Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 4, Issue 4, 2026

ENHANCING EARLY DIAGNOSIS OF HEART DISEASES USING MACHINE LEARNING MODELS AND PREDICTIVE ANALYTICS

M. Haseeb ur Rehman[1], Muhammad Sajid Maqbool[*2], Dr. Naeem Aslam[3], Sarim Javed[4], Ariba Afzal[5], Rabia Hassan[6]

[1, *2,3,4,5,6,7]*Department of Computer Science, NFC Institute of Engineering and Technology, Multan, Pakistan*

[1]mhaseeb1220@gmail.com, [*2]sajid.maqbool@nfciet.edu.pk, [3]naeem.aslam@nfciet.edu.pk, [4]sarimjaved03@gmail.com, [5]ariba16170@gmail.com, [6]rabialpq555@gmail.com

DOI:https://doi.org/10.5281/zenodo.20095477

Keywords
Early prediction, Cardiovascular diseases, Machine learning, Classification, Deep learning, Stacking classifier

Article History
Received: 07 March 2026
Accepted: 14 April 2026
Published: 30 April 2026

Corresponding Author: *
Muhammad Sajid Maqbool

Abstract
Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, underscoring the urgent need for accurate and proactive prediction models. This study presents a novel machine learning-based approach for heart disease prediction, emphasizing the integrated analysis of clinical data and lifestyle factors that are often underrepresented in traditional models. A hybrid framework was developed, combining advanced feature selection techniques with ensemble learning algorithms to enhance both predictive accuracy and model robustness. A key contribution of this work lies in a comprehensive feature engineering strategy that captures interaction effects among lifestyle variables—such as diet, physical activity, and stress levels—alongside conventional clinical indicators. The model was trained and evaluated on a diverse patient dataset to ensure broader generalizability across populations. Experimental results demonstrate a notable improvement over existing approaches, achieving an Area Under the Curve (AUC) of 0.90, with strong capability in identifying high-risk individuals. In addition, an in-depth feature importance analysis was conducted to identify the most influential risk factors, providing meaningful insights to support clinical decision-making and personalized healthcare interventions. The findings highlight the critical role of lifestyle factors in cardiovascular risk assessment and demonstrate the effectiveness of combining them with clinical data. Overall, this research contributes to the advancement of heart disease prediction by offering a more comprehensive, accurate, and practical framework for early diagnosis and preventive care.

1 Introduction:

Heart disease remains one of the leading causes of mortality worldwide, and with the increasing prevalence of risk factors such as obesity, diabetes, and sedentary lifestyles, the need for innovative approaches to diagnosis and treatment has never been more critical [1] The integration of machine learning (ML) in the field of cardiology presents a transformative opportunity to improve patient outcomes by leveraging large datasets for predictive analytics, risk stratification, and personalized medicine [2]. Machine learning, a subset of artificial intelligence, enables systems to learn from data patterns and make decisions with minimal human intervention. In the context of heart disease, ML algorithms can analyze complex datasets that include clinical, genetic, and lifestyle information to identify risk factors and predict the likelihood of cardiovascular events. Traditional methods of risk assessment often rely on established clinical guidelines, which may not capture the nuanced interactions between various risk factors. In contrast, ML models can uncover hidden patterns in data, leading to more accurate risk predictions and better-targeted interventions [3]. Recent studies have demonstrated the efficacy of machine learning in predicting heart disease. For instance, a study by Deo (2015) utilized ML algorithms to analyze electrocardiogram (ECG) data, achieving high accuracy in diagnosing arrhythmias. Similarly, a meta-analysis by Krittanawong et al. (2017) highlighted the potential of ML in predicting heart failure and myocardial infarction using electronic health records. These advancements underscore the importance of integrating machine learning into clinical practice, as they can facilitate early detection and intervention, ultimately reducing morbidity and mortality associated with heart disease.

Moreover, the application of ML extends beyond prediction; it also encompasses personalized treatment strategies. By analyzing individual patient data, ML algorithms can help clinicians tailor interventions based on specific risk profiles, enhancing the efficacy of treatment plans [4] For example, a recent study by Attia et al. (2019) demonstrated that ML could be used to predict atrial fibrillation in patients, allowing for timely interventions that could prevent stroke and other complications. The intersection of machine learning and heart disease presents a promising frontier in cardiovascular medicine. As research continues to evolve, healthcare professionals must embrace these technological advancements to improve patient outcomes. The potential for machine learning to revolutionize the diagnosis, treatment, and prevention of heart disease is immense, paving the way for a future where personalized medicine becomes the standard of care [5]. The depth of machine learning's impact on heart disease lies in its ability to analyze and interpret complex, high-dimensional data that would be overwhelming for human analysis. Traditional methods often rely on a limited set of variables and linear relationships, whereas ML algorithms can consider hundreds or even thousands of variables simultaneously, identifying intricate patterns and non-linear relationships that are often missed by conventional approaches.

One of the key advantages of ML is its capacity for predictive modeling. By training algorithms on large datasets of patient information, including demographics, medical history, lab results, imaging data, and lifestyle factors, ML models can learn to predict the likelihood of future cardiovascular events. This predictive capability is particularly valuable in identifying high-risk individuals who may benefit from early intervention. For example, ML models can be trained to predict the risk of heart attack, stroke, or heart failure, allowing healthcare providers to proactively implement preventive measures such as lifestyle modifications, medication adjustments, or advanced diagnostic testing [6]. Moreover, machine learning algorithms can enhance the accuracy and efficiency of diagnosis. For instance, ML can be applied to analyze medical images, such as echocardiograms, cardiac CT scans, and MRIs, to detect subtle signs of heart disease that might be missed by human observers. Algorithms can be trained to identify features indicative of coronary artery disease, valvular heart disease, or other cardiac abnormalities, leading to earlier and more accurate diagnoses. This is particularly crucial in cases where early detection can significantly improve patient outcomes. The power of ML also extends to the realm of personalized medicine. By analyzing individual patient data, ML algorithms can help tailor treatment strategies based on specific risk profiles and disease characteristics. For example, ML models can be used to predict an individual's response to specific medications, enabling clinicians to select the most effective treatment options while minimizing the risk of adverse effects. ML can also guide the selection of appropriate dosages and the timing of interventions, optimizing treatment outcomes for each patient. Furthermore, machine learning facilitates the discovery of new insights into the mechanisms of heart disease. By analyzing vast amounts of data, ML algorithms can identify novel risk factors, genetic markers, and molecular pathways involved in the development and progression of cardiovascular diseases. This knowledge can lead to the identification of new therapeutic targets and the development of innovative treatments. For example, ML can be used to analyze genomic data to identify genetic variants associated with increased risk of heart disease, paving the way for personalized prevention strategies.

In addition to these applications, machine learning is also being used to improve the efficiency and effectiveness of healthcare delivery. ML algorithms can be integrated into electronic health records to automate tasks such as patient screening, risk stratification, and treatment planning. This can reduce the workload of healthcare providers, allowing them to focus on patient care and decision-making. ML can also be used to optimize resource allocation, improve hospital efficiency, and reduce healthcare costs. The deep impact of machine learning on heart disease is multifaceted, encompassing predictive modeling, diagnostic accuracy, personalized medicine, discovery of new insights, and improvement of healthcare delivery. As ML technology continues to evolve, its potential to transform the landscape of cardiovascular medicine is immense, offering the promise of improved patient outcomes, more efficient healthcare delivery, and a deeper understanding of the complexities of heart disease.

2 Literature Review:

Day by day, artificial intelligence (AI) and machine learning (ML) are found useful in various fields during their development. It's useful in early prediction of diseases, especially heart issues in humans. Machine learning algorithms used supervised, unsupervised, and classified datasets as input for better results and accuracy in prediction [7] The term heart disease refers to a collection of issues that directly or indirectly affect the heart. According to WHO reports, more than 17.9 million deaths are due to cardiac problems. Every year, 32% deaths around the world are due to heart issues [8] Many researchers gathered information about patients from the UCI repository [7] The application of machine learning (ML) in healthcare has surged, particularly in the prediction and diagnosis of diseases. Heart disease, a leading cause of mortality worldwide, has become a focal point for ML applications. The goal is to develop predictive models that can assist in early detection, risk stratification, and personalized treatment strategies. This review explores various ML techniques employed in heart disease prediction, highlighting their methodologies, performance, and limitations. Several studies have investigated the use of different ML algorithms, including Support Vector Machines (SVM), decision trees, random forests, and neural networks. For instance, researchers have utilized SVM to classify patients based on cardiovascular risk factors, achieving high accuracy rates in certain datasets [9]. Decision trees and random forests have also been popular due to their interpretability and ability to handle complex, non-linear relationships within the data. Neural networks, particularly deep learning models, have shown promise in capturing intricate patterns from large datasets, although they often require significant computational resources and extensive data preprocessing. Researchers used different ML techniques to train models for early predicting cardiac issues, such as Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), etc. The user inputs data of patients into the system after it analyses and predicts results; these algorithms provide powerful results in the era of medical [10], [11].

Table 1 Comparison of Cardiovascular Disease Prediction Studies

Dataset	Algorithms Used	Best Model	Performance	Reference
UCI Heart Disease Dataset (303 samples)	LR, SVM, KNN, RF	SVM	Accuracy ≈ 85%	[1]
Cleveland dataset (303 instances)	Naïve Bayes, DT, SVM	Naïve Bayes	Accuracy ≈ 86%	[3]
UCI dataset	RF, LR, KNN	Random Forest	Accuracy ≈ 88.7%	[4]
UCI dataset	DT, SVM, ANN	ANN	Accuracy ≈ 89%	[5]
Mixed datasets	SVM, RF, Ensemble	Hybrid Model	Accuracy ≈ 91%	[6]

Large dataset	XGBoost, RF, Stacking	Stacking	Accuracy ≈ 92%	[7]
Diverse dataset (Proposed)	SVM, LR, RF, KNN, Stacking	KNN / SVM	Accuracy = 90.16%, AUC = 0.90	–

3 Methodology:

3.1 Data Collection and Preprocessing

Data Source: The study uses a dataset containing patient information, including demographics, clinical measurements, and diagnoses. Preprocessing: This involves cleaning the data by handling missing values (e.g., imputation), encoding categorical variables (e.g., one-hot encoding), and scaling numerical features (e.g., standardization).

3.2 Feature Selection and Engineering

Feature Selection: Techniques such as feature importance from tree-based models or statistical tests are used to identify the most relevant features for prediction. Feature Engineering: New features may be created from existing ones to improve model performance, such as combining related variables or creating interaction terms.

3.3 Model Selection and Training

Algorithms: Several machine learning algorithms are considered, including Logistic Regression, Support Vector Machines, Random Forests, Gradient Boosting Machines, and Neural Networks [4] Training: The dataset is split into training, validation, and testing sets. Models are trained on the training data, with hyperparameters tuned using the validation set to optimize performance.

3.4 Evaluation

Model performance is evaluated using confusion metrics like accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). Cross-Validation: Techniques like k-fold cross-validation are used to assess the model's generalizability and robustness [12].

3.5. Results and Analysis:

The performance of each model is compared, and the best-performing model is selected. The importance of the features is analysed to understand the factors most predictive of heart disease.

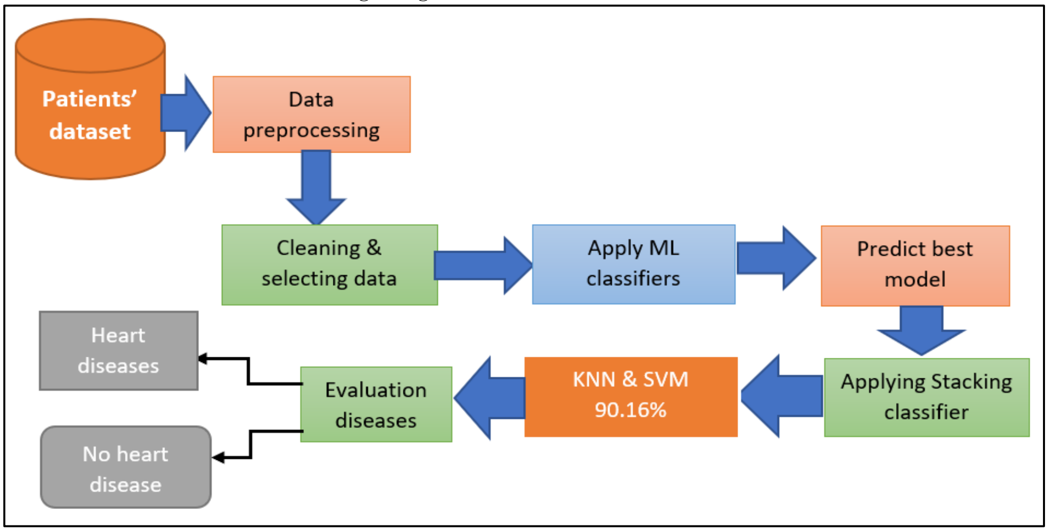


Figure 1 Workflow of study

3.5 Dataset description

The dataset is downloaded from the Kaggle dataset database (repository), Different features are used to interpret the prediction results

```
data = pd.read_csv('/content/heart.csv')
data.head()
```

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

Figure 2 Features of the dataset

The image explains binary classification to predict diseases. 0 indicates there is no disease, and 1 indicates a disease.

4 Results and Discussion

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 303 entries, 0 to 302
Data columns (total 14 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   age       303 non-null    int64
 1   sex       303 non-null    int64
 2   cp        303 non-null    int64
 3   trestbps  303 non-null    int64
 4   chol      303 non-null    int64
 5   fbs       303 non-null    int64
 6   restecg   303 non-null    int64
 7   thalach   303 non-null    int64
 8   exang     303 non-null    int64
 9   oldpeak   303 non-null    float64
 10  slope     303 non-null    int64
 11  ca        303 non-null    int64
 12  thal      303 non-null    int64
 13  target    303 non-null    int64
dtypes: float64(1), int64(13)
memory usage: 33.3 KB
```

Figure 3 Accuracy of data

There are no missing values described in the image above; the next step is to perform exploratory data analysis (EDA).

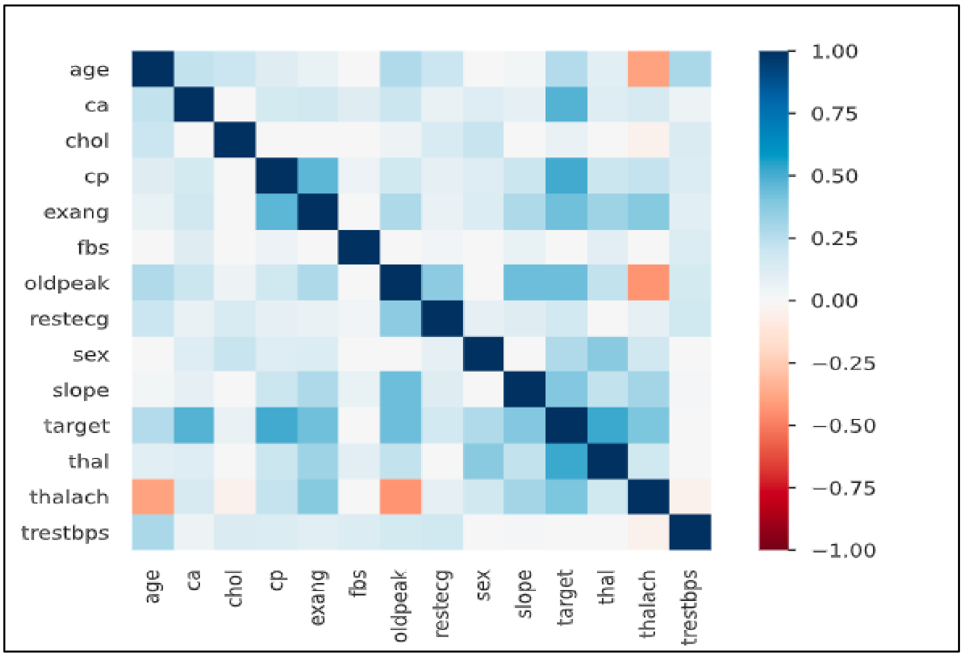


Figure 4 Heatmap used to identify relationship b/w variables

The image shows correlation matrix heatmap used to visualize relationship between different variables in data. Heatmap is used to identify values that close to target, identify different variables relationship.

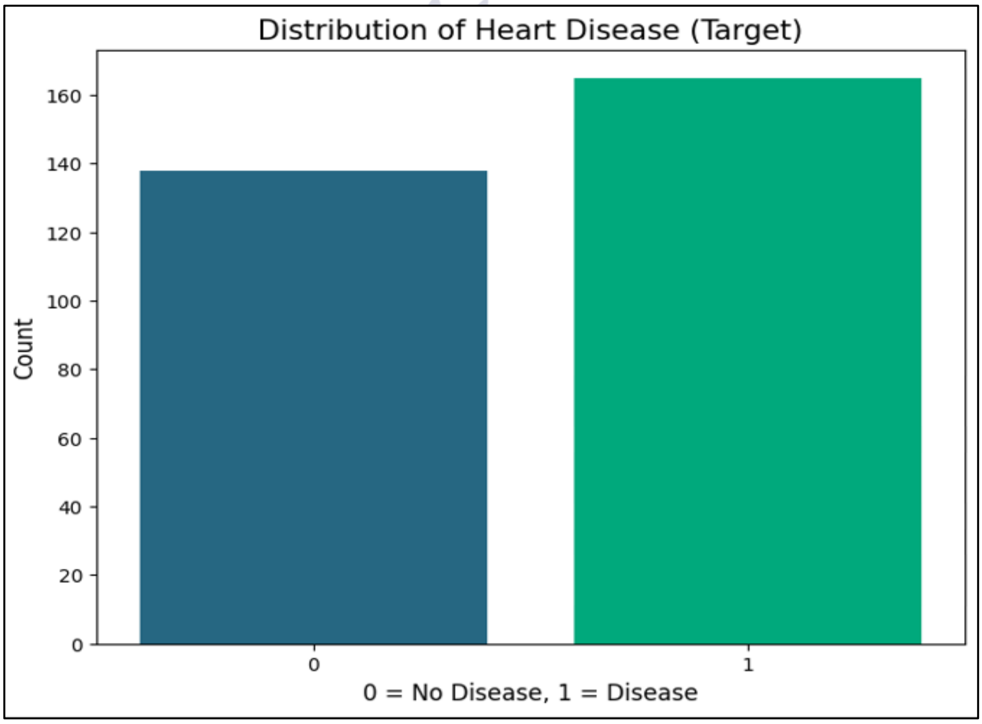


Figure 5 Balanced dataset for predicting heart diseases

This bar chart shows the dataset balance used for predicting heart disease using binary classification. A balanced dataset is best for training ML models.

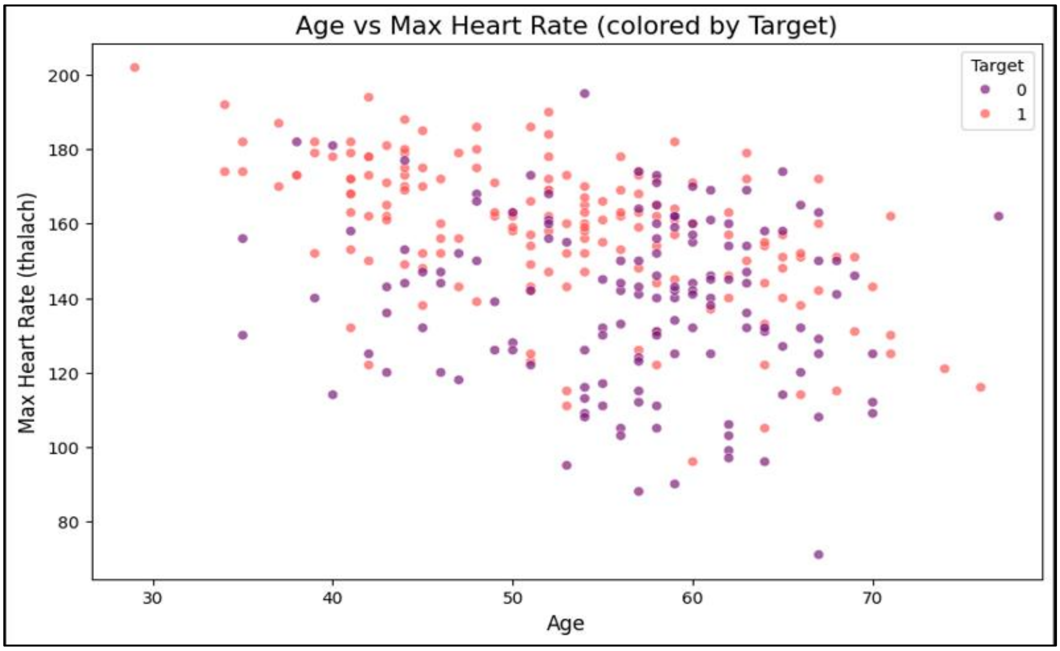


Figure 6 Maximum heart issues with the impact of age

The scatter plots highlight the relationship between age and maximum heart rate with the distribution of target variables.

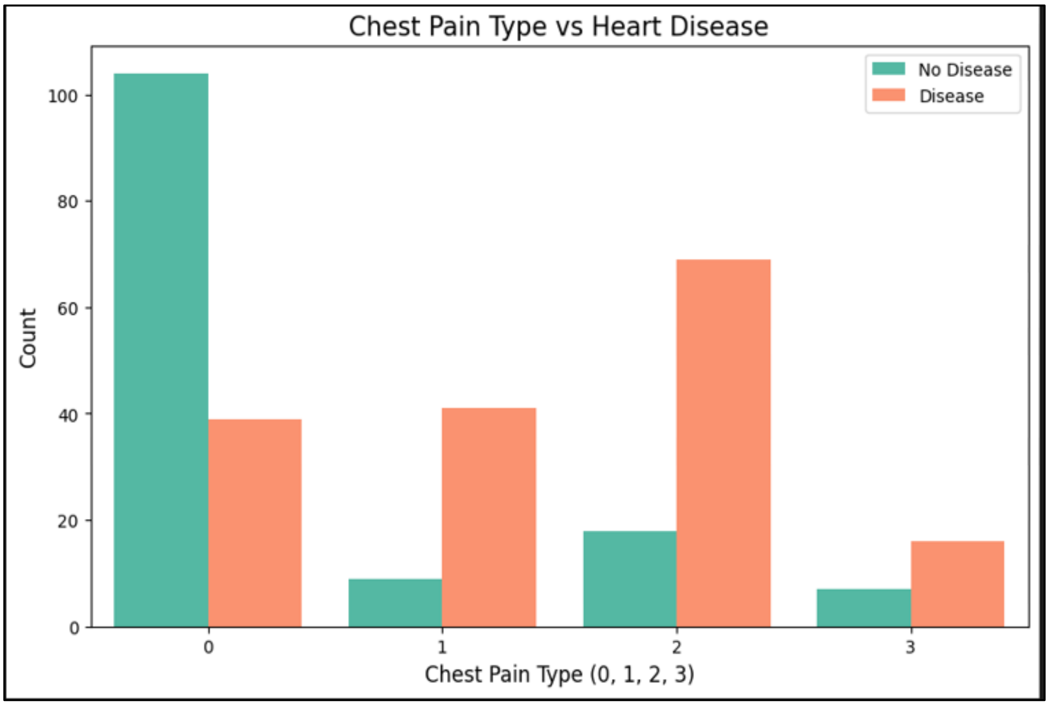


Figure 7 Types of chest pain related heart problem

This graph shows four different types of chest pain and heart diseases. The chart suggests that chest pain types 1 and 2 are more strongly associated with heart disease, as a higher proportion of individuals with these pain types have the disease compared to those with chest pain types 0 and 3.

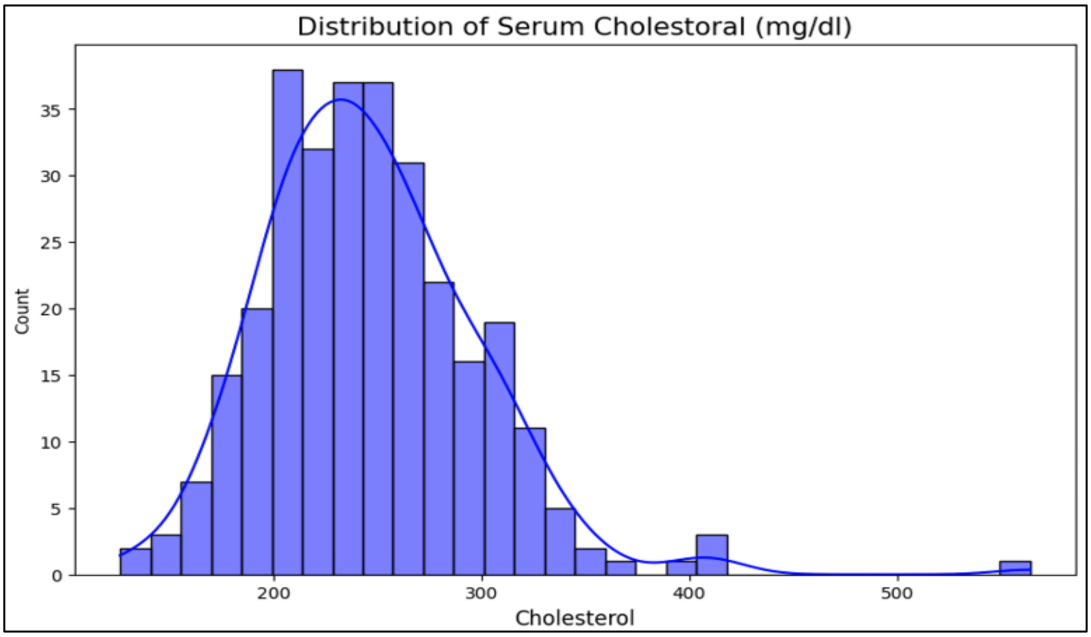
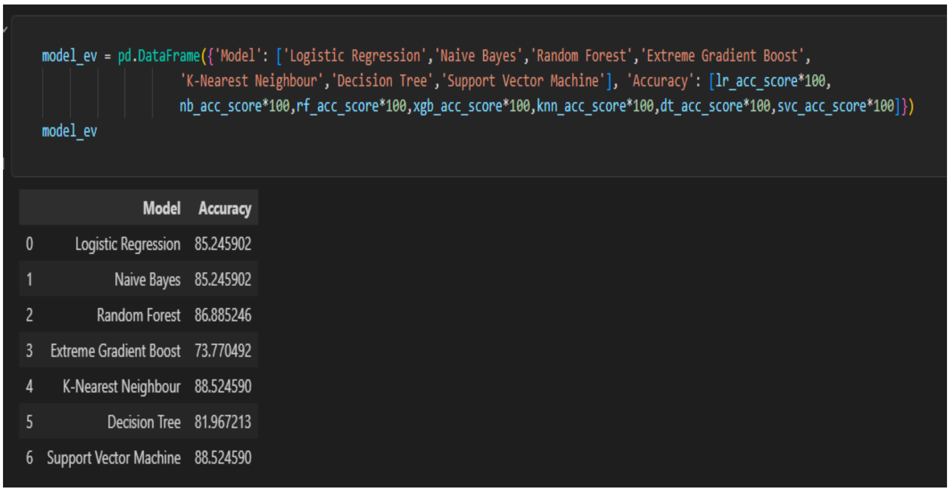


Figure 8 Visualization of the cholesterol range

The image displays a histogram showing the distribution of serum cholesterol levels in mg/dl. The x-axis represents the cholesterol level, and the y-axis represents the count of individuals within each cholesterol range. The histogram shows that the majority of individuals have serum cholesterol levels between 200 and 300 mg/dl, with the peak count occurring around 220-250 mg/dl. There are fewer individuals with very low or very high cholesterol levels. A smooth curve is overlaid on the histogram, indicating a possible normal distribution, though it appears to be right-skewed due to the tail extending towards higher cholesterol values. Here, applies the Logistic Regression model to check the performance of predicting heart diseases. The overall accuracy of the model is approximately 85.25%. We will improve results by using the confusion matrix of the Naive Bayes model and various performance metrics. The accuracy of the model is 85.25%. By applying Random forest accuracy level reach at 86.88% for classifying diseases. The Extreme Gradient Boost model has an overall accuracy of about 73.77%. It correctly identifies all instances of class 1 (recall of 1.00) but struggles to identify class 0 instances, with a recall of only 0.41. This results in a lower F1-score for class 0 (0.58) compared to class 1 (0.81). The weighted average metrics are 0.82 for precision, 0.74 for recall, and 0.71 for F1-score.

The K-Neighbours Classifier used for strong performance with an overall accuracy of about 88.52%. It performs well on both classes, with class 1 having a slightly higher F1-score (0.90) than class 0 (0.87). The precision and recall values are balanced across both classes, indicating a robust model. The weighted average metrics also reflect this overall high performance, with precision, recall, and F1-score all at 0.89. The Decision Tree Classifier achieved an accuracy of approximately 81.97%. It shows decent performance for both classes, with class 1 having a slightly higher F1-score (0.83) than class 0 (0.81). The model has a recall of 0.85 for class 0 and 0.79 for class 1. The macro and weighted averages for precision, recall, and F1-score are all 0.82, indicating balanced performance across classes. The Support Vector Classifier demonstrates strong performance with an overall accuracy of about 88.52%. It achieves a high F1-score of 0.90 for class 1 and 0.87 for class 0. The recall for class 1 is particularly impressive at 0.91, suggesting the model is good at identifying actual positive cases. The weighted averages for precision, recall, and F1-score are all 0.89, indicating a balanced and effective model overall.



```
model_ev = pd.DataFrame({'Model': ['Logistic Regression','Naive Bayes','Random Forest','Extreme Gradient Boost',
                    'K-Nearest Neighbour','Decision Tree','Support Vector Machine'], 'Accuracy': [lr_acc_score*100,
                    nb_acc_score*100,rf_acc_score*100,xgb_acc_score*100,knn_acc_score*100,dt_acc_score*100,svc_acc_score*100]})
model_ev
```

	Model	Accuracy
0	Logistic Regression	85.245902
1	Naive Bayes	85.245902
2	Random Forest	86.885246
3	Extreme Gradient Boost	73.770492
4	K-Nearest Neighbour	88.524590
5	Decision Tree	81.967213
6	Support Vector Machine	88.524590

Figure 9 Comparison of ML models

The image presents a summary of the accuracy of several machine learning models. The models evaluated are Logistic Regression, Naive Bayes, Random Forest, Extreme Gradient Boost, K-Nearest Neighbours, Decision Tree, and Support Vector Machine. The accuracy scores range from 73.77% to 88.52%.

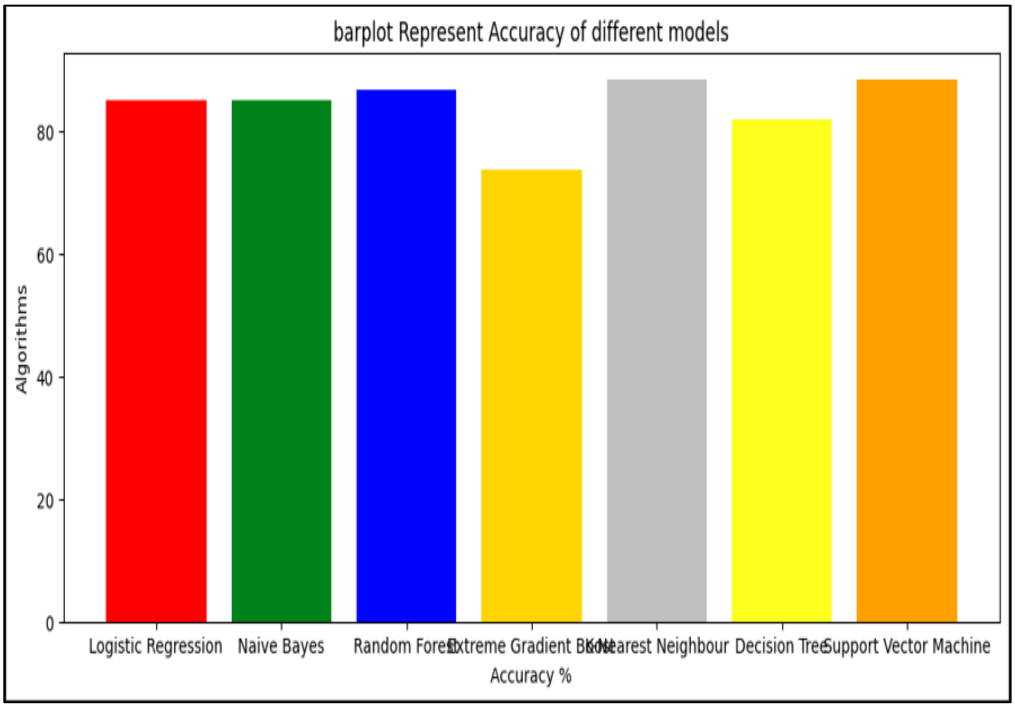


Figure 10 Graph of comparison models

The bar plot represents the accuracy of several machine-learning models. The models displayed are Logistic Regression, Naive Bayes, Random Forest, Extreme Gradient Boost, K-Nearest Neighbour, Decision Tree, and Support Vector Machine. The Support Vector Machine and K-Nearest Neighbour appear to have the highest accuracy, while Extreme Gradient Boost has the lowest accuracy. The graph is showing a comparison of different machine learning models, with the Support Vector Machine and K-Nearest Neighbour having the best performance [13].

```
confusion matrix (StackingClassifier)
[[23  4]
 [ 2 32]]


Accuracy of StackingClassifier: 90.1639344262295

              precision    recall  f1-score   support

           0       0.92      0.85      0.88        27
           1       0.89      0.94      0.91        34

    accuracy                           0.90        61
   macro avg       0.90      0.90      0.90        61
weighted avg       0.90      0.90      0.90        61
```

Figure 11 Improvement of all models

The image displays the results of a Stacking Classifier model. The overall accuracy of the model is approximately 90.16%.

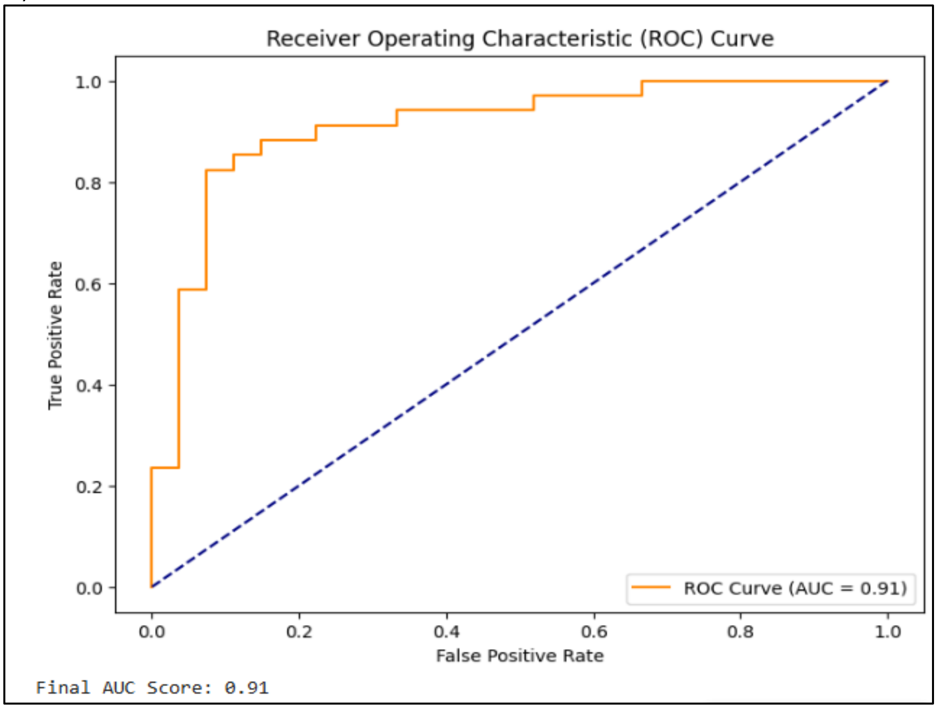


Figure 12 Visualization of the model's result

The image displays a Receiver Operating Characteristic (ROC) curve. The curve shows the performance of a binary classifier system at various threshold settings. The x-axis represents the False Positive Rate, and the y-axis represents the True Positive Rate. The dashed line indicates a random classifier. The orange line represents the ROC curve for the model, and the area under this curve (AUC) is given as 0.91. This indicates a very good performance of the classifier. The final AUC score is also stated as 0.91.

5 Conclusion

In this study, machine learning (ML) classifiers were employed to predict early-stage heart diseases, demonstrating the potential of data-driven approaches in modern healthcare. The results indicate that ML classifiers can effectively identify heart disease with a high degree of accuracy. Multiple classification algorithms were utilized, including Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), K-Nearest Neighbours (KNN), and a Stacking Classifier. Among these models, KNN and SVM achieved the highest performance, reaching an accuracy of 90.16%, and were therefore considered the best-performing models in this study. The findings highlight the capability of machine learning techniques to assist in early diagnosis, which is critical for reducing mortality rates and improving patient outcomes. Additionally, the use of multiple classifiers and ensemble approaches such as stacking demonstrates the importance of comparative analysis in selecting the most suitable model for medical prediction tasks.

For future work, the study can be extended by incorporating deep learning techniques to capture more complex and non-linear patterns within medical datasets. Furthermore, integrating real-time data processing frameworks and wearable health monitoring systems could significantly enhance the reliability and applicability of the proposed models in practical healthcare environments. Improving model interpretability and ensuring clinical validation will also be essential steps toward deploying these systems in real-world medical settings. Ultimately, such advancements can contribute to more accurate, efficient, and accessible heart disease diagnosis and patient care.

REFERENCES

R. Bharti, A. Khamparia, M. Shabaz, G. Dhiman, S. Pande, and P. Singh, “Prediction of Heart Disease Using a Combination of Machine Learning and Deep Learning,” Comput. Intell. Neurosci., vol. 2021, 2021, doi: 10.1155/2021/8387680.

B. Shesharao Ingole, V. Ramineni, N. Bangad, K. K. Ganeeb, and P. Patel, “Advancements in Heart Disease Prediction: A Machine Learning Approach For Early Detection And Risk Assessment,” IJRAR24D1253 International Journal of Research and Analytical Reviews, vol. 11, p. 164, 2024, [Online]. Available: www.ijrar.org

A. R. Ilyas, S. Javaid, and I. L. Kharisma, “Heart Disease Prediction Using ML †,” Engineering Proceedings, vol. 107, no. 1, 2025, doi: 10.3390/engproc2025107124.

T. R. Ramesh, U. K. Lilhore, M. Poongodi, S. Simaiya, A. Kaur, and M. Hamdi, “PREDICTIVE ANALYSIS OF HEART DISEASES WITH MACHINE LEARNING APPROACHES,” Malaysian Journal of Computer Science, vol. 2022, no. Special Issue 1, pp. 132–148, 2022, doi: 10.22452/mjcs.sp2022no1.10.

S. Nikhar and A. M. Karandikar, “Prediction of Heart Disease Using Machine Learning Algorithms,” International Journal of Advanced Engineering, Management and Science (IJAEMS), vol. 2, no. 6, 2016, [Online]. Available: www.ijaems.com

N. Ryadh Hamza and F. Jawad Al-Ghanim, “Performance Comparison of Machine Learning Algorithms in Heart Disease Prediction with Enhanced Accuracy through Hyperparameter Tuning,” Journal of Al-Qadisiyah for Computer Science and Mathematics, vol. 17, no. 2, pp. 60–71, Jun. 2025, doi: 10.29304/jqcsm.2025.17.22180.

M. K. Hossen and M. Khalid, “Heart Disease Prediction Using Machine Learning Techniques,” American Journal of Computer Science and Technology, vol. 5, no. 3, pp. 146–154, 2022, doi: 10.11648/j.ajcst.20220503.11.

M. A. Bouqentar et al., “Early heart disease prediction using feature engineering and machine learning algorithms,” Heliyon, vol. 10, no. 19, Oct. 2024, doi: 10.1016/j.heliyon. 2024.e38731.

M. Qadeer, R. Ayaz, and M. I. Thohir, “Heart Failure Prediction Through a Comparative Study of Machine Learning and Deep Learning Models †,” Engineering Proceedings, vol. 107, no. 1, 2025, doi: 10.3390/engproc2025107061.

A. Oliva et al., "Personalized Approaches to Antiplatelet Treatment for Cardiovascular Diseases: An Umbrella Review," 2023, Dove Medical Press Ltd. doi: 10.2147/PGPM.S391400.

H. Jindal, S. Agrawal, R. Khera, R. Jain, and P. Nagrath, "Heart disease prediction using machine learning algorithms," in IOP Conference Series: Materials Science and Engineering, IOP Publishing Ltd, Jan. 2021. doi: 10.1088/1757-899X/1022/1/012072.

Maqbool, M. S., Hanif, I., Iqbal, S., Basit, A., & Shabbir, A. (2023). Optimized feature extraction and cross-lingual text reuse detection using ensemble machine learning models. Journal of Computing & Biomedical Informatics, 5(01), 26-40.

Abid, K., Aslam, N., Fuzail, M., Maqbool, M. S., & Sajid, K. (2023). An efficient deep learning approach for the prediction of student performance using a neural network. VFAST Transactions on Software Engineering, 11(4), 67-79.

Kanwal, F., Abid, M. K., Maqbool, M. S., Aslam, N., & Fuzail, M. (2023). Optimized classification of cardiovascular disease using machine learning paradigms. VFAST Transactions on Software Engineering, 11(2), 140-148.

Aslam, N., Meeran, M. T., Aslam, M., Maqbool, M. S., & Saeed, B. (2025). Understanding Urban Expansion Through Multi-Temporal Satellite Data Analysis. Kashf Journal of Multidisciplinary Research, 2(09), 252-273.

Hasnain, M. A., Ali, S., Malik, H., Irfan, M., & Maqbool, M. S. (2023). Deep learning-based classification of dental disease using X-rays. Journal of Computing & Biomedical Informatics, 5(01), 82-95.

Basit, A., Hanif, I., Maqbool, M. S., Qayyum, W., Hasnain, M. A., & Nazeer, R. (2023). Cross-lingual information retrieval in a hybrid query model for optimality. Journal of Computing & Biomedical Informatics, 5(01), 130-141.

Hasnain, M. A., Ali, Z., Maqbool, M. S., & Aziz, M. (2024). X-ray image analysis for dental disease: A deep learning approach using EfficientNet. VFAST Transactions on Software Engineering, 12(3), 147-165.

Rafiqee, M. M., Qaiser, Z. H., Fuzail, M., Aslam, N., & Maqbool, M. S. (2023). Implementation of an efficient deep fake detection technique on a video dataset using a deep learning method. Journal of Computing & Biomedical Informatics, 5(01), 345-357.

Maqbool, M. S., Fatima, N., Nazeer, R., Aslam, N., Abbas, F., Sumra, U., & Nadeem, M. (2025). A hybrid dataset-based ensemble strategy for efficient breast cancer detection. Kashf Journal of Multidisciplinary Research, 2(12), 39-57.

Muhammad Noman, Muhammad Sajid Maqbool, Dr. Naeem Aslam, Muqadas Nadeem, Hira Saleem, & Hanzla. (2026). Sleep disorder scoring is automated using advanced data science and machine learning techniques. Policy Research Journal, 4(3), 853–868. Retrieved from https://policyrj.com/1/article/view/1713

Zainab Naveed, Rubaina Nazeer, Muhammad Sajid Maqbool, Dr. Naeem Aslam, Hira Saleem, & Muqadas Nadeem. (2026). An end-to-end orthopedic disease image classification system using convolutional neural networks.

Mahnoor Zaman, Nosheen Fatima, Muhammad Sajid Maqool, Dr. Naeem Aslam, Rubaina Nazeer, & Hira Saleem. (2026). Ingredient: Intelligent CNN for food ingredient recognition and classification. Policy Research Journal, 4(3), 789–805.

Aslam, N., Meeran, M. T., Aslam, M., Maqbool, M. S., & Saeed, B. (2025). Understanding Urban Expansion Through Multi-Temporal Satellite Data Analysis. Kashf Journal of Multidisciplinary Research, 2(09), 252-273.

M. A., Ali, Z., Maqbool, M. S., & Aziz, M. (2024). X-ray image analysis for dental disease: A deep learning approach using EfficientNet. VFAST Transactions on Software Engineering, 12(3), 147-165.

Farwa Zainab, Farwa Nazim, Muhammad Kashaf, Naeem Aslam, & Muhammad Sajid Maqbool. (2026). PREDICTIVE ANALYTICS FOR CUSTOMER CHURN IN SUBSCRIPTION-BASED BUSINESSES USING MACHINE LEARNING. Spectrum of Engineering Sciences, 4(4), 596–618. Retrieved from https://thesesjournal.com/index.php/1/article/view/2460.

Meiraj Aslam, Mohammad Sajid Maqbool, Muhammad Aoun, Naeem Aslam, Abdul Manan Razzaq, Abdul Manan Razzaq, & Salman Ali. (2026). HIGH-PERFORMANCE AND EFFICIENT BRAIN TUMOR SEGMENTATION FOR ENHANCED CLINICAL ANALYSIS. Spectrum of Engineering Sciences, 4(3), 195–210. Retrieved from https://thesesjournal.com/index.php/1/article/view/2169.

Syeda Qanitah Naqvi, Syeda Rabail Zahra, Muhammad Sajid Maqbool, Muqadas Nadeem, Hira Saleem, & Mahnoor Zaman. (2026). AN AUTOMATED AND ARTIFICIAL INTELLIGENCE-BASED SYSTEM FOR THE DIAGNOSIS OF SKIN CANCER. Policy Research Journal, 4(4), 58–72. Retrieved from https://policyrj.com/1/article/view/1769.

Sarim Javed, Muhammad Sajid Maqbool, Dr. Naeem Aslam, Muhammad Haseeb Ur Rehman, Muqadas Nadeem, & Hira Saleem. (2026). HIGH ACCURACY INTRUSION DETECTION IN IOT VIA HYBRID ML DL MODELS. Policy Research Journal, 4(4), 73–85. Retrieved from https://policyrj.com/1/article/view/1770.

Rabia Hassan, Muhammad Sajid Maqbool, Dr. Naeem Asalam, Ariba Afzal, Hira Saleem, & Muqadas Nadeem. (2026). AN IN-DEPTH STUDY ON STUDENTS' PERFORMANCE EVALUATION USING MULTIPLE MACHINE LEARNING CLASSIFIERS AND DATA ANALYTICS APPROACHES. Policy Research Journal, 4(4), 86–99. Retrieved from https://policyrj.com/1/article/view/1771.

Rabia Ikhlaq, Muhammad Sajid Maqbool, Hira Saleem, Dr. Naeem Aslam, Zeeshan Manzoor, & Muqadas Nadeem. (2026). DEEP CONVOLUTIONAL NEURAL NETWORKS FOR AUTOMATED BREAST CANCER DIAGNOSIS. Policy Research Journal, 4(4), 170–182. Retrieved from https://policyrj.com/1/article/view/1795.

Izhar, Dr. Naeem Aslam, Muhammad Sajid Maqbool, Muqadas Nadeem, & Hira Saleem. (2026). DEEPFAKESHIELD: ENHANCED VIDEO AUTHENTICITY DETECTION VIA CONVOLUTIONAL VISION TRANSFORMER. Spectrum of Engineering Sciences, 4(3), 1650–1665. Retrieved from https://thesesjournal.com/index.php/1/article/view/2360

A. H. Gonsalves, F. Thabtah, R. M. A. Mohammad, and G. Singh, "Prediction of coronary heart disease using machine learning: An experimental analysis," in ACM International Conference Proceeding Series, Association for Computing Machinery, Jul. 2019, pp. 51–56. doi: 10.1145/3342999.3343015.

A. Saboor, M. Usman, S. Ali, A. Samad, M. F. Abrar, and N. Ullah, "A Method for Improving Prediction of Human Heart Disease Using Machine Learning Algorithms," Mobile Information Systems, vol. 2022, 2022, doi: 10.1155/2022/1410169.

S. Subramani et al., "cardiovascular diseases prediction by machine learning incorporation with deep learning," Frontiers in Medicine, vol. 10, 2023.

T. Islam et al., "Cardiovascular Disease Prediction Using Machine Learning Approaches," in Proc. International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), 2023.

A. Tiwari, A. Chugh, and A. Sharma, "Ensemble Framework for Cardiovascular Disease Prediction," arXiv preprint, 2023.

H. A. Al-Alshaikh et al., "Comprehensive evaluation and performance analysis of machine learning in heart disease prediction," Scientific Reports, vol. 14, 2024.

W. Sun et al., "Machine Learning-Based Prediction of Cardiovascular Diseases," ICCK Transactions on Internet of Things, vol. 2, no. 2, 2024.

A. Ameen et al., "Advances in ECG and PCG-based cardiovascular disease classification: A review of deep learning and machine learning methods," Journal of Big Data, 2024.

A. Suliman et al., "Predictive performance of machine learning compared to statistical methods in cardiovascular disease analysis," BMJ Open, vol. 14, no. 4, 2024.

T. J. H. Mim et al., "Machine Learning Approaches for Cardiovascular Disease Prediction: A Comparative Study," Biomedical Materials & Devices, 2025.

R. S. Ramesh et al., "Cardiovascular Disease Prediction using Machine Learning: A Comparative Analysis," arXiv preprint, 2025.