the true positives (TP), the true negatives (TN), the false positives (FP), and the false negatives (FN). Evaluation metrics are calculated according to these values. Fig.4 shows the output prediction page of heart disease.

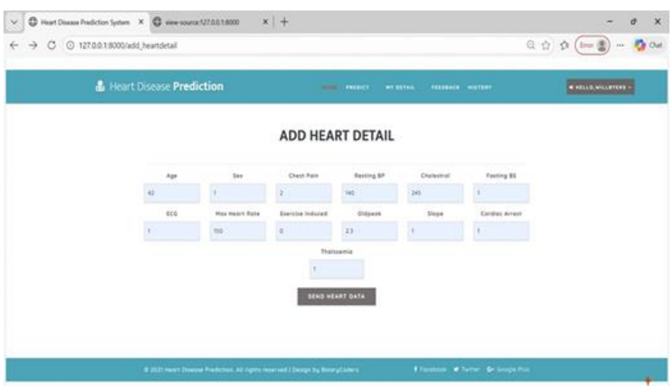

Fig. 4. Patient Data Entry Form for Heart Disease Prediction

Accuracy is defined as:

(4)

$$TP + TN + FP + FN$$

Precision measures the correctness of positive predictions and is given by:

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

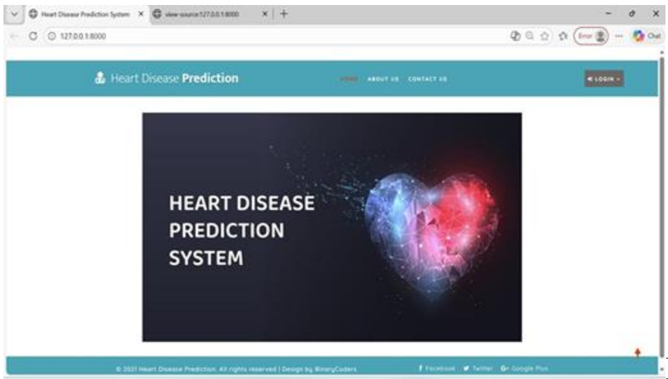

Fig. 2. Home Page

Recall evaluates the ability of the model to correctly identify

The implementation is done in Python with Scikit-learn, Pandas and NumPy libraries and the trained model can be

positive cases:

$$Recall = \frac{TP}{TP + FN} \quad (6)$$

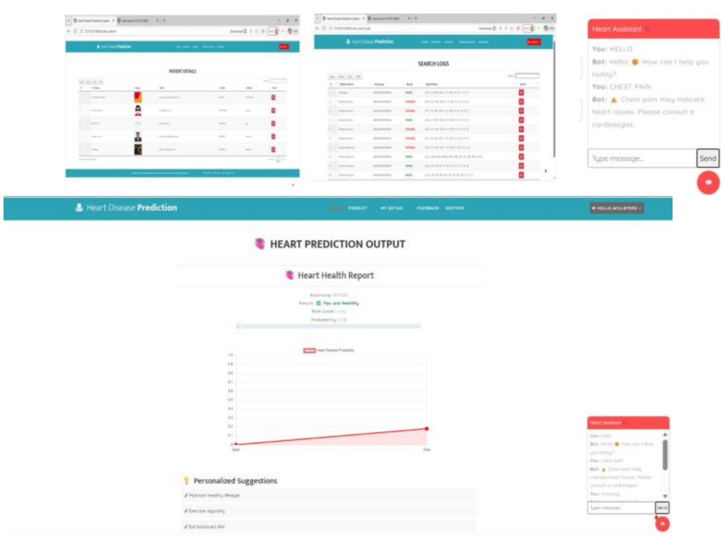

Fig. 5. Prediction Output Display

The F1-score provides a balance between precision and recall:Fig. 6. Result prediction of patient

disease risk assessment systems. Fig.6 is the representation of the admin dashboard showing the system statistics.

E. System-Level Results

The trained Gradient Boosting model is integrated into a Django-based web application, enabling real-time heart

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

disease risk prediction through an interactive user interface

.The application also supports secure user authentication and

These metrics are essential in medical prediction tasks, where both false positives and false negatives must be mini-mized.

C. Model Performance Analysis

The Gradient Boosting Classifier demonstrates strong pre-dictive performance on the test dataset, ensuring reliable heart disease risk classification . The model is evaluated using key performance metrics such as accuracy, precision, recall, and F1-score, which collectively indicate its effectiveness in distinguishing between patients with and without heart disease. The results show that the model maintains a good balance between correctly identifying high-risk patients and minimizing false predictions, making it suitable for real-time healthcare applications.

The improved performance of the model is attributed to its boosting mechanism, where multiple weak learners are combined sequentially to reduce prediction errors and cap-ture complex nonlinear relationships among clinical features. Additionally, proper data preprocessing and feature selection techniques enhance the model's efficiency by focusing on the most relevant medical attributes. Fig.5 illustrates the input form used to enter patient clinical details.

D. Comparative Discussion

The Gradient Boosting approach used in this project pro-vides higher accuracy and robustness compared to traditional machine learning models such as Logistic Regression and Decision Tree . As an ensemble technique, it improves predic-tion performance by sequentially correcting errors of previous models and reducing overall prediction loss. This makes it highly effective in handling complex medical datasets and accurately classifying heart disease risk levels.

Furthermore, the model demonstrates strong generalization ability by maintaining consistent performance on unseen test data.This results in more stable, reliable, and scalable predic-tions, making it well-suited for real-world deployment in heart

efficient data management, ensuring safe storage and access to prediction records. These features enhance usability, acces-sibility, and overall system practicality.

The end-to-end implementation demonstrates that the pro-posed system is not only accurate but also suitable for real-world deployment. By providing immediate predictions along with personalized recommendations, chatbot assistance, and doctor suggestions, the system supports both healthcare pro-fessionals and individuals in early diagnosis and preventive decision-making.

F. *Discussion*

According to the experimental results, machine learn-ing techniques, particularly ensemble methods like Gradient Boosting, are highly effective for heart disease prediction . The model successfully captures complex relationships among clinical features and provides accurate and reliable risk pre-dictions using evaluation metrics such as accuracy, precision, recall, and F1-score. However, certain limitations exist, in-cluding dependence on structured healthcare datasets and the need for more diverse and large-scale data to improve model generalization in real-world scenarios.

Future enhancements of the system may include integration of real-time health monitoring data, incorporation of advanced machine learning or deep learning models, and expansion of system features for improved scalability and performance. Additional improvements such as enhanced visualization, con-tinuous monitoring, and better data integration can further strengthen the system.

G. *Conclusion*

In this project, a heart disease prediction system based on structured clinical data has been developed using an intelli-gent machine learning framework called HeartGuard . The system utilizes a Gradient Boosting Classifier to analyze key cardiovascular attributes and identify risk patterns effectively. The model is trained using proper data preprocessing, feature

selection, and evaluation techniques, achieving strong per-formance in accurately distinguishing between patients with and without heart disease. The use of performance metrics such as accuracy, precision, recall, and F1-score validates the reliability of the proposed approach.

The results demonstrate that ensemble learning methods, particularly Gradient Boosting, are highly effective in captur-ing complex nonlinear relationships among medical features, leading to improved predictive performance compared to tra-ditional machine learning models. Furthermore, the trained model is integrated into a Django-based web application that enables real-time prediction through a user-friendly interface. The system also includes features such as risk classification, visualization, personalized recommendations, chatbot assis-tance, and doctor suggestions, making it practical and acces-sible for both healthcare professionals and general users.

Overall, the proposed system provides a scalable, efficient, and user-centric solution for early detection of heart disease and clinical decision support. By combining machine learning accuracy with real-time usability and interactive features, HeartGuard contributes to the advancement of data-driven healthcare systems. It highlights the importance of integrating predictive analytics with accessible technologies to improve patient awareness, support preventive care, and enhance overall healthcare outcomes.

References

[1] A. Janosi, W. Steinbrunn, M. Pfisterer, and R. Detrano, "Heart Disease," *UCI Machine Learning Repository*, 1989. doi: 10.24432/C52P4X.

[2] R. Detrano, A. Janosi, W. Steinbrunn, M. Pfisterer, J. J. Schmid,S. Sandhu, K. H. Guppy, S. Lee, and V. Froelicher, "International application of a new probability algorithm for the diagnosis of coronary artery disease," *American Journal of Cardiology*, vol. 64, no. 5, pp. 304–310, 1989. doi: 10.1016/0002-9149(89)90524-9.

[3] R. Alizadehsani, J. Habibi, M. J. Hosseini, H. Mashayekhi, R. Boghrati,A. Ghandeharioun, B. Bahadorian, and Z. A. Sani, "A data mining approach for diagnosis of coronary artery disease," *Computer Methods and Programs in Biomedicine*, vol. 111, no. 1, pp. 52–61, 2013. doi: 10.1016/j.cmpb.2013.03.004.

[4] Z. Arabasadi, R. Alizadehsani, M. Roshanzamir, H. Moosaei, andA. A. Yarifard, "Computer aided decision making for heart disease detection using hybrid neural network-genetic algorithm," *Computer Methods and Programs in Biomedicine*, vol. 141, pp. 19–26, 2017. doi: 10.1016/j.cmpb.2017.01.004.

[5] S. Mohan, C. Thirumalai, and G. Srivastava, "Effective heart disease prediction using hybrid machine learning techniques," *IEEE Access*, vol. 7, pp. 81542–81554, 2019. doi: 10.1109/ACCESS.2019.2923707.

[6] H. Ayatollahi, L. Gholamhosseini, and M. Salehi, "Predicting coronary artery disease: A comparison between two data mining algorithms," *BMC Public Health*, vol. 19, Art. no. 448, 2019. doi: 10.1186/s12889-019-6721-5.

[7] A. K. Ga´rate-Escamila, A. Hajjam El Hassani, and E. Andre`s, "Classi-fication models for heart disease prediction using feature selection and PCA," *Informatics in Medicine Unlocked*, vol. 19, Art. no. 100330, 2020. doi: 10.1016/j.imu.2020.100330.

[8] R. Spencer, F. Thabtah, N. Abdelhamid, and M. Thompson, "Exploring feature selection and classification methods for predicting heart dis-ease," *Digital Health*, vol. 6, Art. no. 2055207620914777, 2020. doi: 10.1177/2055207620914777.

[9] D. Velusamy and K. Ramasamy, "Ensemble of heterogeneous classifiers for diagnosis and prediction of coronary artery disease with reduced feature subset," *Computer Methods and Programs in Biomedicine*, vol. 198, Art. no. 105770, 2021. doi: 10.1016/j.cmpb.2020.105770.

[10] A. Akella and S. Akella, "Machine learning algorithms for predicting coronary artery disease: Efforts toward an open source solution," *Future Science OA*, vol. 7, no. 6, Art. no. FSO698, 2021. doi: 10.2144/fsoa-2020-0206.

[11] R. R. Sarra, A. M. Dinar, M. A. Mohammed, and K. H. Abdulkareem, "Enhanced heart disease prediction based on machine learning and χ^2 statistical optimal feature selection model," *Designs*, vol. 6, no. 5, Art. no. 87, 2022. doi: 10.3390/designs6050087.

[12] J. Azmi, M. Arif, M. T. Nafis, M. A. Alam, S. Tanweer, and

G. Wang, "A systematic review on machine learning approaches for cardiovascular disease prediction using medical big data," *Med-ical Engineering & Physics*, vol. 105, Art. no. 103825, 2022. doi: 10.1016/j.medengphy.2022.103825.

[13] J. Yang and J. Guan, "A heart disease prediction model based on feature optimization and SMOTE-XGBoost algorithm," *Information*, vol. 13, no. 10, Art. no. 475, 2022. doi: 10.3390/info13100475.

[14] S. Subramani, N. Varshney, M. V. Anand, M. E. M. Soudagar, L. A. Al-keridis, T. K. Upadhyay, N. Alshammari, M. Saeed, K. Subramanian, K. Anbarasu, and K. Rohini, "Cardiovascular diseases prediction by ma-chine learning incorporation with deep learning," *Frontiers in Medicine*, vol. 10, Art. no. 1150933, 2023. doi: 10.3389/fmed.2023.1150933.

E. N. A. Baghdadi, S. M. F. Abdelaliem, A. Malki, I. Gad, A. Ewis, andAtlam, "Advanced machine learning techniques for cardiovascular disease early detection and diagnosis," *Journal of Big Data*, vol. 10, Art. no. 144, 2023. doi: 10.1186/s40537-023-00817-1.

[15] H. El-Sofany, B. Bouallegue, and Y. M. Abd El-Latif, "A proposed technique for predicting heart disease using machine learning algorithms and an explainable AI method," *Scientific Reports*, vol. 14, Art. no. 23277, 2024. doi: 10.1038/s41598-024-74656-2.

[16] J. Wang, Q. Xue, C. W. J. Zhang, K. K. L. Wong, and Z. Liu, "Ex-plainable coronary artery disease prediction model based on AutoGluon from AutoML framework," *Frontiers in Cardiovascular Medicine*, vol. 11, Art. no. 1360548, 2024. doi: 10.3389/fcvm.2024.1360548.

[17] A. B. Teshale, H. L. Htun, M. Vered, A. J. Owen, and R. Freak-Poli, "A systematic review of artificial intelligence models for time-to-event outcome applied in

cardiovascular disease risk prediction," *Journal of Medical Systems*, vol. 48, no. 1, Art. no. 68, 2024. doi: 10.1007/s10916-

024-02087-7.

[18] T. Liu, A. J. Krentz, L. Lu, and V. Curcin, "Machine learning based prediction models for cardiovascular disease risk using electronic health records data: Systematic review and meta-analysis," *European Heart Journal - Digital Health*, vol. 6, no. 1, pp. 7–22, 2025. doi: 10.1093/ehjdh/ztae080.

[19] Y. Mao, B. L. Jimma, and T. B. Mihretie, "Machine learning al-gorithms for heart disease diagnosis: A systematic review," *Current Problems in Cardiology*, vol. 50, no. 8, Art. no. 103082, 2025. doi: 10.1016/j.cpcardiol.2025.103082.