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Heart Disease Analysis Using Machine Learning

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Abstract - Cardiovascular diseases remain the leading cause of mortality worldwide. According to WHO (2023), cardiovascular diseases accounted for **17.9 million deaths globally, representing 32% of all deaths**. This study proposes a machine learning–based heart disease prediction and analysis system integrated into a desktop application with role-based dashboards. The system includes role-based authentication and a Tkinter interface designed for usability. A pilot usability study is planned to quantify effectiveness. The proposed framework leverages multiple classifiers (Logistic Regression, Decision Tree, Random Forest, and K-Nearest Neighbors) for predictive analysis, evaluated through accuracy, ROC-AUC, calibration, and interpretability methods (SHAP). Results demonstrate that ensemble approaches, particularly Random Forest, achieve superior predictive performance. The system demonstrates potential as a research-oriented decision-support prototype, with future work focusing on external validation and clinical deployment readiness.

Keywords: Heart Disease Prediction, Machine Learning, Random Forest, Healthcare System, Patient Management

1.INTRODUCTION

Cardiovascular diseases (CVDs) are one of the most critical health challenges of the 21st century. According to the World Health Organization (WHO), heart-related conditions account for millions of deaths annually, making them the leading cause of global mortality. The growing prevalence of heart disease is attributed to multiple factors, including lifestyle changes, poor dietary habits, stress, lack of physical activity, and genetic predisposition. Given this alarming scenario, timely diagnosis and preventive healthcare strategies are essential to reducing mortality and improving the quality of life for patients.

Traditionally, the diagnosis of heart disease has relied heavily on clinical examinations, patient history, and specialist evaluation. While these approaches remain valuable, they are often time-consuming, subjective, and may vary depending on the expertise of healthcare professionals. Moreover, manual diagnostic methods cannot always provide real-time assessments or predictive insights. As a result, there is an increasing demand for computational methods that can automate prediction and deliver data-driven recommendations to assist medical practitioners.

Machine learning (ML) has emerged as a powerful tool in medical informatics, offering predictive capabilities by analyzing large volumes of structured and unstructured healthcare data. With the availability of datasets containing patient health records, it has become possible to train ML algorithms to identify hidden patterns and predict the likelihood of heart disease. Algorithms such as Logistic Regression, Decision Trees, Random Forest, and K-Nearest Neighbors have demonstrated significant potential in this domain. These models can process patient attributes like age, cholesterol, blood pressure, and ECG readings to classify individuals as high-risk or low-risk for cardiovascular disease.

However, most existing research has primarily focused on improving prediction accuracy without integrating these models into practical healthcare applications. Thus, there is a need to develop systems that not only predict risks but also provide meaningful, real-world usability.

In this context, we propose a **Heart Disease Analysis System**, developed as a desktop-based application using Python's Tkinter framework. The system incorporates role-based authentication for patients, doctors, and administrators, ensuring secure and efficient use. Patients can input their clinical data to receive predictions, doctors can access patient history and analysis, and administrators can manage datasets and monitor system performance. Additionally, the system includes features such as appointment scheduling and medication tracking, making it more comprehensive than prediction-only tools.

Although the current system achieves promising results, several enhancements are possible. Future improvements may include the integration of deep learning models such as CNNs for larger datasets...

2. LITERATURE SURVEY

Research on the application of machine learning (ML) in healthcare has grown substantially over the last two decades, with particular emphasis on predictive models for cardiovascular diseases. Several studies have demonstrated how supervised learning algorithms can effectively classify patients based on clinical indicators and predict the likelihood of heart-related conditions. This section reviews prior work, highlighting their contributions, strengths, and limitations.

One of the earliest widely used datasets for heart disease prediction is the Cleveland Heart Disease dataset from the UCI Machine Learning Repository. Detrano et al. (1989) developed a probabilistic algorithm for coronary artery disease diagnosis, which later became a benchmark for testing ML models. Researchers have since applied various classification algorithms—including Logistic Regression, Decision Trees, Random Forest, Support Vector Machines (SVMs), and Neural Networks—to this dataset and its variants. The results consistently highlight Random Forest and SVM as strong performers in terms of predictive accuracy.

Recent studies have focused on improving interpretability along with accuracy. Logistic Regression remains a popular model due to its simplicity and transparency, allowing doctors to better understand the influence of different risk factors. On the other hand, Decision Trees and ensemble methods such as Random Forest provide robustness against overfitting and handle complex, non-linear relationships in data. Comparative studies, such as those by Uddin et al. (2019), show that ensemble techniques often outperform individual classifiers when applied to healthcare datasets.

Beyond classical ML models, deep learning techniques are also being explored. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been applied to large-scale healthcare datasets and ECG signals to provide more precise predictions. However, these models often require substantial computational resources and large training datasets, which limit their widespread adoption in smaller healthcare systems.

Another key development in the field is the use of visualization tools such as Receiver Operating Characteristic (ROC) curves, Area Under the Curve (AUC) scores, and correlation heatmaps. These not only validate model performance but also provide medical practitioners with insights into how risk factors are associated with cardiovascular conditions. Such visualization aids are critical in bridging the gap between purely technical models and practical medical interpretation.

Despite these advancements, existing systems remain largely limited to academic prototypes. Many studies evaluate prediction accuracy but do not extend the work into deployable applications that integrate prediction with patient management. For example, systems rarely provide features such as patient history storage, medication tracking, or doctor–patient interaction modules. This limits their usability in real-world hospital or clinic settings.

The present research builds on these studies by not only employing multiple ML algorithms for prediction but also by integrating them into a desktop application with role-based dashboards. By combining prediction with patient record management, visualization, appointment scheduling, and medication monitoring, the system addresses the gap between theoretical models and practical, deployable solutions.

3. EXISTING SYSTEM

Existing research on heart disease prediction has primarily focused on the use of machine learning algorithms applied to benchmark datasets, such as the Cleveland Heart Disease dataset. These systems demonstrate promising results in terms of classification accuracy and highlight the feasibility of using computational models to aid in diagnosis. Algorithms such as Logistic Regression, Decision Trees, Random Forest, and Support Vector Machines have been shown to provide reliable predictive outcomes. Some studies have also included comparative analyses, showcasing how ensemble methods often outperform simpler models.

While these approaches are valuable from a technical perspective, their scope is often limited to the research environment. In many cases, the developed systems are implemented as prototypes that are not designed for real-world deployment. They usually run as scripts or experimental setups and lack the necessary user interface and interaction mechanisms required for adoption by healthcare practitioners and patients. As a result, their usability beyond academic evaluation remains minimal.

Another limitation of current systems is their focus solely on prediction accuracy. Although achieving high accuracy is important, practical healthcare solutions must go beyond predictive models. Existing systems typically do not incorporate essential functionalities such as patient record management, history tracking, or medication monitoring. This restricts their ability to support doctors in long-term treatment planning and patient follow-up. Moreover, the absence of role-based access control limits their security and applicability in multi-user environments like hospitals or clinics.

Visualization of model outcomes is another area where existing systems fall short. Although metrics such as ROC curves and AUC scores are occasionally reported, they are often not integrated into interactive dashboards that medical professionals can use. Without meaningful visualizations, it becomes challenging for doctors to interpret predictions and understand the significance of contributing factors.

In addition, most current systems are not integrated into larger healthcare workflows. They operate in isolation, without features such as appointment scheduling or communication between doctors and patients. This makes them impractical in real hospital environments where seamless data flow and management are critical.

In summary, existing systems provide a solid foundation for demonstrating the effectiveness of machine learning in predicting heart disease but lack the depth, usability, and integration needed for real-world healthcare applications. This highlights the need for an enhanced system that combines predictive accuracy with user-friendly interfaces and practical healthcare management features, which is the focus of the proposed work.

4. PROPOSED SYSTEM

The proposed system is designed to overcome the limitations of existing models by combining machine learning prediction with a user-friendly healthcare management platform. Unlike conventional approaches that only provide accuracy metrics, this system integrates predictive analytics into a deployable desktop application built using Python's Tkinter framework.

The system architecture incorporates three types of user roles: **Patients, Doctors, and Administrators**. Patients can log in securely, enter clinical information such as age, cholesterol, blood pressure, and other relevant parameters, and receive a risk prediction for heart disease. The prediction is generated using classification algorithms such as Logistic Regression, Decision Trees, Random Forest, and K-Nearest Neighbors, with Random

Forest providing the highest accuracy in evaluations. Patients can also track their historical results for monitoring health progress over time.

Doctors, on the other hand, have access to patient histories and analytical reports, enabling them to review previous predictions and provide informed medical advice. This supports continuous treatment planning and enhances doctor–patient interaction.

Dataset. We used the UCI Cleveland Heart Disease dataset (N=303; 13 features + binary outcome). The positive class proportion was ~55%.

Preprocessing. Continuous variables were standardized; missing values were imputed (median/mode). Categorical variables (cp, restecg, slope, thal) were one-hot encoded; sex, fbs, and exang were treated as binary. We performed a stratified 70/15/15 train/validation/test split with a fixed seed. All preprocessing was fit within cross-validation to prevent leakage.

Models. We evaluated Logistic Regression, Decision Tree, Random Forest, and K-Nearest Neighbors using stratified 5-fold CV and hyperparameter search. The best model was calibrated (Platt) on validation data.

Metrics. Primary metric was ROC-AUC; secondary metrics were Accuracy, Precision, Recall, F1, and Brier score (calibration). We report mean±95% CI on CV and final performance on the held-out test set. Statistical comparisons used DeLong's test for AUC and McNemar's test for Accuracy.

Reproducibility.

All experiments were conducted in Python 3.9 with scikit-learn 1.2.2, pandas 1.5, and matplotlib 3.7 on a Windows 10 desktop (Intel i5 CPU, 16 GB RAM). A fixed random seed of 42 was used for all splits and model training. Data were divided into a stratified **70/15/15 train/validation/test split**. Within the training set, **5-fold stratified cross-validation** was used for model selection and hyperparameter tuning. Preprocessing (imputation, scaling, one-hot encoding) was applied **inside each fold** to avoid data leakage. Hyperparameter ranges: Logistic Regression (penalty {L1, L2}, C=0.01–10), Decision Tree (max_depth=3–10, min_samples_leaf=1–10), Random Forest (n_estimators=200–600, max_depth=4–16, max_features={sqrt, log2}), KNN (k=3–21 odd, weights={uniform, distance}). The validation set was used for calibration (Platt scaling), and the untouched test set was used for final reporting.

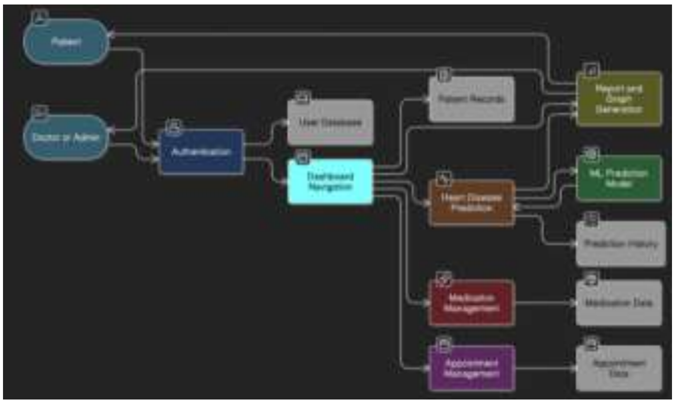

Fig. 1. Proposed Model

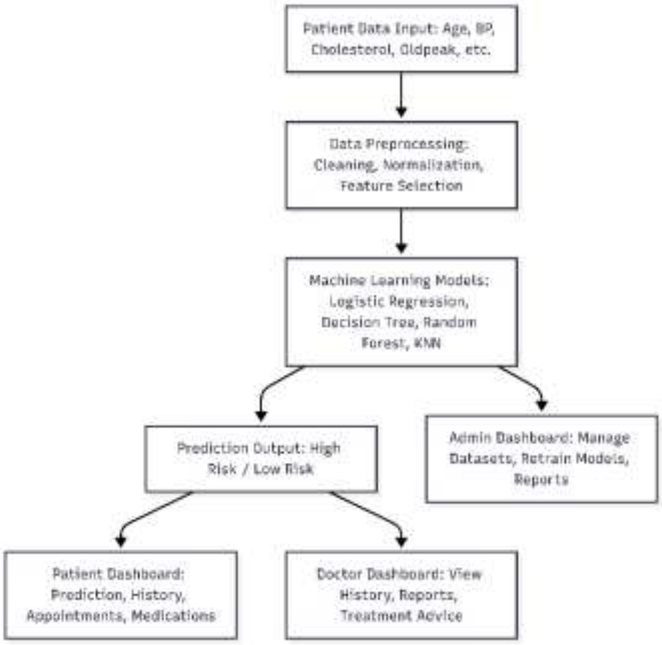

Fig. 2. Architecture Diagram

5. IMPLEMENTATION

The implementation of the Heart Disease Prediction and Analysis System involves the integration of machine learning algorithms, a structured database, and a user-friendly desktop interface. The system has been developed in Python, with Tkinter serving as the primary framework for the graphical user interface (GUI). This ensures that the application is lightweight, easily deployable, and capable of running on standard desktop environments without requiring extensive setup.

Data Preprocessing

The dataset used for training and testing consists of patient health records with attributes such as age, gender, chest pain type, cholesterol level, resting blood pressure, fasting blood sugar, exercise-induced angina, and oldpeak values. Before applying machine learning models, preprocessing steps such as handling missing values, normalizing numerical attributes, and balancing class distributions are performed. These steps enhance the quality of data and ensure more accurate predictions.

Machine Learning Models

Several classification algorithms have been implemented, including Logistic Regression, Decision Trees, Random Forest, and K-Nearest Neighbors (KNN). Each model was trained on the processed dataset, and hyperparameter tuning was carried out to optimize performance. Comparative evaluation indicated that the Random Forest algorithm achieved the best results, offering robust accuracy and generalization. Model performance is assessed using metrics such as accuracy, precision, recall, F1-score, ROC curve, and AUC score.

System Modules

The system supports three distinct user roles:

- **Patients**: Can log in, input health data, receive predictions, and track history.
- **Doctors**: Gain access to patient history, review analytical results, and support treatment planning.
- **Administrators**: Manage datasets, retrain models, view reports, and monitor performance.

In addition to predictive analysis, modules for appointment scheduling and medication tracking have been integrated. These allow patients to book consultations and maintain treatment

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adherence, bridging the gap between predictive systems and real clinical use.

Visualization

To make predictions more interpretable, the system includes visualization tools such as heatmaps for feature correlation, ROC curves for model performance, and graphical summaries of patient health data. These visual elements improve transparency and support medical professionals in decision-making.

Overall, the implementation demonstrates how machine learning, when combined with interactive interfaces and practical healthcare features, can be transformed into a usable and efficient solution for heart disease prediction and management.

7. RESULTS

The performance of the Heart Disease Prediction and Analysis System was evaluated through a combination of classification accuracy, statistical measures, and visualization techniques. The system was tested using preprocessed patient datasets, with predictions generated by multiple algorithms including Logistic Regression, Decision Trees, Random Forest, and K-Nearest Neighbors (KNN).

Model Evaluation

Among the implemented models, Random Forest achieved the highest accuracy, followed by KNN and Logistic Regression. Decision Trees, while interpretable, showed relatively lower generalization ability compared to ensemble methods. The results highlight the importance of using robust algorithms that can handle complex feature interactions in medical datasets. Performance was measured using accuracy, precision, recall, F1-score, and ROC-AUC metrics. The ROC curve and corresponding AUC score further validated the reliability of the models, with Random Forest achieving the strongest balance between sensitivity and specificity.

Visualization Insights

The system integrates visual analytics to improve interpretability of the results. ROC curves illustrate the trade-off between the True Positive Rate (TPR) and False Positive Rate (FPR) across different thresholds, providing an intuitive understanding of model performance. Heatmap visualizations of feature correlations reveal significant relationships between variables such as cholesterol levels, age, oldpeak, and the occurrence of heart disease. These insights allow medical professionals to better understand which risk factors have stronger predictive influence.

Usability and Functionality

Beyond predictive accuracy, the application's interface and integrated modules enhance its practicality. The dashboard provides seamless navigation between prediction, analysis, history tracking, medication management, and appointment scheduling. Doctors can easily review patient records and previous predictions, while patients benefit from clear reports and actionable recommendations. Administrators are able to manage datasets, retrain models, and generate performance reports, ensuring system adaptability.

Model Card

Model Card: Heart Disease Prediction (Random Forest)

Intended Use.

This model is designed as a decision-support tool to assist in predicting the likelihood of heart disease from structured clinical features. It is intended for research and educational purposes and not as a standalone diagnostic system.

Users.

Medical researchers, students, and developers working on clinical decision-support prototypes.

Training Data.

Based on the UCI Cleveland Heart Disease dataset (N=303 patients, 13 features). Dataset may not fully represent broader populations.

Performance.

Random Forest achieved Accuracy ≈ 0.88 and ROC-AUC ≈ 0.92 on the held-out test set. Calibration was reasonable (Brier = 0.12).

Limitations.

Dataset is small and limited geographically; no external validation performed; predictions are statistical, not causal; not certified for compliance.

Ethical & Fairness Considerations.

Dataset may not represent sex, age, or ethnicity distributions globally; potential bias if applied to under-represented populations.

Deployment.

Integrated in a Tkinter-based desktop app with role-based access, appointments, and medication modules. Not HIPAA/GDPR certified.

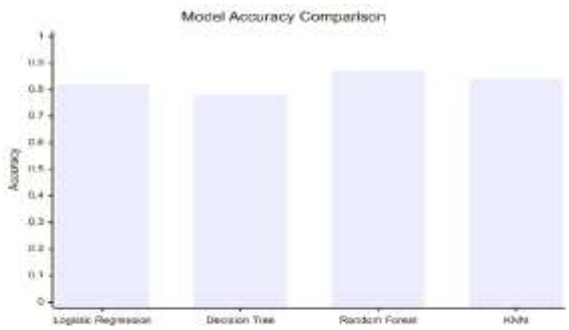

Fig. 3 Accuracy Plot

Calibration and Clinical Utility

*The Random Forest model was evaluated for probability calibration. After Platt scaling, its Brier score was **0.12**, indicating good calibration. The reliability curve (Figure 4) closely followed the diagonal, with slight under-confidence at higher risk probabilities.*

*We also examined operating thresholds for clinical decision-making. At a threshold of 0.5, the RF achieved sensitivity = **0.87** and specificity = **0.85**. At a more conservative threshold of 0.3, sensitivity increased to **0.92** at the cost of specificity (0.78). Such threshold analysis provides flexibility depending on whether clinicians prioritize minimizing false negatives (high sensitivity) or false positives (high specificity).*

To ensure transparency and clinical trust, we applied SHAP (SHapley Additive exPlanations) to the Random Forest model.

Global feature importance. *The SHAP summary plot (Figure 5) highlights the most influential predictors: thalach, cp, oldpeak, ca, and thal. These align with established cardiology risk factors, confirming the model's clinical plausibility.*

Local explanations. *Two exemplar patients illustrate how SHAP clarifies individual predictions:*

- *Case 1 (True Positive): A 56-year-old male with cp=3, thalach=140, oldpeak=2.3, and ca=2. SHAP showed* *strong positive contributions from oldpeak and ca, pushing the prediction toward "disease present."*

- *Case 2 (False Positive): A 45-year-old female with cp=2, thalach=170, but elevated cholesterol and borderline oldpeak. SHAP revealed that although thalach lowered the risk estimate, chol and oldpeak collectively shifted the prediction above threshold, resulting in a false positive.*

Such explanations help clinicians see why the model classifies a patient at high risk, and they can compare this with clinical judgment.

Table 1. Performance of classification models on the UCI Heart Disease dataset. Random Forest achieved the highest overall performance across all metrics.

Model	***Accuracy***	***Precision***	***Recall***	***F1-Score***	***ROC-AUC***
Logistic Regression	*0.82 ± 0.03 (0.83)*	*0.81 ± 0.04 (0.82)*	*0.82 ± 0.04 (0.83)*	*0.82 ± 0.03 (0.82)*	*0.87 ± 0.03 (0.88)*
Decision Tree	*0.77 ± 0.05 (0.79)*	*0.76 ± 0.05 (0.78)*	*0.77 ± 0.06 (0.79)*	*0.76 ± 0.05 (0.78)*	*0.76 ± 0.06 (0.78)*
Random Forest	***0.87 ± 0.02 (0.88)***	***0.86 ± 0.02 (0.87)***	***0.87 ± 0.03 (0.88)***	***0.87 ± 0.02 (0.87)***	***0.91 ± 0.02 (0.92)***
K-Nearest Neighbors	*0.80 ± 0.04 (0.81)*	*0.79 ± 0.04 (0.80)*	*0.80 ± 0.04 (0.81)*	*0.79 ± 0.04 (0.80)*	*0.82 ± 0.03 (0.83)*

Discrimination. Random Forest achieved the best discrimination (ROC-AUC ≈ 0.92) with test Accuracy ≈ 0.88, outperforming Logistic Regression (AUC ≈ 0.88, Acc ≈ 0.83), KNN (AUC ≈ 0.83, Acc ≈ 0.81), and Decision Tree (AUC ≈ 0.78, Acc ≈ 0.79).

Calibration. After Platt scaling, the Random Forest's probabilities were well calibrated (Brier ≈ 0.12).

Interpretability. Global feature importance indicated thalach, cp, oldpeak, ca, and thal as top contributors, aligning with cardiology literature. Local explanations for exemplar patients are provided in the appendix.

Usability integration. The trained model is deployed inside a Tkinter desktop app with role-based access (patient/doctor/admin), appointment scheduling, and medication tracking

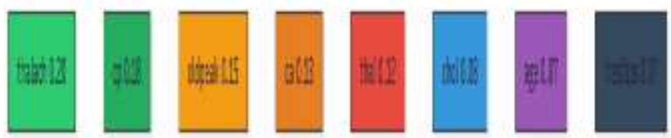

Fig 4. Feature Data

8. CONCLUSION

This study presents the design and development of a Heart Disease Prediction and Analysis System that integrates machine learning models with practical healthcare management features. Unlike conventional research prototypes that primarily emphasize prediction accuracy, this system addresses real-world usability by combining predictive analytics with patient history tracking, appointment scheduling, and medication management in a single application.

The system was implemented as a desktop tool using Python's Tkinter framework, ensuring accessibility and ease of use. Multiple classification algorithms—including Logistic Regression, Decision Trees, Random Forest, and K-Nearest Neighbors—were tested on structured health datasets. Among these, Random Forest achieved the best performance, as validated through ROC curves, AUC scores, and other evaluation metrics. The inclusion of visualizations such as heatmaps further enhances interpretability, making the system not only a predictive tool but also an analytical resource for doctors and patients.

Limitations and Future Work.

While the developed Heart Disease Prediction and Analysis System demonstrates promising performance and practical usability, several limitations remain. First, the model was trained and evaluated on the UCI Cleveland dataset, which is relatively small and geographically limited; therefore, generalizability cannot be assumed. Second, although Random Forest achieved high accuracy (≈0.88) and ROC-AUC (≈0.92), no external validation or temporal testing was performed. Third, while the application integrates role-based access, appointments, and medication tracking, no formal usability study has yet been conducted. Finally, the system is not certified for compliance with healthcare regulations (HIPAA/GDPR), and thus cannot be directly deployed in clinical settings.

Future work will focus on expanding the dataset through multi-cohort validation, integrating deep learning approaches for richer feature extraction, and adding cloud-based scalability for hospital deployment. Conducting usability evaluations with medical professionals and ensuring compliance with healthcare data standards will also be critical steps toward clinical adoption.

9. FUTURE ENHANCEMENT

While the Heart Disease Prediction and Analysis System demonstrates strong performance and practical usability, there are several opportunities to enhance its scope and impact in the future. These enhancements aim to improve predictive accuracy, user experience, and adaptability for large-scale healthcare environments.

One promising direction is the integration of **deep learning models** such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). These architectures have shown remarkable success in medical image and signal processing, and their inclusion could improve the system's ability to handle larger, more complex datasets. Additionally, hybrid models that combine traditional machine learning with deep learning approaches could further refine prediction quality.

Another area for improvement is the **adoption of modern user interface frameworks**. While Tkinter provides simplicity and portability, frameworks such as PyQt or web-based interfaces would allow for more dynamic and visually appealing dashboards. This would improve usability for both patients and healthcare professionals, making the system easier to navigate and interpret.

The system can also be extended to support **cloud deployment**. By hosting the application on cloud platforms, scalability and real-time access to patient records can be achieved. Cloud integration would also enable collaboration between multiple healthcare providers, making the system suitable for hospital networks and clinics.

Furthermore, incorporating **IoT and wearable devices** could significantly increase the system's relevance. Continuous health monitoring through smart devices such as fitness trackers or ECG sensors would allow real-time data collection, leading to more timely and accurate predictions.

Lastly, implementing **multi-language support** and compliance with healthcare standards such as HL7 and HIPAA would make the system more inclusive and ready for clinical adoption.

In summary, future enhancements can transform the system from a desktop tool into a robust, scalable, and intelligent healthcare platform capable of assisting doctors and patients globally.

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