International Journal of Emerging Research in Science, Engineering, and Management
Vol. 2, Issue 1, pp.86-93, January 2026.
www.ijersem.com eISSN- 3107-9075

Cardiovascular Disease Prediction Using Deep Learning Techniques

[1]B Jhansi, [2]V. M. Saraswathi, [3]P Sudarshan, [4]M Venkata Likhil, [5]A Venu Gopal Reddy, [6]E Santhosh

Department of CSE, Siddartha Institute of Science and Technology, Puttur, India

[1]jhansisathish.bcn@gmail.com, [2]saraswathivms16@gmail.com, [3]sudarshanpasupuleti0@gmail.com, [4]likhilmaddala9676@gmail.com, [5]avenugopalreddy000@gmail.com, [6]enjamsanthosh07@gmail.com

Abstract: This research focuses on developing a cardiovascular disease prediction system using deep learning and machine learning techniques applied to a structured CSV dataset containing patient health parameters. The system classifies cardiovascular risk into five categories—0: Normal, 1: Mild, 2: Moderate, 3: Severe, and 4: Very Severe—allowing for early diagnosis and timely intervention. Multiple algorithms, including SVM, Random Forest, KNN, Decision Tree, and ANN, are implemented and compared to determine the most accurate predictive model. The backend is built using Python with the Flask framework, while the frontend is designed with HTML, CSS, and JavaScript to provide a smooth and interactive user interface. Data preprocessing steps such as cleaning, normalization, and feature selection are applied to ensure optimal model accuracy. The system evaluates model performance using accuracy, precision, recall, and F1-score, delivering a reliable and efficient platform for cardiovascular risk assessment that supports both healthcare professionals and individuals in informed preventive healthcare decision-making.

Keywords: Multi-Disease Detection, Healthcare Analytics, Medical Data Classification, Disease Prediction, Early Disease Detection.

1 INTRODUCTION

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, accounting for a significant percentage of global deaths each year. These diseases include conditions such as coronary artery disease, heart failure, stroke, and hypertension, which often develop silently over time and manifest only at advanced stages [1]. Early detection and timely intervention are crucial in reducing mortality rates and improving patient outcomes. However, traditional diagnostic methods often rely on manual evaluation and clinical expertise, which may be time-consuming and prone to human error, especially when handling large volumes of patient data.

With the rapid growth of digital healthcare systems, vast amounts of medical data are being generated in the form of electronic health records. This data contains valuable information related to patient demographics, lifestyle factors, and clinical measurements. Extracting meaningful insights from such data using conventional statistical techniques is challenging due to its complexity and high dimensionality [2]. As a result, machine learning and deep learning techniques have emerged as powerful tools for medical data analysis and disease prediction.

Deep learning models are capable of learning complex, non-linear relationships within data, making them highly effective for predictive healthcare applications. In cardiovascular disease prediction, these models can analyze multiple health parameters simultaneously and identify patterns that may not be evident through traditional methods [3]. By leveraging structured datasets, deep learning-based systems can provide accurate and consistent risk assessments, supporting early diagnosis and preventive healthcare.

This research focuses on developing a cardiovascular disease prediction system using machine learning and deep learning techniques applied to a structured CSV dataset containing patient health parameters. The system classifies cardiovascular risk into five severity levels—Normal, Mild, Moderate, Severe, and Very Severe—allowing for detailed risk stratification rather than simple binary classification [4]. Multiple algorithms, including Support Vector Machine, Random Forest, K-Nearest Neighbors, Decision Tree, and Artificial Neural Networks, are implemented and evaluated to determine the most effective predictive model.

The integration of a Flask-based backend with an interactive web-based frontend ensures ease of use and accessibility for both healthcare professionals and individuals. By combining data preprocessing, model comparison, and performance evaluation metrics such as accuracy, precision, recall, and F1-score, the proposed system delivers a reliable and efficient platform for cardiovascular disease risk prediction and informed decision-making [5].

2 LITERATURE SURVEY

Cardiovascular disease prediction has been a major research focus in the healthcare and data science communities due to the increasing prevalence of heart-related disorders worldwide. Early studies relied primarily on traditional statistical methods such as logistic regression and rule-based clinical scoring systems to assess cardiovascular risk. While these approaches provided basic insights, their predictive accuracy was limited, particularly when dealing with complex interactions among multiple health parameters. With the advancement of machine learning, researchers began applying supervised learning algorithms to cardiovascular datasets [2]. Support Vector Machines (SVM) have been widely used due to their effectiveness in handling high-dimensional data and their ability to find optimal decision boundaries. Several studies reported improved prediction accuracy using SVM compared to traditional statistical models, especially when kernel functions were employed to capture non-linear relationships between clinical features.

Random Forest algorithms have also gained significant attention in cardiovascular disease prediction. Random Forest models leverage ensemble learning by combining multiple decision trees, which improves robustness and reduces overfitting. Research findings indicate that Random Forest performs well on structured medical datasets, offering high accuracy and reliable feature importance analysis. This has made Random Forest a popular choice for identifying key risk factors such as cholesterol levels, blood pressure, and age. K-Nearest Neighbors (KNN) has been explored as a simple yet effective classification technique for heart disease prediction. KNN classifies patients based on similarity measures, making it intuitive for medical applications. However, studies highlight that KNN performance is highly dependent on feature scaling and the choice of distance metric [6]. Its computational cost also increases with dataset size, limiting its scalability in large healthcare systems.

Decision Tree models are widely used due to their interpretability, which is particularly important in medical decision-making. Researchers have shown that Decision Trees provide transparent decision rules that clinicians can easily understand. However, single Decision Tree models are prone to overfitting and instability, which often results in lower generalization performance compared to ensemble-based approaches. In recent years, deep learning techniques such as Artificial Neural Networks (ANNs) have shown superior performance in cardiovascular disease prediction. ANNs can model complex, non-linear relationships within medical data that traditional machine learning algorithms may fail to capture [7]. Studies demonstrate that neural networks achieve higher prediction accuracy when trained on well-preprocessed datasets with appropriate feature selection and normalization.

Several comparative studies have evaluated multiple machine learning and deep learning models on heart disease datasets. These studies consistently report that ensemble methods and neural networks outperform individual classifiers. Performance evaluation metrics such as accuracy, precision, recall, and F1-score are commonly used to assess model effectiveness, ensuring balanced evaluation beyond simple accuracy. Recent research has also emphasized the importance of multi-class classification in cardiovascular risk prediction. Unlike binary classification approaches that only predict the presence or absence of disease, multi-level risk categorization enables more precise clinical assessment and early intervention. This aligns with modern preventive healthcare practices that focus on risk stratification rather than late-stage diagnosis [8].

The literature indicates that combining data preprocessing techniques with machine learning and deep learning models significantly enhances prediction accuracy. Despite notable progress, challenges such as data imbalance, feature redundancy, and model interpretability remain. These findings motivate the development of integrated, user-friendly cardiovascular disease prediction systems that compare multiple algorithms and provide reliable risk assessments, as proposed in this research.

3 CARDIOVASCULAR DISEASE CHARACTERISTICS AND DATA ATTRIBUTES FOR AI-DRIVEN RISK PREDICTION

An AI-driven cardiovascular disease prediction system relies heavily on the effective representation, integration, and analysis of diverse patient health attributes. Cardiovascular diseases arise due to complex interactions among demographic factors, lifestyle habits, clinical measurements, and physiological conditions. Accurately capturing these heterogeneous attributes in a structured dataset enables machine learning and deep learning models to identify hidden patterns associated with disease progression and risk severity [9]. This research adopts a data-centric approach, utilizing structured CSV-based patient records to perform multi-class cardiovascular risk prediction. The following subsections describe the key categories of data attributes used in the proposed system and explain their importance in automated cardiovascular risk assessment.

3.1. Patient Demographics and Lifestyle Factors

Patient demographic and lifestyle attributes form the foundational layer of cardiovascular risk analysis. Factors such as age, gender, body mass index (BMI), smoking status, alcohol consumption, and physical activity levels are strongly associated with cardiovascular health. Age is one of the most critical predictors, as the risk of cardiovascular disease increases significantly with advancing age due to arterial stiffening and cumulative metabolic stress [10].

Gender-based differences also play a significant role, with males generally exhibiting higher risk at earlier ages, while post-menopausal females experience increased susceptibility due to hormonal changes. Lifestyle habits such as smoking and sedentary behavior contribute directly to atherosclerosis, hypertension, and heart failure. In the proposed system, these attributes are used to establish baseline cardiovascular risk profiles, enabling the model to personalize predictions based on individual lifestyle and demographic characteristics.

3.2. Clinical and Physiological Parameters

Clinical and physiological measurements provide objective indicators of cardiovascular health and disease progression. Attributes such as blood pressure levels (systolic and diastolic), cholesterol levels, glucose concentration, heart rate, and resting ECG values are essential for identifying cardiovascular abnormalities. Elevated blood pressure and abnormal cholesterol levels are among the strongest predictors of heart disease and stroke. These numerical features are well-suited for machine learning models, as they allow algorithms to learn threshold-based and non-linear relationships associated with disease severity. In this research, clinical parameters are normalized and standardized to ensure uniform scale and stable model training [11]. Their inclusion significantly improves prediction accuracy and enables the system to distinguish between varying levels of cardiovascular risk.

3.3. Medical History and Comorbidity Indicators

Patient medical history plays a crucial role in cardiovascular disease prediction. Pre-existing conditions such as diabetes, hypertension, obesity, and previous cardiac events significantly increase the likelihood of severe cardiovascular outcomes. These conditions often coexist and amplify overall cardiovascular risk through interconnected physiological mechanisms. In the proposed system, historical and comorbidity-related attributes are incorporated as categorical and numerical features within the dataset. Machine learning models utilize these features to identify cumulative risk patterns that may not be apparent from individual parameters alone. Including medical history enhances early detection capability and supports more accurate multi-level risk classification.

3.4. Feature Engineering and Risk Severity Classification

Feature engineering is a critical component of the proposed cardiovascular disease prediction framework. Raw dataset attributes are processed through cleaning, normalization, and feature selection techniques to remove redundancy and noise. Relevant features are selected based on statistical significance and model contribution to prediction performance. Unlike traditional binary classification systems, this research adopts a five-level cardiovascular risk categorization: Normal, Mild, Moderate, Severe, and Very Severe [12]. This granular classification enables more precise risk stratification and supports preventive healthcare planning. Machine learning and deep learning models learn to associate specific feature combinations with each severity level, improving clinical relevance and interpretability.

3.5. Algorithmic Perspective and Model Interdependency

Different machine learning and deep learning algorithms capture cardiovascular risk patterns in distinct ways. Models such as SVM and KNN focus on boundary-based and similarity-based learning, while Decision Trees and Random Forests emphasize rule-based and ensemble decision-making. Artificial Neural Networks (ANNs) model complex non-linear relationships across multiple features simultaneously. By implementing and comparing multiple algorithms, the proposed system identifies the most effective predictive model for structured cardiovascular data. This comparative approach ensures robustness, reduces algorithmic bias, and improves confidence in prediction outcomes. Feature interdependencies learned by deep learning models further enhance the system’s ability to handle complex cardiovascular risk patterns.

3.6. Data Quality, Preprocessing, and Reliability

The reliability of any AI-driven healthcare system depends heavily on data quality and preprocessing strategies. Cardiovascular datasets often contain missing values, class imbalance, and measurement variability. If not addressed, these issues can negatively impact model performance and fairness. The proposed system employs comprehensive preprocessing techniques, including data cleaning, normalization, feature scaling, and class balancing. These steps ensure stable learning behavior and improved generalization across diverse patient profiles. By prioritizing data integrity and preprocessing, the system delivers consistent and reliable cardiovascular risk predictions suitable for real-world healthcare applications.

4 SYSTEM DESIGN

The implementation of the proposed Cardiovascular Disease Prediction System is designed to ensure accurate risk prediction, scalability, and ease of deployment for real-world healthcare applications. The system follows a modular and layered architecture that enables efficient handling of structured patient health data, seamless integration of multiple machine learning and deep learning models, and reliable delivery of cardiovascular risk predictions. Each functional module performs a clearly defined role while collectively forming an end-to-end automated pipeline that supports early diagnosis and preventive healthcare decision-making. The system architecture is given in Fig. 1.

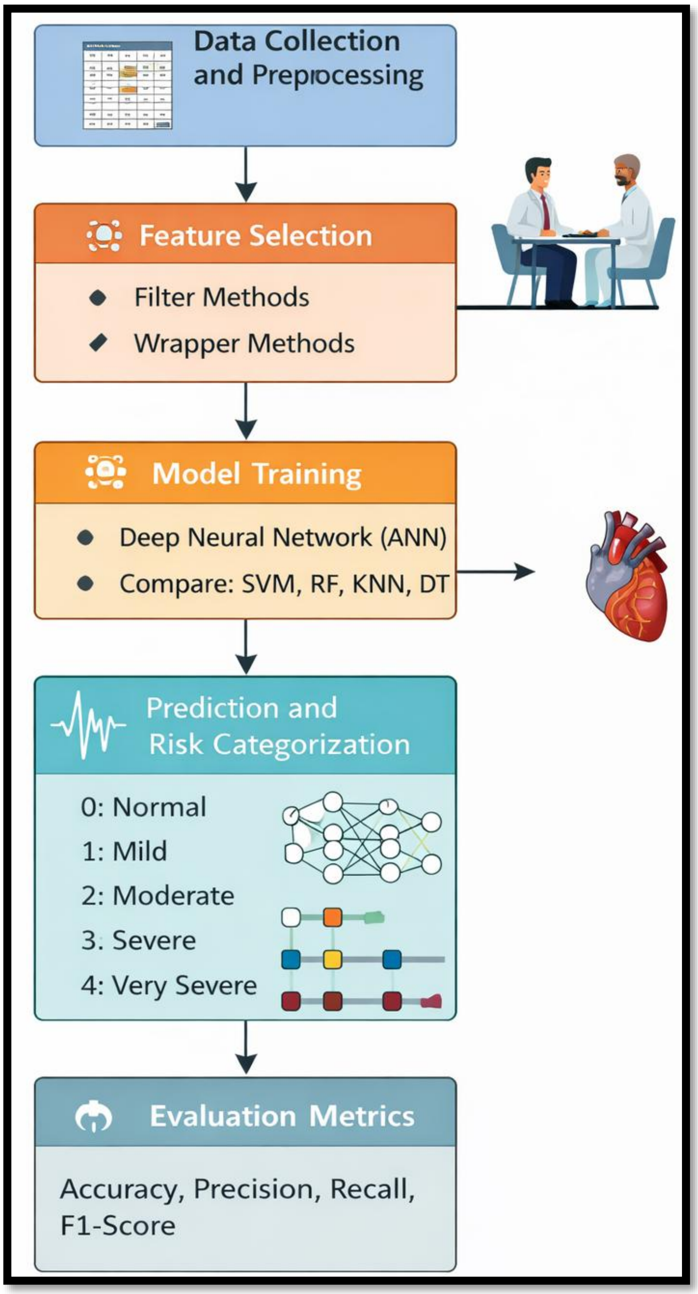

Fig. 1. System Architecture

4.1. Overall System Architecture

The proposed system adopts a modular, layered architecture composed of interconnected components, including data input, preprocessing, feature engineering, model training, classification, and result visualization. This structured design improves system flexibility, maintainability, and extensibility, allowing the framework to be easily enhanced with additional datasets, algorithms, or risk categories in the future. The data input layer accepts structured patient health records in CSV format.

These records contain demographic information, lifestyle attributes, clinical measurements, and medical history parameters relevant to cardiovascular disease prediction. Each input dataset undergoes validation to ensure compliance with required formats, completeness, and data consistency before entering the processing pipeline. The layered workflow supports both offline batch processing for model training and real-time inference for cardiovascular risk prediction. By decoupling system components, the architecture ensures robustness, low latency, and adaptability, making it suitable for deployment in clinical decision support systems and web-based healthcare platforms.

4.2. Data Preprocessing Module

Data preprocessing is a critical stage in the cardiovascular disease prediction pipeline, as structured medical datasets often contain missing values, noise, inconsistent scales, and class imbalance. The preprocessing module ensures that all input data is transformed into standardized and high-quality representations suitable for machine learning and deep learning analysis. Missing values are handled using appropriate imputation techniques, while inconsistent or outlier values are identified and corrected. Numerical features such as blood pressure, cholesterol levels, and glucose concentration are normalized and scaled to ensure uniform contribution during model training. Categorical features are encoded into numerical representations to facilitate algorithm compatibility. To address class imbalance across cardiovascular risk categories, resampling techniques are applied to ensure balanced learning. These preprocessing steps improve model stability, reduce bias, and enhance generalization performance across diverse patient profiles.

4.3. Feature Engineering and Representation

Feature engineering plays a crucial role in improving predictive accuracy and interpretability. Relevant features are selected based on statistical significance and their contribution to cardiovascular risk prediction. Redundant and less informative attributes are removed to reduce dimensionality and computational complexity. The engineered feature set represents a compact yet informative summary of patient health status, capturing both short-term clinical indicators and long-term risk factors. This structured representation enables machine learning and deep learning models to learn complex relationships between patient attributes and cardiovascular disease severity. By emphasizing meaningful feature representation, the system ensures efficient learning, reduced overfitting, and improved prediction reliability.

4.4. Machine Learning and Deep Learning Models

The system integrates multiple machine learning and deep learning models to ensure reliable and accurate cardiovascular disease prediction. Algorithms such as Support Vector Machine (SVM), Random Forest, K-Nearest Neighbors (KNN), and Decision Tree are implemented to capture different learning perspectives from structured data. In addition, Artificial Neural Networks (ANN) are employed to model complex non-linear relationships among patient attributes. The ANN architecture consists of multiple hidden layers with activation functions that enable deep feature learning. Each model is trained using supervised learning on labeled cardiovascular datasets. Regularization techniques such as early stopping and parameter tuning are applied to prevent overfitting and improve generalization. By evaluating multiple algorithms, the system identifies the most effective predictive model for cardiovascular risk classification.

4.5. Multi-Level Cardiovascular Risk Classification Strategy

Unlike traditional binary prediction systems, the proposed framework adopts a multi-level cardiovascular risk classification strategy. The system categorizes patients into five risk levels: Normal, Mild, Moderate, Severe, and Very Severe. This severity-based approach provides more granular and clinically meaningful insights into patient health status.

Each trained model outputs a predicted risk class along with confidence scores, enabling healthcare professionals to assess prediction certainty. This multi-level classification strategy supports early intervention, personalized treatment planning, and improved preventive healthcare outcomes.

4.6. User Interface and Output Module

The user interface acts as the interaction layer between users and the cardiovascular disease prediction system. It is designed to be intuitive, responsive, and accessible, allowing both healthcare professionals and individuals to utilize the system with minimal technical expertise. Through the interface, users can upload CSV-based patient data or enter individual health parameters manually. Upon submission, the system processes the input data and displays predicted cardiovascular risk levels in a clear and interpretable format. The output includes risk category labels and performance insights that support informed decision-making. The frontend is implemented using HTML, CSS, and JavaScript, while the backend is developed using Python and the Flask framework. This integration ensures smooth communication between data input, model inference, and result visualization.

4.7. System Reliability, Scalability, and Deployment

The system is designed for reliability and scalability. The modular architecture allows independent updates to data preprocessing, model training, or visualization components without affecting overall functionality. This design supports future expansion, including the incorporation of new datasets or advanced deep learning architectures. The Flask-based backend enables lightweight deployment on local servers or cloud platforms. By ensuring efficient processing and reliable predictions, the system is well-suited to real-world healthcare settings, where accuracy, responsiveness, and consistency are critical.

5 COMPARATIVE EVALUATION AND DISCUSSION FOR CARDIOVASCULAR DISEASE PREDICTION

Evaluating an AI-driven cardiovascular disease prediction system is essential to validate its predictive accuracy, robustness, and clinical relevance. In this research, a comprehensive comparative analysis was conducted to assess the performance of multiple machine learning and deep learning models for cardiovascular risk prediction using structured patient health data. The evaluation framework emphasizes standard medical classification metrics and includes a detailed discussion comparing AI-based predictive outcomes with conventional clinical assessment methods.

5.1. Cardiovascular Risk Prediction Performance Comparison

To ensure objective and clinically meaningful evaluation, the implemented machine learning and deep learning models were assessed using standard performance metrics, including accuracy, precision, recall, and F1-score. These metrics collectively provide a comprehensive understanding of each model's ability to correctly classify patients into predefined cardiovascular risk categories. Accuracy reflects the overall correctness of predictions, while precision measures the proportion of correctly predicted cardiovascular risk cases among all predicted positive cases. Recall is particularly critical in cardiovascular disease prediction, as it represents the system's ability to correctly identify high-risk patients and minimize false negatives, which could delay early intervention. The F1-score provides a balanced assessment by combining precision and recall, ensuring fair evaluation across imbalanced risk categories.

Comparative analysis revealed that ensemble-based and deep learning models, particularly Random Forest and Artificial Neural Networks (ANN), consistently outperformed traditional classifiers such as K-Nearest Neighbors and standalone Decision Trees. Deep learning models demonstrated superior capability in capturing complex non-linear relationships among clinical and lifestyle attributes, leading to improved prediction reliability across all risk levels.

5.2. Discussion of Classification Results

The classification results indicate that the proposed AI-driven framework significantly enhances cardiovascular disease risk prediction accuracy and consistency. Models trained on well-preprocessed and normalized datasets demonstrated stable performance across multiple evaluation runs and patient profiles. A key observation was the system's ability to accurately differentiate between adjacent risk levels such as Mild, Moderate, and Severe categories. This granularity is particularly valuable in preventive healthcare, where early-stage risk identification enables timely lifestyle modification and medical intervention. The multi-class prediction strategy proved more informative than traditional binary classification approaches.

Compared to manual clinical assessment methods, the AI-based system produced consistent predictions without variability due to clinician workload or subjective interpretation. The learned feature representations enabled the system to detect subtle patterns that may not be immediately apparent through traditional risk scoring methods. These results confirm the effectiveness of AI-assisted cardiovascular risk assessment as a reliable decision-support tool.

5.3. Factors Affecting Prediction Accuracy

Several factors influencing cardiovascular risk prediction accuracy were identified during evaluation. Data quality emerged as a critical determinant, as missing values, inconsistent measurements, and class imbalance adversely affected model performance. Comprehensive preprocessing techniques, including normalization, feature scaling, and class balancing, played a crucial role in mitigating these challenges. Feature selection and representation significantly influenced predictive performance. Models benefited from carefully engineered features that captured both short-term physiological indicators and long-term lifestyle-related risk factors. Deep learning models were particularly effective in learning complex interdependencies among attributes such as blood pressure, cholesterol levels, glucose concentration, and age. Algorithm selection and hyperparameter tuning also impacted results. Ensemble methods demonstrated robustness to noise, while neural networks showed superior adaptability to complex patterns. Regularization and model validation techniques further enhanced generalization across diverse patient populations.

5.4. Conventional Risk Assessment vs AI-Based Cardiovascular Prediction

Traditional cardiovascular risk assessment relies on clinician expertise, manual evaluation of test results, and predefined risk scoring systems. While effective, these approaches can be time-consuming, subjective, and less scalable in high-volume healthcare environments. In contrast, the proposed AI-based cardiovascular prediction system offers improved speed, consistency, and scalability. Once trained, the system can analyze large patient datasets rapidly while applying uniform predictive criteria across all cases. This capability reduces diagnostic delays and supports proactive healthcare planning. Importantly, the system is designed to complement—not replace—medical professionals. By serving as an intelligent decision-support tool, it assists clinicians in identifying high-risk individuals, prioritizing interventions, and enhancing preventive care. The comparative evaluation highlights the potential of AI-driven cardiovascular prediction systems in advancing data-driven, efficient, and reliable healthcare delivery.

6 CONCLUSION

This research presented an AI-driven cardiovascular disease prediction system that leverages machine learning and deep learning techniques to provide accurate, scalable, and severity-aware cardiovascular risk assessment. Cardiovascular diseases remain one of the leading causes of mortality worldwide, emphasizing the importance of early detection and preventive intervention. By utilizing structured patient health data and advanced predictive models, the proposed system addresses limitations of traditional risk assessment methods and supports data-driven clinical decision-making. The system integrates multiple machine learning algorithms, including Support Vector Machine, Random Forest, K-Nearest Neighbors, Decision Tree, and Artificial Neural Networks, enabling comprehensive comparative analysis and robust prediction performance. Data preprocessing steps such as cleaning, normalization, feature selection, and class balancing played a critical role in improving model stability and generalization. The adoption of a five-level cardiovascular risk classification—Normal, Mild, Moderate, Severe, and Very Severe—provided granular insights into patient health status and enhanced clinical relevance beyond conventional binary prediction approaches.

Experimental evaluation demonstrated that ensemble-based and deep learning models achieved superior accuracy, precision, recall, and F1-score compared to traditional classifiers. The system effectively captured complex non-linear relationships among demographic, lifestyle, and clinical attributes, allowing reliable differentiation across cardiovascular risk levels. Compared to manual clinical assessment methods, the AI-based framework delivered consistent and scalable predictions, reducing variability and supporting early intervention strategies. The proposed cardiovascular disease prediction system serves as an effective decision-support tool for healthcare professionals and individuals. By enabling early risk identification and informed preventive planning, the system contributes to improved patient outcomes and modern, data-driven healthcare practices. Future enhancements may include integration with real-time health monitoring devices, expansion to larger and more diverse datasets, and incorporation of advanced deep learning architectures to further improve predictive performance and real-world applicability.

FUNDING INFORMATION

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ETHICS STATEMENT

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

STATEMENT OF CONFLICT OF INTERESTS

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

LICENSING

REFERENCES

[1] S. Zertal, A. Saighi, S. Kouah, S. Meshoul, and Z. Laboudi, "A Real-Time Deep Learning Approach for Electrocardiogram-Based Cardiovascular Disease Prediction with Adaptive Drift Detection and Generative Feature Replay," *Computer Modeling in Engineering & Sciences*, vol. 144, no. 3, pp. 3737–3782, Jan. 2025, doi: 10.32604/cmes.2025.068558.

[2] M. N. Hasan, M. A. Hossain, and M. A. Rahman, "An ensemble based lightweight deep learning model for the prediction of cardiovascular diseases from electrocardiogram images," *Engineering Applications of Artificial Intelligence*, vol. 141, p. 109782, Dec. 2024, doi: 10.1016/j.engappai.2024.109782.

[3] X. Sun, S. Guan, L. Wu, T. Zhang, and L. Ying, "A multimodal deep learning framework for automated major adverse cardiovascular events prediction in patients with end-stage renal disease integrating clinical and cardiac MRI data," *Displays*, vol. 88, p. 102998, Feb. 2025, doi: 10.1016/j.displa.2025.102998.

[4] M. Adil, N. Javaid, I. Ahmed, A. Ahmed, and N. Alrajeh, "A Deep Learning Framework for Heart Disease Prediction with Explainable Artificial Intelligence," *Computers, Materials & Continua/Computers, Materials & Continua (Print)*, vol. 86, no. 1, pp. 1–20, Oct. 2025, doi: 10.32604/cmc.2025.071215.

[5] P. Pal, H. V. Singh, V. Grover, R. Manikandan, R. Karimi, and M. Khishe, "Interactive cardiovascular disease prediction system using learning techniques: Insights from extensive experiments," *Results in Control and Optimization*, vol. 19, p. 100560, Apr. 2025, doi: 10.1016/j.rico.2025.100560.

[6] Panigrahi *et al.*, "Advanced ECG signal analysis for cardiovascular disease diagnosis using AVOA optimized ensembled Deep transfer learning approaches," *Computers, Materials & Continua/Computers, Materials & Continua (Print)*, vol. 84, no. 1, pp. 1633–1657, Jan. 2025, doi: 10.32604/cmc.2025.063562.

[7] Venkata Lakshmi Keerthi. K, J Venkatagiri, Kuruma Purnima, Aravabhumi Divya, T.V.V. Satyanarayana, Rentamallu Ramaiah, "Deep Belief Networks for Ovarian Tumour Detection From Gene Data," *2025 6th International Conference on Data Intelligence and Cognitive Informatics (ICDICI)*, Tirunelveli, India, 2025, pp. 764-770, doi: 10.1109/ICDICI66477.2025.11134883.

[8] M. Bhagawati *et al.*, "Attention-based hybrid deep learning models and its scientific validation for cardiovascular disease risk stratification," *Biomedical Signal Processing and Control*, vol. 108, p. 107824, Apr. 2025, doi: 10.1016/j.bspc.2025.107824.

[9] Kuruma Purnima *et al*., "Detection of Parkinson's Disease using Machine Learning with Feature Analysis from Audio Signals," *2024 4th International Conference on Mobile Networks and Wireless Communications (ICMNWC)*, Tumkuru, India, 2024, pp. 1-7, doi: 10.1109/ICMNWC63764.2024.10872307.

[10] M. M. Kumar, R. Siva, and M. Baskar, "Real-time multi level chronic disease prediction and recommendation model using deep learning," *Results in Engineering*, vol. 28, p. 107478, Sep. 2025, doi: 10.1016/j.rineng.2025.107478.

[11] W. Li *et al.*, "Quantification of breast arterial calcification in mammograms using a UNET-Based deep learning for detecting cardiovascular disease," *Academic Radiology*, vol. 32, no. 9, pp. 5028–5038, Jun. 2025, doi: 10.1016/j.acra.2025.05.036.

[12] K. Purnima, Y. Siddamma, R. G. Rajesh, S. K. Premchandh, T. Naresh and J. K. Sunkara, "AI-based Helmet Detection and Alert System using YOLOv5 and Cloud Deployment," *2025 6th International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS)*, Bengaluru, India, 2025, pp. 46-51, doi: 10.1109/ICICNIS66685.2025.11315521.