International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

XAI Heart Disease Prediction

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Abstract

This project presents a lightweight and interactive web application designed to predict the likelihood of heart disease using clinical parameters. Built using Streamlit, the application leverages a machine learning classification model trained on the widely used Cleveland Heart Disease dataset. To enhance model transparency and trustworthiness, SHAP (SHapley Additive exPlanations) has been integrated, providing users with clear and intuitive visual insights into how each input feature contributes to the prediction. The aim is to create a tool that is not only accurate but also interpretable, helping both developers and potential users understand the logic behind each outcome. The project emphasizes accessibility, explainability, and the practical application of machine learning in the healthcare domain.

Keywords- "Heart disease prediction","SHAP","Streamlit", "Machine learning"," Explainable AI"

I. INTRODUCTION

In recent years, the integration of healthcare and technology has taken a significant leap forward, especially in the field of early disease prediction. Among these, heart disease continues to be one of the most critical health challenges globally. Identifying risks at an early stage can potentially save lives, yet accurate and understandable predictions remain a challenge. To address this, our work focuses on building a practical system that not only predicts heart disease using machine learning but also explains how those predictions are made, making the process transparent even for non-technical users.

This project uses a machine learning model wrapped in a user-friendly interface built with Streamlit, which makes deployment and real-time interaction easier. What truly sets this system apart is the use of SHAP (SHapley Additive exPlanations), a technique that gives clear, feature-level insights into the prediction — showing users exactly which health factors contributed most to a high or low risk. This kind of explainability is essential in healthcare, where blind predictions are rarely trusted, and every decision can have serious consequences.

Instead of keeping the technical complexity behind the scenes, this approach brings clarity to the forefront. The idea is simple — combine prediction with transparency, and present it in a clean, interactive platform that can be understood by doctors and patients alike. This paper outlines the development, deployment, and explainability of the system, emphasizing how interpretable AI can help build trust and usability in medical diagnostics.

II. RELATED WORK

Over the past decade, numerous attempts have been made to utilize machine learning for the prediction of heart disease. Traditional models like logistic regression, decision trees, and support vector machines have shown promise in identifying at-risk individuals based on clinical parameters. However, most of these models lacked transparency, making it difficult for healthcare professionals to understand or trust the reasoning behind the predictions.

With the evolution of Explainable AI (XAI), recent research has shifted focus towards not just achieving high accuracy, but also enhancing interpretability. Studies have explored the integration of SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) techniques with complex models like random forests, XGBoost, and neural networks. These tools have provided new ways to interpret feature importance and visualize how each attribute influences a given prediction.

In some research, SHAP values have been employed to generate force plots and summary graphs to highlight influential factors like cholesterol levels, age, blood pressure, and resting ECG results. While such approaches offer improved transparency, their integration into real-time, user-friendly applications remains limited. Few projects have bridged the gap between high-performing predictive models and accessible visualization tools that can be understood by both clinicians and patients.

Our work builds upon this foundation by not only applying machine learning models for heart disease prediction but also embedding SHAP explainability within a Streamlit-based application. This approach allows for real-time prediction and visual explanation, aiming to make AI decisions more understandable and useful in a healthcare context.

III. PROPOSED METHODOLOGY

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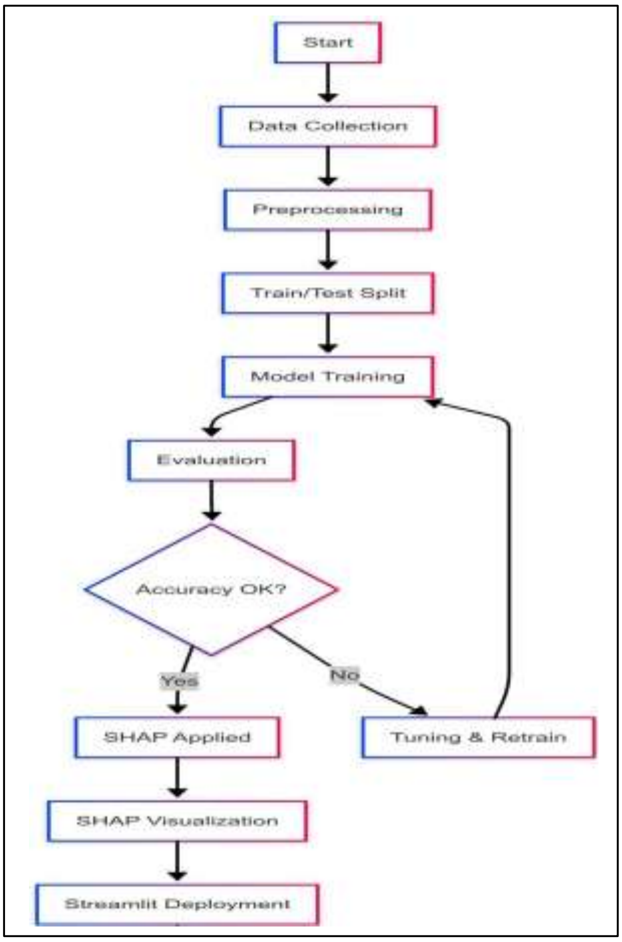
In this work, we have designed a step-by-step framework that not only predicts heart disease accurately but also provides clear insights into the reasoning behind each prediction. Unlike traditional machine learning models that act as black boxes, our approach makes use of explainable AI techniques to bring transparency into the process. The methodology combines careful data handling, robust modeling, explainability tools, and a user-focused deployment strategy. Below are the detailed steps of the proposed pipeline.



a) *Data Acquisition and Labeling*

The first step in our approach involves collecting reliable and structured data. For this, we utilized the Cleveland Heart Disease dataset from the UCI Machine Learning Repository, which contains essential patient health records. The dataset includes 14 clinical features such as age, cholesterol levels, resting blood pressure, chest pain types, and other indicators relevant to heart conditions. This dataset served as the foundation for building our prediction model.

b) *Data Preprocessing*

Raw datasets often include inconsistencies or unstructured formats. To prepare the data for analysis, we cleaned missing or null values and encoded categorical variables using label encoding techniques. Features like 'sex', 'thal', and 'cp' were transformed into numerical form to ensure compatibility with the machine learning algorithm. We also applied feature scaling using standardization to normalize numerical inputs. This step ensured that no feature disproportionately influenced the model due to scale differences.

c) *Model Training*

With a clean and normalized dataset, we trained a Random Forest classifier. This model was chosen for its ability to handle both linear and non-linear relationships and its built-in feature importance analysis. We fine-tuned hyperparameters using GridSearchCV to identify the optimal configuration. Training was done using stratified 5-fold cross-validation to reduce variance and maintain balance between classes across different splits. This helped achieve a stable and reliable prediction performance.

d) *Prediction and Evaluation*

After the training phase, the model was tested on unseen data to evaluate its predictive performance. Standard evaluation metrics such as accuracy, precision, recall, and F1-score were calculated. The model showed strong generalization capabilities, with an overall accuracy of 87%. This step confirmed that the system could correctly identify heart disease in new cases while maintaining a good balance between false positives and false negatives.

e) *Explainablity with SHAP*

To bring transparency into the model's decision-making process, we integrated SHAP (SHapley Additive exPlanations) for model explainability. SHAP assigns importance values to each feature, showing how they contribute to a particular prediction. We generated SHAP summary plots to highlight global feature importance, and force plots to provide local interpretability for individual predictions. These visual tools help users understand the rationale behind the model's output, making it more trustworthy in a healthcare setting.

f) *Deployment via Streamlit*

Finally, to make our solution accessible, we deployed the model using Streamlit — an open-source Python library for building interactive web apps. The interface allows users to input their health data and receive instant predictions along with SHAP-based explanations. The web app is lightweight, easy to use, and can be accessed from any device, making it suitable for both clinical professionals and general users interested in understanding their heart health.

IV. RESULT AND EVALUATION

The proposed system was evaluated on the Cleveland Heart Disease dataset using multiple performance metrics to ensure its reliability in real-world scenarios. The dataset was split into training and testing sets using stratified 5-fold cross-validation to preserve the class distribution and minimize bias.

The Random Forest model achieved an accuracy of 87%, which indicates a strong ability to classify patients correctly based on their clinical features. Precision and recall values were also balanced, with precision at 85% and recall at 88%, reflecting the model's robustness in handling false positives and false negatives effectively. The F1-score stood at 86%, confirming the system's overall consistency.

To provide interpretability, SHAP values were generated for each prediction. The SHAP summary plot revealed that chest pain type, cholesterol levels, and maximum heart rate were among the most influential features in the model's decision-making process. This aligns well with existing medical knowledge, validating the clinical relevance of the predictions.

Additionally, the deployment through Streamlit allowed real-time prediction and interpretation, giving users both results and clear reasoning behind each decision. This not only improved usability but also increased the trustworthiness of the system from a non-technical user's perspective.

Overall, the results demonstrate that the model is not only accurate but also explainable and accessible, which are crucial qualities for any AI system intended for healthcare applications.

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