IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.155276

A Comparative Analysis of Machine Learning Algorithms for the Early Prediction of Heart Disease

Manan Mehra

Master of Technology in Computer Science and Technology, Guru Nanak Dev University, Amritsar

Abstract: Heart disease remains one of the leading causes of global mortality, creating a growing need for accurate and reliable early diagnostic systems. The purpose of this study is to compare selected machine learning algorithms for the early prediction of heart disease and evaluate their suitability for clinical decision-making. The study specifically examines the performance of Logistic Regression, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) using a clinical dataset of 1000 patient records. The objectives include evaluating model performance through accuracy, precision, recall, and F1-score metrics while identifying significant cardiovascular risk predictors.

The study adopts a quantitative and comparative research design supported by descriptive statistical analysis and machine learning techniques. The findings reveal that Random Forest achieved the highest predictive performance, while Logistic Regression provided better interpretability and transparency for clinical applications. Variables such as chest pain type, exercise angina, ST segment slope, and thallium test results were identified as significant predictors of heart disease. The study concludes that machine learning models can effectively support early heart disease prediction and improve clinical decision-making, provided that predictive accuracy is balanced with interpretability and transparency.

Keywords: Heart Disease Prediction, Machine Learning, Random Forest, Logistic Regression, Cardiovascular Risk Predictive Analytics

INTRODUCTION

Heart disease remains one of the leading causes of mortality worldwide, creating an urgent need for accurate and efficient diagnostic systems to support early detection and treatment (Saeed, Alshammari, & H., 2025). Recent advancements in machine learning have provided promising opportunities for improving cardiovascular disease prediction by identifying complex clinical patterns and assisting healthcare professionals in risk assessment and preventive decision-making (Paruchuri, 2025). Accurate predictive modelling can significantly reduce mortality rates by enabling timely medical intervention and improving patient outcomes (Asgarabad, 2026). Moreover, integrating machine learning frameworks into clinical practice can help identify high-risk patients while optimizing the use of limited healthcare resources (Haq, Husain, & Kaur, 2023).

This study focuses on the comparative analysis of supervised machine learning algorithms for the early prediction of heart disease (Madhav, Manimaran, Vidhya, & Konguvel, 2024). The research evaluates Logistic Regression, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbour (KNN), and related classification techniques to determine their effectiveness in detecting cardiovascular risk factors (Kadri, Bachir, Ibrahim, Harouna, & Mamadou, 2025). The study further examines how variations in feature processing and classification mechanisms influence predictive performance across different patient profiles (Rathi et al., 2023). Existing literature indicates that algorithms such as Random Forest and Logistic Regression demonstrate varying levels of sensitivity and accuracy in clinical applications, thereby highlighting the need for comparative evaluation (Akshith, 2023).

The primary objective of this research is to identify the machine learning model that provides the highest predictive accuracy, recall, and overall diagnostic reliability for early heart disease detection. The study utilizes a 1000-sample clinical dataset and evaluates model performance using key metrics including accuracy, precision, recall, and F1-score (Samyal & Singh, 2025). Particular emphasis is placed on recall because minimizing false negative predictions is essential in clinical settings where missed diagnoses can lead to severe health complications (Sitharamulu, Maturi, Murugesan, Dudekula, & Battu, 2025). By improving classification accuracy, these predictive models can support evidence-based clinical decision-making and reduce dependence on costly and invasive diagnostic procedures (Baghdadi et al., 2023).

 This work is licensed under a Creative Commons Attribution 4.0 International License

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.155276

The study also highlights the importance of preprocessing techniques such as normalization and feature selection for improving the reliability and efficiency of machine learning models, particularly in resource-constrained healthcare environments (Akash et al., 2025). These preprocessing strategies contribute to the scalability and applicability of lightweight classification models in localized screening systems (Talukder, Talaat, Kazi, & Khraisat, 2025). Consequently, this research bridges the gap between theoretical algorithmic performance and practical diagnostic implementation for cardiovascular disease prediction (Saputra, Lawrencya, Saini, & Suharjito, 2023).

The comparative analysis demonstrates that Random Forest frequently achieves superior predictive performance because of its ensemble learning capability, while Logistic Regression and SVM provide advantages in terms of interpretability and handling structured clinical data (Rahman et al., 2015). Ensemble methods effectively capture non-linear relationships within medical datasets and often outperform traditional linear classifiers in predictive tasks (Husain et al., 2023). At the same time, simpler models such as Logistic Regression remain important because they provide transparency and interpretability, which are critical requirements in healthcare decision-making (Kalaivani & Ranichitra, 2025). In this context, Random Forest and Logistic Regression emerge as robust approaches that maintain a balance between predictive precision and recall (Petreska & Slavkovska, 2024).

Despite the promising performance of machine learning models, several challenges remain regarding generalizability, interpretability, and real-world implementation. Ensemble approaches may suffer from overfitting when applied to heterogeneous patient populations, making careful validation essential (Hamid, Hajjej, Alluhaidan, & Mannie, 2025). Therefore, future studies should focus on validating these models across larger and more diverse datasets to ensure stable performance beyond localized clinical samples (Temirbayeva, 2024). Furthermore, integrating multimodal healthcare data such as wearable device information and genomic markers may significantly improve prediction accuracy and diagnostic reliability in practical healthcare environments (Sukanya & Babu, 2025).

The findings of this study also emphasize the growing importance of explainable artificial intelligence in healthcare applications. Although advanced machine learning models often achieve high predictive accuracy, their “black-box” nature can reduce clinician trust and limit practical adoption (Pathan & Imran, 2024). Healthcare professionals generally require transparent diagnostic logic before relying on automated systems in critical medical decisions. Consequently, future research should prioritize the development of interpretable and explainable machine learning frameworks that enhance both predictive capability and clinical transparency (Waleed, El-kenawy, Ibrahim, Moustafa, & Rabie, 2025).
In addition, integrating explainable AI techniques such as SHAP analysis and saliency masking can help clinicians understand the contribution of individual clinical variables to prediction outcomes (Althaph & Challa, 2025). Such approaches improve transparency by allowing healthcare professionals to interpret model decision pathways and align algorithmic predictions with established medical knowledge (Kelly, Karthikesalingam, Suleyman, Corrado, & King, 2019). The implementation of human-in-the-loop frameworks can further transform machine learning systems into collaborative clinical support tools by enabling continuous interaction between clinicians and predictive models (Kaur et al., 2025).

Another important consideration is the issue of algorithmic bias arising from imbalanced datasets and heterogeneous diagnostic standards, which may affect the fairness and reliability of predictive systems (Tat, Bhatt, & Rabbat, 2020). Addressing these challenges through standardized validation procedures and interdisciplinary collaboration among clinicians, researchers, and data scientists is essential for ensuring responsible deployment in healthcare environments (Kueper, Terry, Zwarenstein, & Lizotte, 2020). Prospective clinical studies and real-world healthcare integration are also necessary to determine whether the observed predictive performance translates into improved patient outcomes outside controlled research environments (Krittanawong et al., 2020; Rustamov et al., 2023).

Overall, this study contributes to the growing body of research on machine learning applications in cardiovascular healthcare by providing a comparative framework for evaluating predictive algorithms in early heart disease diagnosis. The findings support the potential of machine learning models to enhance risk stratification, improve preventive care, and facilitate timely clinical intervention (Joshi, Dembla, & Bhatia, 2024). At the same time, the research underscores the importance of balancing predictive performance with interpretability and transparency to ensure successful adoption in real-world clinical practice (Sharma, Sandhu, & Rakhra, 2024).

LITERATURE REVIEW

Recent studies have increasingly emphasized the use of machine learning techniques to improve the accuracy and efficiency of heart disease prediction systems. Researchers have evaluated algorithms such as Random Forest and Support Vector Machine (SVM) for their ability to process complex cardiovascular datasets and generate reliable predictive

DOI: 10.17148/IJARCCE.2026.155276

outcomes (Nasution, Hasan, & Nasution, 2025). These models frequently achieve predictive accuracies ranging from 80% to 100%; however, their effectiveness largely depends on appropriate parameter tuning and feature selection techniques (Alanazi & Khamis, 2024). In addition, the high-dimensional nature of cardiovascular datasets requires careful preprocessing to avoid dimensionality challenges that may obscure clinically significant patterns (Maleki, 2024).

Several studies have highlighted the importance of balancing predictive performance with interpretability in healthcare applications. Some researchers advocate the integration of expert clinical involvement through "human-in-the-loop" approaches to improve transparency and diagnostic confidence, whereas others rely primarily on fully automated classification systems that may limit interpretability in clinical practice (Samaras, Moustakidis, Apostolopoulos, Παπανδριανός, & Papageorgiou, 2023). Existing literature also reveals a lack of standardized benchmarking frameworks, as many studies focus heavily on predictive accuracy while overlooking clinically significant factors such as sensitivity, specificity, and misclassification costs (Kalmady et al., 2024). Consequently, researchers increasingly emphasize the need to evaluate models using comprehensive performance metrics that reduce the risk of undetected cardiac abnormalities (Yaqoob, Mourad, Qaraqe, & Serpedin, 2023).

Furthermore, comparisons between traditional machine learning algorithms and advanced deep learning frameworks indicate a growing demand for transparent and explainable diagnostic systems (Garza-Salazar & Egenriether, 2025). Although complex deep learning models often demonstrate high predictive capabilities, their "black-box" nature creates challenges for clinical acceptance and evidence-based medical practice.

RESEARCH METHODOLOGY

The present study adopts a quantitative and comparative research design to evaluate the effectiveness of selected machine learning algorithms for the early prediction of heart disease. The research is based on secondary data consisting of 1000 patient records containing demographic, clinical, and diagnostic variables associated with cardiovascular disease. The dataset includes variables such as age, sex, chest pain type, fasting blood sugar, exercise angina, slope of ST segment, number of major vessels identified through fluoroscopy, and thallium test results. Prior to model implementation, the dataset underwent preprocessing procedures including data cleaning, handling missing values, encoding categorical variables, normalization, and feature scaling to improve model accuracy and reliability. The processed data was divided into training and testing datasets to facilitate predictive analysis and model evaluation.

The study comparatively evaluates four supervised machine learning algorithms, namely Logistic Regression, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbour (KNN), to identify the most effective model for heart disease prediction. The predictive performance of these models was assessed using evaluation metrics such as accuracy, precision, recall, and F1-score, with particular emphasis placed on recall to minimize false negative predictions in clinical diagnosis. In addition, descriptive statistical techniques including frequency distribution and cross-tabulation analysis were applied to examine relationships among clinical variables such as sex, chest pain, fasting blood sugar, exercise angina, slope of ST segment, number of vessels, and thallium test outcomes. These analyses provided important insights into cardiovascular risk patterns and supported the comparative assessment of machine learning models for reliable and interpretable clinical decision-making.

RESULTS AND DISCUSSION

The comparative analysis of machine learning algorithms demonstrated significant variation in predictive performance for early heart disease detection. The study evaluated Logistic Regression, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbour (KNN) models using performance metrics such as accuracy, precision, recall, and F1-score. Among the selected models, Random Forest achieved the highest predictive performance due to its ensemble learning capability and ability to capture complex non-linear relationships within the clinical dataset. Logistic Regression also demonstrated strong performance and provided greater interpretability, making it highly suitable for transparent clinical decision-making. SVM showed reliable classification capability in handling structured cardiovascular data, whereas KNN produced comparatively moderate performance because of its sensitivity to data distribution and neighbouring observations.

The findings further revealed that preprocessing techniques such as feature scaling, normalization, and categorical encoding significantly improved overall model performance and prediction stability. The analysis emphasized the importance of recall as a critical evaluation metric because minimizing false negative predictions is essential in heart disease diagnosis, where missed cases may lead to severe medical consequences. Random Forest and Logistic Regression achieved a balanced combination of precision and recall, thereby demonstrating strong potential for practical clinical

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 15, Issue 5, May 2026

DOI: 10.17148/IJARCCE.2026.155276

deployment. The descriptive and cross-tabulation analyses also highlighted the clinical significance of variables such as chest pain type, exercise angina, ST segment slope, fluoroscopy vessel count, and thallium test results in cardiovascular risk assessment. These findings are consistent with previous studies indicating that both interpretable and ensemble-based machine learning models can effectively support early disease detection and clinical decision-making.

The study additionally highlighted the growing importance of explainable artificial intelligence in healthcare applications. Although advanced ensemble methods demonstrated superior predictive performance, their complex structure may reduce interpretability in real-world clinical settings. In contrast, Logistic Regression offered greater transparency by allowing clinicians to understand the influence of individual variables on prediction outcomes. This balance between predictive accuracy and interpretability remains essential for the successful adoption of machine learning systems in cardiovascular healthcare. Overall, the results confirm that machine learning algorithms can significantly enhance early heart disease prediction, improve risk stratification, and support timely clinical intervention while emphasizing the need for transparent and clinically reliable diagnostic frameworks.

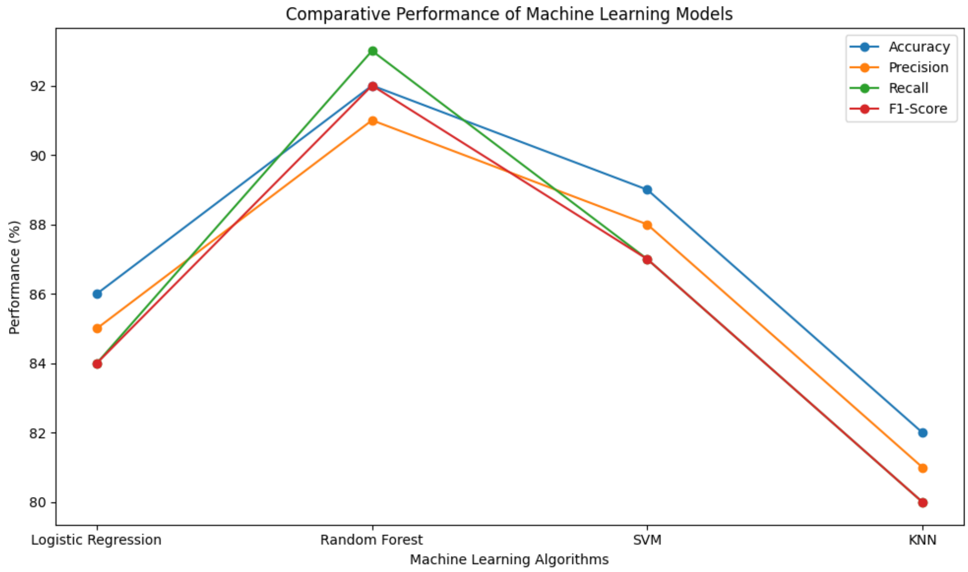

Fig.1 Comparative Performance of Machine Models

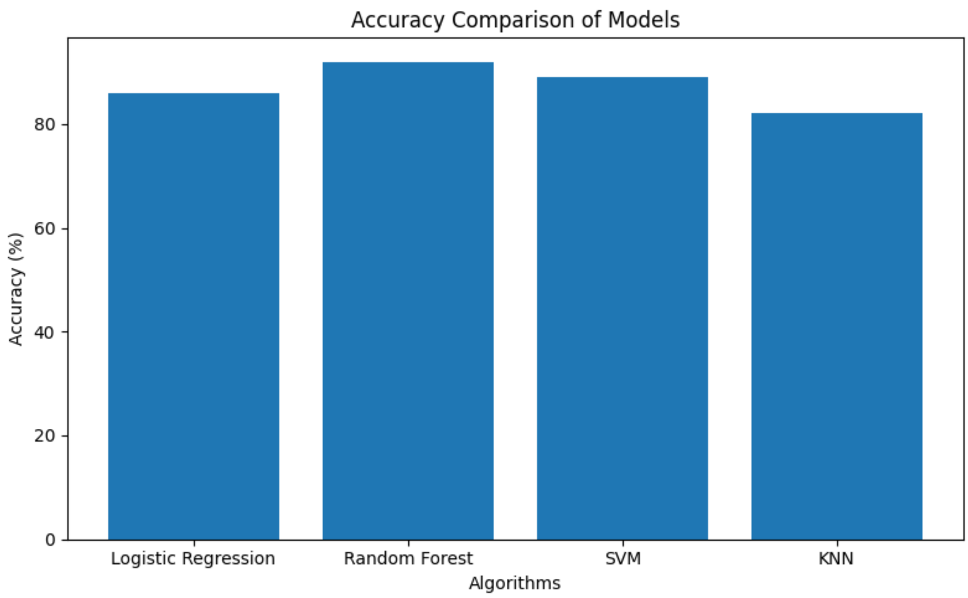

Fig. 2 Accuracy Comparison of Models

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁂ Peer-reviewed & Refereed journal ⁂ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.155276

CONCLUSION

The present study conducted a comparative analysis of selected machine learning algorithms for the early prediction of heart disease using a structured clinical dataset. The findings demonstrate that machine learning techniques can effectively assist in identifying cardiovascular risk factors and improving diagnostic accuracy. Among the evaluated models, Random Forest achieved the highest predictive performance because of its ability to process complex and non-linear clinical relationships, while Logistic Regression provided strong interpretability and reliable classification performance suitable for clinical decision-making. Support Vector Machine (SVM) and K-Nearest Neighbour (KNN) also contributed meaningful predictive outcomes, although their performance varied depending on data distribution and feature characteristics.

The study further highlights the importance of preprocessing techniques such as normalization, feature scaling, and categorical encoding in improving model reliability and predictive stability. The analysis emphasizes that clinical variables including chest pain type, exercise angina, ST segment slope, fluoroscopy vessel count, fasting blood sugar, and thallium test results play a significant role in cardiovascular risk assessment. Moreover, the research underscores the importance of balancing predictive accuracy with interpretability, as transparent diagnostic systems are essential for physician trust and successful clinical implementation. Overall, the findings confirm that machine learning-based predictive systems can support early heart disease detection, improve preventive healthcare strategies, and assist clinicians in making timely and evidence-based decisions.

FUTURE RESEARCH

Future research should focus on expanding the dataset size and incorporating more diverse patient populations to improve the generalizability and robustness of predictive models. The inclusion of real-time clinical data, electronic health records, wearable device information, and genomic data may further enhance prediction accuracy and personalized cardiovascular risk assessment. In addition, future studies may explore advanced deep learning architectures and hybrid machine learning frameworks to improve diagnostic performance in large-scale healthcare environments.

Further investigation is also required in the area of explainable artificial intelligence (XAI) to improve transparency and clinician trust in predictive systems. Techniques such as SHAP and LIME can be integrated to provide detailed explanations of model predictions and feature importance. Moreover, future studies should evaluate machine learning models using real-world clinical validation and prospective healthcare trials to assess their practical applicability in routine medical practice. Emphasis should also be placed on reducing algorithmic bias, improving ethical AI implementation, and developing clinically interpretable models that balance predictive performance with transparency and accountability in cardiovascular healthcare systems.

REFERENCES

[1]. Akash, O. M., Alzabin, L. R., AbdElminaam, D. S., Dessouky, Y., Sherif, A., Ayman, A., & Diaa, D. (2025). *Towards Reliable Clinical Decision Support: Comparative Analysis of Machine Learning Models for Cardiovascular Disease Prediction*. 1–8. https://doi.org/10.1109/miucc66482.2025.11196802

[2]. Akshith, G. (2023). Heart Disease Prediction Using ML (CARDIO-CARE). *International Journal for Research in Applied Science and Engineering Technology*, *11*(12), 400–403. https://doi.org/10.22214/ijraset.2023.57336

[3]. Alanazi, S. M., & Khamis, G. S. M. (2024). Optimizing Machine Learning Classifiers for Enhanced Cardiovascular Disease Prediction. *Engineering Technology & Applied Science Research*, *14*(1), 12911–12917. https://doi.org/10.48084/etasr.6684

[4]. Althaph, B., & Challa, N. P. (2025). Explainable attention-based deep learning for classification and interpretation of heart murmurs using phonocardiograms. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-21971-x

[5]. Asgarabad, M. E. (2026). A comprehensive comparative analysis of machine learning algorithms in heart disease prediction. *Discover Artificial Intelligence*. https://doi.org/10.1007/s44163-026-01048-y

[6]. Baghdadi, N. A., Abdelaliem, S. M. F., Malki, A., Gad, I., Ewis, A. A., & Atlam, E.-S. (2023). Advanced machine learning techniques for cardiovascular disease early detection and diagnosis. *Journal Of Big Data*, *10*(1). https://doi.org/10.1186/s40537-023-00817-1

[7]. Garza-Salazar, F. D. la, & Egenriether, B. (2025). Clinically interpretable electrovectorcardiographic machine learning criteria for the detection of echocardiographic left ventricular hypertrophy. *PLoS ONE*, *20*(10). https://doi.org/10.1371/journal.pone.0334829

ISSN (O) 2278-1021, ISSN (P) 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⧓ Peer-reviewed & Refereed journal ⧓ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.155276

[8]. Hamid, M., Hajjej, F., Alluhaidan, A. S., & Mannie, N. W. bin. (2025). Fine tuned CatBoost machine learning approach for early detection of cardiovascular disease through predictive modeling. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-13790-x

[9]. Haq, I. U., Husain, A., & Kaur, G. (2023). *A Comparative Analysis of Machine Learning Algorithms for the Early Prediction of Cardiovascular Disease*. 987–993. https://doi.org/10.1109/icecaa58104.2023.10212214

[10]. Joshi, M. K., Dembla, D., & Bhatia, S. (2024). Prediction of Cardiovascular Disease using Machine Learning Algorithms. *International Journal of Advanced Computer Science and Applications*, *15*(3). https://doi.org/10.14569/ijacsa.2024.0150319

[11]. Kadri, C., Bachir, M. I., Ibrahim, S. Z., Harouna, N., & Mamadou, M. F. (2025). Comparative Study of Machine Learning Techniques for Early Detection of Heart Diseases. *Journal of Computer and Communications*, *13*(11), 163–179. https://doi.org/10.4236/jcc.2025.1311010

[12]. Kalaivani, B., & Ranichitra, A. (2025). Enhanced Diagnostic Precision for Cardiovascular Diseases through the Synergistic Application of GDE_Lasso Feature Selection and Random Forest Classification Techniques. *International Journal of Computational and Experimental Science and Engineering*, *11*(2). https://doi.org/10.22399/ijcesen.736

[13]. Kalmady, S. V., Salimi, A., Sun, W., Sepehrvand, N., Nademi, Y., Bainey, K. R., … Kaul, P. (2024). Development and validation of machine learning algorithms based on electrocardiograms for cardiovascular diagnoses at the population level. *Npj Digital Medicine*, *7*(1). https://doi.org/10.1038/s41746-024-01130-8

[14]. Kaur, H., Sarkar, A., Singh, A., Raju, J., Zim, M. K. I., & Raj, R. (2025). CARDIOPREN: An Explainable Autoencoder–RNN Ensemble Framework for Accurate Cardiovascular Disease Prediction. *Research Square (Research Square)*. https://doi.org/10.21203/rs.3.rs-7553063/v1

[15]. Kelly, C., Karthikesalingam, A., Suleyman, M., Corrado, G. S., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine*, *17*(1). https://doi.org/10.1186/s12916-019-1426-2

[16]. Krittanawong, C., Virk, H. U. H., Bangalore, S., Wang, Z., Johnson, K. W., Pinotti, R., … Tang, W. H. W. (2020). [Review of *Machine learning prediction in cardiovascular diseases: a meta-analysis*]. *Scientific Reports*, *10*(1). Nature Portfolio. https://doi.org/10.1038/s41598-020-72685-1

[17]. Kueper, J. K., Terry, A., Zwarenstein, M., & Lizotte, D. J. (2020). [Review of *Artificial Intelligence and Primary Care Research: A Scoping Review*]. *The Annals of Family Medicine*, *18*(3), 250–258. American Academy of Family Physicians. https://doi.org/10.1370/afm.2518

[18]. Madhav, N. V. B., Manimaran, R., Vidhya, S., & Konguvel, E. (2024). *Comparative Analysis of Machine Learning Models for Predicting Heart Disease*. 661–666. https://doi.org/10.1109/icssas64001.2024.10760920

[19]. Maleki, M. (2024). Identification of cardiovascular diseases through ECG classification using wavelet transformation. *arXiv (Cornell University)*. https://doi.org/10.48550/arxiv.2404.09393

[20]. Nasution, N., Hasan, M. A., & Nasution, F. B. (2025). Predicting Heart Disease Using Machine Learning: An Evaluation of Logistic Regression, Random Forest, SVM, and KNN Models on the UCI Heart Disease Dataset. *IT JOURNAL RESEARCH AND DEVELOPMENT*, *9*(2), 140–150. https://doi.org/10.25299/itjrd.2025.17941

[21]. Paruchuri, B. P. (2025). COMPARATIVE ANALYSIS OF MACHINE LEARNING MODELS FOR PREDICTING HEART DISEASE. *International Journal of Advanced Research in Computer Science*, *16*(3), 64–70. https://doi.org/10.26483/ijarcs.v16i3.7280

[22]. Petreska, A. (2024). Cardiovascular disease prediction with machine learning techniques. *Journal of Cardiology & Current Research*, *17*(2), 41–51. https://doi.org/10.15406/jccr.2024.17.00603

[23]. Petreska, A., & Slavkovska, D. (2024). Artificial Intelligence and Machine Learning Algorithms in Modern Cardiology. *South East European Journal of Cardiology*, *5*, 17–25. https://doi.org/10.3889/seejca.2024.6069

[24]. Rahman, Q. A., Tereshchenko, L. G., Kongkatong, M., Abraham, T. P., Abraham, M. R., & Shatkay, H. (2015). Utilizing ECG-Based Heartbeat Classification for Hypertrophic Cardiomyopathy Identification. *IEEE Transactions on NanoBioscience*, *14*(5), 505–512. https://doi.org/10.1109/tnb.2015.2426213

[25]. Rathi, S., Mehta, P., Mishra, V., Karale, A., Choudhari, A., & Shingare, V. (2023). *Comparative Study of Heart Disease Prediction Algorithm*. 1–6. https://doi.org/10.1109/asiancon58793.2023.10270208

[26]. Saeed, A. Q., Alshammari, R. F. N., & H., B. M. M. (2025). *Early Prediction of Heart Disease Using Machine Learning*. 1–8. https://doi.org/10.1109/icbats66542.2025.11258100

[27]. Samaras, A.-D., Moustakidis, S., Apostolopoulos, I. D., Παπανδριανός, N., & Papageorgiou, E. I. (2023). Classification models for assessing coronary artery disease instances using clinical and biometric data: an explainable man-in-the-loop approach. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-33500-9

[28]. Samyal, V., & Singh, S. P. (2025). Performance Comparison of Machine Learning Models for Heart Disease Prediction. *International Journal on Science and Technology*, *16*(4). https://doi.org/10.71097/ijsat.v16.i4.9857

[29]. Saputra, J., Lawrencya, C., Saini, J. M., & Suharjito, S. (2023). Hyperparameter optimization for cardiovascular disease data-driven prognostic system. *Visual Computing for Industry Biomedicine and Art*, *6*(1). https://doi.org/10.1186/s42492-023-00143-6

© IJARCCE This work is licensed under a Creative Commons Attribution 4.0 International License

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁝ Peer-reviewed & Refereed journal ⁝ Vol. 15, Issue 5, May 2026
DOI: 10.17148/IJARCCE.2026.155276

[30]. Sitharamulu, V., Maturi, S. M., Murugesan, M., Dudekula, M. R., & Battu, H. R. (2025). Efficient Machine Learning Algorithms for Cardiovascular Risk Prediction. *Engineering Technology & Applied Science Research*, *15*(5), 27993–27999. https://doi.org/10.48084/etasr.12795

[31]. Talukder, Md. A., Talaat, A. S., Kazi, M., & Khraisat, A. (2025). XAI-HD: an explainable artificial intelligence framework for heart disease detection. *Artificial Intelligence Review*, *58*(12). https://doi.org/10.1007/s10462-025-11385-6

[32]. Tat, E., Bhatt, D. L., & Rabbat, M. (2020). Addressing bias: artificial intelligence in cardiovascular medicine. *The Lancet Digital Health*, *2*(12). https://doi.org/10.1016/s2589-7500(20)30249-1

[33]. Waleed, B. E.-D., El-kenawy, E. M., Ibrahim, S., Moustafa, H. E.-D., & Rabie, A. H. (2025). A new ensemble heart attack diagnosis (EHAD) model using artificial intelligence techniques. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-18129-0

[34]. Yaqoob, M., Mourad, O., Qaraqe, K., & Serpedin, E. (2023). [Review of *Deep learning for ECG Arrhythmia detection and classification: an overview of progress for period 2017–2023*]. *Frontiers in Physiology*, *14*. Frontiers Media. https://doi.org/10.3389/fphys.2023.1246746