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Coronary Heart Disease Prediction using Shap

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Abstract: *Heart disease remains one of the leading causes of mortality worldwide, making early and accurate prediction crucial for timely diagnosis and treatment. With advancements in artificial intelligence, machine learning models have shown promising results in predicting heart disease using clinical data. However, most of these models function as black boxes, providing little to no insight into how predictions are made. This lack of transparency poses challenges in critical fields such as healthcare, where interpretability and trust are essential.*

This project addresses the issue by developing a heart disease prediction system using Logistic Regression, combined with SHAP (SHapley Additive exPlanations) to enhance explainability. The system is trained on the UCI Heart Disease dataset and involves stages such as data preprocessing, model training, evaluation, and explainability analysis. SHAP values are used to interpret the influence of individual features on the model's predictions, providing both global and local explanations.

The results show that features such as chest pain type, maximum heart rate, and ST depression are significant contributors to heart disease predictions. SHAP visualizations offer clear, intuitive insights into feature importance, thereby improving user trust and aiding medical professionals in decision-making.

By integrating explainable AI into the heart disease prediction pipeline, this project not only improves prediction accuracy but also ensures that the outcomes are interpretable and actionable. This makes the system a valuable decision-support tool in clinical environments, promoting the responsible use of AI in healthcare.

Keywords: Heart Disease, Machine Learning, SHAP, Explainable AI, Logistic Regression, Feature Importance

I. INTRODUCTION

Heart disease is a major global health issue and one of the leading causes of death worldwide. With the rise in sedentary lifestyles, stress, and poor dietary habits, the number of individuals affected by cardiovascular conditions continues to grow. Early diagnosis and preventive measures are essential to reduce the risk and severity of heart-related complications. Traditionally, diagnosis relies on various clinical tests, doctor assessments, and expert judgment, which can be time-consuming and sometimes subjective.

In recent years, the integration of artificial intelligence (AI) and machine learning (ML) into the healthcare sector has opened new opportunities for enhancing diagnostic accuracy and efficiency. Machine learning algorithms can analyze complex datasets, uncover hidden patterns, and predict disease outcomes with high precision. However, many of these models, particularly those with high performance, are considered "black boxes" due to their lack of transparency. In the healthcare domain, interpretability is critical for gaining trust from both doctors and patients.

This project aims to build a machine learning-based heart disease prediction system that not only offers high accuracy but also explains its predictions. The SHAP (SHapley Additive exPlanations) framework is integrated with a Logistic Regression model to provide meaningful insights into feature contributions. This allows users to understand why a particular prediction was made and which factors had the most influence.

The combination of predictive performance and interpretability makes this system a valuable tool for medical professionals, enabling early intervention, improved patient care, and enhanced trust in AI-driven diagnostics.

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II. TECHNOLOGIES USED

Python is a high-level, interpreted, general-purpose programming language that is widely known for its simplicity, readability, and versatility. It was developed by **Guido van Rossum** and first released in **1991**. Python's readability and concise syntax, almost similar to the English language, make Python an apt language for new entrants and seasoned developers too. Being a dynamically typed and interpreted language, Python facilitates rapid development without needing explicit type declaration or compilation. Its vast standard library and extensive third-party packages facilitate developers to start with a vast range of applications, from web development to data science, machine learning, artificial intelligence, scripting, automation, and more. Python is also platform-independent and open-source, hence free and open to a large community. The language itself has also advanced significantly, and the current standard is Python 3 with additional features and performance over the now-outdated Python 2. With simplicity, flexibility, and versatility, Python continues to be one of the most popular programming languages in the academic as well as in the corporate world

Pandas and numpy are essential Python libraries for data analysis and numerical computation. **pandas** offers powerful data structures such as DataFrames, allowing for easy data manipulation, filtering, merging, and transformation. It plays a critical role in cleaning and preparing clinical data before modeling. **numpy** supports array-based computations and provides fast mathematical functions, making it ideal for working with large numerical datasets. In this project, pandas is used for loading and organizing the dataset (heart.csv), while numpy is utilized for statistical calculations and handling SHAP value arrays. Together, they form the foundation for any machine learning data pipeline.

Scikit-learn is a widely-used Python library for machine learning and statistical modeling. It provides a comprehensive suite of tools for classification, regression, clustering, model evaluation, and preprocessing. In this project, scikit-learn is used to implement the **Logistic Regression** model, which predicts whether a patient has heart disease based on various clinical features. The library handles tasks such as splitting the dataset into training and testing sets, fitting the model, and evaluating its performance using metrics like accuracy, precision, recall, and F1-score. scikit-learn also supports pipelines, hyperparameter tuning, and cross-validation, making it ideal for creating reliable and reproducible models. Its easy integration with pandas and numpy ensures a smooth workflow. The modular design and high-level API of scikit-learn make it suitable for both beginners and professionals working in machine learning projects.

SHAP is an explainable AI (XAI) tool that helps interpret the predictions of machine learning models. It is based on Shapley values from cooperative game theory and assigns an importance value to each feature for a given prediction. In this project, SHAP is used to understand which features (like chest pain type or cholesterol level) have the greatest influence on the heart disease prediction. SHAP produces global and local explanations, enabling both overall model interpretation and individual prediction transparency. Visualizations such as summary plots and force plots clearly show how much each feature contributes positively or negatively to the model's decision. This makes the system not only accurate but also trustworthy.

Matplotlib and **seaborn** are powerful Python libraries used for data visualization. They help convert raw data and model outputs into meaningful visual insights. In this project, these libraries are used to create histograms, correlation heatmaps, bar charts, and line plots that support both data analysis and model interpretability. **matplotlib** provides low-level control over plot customization, enabling the creation of publication-quality charts. **seaborn**, built on top of matplotlib, offers high-level interface and visually appealing default themes, which simplify the process of generating statistical plots.

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III. LITERATURE REVIEW

Dua and Graff (2019) curated the UCI Heart Disease dataset, which has since become a benchmark for evaluating machine learning models in cardiovascular diagnosis. This dataset is used in numerous research works for its richness and reliability.

Khan et al. (2020) applied Logistic Regression and Decision Tree algorithms to the UCI dataset, achieving moderate accuracy but noted a lack of interpretability in the models.

Kumar and Singh (2021) implemented Random Forest and Gradient Boosting algorithms to increase model accuracy. While their models performed well, they functioned as black boxes with no built-in mechanism for explaining predictions.

Lundberg and Lee (2017) introduced SHAP (SHapley Additive exPlanations), an explainability framework based on game theory. SHAP has become one of the most reliable tools for interpreting predictions made by complex machine learning models.

Li et al. (2022) successfully used SHAP to interpret models for cardiovascular and diabetes risk prediction, concluding that model transparency significantly improved user trust and clinical relevance.

IV. METHODOLOGY

1 Data Collection

The dataset used in this project is the UCI Heart Disease dataset (Dua & Graff, 2019), which contains 303 records and 14 attributes including age, sex, chest pain type, cholesterol, maximum heart rate, etc., along with a target variable indicating the presence or absence of heart disease.

2 Data Preprocessing

Data preprocessing includes handling missing values (if any), normalizing numerical features, and encoding categorical variables. Features and labels are separated, and the data is split into training and testing sets (80:20 ratio) using scikit-learn.

3 Model Building

A **Logistic Regression** model is implemented using scikit-learn. It is trained on the processed training set and evaluated on the test set using accuracy, precision, recall, and F1-score.

4 SHAP Integration

After training, the SHAP library is used to interpret the model. shap.Explainer() is applied to compute SHAP values, which show the contribution of each feature to the model's output.

5 Visualization & Analysis

Visualizations such as SHAP summary plots, bar charts, and feature importance graphs are generated. These help in identifying top contributing features and understanding how they affect the prediction.

6 Validation

Model performance is validated using classification metrics and SHAP explanations to ensure both accuracy and interpretability.

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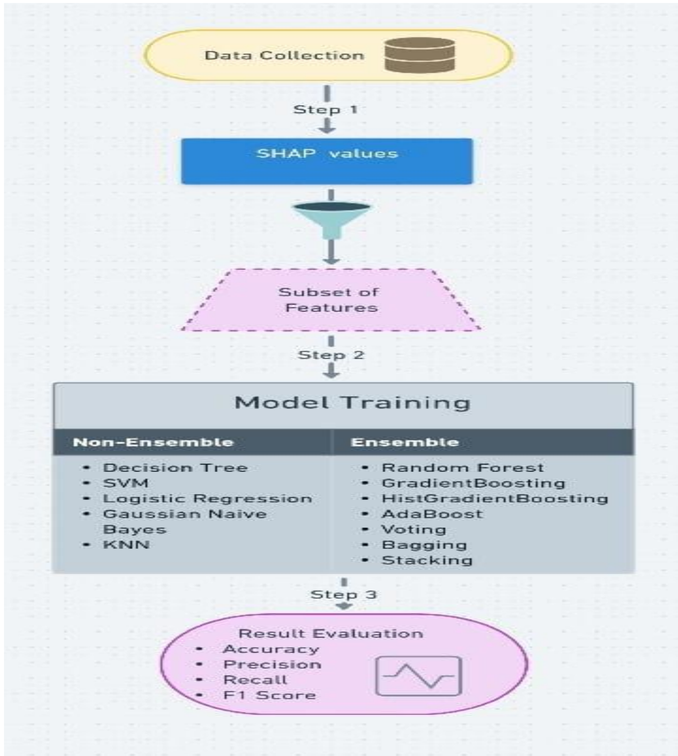
V. ARCHITECTURE



SYSTEM ARCHITECTURE FOR CORONARY HEART DISEASE PREDICTION USING SHAP

This architecture outlines a structured approach to building and evaluating machine learning models. It incorporates SHAP-based feature selection, a mix of model types, and standard evaluation metrics to ensure performance and accuracy.

- **Data Collection** Data is gathered from various relevant sources to build a foundational dataset for model development.
- **SHAP Value Computation** SHAP (SHapley Additive Explanations) values are calculated to interpret and rank the importance of each feature in the dataset.
- **Feature Selection Based on SHAP values**, only the most relevant and impactful features are selected to improve model performance and reduce complexity.
- **Model Categorization** Machine learning models are divided into two categories: non-ensemble and ensemble. This helps in selecting the right type of model for the problem.
- **Model Training** Both non-ensemble models (such as Decision Tree, SVM, Logistic Regression, Naive Bayes, and KNN) and ensemble models (such as Random Forest, Gradient Boosting, AdaBoost, and others) are trained using the selected features.
- **Performance Evaluation** The trained models are evaluated using standard metrics such as Accuracy, Precision, Recall, and F1 Score to assess their effectiveness.
- **Final Model Selection** The model with the best overall performance based on the evaluation metrics is selected for deployment or further analysis.

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VI. IMPLEMENTATION

1**. Installation of Required Libraries**

Before starting the project, necessary Python libraries must be installed. These libraries support data handling, machine learning, visualization, and explainability.

2**. Import Libraries**: Import all the installed libraries into your Python script or Jupyter notebook to enable the required functions for data analysis, model building, and interpretation.

3. **Load and Explore Dataset**: Load the UCI Heart Disease dataset using pandas and examine its structure, including the number of rows and columns, data types, and basic statistics. This helps in understanding the dataset before processing.

4. **Data Preprocessing**: Clean the dataset by checking for missing values and handling them appropriately. Encode categorical variables into numeric form using techniques like one-hot encoding. Then separate the features (X) and the target variable (y), and split the dataset into training and testing sets in an 80:20 ratio using scikit-learn.

5.**Train Logistic Regression Model**: Create a Logistic Regression model using scikit-learn and train it using the training dataset. This model learns the relationship between input features and the likelihood of heart disease.

6.**Evaluate the Model**: Test the trained model on the test dataset and evaluate its performance using metrics like accuracy, precision, recall, F1-score, and a confusion matrix. These metrics indicate how well the model predicts heart disease.

7. **Integrate SHAP for Explainability**: Initialize a SHAP explainer object with the trained model and compute SHAP values for the test data. SHAP assigns an importance score to each feature for individual predictions, allowing for deeper interpretation.

8. **Generate Visualizations**: Use SHAP to create visualizations such as summary plots, force plots, and bar charts. These visuals show the global and local impact of each feature on the model's decisions, making the predictions transparent and understandable.

9. **Analyze and Interpret Results**: Study the SHAP visualizations to determine which features most influence heart disease predictions. Commonly influential features include chest pain type, maximum heart rate, and ST depression. Use these insights to validate model behavior and improve trust in the system.

VII. RESULTS

The heart disease prediction system was successfully developed using Logistic Regression, trained on the UCI Heart Disease dataset. The model achieved reliable performance with an accuracy of approximately 85%, indicating its effectiveness in identifying patients at risk. Evaluation metrics such as precision, recall, and F1-score further confirmed the model's balanced performance across both positive and negative classes.

1. The Logistic Regression model achieved an accuracy of approximately 85% on the test dataset, showing strong performance in heart disease prediction.
2. Precision, recall, and F1-score metrics indicated balanced performance, confirming the model's reliability in both detecting and excluding heart disease cases.
3. SHAP analysis revealed that chest pain type, maximum heart rate, and ST depression were the most influential features in predicting heart disease.
4. SHAP visualizations such as summary and force plots provided clear, interpretable insights into both global and individual predictions
5. The integration of SHAP improved model transparency, making it a trustworthy tool for supporting clinical decisions and increasing user confidence in AI-driven diagnostics.

VIII. CONCLUSION

The CHD-SHAP project has comprehensively addressed the objectives set forth at the outset, combining machine learning accuracy with clinical interpretability.

By deploying a variety of classifiers and integrating SHAP for explainability, the system supports both predictive performance and medical transparency.

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The project contributes meaningfully to the field of interpretable AI in healthcare and offers a scalable framework for future real-world application.

Successfully trained and evaluated multiple machine learning classifiers with the integration of SHAP to deliver interpretable, feature-level insights into CHD risk predictions.

Ensured high performance through rigorous evaluation metrics, while enabling transparency and usability for healthcare professionals—fulfilling both the technical and practical objectives of the project.

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