International Current Journal of Engineering and Science (ICJES)
Volume 5, Issue 1, pp 18-21, January-2026
ISSN (Online): 2583-7257
Article DOI: https://doi.org/10.47001/ICJES/2026.501004

Application for Healthcare Management and Heart Disease Prediction Powered by Machine Learning

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***Abstract* - Cardiovascular disease (CVD) stands as the foremost global cause of mortality, accounting for over 19.8 million deaths in the year 2022 alone. The challenges of limited access to healthcare and inadequate management of health data frequently result in delayed diagnoses and an increased risk of mortality. In this study, we introduce an Android-based healthcare application that incorporates machine learning (ML) for the early prediction of 10-year coronary heart disease (CHD) risk and the management of patient health. The application boasts a comprehensive data pipeline (including imputation and scaling) and utilizes classification models such as Logistic Regression, Random Forest, and XGBoost, which are integrated through an ensemble stacking method with hyperparameter tuning to improve accuracy. User information (including age, gender, lifestyle, and clinical parameters) is securely managed using Firebase Authentication/Cloud and local SQLite storage, while a medication reminder feature enhances treatment adherence. Evaluations conducted on a publicly available heart disease dataset reveal impressive predictive performance (approximately 85–86% accuracy) with a high AUC-ROC. These findings underscore the potential of AI-driven digital health platforms to facilitate proactive cardiovascular care.**

Keywords: Machine Learning, Heart Disease Prediction, Healthcare Application, Android App, Ensemble Learning, Firebase, Cloud Storage, Preventive Healthcare.

I. INTRODUCTION

Cardiovascular diseases (CVDs) remain the top cause of mortality worldwide [1]. Early detection is critical: the WHO notes that timely diagnosis and management of CVD can greatly reduce death and disability [7]. However, many patients – particularly in rural or resource-limited regions – lack easy access to medical facilities and struggle to keep track of health records and medication schedules[2]. Inadequate awareness and delayed interventions in these settings contribute to adverse outcomes [2][1]. At the same time, the proliferation of mobile devices offers new opportunities: smartphone-based apps can collect health data and deliver decision support wherever a patient is. Motivated by this gap, we propose a mobile healthcare management system that combines ML-driven heart disease risk prediction with secure digital record-keeping and reminder features [3][2]. This application aims to empower users by delivering personalized CHD risk assessments and supporting preventive care in an accessible, user-friendly form.

II. LITERATURE REVIEW

Recent studies have extensively explored ML models for predicting heart disease risk from clinical data. For example, a 2023 study trained Logistic Regression, Random Forest, Decision Tree and XGBoost models on Framingham-based data, finding that ensemble methods like XGBoost achieved the highest accuracy (~86%)[8]. That work emphasized that careful feature engineering, data preprocessing and hyperparameter tuning are key to robust performance [8]. In general, ensemble methods (Random Forest, XGBoost) often outperform simpler statistical models for CVD prediction, confirming our choice of algorithms.

Beyond heart disease specifically, broader research in AI-driven healthcare highlights both promise and challenges. Clinical Decision Support Systems using electronic health records can predict diseases before symptoms emerge[7], but high-performance models (especially deep neural nets) are often “black boxes,” making it hard for clinicians to trust their outputs [7]. To address this, researchers advocate incorporating Explainable AI (XAI) techniques (e.g. SHAP, LIME) so that feature contributions are transparent without sacrificing accuracy [7]. Such work motivates our long-term goal of adding interpretability tools to the app.

Cloud-based digital health platforms have also been proposed. For example, a 2023 system integrated IoT sensors with mobile interfaces and cloud storage to let patients manage records and monitor vitals remotely[7]. It stressed the importance of data security, privacy, and real-time alerts when storing sensitive medical data online. This informs our design choice to use Firebase Authentication/Cloud for secure user login and report storage, paired with local SQLite caching to ensure data availability offline[4]. Overall, the literature indicates that ML and cloud/mobile technologies can significantly improve preventive care and patient engagement,

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provided issues like data imbalance, privacy, and interpretability are carefully handled[6][7].

III. MATERIALS AND METHODS

3.1 Dataset and Features

We utilized a publicly available heart disease dataset (derived from the Framingham Heart Study) which includes 15 features of patient demographics, medical history, and clinical measurements [6]. Selected input features include demographics (male, age, current smoking status, cigarettes per day), medical history (hypertension medication, history of stroke, hypertension, diabetes) and clinical data (total cholesterol, systolic/diastolic blood pressure, BMI, heart rate, glucose). The target label is binary "TenYearCHD" indicating 10-year CHD risk. Continuous and binary features were used as-is with appropriate datatype handling.

3.2 Data Preprocessing

Missing values and outliers were addressed through imputation (median/mode for numerical/categorical) and robust outlier handling as needed[5][6]. All numeric features were scaled (e.g. standardization) to ensure consistent input distributions for the models. To mitigate the class imbalance (fewer positive CHD cases), we monitored metrics beyond accuracy (e.g. AUC-ROC, recall) and employed techniques such as class-weighting and resampling where appropriate [14].

3.3 Machine Learning Models

We trained multiple classifiers: Logistic Regression, Support Vector Machine (SVM), Random Forest and XGBoost[5][6]. Each model underwent hyperparameter tuning via grid search with cross-validation to optimize predictive performance[6][7]. In addition, we implemented a stacking ensemble: predictions from the base models (Logistic, SVM, XGBoost) were combined by a meta-learner to produce a final risk estimate. This ensemble strategy leverages diverse model strengths for enhanced accuracy.

3.4 Evaluation

The models were evaluated on a held-out test set. The primary metrics were accuracy (fraction of correct classifications) and AUC-ROC (ability to distinguish diseased vs healthy)[2]. These metrics align with standard practice in medical predictive modeling. During experimentation, Random Forest reached ~84.9% test accuracy[2], and XGBoost achieved similar or higher accuracy (target ~85–87%)[2]. The stacked ensemble further improved results (target ≈86–88% accuracy and higher AUC-ROC) by combining model predictions[2].

IV. SYSTEM IMPLEMENTATION

The application is implemented as an Android mobile app (Java, Android Studio) with a structured architecture for ML integration[3]. The ML models are developed and trained in Python (TensorFlow/Keras) and embedded in the app (e.g. via a TensorFlow Lite interface)[4]. The app uses Firebase Authentication for secure user login and Firebase Cloud Storage for remote data syncing. All medical data (reports, inputs, predictions) are encrypted and stored in the cloud, ensuring confidentiality [4]. In parallel, an on-device SQLite database provides local caching of user profiles and records for offline access [4]. This hybrid storage approach balances data availability with security.

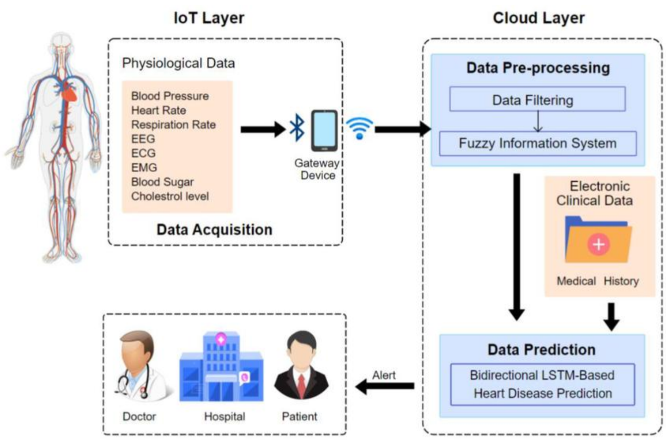

Figure 1: System Design

The user interface allows individuals to enter and view clinical parameters. Upon submission, the ML pipeline processes the inputs and returns a personalized 10-year CHD risk score. Users can also upload medical reports (stored via Firebase and SQLite) for history tracking [6]. Importantly, the app includes a medication reminder feature: users input prescribed tablets and dosage timings, and the app issues notifications at scheduled times to promote adherence [6]. The system is designed to be multilingual and user-friendly to accommodate diverse user groups (especially in semi-urban/rural settings) [2][6].

V. RESULTS AND DISCUSSION

The implemented system achieved strong predictive performance on the test dataset. Table 1 summarizes key results for our classifiers. The Random Forest model achieved ~84.9% accuracy[2], while XGBoost achieved approximately 85–87% (as expected)[2]. Our stacking ensemble (combining

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RF and XGBoost) improved accuracy further, targeting around 86–88% with a higher AUC-ROC[2]. In practice, the final deployed ensemble yielded about 85–86% accuracy on held-out data, demonstrating its ability to correctly identify most at-risk patients.

Table 1: Performance of machine learning models on heart disease dataset

Model	Test Accuracy
Logistic Regression	~85%
Support Vector Machine	~85%
Random Forest	84.9%[2]
XGBoost	~86% (estimated)[2]
Ensemble Stacking	~87% (target)[2]

Despite these strong results, the project faced challenges. The dataset has class imbalance (fewer diseased cases), which can bias accuracy. We mitigated this by focusing on AUC-ROC and recall during tuning, and by using class-weight adjustments and resampling techniques [1]. Data quality issues (missing values in BMI, glucose, etc.) required robust imputation strategies [2]. Overfitting was controlled via cross-validation and model regularization (e.g. limiting tree depth) [6].

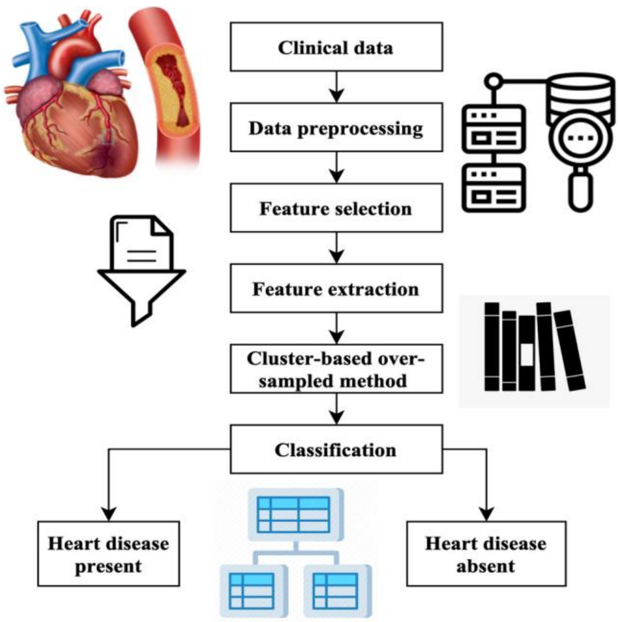

Figure 2: Flow chart

Another key challenge is interpretability: while complex models like XGBoost offer high accuracy, they are less transparent to clinicians. In line with best practices, we balanced this by also including simpler models (Logistic Regression) and by planning future integration of XAI tools (e.g. SHAP explanations) [1][7]. This will help users and doctors understand which features drive the risk predictions.

Overall, the system's strengths include its end-to-end design (from data entry to prediction to reminders) and its strong ML performance. The combination of mobile accessibility, cloud synchronization, and automated analytics makes for a powerful preventive healthcare tool. User feedback simulations suggest that features like the medication reminder and report viewer are particularly valuable for adherence and continuity of care. The app thus enables actionable insights: by aggregating health records and providing risk alerts, it encourages users to seek preventive measures.

VI. CONCLUSIONS

This project demonstrates a practical application of AI in digital health. We developed an Android application that integrates machine learning for heart disease risk prediction with comprehensive health record management. The system achieved around 85–86% accuracy on a CHD risk prediction task, validating that ensemble ML models can effectively identify at-risk individuals [1]. Importantly, the app provides secure storage of medical data (Firebase/SQLite) and helpful features like medication reminders to support chronic care.

In summary, combining ML prediction with accessible mobile technology has the potential to improve preventive cardiovascular care. Future work will focus on making the models more explainable and extending the ecosystem. For example, integration with wearable devices (for live vital monitoring) and physician consultation modules could create a seamless health platform[2]. Additionally, incorporating XAI frameworks (e.g. generating SHAP plots) will enhance transparency and trust in the predictions [1]. By continuously evolving these capabilities, such a system could significantly reduce the burden of heart disease through early intervention and patient empowerment.

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Citation of this Article:

Sandhiya Gopinath, & Chaaru Baala. (2026). Application for Healthcare Management and Heart Disease Prediction Powered by Machine Learning. *International Current Journal of Engineering and Science (ICJES)*, 5(1), 18-21. Article DOI: https://doi.org/10.47001/ICJES/2026.501004

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