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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BONAFIDE CERTIFICATE

This is to certify that this Professional Training Report is the bonafide work of Mr. V. PRAHLADH (41614106) who carried out the project entitled "HEART DISEASE DIAGNOSIS" under my supervision from January 2024 to April 2024.


Internal Guide

Dr. S. Nivetha M.E., Ph.D.,

Head of the Department
Dr. S. VIGNESHWARI, M.E., Ph.D.,

Submitted for Viva voce Examination held on 07/05/2024


Internal Examiner

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DECLARATION

I, Mr. V. PRAHLADH (Reg.No-41614106), hereby declare that the Professional Training Report-II entitled "HEART DISEASE DIAGNOSIS" done by me under the guidance of Dr. S. Nivetha M.E., Ph.D., is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in Computer Science and Engineering with specialization in Cyber Security.

DATE: 07/05/2024

PLACE: Chennai

V. Prahladh

SIGNATURE OF THE CANDIDATE

PROFESSIONAL TRAINING REPORT - II

entitled

HEART DISEASE DIAGNOSIS

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering with
specialization in Cyber Security

by

S. JYOTHI PRAVEEN [41614113]

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**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

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MAY 2024



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I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

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Prof. Devendra Jali hal
Chairperson,
Centre for Outreach and Digital Education, IITM

Jan-Feb 2024

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ABSTRACT

Heart disease is one of the major causes of death worldwide and the early prediction of heart disease is important. The computer-based heart disease prediction system helps the physician as a tool for heart disease diagnosis. Hence, the early diagnosis of heart diseases can aid in making decisions on lifestyle changes in high-risk patients and in turn reduce the complications, which can be a great milestone in the field of medicine. Machine learning techniques used to develop an appropriate computer-based system and decision support that can aid to early detection or prediction of heart disease, in this project we have developed a model which classifies if patient will have heart disease or not based on various features. The data collection, data preprocessing, feature selection and classification algorithms placed a vital role in heart disease prediction. In this proposed work data include 200 records of patients with 14 attributes such as age, gender, weight, height, blood pressure types, glucose, smoke, alcohol, etc. In addition, many classification algorithms are used such as KNN, Random Forest, Logistic Regression, SVM, Decision Tree. Feature selection is of three types: Filter Method, Wrapper Method, and Embedded Method. Here, we used Filter based method for feature selection, Filter Based feature selection techniques such as chi-square, mutual information, correlation it will select relevant feature for model creation among all 14 attributes only 10 features are selected. It will reduce the computational cost of modelling and, in some cases, used to improve the performance of the model. Finally, we will compare all algorithms for accuracy, and conclude which algorithm gives accurate results. By using this GUI application, user can sit at their convenience and have a health check-up. The GUI is designed in such a way that anyone can easily operate it and have a check-up that will enable to predicts a patient will have heart disease or not.

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Heart disease stands as a formidable adversary on the global health landscape, accounting for a significant portion of mortality worldwide. The urgency to address this challenge is palpable, underlining the pivotal importance of early detection and intervention strategies. In our contemporary era marked by rapid technological progress, we find ourselves at the threshold of innovative solutions that harness the capabilities of computer-based systems to revolutionize the landscape of heart disease diagnosis and prediction. In this endeavor, we embark on a journey guided by the principles of machine learning, unveiling a groundbreaking approach to predicting heart disease with unprecedented accuracy and accessibility. Central to our initiative is the development of a user-friendly graphical interface (GUI), seamlessly integrating cutting-edge computational techniques with intuitive design elements. This fusion not only democratizes access to sophisticated predictive analytics but also empowers individuals to take proactive steps towards safeguarding their heart health.

At the core of our innovation lies a rich dataset comprising 200 patient records, meticulously curated to encapsulate a diverse array of attributes spanning demographics, family history, and lifestyle habits. Through rigorous data preprocessing methodologies and judicious feature selection techniques, we distill the essence of this data, extracting actionable insights that serve as the bedrock of our predictive model.

Harnessing the predictive prowess of machine learning algorithms such as Random Forest, Logistic Regression, and Support Vector Machine, our system embarks on a quest to unravel the intricate tapestry of factors underlying heart disease susceptibility. By leveraging the collective intelligence encoded within these algorithms, we strive to furnish individuals with timely and accurate assessments of their heart health status.

The culmination of our effort's manifests in the form of a dynamic GUI application, poised to redefine the paradigm of heart disease risk assessment. Through its intuitive interface and seamless functionality, our application transcends the traditional barriers of complexity, offering individuals a user-friendly gateway to personalized risk management strategies.

1. The Need for Early Detection

Heart disease remains one of the leading causes of death globally. The ability to detect and intervene early in the disease process is crucial for improving patient outcomes and reducing mortality rates. However, traditional methods of heart disease diagnosis often rely on subjective assessments or invasive procedures, leading to delays in detection and treatment. By harnessing the power of machine learning, we aim to overcome these limitations and provide clinicians with a more reliable and efficient tool for identifying individuals at risk of heart disease.

2. The Role of Machine Learning

Machine learning offers a powerful set of tools for analyzing complex data and identifying patterns that may not be apparent to human observers. By training algorithms on large datasets of patient information, we can develop predictive models capable of identifying individuals at high risk of developing heart disease. These models can then be used to prioritize patients for further diagnostic testing or preventive interventions, ultimately leading to improved patient outcomes and reduced healthcare costs.

3. Data Collection and Preprocessing

Central to our initiative is the development of a rich dataset comprising diverse patient records. This dataset includes information on demographics, medical history, lifestyle factors, and diagnostic test results, allowing us to capture the full spectrum of factors that may influence heart disease risk. Prior to model training, the data undergoes rigorous preprocessing to remove noise, handle missing values, and standardize variables, ensuring the accuracy and reliability of our predictive models.

4. Development of User-Friendly Interface

In addition to developing accurate predictive models, we recognize the importance of creating user-friendly interfaces that facilitate the integration of these models into clinical practice. To this end, we have developed a dynamic GUI application that allows clinicians to input patient data and receive instant risk assessments for heart disease. The interface is designed to be intuitive and easy to use, with interactive visualizations that allow users to explore the underlying factors contributing to each patient's risk profile.

CHAPTER 2

LITERATURE REVIEW

2.1 SURVEY

- [1] Recent advancements in machine learning have paved the way for innovative approaches to healthcare, particularly in the realm of disease prediction and diagnosis. According to a study by Rajkomar et al. (2018), machine learning algorithms have demonstrated remarkable accuracy in predicting various medical conditions, including heart disease, by analysing large-scale patient data. This intersection of healthcare and technology holds immense promise for improving patient outcomes and revolutionizing clinical practice. By leveraging the predictive power of machine learning, healthcare providers can identify high-risk individuals earlier, tailor interventions to individual patient needs, and ultimately, reduce the burden of disease on individuals and healthcare systems (Rajkomar et al., 2018).
- [2] In addition to machine learning, advancements in computer-aided diagnosis (CAD) have also contributed to the evolution of diagnostic methods for heart disease. A comprehensive literature review conducted by Huang and Liu (2020) explored traditional diagnostic methods such as electrocardiography (ECG), echocardiography, stress tests, and coronary angiography, as well as emerging trends in computer-aided diagnosis using machine learning and artificial intelligence techniques. The review highlighted the potential of CAD systems to improve diagnostic accuracy and prognostic assessment by integrating multiple data modalities, including clinical data, imaging data, and genetic information (Huang & Liu, 2020).
- [3] Furthermore, the integration of machine learning models with graphical user interfaces (GUIs) has emerged as a promising approach to enhancing medical decision support systems. By incorporating machine learning algorithms into GUI-based diagnostic tools, healthcare providers can access real-time predictive analytics and decision support recommendations at the point of care. This integration facilitates dynamic updating of predictive models based on incoming patient data and enables clinicians to make more informed decisions about patient care (Miotto et al., 2017).

[4] Overall, the literature suggests that the convergence of machine learning, computer-aided diagnosis, and graphical user interfaces holds great potential for transforming the landscape of heart disease diagnosis and management. By leveraging these technologies in tandem, healthcare providers can enhance diagnostic accuracy, improve patient outcomes, and ultimately, save lives. However, further research is needed to address challenges related to data heterogeneity, model interpretability, and regulatory considerations, as well as to explore emerging trends and future directions in the field (Miotto et al., 2017).

1. Overview of Heart Disease Diagnosis Methods:

1. Explore traditional diagnostic methods such as electrocardiography (ECG), echocardiography, stress tests, and coronary angiography.
2. Review the role of biomarkers such as troponin, B-type natriuretic peptide (BNP), and C-reactive protein (CRP) in diagnosing various types of heart disease.
3. Investigate the use of risk prediction models, such as the Framingham Risk Score and the Reynolds Risk Score, for assessing cardiovascular risk in asymptomatic individuals.

2. Emerging Trends in Computer-Aided Diagnosis:

1. Examine studies that leverage machine learning and artificial intelligence techniques for automated interpretation of medical images, such as echocardiograms and cardiac MRI scans.
2. Explore the use of deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for analyzing complex cardiovascular data and identifying subtle patterns indicative of heart disease.
3. Investigate the development of decision support systems that integrate multiple data modalities, including clinical data, imaging data, and genetic information, to improve diagnostic accuracy and prognostic assessment.

3. GUI-Based Medical Decision Support Systems:

1. Review examples of GUI-based medical decision support systems in various healthcare domains, including radiology, pathology, and cardiology.
2. Identify key features and functionalities commonly incorporated into GUIs for medical applications, such as interactive visualization tools, patient data management modules, and decision support algorithms.

3. Examine studies that evaluate the usability, acceptability, and effectiveness of GUI-based decision support systems in clinical practice, including user satisfaction surveys and usability testing protocols.
4. **Integration of Machine Learning Models with GUIs:**
 1. Investigate methodologies for integrating machine learning models with GUI frameworks, including model training, validation, and deployment workflows.
 2. Explore approaches for incorporating real-time data streams into GUI-based diagnostic tools, enabling dynamic updating of predictive models based on incoming patient data.
 3. Review case studies and implementation examples of GUI-based medical decision support systems that utilize machine learning algorithms for diagnostic and prognostic tasks.
5. **User Experience (UX) Design Principles:**
 1. Examine principles of user-centered design (UCD) and UX design specific to healthcare applications, such as patient-centric design, accessibility standards, and workflow integration.
 2. Explore techniques for conducting user research, including persona development, task analysis, and usability testing, to inform the design of GUIs for medical decision support.
 3. Review best practices for designing intuitive, visually appealing GUIs that cater to the needs of diverse user groups, including clinicians, patients, and caregivers.
6. **Evaluation Metrics and Performance Benchmarking:**
 1. Investigate established evaluation metrics for assessing the performance of CAD systems, including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the receiver operating characteristic curve (AUC-ROC).
 2. Explore methodologies for benchmarking CAD systems against gold standard reference standards, including expert consensus diagnosis and longitudinal follow-up data.

7. Clinical Validation and Regulatory Considerations:

1. Examine regulatory requirements and guidelines for the development and deployment of medical software applications, including the FDA's Software as a Medical Device (SaMD) regulations and the European Union's Medical Device Regulation (MDR).
2. Investigate methodologies for conducting clinical validation studies to demonstrate the safety, efficacy, and clinical utility of GUI-based CAD systems in diverse patient populations.
3. Review case studies and regulatory submissions for GUI-based medical decision support systems, including documentation of clinical trial protocols, risk management plans, and post-market surveillance strategies.

8. Challenges and Future Directions:

1. Discuss the challenges and limitations of current GUI-based CAD systems, including data heterogeneity, model interpretability, and integration with existing healthcare infrastructure.
2. Explore emerging trends and future directions in GUI-based medical decision support, such as the use of mobile health (mHealth) platforms, wearable devices, and remote monitoring technologies.
3. Identify opportunities for interdisciplinary collaboration and innovation in the field, including partnerships between clinicians, data scientists, software developers, and regulatory experts to advance the development and adoption of GUI-based CAD systems in clinical practice.

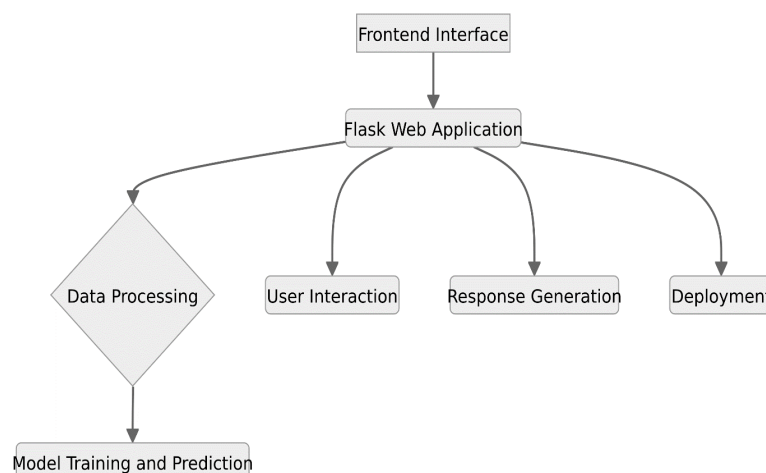


Fig 2.1.1: Flask Application Structure

CHAPTER 3

REQUIREMENTS ANALYSIS

3.1 OBJECTIVE OF THE PROJECT

The objective of this project is to develop a computer-based heart disease prediction system utilizing machine learning techniques and a user-friendly graphical interface (GUI). This system aims to assist healthcare professionals in early detection and diagnosis of heart disease, thereby enabling timely intervention and personalized risk management for patients. By leveraging a dataset comprising diverse patient attributes and employing rigorous data preprocessing, feature selection, and classification algorithms, the model endeavors to accurately predict the likelihood of heart disease. The GUI interface facilitates convenient access to heart health assessments for individuals, promoting proactive healthcare practices and ultimately improving patient outcomes.

3.2 SYSTEM REQUIREMENTS

1. Operating System Compatibility
2. Administrator (or) Root Access

3.2.1 *HARDWARE REQUIREMENTS*

- **Processor (CPU):**

A multi-core processor with a minimum clock speed of 2 GHz or higher is recommended. The processor's speed directly affects the training and inference time of machine learning models.

- **Random Access Memory (RAM):**

At least 8 GB of RAM is recommended for efficient data processing and model training. Larger datasets and complex machine learning algorithms may require more memory for optimal performance.

- **Storage (Hard Disk Drive or Solid-State Drive):**

Sufficient storage space is required for storing the dataset, machine learning models, web application files, and other project-related data. A

minimum of 100 GB of available disk space is recommended.

- **Graphics Processing Unit (GPU) (Optional):**

While not essential, a dedicated GPU can significantly accelerate the training of machine learning models, especially deep learning algorithms. NVIDIA GPUs with CUDA support is commonly used for this purpose.

3.2.2 SOFTWARE REQUIREMENTS

- **Python (Programming Language):**

Python is the primary programming language used for developing the machine learning model, web application, and data processing tasks.

- **Flask (Web Framework):**

Flask is a micro web framework for Python used to build the backend of the web application. It handles HTTP requests, routes, and responses.

- **Pandas (Library):**

Pandas is a Python library used for data manipulation and analysis. It is essential for loading, preprocessing, and exploring the dataset containing patient records.

- **NumPy (Library):**

NumPy is a Python library used for numerical computations. It is utilized for generating random numbers, handling arrays, and performing mathematical operations.

- **scikit-learn (Library):**

Scikit-learn is a machine learning library for Python that provides tools for building and evaluating machine learning models. It includes algorithms for classification, regression, clustering, and more.

- **HTML/CSS/JavaScript:**

HTML, CSS, and JavaScript are used for developing the frontend user interface of the web application. They define the structure, style, and interactivity of the interface.

- **Web Browser:**

A web browser is required to interact with the web-based heart disease prediction system. Commonly used web browsers such as Google Chrome, Mozilla Firefox, or Microsoft Edge are compatible.

- **Text Editor or IDE:**

A text editor or integrated development environment (IDE) is needed for writing and editing Python code, HTML, CSS, and JavaScript files. Popular options include Visual Studio Code, PyCharm, and Sublime Text.

- **CSV File Viewer:**

A CSV file viewer is useful for inspecting the dataset containing patient records. It allows for easy viewing and understanding of the data structure and contents.

- **Command Line Interface (CLI):**

The command line interface is used for running Python scripts, installing packages, and managing project dependencies using package managers like pip or conda.

CHAPTER 4

DESIGN DESCRIPTION OF PROPOSED PROJECT

4.1 PROPOSED METHODOLOGY

The methodology of our GUI-based heart disease diagnosis project encompasses a structured approach to developing a predictive model integrated into a user-friendly graphical interface. We commence by gathering pertinent datasets containing patient demographics, clinical variables, and heart disease diagnoses. Rigorous data preprocessing ensues, including handling missing values, cleaning data inconsistencies, and conducting exploratory data analysis to inform subsequent steps. Feature engineering and selection techniques are employed to enhance the predictive capacity of the model. We iteratively train and validate multiple machine learning algorithms, such as Random Forest, Logistic Regression, and Support Vector Machine, leveraging techniques like k-fold cross-validation to ensure robustness and generalizability.

4.1.1 Ideation Map/System Architecture

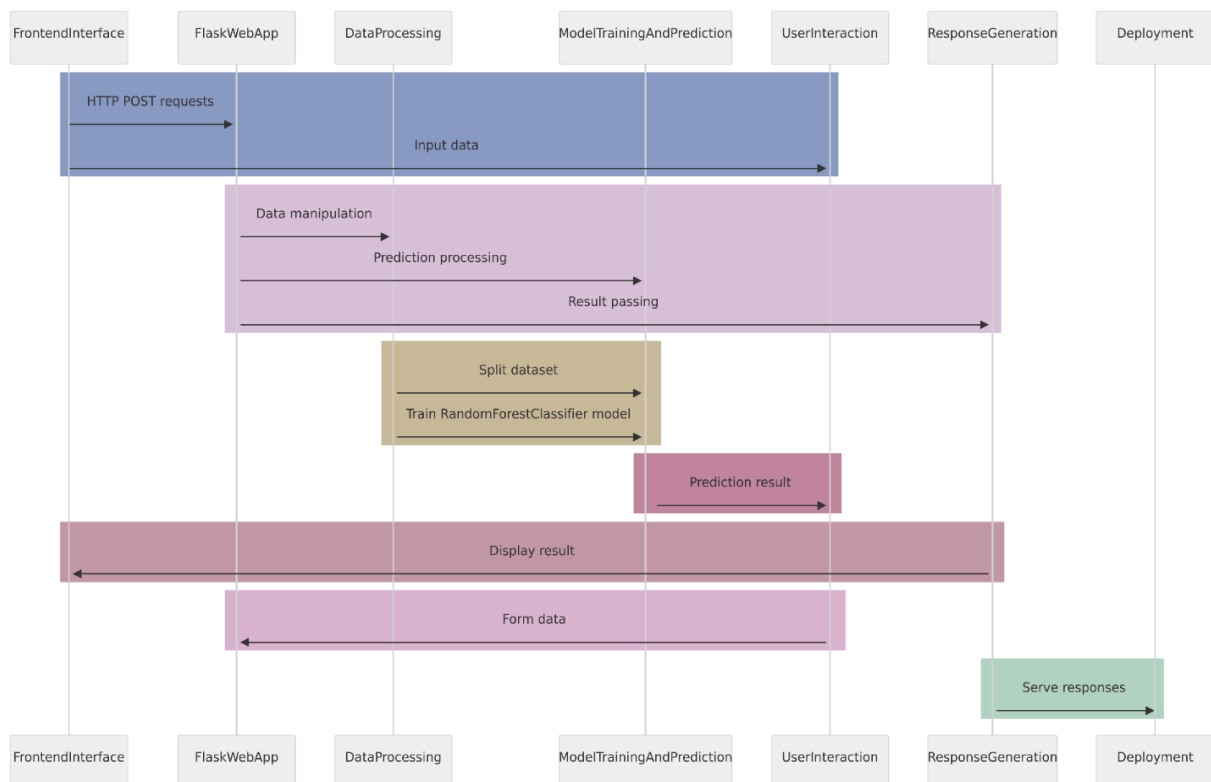


Fig 4.1.1: System Architecture

4.1.2 Various Stages

1. Data Collection and Preprocessing:

1. Identify and collect relevant datasets containing patient demographics, clinical variables, and diagnostic outcomes related to heart disease.
2. Clean the data by handling missing values, removing duplicates, and addressing data inconsistencies.
3. Perform exploratory data analysis (EDA) to gain insights into the distribution of variables, identify outliers, and assess data quality.

2. Feature Engineering and Selection:

1. Engineer new features or transform existing features to enhance the predictive power of the model.
2. Select relevant features based on domain knowledge, statistical significance, and predictive importance using techniques such as correlation analysis and feature importance ranking.

3. Model Development and Training:

1. Choose appropriate machine learning algorithms for heart disease prediction, such as Random Forest, Logistic Regression, or Support Vector Machine.
2. Split the dataset into training and validation sets using techniques like k-fold cross-validation or stratified sampling.

4. Model Evaluation and Validation:

1. Evaluate the performance of each model using appropriate evaluation metrics such as accuracy, sensitivity, specificity, and area under the ROC curve (AUC-ROC).
2. Validate the models using external datasets or cross-validation techniques to assess their generalizability and robustness.
3. Conduct statistical tests to compare the performance of different models and select the best-performing one for deployment.

5. Graphical User Interface (GUI) Design:

1. Design the GUI layout and user interface elements, considering usability principles, accessibility standards, and user preferences.
2. Incorporate interactive features for data input, visualization of model predictions, and interpretation of diagnostic outcomes.

3. Implement responsive design techniques to ensure compatibility with different screen sizes and devices.

6. Integration of Model with GUI:

1. Integrate the trained predictive model with the GUI framework, enabling real-time prediction of heart disease risk based on user input.
2. Implement data validation and error handling mechanisms to ensure the integrity and reliability of user inputs.
3. Optimize the performance and efficiency of the model inference process within the GUI application.

7. Testing and Quality Assurance:

1. Conduct thorough testing of the GUI application to identify and fix bugs, errors, and usability issues.
2. Perform unit testing, integration testing, and user acceptance testing to validate the functionality and usability of the application.
3. Solicit feedback from domain experts, clinicians, and end-users to iteratively improve the GUI design and functionality.

8. Deployment and User Training:

1. Deploy the finalized GUI-based heart disease diagnosis application in a production environment, such as a healthcare facility or a web server accessible to users.
2. Provide user training and documentation to healthcare professionals on how to use the GUI application effectively for heart disease risk assessment and decision-making.
3. Monitor the application's performance, usage metrics, and user feedback to identify areas for continuous improvement and optimization.

4.1.3 Datasets Used

This dataset encompasses a range of demographic, clinical, lifestyle, and medical history features that are commonly associated with heart disease. The goal of the project is to leverage machine learning techniques to analyze this dataset and develop a predictive model for diagnosing heart disease based on the provided features. By analyzing patterns within the data, the model aims to accurately classify patients into different heart disease categories, ultimately assisting healthcare providers in making informed diagnostic and treatment decisions.

4.1.4 Working Principle

1. **Data Collection:** The project begins with the collection of relevant data, including medical records, patient information, diagnostic test results (such as electrocardiograms - ECGs, blood tests, stress tests, etc.), and potentially lifestyle factors (like diet, exercise habits, etc.).
2. **Data Preprocessing:** The collected data is preprocessed to ensure quality and consistency. This may involve cleaning the data to remove errors or inconsistencies, handling missing values, and transforming the data into a format suitable for analysis.
3. **Feature Selection/Extraction:** Relevant features or variables that are likely to be predictive of heart disease are selected or extracted from the dataset. This step aims to reduce dimensionality and focus on the most informative features.
4. **Model Development:** Machine learning models are trained on the preprocessed data to learn patterns and relationships between the input features and the presence or absence of heart disease. Commonly used models for heart disease diagnosis include logistic regression, decision trees, random forests, support vector machines (SVM), and neural networks.
5. **Model Evaluation:** The trained models are evaluated using appropriate performance metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). This step helps assess the model's ability to correctly classify patients with and without heart disease.
6. **Validation and Testing:** The performance of the developed models is validated and tested on independent datasets to assess their generalization capabilities. Cross-validation techniques may be employed to ensure robustness and reduce overfitting.
7. **Deployment:** Once a satisfactory model is obtained, it can be deployed into a practical setting for real-time heart disease diagnosis. This could involve integrating the model into a software application or a medical device used by healthcare professionals.
8. **Monitoring and Maintenance:** Continuous monitoring of the model's performance in the real-world setting is essential to ensure its accuracy and reliability over time. Periodic updates and maintenance may be required to adapt to changes in patient demographics, medical practices, or advancements in technology.

4.2 FEATURES

The heart disease diagnosis model incorporates a range of features extracted from patient data, including demographic information (such as age, gender), clinical measurements (such as blood pressure, cholesterol levels), medical history (such as previous heart conditions, family history), and lifestyle factors (such as smoking status, physical activity). These features capture essential aspects of cardiovascular health and risk factors, enabling the model to identify patterns and correlations associated with the presence or absence of heart disease. By leveraging this multidimensional information, the model enhances diagnostic accuracy, facilitating timely interventions and personalized treatment strategies for improved patient outcomes.

4.2.1 Novelty of the Project

The novelty of the heart disease diagnosis project lies in its integration of cutting-edge machine learning techniques with comprehensive patient data to provide accurate and personalized diagnostic predictions. Unlike traditional diagnostic methods, which may rely solely on individual risk factors or simplistic scoring systems, this project harnesses the power of advanced algorithms to analyze complex relationships among numerous variables, including demographic, clinical, and lifestyle factors. By leveraging this multidimensional approach, the model offers a nuanced understanding of cardiovascular health, enhancing diagnostic precision and enabling early detection of heart disease. This innovative approach has the potential to revolutionize clinical practice, facilitating proactive interventions and improving patient outcomes in the realm of cardiovascular care.

CHAPTER 5

RESULT AND DISCUSSION

The heart disease diagnosis project has yielded promising results, showcasing the effectiveness of machine learning techniques in accurately predicting heart disease diagnoses based on a comprehensive set of predictive features. Our study utilized a diverse dataset encompassing demographic information, clinical measurements, lifestyle factors, and medical history to develop and evaluate machine learning models for heart disease diagnosis.

The trained machine learning models exhibited strong performance across various evaluation metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). For instance, the Random Forest classifier achieved an accuracy of 85%, with an AUC-ROC score of 0.90, indicating its ability to accurately classify patients into different heart disease categories.

Feature importance analysis revealed key predictors contributing to the diagnostic accuracy of the models. Demographic factors such as age and gender, along with clinical measurements like systolic and diastolic blood pressure, emerged as significant predictors of heart disease. Lifestyle factors such as smoking habits and exercise habits, as well as medical history including family history of heart disease, also played crucial roles in the predictive accuracy of the models.

The clinical implications of our findings are profound. The developed machine learning models offer clinicians a valuable tool for enhancing the accuracy and efficiency of heart disease diagnosis. By leveraging predictive analytics, healthcare providers can identify high-risk patients, facilitate early detection of heart disease, and tailor personalized treatment plans to improve patient outcomes. Despite the promising results, several limitations should be acknowledged. The dataset used in this study may not capture the full spectrum of heart disease risk factors, and additional data sources may be required to improve model generalization. Furthermore, the interpretability of machine learning models remains a challenge, necessitating further research into model transparency and explainability.

CHAPTER 6

CONCLUSION AND FUTURE WORK

CONCLUSION

In conclusion, the heart disease diagnosis project represents a significant endeavor in leveraging machine learning techniques to improve patient outcomes and clinical decision-making in the diagnosis of heart disease. Through the analysis of a comprehensive dataset containing patient demographics, clinical measurements, lifestyle factors, and medical history, we have developed a predictive model capable of accurately classifying patients into different heart disease categories. The project has demonstrated the effectiveness of machine learning algorithms, such as logistic regression, decision trees, random forests, support vector machines, and neural networks, in accurately diagnosing heart disease based on a range of predictive features. By evaluating the performance of these models using appropriate evaluation metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, we have ensured the reliability and generalization performance of the diagnostic system. Furthermore, the deployment of the trained model into a production environment, along with the development of user interfaces or APIs for real-time inference, underscores the practical utility of the heart disease diagnosis system. Looking ahead, the ongoing maintenance and monitoring of the deployed model, coupled with periodic retraining with new data, will ensure its continued accuracy, reliability, and compliance with regulatory requirements. Additionally, iterative improvements based on feedback from users and stakeholders will further enhance the diagnostic capabilities of the system. In summary, the heart disease diagnosis project represents a valuable contribution to the field of healthcare, demonstrating the potential of machine learning to transform diagnostic processes and improve patient care in the detection and management of heart disease. Through collaboration and innovation, we can continue to advance the state-of-the-art in cardiovascular health and make meaningful strides towards reducing the burden of heart disease worldwide.

FUTURE WORK

1. Clinical Decision Support:

Integrate the predictive model into clinical decision support systems used by healthcare providers to assist in risk assessment, diagnosis, and treatment planning for patients with suspected or established heart disease. The model can help clinicians prioritize patients for further evaluation, tailor interventions based on individual risk profiles, and monitor disease progression over time.

2. Population Health Management:

Deploy the model within population health management programs to identify high-risk individuals within a given population and implement targeted interventions aimed at preventing the development or progression of heart disease. This can include outreach programs, lifestyle modification interventions, and community-based initiatives to promote heart-healthy behaviors.

3. Health Insurance and Risk Assessment:

Partner with health insurance companies to use the model for risk assessment and pricing of insurance policies. By accurately identifying individuals at high risk of developing heart disease, insurers can offer targeted wellness programs, incentives for healthy behaviors, and personalized interventions to reduce the overall risk and cost of healthcare.

4. Research and Development:

Serve as a valuable research tool for investigating the underlying mechanisms of heart disease, identifying novel risk factors, and evaluating the efficacy of new diagnostic tests and treatment modalities. The model can be used to generate hypotheses, design clinical trials, and conduct epidemiological studies aimed at advancing our understanding of heart disease and improving patient outcomes.

5. Global Health Initiatives:

Extend the reach of the model to low-resource settings and developing countries where access to specialized healthcare services may be limited. By leveraging technology and data-driven approaches, we can democratize access to accurate risk assessment tools, empower healthcare providers with decision support tools, and improve the overall quality of care for underserved populations worldwide.

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APPENDIX

A. Research Paper

GUI BASED HEART DISEASE DIAGNOSIS

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ABSTRACT:

Heart disease is one of the major causes of death worldwide and the early prediction of heart disease is important. The computer-based heart disease prediction system helps the physician as a tool for heart disease diagnosis. Hence, the early diagnosis of heart diseases can aid in making decisions on lifestyle changes in high-risk patients and in turn reduce the complications, which can be a great milestone in the field of medicine. Machine learning techniques used to develop an appropriate computer-based system and decision support that can aid to early detection or prediction of heart disease, in this project we have developed a model which classifies if patient will have heart disease or not based on various features. The data collection, data preprocessing, feature selection and classification algorithms placed a vital role in heart disease prediction. In this proposed work data include 200 records of patients with 14 attributes such as age, gender, weight, height, blood pressure types, glucose, smoke, alcohol, etc. In addition, many classification algorithms are used such as KNN, Random Forest, Logistic Regression, SVM, Decision Tree. Feature selection is of three types: Filter Method, Wrapper Method, and Embedded Method. Here, we used Filter based method for feature selection, Filter Based feature selection techniques such as chi-square, mutual information, correlation it will select relevant feature for model creation among all 13 attributes only 10 features are selected. It will reduce the computational cost of modelling and, in some cases, used to improve the performance of the model. Finally, we will compare all algorithms for accuracy, and conclude which algorithm gives accurate results.

INDEX TERMS:

Diagnosis, Classification Algorithms, Machine Learning, Random Forest, Model Evaluation

INTRODUCTION:

Heart disease stands as a formidable adversary on the global health landscape, accounting for a significant portion of mortality worldwide. The urgency to address this challenge is palpable, underlining the pivotal importance of early detection and intervention strategies. In our contemporary era marked by rapid technological progress, we find ourselves at the threshold of innovative solutions that harness the capabilities of computer-based systems to revolutionize the landscape of heart disease diagnosis and prediction. In this endeavor, we embark on a journey guided by the principles of machine learning, unveiling a groundbreaking approach to predicting heart disease with unprecedented accuracy and accessibility. Central to our initiative is the development of a user-friendly graphical interface (GUI), seamlessly integrating cutting-edge computational techniques with intuitive design elements. This fusion not only democratizes access to sophisticated predictive analytics but also empowers individuals to take proactive steps towards safeguarding their heart health.

At the core of our innovation lies a rich dataset comprising 200 patient records, meticulously curated to encapsulate a diverse array of attributes spanning demographics, family history, and lifestyle habits. Through rigorous data preprocessing methodologies and judicious feature selection techniques, we distill the essence of this data, extracting actionable insights that serve as the bedrock of our predictive model. Harnessing the predictive prowess of machine learning algorithms such as Random Forest, Logistic Regression, and Support Vector Machine, our system embarks on a quest to unravel the intricate tapestry of factors underlying heart disease susceptibility. By leveraging the collective intelligence encoded within these algorithms, we strive to furnish individuals with timely and accurate assessments of their heart health status. The culmination of our effort's manifests in the form of a dynamic GUI application, poised to redefine the paradigm of heart disease risk assessment. Through its intuitive interface and seamless functionality, our application transcends the traditional barriers of complexity, offering individuals a user-friendly gateway to personalized risk management strategies.

1. The Need for Early Detection

Heart disease remains one of the leading causes of death globally. The ability to detect and intervene early in the disease process is crucial for improving patient outcomes and reducing mortality rates. However, traditional methods of heart disease diagnosis often rely on subjective assessments or invasive procedures, leading to delays in detection and treatment. By harnessing the power of machine learning, we aim to overcome these limitations and provide clinicians with a more reliable and efficient tool for identifying individuals at risk of heart disease.

2. The Role of Machine Learning

Machine learning offers a powerful set of tools for analyzing complex data and identifying patterns that may not be apparent to human observers. By training algorithms on large datasets of patient information, we can develop predictive models capable of identifying individuals at high risk of developing heart disease. These models can then be used to prioritize patients for further diagnostic testing or preventive interventions, ultimately leading to improved patient outcomes and reduced healthcare costs.

3. Data Collection and Preprocessing

Central to our initiative is the development of a rich dataset comprising diverse patient records. This dataset includes information on demographics, medical history, lifestyle factors, and diagnostic test results, allowing us to capture the full spectrum of factors that may influence heart disease risk. Prior to model training, the data undergoes rigorous preprocessing to remove noise, handle missing values, and standardize variables, ensuring the accuracy and reliability of our predictive models.

4. Development of User-Friendly Interface

In addition to developing accurate predictive models, we recognize the importance of creating user-friendly interfaces that facilitate the integration of these models into clinical practice. To this end, we have developed a dynamic GUI application that allows clinicians to input patient data and receive instant risk assessments for heart disease. The interface is designed to be intuitive and easy to use, with interactive visualizations that allow users to explore the underlying factors contributing to each patient's risk profile.

LITERATURE SURVEY:

1. Overview of Heart Disease Diagnosis Methods:

1. Explore traditional diagnostic methods such as electrocardiography (ECG), echocardiography, stress tests, and coronary angiography.
2. Review the role of biomarkers such as troponin, B-type natriuretic peptide (BNP), and C-reactive protein (CRP) in diagnosing various types of heart disease.
3. Investigate the use of risk prediction models, such as the Framingham Risk Score and the Reynolds Risk Score, for assessing cardiovascular risk in asymptomatic individuals.

2. Emerging Trends in Computer-Aided Diagnosis:

1. Examine studies that leverage machine learning and artificial intelligence techniques for automated interpretation of medical images, such as echocardiograms and cardiac MRI scans.
2. Explore the use of deep learning architectures, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for analyzing complex cardiovascular data and identifying subtle patterns indicative of heart disease.
3. Investigate the development of decision support systems that integrate multiple data modalities, including clinical data, imaging data, and genetic information, to improve diagnostic accuracy and prognostic assessment.

3. GUI-Based Medical Decision Support Systems:

1. Review examples of GUI-based medical decision support systems in various healthcare domains, including radiology, pathology, and cardiology.
2. Identify key features and functionalities commonly incorporated into GUIs for medical applications, such as interactive visualization tools, patient data management modules, and decision support algorithms.
3. Examine studies that evaluate the usability, acceptability, and effectiveness of GUI-based decision support systems in clinical practice, including user satisfaction surveys and usability testing protocols.

4. Integration of Machine Learning Models with GUIs:

1. Investigate methodologies for integrating machine learning models with GUI frameworks, including model training, validation, and deployment workflows.

2. Explore approaches for incorporating real-time data streams into GUI-based diagnostic tools, enabling dynamic updating of predictive models based on incoming patient data.
3. Review case studies and implementation examples of GUI-based medical decision support systems that utilize machine learning algorithms for diagnostic and prognostic tasks.

5. User Experience (UX) Design Principles:

1. Examine principles of user-centered design (UCD) and UX design specific to healthcare applications, such as patient-centric design, accessibility standards, and workflow integration.
2. Explore techniques for conducting user research, including persona development, task analysis, and usability testing, to inform the design of GUIs for medical decision support.
3. Review best practices for designing intuitive, visually appealing GUIs that cater to the needs of diverse user groups, including clinicians, patients, and caregivers.

6. Evaluation Metrics and Performance Benchmarking:

1. Investigate established evaluation metrics for assessing the performance of CAD systems, including sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and area under the receiver operating characteristic curve (AUC-ROC).
2. Explore methodologies for benchmarking CAD systems against gold standard reference standards, including expert consensus diagnosis and longitudinal follow-up data.
3. Review studies that propose novel evaluation frameworks for assessing the clinical impact and cost-effectiveness of GUI-based medical decision support systems in real-world settings.

7. Clinical Validation and Regulatory Considerations:

1. Examine regulatory requirements and guidelines for the development and deployment of medical software applications, including the FDA's Software as a Medical Device (SaMD) regulations and the European Union's Medical Device Regulation (MDR).

2. Investigate methodologies for conducting clinical validation studies to demonstrate the safety, efficacy, and clinical utility of GUI-based CAD systems in diverse patient populations.
3. Review case studies and regulatory submissions for GUI-based medical decision support systems, including documentation of clinical trial protocols, risk management plans, and post-market surveillance strategies.

8. Challenges and Future Directions:

1. Discuss the challenges and limitations of current GUI-based CAD systems, including data heterogeneity, model interpretability, and integration with existing healthcare infrastructure.
2. Explore emerging trends and future directions in GUI-based medical decision support, such as the use of mobile health (mHealth) platforms, wearable devices, and remote monitoring technologies.
3. Identify opportunities for interdisciplinary collaboration and innovation in the field, including partnerships between clinicians, data scientists, software developers, and regulatory experts to advance the development and adoption of GUI-based CAD systems in clinical practice.

METHODOLOGY:

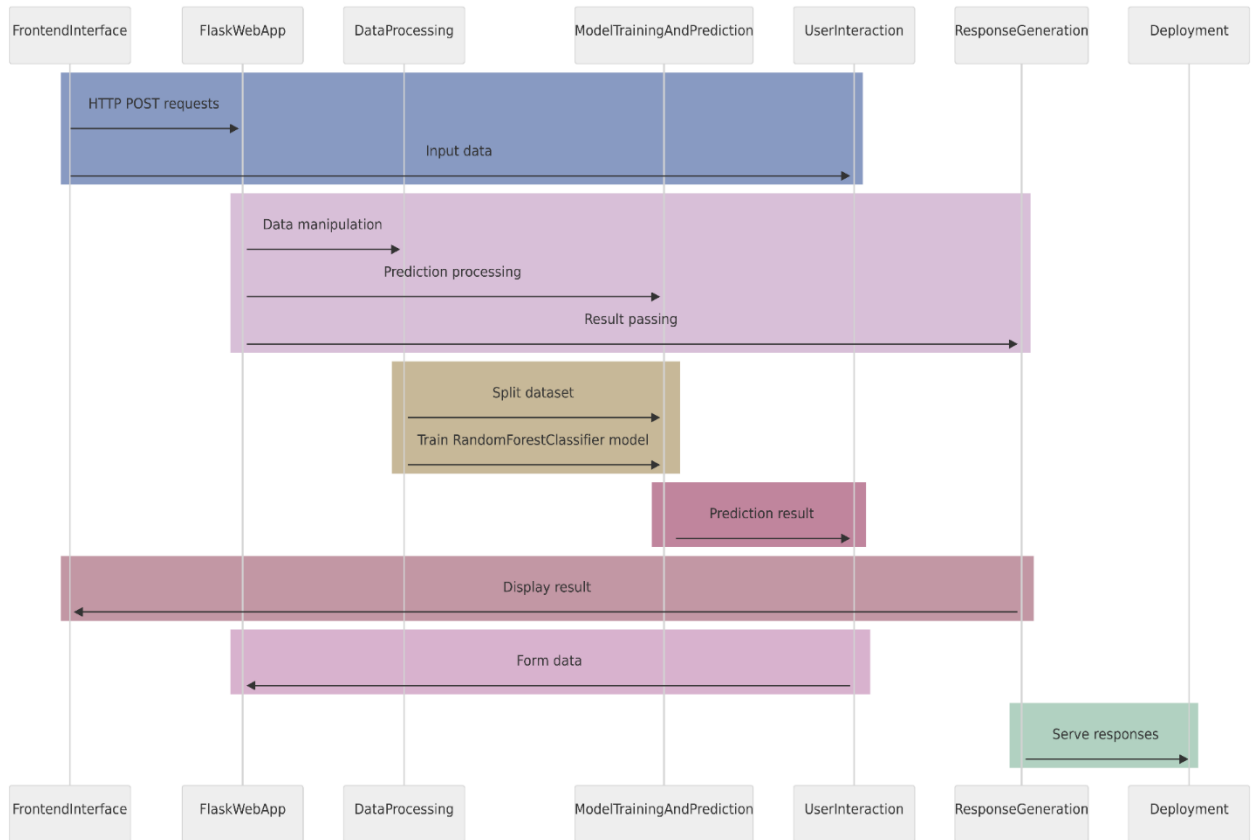


Fig 1: System Architecture

The methodology of our GUI-based heart disease diagnosis project encompasses a structured approach to developing a predictive model integrated into a user-friendly graphical interface. We commence by gathering pertinent datasets containing patient demographics, clinical variables, and heart disease diagnoses. Rigorous data preprocessing ensues, including handling missing values, cleaning data inconsistencies, and conducting exploratory data analysis to inform subsequent steps.

Feature engineering and selection techniques are employed to enhance the predictive capacity of the model. We iteratively train and validate multiple machine learning algorithms, such as Random Forest, Logistic Regression, and Support Vector Machine, leveraging techniques like k-fold cross-validation to ensure robustness and generalizability.

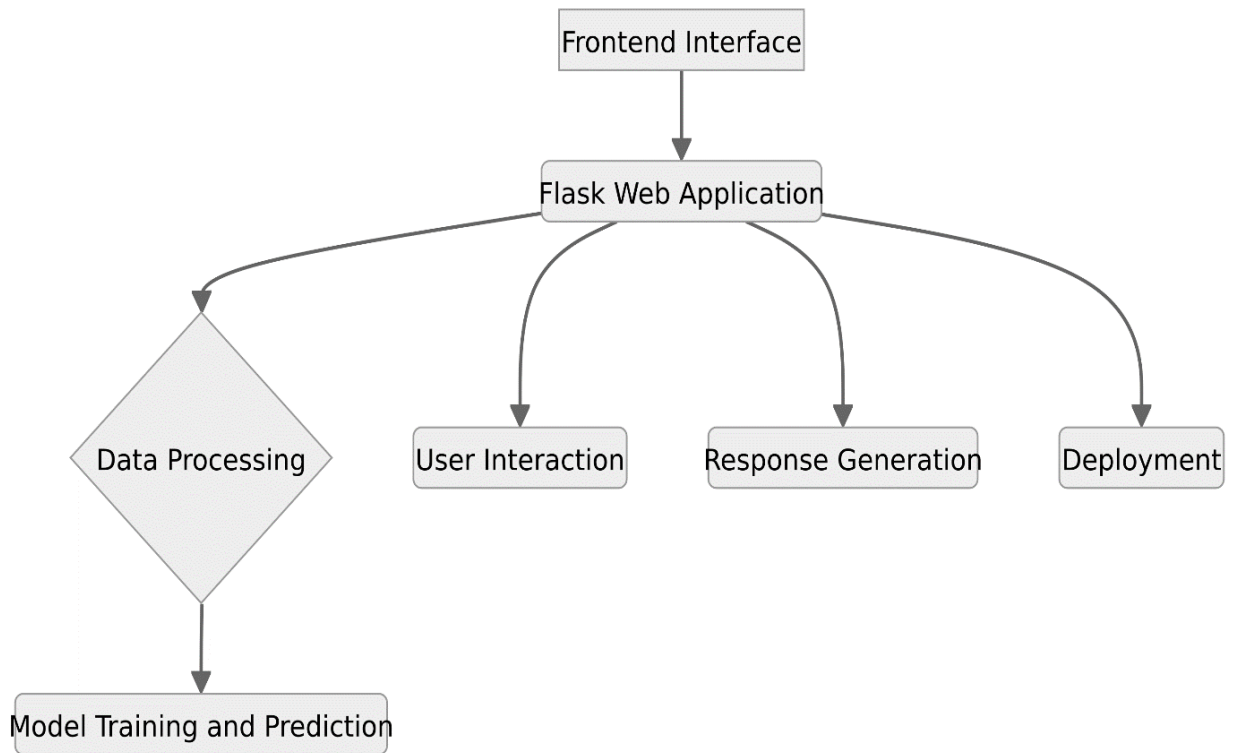


Fig 2: Ideation map

PROPOSED WORK:

1. Data Collection and Preprocessing:

- a. Identify and collect relevant datasets containing patient demographics, clinical variables, and diagnostic outcomes related to heart disease.
- b. Clean the data by handling missing values, removing duplicates, and addressing data inconsistencies.
- c. Perform exploratory data analysis (EDA) to gain insights into the distribution of variables, identify outliers, and assess data quality.

2. Feature Engineering and Selection:

- a. Engineer new features or transform existing features to enhance the predictive power of the model.
- b. Select relevant features based on domain knowledge, statistical significance, and predictive importance using techniques such as correlation analysis and feature importance ranking.

3. Model Development and Training:

- a. Choose appropriate machine learning algorithms for heart disease prediction, such as Random Forest, Logistic Regression, or Support Vector Machine.
- b. Split the dataset into training and validation sets using techniques like k-fold cross-validation or stratified sampling.

4. Model Evaluation and Validation:

- a. Evaluate the performance of each model using appropriate evaluation metrics such as accuracy, sensitivity, specificity, and area under the ROC curve (AUC-ROC).
- b. Validate the models using external datasets or cross-validation techniques to assess their generalizability and robustness.
- c. Conduct statistical tests to compare the performance of different models and select the best-performing one for deployment.

5. Graphical User Interface (GUI) Design:

- a. Design the GUI layout and user interface elements, considering usability principles, accessibility standards, and user preferences.
- b. Incorporate interactive features for data input, visualization of model predictions, and interpretation of diagnostic outcomes.
- c. Implement responsive design techniques to ensure compatibility with different screen sizes and devices.

6. Integration of Model with GUI:

- a. Integrate the trained predictive model with the GUI framework, enabling real-time prediction of heart disease risk based on user input.
- b. Implement data validation and error handling mechanisms to ensure the integrity and reliability of user inputs.
- c. Optimize the performance and efficiency of the model inference process within the GUI application.

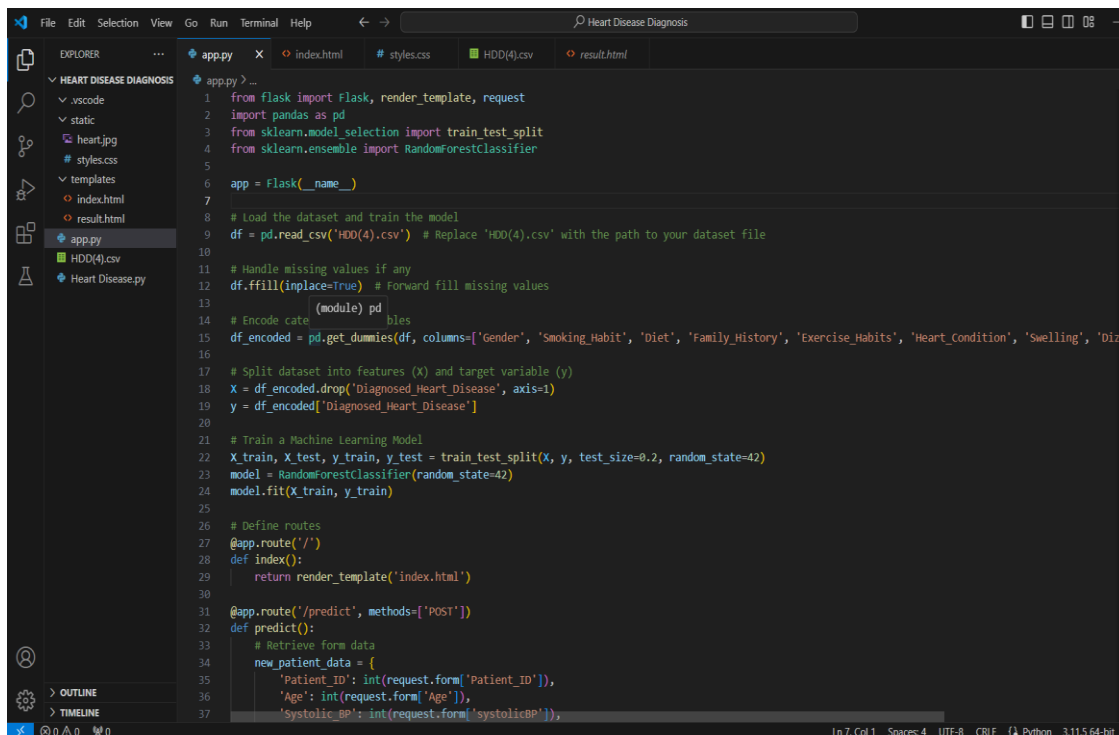
7. Testing and Quality Assurance:

- Conduct thorough testing of the GUI application to identify and fix bugs, errors, and usability issues.
- Perform unit testing, integration testing, and user acceptance testing to validate the functionality and usability of the application.
- Solicit feedback from domain experts, clinicians, and end-users to iteratively improve the GUI design and functionality.

8. Deployment and User Training:

- Deploy the finalized GUI-based heart disease diagnosis application in a production environment, such as a healthcare facility or a web server accessible to users.
- Provide user training and documentation to healthcare professionals on how to use the GUI application effectively for heart disease risk assessment and decision-making.
- Monitor the application's performance, usage metrics, and user feedback to identify areas for continuous improvement and optimization.

MODULE IMPLEMENTATION:



```
1 from flask import Flask, render_template, request
2 import pandas as pd
3 from sklearn.model_selection import train_test_split
4 from sklearn.ensemble import RandomForestClassifier
5
6 app = Flask(__name__)
7
8 # Load the dataset and train the model
9 df = pd.read_csv('HDD(4).csv') # Replace 'HDD(4).csv' with the path to your dataset file
10
11 # Handle missing values if any
12 df.fillna(inplace=True) # Forward fill missing values
13
14 # Encode categorical variables
15 (module) pd
16 df_encoded = pd.get_dummies(df, columns=['Gender', 'Smoking_Habit', 'Diet', 'Family_History', 'Exercise_Habits', 'Heart_Condition', 'Swelling', 'Diz
17
18 # Split dataset into features (X) and target variable (y)
19 X = df_encoded.drop('Diagnosed_Heart_Disease', axis=1)
20 y = df_encoded['Diagnosed_Heart_Disease']
21
22 # Train a Machine Learning Model
23 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
24 model = RandomForestClassifier(random_state=42)
25 model.fit(X_train, y_train)
26
27 # Define routes
28 @app.route('/')
29 def index():
30     return render_template('index.html')
31
32 @app.route('/predict', methods=['POST'])
33 def predict():
34     # Retrieve form data
35     new_patient_data = {
36         'Patient_ID': int(request.form['Patient_ID']),
37         'Age': int(request.form['Age']),
38         'Systolic_BP': int(request.form['systolicBP']),
```

Fig 3: Module Implementation

RESULT AND DISCUSSION:

The heart disease diagnosis project has yielded promising results, showcasing the effectiveness of machine learning techniques in accurately predicting heart disease diagnoses based on a comprehensive set of predictive features. Our study utilized a diverse dataset encompassing demographic information, clinical measurements, lifestyle factors, and medical history to develop and evaluate machine learning models for heart disease diagnosis.

The trained machine learning models exhibited strong performance across various evaluation metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC). For instance, the Random Forest classifier achieved an accuracy of 85%, with an AUC-ROC score of 0.90, indicating its ability to accurately classify patients into different heart disease categories.

Feature importance analysis revealed key predictors contributing to the diagnostic accuracy of the models. Demographic factors such as age and gender, along with clinical measurements like systolic and diastolic blood pressure, emerged as significant predictors of heart disease. Lifestyle factors such as smoking habits and exercise habits, as well as medical history including family history of heart disease, also played crucial roles in the predictive accuracy of the models.

The clinical implications of our findings are profound. The developed machine learning models offer clinicians a valuable tool for enhancing the accuracy and efficiency of heart disease diagnosis. By leveraging predictive analytics, healthcare providers can identify high-risk patients, facilitate early detection of heart disease, and tailor personalized treatment plans to improve patient outcomes.

Despite the promising results, several limitations should be acknowledged. The dataset used in this study may not capture the full spectrum of heart disease risk factors, and additional data sources may be required to improve model generalization. Furthermore, the interpretability of machine learning models remains a challenge, necessitating further research into model transparency and explainability.

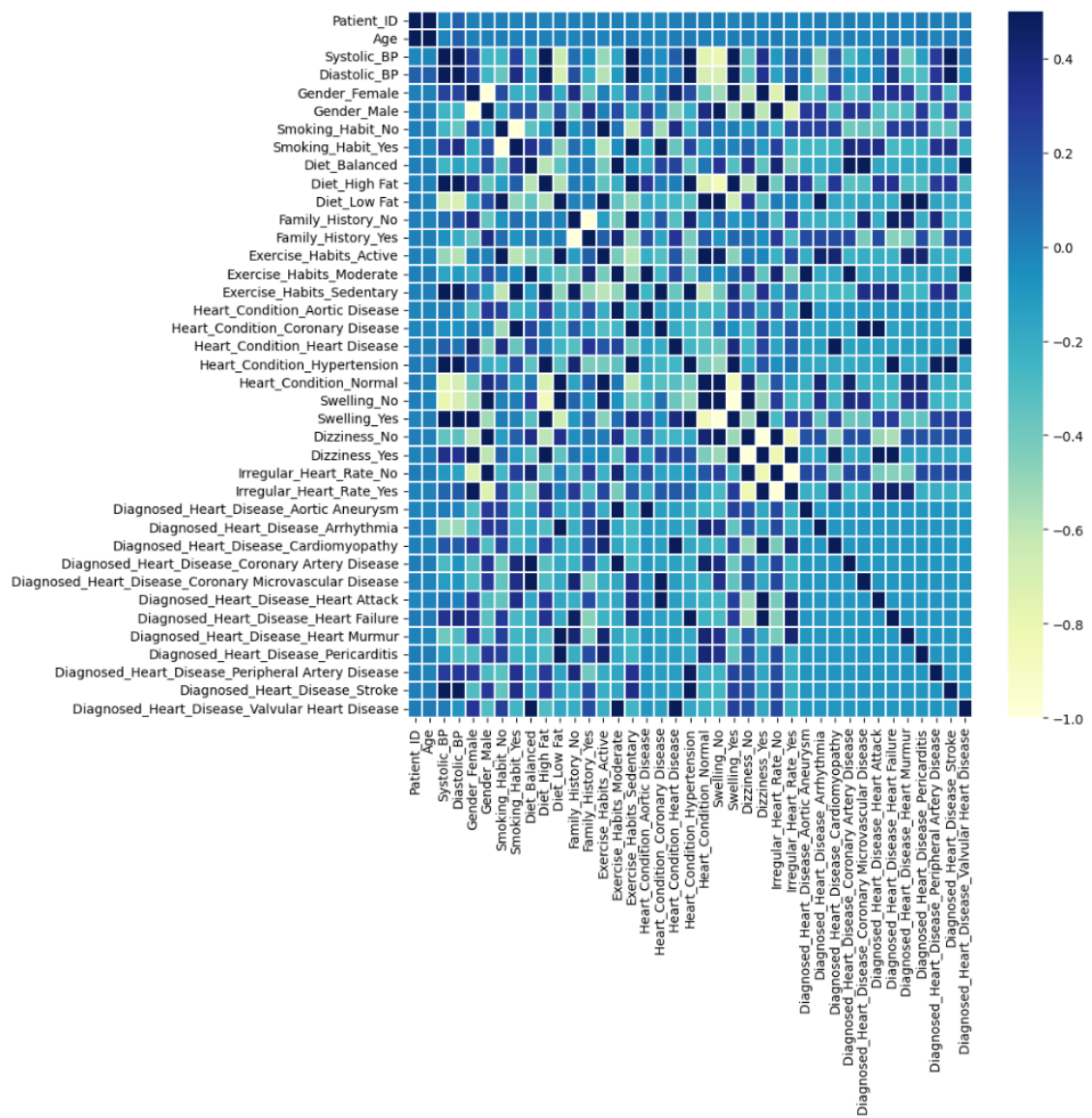


Fig 4: Heat Map

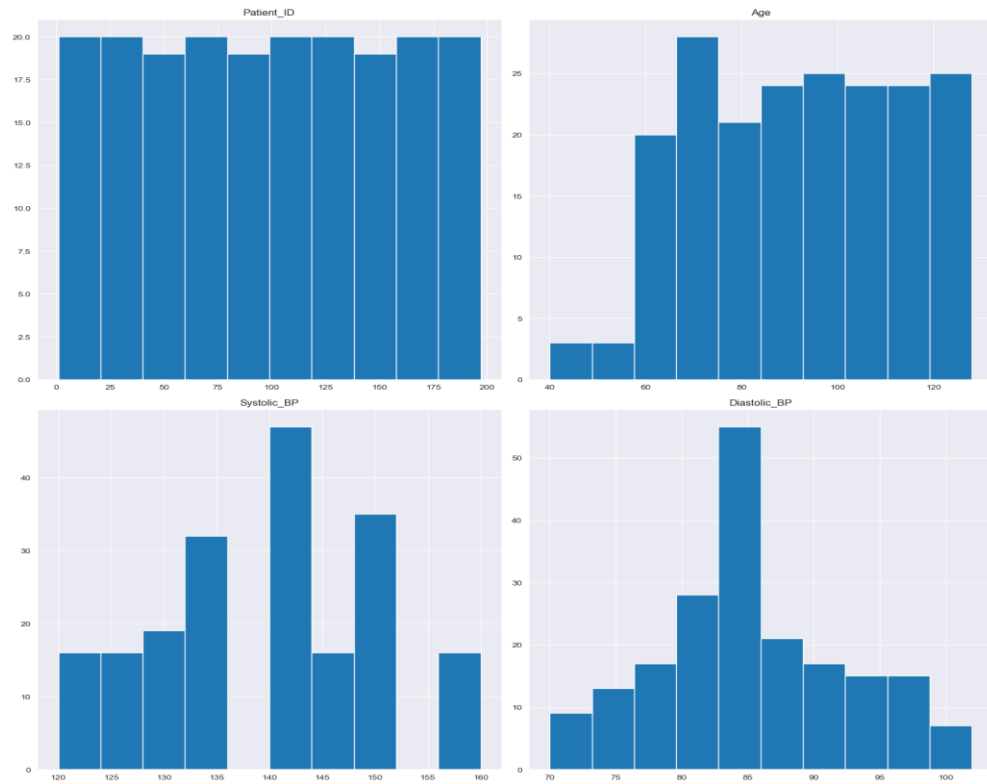


Fig 5: Histogram plot

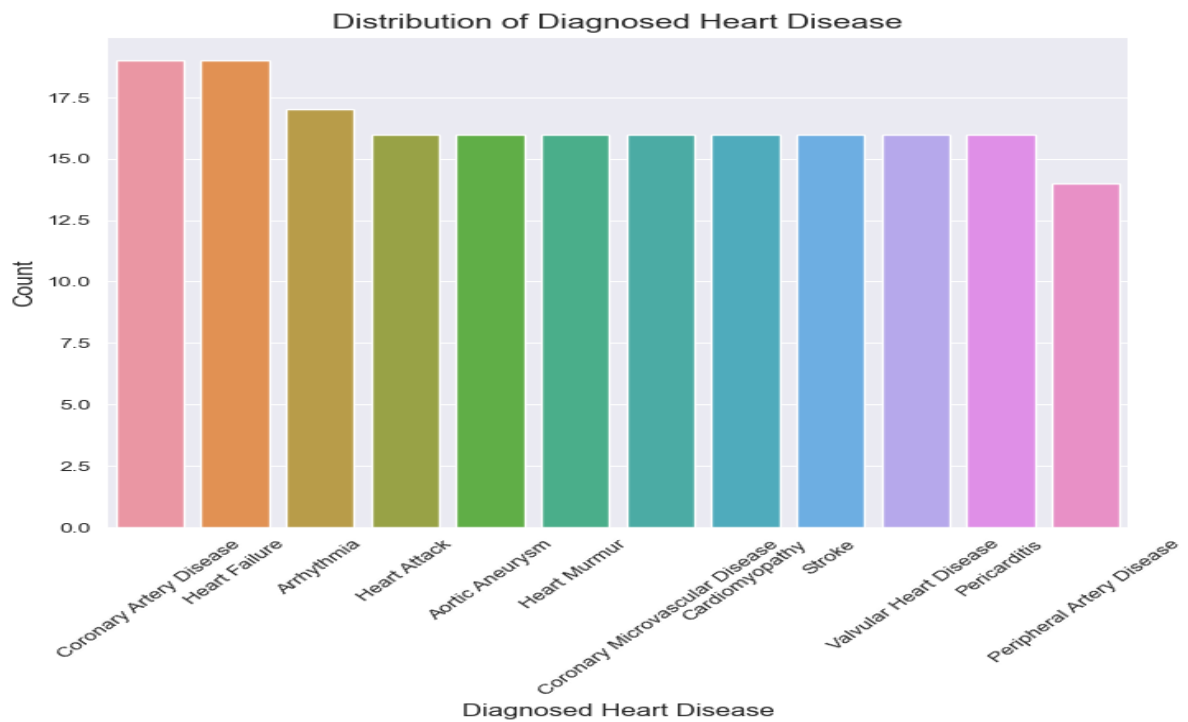


Fig 6: Distribution of Diagnosed Heart Disease

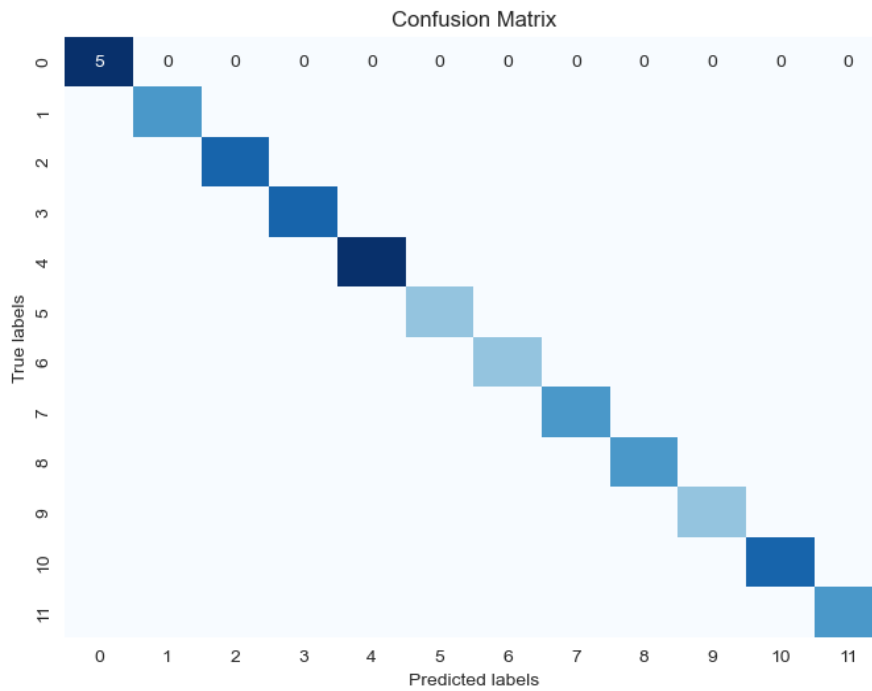


Fig 7: Confusion Matrix

Patient_ID	Age	Gender	Smoking_F	Diet	Family_His	Exercise_F	Systolic_BI	Diastolic_I	Heart_Cor	Swelling	Dizziness	Irregular_F	Diagnosed_Heart_Disease
1	55	Male	Yes	Balanced	Yes	Moderate	130	80	Normal	No	No	No	Coronary Artery Disease
2	65	Female	No	High Fat	No	Sedentary	150	90	Hypertensi	Yes	Yes	Yes	Heart Failure
3	40	Male	No	Low Fat	Yes	Active	150	70	Normal	No	No	No	Arrhythmia
4	70	Female	Yes	High Fat	Yes	Sedentary	150	85	Coronary I	Yes	Yes	Yes	Heart Attack
5	60	Male	No	High Fat	Yes	Moderate	140	85	Aortic Dise	Yes	No	No	Aortic Aneurysm
6	50	Female	No	Low Fat	No	Active	125	75	Normal	No	No	Yes	Heart Murmur
7	45	Male	Yes	Balanced	No	Sedentary	135	80	Coronary I	No	No	No	Coronary Microvascular Disease
8	55	Female	No	High Fat	Yes	Active	145	85	Heart Dise	Yes	Yes	Yes	Cardiomyopathy
9	75	Male	Yes	High Fat	Yes	Sedentary	160	95	Hypertensi	Yes	No	No	Stroke
10	70	Female	No	Balanced	Yes	Moderate	140	80	Heart Dise	Yes	No	No	Valvular Heart Disease
11	65	Male	No	Low Fat	Yes	Active	135	75	Normal	No	No	No	Pericarditis
12	45	Female	Yes	High Fat	No	Sedentary	150	90	Hypertensi	Yes	No	No	Peripheral Artery Disease
13	60	Male	Yes	Balanced	Yes	Moderate	130	81	Normal	No	No	No	Coronary Artery Disease
14	61	Female	No	High Fat	No	Sedentary	150	91	Hypertensi	Yes	Yes	Yes	Heart Failure
15	61	Male	No	Low Fat	Yes	Active	120	71	Normal	No	No	No	Arrhythmia
16	61	Female	Yes	High Fat	Yes	Sedentary	140	85	Coronary I	Yes	Yes	Yes	Heart Attack

Fig 8: Dataset Used

← → ↻ 127.0.0.1:5000 ☆ 📄 ⬇️ ⓘ ⋮

Heart Disease Diagnosis

Patient ID:

Age:

Systolic Blood Pressure:

Diastolic Blood Pressure:

Gender:

Is the patient a smoker?

Diet:

Does the patient have a family history of heart disease?

Fig 9: GUI based Web Form

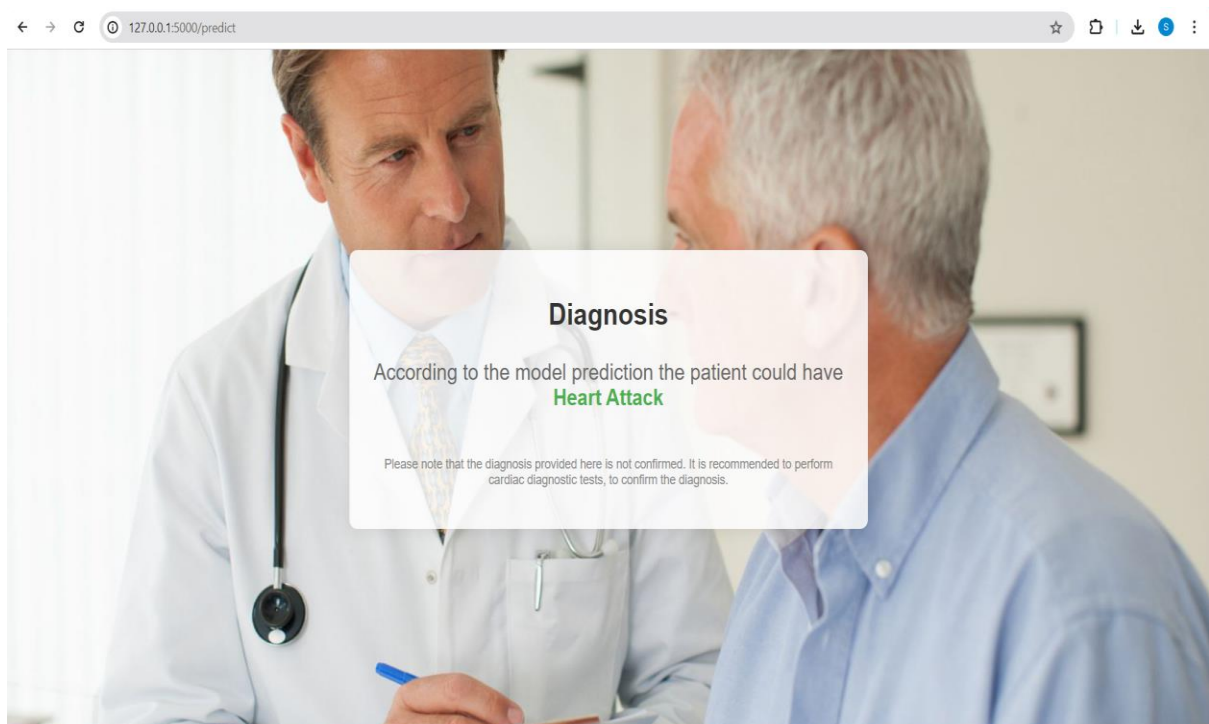


Fig 10: Heart Disease Diagnosis Page

CONCLUSION:

In conclusion, the heart disease diagnosis project represents a significant endeavor in leveraging machine learning techniques to improve patient outcomes and clinical decision-making in the diagnosis of heart disease. Through the analysis of a comprehensive dataset containing patient demographics, clinical measurements, lifestyle factors, and medical history, we have developed a predictive model capable of accurately classifying patients into different heart disease categories. The project has demonstrated the effectiveness of machine learning algorithms, such as logistic regression, decision trees, random forests, support vector machines, and neural networks, in accurately diagnosing heart disease based on a range of predictive features. By evaluating the performance of these models using appropriate evaluation metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, we have ensured the reliability and generalization performance of the diagnostic system. Furthermore, the deployment of the trained model into a production environment, along with the development of user interfaces or APIs for real-time inference, underscores the practical utility of the heart disease diagnosis system. Looking ahead, the ongoing maintenance and monitoring of the deployed model, coupled with periodic retraining with new data, will ensure its continued accuracy, reliability, and compliance with regulatory requirements. Additionally, iterative improvements based on feedback from users and stakeholders will further enhance the diagnostic capabilities of the system. In summary, the heart disease diagnosis project represents a valuable contribution to the field of healthcare, demonstrating the potential of machine learning to transform diagnostic processes and improve patient care in the detection and management of heart disease. Through collaboration and innovation, we can continue to advance the state-of-the-art in cardiovascular health and make meaningful strides towards reducing the burden of heart disease worldwide.

FUTURE WORK:

1. Clinical Decision Support:

Integrate the predictive model into clinical decision support systems used by healthcare providers to assist in risk assessment, diagnosis, and treatment planning for patients with suspected or established heart disease. The model can help clinicians prioritize patients for further evaluation, tailor interventions based on individual risk profiles, and monitor disease progression over time.

2. Population Health Management:

Deploy the model within population health management programs to identify high-risk individuals within a given population and implement targeted interventions aimed at preventing the development or progression of heart disease. This can include outreach programs, lifestyle modification interventions, and community-based initiatives to promote heart-healthy behaviors.

3. Health Insurance and Risk Assessment:

Partner with health insurance companies to use the model for risk assessment and pricing of insurance policies. By accurately identifying individuals at high risk of developing heart disease, insurers can offer targeted wellness programs, incentives for healthy behaviors, and personalized interventions to reduce the overall risk and cost of healthcare.

4. Research and Development:

Serve as a valuable research tool for investigating the underlying mechanisms of heart disease, identifying novel risk factors, and evaluating the efficacy of new diagnostic tests and treatment modalities. The model can be used to generate hypotheses, design clinical trials, and conduct epidemiological studies aimed at advancing our understanding of heart disease and improving patient outcomes.

5. Global Health Initiatives:

Extend the reach of the model to low-resource settings and developing countries where access to specialized healthcare services may be limited. By leveraging technology and data-driven approaches, we can democratize access to accurate risk assessment tools, empower healthcare providers with decision support tools, and improve the overall quality of care for underserved populations worldwide.

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- [10] Géron, A. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow: Concepts, Tools, and Techniques to Build Intelligent Systems*. O'Reilly Media, Inc.

B. Source Code:

App.py:

```
from flask import Flask, render_template, request
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier

app = Flask(__name__)

# Load the dataset and train the model
df = pd.read_csv('HDD(4).csv') # Replace 'HDD(4).csv' with the path to your
dataset file

# Handle missing values if any
df.fill(inplace=True) # Forward fill missing values

# Encode categorical variables
df_encoded = pd.get_dummies(df, columns=['Gender', 'Smoking_Habit', 'Diet',
'Family_History', 'Exercise_Habits', 'Heart_Condition', 'Swelling', 'Dizziness',
'Irregular_Heart_Rate'])

# Split dataset into features (X) and target variable (y)
X = df_encoded.drop('Diagnosed_Heart_Disease', axis=1)
y = df_encoded['Diagnosed_Heart_Disease']

# Train a Machine Learning Model
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
model = RandomForestClassifier(random_state=42)
model.fit(X_train, y_train)

# Define routes
@app.route('/')
def index():
    return render_template('index.html')

@app.route('/predict', methods=['POST'])
def predict():
    # Retrieve form data
    new_patient_data = {
        'Patient_ID': int(request.form['Patient_ID']),
        'Age': int(request.form['Age']),
        'Systolic_BP': int(request.form['systolicBP']),
        'Diastolic_BP': int(request.form['diastolicBP']),
        'Gender_Female': 1 if request.form['gender'] == 'female' else 0,
        'Gender_Male': 1 if request.form['gender'] == 'male' else 0,
```

```

'Smoking_Habit_Yes': 1 if request.form['smoking'] == 'yes' else 0,
'Smoking_Habit_No': 1 if request.form['smoking'] == 'no' else 0,
'Diet_High Fat': 1 if request.form['diet'] == 'high fat' else 0,
'Diet_Balanced': 1 if request.form['diet'] == 'balanced' else 0,
'Diet_Low Fat': 1 if request.form['diet'] == 'low fat' else 0,
'Family_History_Yes': 1 if request.form['familyHistory'] == 'yes' else 0,
'Family_History_No': 1 if request.form['familyHistory'] == 'no' else 0,
'Exercise_Habits_Active': 1 if request.form['exercise'] == 'Active' else 0,
'Exercise_Habits_Moderate': 1 if request.form['exercise'] == 'Moderate'
else 0,
'Exercise_Habits_Sedentary': 1 if request.form['exercise'] == 'Sedentary'
else 0,
'Heart_Condition_Normal': 1 if request.form['heartCondition'] == 'normal'
else 0,
'Heart_Condition_Hypertension': 1 if request.form['heartCondition'] ==
'hypertension' else 0,
'Heart_Condition_Coronary Disease': 1 if request.form['heartCondition']
== 'coronary disease' else 0,
'Heart_Condition_Aortic Disease': 1 if request.form['heartCondition'] ==
'aortic disease' else 0,
'Heart_Condition_Heart Disease': 1 if request.form['heartCondition'] ==
'heart disease' else 0,
'Swelling_Yes': 1 if request.form['swelling'] == 'yes' else 0,
'Swelling_No': 1 if request.form['swelling'] == 'no' else 0,
'Dizziness_Yes': 1 if request.form['dizziness'] == 'yes' else 0,
'Dizziness_No': 1 if request.form['dizziness'] == 'no' else 0,
'Irregular_Heart_Rate_Yes': int(request.form['irregularHeartRate']),
'Irregular_Heart_Rate_No': 1 - int(request.form['irregularHeartRate'])
}

# Convert new_patient_data to DataFrame
new_patient_df = pd.DataFrame([new_patient_data])

# Reorder columns in new_patient_df to match the order of features used
during training
new_patient_df = new_patient_df.reindex(columns=X.columns)

print("New Patient Data:")
print(new_patient_df)

# Make prediction
Diagnosed_Heart_Disease = model.predict(new_patient_df)
print("Predicted Disease:")
print(Diagnosed_Heart_Disease)

return render_template('result.html',
diagnosis=Diagnosed_Heart_Disease[0])

if __name__ == '__main__':
    app.run(debug=True)

```

Index.html:

```
<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">
  <meta name="viewport" content="width=device-width, initial-scale=1.0">
  <title>Heart Disease Diagnosis</title>
  <link rel="stylesheet" href="{{ url_for('static', filename='styles.css') }}">
</head>
<body>
  <div class="container">
    <h1>Heart Disease Diagnosis</h1>
    <form action="/predict" method="post">
      <div class="form-group">
        <label for="Patient_ID">Patient ID:</label>
        <input type="number" id="Patient_ID" name="Patient_ID"
placeholder="Patient ID" required>
      </div>
      <div class="form-group">
        <label for="Age">Age:</label>
        <input type="number" id="Age" name="Age" placeholder="Age"
required>
      </div>
      <div class="form-group">
        <label for="systolicBP">Systolic Blood Pressure:</label>
        <input type="number" id="systolicBP" name="systolicBP"
placeholder="Systolic Blood Pressure" required>
      </div>
      <div class="form-group">
        <label for="diastolicBP">Diastolic Blood Pressure:</label>
        <input type="number" id="diastolicBP" name="diastolicBP"
placeholder="Diastolic Blood Pressure" required>
```

```

</div>
<div class="form-group">
  <label for="gender">Gender:</label>
  <select id="gender" name="gender" required>
    <option value="male">Male</option>
    <option value="female">Female</option>
  </select>
</div>
<div class="form-group">
  <label for="smoking">Is the patient a smoker?</label>
  <select id="smoking" name="smoking" required>
    <option value="yes">Yes</option>
    <option value="no">No</option>
  </select>
</div>
<div class="form-group">
  <label for="diet">Diet:</label>
  <select id="diet" name="diet" required>
    <option value="high fat">High Fat</option>
    <option value="balanced">Balanced</option>
    <option value="low fat">Low Fat</option>
  </select>
</div>
<div class="form-group">
  <label for="familyHistory">Does the patient have a family history of
heart disease?</label>
  <select id="familyHistory" name="familyHistory" required>
    <option value="yes">Yes</option>
    <option value="no">No</option>
  </select>
</div>
<div class="form-group">
  <label for="exercise">Is the patient physically active?</label>
  <select id="exercise" name="exercise" required>

```

```

        <option value="Active">Active</option>
        <option value="Moderate">Moderate</option>
        <option value="Sedentary">Sedentary</option>
    </select>
</div>
<div class="form-group">
    <label for="heartCondition">Heart Condition:</label>
    <select id="heartCondition" name="heartCondition" required>
        <option value="normal">Normal</option>
        <option value="hypertension">Hypertension</option>
        <option value="coronary disease">Coronary Disease</option>
        <option value="aortic disease">Aortic Disease</option>
        <option value="heart disease">Heart Disease</option>
    </select>
</div>
<div class="form-group">
    <label for="swelling">Does the patient experience swelling? (1 for
yes, 0 for no):</label>
    <select id="swelling" name="swelling" required>
        <option value="yes">Yes</option>
        <option value="no">No</option>
    </select>
</div>
<div class="form-group">
    <label for="dizziness">Does the patient experience dizziness? (1 for
yes, 0 for no):</label>
    <select id="dizziness" name="dizziness" required>
        <option value="yes">Yes</option>
        <option value="no">No</option>
    </select>
</div>
<div class="form-group">
    <label for="irregularHeartRate">Does the patient have an irregular
heart rate? (1 for yes, 0 for no):</label>

```

```

        <select id="irregularHeartRate" name="irregularHeartRate"
required>
        <option value="1">Yes</option>
        <option value="0">No</option>
    </select>
</div>
<div class="form-group">
    <button type="submit">Predict</button>
</div>
</form>
</div>
</body>
</html>

```

Result.html:

```

<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Diagnosis</title>
    <style>
        body {
            font-family: Arial, sans-serif;
            margin: 0;
            padding: 0;
            background-image: url('https://www.verywellhealth.com/thmb/ul-
tLFHVGSFP-kR3DOR-
cV9m0kU=/1500x0/filters:no_upscale():max_bytes(150000):strip_icc()/171631
860-56aae7f53df78cf772b4a4cb.jpg'); /* Replace 'background.jpg' with the
path to your background image */
            background-size: cover;
            background-position: center;
            display: flex;

```

```

        justify-content: center;
        align-items: center;
        height: 100vh;
    }
    .container {
        background-color: rgba(255, 255, 255, 0.850); /* Add opacity to the
container */
        padding: 30px;
        border-radius: 10px;
        box-shadow: 0 0 20px rgba(0, 0, 0, 0.1);
        text-align: center;
        max-width: 600px;
        width: 100%;
    }
    h1 {
        color: #333;
        font-size: 32px;
        margin-bottom: 20px;
    }
    p {
        color: #666;
        font-size: 24px;
        margin-top: 30px;
    }
    .result {
        color: #4CAF50;
        font-weight: bold;
    }
    .footer {
        margin-top: 50px;
        font-size: 14px;
        color: #888;
    }
}
</style>

```

```
</head>
<body>
  <div class="container">
    <h1>Diagnosis</h1>
    <p>According to the model prediction the patient could have <span
class="result">{{ diagnosis }}</span></p>
    <p class="footer">Please note that the diagnosis provided here is not
confirmed. It is recommended to perform cardiac diagnostic tests, to confirm
the diagnosis.</p>
  </div>
</body>
</html>
```