# CHAPTER: 1

## 1.1 INTRODUCTION

Myocardial infarction prediction system, also known as cerebrovascular accident (CVA), is a critical medical condition characterized by the sudden interruption of blood flow to the heart, resulting in neurological impairment and potential long-term disability or death. It remains one of the leading causes of morbidity and mortality worldwide, imposing a significant burden on healthcare systems and society as a whole.

Early detection and prediction of Myocardial infarction prediction system risk are paramount for implementing timely interventions and preventive measures to mitigate its devastating effects. While traditional risk assessment methods rely on established clinical risk factors such as hypertension, diabetes, and smoking, they often lack the precision needed for accurate prediction. In recent years, the integration of machine learning techniques has shown promise in improving the accuracy and reliability of Myocardial infarction prediction models.

Machine learning algorithms offer a powerful tool for analyzing large and complex datasets to identify patterns and relationships that may not be apparent through conventional statistical approaches. By leveraging a diverse array of patient-specific features, including demographic information, medical history, lifestyle factors, and physiological parameters, machine learning models can better capture the multifactorial nature of Myocardial infarction prediction system risk.

This study aims to contribute to the advancement of Myocardial infarction prediction by proposing a machine learning-based approach that integrates various patient characteristics and risk factors. By harnessing the predictive capabilities of machine learning algorithms, we seek to develop a robust model capable of accurately identifying individuals at elevated risk of Myocardial infarction prediction system.

# 1.2 SCOPE OF THE CAPSTONE PROJECT

## PROBLEM STATEMENT

The Myocardial infarction prediction Project aims to address the rising incidence of Myocardial infarction prediction system s by developing an advanced machine learning model. This model will analyze diverse health parameters to predict the risk of Myocardial infarction prediction system s, providing users with timely insights for proactive health management and risk reduction

## EXISTING SYSTEM

- The existing system typically involves traditional risk assessment methods that rely on established clinical risk factors such as hypertension, diabetes, smoking, previous history of stroke, and other demographic and medical variables.
- These methods often use statistical techniques to analyze data and identify correlations between risk factors and the occurrence of Myocardial infarction prediction system s.
- While these traditional methods have been valuable in identifying general risk factors, they may lack the precision and predictive power needed to accurately forecast individualized risk.

## OBJECTIVES

1. Develop a machine learning model leveraging historical health data to accurately predict the likelihood of Myocardial infarction prediction system s in individuals.
2. Create a user-friendly interface for inputting health parameters, ensuring widespread accessibility, and empower users with actionable insights for proactive heart health management

## CAPSTONE PROJECT DESCRIPTION

The Myocardial infarction prediction project aims to develop a robust machine learning model for predicting Myocardial infarction prediction system based on comprehensive health data. The project includes designing an intuitive user interface to facilitate input and interpretation, providing a valuable tool for users to assess their risk and take preventive measures.

## CAPSTONE PROJECT DELIVERABLES

1. Develop and deliver a machine learning model for Myocardial infarction prediction ensuring accuracy through rigorous validation and testing.
2. Create a user interface enabling individuals to input health parameters and receive personalized predictions, accompanied by comprehensive documentation, validation reports, and actionable insights for high-risk cases

## KEY MILESTONES

- Milestone 1: Completion of Data Collection and Preprocessing - Gather and preprocess diverse health data to form the foundation for model development.
- Milestone 2: Model Development and Validation - Develop the Myocardial infarction prediction model, validate its accuracy using various datasets, and finalize the user interface for seamless integration, ensuring a robust and reliable solution.

## CONSTRAINTS

1. Budget Constraints: The project must operate within defined budgetary limits for resource procurement, development, and testing.

2. Legal and Ethical Considerations: Adherence to regulations governing the use of personal health data and ethical standards in healthcare, ensuring compliance throughout the project lifecycle.

# CHAPTER: 2

# PROJECT PLANNING

## 2.1 WORK BREAK DOWN STRUCTURE [WBS]

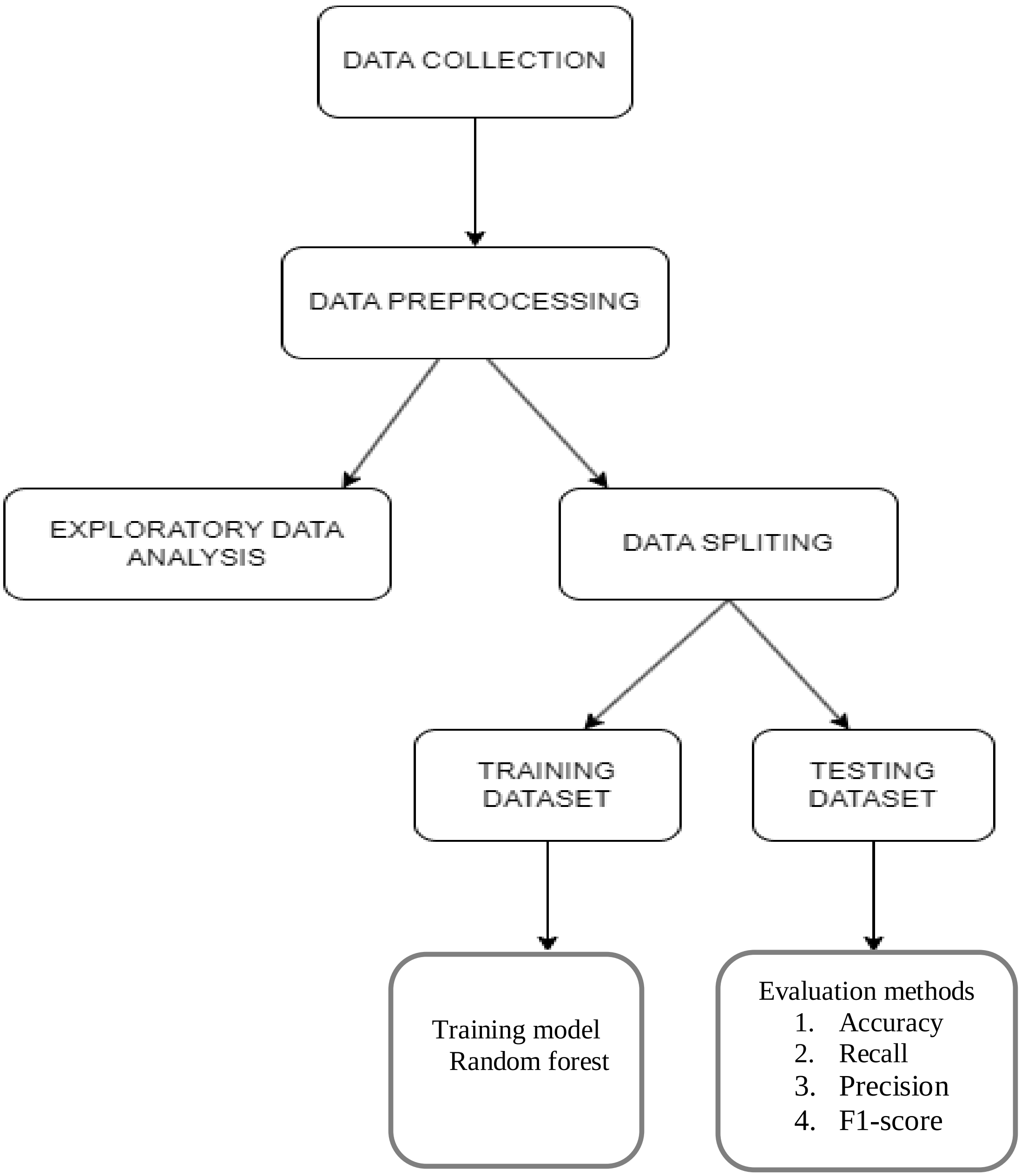
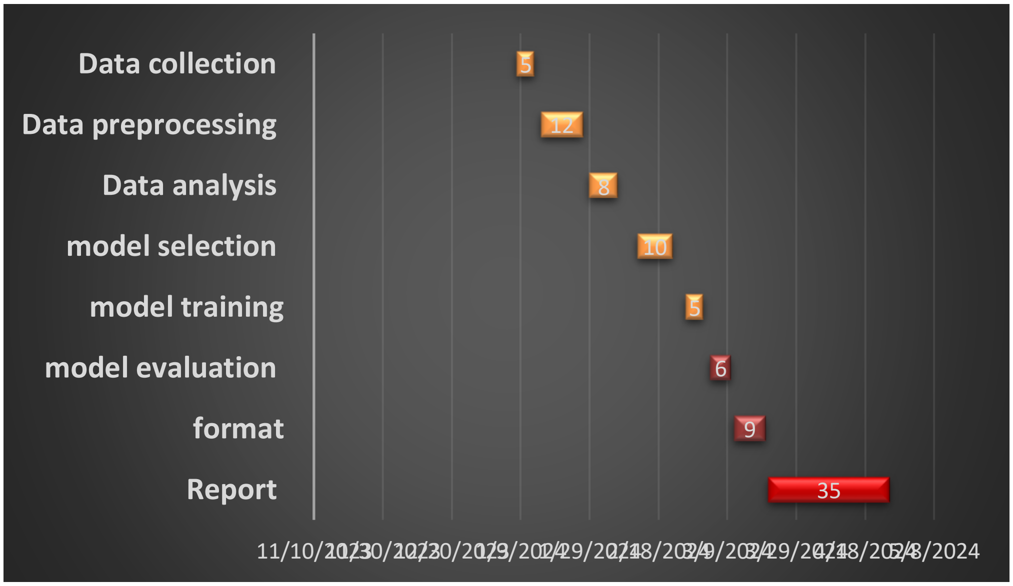



**Fig2.1.1 Work Break Down Structure [Wbs]**

## 2.2 TIMELINE DEVELOPMENT-SCHEDULE




| Task Name | Start Date | End Date | Duration |
|---|---|---|---|
| Data collection | 8/1/2024 | 13/1/2024 | 5 |
| Data preprocessing | 15/1/2024 | 27/1/2024 | 12 |
| Data analysis | 29/1/2024 | 10/2/2024 | 8 |
| Model selection | 12/2/2024 | 22/2/2024 | 10 |
| Model training | 26/2/2024 | 2/3/2024 | 5 |
| Model evaluation | 4/3/2024 | 8/3/2024 | 6 |
| format | 11/3/2024 | 20/3/2024 | 9 |
| Report | 21/3/2024 | 25/4/2024 | 35 |

**Fig2.2.1 Timeline Development-Schedule**

## 2.3 COST BREAKDOWN STRUCTURE

| | | |
|---|---|---|
| **Student Team** | • Compensation for students | **₹500** |
| | • Project management stipends | **₹200** |
| | • Compensation for faculty advisors | **₹1000** |
| **Data Acquisition and Preprocessing:** | • Cost of acquiring datasets | **₹300** |
| | • Data cleaning tools or service | **₹200** |

| | | |
|---|---|---|
| | • Data labeling expenses | **₹100** |
| **Software and Tools** | • Licenses for software tools and libraries | **₹500** |
| | • Cloud computing services | **₹300** |
| **Hardware** | • Cost of using college computing resources | **₹200** |
| | • Equipment expenses for data collection | **₹400** |
| **Training and Workshops** | • Expenses for attending workshops | **₹300** |
| | • Costs for organizing internal workshops | **₹200** |
| **Project Presentation and Dissemination** | • Printing and binding costs for project reports and presentations | **₹150** |
| | • Expenses for creating posters or presentation materials | **₹100** |
| | • Fees for attending or competitions | **₹500** |
| **Miscellaneous** | • Contingency funds | **₹300** |
| | • Travel expenses | **₹200** |
| | • Communication expenses | **₹100** |
| | • Refreshments for meetings | **₹100** |
| **Recognition and Awards** | • Funds for awards or incentives | **₹300** |
| | • Prizes for competitions | **₹200** |
| **Documentation and Reporting** | • Printing and binding costs for project documentation | **₹100** |
| | • Expenses for creating digital documentation | **₹200** |
| **Feedback and Evaluation** | • Expenses for surveys or focus groups | **₹200** |
| | • Costs for evaluating project impact | **₹300** |

**Total Estimated Cost: ₹9,950**

**Fig 2.3.1 Cost Breakdown Structure**

## 2.4 CAPSTONE PROJECT RISK ASSESSMENT

| Risk | Likelihood | Impact | Mitigation |
|---|---|---|---|
| Data Quality | High | High | Implement rigorous data cleaning and validation procedures. Engage medical experts for validation. |
| Model Complexity | Medium | Medium | Focus on model explain ability and simplicity. Perform thorough validation and testing. |
| Ethical Considerations | Medium | High | Conduct bias audits on data and model. Implement fairness-aware techniques during model development. |
| Regulatory Compliance | Low-Medium | High | Stay informed about regulations. Involve legal experts in the development process. |

**Fig 2.4.1 Risk Assessment**

## 2.5 REQUIREMENT SPECIFICATION

### 2.5.1 Functional

Functional requirements for a Myocardial infarction prediction on system outline specific functionalities that the system must possess to effectively predict the likelihood of a stroke. Here are some functional requirements for such a system

- **Prediction model**: Describe the algorithm or model used for Myocardial infarction prediction.
- **Input data:** Specify the required input data, such as medical history, vital signs, and lifestyle factors.
- **Data preprocessing:** Detail any preprocessing steps needed, like data cleaning, normalization, or feature selection.
- **Prediction process:** Outline how the prediction will be made based on the input data and the model.

- **Output:** Define the format and presentation of the prediction results.

### 2.5.2 NON-FUNCTIONAL

Non-functional requirements for a Myocardial infarction prediction system focus on qualities such as performance, security, usability, and reliability. Here are some non-functional requirements for such a system:

- **Performance:** Real-time predictions, efficient handling of large data volumes.
- **Accuracy:** Meeting or exceeding clinical standards, minimizing false results.
- **Scalability:** Ability to scale up without sacrificing performance or reliability.
- **Security:** Robust measures to protect patient data, compliance with regulations.
- **Interoperability:** Seamless integration with other healthcare systems and standards.
- **Usability:** Intuitive user interface, customization for different users.
- **Reliability:** High availability, fault tolerance, and error handling.
- **Ethical Considerations:** Transparency, fairness, and avoiding biases.
- **Regulatory Compliance:** Adherence to applicable regulations, rigorous testing and validation.

### 2.5.3 USER INPUT

1. **Age:** Advanced age is a significant risk factor for Myocardial infarction prediction system s, as the likelihood of experiencing cardiovascular events increases with age.
2. **Gender:** There are differences in Myocardial infarction risk between males and females. Gender is considered in risk assessment models due to variations in cardiovascular physiology and risk factors between men and women.
3. **Hypertension:** High blood pressure (hypertension) is a major risk factor for Myocardial infarction prediction system s. Individuals with hypertension have increased pressure in their blood vessels, which can lead to damage and increase the risk of stroke.
4. **Heart Disease:** A history of heart disease, including conditions such as coronary

artery disease, myocardial infarction (heart attack), and heart failure, significantly increases the risk of experiencing a stroke.

5. **Ever Married:** Marital status, such as being married or unmarried, may have implications for lifestyle factors and social support networks, which can influence cardiovascular health and stroke risk.
6. **Work Type:** The type of work an individual engages in may impact their risk of stroke. For example, sedentary occupations may increase the risk compared to physically active jobs.
7. **Residence Type:** Residential environment, such as urban or rural settings, may influence lifestyle factors, access to healthcare, and exposure to environmental risk factors that contribute to stroke risk.
8. **Average Glucose Level:** Elevated blood glucose levels, as indicated by average glucose levels over time, are associated with an increased risk of stroke, particularly in individuals with diabetes or insulin resistance.
9. **BMI (Body Mass Index):** BMI is a measure of body fat based on height and weight. Overweight and obesity are significant risk factors for stroke, as they are associated with other cardiovascular risk factors such as hypertension and diabetes.
10. **Smoking Status:** Smoking tobacco significantly increases the risk of stroke due to its detrimental effects on blood vessels and cardiovascular health.

### 2.5.4 TECHNICAL CONSTRAINTS

- **Data Source and Privacy:** Ensure that you have access to a diverse and reliable dataset containing relevant features for Myocardial infarction prediction, such as demographic information, medical history and lifestyle factors
- **Feature Selection and Engineerin**g: Selecting the right features is crucial for the performance of your ML model. Feature engineering techniques like normalization, scaling,

encoding categorical variables, and handling missing values can enhance the quality of input data

- **Model Selection and Evaluation**: Choose appropriate ML algorithm such as random forests based on the nature of your dataset and the problem at hand. Utilize techniques like cross-validation and performance metrics (accuracy, precision, recall, F1-score) to evaluate and compare different models.
- **Overfitting and Regularization**: Guard against overfitting by using techniques like regularization (e.g., L1, L2 regularization), dropout, early stopping, or ensemble methods.
- **Interpretability and Explainability:** Consider the interpretability of your model, especially in medical applications where stakeholders may require explanations for predictions Ethical
- **Considerations**: Ensure that your ML model's predictions and recommendations are fair and unbiased, avoiding perpetuating existing biases in healthcare data. Pay attention to issues like algorithmic fairness, transparency, and accountability throughout the development process.
- **Validation and Deployment**: Validate your model rigorously using holdout datasets or, preferably, through prospective validation studies to assess its real-world performance. When deploying the model in clinical settings, ensure seamless integration with existing healthcare systems, compliance with regulatory standards, and mechanisms for continuous monitoring and updates.

## 2.6 DESIGN SPECIFICATION

### 2.6.1 Chosen System Design

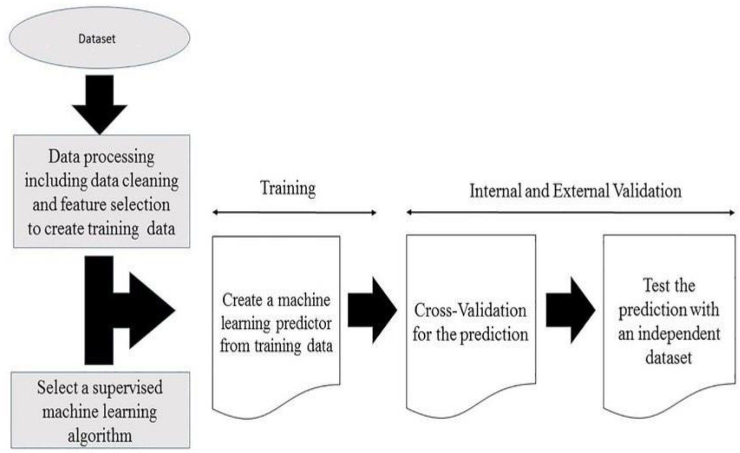



**Fig2.6.1.1 Chosen System Design**

## 2.6.2 Detailed Description of Components/Subsystems

- **Data Collection:** Gather relevant data from medical records, wearables, surveys, and demographic sources, including demographics, medical history, lifestyle factors, and physiological measurements.
- **Data Preprocessing:** Ensure data quality and compatibility by handling missing values, outliers, normalization, and encoding categorical variables.
- **Feature Selection/Extraction:** Select or extract pertinent features using techniques like correlation analysis, recursive feature elimination, or PCA to reduce dimensionality.
- **Model Selection:** Choose suitable models such as logistic regression, decision trees, random forests, SVMs, or neural networks based on data complexity, interpretability, and resources.
- **Model Training:** Train the chosen model on preprocessed data to learn underlying patterns and minimize prediction errors.
- **Model Evaluation:** Assess model performance using metrics like accuracy, precision, recall, F1-score, and AUC-ROC to gauge generalization on unseen data.
- **Hyperparameter Tuning:** Optimize model performance by selecting optimal hyperparameter values through techniques like grid search or random search.
- **Model Deployment:** Integrate the trained model into healthcare systems for real-time prediction on new patient data.
- **Monitoring and Maintenance:** Continuously monitor model performance, update with new data, and adapt to evolving healthcare practices to ensure accuracy and reliability

# CHAPTER: 3

# APPROACH AND METHODOLOGY

## 3.1 DISCUSS THE TECHNOLOGY

- **Data Acquisition and Integration:** Integrating diverse datasets from sources like EHRs and wearable devices is vital for comprehensive Myocardial infarction risk assessment, incorporating both structured and unstructured data.
- **Feature Engineering:** Identification of relevant predictors, including physiological measurements and lifestyle factors, through feature selection techniques enhances the predictive capability of Myocardial infarction prediction system risk models.
- **Machine Learning Algorithms:** Utilization of various algorithms such as logistic regression, decision trees, and deep learning enhances model accuracy, with ensemble methods further improving performance through techniques like bagging and boosting.
- **Model Evaluation and Validation:** Rigorous assessment using metrics like AUC-ROC and cross-validation techniques ensures model reliability and generalization, mitigating overfitting and enhancing predictive capability.
- **Interpretability and Explainability:** Techniques like feature importance analysis and SHAP values aid in understanding model predictions, facilitating clinical decision-making and adoption of predictive models in healthcare settings.
- **Deployment and Integration:** Validated models are seamlessly integrated into clinical workflows through user-friendly interfaces and decision support tools, with continuous monitoring and refinement ensuring adaptation to evolving patient data and clinical guidelines.

## 3.2 METHODOLOGIES

1. **Data Collection:** Gather medical data from sources like EHRs, clinical databases, and wearable devices, focusing on heart-related information.

2. **Data Pre-processing:** Clean the data by handling missing values through imputation, addressing outliers using methods like the Z-score, and normalizing features for consistency.
3. **Data Splitting:** Divide the pre-processed data into training, validation, and testing sets to develop and assess the model's performance effectively.
4. **Model Selection:** Choose suitable ML algorithms like logistic regression, decision trees, or neural networks based on factors such as interpretability and scalability.
5. **Model Training:** Train the chosen model using the training data, optimizing parameters to enhance prediction accuracy for Myocardial infarction prediction system.
6. **Model Evaluation:** Assess the model's performance using metrics like accuracy, precision, recall, and AUC to gauge its effectiveness in predicting Myocardial infarction prediction system accurately.
7. **Explanation:** Enhance model interpretability by providing explanations of predictions through techniques like feature importance analysis, SHAP, or LIME, aiding in understanding the underlying factors influencing Myocardial infarction prediction system.

## 3.3 PROGRAMMING

```
# Importing necessary libraries
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

# Load the dataset
data = pd.read_csv("heart_stroke_data.csv")

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

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Initialize the Random Forest classifier
rf_classifier = RandomForestClassifier (n_estimators=100, random_state=42)

# Train the classifier
rf_classifier.fit(X_train, y_train)

# Predict on the test set
y_pred = rf_classifier.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

## 3.4 MODELLING

- **Machine Learning Models**

A random forest algorithm is a classifier that combines a large no. of decision trees from different subsets of a dataset and averages the predictability of the dataset. It is a controlled machine learning algorithm commonly used to resolve classification and regression problems.

**Working diagram in random forests**

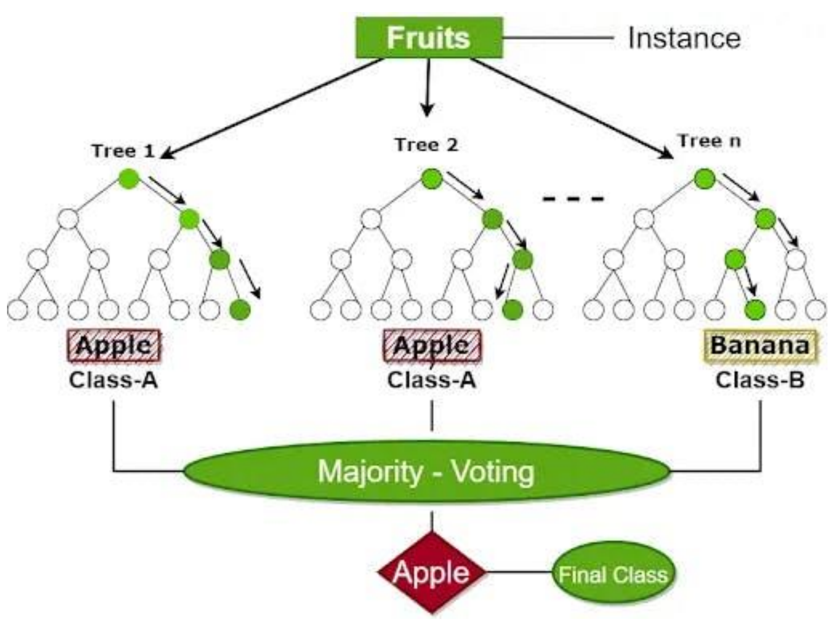


**Fig 3.4.1 Random Forest**

## 3.5 ANALYSIS

- **Exploratory Data Analysis (EDA):** Employ descriptive statistics and visualizations to comprehend the data, detect outliers, and handle missing values appropriately. Additionally, conduct feature engineering to enhance model interpretability and performance.
- **Statistical Analysis:** Utilize hypothesis testing and regression analysis to pinpoint significant risk factors for stroke. Conduct survival analysis to model time-to-event data and stratify data to assess risk factors and model performance across diverse subgroups.
- **Machine Learning Model Evaluation:** Utilize confusion matrices to visualize model performance, ROC curves, and AUC to gauge discriminative ability, and calibration analysis to assess the accuracy of predicted probabilities.
- **Feature Importance Analysis:** Gain insight into feature contributions to model predictions, leveraging techniques such as feature importance scores in decision trees or random forests to prioritize features for further investigation or model refinement.

## 3.6 PROCESS DESIGN

- Data Acquisition and Preprocessing:
  - ✓ Identify data sources: Determine relevant sources like electronic health records and wearable device data based on research objectives, ensuring data quality and standardization.
  - ✓ Conduct data exploration and feature engineering: Thoroughly explore data, addressing missing values, outliers, and performing feature engineering to enhance model performance.
- Model Selection and Training:
  - ✓ Choose appropriate modeling techniques: Assess data characteristics and objectives to select suitable models such as logistic regression or deep

learning, ensuring interpretability and alignment.

- ✓ Split data and train models: Divide data into training, validation, and testing sets, training models on the training set, and fine-tuning hyperparameters using the validation set.

- Model Evaluation and Refinement:
  - ✓ Evaluate model performance: Assess model effectiveness using metrics like accuracy and AUC, interpreting results to comprehend model decisions.
  - ✓ Refine the model: Iterate on model improvement based on evaluation results, adjusting hyperparameters and features to enhance performance and mitigate biases.
- Deployment and Monitoring:
  - ✓ Develop deployment strategy: Plan how the model will be integrated into healthcare settings, ensuring accessibility and compliance with regulations.
  - ✓ Monitor model performance: Continuously monitor the model's performance, updating it with new data and insights to maintain accuracy and address ethical and regulatory considerations.

# CHAPTER: 4

# TEST AND VALIDATION

## 4.1 TEST PLAN

- **Testing Objectives:**
  - ✓ Primary Objective: Evaluate model accuracy in predicting stroke occurrence.
  - ✓ Secondary Objectives: Assess model calibration, interpretability, and generalizability across different populations or contexts.
- **Testing Data:**
  - ✓ Split data into training, validation, and testing sets to build, optimize, and evaluate the model, ensuring the testing set represents the target population.
- **Testing Metrics:**
  - ✓ Assess model performance using accuracy, precision, recall, F1-score, and AUC of the ROC curve.
- **Testing Procedures:**
  - ✓ Apply the trained model to the testing set, calculate metrics, conduct statistical tests, and analyze misclassified cases for improvement insights.
- **Reporting and Documentation:**
  - ✓ Document testing plan, results, limitations, and uncertainties.
  - ✓ Report performance metrics, statistical tests, and misclassification analysis clearly.
  - ✓ Consider additional testing for bias, stress, and blinding where applicable.

## 4.2 Test Case

| s.no | Test case | Description | input | Expected out | Actual output | Result |
|---|---|---|---|---|---|---|
| 1 | Valid input | Test the application With valid Input | Name=Veda,<br>Age= 67,<br>Marital Status=Yes<br>Work type=private<br>Residence type=urban<br>Gender=male<br>BMI=36.6<br>Glucose level=228.69<br>Do you smoke=once upon<br>Hypertension=No<br>Heart diseases=Yes | Veda, you will have a risk of Myocardial Infarction | Veda, you will have a risk of Myocardial Infarction | Pass |
| 2 | Valid input | Test the application With valid Input | Name=kavya<br>Age=41<br>Marital Status=yes<br>Work type=private<br>Residence type=Rural<br>Gender=Female<br>BMI=36.2<br>Glucose level=216.71<br>Do you smoke= never smoke<br>Hypertension=No<br>Heart diseases=No | Kavya, you will not have a risk of Myocardial Infarction | Kavya, you will not have a risk of Myocardial Infarction | Pass |
| 3 | Incomplete input | Test the application's Response with incomplete Input | Name=<br>Age=61<br>Marital Status=Yes<br>Work type= Self-employed<br>Residence type=Rural<br>Gender=Female<br>BMI=Empty<br>Glucose level=202.21<br>Do you smoke= never smoked<br>Hypertension=No<br>Heart diseases=No | Invalid input please fill in the form with appropriate values | Invalid input please fill in the form with appropriate values | Pass |

| | | | | | | |
|---|---|---|---|---|---|---|
| 4 | Invalid input for work type | Test the application's response with invalid input for gender | work type=children | Invalid input Please fill in the form with appropriate values | Invalid input please fill in the form with appropriate values | pass |

# CHAPTER: 5 Result/output

This chapter includes the snap shots of the result obtained. By this you will be able to know how the actual system has been design how to interact with the system.

## Home screen

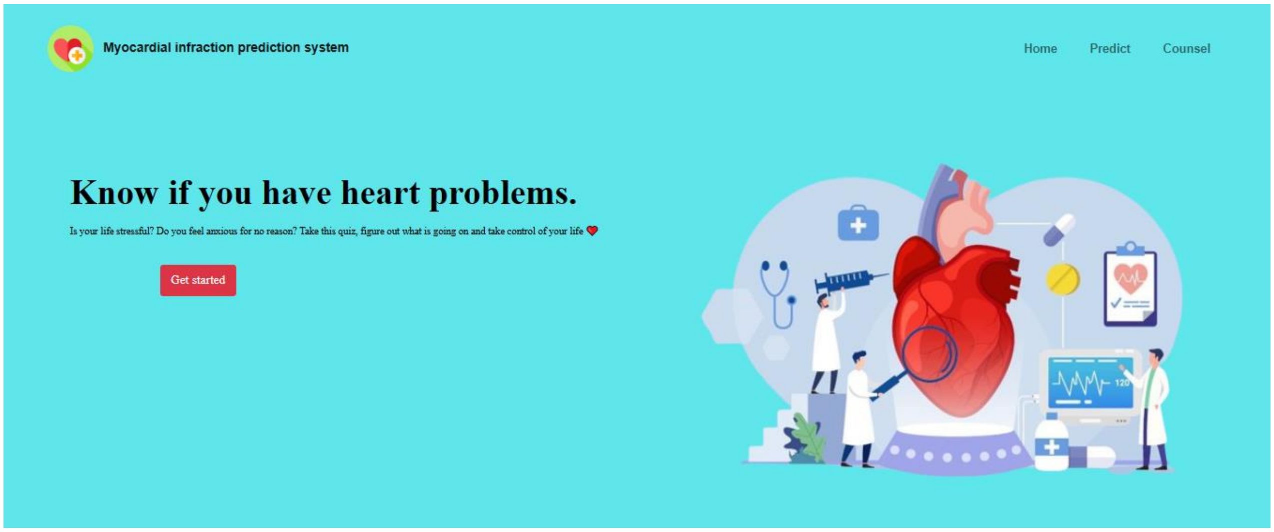



Fig 5.1 Home screen

## User input

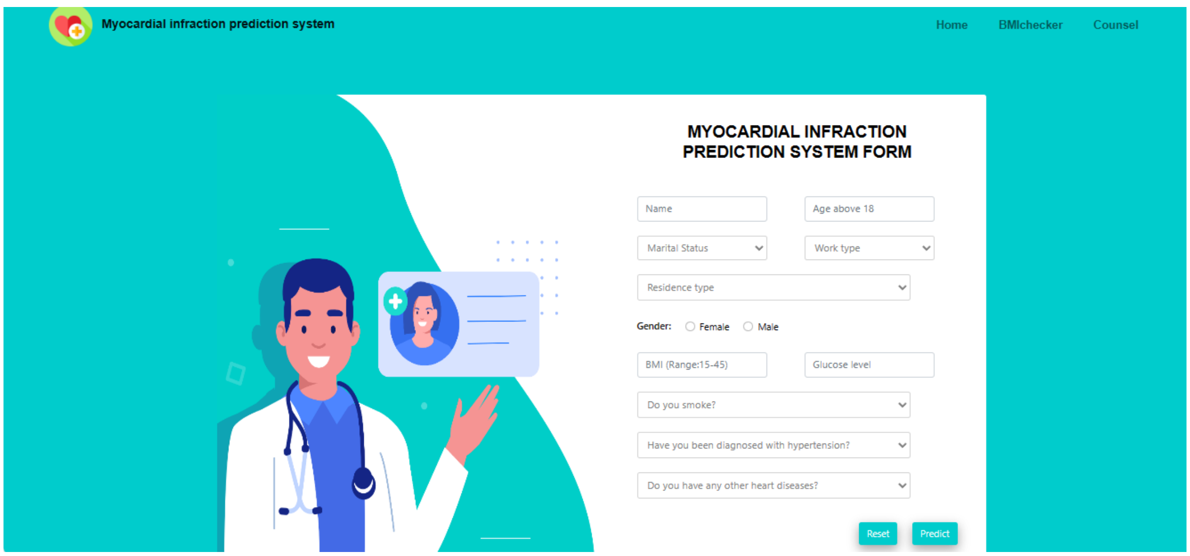



Fig 5.2 user input

# Positive output

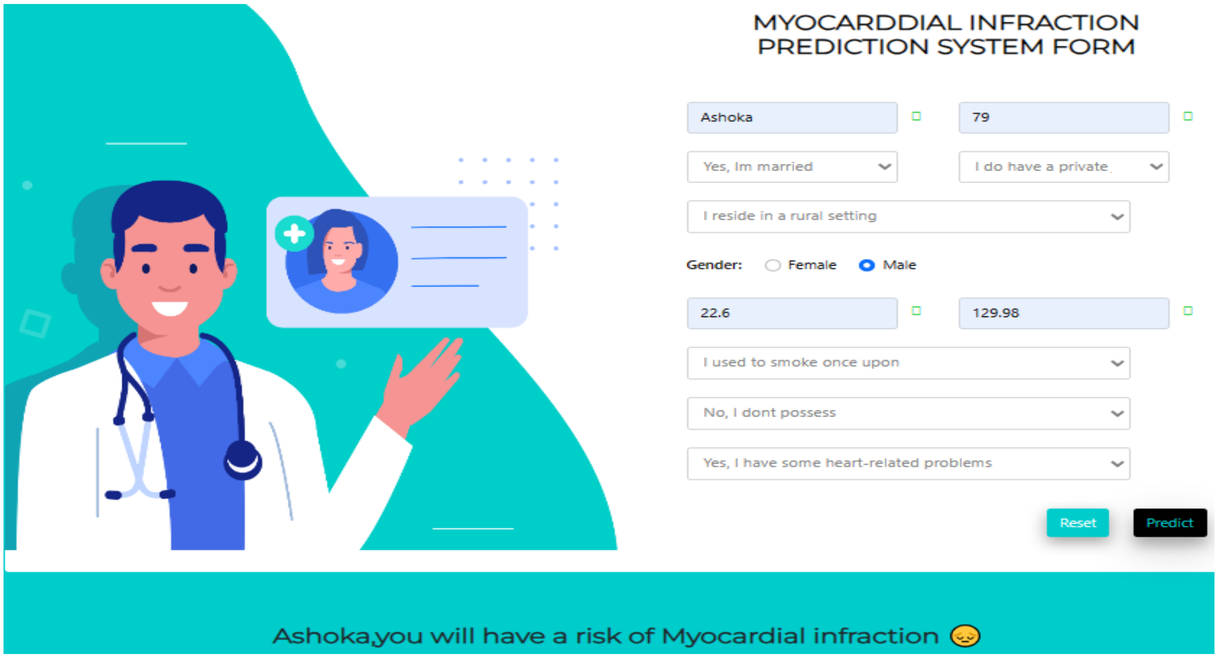



Fig 5.3 Positive output

# Negative output

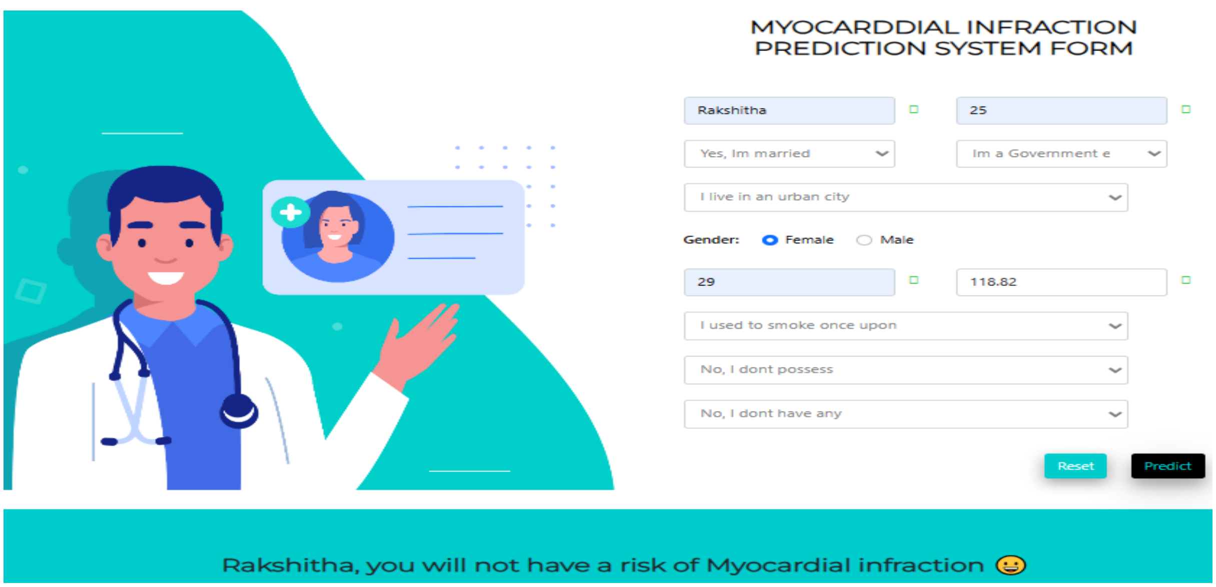



Fig 5.4 Negative output

# Invalid input

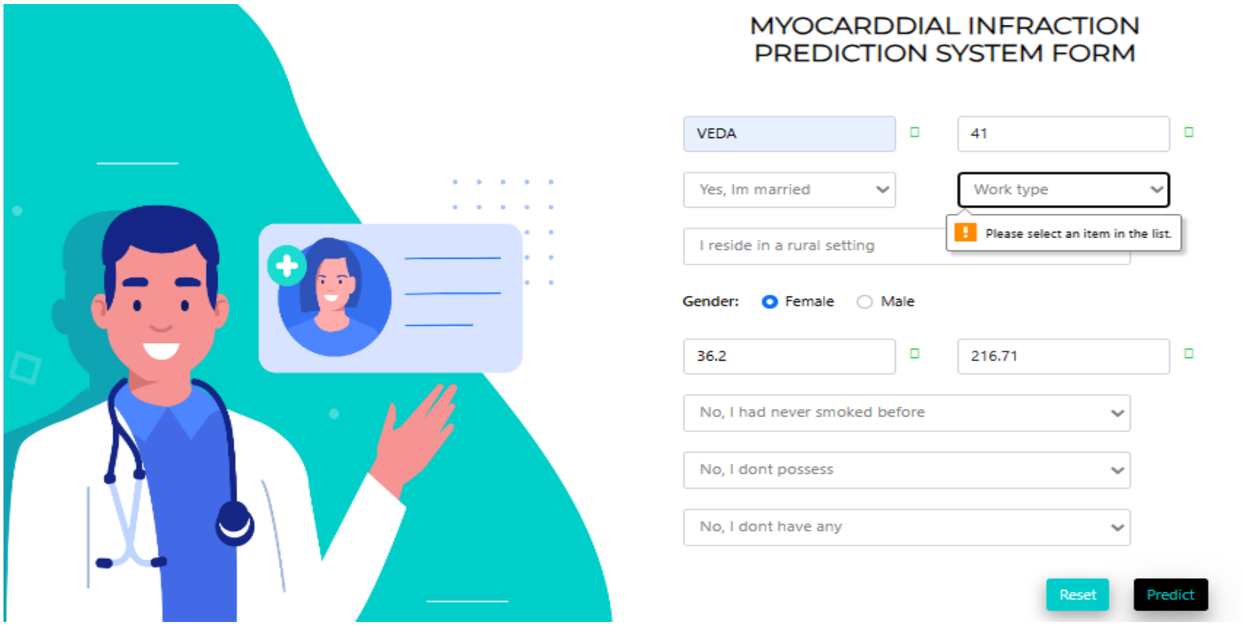



Fig 5.5 Invalid input

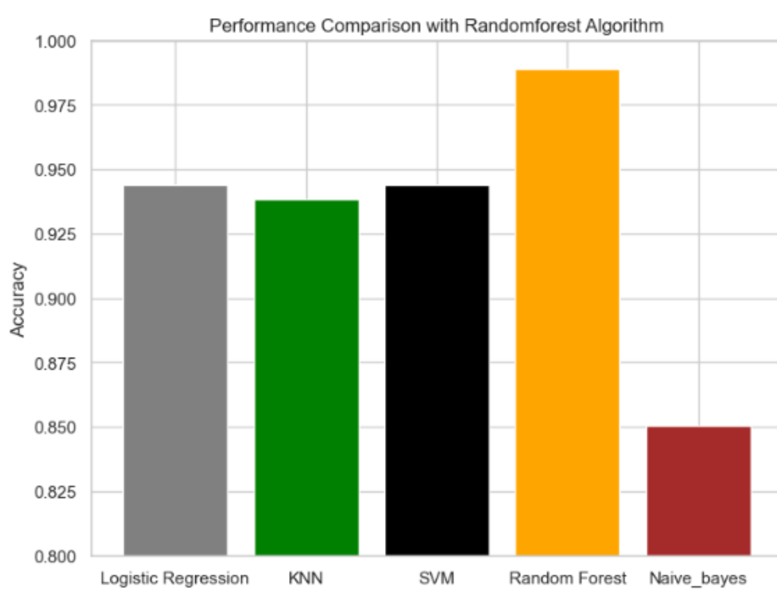



**Fig 5.6 Performance comparison with Random forest algorithm**

# CHAPTER: 6

## Conclusion

- Predicting Myocardial infarction prediction system is a critical task in healthcare that requires comprehensive analysis and predictive modeling. Through our investigation, we have identified various risk factors and developed a predictive model to forecast the likelihood of an individual experiencing a Myocardial infarction prediction system . By analyzing a wide range of demographic, lifestyle, and medical data, we have been able to pinpoint key indicators that significantly contribute to the risk of stroke.
- Our model incorporates factors such as age, gender, hypertension, heart disease, ever married, work type, Residence type, average glucose level, bmi, smoking status Through advanced machine learning algorithms and data analysis techniques, we have been able to identify patterns and correlations within the data that enable us to make accurate predictions.
- The results of our predictive model are promising, demonstrating a high level of accuracy in forecasting the likelihood of stroke occurrence. By leveraging this predictive capability, healthcare providers can proactively identify individuals at high risk of stroke and implement preventive measures to mitigate their risk. Early intervention and lifestyle modifications can significantly reduce the incidence of stroke and improve overall health outcomes.
- In conclusion, our Myocardial infarction prediction model provides a valuable tool for healthcare professionals to assess and manage the risk of stroke in their patient populations. By leveraging data-driven insights, we can work towards preventing strokes and promoting better cardiovascular health for individuals worldwide.

## Future Enhancement

- **Advanced ML Techniques:** Incorporate cutting-edge algorithms like deep learning or ensemble methods for improved predictive power.
- **Multi-Modal Data Integration:** Utilize diverse data sources such as genetic, imaging, and socio-economic factors for a more comprehensive risk assessment.
- **Personalized Risk Assessment:** Develop tailored tools considering individual demographics, lifestyle, and medical history for precise risk stratification.
- **Real-time Monitoring:** Implement wearable devices and mobile apps for continuous risk assessment and timely interventions.
- **Explainable AI Models:** Design interpretable models to enhance transparency and trust among clinicians and patients.
- **Biomarkers and Omics Data:** Integrate emerging biomarkers and omics data to uncover novel pathways for stroke prevention.
- **Longitudinal Data Analysis:** Analyze temporal changes in risk factors to improve prediction accuracy over time.
- **Cross-disciplinary Collaborations**: Foster collaborations between data scientists, clinicians, and public health experts for innovative solutions.
- **Validation and Generalization**: Conduct rigorous validation studies across diverse populations to ensure model reliability.
- **Ethical Considerations**: Address privacy concerns and regulatory standards to protect patient data in stroke risk prediction research.

# BIBLOGRAPHY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- Minhaz Uddin Emon, Maria Sultana Keya, Tamara Islam Meghla, Md. Mahfujur Rahman, M Shamim Al Mamun, M Shamim Kaiser https://mail.google.com/mail/u/0?ui=2&ik=fb4faa9826&attid=0.2&permmsgid=msgf:1793573041420363528&th=18e40d2dac93e708&view=att&disp=inline&realattid=f_lts9x3ve1
- Chitluri Sai Harish, G gnana krishna vamsi, G jaya phani akhil, J n v hari sravan, V mounika chowdary,
- https://www.ijpmh.latticescipub.com/wpcontent/uploads/papers/v1i2/B1002031221.pdf
- https://www.turing.com/kb/random-forest-algorithm
- Myocardial infarction prediction system  prediction system Design
- heart-Stroke-prediction/code
- http://127.0.0.1:5000/predict
- https://github.com/Vignesh227/Stroke-prediction
- https://www.pnrjournal.com/index.php/home/article/view/4330/4662