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AI-Powered Heart Disease Prediction with Appropriate Feature Selection

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Abstract: Heart disease remains one of the major causes of death worldwide, making early prediction and prevention extremely important. This study presents an ai-powered heart disease prediction system that uses machine learning techniques to estimate a patient's risk of developing heart disease based on clinical parameters such as age, blood pressure, cholesterol level, heart rate, and other medical factors. multiple machine learning models were trained and evaluated using the cleveland heart disease dataset, and the best performing model was integrated into a flask based web application for real time prediction. To improve transparency and user trust, shap (shapley additive explanations) is used to explain how different features influence the prediction results, The proposed system demonstrates how explainable artificial intelligence can assist healthcare professionals and patients in understanding prediction outcomes, promoting preventive healthcare, and supporting informed clinical decision making.

Keyword—Heart Disease Prediction, Machine Learning, Explainable Artificial Intelligence, SHAP, Risk Assessment, Flask Web Application.

I. INTRODUCTION

Heart disease is one of the leading causes of death worldwide and poses a serious challenge to healthcare systems. Early detection of heart disease is important because it can help patients receive timely treatment and reduce the risk of severe complications. Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) have made it possible to analyze medical data and predict diseases with high accuracy. Machine learning models can identify patterns in patient health records and assist doctors in making better decisions. In addition to prediction, the system incorporates Explainable Artificial Intelligence (XAI) using SHAP to explain the factors influencing each prediction. A Flask based web application provides a user-friendly interface for patient data entry, risk prediction, visualization of explanations, and personalized health recommendations. The proposed system aims to provide an accurate, transparent, and practical solution for heart disease risk assessment.

II. LITERATURE REVIEW

The literature review shows that many researchers have worked on heart disease prediction using machine learning techniques. Algorithms like Logistic Regression, Decision Tree, Random Forest, and XGBoost are commonly used to predict disease risk with good accuracy. Most studies focus on improving prediction performance using feature selection and data preprocessing methods. Recently, Explainable AI techniques such as SHAP and LIME are also used to understand how the model makes decisions. However, many existing systems do not provide a user-friendly interface or clear visualization for users. This project improves upon previous work by combining accurate prediction with clear explanations and an interactive web application.

Navita et al. (2025) proposed an advanced hybrid machine learning model for the early detection of cardiovascular disease by combining multiple preprocessing and classification techniques. The proposed model addresses the problem of imbalanced medical data using the SMOTE-ENN sampling method and selects the most relevant clinical features through the Chi-square feature selection technique [1]. A stacking ensemble classifier consisting of Random Forest, K-Nearest Neighbors (KNN), and AdaBoost with Logistic Regression as the meta learner was developed and optimized using Grid Search Cross Validation. The model was evaluated on a combined dataset of 1,190 patient records with 11 clinical features and achieved an accuracy of 97.8%, sensitivity of 96.15%, specificity of 96.75%, and ROC-AUC score of 98.6%. The study also demonstrated that applying SMOTE-ENN and Chi-square feature selection significantly improved prediction performance compared to using the classifier alone, making the proposed approach suitable for early cardiovascular disease detection and clinical decision support.

S. Venkatesh Babu et al. (2024) explores the use of Quantum Enhanced Machine Learning (QuEML) for heart disease prediction and compares its performance with traditional machine learning techniques using the Kaggle heart disease dataset. The proposed quantum approach was evaluated using accuracy, precision, recall, specificity, F1 score, and training time, and the results showed that QuEML achieved slightly higher prediction accuracy while requiring less training time than conventional machine learning models [2]. The study reported that QuEML improved the overall accuracy by approximately 0.6% and reduced the average training time by 192.5 μs, demonstrating its potential for faster and more efficient heart disease diagnosis. However, the authors also discussed practical challenges such as quantum decoherence and incorrect qubit rotations, suggesting that future research could further enhance performance by integrating deep learning techniques with quantum machine learning approaches.

Y. Bao (2024) investigated the use of machine learning techniques for early heart disease prediction using patient health data. The dataset was preprocessed and several models, including Logistic Regression, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN), were evaluated based on accuracy, precision, recall, and F1-score. The authors found that Logistic Regression and Random Forest achieved better prediction performance than the other models, making them suitable for medical decision support [3]. The study also highlighted that machine learning can help hospitals identify high risk patients at an early stage and improve healthcare efficiency. The authors suggested that future work should focus on combining multiple models and using larger and more diverse datasets to further improve prediction accuracy and real world applicability.

A. Singh et al. (2024) explored the use of supervised machine learning algorithms, including Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM), for early heart disease detection. The authors highlighted that early diagnosis can reduce medical costs and improve patient survival by identifying high risk patients at an early stage [4]. The proposed learning system achieved better performance than several existing heart failure prediction methods while reducing the number of features, which helped improve model efficiency and minimize overfitting. The study concluded that machine learning can support clinicians in making more accurate diagnoses and contribute to better healthcare outcomes.

R. Kumar et al. (2025) examined the use of machine learning and artificial intelligence techniques for heart disease prediction by analyzing recent studies in five major areas, including disease detection, machine learning algorithms, feature engineering, emerging healthcare technologies, and AI applications across different diseases. The review found that hybrid deep learning models, such as CNN-LSTM, generally achieve better prediction performance than traditional machine learning methods [5]. It also highlighted the growing use of Explainable AI (XAI), federated learning, and wearable health monitoring systems to improve clinical decision making and patient care. The authors concluded that future research should focus on developing transparent, clinically validated, and patient centered AI systems that can be safely integrated into real world healthcare environments.

Y. Chen et al. (2025) proposed a stacking-based machine learning model for heart disease prediction by combining Decision Tree (DT), Naïve Bayes (NB), CatBoost, and Gradient Boosting (GB) classifiers. The authors used Borderline SMOTE to handle class imbalance and applied SHAP for both global and local model interpretation to identify the most important risk factors [6]. The proposed model achieved 86.69% accuracy, 86.91% F1-score, and 97% AUC-ROC, outperforming the individual base classifiers. The study also showed that features such as age, sleep duration, body mass index (BMI), and self rated health status significantly influence heart disease prediction, demonstrating the usefulness of explainable AI in supporting clinical decision making.

P. Shinde et al. (2025) analyzed 68 research studies published between 2018 and 2023 to evaluate the use of machine learning techniques for heart disease prediction and classification. The study found that algorithms such as Random Forest (RF), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Logistic Regression (LR), and Naïve Bayes (NB) have been widely applied for early heart disease detection [7]. Among these, Random Forest and Logistic Regression achieved the best overall performance and prediction accuracy. The authors concluded that machine learning can significantly support cardiologists in making faster and more accurate diagnoses and recommended further research using larger datasets and advanced prediction models.

P. H. Hutagalung and A. Andrianingsih (2026) evaluated Random Forest and XGBoost models for heart disease prediction using different hyperparameter optimization methods, including Random Search, Bayesian Optimization, and Particle Swarm Optimization (PSO). The study showed that Random Forest with PSO achieved the highest prediction performance, while XGBoost produced comparable results [8]. SHAP was used to explain the model predictions and consistently identified oldpeak, ca, thal, cp, thalach, and exang as the most important features influencing heart disease risk. The authors concluded that combining optimized machine learning models with SHAP based explainability improves both prediction accuracy and model transparency, while recommending validation on larger and more recent clinical datasets for better clinical applicability.

T. S. Baskaran and B. Madhuvanthi (2023) reviewed several machine learning algorithms for heart disease prediction, including Support Vector Machine (SVM), Logistic Regression (LR), K-Nearest Neighbors (KNN), Naïve Bayes (NB), Neural Network (NN), and Decision Tree (DT). The authors compared these algorithms based on their features and prediction performance and found that machine learning can assist doctors in the early detection of heart disease [9]. The study also concluded that existing models achieve only moderate prediction accuracy and suggested that more advanced and efficient machine learning models are needed to improve early diagnosis while reducing cost and computational complexity.

M. Einollahi Asgarabad (2026) evaluated 13 machine learning algorithms for heart disease prediction using a balanced dataset containing 14 clinical features. The results showed that tree based models, especially Random Forest, achieved the highest accuracy and reliability, while XGBoost, LightGBM, Extra Trees, and Decision Tree also performed well [10]. The study highlighted that feature analysis and ensemble learning improve both prediction accuracy and model interpretability, making these approaches useful for early heart disease detection and clinical decision support. However, the authors noted that the relatively small integrated dataset may limit the generalizability of the results.

Walia et al. (2026) proposed a soft voting ensemble model using Random Forest, Decision Tree, and Support Vector Machine for heart disease prediction and improved both accuracy and interpretability [11]. The model achieved high prediction performance by combining multiple classifiers, while SHAP and LIME explained how important features such as chest pain type (cp), thal, ca, and oldpeak influenced the prediction. The study concluded that combining ensemble learning with explainable AI can provide reliable and clinically meaningful heart disease prediction, making the system more transparent and useful for healthcare applications.

C. Legeret et al. (2021) explained how machine learning can be used to predict heart disease by analyzing the importance of different patient features and their relationship with disease risk [12]. The authors used tree diagrams, confusion matrices, ROC curves, and SHAP explanations to make the prediction process more understandable, including analyzing how different features affect heart disease risk in men and women. The study concluded that combining machine learning with SHAP based explanations improves prediction transparency and can support early diagnosis and better clinical decision making.

S. D. Dhandapani et al. (2025) focuses on improving heart disease detection using ECG signals and deep learning techniques. It explains that cardiovascular diseases are a major cause of death worldwide, and early diagnosis is very important for better treatment and lower healthcare costs. Since ECG interpretation is usually done by medical experts, it can sometimes lead to human errors and variability. To overcome this, the authors propose a hybrid deep learning approach based on artificial neural networks (ANN) that can automatically detect heart disorders with reduced computational complexity. The model is trained using an ECG heartbeat dataset from Kaggle and shows better performance compared to existing methods. [13] The results demonstrate high accuracy and strong performance metrics, including 93.6% accuracy and good sensitivity and scalability. Overall, the study concludes that ANN based systems can provide reliable and efficient heart disease prediction and can be useful in real medical applications

H. El-Sofany et al. (2024) focuses on improving early prediction of heart disease using machine learning techniques on medical datasets. It highlights that accurate detection of heart disease is very important for timely treatment, but continuous monitoring by doctors is not always possible. To solve this problem, the authors use machine learning models to support medical decisionmaking based on patient data. [14] They apply different feature selection methods such as chi-square, ANOVA, and mutual information to identify the most useful features for prediction. Multiple algorithms including SVM, XGBoost, decision trees, bagging, and random forest are tested using both public and private datasets, along with SMOTE to balance the data. The results show that XGBoost performs best with high accuracy and strong evaluation scores. The study also integrates SHAP based explainable AI to help understand model predictions and improve trust in the system. Overall, the proposed approach provides an effective and interpretable solution for early heart disease detection and can support mobile based healthcare applications

R. Agrawal et al. (2025) focuses on improving disease prediction in healthcare by using machine learning models along with explainable AI techniques. It highlights that many AI systems are not widely trusted in medical practice because their decision making process is not clear, which creates a “black box” problem.[15] To solve this, the authors propose a hybrid framework that combines multiple machine learning algorithms such as Decision Trees, Naive Bayes, Random Forest, and XGBoost for predicting diseases including heart disease and other conditions. The system also uses

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explainable AI methods like SHAP and LIME to show which features influence the predictions, making the results easier for doctors to understand. The model achieves very high accuracy of about 99.2% and improves transparency and trust in AI based healthcare systems. Overall, the study shows that combining prediction models with explanation tools can help doctors make better and more reliable clinical decisions

Md. M. Ali et al. (2021) focuses on using machine learning methods to improve early detection of heart disease, which is often difficult due to limited medical expertise and misdiagnosis in many regions. The authors explain that clinical decision making can be supported by analyzing digital patient records using different machine learning models. Several supervised algorithms such as K-Nearest Neighbors (KNN), Decision Tree (DT), and Random Forest (RF) were tested and compared for performance. Feature importance was also analyzed to identify the most useful factors for prediction.[16] The results show that the Random Forest model performed the best, achieving very high accuracy along with perfect sensitivity and specificity on the dataset. Overall, the study concludes that simple machine learning models can effectively support accurate and early heart disease prediction in healthcare systems.

C.-Y. Ma et al. (2024) focuses on predicting the risk of coronary heart disease (CHD) in patients with diabetes using artificial intelligence and machine learning techniques. It explains that diabetes can lead to serious complications like CHD, which is a major cause of death worldwide, so early risk detection is very important. The researchers analyzed data from more than 300,000 diabetes patients in southwest China and studied different types of health information, including demographic data, medical test results, and lifestyle factors [17]. They applied machine learning models such as XGBoost, Random Forest, and Logistic Regression to predict disease risk and identified key important features like age, BMI, smoking, and drinking habits. The results showed moderate predictive performance with an AUC of 0.701, indicating that the model can help in early warning and prevention of CHD in diabetic patients.

D. Bertsimas et al. (2021) highlighted that heart disease often goes unnoticed until severe events occur, making early detection critical. Recent advances show that machine learning can analyze digital ECGs to spot anomalies quickly. In this study, researchers used nearly 40,000 ECGs labeled by cardiologists from multiple hospitals and countries to train models with the XGBoost algorithm. The system can classify seven types of signals (Normal, AF, Tachycardia, Bradycardia, Arrhythmia, Other, or Noisy) in under 30 milliseconds, achieving very high F1 scores (0.93–0.99) [18]. This work is notable because it demonstrates consistent performance across diverse hospitals, countries, and recording standards, highlighting the potential of machine learning for real time heart anomaly detection.

L. Kanisettypalli et al. (2026) shows that combining traditional statistical tests with machine learning can make heart disease prediction both more accurate and easier to understand. Researchers used two datasets the Framingham Heart Study (4,240 samples) and Heart Failure Clinical Records (299 samples)and applied t-tests, chi-square tests, and correlation analysis to pick out the most important features. [19]. This improved the accuracy of Support Vector Machines from 0.58 to 0.72 in the Heart Failure dataset, while keeping accuracy at 0.84 in the Framingham dataset. They also found gender specific effects of BMI and education on heart disease risk, confirming or challenging existing clinical beliefs. To make the results practical, they built an interactive tool for real world use, showing that hypothesis driven feature selection can highlight meaningful medical insights while keeping models simple and effective.

Gopalakrishnan et al. (2023) introduces a deep learning based heart disease prediction system using Convolutional Neural Networks (CNNs) to enhance diagnostic accuracy compared to traditional machine learning methods [20]. The proposed approach integrates preprocessing, segmentation, feature extraction, and CNN classification to analyze patient medical data, enabling precise detection of cardiovascular conditions. Experiments using datasets from Kaggle and other healthcare sources demonstrated that the CNN model significantly outperforms Support Vector Machine (SVM) and Recurrent Neural Network (RNN) algorithms, achieving up to 96% prediction accuracy with lower error rates. Although CNNs required higher computational time than other models, their predictive performance proved superior, highlighting their potential for early detection and intervention in heart disease. The study concludes that deep learning techniques, particularly CNNs, can provide reliable decision support systems in healthcare, aiding physicians in timely and accurate diagnosis of cardiac conditions.

III. DATASET

The UCI Cleveland Heart Disease Dataset is a widely used medical dataset for heart disease prediction. It contains patient information such as age, sex, chest pain type, blood pressure, cholesterol level, ECG results, maximum heart rate, and other clinical features. The dataset includes 303 patient records with 13 input attributes and one target variable indicating the presence or absence of heart disease. It is commonly used for machine learning classification tasks and helps

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researchers develop and evaluate predictive models for early heart disease detection. In this project, the dataset is used to train and compare different machine learning algorithms for accurate risk prediction.[21]

IV.METHODOLOGY

The proposed AI-Powered Heart Disease Prediction System follows a structured machine learning and Explainable AI (XAI) pipeline designed to support accurate, transparent, and clinically interpretable decision-making. The methodology integrates data preprocessing, model development, evaluation, and deployment through a web-based interface, ensuring an end-to-end healthcare decision support system. The complete workflow is divided into several stages as described below.

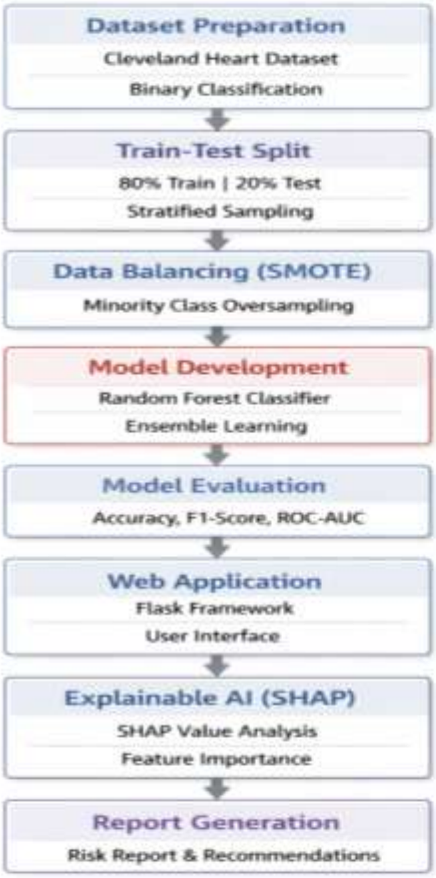

Figure 1: End-to-End Workflow of the System

A. Dataset Preparation

The system uses the Cleveland Heart Disease dataset, a widely accepted benchmark in cardiovascular research. The dataset was carefully analyzed and preprocessed to ensure consistency and reliability. The target variable was converted into a binary classification format, where "0" represents the absence of heart disease and "1" represents the presence of heart disease. All relevant clinical attributes, including age, sex, chest pain type, resting blood pressure, cholesterol level, maximum heart rate, and other diagnostic indicators, were retained as input features. This transformation framed the problem as a binary classification task suitable for machine learning models.

B. Train-Test Split

To evaluate model generalization, the dataset was divided into training and testing subsets using an 80:20 ratio. Stratified sampling was applied to preserve the original class distribution across both sets. This ensures that both positive (heart disease) and negative (no heart disease) cases are proportionally represented, reducing bias and improving the reliability of performance evaluation.

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C. Data Balancing using SMOTE

Medical datasets are often imbalanced, which can negatively impact model learning. To address this issue, Synthetic Minority Oversampling Technique (SMOTE) was applied to the training dataset. SMOTE generates synthetic samples for the minority class instead of duplicating existing data, thereby improving class balance. This step enhances the model's ability to correctly identify heart disease cases and reduces bias toward the majority class.[22]

D. Model Development

The prediction model is built using the Random Forest Classifier, an ensemble learning technique that combines multiple decision trees and uses majority voting for final prediction. Random Forest is selected due to its ability to handle nonlinear relationships, robustness to overfitting, and strong performance in medical classification tasks. The model learns patterns from patient clinical attributes such as cholesterol level, blood pressure, chest pain type, and maximum heart rate to predict heart disease risk effectively.

E. Model Evaluation

The performance of the trained model is evaluated using multiple metrics, including Accuracy, F1-score, and ROC-AUC. Accuracy measures overall correctness, F1-score balances precision and recall, and ROC-AUC evaluates the model's ability to distinguish between classes across different thresholds. The combined evaluation ensures a comprehensive assessment of model performance in a clinical context.

F. Web Application Development

The trained machine learning model is deployed using the Flask web framework to create an interactive healthcare application. The system provides user authentication, patient registration, medical data input, prediction generation, and report visualization. The workflow begins with secure user login, followed by patient detail entry. Clinical parameters are then submitted to the prediction engine, where the trained model computes the probability of heart disease and classifies the patient into Low, Moderate, or High risk categories. The results are displayed on a dedicated result page along with visual explanations.

G. Explainable AI Integration using SHAP

To enhance transparency and interpretability, SHAP (SHapley Additive exPlanations) is integrated into the system. SHAP values are computed using TreeExplainer for the trained Random Forest model to quantify the contribution of each feature toward the final prediction. Positive SHAP values indicate increased risk, while negative values indicate reduced risk. A waterfall plot is generated for each patient, providing a local explanation of how individual features influence the prediction outcome. Additionally, SHAP outputs are converted into simple English explanations, making the system more understandable for both patients and healthcare professionals.

H. Report Generation

The final stage of the system is report generation, which provides a comprehensive and patient-friendly summary of the prediction. The report includes patient details, predicted risk percentage, risk category, a plain English SHAP explanation with appropriate feature selection that highlights only modifiable features such as cholesterol, blood pressure, or lifestyle factors. Based on the predicted risk level, personalized recommendations and a clinical advisory note are generated to support informed decision-making and encourage medical consultation.

VI. EXPERIMENTAL RESULTS

A. Model Performance

TABLE I: Model Performance on Test Set

Model	Acc	Precision	Recall	F1Score	ROC-AUC
RF	96.10	95.33	97.14	96.23	98.50

Table I show the Random Forest model demonstrated excellent predictive performance for heart disease risk assessment. It achieved an accuracy of 96.10%, meaning it correctly classified most patients. Precision was 95.33%, showing that when the model predicted heart disease, it was almost always correct. Recall reached 97.14%, indicating its strong ability to detect actual cases of heart disease. The F1-Score of 96.23% reflects a balanced trade off between precision and recall. Finally, the ROC-AUC score of 98.50% confirms the model's outstanding capability to distinguish between patients with and without heart disease, making it highly reliable for clinical decision support.

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B. AUC-ROC Curve

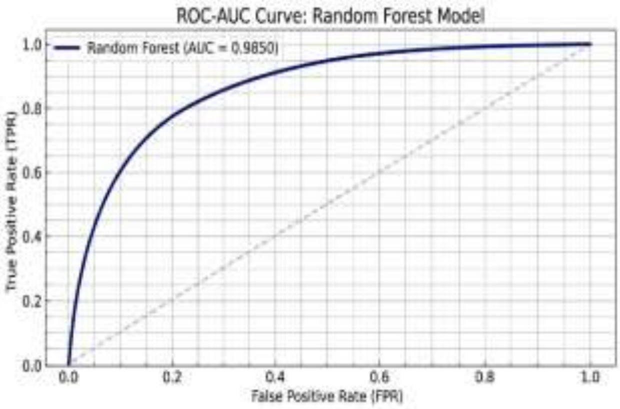

Figure 2:ROC-AUC Curve

Figure 3 Show the Receiver Operating Characteristic (ROC) curve for Random Forest model. By plotting the True Positive Rate against the False Positive Rate, the graph visually represents the model's ability to detect heart disease accurately. The curve's aggressive arch toward the upper left corner signifies highly efficient classification thresholds. With an outstanding Area Under the Curve (AUC) score of 98.50%, the Random Forest model minimizes dangerous false negatives while keeping false alarms exceptionally low, proving its reliability as a diagnostic screening tool.

D. SHAP Explainability Graph

Figure 4: After Prediction SHAP Graph

Figure 4 shows a sample SHAP output for a patient predicted as HIGH RISK. Unlike a simple graph, the waterfall chart explains how each individual feature contributes to the prediction for a single patient.

In this figure, red bars represent features that increase the probability of heart disease, while blue bars represent features that decrease the predicted risk. The length of each bar indicates the strength of that feature's contribution.

Features such as number of major vessels (ca), resting blood pressure (restbps), and thalassemia type (thal) have strong positive SHAP values, meaning they increase the predicted risk. In contrast, features like maximum heart rate (thalach) and cholesterol level (chol) have negative SHAP values, indicating they reduce the risk. The right side displays the Heart Disease Prediction Report, where the patient is classified as High Risk with a 98.42% probability.

Overall, the waterfall chart clearly demonstrates how the model arrives at its prediction by combining the influence of patient features. Instead of providing only a risk percentage, the SHAP explanation enables doctors and patients to understand which clinical factors are primarily responsible for the High Risk prediction, making the AI system more transparent, interpretable, and suitable for clinical decision support.

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VII. LIMITATIONS AND FUTURE WORK

The proposed system was developed using the Cleveland Heart Disease dataset, which contains a limited number of patient records. As a result, the model may not fully represent all patient populations. The prediction results also depend on the accuracy of the medical information entered by the user, and incorrect inputs may affect the outcome. The system is intended to support decision making and should not replace professional medical diagnosis. Although SHAP improve transparency. In addition, the system uses only the features available in the dataset and focuses solely on heart disease prediction.

Future work can focus on training the system with larger and more diverse medical datasets to improve prediction performance and reliability. Additional explainable AI techniques can also be integrated to provide deeper insights into prediction results. An AI-powered chatbot may be added to explain risk factors, SHAP results, and recommendations in simple language. The system can also be enhanced through real time health monitoring using wearable devices, more personalized recommendations, and integration with hospital information systems. Furthermore, the platform can be expanded to predict other diseases such as diabetes, stroke, and hypertension, making it a more comprehensive healthcare decision support system.

VIII. CONCLUSION

This research proposed an ai-powered heart disease prediction framework that integrates machine learning and explainable artificial intelligence for accurate and transparent clinical decision support. the uci cleveland heart disease dataset was preprocessed using train-test splitting, smote, and machine learning models were evaluated using accuracy, precision, recall, f1-score, and roc-auc metrics. among the evaluated models, random forest achieved the best performance with an accuracy of 96.10% and a roc-auc score of 98.50%, making it the selected prediction model. to address the black box problem, shap Explainability was incorporated to provide patient specific feature contributions through waterfall visualizations and simple English explanations. the integration of explainable predictions, probability based risk assessment, and personalized recommendations makes the proposed framework a reliable and interpretable tool for early heart disease risk prediction and clinical decision support.

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