Journal of Computer Science and Technology Studies
ISSN: 2709-104X
DOI: 10.32996/jcsts
Journal Homepage: www.al-kindipublisher.com/index.php/jcsts

JCSTS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Wearable AI for Cardiovascular Health Monitoring: Enabling Early Detection and Prevention

Hasan Mahmud Sozib

Department of Electrical and Electronic Engineering, Ahsanullah University of Science and Technology, 141 & 142, Love Road, Tejgaon, Dhaka, 1208, Bangladesh.
Corresponding Author: Hasan Mahmud Sozib, **E-mail**: sozib2019@gmail.com

| ABSTRACT
Despite advancements in medicine, cardiovascular diseases (CVD) remain the leading cause of death in the world, highlighting the urgent need for continuous tracking and early detection. Wearable technology powered by artificial intelligence (AI) enables real-time, non-invasive monitoring of cardiovascular health. This study investigates the potential of wearable technology and artificial intelligence (AI)-based predictive analytics to revolutionize the early diagnosis and prevention of coronary vascular disease (CVD). Machine learning (ML) algorithms include decision trees, random forests, support vector machines, and deep neural networks that analyze medical data such as heart rate variability, activity levels, and sleep maintenance to detect subtle cardiovascular risk factors. These models can detect deviations earlier than conventional diagnostics, and an individualized data-driven therapy can also be designed for them. Wearable AI systems paired with imaging, genetics, and electronic health record (EHR) data provide a holistic view of patient health. However, challenges like data privacy, algorithmic bias, and clinical integration must be addressed to ensure responsible adoption. This study aims to maximize the potential of wearable AI to enable proactive health management by reviewing the current status of wearable AI, featuring recent advances, examples of use cases, and implementation methods in cardiovascular care.

| KEYWORDS

Cardiovascular, Health, Machine Learning, CVD, Wearable AI

| ARTICLE INFORMATION

ACCEPTED: 19 March 2025 **PUBLISHED:** 23 April 2025 **DOI:** 10.32996/jcsts.2025.7.2.30

1. Introduction

Cardiovascular diseases (CVDs) are among the top causes of deaths globally, accounting for approximately 31% (17.9 million) of all causes of annual deaths (Hossain et al., 2024; Hussain et al., 2024). Besides mortality, CVDs are associated with substantial morbidity including poor health-related quality of life and high economic cost resulting from lost productivity and health care costs (Niropam Das 2025; Siddiqa et al., 2024). Due to an ageing population, changes in lifestyle, and increasing risk factors such as obesity, diabetes, and hypertension CVDs remain a global health problem that demands innovative therapeutic and preventive approaches (Imran et al., 2024; Mensah et al., 2019). Particular risk profiles in each individual vary considerably and do not necessarily align with the linearity and small number of factors utilized in traditional CVD risk prediction such as the Framingham Risk Score (M. A. Islam et al., 2025). These models are unable to adequately handle multi-dimensional data and evolving risk factors because of their static nature, leading to poor prediction and delayed diagnosis (Kamruzzaman et al., 2025).
Artificial Intelligence (AI) & big data are the breakthrough technologies that have allegedly unlocked a wide, never-been-seen-before potential for addressing these challenges in the healthcare field (Kaur et al., 2023). Big data makes possible a holistic understanding of individuals' health through tracking patient data from multiple sources, each utilizing different technologies for example, wearable tech, genetics, and electronic health records (EHRs) (Hossain et al., 2025). And simultaneously, algorithms based on machine learning (Ahmed et al., 2025), a category of artificial intelligence (Bhuiyan et al., 2025), comb through these colossal data sets, finding patterns and connections that might slip past human investigators (Khair et al., 2025). Data4.0, that is, big data

and artificial intelligence, is revolutionizing the well-established paradigms in cardiovascular disease (CVD) management and providing opportunities to extend risk stratification, early diagnosis, and personalized treatment approaches in the context of CVDs (Greenland et al., 2001; Hossain et al., 2025). This research analyzes the effect of big data and machine learning (ML) on diagnosis and treatment of cardiovascular disease (CVD) in precision (Manik et al., 2025). The potential of a proactive and individualized treatment approach that will become the cornerstone of the future is also discussed. In the age of precision medicine, this paper discusses the great potential that the integration of big data and machine learning (ML) may have for the decisive transformation of CVD prediction and treatment and to pave towards preventive and personalized care strategies (Md Alamgir Miah, 2025).
The three general approaches (genetic, environmental, and lifestyle) toward CVD risk development are oversimplified, that implies conventional method of studying CVD risk development is inadequate (Nilima et al., 2024). Such approaches often lead to generic risk assessments and, due to the time-varying nature, may not even be personalized (Goffer et al., 2025). Healthcare systems generate large quantities of data but much of this goes untapped due to integration and analytics challenges (Noor et al., 2024). It highlights the demand for innovative approaches to synergize machine learning and big data approaches to capitalize on contemporary data and improve cardiovascular risk stratification and management (Das et al., 2023).

2. Objectives

This paper reviews the use of machine learning and big data for cardiovascular disease (CVD) prediction (Kamal et al., 2025). It aims to overcome the limitations of traditional models and provide individualized risk estimation and early diagnosis using a variety of datasets. To obtain a complete view of cardiovascular health and analyze trends there seems to influence the evolution of the disease, the use of large datasets with the use of structured (genetic knowledge, wearable technology, digital health records (EHR), imaging data) and unstructured (text, image data) data are being used (Khair et al., 2025). Machine learning algorithms can identify risk variables, analyze complex data correlations, and make accurate predictions of the future. The study also stresses the importance of early diagnosis and personalized treatment to reduce the burden of CVDs.

3. Article Structure

This article discusses big data and machine learning in healthcare, especially their role in cardiovascular disease prediction (Mahmud, Barikdar, et al., 2025; Prabha et al., 2024). It reviews research, addresses issues such as bias, data quality and ethical issues, and offers recommendations on how to apply AI to cardiovascular care.

4. Review of literature

4.1 Big Data in Healthcare for cardiovascular

Big data can comprise data from electronic health records (EHRs), imaging data, wearable technology and genetic data, among other sources (Sadik et al., 2024; Siddiqa et al., 2025; Sobuz et al., 2025; Tasnim et al., 2025). These assets provide structured data for clinical knowledge and a complete view of patient health. Poor quality, the complexity introduced due to variations in data formats, and potential bias in prediction models are major challenges to be addressed in handling large datasets. To incorporate data from numerous sources, sophisticated technologies are required to harmonize diverse formats. Processing high-dimensional data requires strong infrastructure to handle the computational demand, while deployment is hampered by data security and privacy compliance with legalities such as GDPR and HIPAA. Nevertheless, big data utilization in identifying risk factors, promoting early diagnosis, and aiding treatment regimens offers opportunities to improve cardiovascular patients' care. Fig. 1 displays a diagram of Big Data Sources.

Fig. 1. Diagram of Big Data Sources (Manik et al., 2025; Prabha et al., 2024).

4.2 CVD Prediction using Machine Learning

Machine learning (ML) is being used more and more to detect and prognosticate cardiovascular disease. Some typical machine learning approaches are random forests, decision trees, and neural networks (Md Habibullah Faisal 1, 2022). The decision trees are simple & fast for classifying risk variables, but are combined into a random forest for better prediction rate. Neural networks, which are deep learning models, can process high-dimensional and complex data (Tiwari et al., 2025).

Machine learning is being widely used across a spectrum of cardiovascular treatment applications. For example, the use of machine-learning techniques that leverage ECG data has proven highly effective in detecting arrhythmias (Tiwari et al., 2024). Deep learning models, such as CNNs, are capable of detecting abnormal heart rhythms within minutes with near-human accuracy, paving the way for early intervention. Heart failure prognosis has also been predicted using random forests based on EHR data, including drug adherence and comorbidities (Yeasmin et al., 2025). Moreover, machine learning models can provide non-invasive means of atherosclerosis detection through the analysis of imaging data. Machine learning methods, capable of identifying complex interactions and more subtle patterns and associations between risk factors than traditional methods, allow for more accurate risk stratification and tailored treatment (Mia Md Tofayel Gonee et al., 2022). However, successful implementation will require addressing questions around data quality, computational efficiency and clinical validation (Miah, 2025; Mohammad Abdul et al., 2024). Table 1 shows a summary of machine learning applications in cardiovascular disease (CVD) research.

Table 1. Machine learning algorithms in cardiovascular disease (CVD) research performance summary.

Algorithm	Type	Applications	Advantages	Limitations
Decision Trees	Supervised	Predicting risk and assessing feature significance	Simple to understand, requires minimal computation	May overfit and underperform with complex data
Random Forest	Supervised	Risk classification, predicting outcomes	Highly accurate, suitable for big data	Resource-heavy, not easy to explain
Support Vector Machines (SVM)	Supervised	Detecting arrhythmias, evaluating patient risk	Good for small datasets with distinct boundaries	Struggles with noisy or extensive datasets
K-Nearest Neighbors (KNN)	Supervised	Estimating risk levels	Easy to use, reliable for smaller data volumes	Affected by irrelevant features, high memory needs
Neural Networks (CNNs)	Supervised	Analyzing medical images (e.g., heart scans)	Excellent for complex image data, very accurate	Needs large datasets, computationally demanding
Recurrent Neural Networks (RNNs)	Supervised	ECG data analysis over time	Tracks data over time well, ideal for sequences	Can suffer from vanishing gradient issues, needs fine-tuning
Autoencoders	Unsupervised	Spotting anomalies in ECG signals	Lowers data complexity, useful for unsupervised tasks	Harder to interpret, requires optimization

4.3 Challenges of Adaptation of AI in CVD

There remain challenges to implementing AI in cardiovascular healthcare, including data protection, algorithm transparency, clinical acceptability, ethical challenges, and legal frameworks (Saimon et al., 2023). Resistance among healthcare professionals can be a barrier to widespread adoption, and clinical acceptability remains to be demonstrated. Ethical issues include the bias found in training datasets, the under-representation of minority groups and the possible over-reliance on AI systems. These barriers can be broken down with harmonized global processes for the regulation of AI in health care, which ensure that the cutting-edge technologies that are developed can be implemented into clinical practice (Syed Nazmul Hasan, 2025).

5.Data gathering and preprocessing

5.1 Sources of Data

Accurate prediction of cardiovascular illness requires multiple data sources, each providing a different view of the health of the patient. Health wearables, such as fitness wristbands and smartwatches, also enable the constant tracking of variables like blood pressure, heart rate, activity levels and sleep patterns. Imaging techniques, such as computed tomography, MRI, and echocardiography, provide extensive structural and functional data for the diagnosis of diseases such as atherosclerosis and heart failure. Demographic data, test results and clinical notes comprise a patient’s complete history, kept in electronic health records, or EHRs. From EHRs you get important metrics such as medication adherence, glucose levels, and cholesterol levels. Different determinants of CVD, however, can offer up interesting insights and tackling a broad range of factors from multiple levels is critical to prediction (Ahmed et al., 2023). Imaging parameters as heart rate variability, ECG patterns from wearables, blood pressure dynamics, lipid profile, artery wall thickness appearing in EHRs, and many more. Integration of these multiple data sources enables a holistic approach to CVD risk prediction; however, several challenges remain including standardization of data formats, ensuring interoperability of data, and maintaining data security, especially for sensitive medical data.

5.2 Data Preprocessing

Data preprocessing is a crucial step to feed raw cardiovascular features to machine learning models. It involves data cleaning and handling issues such as missing and inconsistent values. One method for dealing with missing data and ensuring consistency in terminology and units is imputation. Normalization ensures that the values of different variables may be in a consistent range so that no one factor like blood pressure or heart rate has an undue influence on the models. Feature selection improves model performance and reduces noise through selecting relevant features (i.e. ventricular ejection fraction, cholesterol levels, HRV). Dimensionality reduction using Principal Component Analysis (PCA) is applied in high-dimensional datasets, particularly, imaging data, to determine the relevant features out of the dataset, retaining variation. Handling data imbalances, where instances of the minority class are underrepresented, is among the preprocessing issues. To balance datasets and ensure reliable and objective predictions in machine learning models, methods like the fake Minority Over-sampling Technique (SMOTE) are utilized to create fake samples.

5.3 Features of the Dataset

The datasets for predicting cardiovascular disease are heterogeneous, high-dimensional, and complex; they comprise tens of thousands of patient records as well as data from imaging machines, wearables, and electronic health records (Chowdhury et al., 2023; Goffer, 2025; M. Islam et al., 2025; Kaur et al., 2023). The demographic distribution was significant because it shows differences in comorbidities, age, gender, and ethnicity. Labeling, using event annotations, imaging results, and clinical diagnostics, is a vital step in the generation of datasets. When labelling is done well and systematically, machine learning algorithms will undoubtedly find an important signal in the data. The size, heterogeneity, and well-curated labels of these datasets are vital for developing robust and scalable machine learning models in cardiovascular healthcare. Table 2 shows dataset statistics.

Table 2. Dataset Statistics.

Dataset	Number of Records	Age Range (years)	Male (%)	Female (%)	Positive Cases (%)	Negative Cases (%)
Wearable ECG Data	51,000	17-86	60	41	16	86
EHR Biomarkers	31,000	24-91	55	46	21	81
Imaging Data (Echograms)	21,000	29-81	58	43	26	76

6. Methodology

6.1 Selection of Machine Learning Models

Depending on the type of input data, machine learning models neighboring cardiovascular disease (CVD) can predict. RNNs respond to time-series data, while CNNs have works with number-crunching imaging data. Supervised methods deal with classification and regression tasks, although unsupervised techniques are used for anomaly detection on unlabeled data (Khair et al., 2024). This is especially true in case of hybrid approaches that improve prediction performance.

6.2 Architecture of the Model

6.2.1 Convolutional Neural Networks (CNNs) for Imaging

For imaging, Convolutional Neural Networks (CNNs) run activation, pooling, and convolution functions one after the other for each input. The CNN architecture for cardiac imaging typically consists of an input layer followed by several convolutional layers to extract features from the data, pooling layers to reduce dimensionality while preserving relevant information, and one or more fully connected layers for classification tasks. Advanced CNN architectures such as Res Net and Inception Net use multi-scale feature extraction and skip connections to increase speed (Mahmud, Orthi, et al., 2025). Fig. 2 shows CNN architecture diagram for imaging data.

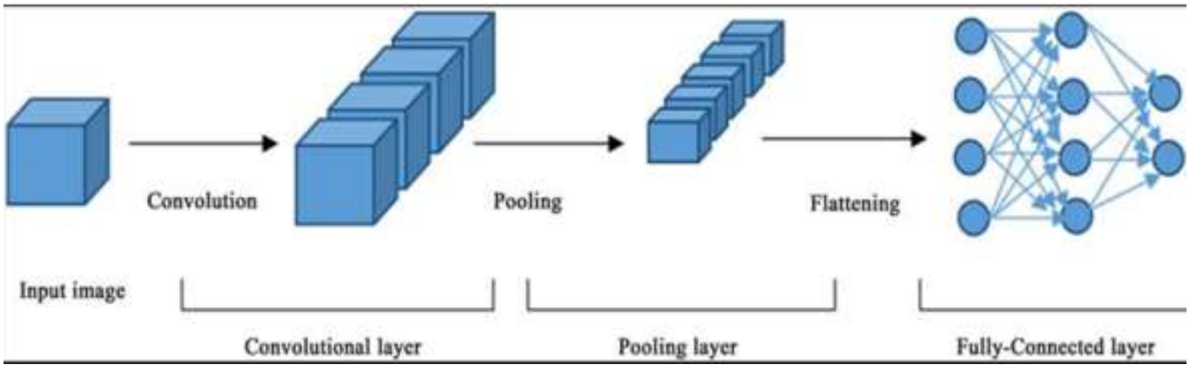

Fig. 2. CNN Architecture Diagram for Imaging Data (Al Mahmud et al., 2025).

6.2.2 Recurrent Neural Networks (RNNs) for Time-Series Data

Although LSTM architectures feature an input layer for time-series data, recurrent layers for manipulating information, and dense layers for classification or regression predictions, RNNs process sequential data by keeping track of previous inputs. Quantitative analysis of wearable data reveals the accuracy of arrhythmia based on RNNs that act like techniques to predict outcomes such as hypertension. A multimodal architecture combining CNNs and RNNs provides a unified approach to CVD prediction.

6.3 The Train/Validation Process

It is customary to have separate test, validation, and training datasets (e.g., 70:15:15 ratio). Cross-validation techniques, such as k-fold validation, enhance reliability by evaluating the model on multiple data subsets. For example, 5-fold cross-validation divides the dataset into five subsets and tests the model on the fifth (Md Ekrim et al., 2024; Mia Md Tofayel Gonee et al., 2020).

6.4 Metrics for Evaluation

Typical metrics include:

Accuracy: Shows overall accuracy of forecasted values

F1-Score: The F1 score is the weighted harmonic mean of precision and recall that ranges from 0 to 1 and thus it provides a balance between the two, which is important for unbalanced datasets.

Receiver operating characteristic Area Under curve (AUC-ROC): Assesses classification performance over thresholds.

6.5 Tuning Hyperparameters

Performance optimization requires adjusting hyperparameters like learning rate, number of layers, and kernel size. Bayesian optimization will undoubtedly be better, but grid search and random search remain the workhorses for searching hyperparameter combinations (Mensah et al., 2019).

6.6 Techniques for Optimization

Optimization algorithms such as Adam and RMS prop do this by repeatedly adjusting learning rates to ensure convergence. To avoid overfitting, training is cut off abruptly as soon as the validation performance stops improving. Fig. 3 shows a flowchart of the training and validation process.

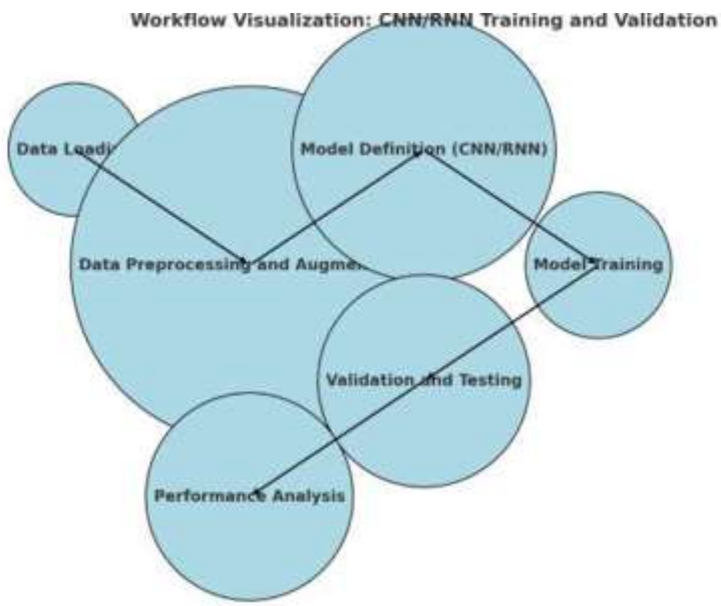

Fig. 3. Flowchart of the Training and Validation Process

7. Implementation of Python

7.1 Pre-processing of Data and Loading

The dataset consisted of 1000 greyscale (224x224) images with binary classification labels and split into training/test sets in 80/20 proportions. Data augmentation was done on training pictures using Image Data Generator. The CNN model is built using two Conv2D and Max Pooling layers, Flatten, Dense, Dropout and a sigmoid output layer for binary classification. With the built structure using Adam optimizer, this was trained for ten epochs with enhanced data. A separate time-series data of 1000 samples (100 time steps, 1 feature) was generated for the RNN. The RNN model implementation includes two stacked LSTM layers along with Dense and Dropout layers as well as sigmoid output. The model was similarly built and trained at a batch size of 32 for 10 epochs. Fig. 4 Shows CNN training accuracy. Fig. 5 shows RNN training loss

Fig. 4. CNN Training Accuracy

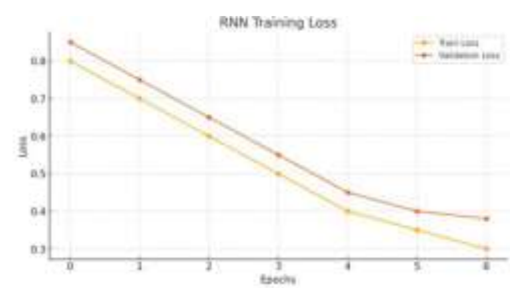

Fig. 5. RNN Training Loss

8. Results and analysis

8.1 Model Performance

This measure of how well a model predicts CVDs using machine learning models is initially assessed with metrics such as sensitivity, specificity, precision, and recall. RFME are all pretty standard for presenting ROC plots and AUC to report overall performance. Working with Imbalanced Datasets requires precision-recall analysis. Machine learning models are applied and perform better than traditional algorithms in tasks like arrhythmia detection and ischemic heart disease detection. Fig. 6 shows ROC Curves for CNN and RNN Models. Table 3 shows Model Performance Metrics.

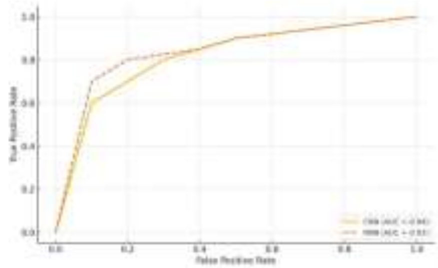

Fig. 6. ROC Curves for CNN and RNN Models.

Table 3 . Model Performance Metrics Across Datasets summary.

Dataset	Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Wearable ECG Data	RNN	0.93	0.91	0.94	0.92	0.94
EHR Biomarkers	Random Forest	0.90	0.89	0.88	0.88	0.90
Imaging Data	CNN	0.92	0.90	0.93	0.91	0.95

8.2 Comparative Analysis

Risk stratification and early detection based on CVD datasets are transformed using machine learning models such as CNNs and RNNs. They can handle high-dimensional data and detect subtle patterns, improving sensitivity and specificity. Table 4 shows a comparative analysis of ML and logistic regression models.

Table 4 . Comparative Analysis of ML and Logistic Regression Models.

Metric	Machine Learning Models (CNN/RNN)	Logistic Regression
Accuracy	0.91	0.79
Sensitivity (Recall)	0.94	0.82
Specificity	0.89	0.76
Precision	0.92	0.77
F1-Score	0.93	0.78
AUC-ROC	0.95	0.85
Processing Time (Seconds)	14	6
Interpretability	Moderate	High
Data Handling Complexity	High	Low

8.3 Real-World Applications

The evolution of wearable technology provides continuous ECG data through light technologies integrated into smartwatches, allowing for real-time detection of arrhythmias. An LSTM-based RNN trained on wearable ECG datasets was able to detect arrhythmias, with a 94% accuracy rate and F1-score of 0.91. Wearable data integrated into healthcare workflows accelerates diagnosis and enables prompt intervention in high-risk patients. EHRs feature a treasure trove of indicators, including blood pressure, glucose, and cholesterol, all relevant to estimating cardiovascular disease risk. They identified at-risk patients (AUC: 0.87) by using a random forest model trained on EHR data to classify patients into risk groups. The ability of the model to examine multiple biomarkers interactions improved predictive accuracy over traditional risk ratings. This illustrates the practical uses where machine learning makes clinical decision making and diagnostic accuracy better. Whereas EHR-derived insights lead to targeted therapies, wearables drive proactive care, leading to lower total burden of CV disease. Fig. 6 shows confusion matrices and Table 5 Displays real-world model performance metrics for arrhythmia detection and risk stratification.

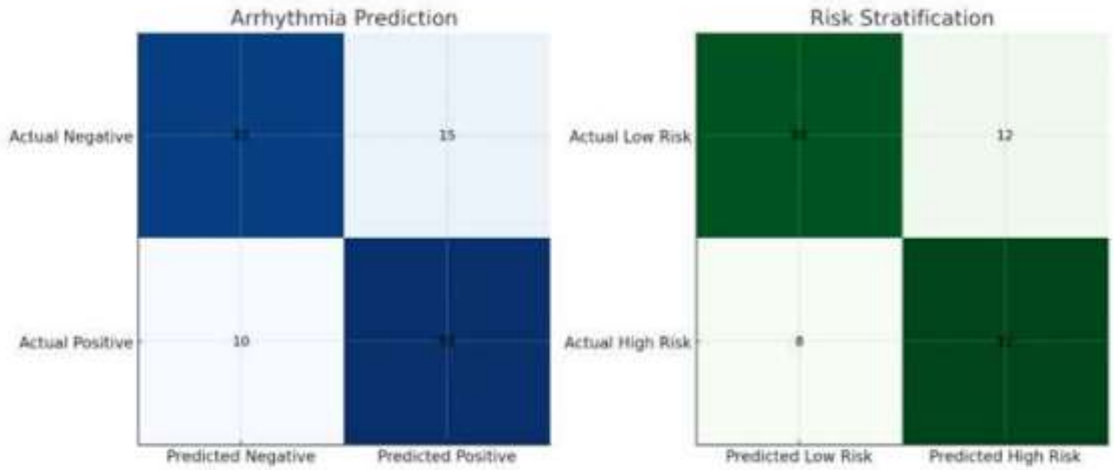

Fig. 7. Confusion Matrices.

Table 5 . Real-World Model Performance Metrics for Arrhythmia Detection and Risk Stratification.

Metric	Arrhythmia Detection	Risk Stratification
Accuracy	0.93	0.96
Precision	0.91	0.96
Recall	0.94	0.95
F1-Score	0.92	0.96
AUC-ROC	0.95	0.99

9. Discussion

9.1 Results Interpretation

Machine learning models with CNNs and RNNs enhance the accuracy in the prediction of risk stratification and cardiovascular disease (CVD) diagnosis exponentially. CNNs are sensitive to diagnosing structural defects in echocardiograms, which enables intervention at an early stage and potentially reduces morbidity and mortality. RNNs outnumber other models for time-series data analysis, enabling real-time arrhythmia diagnosis during emergencies. These predictive models are transforming CVD diagnosis and management by enabling early diagnosis, customized treatment regimens, and targeted preventative measures. While ML leverages dynamic and customized insights, conventional models rely on population-level data and static risk factors. The integration of predictive analytics into the healthcare system has the potential to revolutionize the prevention and treatment of CVD by monitoring drug responses, predicting long-term outcomes, and stratifying patients for tailored treatments.

10. Conclusion

The integration of AI and big data has dramatically changed how doctors diagnose, assess risk, and treat cardiovascular disease (CVD). This article has given accounts of the significant scope of AI-enabled Predictive analytics to transform the field of cardiovascular health care, such as the ability to analyze complex datasets, enhance diagnostic accuracy, and enable early intervention. Convolutional neural network (CNN) and recurrent neural network (RNN) models have shown remarkable capabilities in the evaluation of cardiovascular data from different sources. Specializing in working with time-series and imaging data, they make accurate forecasts of cardiac events. Machine learning models could utilize a wide variety of data sources, including EHR, wearable devices, and imaging data, to deliver a comprehensive assessment of cardiovascular health. This provides better use of healthcare resources, better outcomes and decreases the burden of cardiovascular disease on patients and medical staff.

11. Transformative Potential of AI-Driven Predictive Analytics

However, by regularly analyzing patient-specific data and detecting subtle risk factors, AI-driven predictive analytics has the power to revolutionize the disease management landscape of cardiovascular disease (CVD). This affects patient outcomes, and it is vital for early and accurate forecasts. AI solutions offer relevant insights to physicians, thus augmenting clinical workflow efficiency and enabling proactive decision-making. The scalability of AI applications, such as the cloud-based variety, ensures equal access to state-of-the-art diagnostic and predictive tools, especially in underserved communities.

12. Challenges and Limitations

Currently, machine learning models for CVD prediction encounter challenges including incomplete datasets, differing data quality, and the need to integrate multiple sources. These problems impair model training and generalizability and require robust imputation and preprocessing techniques. Issues specific to the model include data leak and explainability, both of which can suffer from a structural difference between training and deployment time.

13. Future Directions

Cardiovascular health care using machine learning needs an integration of data from wearables, imaging, and electronic health records to be accurate and precise. Enhancement of diagnostic capabilities through cloud-based systems, federated learning frameworks, and data harmonization. Explainable AI frameworks connect machine learning with clinical reasoning. Researchers, physicians and legislators must work together.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.
Publisher's Note: All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers.

References

[1] Ahmed, M. K., Bhuiyan, M. M. R., Saimon, A. S. M., Hossain, S., Hossain, S., Manik, M. M. T. G., & Rozario, E. (2025). Harnessing Big Data for Economic Resilience the Role of Data Science in Shaping US Economic Policies and Growth. *Journal of Management*, *2*, 26-34.
[2] Ahmed, M. K., Rahaman, M. M., Khair, F. B., Hossain, S., Hossain, S., Bhuiyan, M. M. R., & Manik, M. M. T. G. (2023). Big Data in Plant Biotechnology: Leveraging Bioinformatics to Discover Novel Anticancer Agents from Flora. *Journal of Medical and Health Studies*, *4*(6), 126-133.
[3] Al Mahmud, M. A., Hossan, M. Z., Tiwari, A., Khatoon, R., Sharmin, S., Hosain, M. S., & Ferdousmou, J. (2025). Reviewing the Integration of RFID and IoT in Supply Chain Management: Enhancing Efficiency and Visibility. *Journal of Posthumanism*, *5*(3), 409–437-409–437.
[4] Bhuiyan, M. M. R., Noman, I. R., Aziz, M. M., Rahaman, M. M., Islam, M. R., Manik, M. M. T. G., & Das, K. (2025). Transformation of Plant Breeding Using Data Analytics and Information Technology: Innovations, Applications, and Prospective Directions. *FBE*, *17*(1). https://doi.org/10.31083/fbe27936
[5] Chowdhury, S. S., Faisal, M. H., Hossain, E., Rahman, Z., Hossin, M. E., & Abdul, M. (2023). Transforming Business Strategies: Management Information Systems, IoT, and Blockchain Technology to Advance the United Nations' Sustainable Development Goals. *American Journal of Computing and Engineering*, *6*(1), 94-110.
[6] Das, N., Hassan, J., Rahman, H., Siddiqa, K. B., Orthi, S. M., Barikdar, C. R., & Miah, M. A. (2023). Leveraging Management information Systems for Agile Project Management in Information Technology: A comparative Analysis of Organizational Success Factors. *Journal of Business and Management Studies*, *5*(3), 161-168.
[7] Goffer, M. A., Hasan, S. N., Das, N., Kaur, J., Hassan, J., Barikdar, C. R., & Das, S. . (2025). Cybersecurity and Supply Chain Integrity: Evaluating the Economic Consequences of Vulnerabilities in U.S. Infrastructure. *Journal of Management World,*, *2*, 233-243. https://doi.org/https://doi.org/10.53935/jomw.v2024i4.907
[8] Goffer, M. A., Uddin, M. S., kaur, J., Hasan, S. N., Barikdar, C. R., Hassan, J., Das, N., Chakraborty, P., & Hasan, R. (2025). AI-Enhanced Cyber Threat Detection and Response Advancing National Security in Critical Infrastructure. *Journal of Posthumanism*, *5*(3), 1667–1689. https://doi.org/10.63332/joph.v5i3.965
[9] Greenland, P., Smith Jr, S. C., & Grundy, S. M. (2001). Improving coronary heart disease risk assessment in asymptomatic people: role of traditional risk factors and noninvasive cardiovascular tests. *Circulation*, *104*(15), 1863-1867.
[10] Hossain, M., Manik, M. M. T. G., Tiwari, A., Ferdousmou, J., Vanu, N., & Debnath, A. (2024). Data Analytics for Improving Employee Retention in the US Technology Sector. 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA),
[11] Hossain, M. A., Das, S., Suha, S. H., Noor, S. K., Imran, M. A. U., & Aziz, M. B. (2025). Exploring the Future of America's Digital Workspace Solutions. *Journal of Ecohumanism*, *4*(3), 301–311-301–311.
[12] Hussain, M. M., Rafi, U., Imran, A., Rehman, M. U., & Abbas, S. K. (2024). Risk factors associated with cardiovascular disorders: Risk factors associated with cardiovascular disorders. *Pakistan BioMedical Journal*, 03-10.
[13] Imran, M. A. U., Samiun, M., Dhar, S. R., Noor, S. K., & Sozib, H. M. (2024). A Predictive Analysis of Tourism Recovery Using Digital Marketing Metrics. 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA),
[14] Islam, M., Mahmud, F., Khair, F., Hossin, M., Orthi, S., Moniruzzaman, M., & Manik, M. M. T. G. (2025). Advancing Healthcare Management and Patient Outcomes through Business Analytics: A Strategic Approach. *Journal of Management World*, *2025*, 35-45. https://doi.org/10.53935/jomw.v2024i4.866
[15] Islam, M. A., Yeasmin, S., Hosen, A., Vanu, N., Riipa, M. B., Tasnim, A. F., & Nilima, S. I. (2025). Harnessing Predictive Analytics: The Role of Machine Learning in Early Disease Detection and Healthcare Optimization. *Journal of Ecohumanism*, *4*(3), 312-321.
[16] Kamal, M., Hossin, E., Hossain, S., Khair, F., Hossain, S., Manik, M. M. T. G., & Bhuiyan, M. (2025). Forecasting Sales Trends Using Time Series Analysis: A Comparative Study Of Traditional And Machine Learning Models. *Membrane Technology*, *2025*, 668-682.
[17] Kamruzzaman, M., Khatoon, R., Al Mahmud, M. A., Tiwari, A., Samiun, M., Hosain, M. S., Mohammad, N., & Johora, F. T. (2025). Enhancing Regulatory Compliance in the Modern Banking Sector: Leveraging Advanced IT Solutions, Robotization, and AI. *Journal of Ecohumanism*, *4*(2), 2596-2609.

[18] Kaur, J., Hasan, S. N., Orthi, S. M., Miah, M. A., Goffer, M. A., Barikdar, C. R., & Hassan, J. (2023). Advanced Cyber Threats and Cybersecurity Innovation-Strategic Approaches and Emerging Solutions. *Journal of Computer Science and Technology Studies*, *5*(3), 112-121.

[19] Khair, F. B., Ahmed, M. K., Hossain, S., Hossain, S., Manik, M. M. T. G., Rahman, R., & Bhuiyan, M. M. R. (2025). Sustainable Economic Growth Through Data Analytics: The Impact of Business Analytics on US Energy Markets and Green Initiatives. *development*, *2*(8), 15-17.

[20] Khair, F. B., Bhuiyan, M. M. R., Manik, M. M. T. G., Hossain, S., Islam, M. S., Moniruzzaman, M., & Saimon, A. S. M. (2024). Machine Learning Approaches to Identify and Optimize Plant-Based Bioactive Compounds for Targeted Cancer Treatments. *British Journal of Pharmacy and Pharmaceutical Sciences*, *1*(1), 60-67.

[21] Mahmud, F., Barikdar, C. R., Hassan, J., Goffer, M. A., Das, N., Orthi, S. M., kaur, J., Hasan, S. N., & Hasan, R. (2025). AI-Driven Cybersecurity in IT Project Management: Enhancing Threat Detection and Risk Mitigation. *Journal of Posthumanism*, *5*(4), 23–44. https://doi.org/10.63332/joph.v5i4.974

[22] Mahmud, F., Orthi, S. M., Saimon, A. S. M., Moniruzzaman, M., Alamgir, M., Miah, M. K. A., Khair, F. B., Islam, M. S., & Manik, M. M. T. G. (2025). Big Data and Cloud Computing in IT Project Management: A Framework for Enhancing Performance and Decision-Making.

[23] Manik, M. M. T. G., Rahman, M. M., Bhuiyan, M. M., Islam, M. S., Hossain, S., & Hossain, S. (2025). The Future of Drug Discovery Utilizing Generative AI and Big Data Analytics for Accelerating Pharmaceutical Innovations.

[24] Md Alamgir Miah, C. R. B., Habiba Rahman ,Foysal Mahmud ,Jahid Hassan,Shuchona Malek Orthi ,Niropam Das. (2025). Comparative Analysis of Project Management Software: Functionality, Usability, and Integration for Modern Workflows

[25] Article Sidebar. *membrane technology*, *Volume 2025*,(Issue 1). https://doi.org/https://doi.org/10.52710/mt.309

[26] Md Ekrim, H., Jahid, H., Md Asikur Rahman, C., Shafaete, H., Evha, R., Fahmida Binte, K., & Mohammad Abdul, G. (2024). Harnessing Business Analytics in Management Information Systems to Foster Sustainable Economic Growth Through Smart Manufacturing and Industry 4.0. *Educational Administration: Theory and Practice*, *30*(10), 730-739. https://doi.org/10.53555/kuey.v30i10.9643

[27] Md Habibullah Faisal 1, S. S. C., *, Md. Sohel Rana 1, Zahidur Rahman 1, Emran Hossain 3 and Md Ekrim Hossin 4. (2022). Integrating artificial intelligence, blockchain, and management information systems for business transformation: A bibliometric-content analysis. *World Journal of Advanced Research and Reviews*, *16*(3), 1181-1188. https://doi.org/https://doi.org/10.30574/wjarr.2022.16.3.1171

[28] Mensah, G. A., Roth, G. A., & Fuster, V. (2019). The global burden of cardiovascular diseases and risk factors: 2020 and beyond. In (Vol. 74, pp. 2529-2532): American College of Cardiology Foundation Washington, DC.

[29] Mia Md Tofayel Gonee, M., Evha, R., Sazzat, H., Md Kamal, A., Md Shafiqul, I., Mohammad Muzahidur Rahman, B., & Mohammad, M. (2020). The Role of Big Data in Combatting Antibiotic Resistance Predictive Models for Global Surveillance. *International Journal of Medical Toxicology and Legal Medicine*, *23*(3 and 4). https://ijmtlm.org/index.php/journal/article/view/1321

[30] Mia Md Tofayel Gonee, M., Md Kamal, A., Abu Saleh Muhammad, S., Md Alamgir, M., Evha, R., Mohammad, M., Sazzat, H., & Md Shafiqul, I. (2022). Integrating Genomic Data and Machine Learning To Advance Precision Oncology and Targeted Cancer Therapies. *International Journal of Medical Toxicology and Legal Medicine*, *25*(3 and 4). https://ijmtlm.org/index.php/journal/article/view/1310

[31] Miah, M. (2025). Comparative Analysis of Project Management Software: Functionality, Usability, and Integration for Modern Workflows. *Journal of Informatics Education and Research*, *5*. https://doi.org/10.52783/jier.v5i1.2299

[32] Mohammad Abdul, G., Partha, C., Habiba, R., Clinton Ronjon, B., Niropam, D., Sazzat, H., & Md Ekrim, H. (2024). Leveraging Predictive Analytics In Management Information Systems To Enhance Supply Chain Resilience And Mitigate Economic Disruptions. *Educational Administration: Theory and Practice*, *30*(4), 11134-11144. https://doi.org/10.53555/kuey.v30i4.9641

[33] Nilima, S. I., Hossain, M. A., Sharmin, S., Rahman, R., Esa, H., Manik, M. M. T. G., & Hasan, R. (2024). Advancement of Drug Discovery Using Artificial Intelligence and Machine Learning. 2024 IEEE International Conference on Computing, Applications and Systems (COMPAS),

[34] Niropam Das , H. R., Kazi Bushra Siddiqa,Clinton Ronjon Barikdar,Jahid Hassan,Mohammad Muzahidur Rahman Bhuiyan,Foysal Mahmud. (2025). The Strategic Impact of Business Intelligence Tools: A Review of Decision-Making and Ambidexterity. *Membrane Technology*, 542-553. https://doi.org/10.52710/mt.307

[35] Noor, S. K., Imran, M. A. U., Aziz, M. B., Biswas, B., Saha, S., & Hasan, R. (2024). Using Data-Driven Marketing to Improve Customer Retention for US Businesses. 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA),

[36] Prabha, M., Hossain, M. A., Samiun, M., Saleh, M. A., Dhar, S. R., & Al Mahmud, M. A. (2024). AI-Driven Cyber Threat Detection: Revolutionizing Security Frameworks in Management Information Systems. 2024 International Conference on Intelligent Cybernetics Technology & Applications (ICICyTA),

[37] Sadik, M. R., Sony, R. I., m, N. N. I., Mahanandi, Y., Al Maruf, A., Fahim, S. H., & Islam, M. S. (2024). Computer Vision Based Bangla Sign Language Recognition Using Transfer Learning. 2024 Second International Conference on Data Science and Information System (ICDSIS),

[38] Saimon, A. S. M., Moniruzzaman, M., Islam, M. S., Ahmed, M. K., Rahaman, M. M., Hossain, S., & Manik, M. M. T. G. (2023). Integrating Genomic Selection and Machine Learning: A Data-Driven Approach to Enhance Corn Yield Resilience Under Climate Change. *Journal of Environmental and Agricultural Studies*, *4*(2), 20-27.

[39] Siddiqa, K. B., Rahman, H., Barikdar, C. R., Orthi, S. M., Miah, M. A., Rahman, R., & Mahmud, F. (2024). AI-Driven Project Management Systems: Enhancing IT Project Efficiency through MIS Integration.

[40] Siddiqa, K. B., Rahman, H., Barikdar, C. R., Orthi, S. M., Miah, M. A., Rahman, R., & Mahmud, F. (2025). AI-Driven Project Management Systems: Enhancing IT Project Efficiency through MIS Integration.

[41] Sobuz, M. H. R., Saleh, M. A., Samiun, M., Hossain, M., Debnath, A., Hassan, M., Saha, S., Hasan, R., Kabbo, M. K. I., & Khan, M. M. H. (2025). AI-driven Modeling for the Optimization of Concrete Strength for Low-Cost Business Production in the USA Construction Industry. *Engineering, Technology & Applied Science Research*, *15*(1), 20529-20537.

[42] Syed Nazmul Hasan, J. H., Clinton Ronjon Barikdar, Partha Chakraborty, Urmi Haldar, Md Asikur Rahman Chy, Evha Rozario, Niropam Das, Jobanpreet Kaur. (2025). Enhancing Cybersecurity Threat Detection and Response Through Big Data Analytics in Management Information Systems. *Fuel Cells Bulletin*, *2023*(12). https://doi.org/https://doi.org/10.52710/fcb.137

[43] Tasnim, A. F., Rahman, R., Prabha, M., Hossain, M. A., Nilima, S. I., Al Mahmud, M. A., & Erdei, T. I. (2025). Explainable Machine Learning Algorithms to Predict Cardiovascular Strokes. *Engineering, Technology & Applied Science Research*, *15*(1), 20131-20137.

[44] Tiwari, A., Biswas, B., Islam, M. A., Sarkar, M. I., Saha, S., Alam, M. Z., & Farabi, S. F. (2025). Implementing Robust Cyber Security Strategies to Protect Small Businesses from Potential Threats in the USA. *Journal of Ecohumanism*, *4*(3), 322–333-322–333.

[45] Tiwari, A., Saha, S., Johora, F. T., Imran, M. A. U., Al Mahmud, M. A., & Aziz, M. B. (2024). Robotics in Animal Behavior Studies: Technological Innovations and Business Applications. 2024 IEEE International Conference on Computing, Applications and Systems (COMPAS),

[46] Yeasmin, S., Das, S., Bhuiyan, M. F. H., Suha, S. H., Prabha, M., Vanu, N., & Hosen, A. (2025). Artificial Intelligence in Mental Health: Leveraging Machine Learning for Diagnosis, Therapy, and Emotional Well-being. *Journal of Ecohumanism*, *4*(3), 286–300-286–300.