International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 03 | March - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

# Real-Time Data Integration and Analysis for Heart Disease Prediction Using Machine Learning

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***Abstract*—The " Heart Disease Risk Assessment Web App" is a cutting-edge web application that uses sophisticated machine learning techniques to deliver individualized cardiovascular risk information. The app uses information from the Behavioral Risk Factor Surveillance System (BRFSS) 2022 to determine personalized risk scores and provide useful advice based on user inputs including age, BMI, physical activity, smoking status, and medical history. While SHAP (SHapley Additive exPlanations) improves transparency by clarifying feature relevance, the app uses advanced models, such as Easy Ensemble with LightGBM, to handle class imbalance and guarantee reliable predictions. With the help of Streamlit, the software effectively reduces the risk of heart disease and encourages proactive health management by fusing accuracy, accessibility, and user interaction to provide people with useful information.**

***Keywords*—health evaluation,heart disease, cardiovascular health,SHAP,Simple Ensemble Classifier Model LightGBM,Streamlit,BRFSS dataset,Individualized health advice,Handling class imbalance**

## I. Introduction

Heart disease is still one of the main causes of morbidity and death globally, creative methods of early identification and prevention are required. Conventional techniques for determining cardiovascular risk frequently depend on recurring clinical evaluations, which not everyone can obtain. Furthermore, these approaches might not be able to offer individualized insights based on a person's particular health profile. The "Heart Disease Risk Assessment Web App" fills this knowledge gap by offering a state-of-the-art solution that uses machine learning to provide precise, customized risk assessments, enabling users to take charge of their heart health.

The app uses data from the Behavioral Risk Factor Surveillance System (BRFSS), a large and detailed resource that includes health-related information on Americans. The app determines the main risk factors for heart disease by combining demographic, lifestyle, and medical history data, including age, gender, BMI, physical activity levels, smoking status, and history of chronic illnesses. To overcome issues like class imbalance and increase prediction accuracy, sophisticated machine learning models are used, such as Easy Ensemble and LightGBM. By employing SHAP (SHapley Additive exPlanations) for feature importance analysis and hyperparameter tweaking, these models are further improved, guaranteeing reliable performance and openness in decision-making.

Streamlit, a lightweight and interactive framework, is used in the app's implementation to let users enter their health information and get immediate response. To encourage user engagement and comprehension, the app offers visual insights and practical recommendations in addition to personalized risk assessments. By bridging the gap between state-of-the-art technology and useful healthcare applications, the app's user-friendly design and evidence-based analytics make cardiovascular risk assessment more impactful, accessible, and intelligible for people looking to effectively manage their heart health.

## II. LITERATURE REVIEW

Researchers are looking into cutting-edge technologies for the early detection and prevention of heart disease due to its rising incidence. Because of their limited accessibility and dependence on clinical visits, traditional approaches frequently fall short. Adam and Mukhtar [1] shown how AI-powered applications may use clinical and demographic data to predict heart health. Similar to this, Ali et al. [2] stressed the application of hybrid machine learning techniques to enhance prediction accuracy, with an emphasis on efficiently managing unbalanced datasets. Arefin [3] illustrated how AI-powered apps may be used to manage chronic illnesses and how they can offer useful information to enhance patient outcomes.

By merging several weak learners, Bhatt et al. [4] showed how effective ensemble techniques like Random Forest and XGBoost are at improving prediction accuracy. In a comparative analysis of machine learning algorithms, Katarya and Meena [5] found that gradient boosting strategies frequently perform better than others because of their capacity to manage non-linear connections. highlighted how crucial feature selection and dimensionality reduction are to improving model performance without sacrificing interpretability [6]. Furthermore, Jindal et al. [7] emphasized how data preparation methods might increase the classification accuracy of models used to predict cardiac disease. Research from IEEE [8] further proved the effectiveness of hybrid machine learning techniques for heart disease prediction, highlighting the need of mixing various algorithms for reliable predictions.

When implementing AI in healthcare, explainability and user accessibility are just as important as model performance. In order to ensure confidence and dependability, Shah et al. [9] emphasized the importance of interpretability tools like SHAP (SHapley Additive exPlanations), which offer insights into model decisions. In order to improve the accessibility of AI-powered applications and facilitate real-time interactions for both patients and physicians, Riyaz et al. [10] investigated user-friendly platforms such as Streamlit. Additionally, Khan et al. [11] talked about how AI and deep learning can be integrated into heart health apps, emphasizing how well they can handle big datasets. The "AI-Powered Heart Disease Risk Assessment App," which incorporates sophisticated ensemble algorithms [12], SHAP for transparency [13], and Streamlit for smooth user interaction, is well-founded on these discoveries taken together.

**SUMMARY OF LITERATURE SURVEY**.

The literature review emphasizes the note worthy developments in using machine learning to detect and treat cardiac disease. Researchers stress that in order to develop precise and scalable prediction models, it is critical to integrate behavioral, clinical, and demographic data. When dealing with complicated and unbalanced datasets, ensemble approaches like Random Forest, XGBoost, and hybrid strategies have shown higher performance. While preserving interpretability, feature selection and preprocessing methods further improve model accuracy. Furthermore, by guaranteeing openness in model predictions, methods such as SHAP promote user trust. Research also highlights the importance of easily navigable platforms, such as Streamlit, in offering interactive and real-time health insights. Together, these results support the necessity for all-encompassing, easily navigable, and interpretable AI solutions, which served as the foundation for the "Heart Disease Risk Assessment Web App."

## III. PROPOSED METHODOLOGY

### A. *Problem Statment*

Heart disease is a major cause of death worldwide, frequently as a result of delayed diagnosis and restricted access to individualized medical evaluations. There is a significant gap in preventative treatment since traditional diagnostic techniques are costly, time-consuming, and lack real-time, customized insights. Adoption of AI solutions in healthcare is further complicated by unbalanced datasets, restricted model interpretability, and a dearth of user-friendly tools. In order to effectively forecast the risk of heart disease, the “Heart Disease Risk Assessment Web App" uses sophisticated machine learning models, including ensemble approaches. The software makes health assessments accessible and actionable by integrating Streamlit for an intuitive user experience with SHAP for transparent decision-making. By offering individualized risk assessments and suggestions, the app encourages users to take charge of their cardiovascular health.

### B. *Objectives*

**1. Develop a Reliable and Accurate Risk Assessment Tool**
This project's main goal is to develop an AI-powered application that can accurately determine a person's risk of heart disease. The app guarantees a thorough assessment of cardiovascular risk by examining important health indicators including age, BMI, gender, physical activity levels, smoking status, and medical history. The goal is to create a highly accurate model that provides users with data-driven insights and performs better than conventional diagnostic techniques.

**2. Handle Class Imbalance in Medical Datasets**
Datasets on heart disease frequently show notable class imbalances, with considerably fewer high-risk instances than low-risk cases. Biased algorithms that perform poorly in identifying high-risk individuals may result from this imbalance. The project uses cutting-edge ensemble learning strategies like Easy Ensemble and LightGBM to overcome this difficulty. In order to increase the model's sensitivity and accuracy for underrepresented classes and guarantee fair and balanced predictions, these approaches include strategies like oversampling and boosting.

**3. Enhance Model Transparency and Interpretability**
The opaqueness of the prediction-making process is a major obstacle to the use of AI in healthcare. SHAP (SHapley Additive Explanations), a top interpretability tool in machine learning, is included into this project. The software helps users and clinicians understand the reasoning behind each risk score by clearly illustrating the significance of each feature, such as age, history of heart attacks, or smoking habits. This increases user confidence in the system and guarantees that the app's predictions provide users a sense of empowerment.

**4. Provide Personalized, Actionable Recommendations**
The program provides customized advice to reduce the evaluated risks in addition to risk scores. These include dietary modifications, quitting smoking, increasing physical

exercise, and recommending regular consultations with the doctor. The software guarantees that users have the necessary tools to enhance their cardiovascular health by matching these suggestions with the particular variables influencing a person's risk.

*C. Data Acquisition*

More than 400,000 adult records make up the BRFSS dataset, which records a variety of parameters such as medical history (heart disease, diabetes, stroke, and renal disease), lifestyle factors (physical activity, smoking, and drinking habits), and demographic information (age, gender, and race). It is perfect for creating a strong heart disease prediction model because of its variety of properties. Because the dataset was downloaded in CSV format, Python-based preprocessing and analysis tools could use it.

**1. Exploration and Understanding**

Investigating the composition and structure of the dataset obtained from the Behavioral Risk Factor Surveillance System (BRFSS) 2022 was the first stage in the data preparation procedure. More than 400,000 records with characteristics encompassing demographic, lifestyle, and medical history information were included in the collection. The project used codebooks and information from the Centers for Disease Control and Prevention (CDC) to better comprehend the variables, their encoded values, and their importance. Interpretability was improved by this documentation, which made it possible to link short labels, like _STATE or FMONTH, to their full descriptive names. In order to guarantee a clean and useable dataset for additional analysis, the exploration phase also found any discrepancies and missing values that needed to be fixed.

**2. Feature Selection**

Not every factor in the dataset was significant for predicting heart disease because of its wide range of variables. To determine which attributes had the strongest link with the goal variable, "Heart Disease," a methodical selection procedure was used. Based on their statistical significance and therapeutic relevance, variables like age, gender, BMI, physical activity levels, smoking habits, and past medical disorders (such as stroke, diabetes, or renal disease) were kept. To simplify the model and increase its efficiency, features that were not related to the prediction of heart disease or that had a lot of noise were eliminated. By ensuring that the model concentrated on significant predictors, this improved feature set improved the model's accuracy and interpretability.

**3. Data Cleaning**

A thorough data cleaning procedure was used to guarantee the dataset's dependability. Distribution-based imputation, which maintains the data's natural distribution and reduces biases induced during imputation, was used to address missing values. Unrealistic weight, height, or age values were among the incorrect entries that were found and either fixed or eliminated. To prevent redundancy, duplicate entries were removed, and standard representations of missing data (such NaN) were used in place of placeholder values like "999" or "N/A." The dataset's overall quality was raised by this thorough cleaning procedure, guaranteeing that the data used in further analyses was accurate and representative.

## IV. PROPOSED WORKFLOW

**1. Data Acquisition**

The Behavioral Risk Factor Surveillance System (BRFSS) 2022 dataset, a comprehensive compilation of health-related information collected from adults nationwide, serves as the project's basis. This dataset includes data on a variety of topics, such as medical history (e.g., history of diabetes, stroke, heart disease), lifestyle behaviors (e.g., smoking, alcohol consumption, physical activity), and demographics (e.g., age, gender, race). This dataset, which was obtained in CSV format, can be directly integrated with Python-based tools for data analysis and preprocessing. Its thorough coverage of risk factors guarantees a thorough study, enabling the app to learn from a wide and varied population sample and produce precise forecasts.

**2. Data Preprocessing**

Preparing the data for efficient machine learning analysis requires preprocessing. Cleaning the dataset by removing outliers, inconsistent data, and missing values is the first stage. Distribution-based imputation approaches, which preserve the inherent properties of the data without introducing appreciable bias, are used to handle missing values. Unrealistic and inaccurate entries—like inaccurate weight or age values—are found and either eliminated or fixed. To make sure the model concentrates on predictors that directly affect the risk of heart disease, feature selection is done to keep just the most pertinent variables, such as BMI, levels of physical activity, smoking status, and chronic health conditions.

**3. Machine Learning Model Development**

The creation of prediction models is at the core of the process. To create a reliable prediction system, a variety of sophisticated machine learning methods are used, such as Easy Ensemble, LightGBM, Random Forest, and Logistic Regression. When it comes to class imbalance, Easy Ensemble works especially well, guaranteeing that minority classes—such as those with a high risk of heart disease—are correctly anticipated. Optuna, an optimization framework that determines the ideal model parameter configuration to optimize performance, is used for hyperparameter tweaking. Metrics like precision, recall, F1-score, and ROC-AUC are used to evaluate the model and give information about how well it predicts the future. To guarantee that customers obtain accurate risk evaluations, the model with the best performance is chosen for deployment.

**4. Explainability with SHAP**

AI applications in healthcare require openness and confidence. The program uses SHAP (SHapley Additive Explanations), a cutting-edge interpretability tool that describes how each feature influences the model's predictions, to do this. For instance, SHAP can demonstrate how an individual's heart disease risk score is influenced by variables such as age, smoking status, or physical inactivity. By guaranteeing that users and medical professionals comprehend the reasoning behind each prediction, this degree of explanation increases system confidence. Users may easily grasp their results because to the application's integration of SHAP visualizations, such as feature significance plots

**5. Deployment**

Users no longer need to install complicated software because the program is hosted on the Streamlit sharing platform. Any device with an internet connection, including PCs, laptops, tablets, and smartphones, can access the app thanks to its cloud-based deployment. The platform is scalable for broad use because it is made to manage several user requests at once. Deployment also entails following privacy best practices, complying with healthcare standards, and putting security measures in place to safeguard user data.

## V. TECHNOLOGY

### *A. Programming Language and Libraries*

Python is the primary programming language used in this project because of its adaptability and the abundance of libraries available for web development, data science, and machine learning. Matplotlib and Seaborn are utilized for data visualization, while NumPy and Pandas are essential libraries for data manipulation and preprocessing. CatBoost effectively encodes categorical information, guaranteeing smooth integration with predictive models, while Scikit-learn offers crucial tools for putting machine learning methods into practice.

### *B. Machine Learning Frameworks*

The initiative uses LightGBM, which is renowned for its speed and effectiveness when working with big datasets, to construct the heart disease prediction models. By addressing class imbalance, Easy Ensemble enhances the model's performance in situations that are underrepresented. Optuna is used to optimize model settings for increased accuracy and dependability through hyperparameter adjustment. To improve transparency, SHAP (SHapley Additive Explanations) is incorporated, offering thorough explanations of the significance of each feature and the logic underlying each prediction.

### *C. UI Development*

Streamlit, a web framework built with Python, is used to create the application's user interface. Streamlit makes it possible to quickly develop dynamic and intuitive applications that let users enter their health information and get risk evaluations right away. Users can have a better understanding of their health state and the variables influencing their risk scores by using dynamic visualizations supported by the framework, such as feature importance charts and risk factor breakdowns.

### *D. Data Storage and Handling*

The "Heart Disease Risk Assessment Web App" stores and manages its dataset using CSV files, or Comma-Separated Values. Since CSV is a commonly used format for tabular data, many data analysis tools and libraries may use it. The Behavioral Risk Factor Surveillance System (BRFSS) 2022 provided the dataset, which is freely accessible on websites like Kaggle, guaranteeing user-friendliness and adherence to data-sharing regulations. Purchasing data from a reliable source, such as Kaggle, guarantees that the information is reliable, thoroughly documented, and includes metadata that helps interpret the variables' structure and meaning.

***Figures and Tables***

**System Architecture:**

The Heart Disease Risk Assessment Web App system architecture is modular in order to guarantee usability, scalability, and transparency. The user input layer of the architecture is where users enter their health information using a Streamlit interface. Preprocessing methods are used to handle missing values, encode categorical variables, and normalize continuous variables for consistency after the data has been verified for accuracy. This guarantees that the data supplied by the user is prepared for the machine learning models to analyze. Advanced models like LightGBM and Easy Ensemble, which were chosen for their effectiveness and capacity to rectify class imbalance, make up the machine learning layer. Based on the input features, these models produce a risk score that forecasts the probability of heart disease.

Through its deployment and feedback systems, the design also prioritizes efficiency and accessibility. Because it is hosted on a cloud-based platform through the Streamlit Sharing Platform, users may access the app without the need for installation from any internet-enabled device, including desktops, tablets, and smartphones. Scalability is guaranteed by this cloud setup, which can support numerous users at once without sacrificing efficiency. In order to improve model performance and optimize the interface, the architecture includes a feedback loop that analyzes user interactions and feedback. In order to improve accuracy and usefulness, this iterative process involves incorporating cutting-edge approaches and updating machine learning algorithms with fresh data.

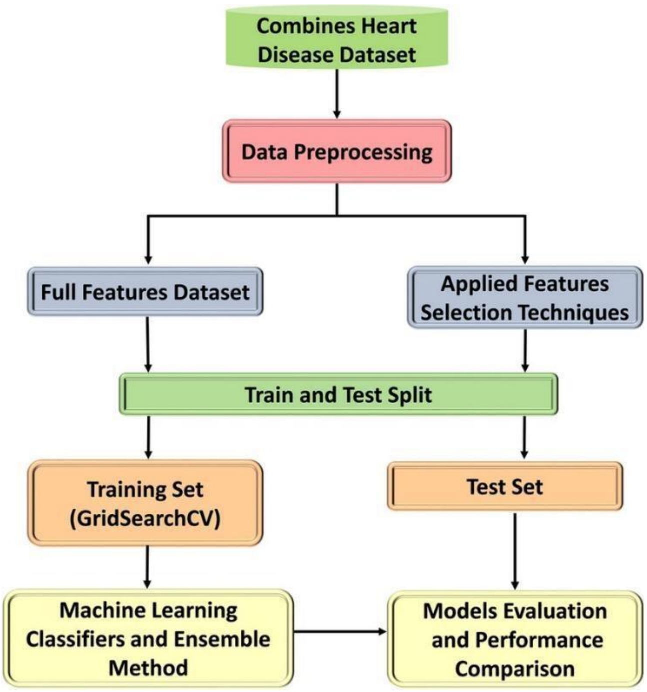



Fig 1 System Architecture

The interpretability layer employs SHAP (SHapley Additive Explanations) to give information about how each feature affects the risk score in order to maintain openness and foster user confidence. In order to help users comprehend the importance of variables like age, BMI, and smoking behaviors in their forecasts, this layer creates explanations and visuals. An interactive output layer that classifies risk as low, moderate, or high and offers practical suggestions is used to display the results. The Streamlit Sharing Platform is used to deploy the system, guaranteeing cross-platform compatibility and simple access without installation. User privacy is protected by strong security measures, such as data encryption, and continual development is made possible by a feedback loop that updates models with fresh data and incorporates user suggestions.

**ACKNOWLEDGMENT**

We would like to thank everyone who helped us complete the Heart Disease Risk Assessment Web App: The Centers for Disease Control and Prevention (CDC) provided the Behavioral Risk Factor Surveillance System (BRFSS) dataset that served as the basis for our analysis, and we are deeply grateful to our mentors and advisors for their excellent advice, constructive criticism, and unwavering support throughout the project; we also thank the creators and contributors of open-source tools and libraries such as Scikit-learn, LightGBM, Streamlit, Python, and SHAP, whose resources made this application possible; and finally, we thank our family and peers for their support and continued faith in our efforts.

## VI RESULTS AND DISCUSSION

Focusing on metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, the analysis demonstrates the effectiveness of several machine learning models in predicting the risk of heart disease. Easy Ensemble and LightGBM.Among the models evaluated, LightGBM did well, particularly for the minority class (those with heart problems). LightGBM achieved a high recall of 0.988894 for the majority class, but a poor recall of 0.244330 for the minority class (no heart disease). Easy Ensemble with LightGBM's balanced performance, which included a recall of 0.792630 for the minority class and a decent ROC-AUC score of 0.885778, showed that it could handle class imbalance.

The poor recall for the minority class in common models such as Random Forest and Logistic Regression shows that class imbalance has a major effect on predictive model performance. This problem was solved by methods such as Easy Ensemble with LightGBM, which maintained high accuracy and precision for the majority class while increasing recall for the minority class. For healthcare applications, this strategy makes sure that high-risk patients are not missed.

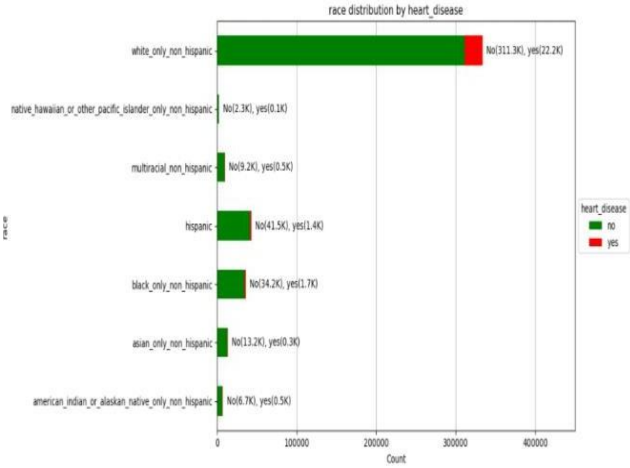
The significance of taking demographic factors into account when assessing the risk of heart disease is highlighted by the examination of distributions depending on race. Racial disparities in the frequency of heart disease raise the possibility that specialized therapies and prevention strategies may be needed to meet particular requirements.

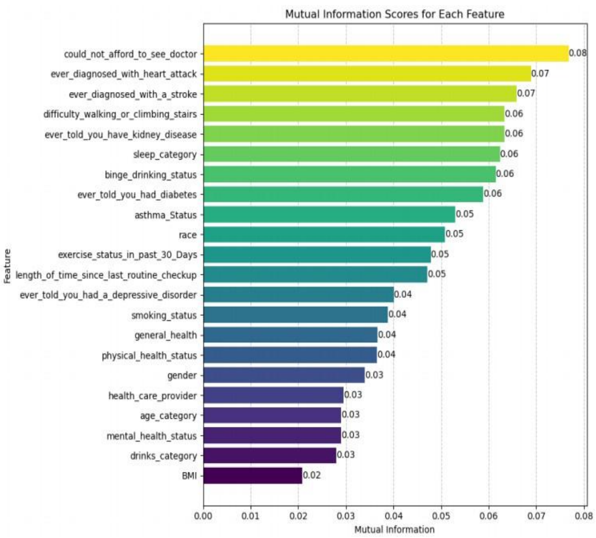
## VII CONCLUSION

In order to estimate cardiovascular risk with high accuracy and interpretability, the Heart Disease Risk Assessment Web App effectively illustrates the fusion of cutting-edge machine learning techniques with user-friendly technology.

The program tackles issues like class imbalance by utilizing models like LightGBM and Easy Ensemble, which results in balanced performance across important measures, including memory for high-risk individuals. In order to draw attention to inequalities and guide focused healthcare efforts, the app also integrates demographic data, such as the prevalence of heart disease by race.

The app bridges the gap between cutting-edge AI technologies and useful healthcare applications by providing users with actionable recommendations through an accessible deployment on the Streamlit platform and a transparent interface driven by SHAP. This initiative establishes a solid basis for growing AI-powered solutions in illness management and preventive healthcare.



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