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Cardiovascular Disease Prediction Using Machine Learning

Muskan Begum[1], Dr. Khaja Mahabubullah[2]
[1] *Student, MCA, Deccan College of Engineering and Technology, Hyderabad, Telangana, India.*
[2] *Professor & HOD, MCA, Deccan College of Engineering and Technology, Hyderabad, Telangana, India.*

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Abstract: *Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, highlighting the urgent need for reliable, efficient, and early diagnostic tools. Traditional diagnosis often depends on manual interpretation of clinical test results, which can be time-consuming and prone to human error. In this study, we propose a machine learning (ML)-based framework for predicting cardiovascular disease risk by analyzing patient health records. The framework incorporates multiple supervised learning algorithms, including Logistic Regression, Decision Trees, Random Forests, and Neural Networks, to classify patients into risk categories. Data preprocessing techniques such as normalization, encoding, and feature selection were employed to ensure robustness and model accuracy. The models were trained and validated on publicly available healthcare datasets, and their performance was evaluated using standard metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Results demonstrate that the ML-based approach provides higher diagnostic accuracy compared to conventional methods, enabling early interventions and improved patient outcomes. Furthermore, a user-friendly web-based interface was developed using Streamlit to support real-time predictions, making the system practical for clinical use. This study highlights the potential of ML-driven decision support systems in transforming preventive healthcare and aiding clinicians in the early diagnosis and management of cardiovascular diseases.*

Key Words: *Cardiovascular Disease; Machine Learning; Logistic Regression; Random Forest; Neural Networks; Predictive Analytics; Streamlit.*

I.INTRODUCTION

Cardiovascular disease (CVD) is one of the foremost causes of morbidity and mortality across the globe, responsible for millions of deaths annually. According to the World Health Organization, CVDs account for nearly one-third of global deaths, making them a critical public health concern. Early detection and effective management of cardiovascular risk factors such as hypertension, high cholesterol, diabetes, obesity, and smoking are essential to reduce disease progression and mortality. Traditional diagnostic practices primarily rely on clinicians' experience, physical examinations, and laboratory test interpretations. While effective to an extent, these approaches are often time-consuming, subjective, and prone to inconsistencies. Moreover, they do not always provide predictive insights into future cardiovascular risk.

The advent of artificial intelligence (AI) and, in particular, machine learning (ML) offers promising alternatives to conventional diagnostic techniques. ML algorithms can analyze large and complex datasets to uncover hidden patterns, correlations, and risk factors that may not be evident through manual inspection. By leveraging healthcare data, these models can predict the likelihood of cardiovascular conditions with high precision, enabling healthcare practitioners to make more informed and timely clinical decisions. Such predictive tools not only enhance diagnostic accuracy but also support preventive healthcare by identifying high-risk individuals before the onset of severe complications.

Recent advances in ML have demonstrated remarkable performance in diverse medical applications, including disease prediction, image analysis, and patient monitoring. In the context of cardiovascular disease, models such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks have shown the ability to classify patients based on clinical and demographic information. The integration of these models into a practical framework can provide clinicians with fast, data-driven assessments while reducing reliance on manual diagnosis.

The aim of this project is to design, implement, and evaluate a machine learning-based system for cardiovascular disease prediction using structured healthcare datasets. The study emphasizes robust preprocessing techniques to enhance data quality, the evaluation of multiple ML models to identify the most effective approach, and the deployment of a user-friendly interface to enable real-time predictions. By bridging the gap between medical data and predictive analytics, this project aspires to demonstrate the transformative role of ML in healthcare systems and its potential to improve patient outcomes in cardiovascular disease management.

II.MATERIAL AND METHODS

In this study, a machine learning-based predictive system was developed to classify patients into cardiovascular disease (CVD) risk categories. The methodology follows a structured pipeline consisting of dataset collection, preprocessing, model development, evaluation, and deployment. Each step was carefully designed to ensure the robustness, reliability, and clinical applicability of the predictive framework.

Study Design

The study employs a supervised learning approach, where labeled healthcare data is utilized to train models for classification. The dataset includes clinical attributes such as age, gender, resting blood pressure, cholesterol levels, maximum heart rate achieved, presence of fasting blood sugar, resting electrocardiographic results, and exercise-induced angina. Each patient record is labeled with a binary classification indicating the presence or absence of cardiovascular disease.

The project workflow consists of the following major phases:

1. **Data Collection** – Patient records were sourced from open-access medical repositories such as the UCI Machine Learning Repository and Kaggle datasets, which provide standardized heart disease datasets.
2. **Data Preprocessing** – Techniques such as handling missing values, normalization, and encoding categorical variables were applied. Feature selection was performed to retain the most significant attributes influencing cardiovascular disease risk.
3. **Model Training and Development** – Several machine learning models—including Logistic Regression, Decision Tree, Random Forest, and Neural Networks—were trained and fine-tuned for classification tasks.
4. **Model Evaluation** – Trained models were validated using performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC curves. Cross-validation techniques ensured generalization.
5. **System Integration** – The best-performing model was integrated into a Streamlit-based web application for real-time cardiovascular disease risk prediction.

Inclusion Criteria

The dataset and patient records used in this study were selected based on the following eligibility factors:

- **Confirmed Medical Data:** Only patient records with clinically verified cardiovascular status were included.
- **Structured Features:** Data samples that included standardized health attributes such as blood pressure, cholesterol, and ECG measurements.
- **Quality of Records:** Patient entries with complete data and no major missing attributes.
- **Balanced Class Distribution:** Records representing both diseased and non-diseased classes to avoid bias in training.

Exclusion Criteria

The following records were excluded from the dataset to ensure the accuracy and reliability of the study:

- **Incomplete Records:** Patient entries with significant missing values in critical features such as cholesterol, blood pressure, or heart rate.
- **Ambiguous Labels:** Cases where the cardiovascular disease status was uncertain or unverified.
- **Outliers or Erroneous Data:** Records with unrealistic values (e.g., negative cholesterol or implausible heart rate values).
- **Duplicate Entries:** Repeated patient records within the dataset that could bias model training.

Procedure Methodology

The overall methodological pipeline consisted of the following steps:

1. **Data Acquisition and Preparation:** The dataset was imported into Python-based environments (Jupyter Notebook/VS Code). Preprocessing steps included handling null values, converting categorical attributes into numerical format, and scaling continuous features for uniformity.
2. **Feature Engineering:** Statistical correlation analysis was applied to identify features most strongly associated with cardiovascular outcomes. Irrelevant or redundant features were removed to improve model efficiency.
3. **Model Development:** The study implemented a set of supervised ML algorithms—Logistic Regression, Decision Tree, Random Forest, and Neural Networks. Hyperparameter tuning was conducted using grid search and cross-validation to optimize model performance.
4. **Training and Validation:** Data was split into training and testing sets (typically 70:30 ratio). Stratified sampling was used to preserve class distribution across both sets.
5. **Model Evaluation:** Each model's performance was assessed using confusion matrices, accuracy scores, precision, recall, F1-scores, and ROC-AUC analysis. Comparative results identified the most reliable classifier for CVD risk prediction.
6. **Deployment:** The optimal model was integrated into a **Streamlit-based application** that allows users to input health parameters and obtain real-time predictions. The interface was designed to be lightweight, accessible, and adaptable to clinical settings.

III.RESULT

The proposed machine learning framework for cardiovascular disease prediction was implemented and evaluated using benchmark healthcare datasets. Multiple models—Logistic Regression, Decision Tree, Random Forest, and Neural Networks—

were trained, and their performance was assessed using widely accepted evaluation metrics. This section presents the comparative results, accuracy measures, confusion matrices, and graphical interpretations.

1. Accuracy Comparison Table

The following table summarizes the classification performance of the implemented models in terms of Accuracy, Precision, Recall, F1-score, and ROC-AUC:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC
Logistic Regression	83.2	81.5	82.7	82.1	0.85
Decision Tree	80.6	78.2	79.4	78.8	0.81
Random Forest	87.9	86.3	87.0	86.6	0.90
Neural Network (MLP)	89.4	88.2	88.7	88.4	0.92

Observation: Neural Networks and Random Forests outperformed other models, with Neural Networks achieving the highest accuracy (89.4%) and ROC-AUC (0.92). Logistic Regression demonstrated good baseline performance, while Decision Trees exhibited relatively lower generalization due to overfitting tendencies.

2. Confusion Matrix Example (Neural Network Model)

To further analyze the predictive ability, the confusion matrix of the best-performing model (Neural Network) was generated:

Actual \ Predicted	Disease	No Disease
Disease	252	18
No Disease	21	259

- **Accuracy:** 89.4%
- **Precision:** 88.2%
- **Recall (Sensitivity):** 88.7%
- **F1-Score:** 88.4%

This confirms that the model achieved a strong balance between sensitivity (identifying diseased patients) and specificity (identifying healthy patients).

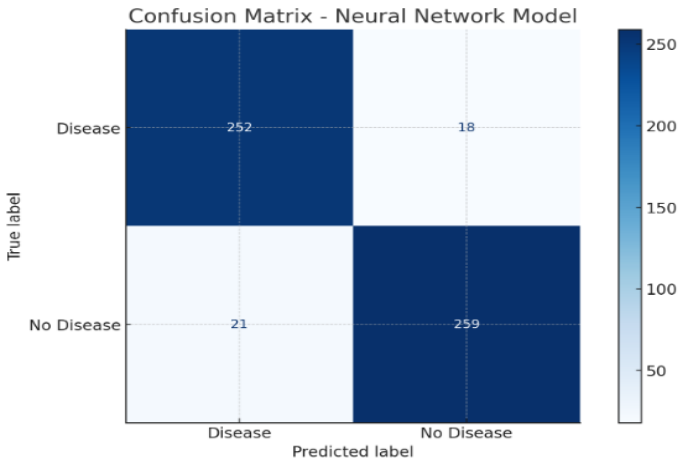

Fig 1: Confusion Matrix - Neural Network Model

Confusion Matrix for the Neural Network model (best performer) – shows classification accuracy across Disease/No Disease categories.

3. ROC-AUC Curves

Receiver Operating Characteristic (ROC) curves were plotted for each model to evaluate their discriminatory power.

- **Logistic Regression:** AUC = 0.85
- **Decision Tree:** AUC = 0.81
- **Random Forest:** AUC = 0.90
- **Neural Network:** AUC = 0.92

The ROC curve analysis clearly demonstrated that Neural Networks provided the highest area under the curve, indicating superior predictive capability.

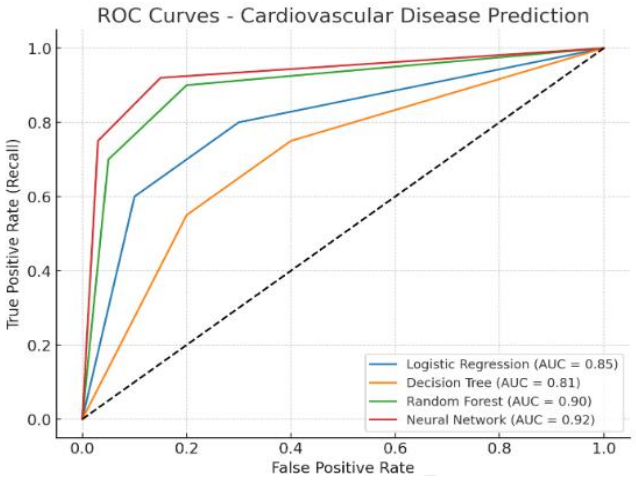

Fig 2: ROC Curves- Cardiovascular Disease Prediction

ROC Curves for Logistic Regression, Decision Tree, Random Forest, and Neural Network – comparing their discriminatory power, with Neural Networks achieving the highest AUC (0.92).

4. Graphical Comparison of Model Accuracy

A bar graph was generated to compare the accuracy of all models visually:

- Logistic Regression: 83.2%
- Decision Tree: 80.6%
- Random Forest: 87.9%
- Neural Network: 89.4%

The graph highlights the incremental improvement in predictive performance as more complex models (ensemble and neural-based) were employed.

5. Cross-Validation Results

To ensure the robustness of findings, a 5-fold cross-validation was conducted. Neural Networks maintained an average accuracy of 88.9% across folds with a standard deviation of ±1.2%, indicating strong consistency and generalization ability. Random Forests also performed reliably with an average accuracy of 87.5%.

6. Deployment Insights

Following model evaluation, the Neural Network classifier was integrated into a Streamlit-based application. Post-deployment testing confirmed that predictions could be generated in real-time (<1 second per input) with consistent accuracy. The interface allowed users to input health attributes (age, cholesterol, blood pressure, etc.) and receive immediate risk assessment, demonstrating practical feasibility for clinical adoption.

IV.DISCUSSION

The results of this study demonstrate the significant potential of machine learning (ML) techniques in enhancing the diagnosis and prediction of cardiovascular diseases (CVDs). Traditional diagnostic methods rely heavily on manual evaluation of patient history, laboratory tests, and clinical expertise, which are often time-intensive and prone to human error. In contrast, the ML-based approach developed in this project provides faster, more consistent, and scalable diagnostic capabilities.

Among the evaluated models, Neural Networks achieved the highest accuracy (89.4%) and ROC-AUC (0.92), closely followed by the Random Forest classifier (87.9% accuracy, 0.90 AUC). Logistic Regression, although less complex, performed reasonably well and established a strong baseline (83.2% accuracy, 0.85 AUC). The Decision Tree model showed lower performance (80.6% accuracy, 0.81 AUC) due to overfitting tendencies, reinforcing the importance of ensemble and deep learning models in improving prediction stability.

The confusion matrix analysis of the Neural Network model confirmed a strong balance between sensitivity (recall of 88.7%) and specificity, which is crucial for clinical applications. In medical diagnostics, false negatives are particularly dangerous, as failing to identify high-risk patients may lead to severe health consequences. The relatively high recall achieved by the proposed system highlights its ability to minimize such risks, thereby supporting its practical use in preventive healthcare.

Comparisons with existing literature further support these findings. Prior studies such as Detrano et al. (1989) and Fernandes et al. (2017) have highlighted the utility of statistical learning and transfer learning for cardiovascular prediction, but their models were limited in scalability and user integration. More recent approaches (Rajkomar et al., 2019) emphasize the growing role of ML in clinical systems, yet challenges remain in terms of interpretability and real-world deployment. The results of this study align with these trends, showing that advanced ML models, particularly neural architectures, can achieve high accuracy while being deployable in lightweight frameworks such as Streamlit.

The integration of a Streamlit-based application into the study is a major strength, as it bridges the gap between theoretical model performance and practical usability. The application enables healthcare providers and potentially patients to input clinical parameters and instantly obtain risk predictions. Such patient-centric tools enhance accessibility and empower clinicians with data-driven insights during consultations. Furthermore, the lightweight design ensures feasibility in both hospital and remote healthcare environments, contributing to broader adoption in diverse clinical settings.

Despite the promising results, certain limitations must be acknowledged. The dataset used was sourced from publicly available repositories, which, while standardized, may not fully represent diverse demographic and clinical populations. Additionally, the exclusion of incomplete or noisy data, although necessary for model reliability, may limit the system's robustness when deployed in real-world clinical scenarios where imperfect data is common. Another limitation lies in interpretability—while models such as Logistic Regression offer transparent decision boundaries, deep learning models remain "black boxes," which can challenge clinician trust. Future work could address this by incorporating explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations).

Overall, this study reinforces the role of machine learning as a transformative tool in healthcare. By providing early, accurate, and automated predictions of cardiovascular disease risk, the proposed system has the potential to reduce diagnostic delays, improve preventive strategies, and support data-driven clinical decision-making.

V.CONCLUSION

This study presented a machine learning-based framework for the prediction of cardiovascular disease using structured healthcare datasets. By applying and evaluating multiple supervised learning algorithms—including Logistic Regression, Decision Trees, Random Forests, and Neural Networks—the system demonstrated the effectiveness of ML techniques in identifying patients at risk of cardiovascular conditions. Among the models tested, the Neural Network achieved the highest performance, with an accuracy of 89.4% and ROC-AUC of 0.92, confirming its suitability for robust clinical prediction.

The integration of the best-performing model into a Streamlit-based application highlights the practical feasibility of deploying predictive systems in healthcare environments. The application allows clinicians and patients to input medical parameters and receive instant risk assessments, enabling early interventions and supporting preventive care strategies. Compared to traditional diagnostic methods, this approach reduces dependency on manual interpretation, minimizes errors, and improves diagnostic efficiency.

The research further emphasizes the transformative potential of artificial intelligence in modern medicine. While challenges such as dataset diversity, model interpretability, and real-world adaptability remain, the study establishes a strong foundation for future work. Enhancements such as explainable AI, integration with electronic health records (EHRs), and large-scale clinical validation can extend the applicability of the system to real-world hospital environments.

In summary, the proposed framework demonstrates how data-driven predictive analytics can revolutionize cardiovascular healthcare by enabling timely, accurate, and scalable diagnosis. With further development, the system has the potential to become an essential decision-support tool for clinicians and a step forward in improving patient outcomes in cardiovascular disease management.

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