Classification-Based Prediction System for Heart Strokes

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A

Applications of Data Mining Course Project Report

In partial fulfilment of the degree

**Bachelor of Technology
in
School of Computer Science & Artificial Intelligence**

By

ESWARAPRGADA SAI ANURATH	2303A51560
PERUMALLA SUSHWANTH	2303A51567
ASWIN V MADHU	2303A51655
AREPALLY RAMCHARAN	2303A51091

Under the guidance of

Bediga Sharan
Assistant Professor

Submitted to

School of Computer Science and Artificial Intelligence

sru

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

CERTIFICATE

This is to certify that the **APPLICATIONS OS DATA MINING**– Course Project Report

entitled "**Classification-Based Prediction System for Heart Strokes**" is a record of bona

fide work carried out by the student(s**) E.SAI ANURATH, P. SUSHWANTH, ASWIN V**

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1 5 6 7,   2 3 0 3 A 5 1 6 5 5, 2 3 0 3 A 5 1 0 9 1 during the academic year 2024-25 in partial

fulfillment of the requirements for the award of the degree of *Bachelor of Technology* in

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Supervisor,   **Head of the Department**

 (Mr. Bediga Sharan)   (Dr. M. Sheshikala)

Assistant Professor(CSE&AI)   Assoc.prof&HOD(CSE & AI)

ABSTRACT

The project focuses on predicting heart stroke using machine learning techniques. By analyzing a dataset with features such as age, blood pressure, cholesterol levels, and smoking habits, a model is developed to predict the likelihood of a stroke. Machine learning algorithms, including decision trees and logistic regression, are used for prediction. The goal is to provide an early detection system that can aid healthcare professionals in timely intervention. This system can reduce stroke-related fatalities by offering accurate predictions.

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 GitHub REPOSITORY OF THE PROJECT

https://github.com/E-SaiAnurath/ADM_final_project

OBJECTIVE

➢ Develop an intelligent machine learning system capable of accurately predicting stroke risk using health indicators such as age, hypertension, heart disease, glucose levels, and BMI, contributing to early diagnosis and preventive care.

➢ Perform thorough data preprocessing and exploratory data analysis (EDA) to clean, transform, and visualize the dataset—handling missing values, outliers, and categorical features while uncovering key patterns and correlations.

➢ Implement and evaluate multiple classification algorithms including Logistic Regression, Decision Trees, and Random Forests, using metrics like Accuracy, Precision, Recall, and F1-Score to ensure model reliability and balance.

➢ Visualize model performance using confusion matrices, ROC curves, and feature importance plots to enhance interpretability and support informed decision-making in clinical settings.

➢ Deliver an ethically responsible, user-friendly decision-support tool for both healthcare professionals and individuals, promoting fair, explainable AI, and raising awareness about stroke prevention and the importance of timely intervention.

DEFINITIONS OF THE ELEMENTS USED IN THE PROJECT

This section outlines the key technical concepts, methods, and elements applied throughout the development of the stroke prediction model. They are grouped into categories based on their role in the data mining process.

➢ DATA ELEMENTS

- Dataset: A structured collection of medical records in CSV format used for analysis. It includes features like age, gender, BMI, hypertension, smoking status, glucose level, heart disease, and stroke status.

- Feature: An individual measurable property or variable of the data. In this context, features include both numerical (e.g., age, avg_glucose_level) and categorical (e.g., gender, smoking_status) attributes.

- Target Variable (Stroke): The output variable the model is trying to predict. It is binary: 1 if the individual has had a stroke, 0 otherwise.

- Label Encoding / One-Hot Encoding: Techniques used to convert categorical features into numerical values so they can be used by machine learning models.

➢ DATA PREPROCESSING & CLEANING

- Missing Values: Blank or null entries in the dataset. These are handled through imputation techniques or by removing affected rows/columns depending on their significance.

- Outliers: Extreme values that deviate significantly from the rest of the dataset. Outlier detection and treatment help ensure accurate model performance.

- Data Normalization / Scaling: Techniques such as Min-Max scaling or Standardization are applied to bring features into a similar range, improving model learning.

- SMOTE (Synthetic Minority Over-sampling Technique): A technique used to address class imbalance in binary classification by creating synthetic examples of the minority class.

➢ EXPLORATORY DATA ANALYSIS (EDA)

- Correlation Matrix: A statistical tool used to examine the strength and direction of relationships between multiple variables.

- Histogram/Boxplot/Scatter Plot: Visualization tools used to understand the distribution, central tendencies, and relationships within data.

- Distribution Plot: A graphical representation that shows how a feature's values are spread out across the dataset.

➢ **MACHINE LEARNING CONCEPTS**

- Supervised Learning: A machine learning paradigm where the model is trained on labeled data to predict outcomes for unseen data.

- Classification: A supervised learning task in which input data is categorized into predefined classes. In this case, predicting stroke or no stroke.

- Logistic Regression: A statistical model used for binary classification problems, estimating the probability of a binary outcome.

- Decision Tree: A flowchart-like model that splits the dataset based on feature values to arrive at a classification decision.

- Random Forest: An ensemble learning technique that constructs multiple decision trees and aggregates their predictions to improve accuracy and reduce overfitting.

➢ **MODEL EVALUATION METRICS**

- Accuracy: The ratio of correctly predicted observations to the total observations.

- Precision: The ratio of correctly predicted positive observations to the total predicted positives. It measures how many selected items are relevant.

- Recall (Sensitivity): The ratio of correctly predicted positive observations to all actual positives. It measures how many relevant items are selected.

- F1 Score: The weighted average of Precision and Recall. It balances both metrics in situations with imbalanced classes.

- Confusion Matrix: A table summarizing prediction results on a classification problem. It displays true positives, false positives, true negatives, and false negatives.

- ROC Curve (Receiver Operating Characteristic Curve): A graphical plot that illustrates the diagnostic ability of a binary classifier system by plotting the True Positive Rate against the False Positive Rate.

- AUC (Area Under the Curve): A metric representing the degree or measure of separability. Higher AUC means better model performance in distinguishing between classes.

➢ **MODEL INTERPRETABILITY**

- Feature Importance: A technique that evaluates which features have the most influence on model predictions.

- Model Explainability: Refers to understanding and interpreting the output of a machine learning model, ensuring that predictions can be trusted, especially in
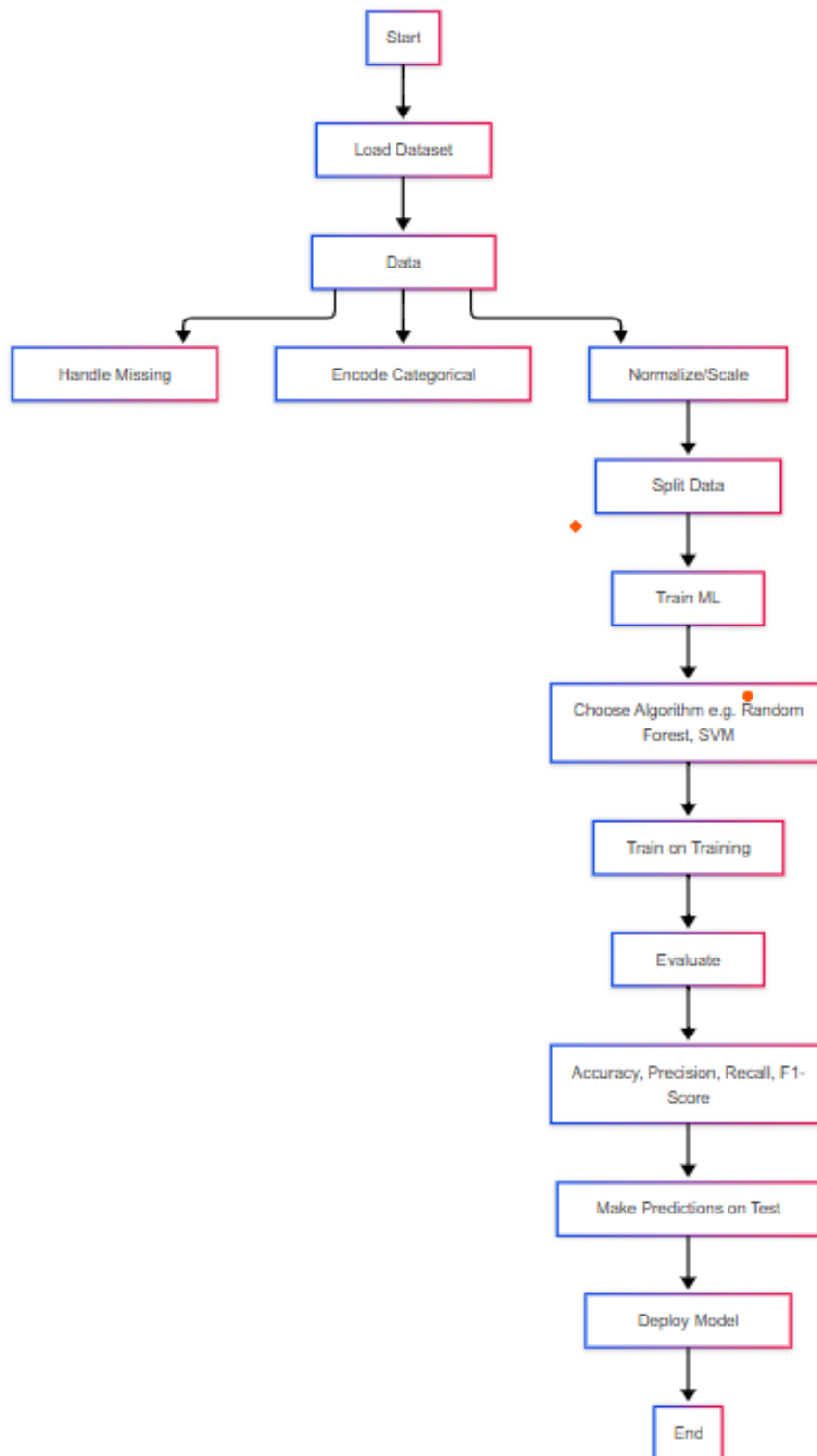
sensitive domains like healthcare.

> **TOOLS & ENVIRONMENT**

- Google Colab: A cloud-based Jupyter notebook environment provided by Google. It
- allows coding in Python, running ML models, and visualizing results with GPU support.
- Pandas: A Python library used for data manipulation and analysis.
- NumPy: A fundamental package for numerical computing with Python.
- Scikit-learn: A popular machine learning library in Python used for model building and evaluation.
- Matplotlib & Seaborn: Visualization libraries in Python used to plot graphs, histograms, heatmaps, and charts for data analysis and result interpretation.

ARCHITECTURE

Start

↓

Load Dataset

↓

Data

Handle Missing | Encode Categorical | Normalize/Scale

↓

Split Data

↓

Train ML

↓

Choose Algorithm e.g. Random Forest, SVM

↓

Train on Training

↓

Evaluate

↓

Accuracy, Precision, Recall, F1-Score

↓

Make Predictions on Test

↓

Deploy Model

↓

End

IMPLEMENTATION

This project is implemented using Python in Google Colab. Key libraries used include pandas, numpy, seaborn, matplotlib, scikit-learn, and imblearn.

CODE

The implementation is divided into the following steps:

- Data Import & Inspection
- Handling Missing Values
- Label Encoding for Categorical Variables
- Feature Scaling using StandardScaler
- Train-Test Split (80/20)
- Balancing Dataset using SMOTE
- Model Training: Logistic Regression, Random Forest, Decision Tree, SVM
- Evaluation Metrics Calculation
- Confusion Matrix Visualization
- Model Comparison Plotting

Insert code snippets and their respective output screenshots for:

- Data preprocessing
- SMOTE balancing
- Model training and evaluation
- Confusion matrix plots for all models
- Final model comparison bar plot

CODE

TRAINING DATA USING Machine Learning Models

```python
# Define models
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(),
    "Decision Tree": DecisionTreeClassifier(),
    "Support Vector Machine": SVC()
}

# Train and evaluate each model
for name, model in models.items():
    model.fit(X_train_smote, y_train_smote)
    y_pred = model.predict(X_test)
    print(f"\n--- {name} ---")
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("Precision:", precision_score(y_test, y_pred, zero_division=0))
    print("Recall:", recall_score(y_test, y_pred))
    print("F1 Score:", f1_score(y_test, y_pred))
    print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
--- Logistic Regression ---
Accuracy: 0.7583170254403131
Precision: 0.1444043321299639
Recall: 0.8
F1 Score: 0.24464831804281345
Confusion Matrix:
 [[735 227]
```

DESIGN

The design of the project follows the typical stages of the data mining lifecycle:

- Data Collection and Loading
- Data Preprocessing (missing value handling, label encoding, feature scaling)
- Exploratory Data Analysis (EDA) using visualization
- Model Training and Evaluation
- Performance Comparison of Models
- Visualization of Confusion Matrix and Feature Importance

RESULT SCREENS

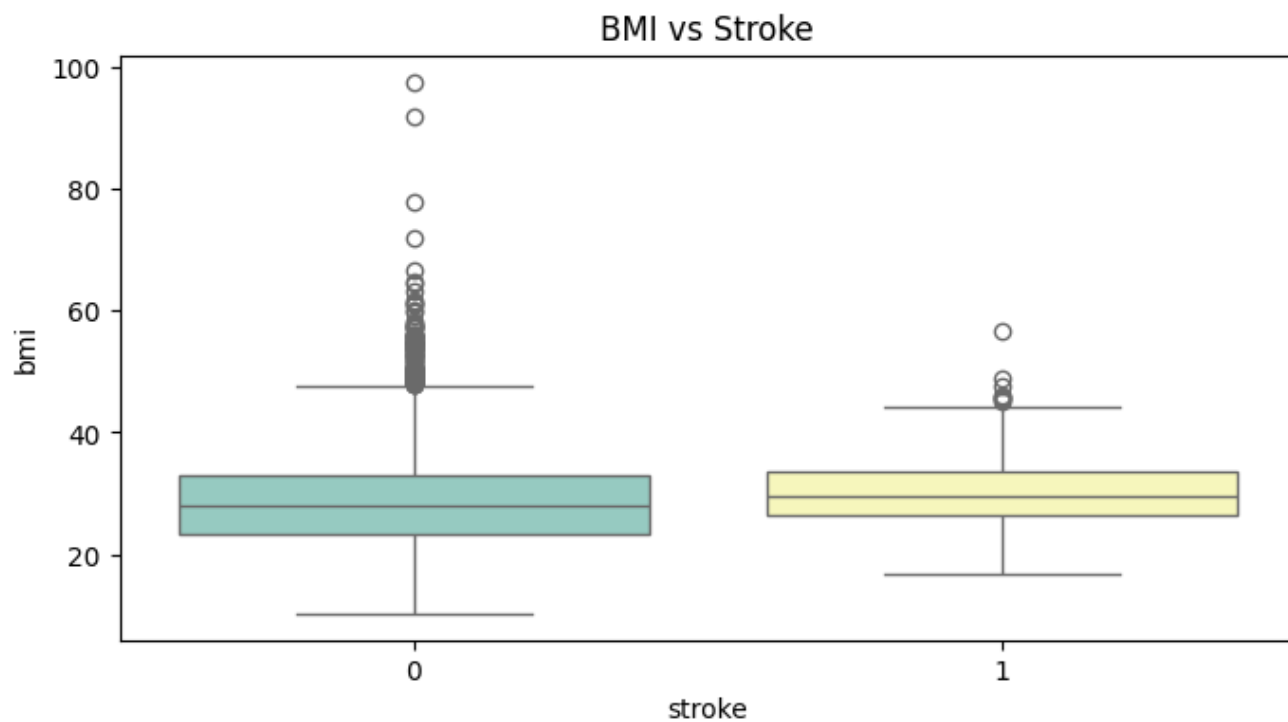## Exploratory Data Analysis (EDA) —

Stroke vs Non-Stroke Insights

Stroke Distribution

Stroke Distribution

Age vs Stroke

Glucose Level Distribution(NO STROKE VS STROKE)

Glucose Level Distribution (No Stroke)   Glucose Level Distribution (Stroke)
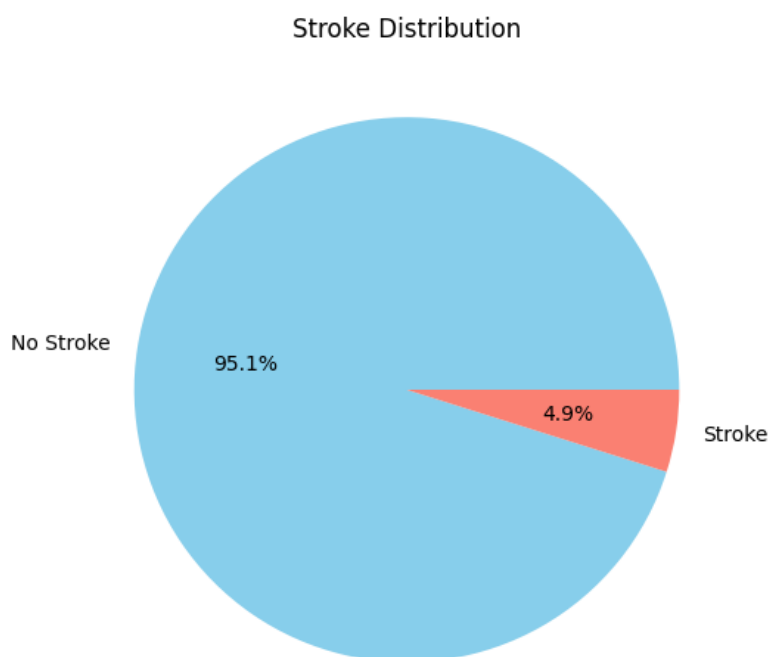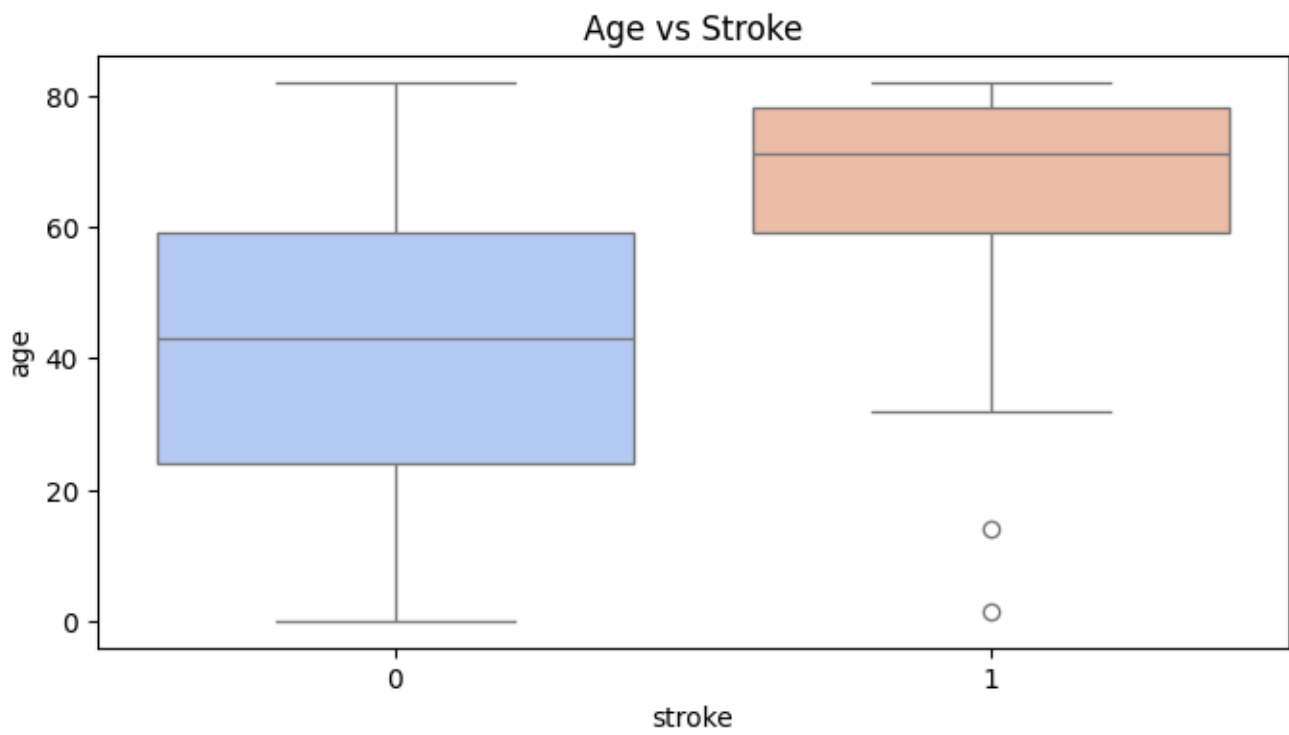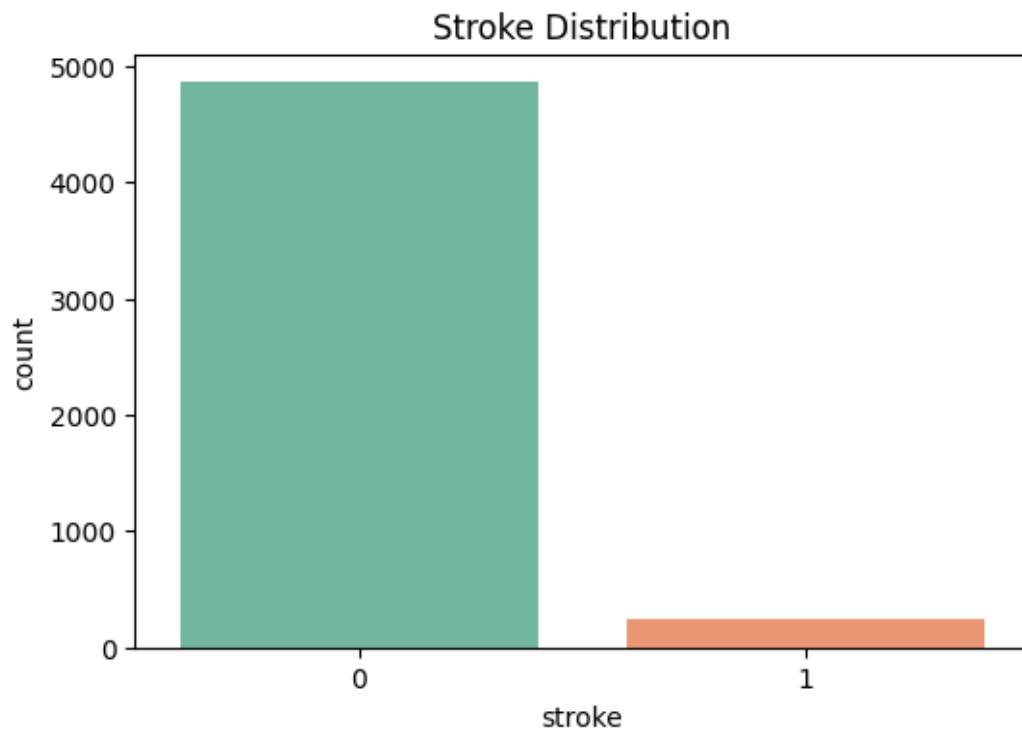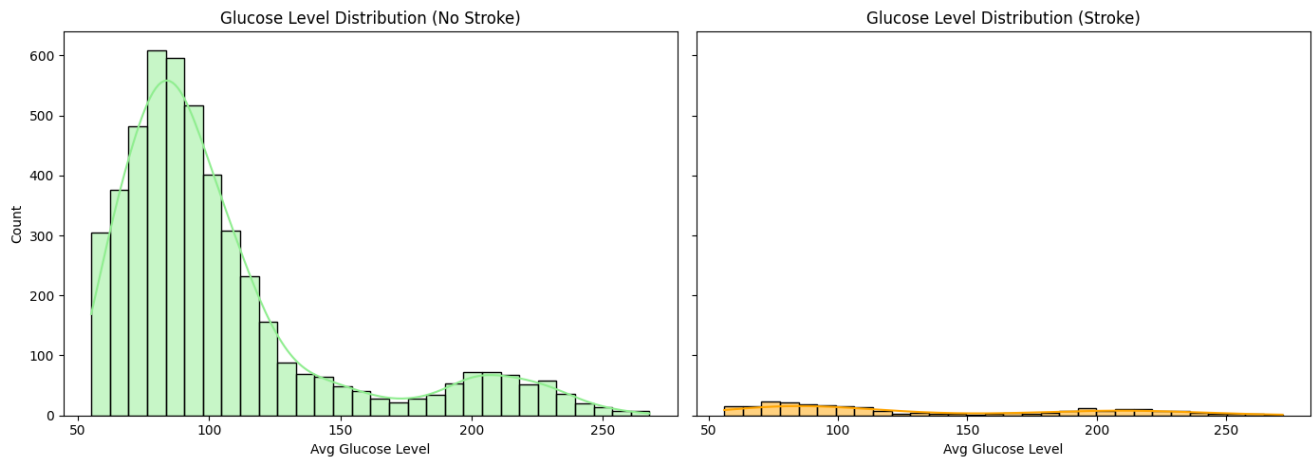
BMI Distrubution(NO STROKE VS STROKE)

BMI Distribution (No Stroke)   BMI Distribution (Stroke)
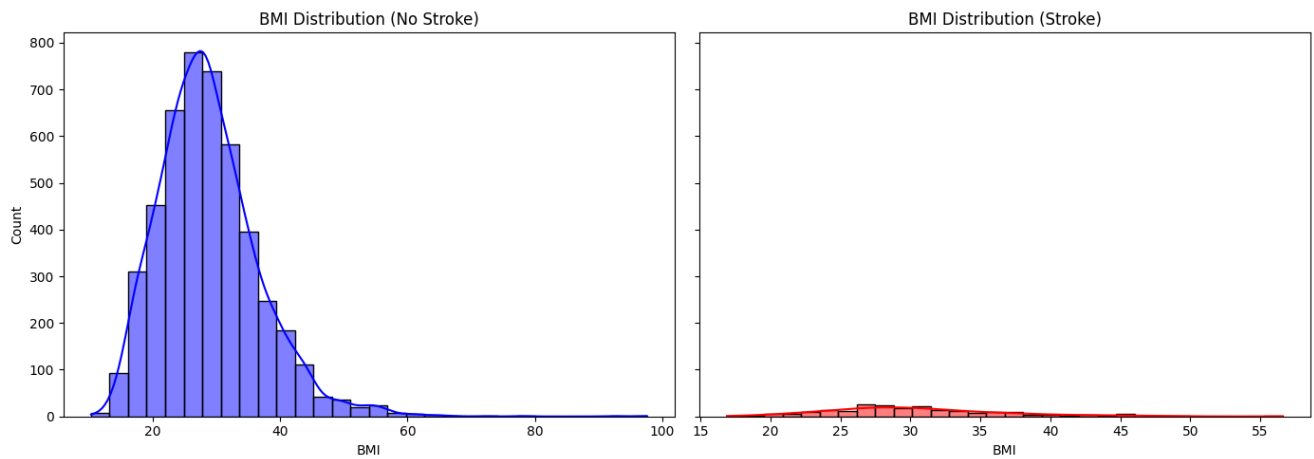
BMI vs Stroke

Age Distribution Graphs

Age Distribution (No Stroke)

Age Distribution (Stroke)

Gender Distribution by Stroke Status
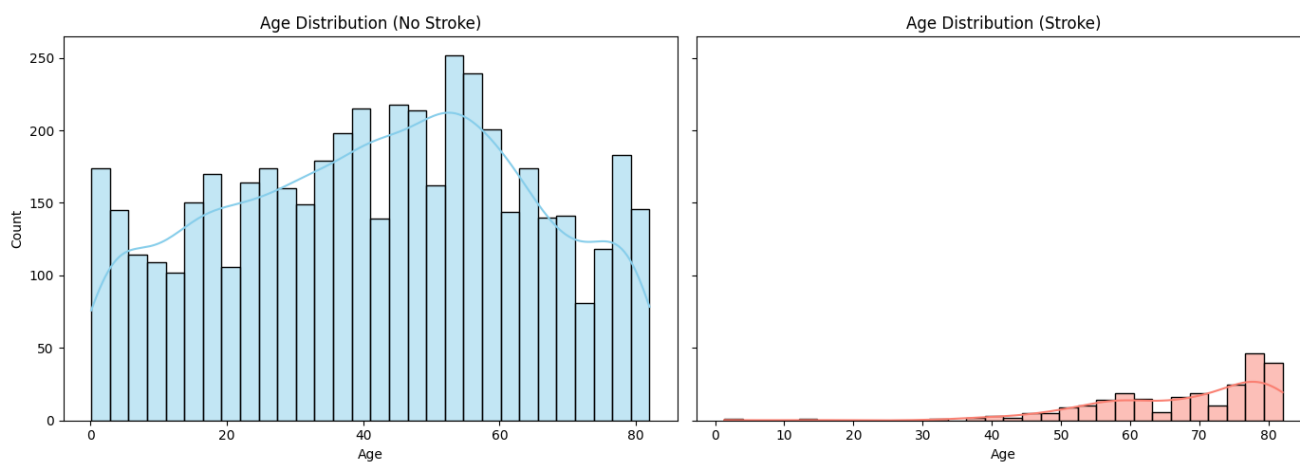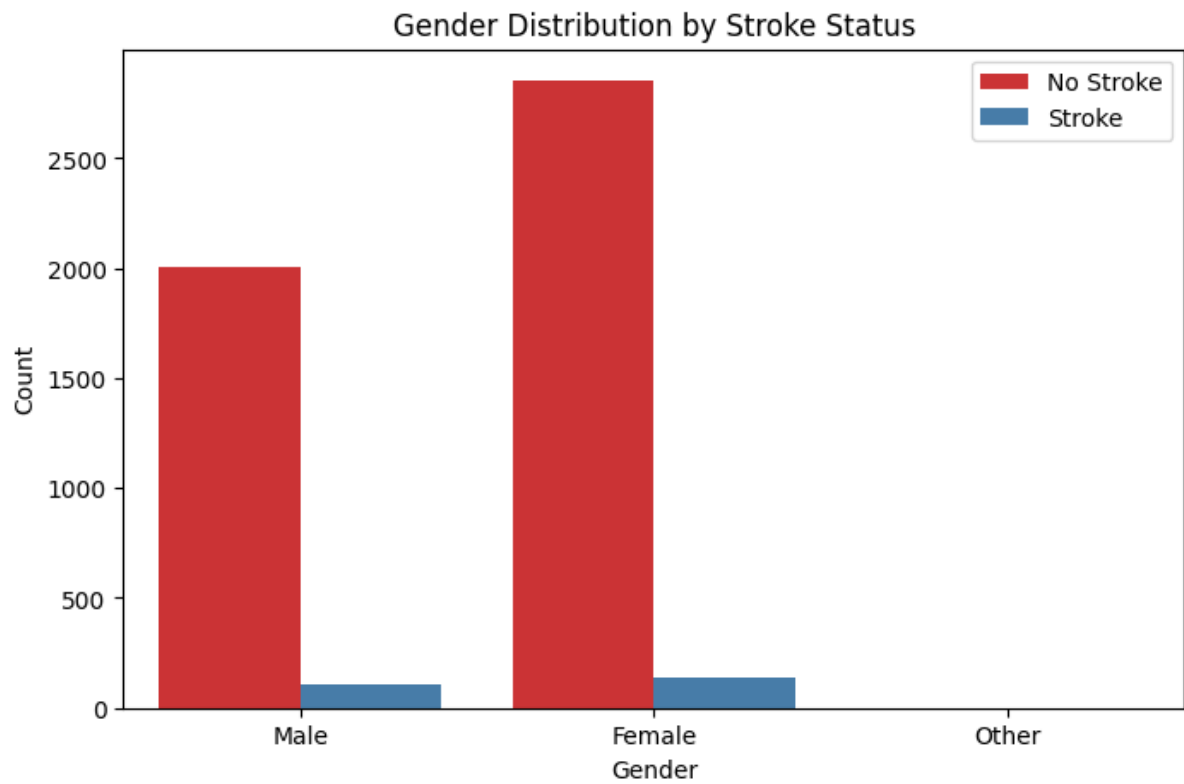
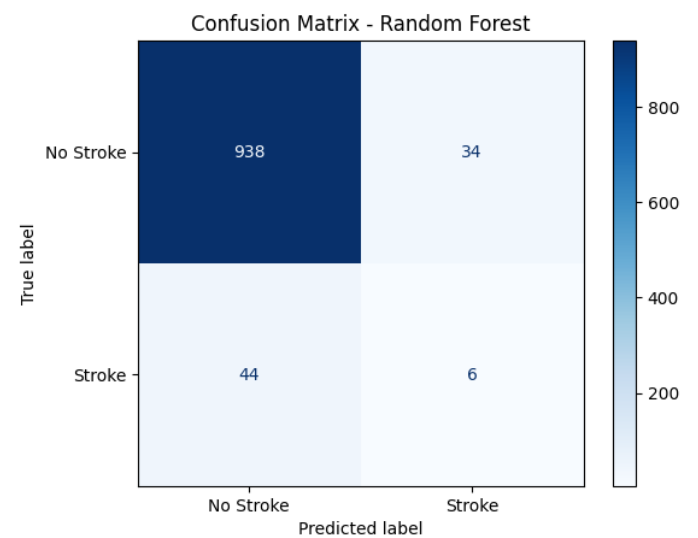## Smoking Status vs Stroke

Smoking Status by Stroke Status
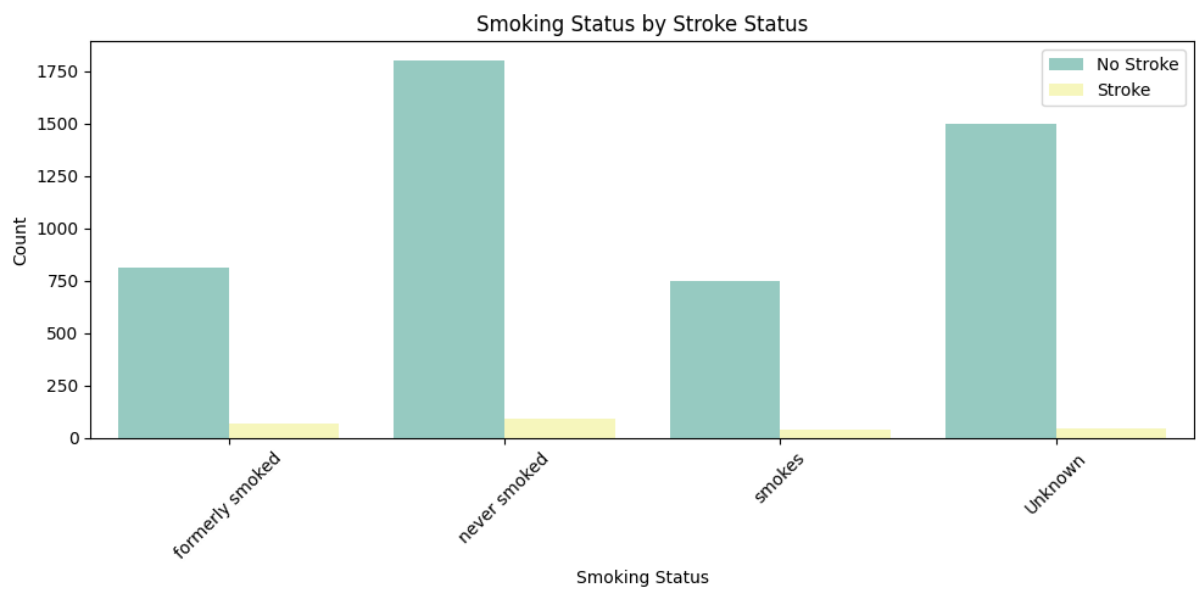
Work Type vs Stroke
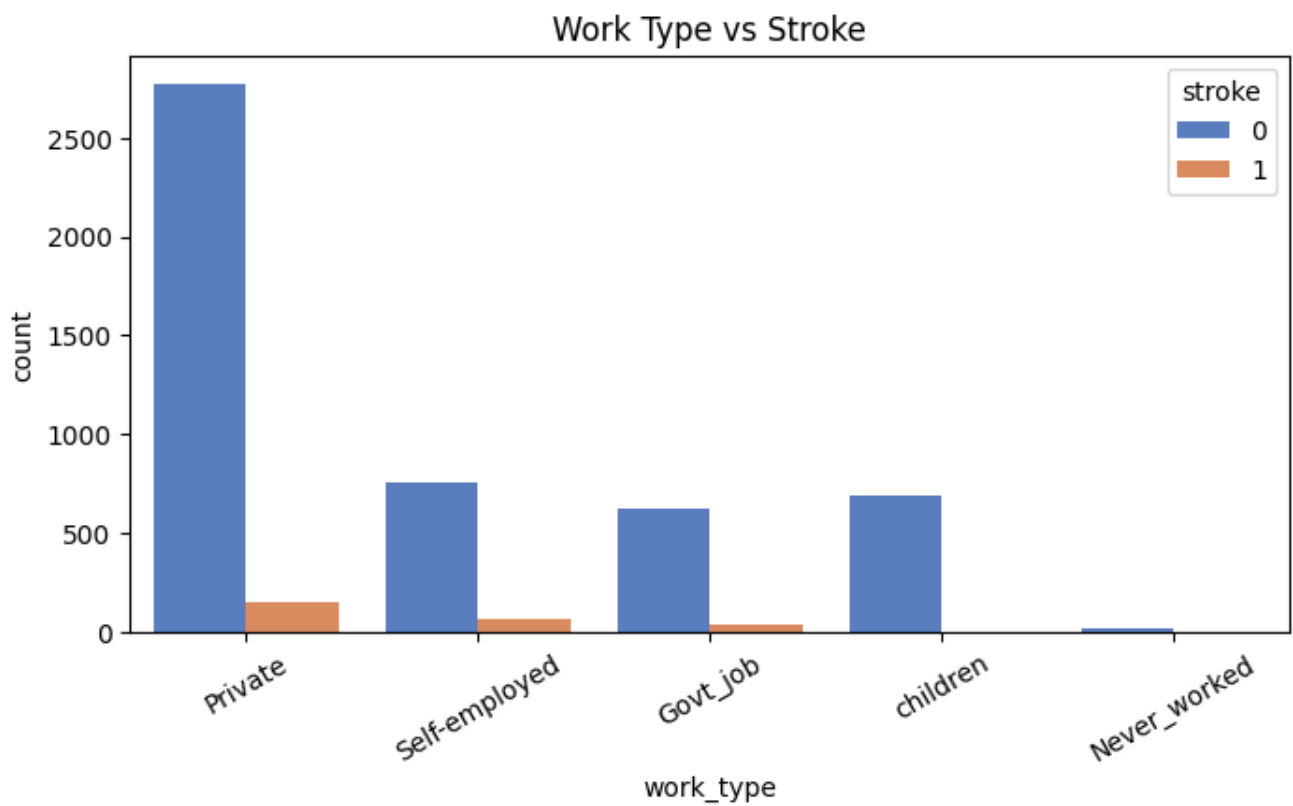
Hypertension vs Stroke

Heart Disease vs Stroke

Feature Importance (Random Forest)
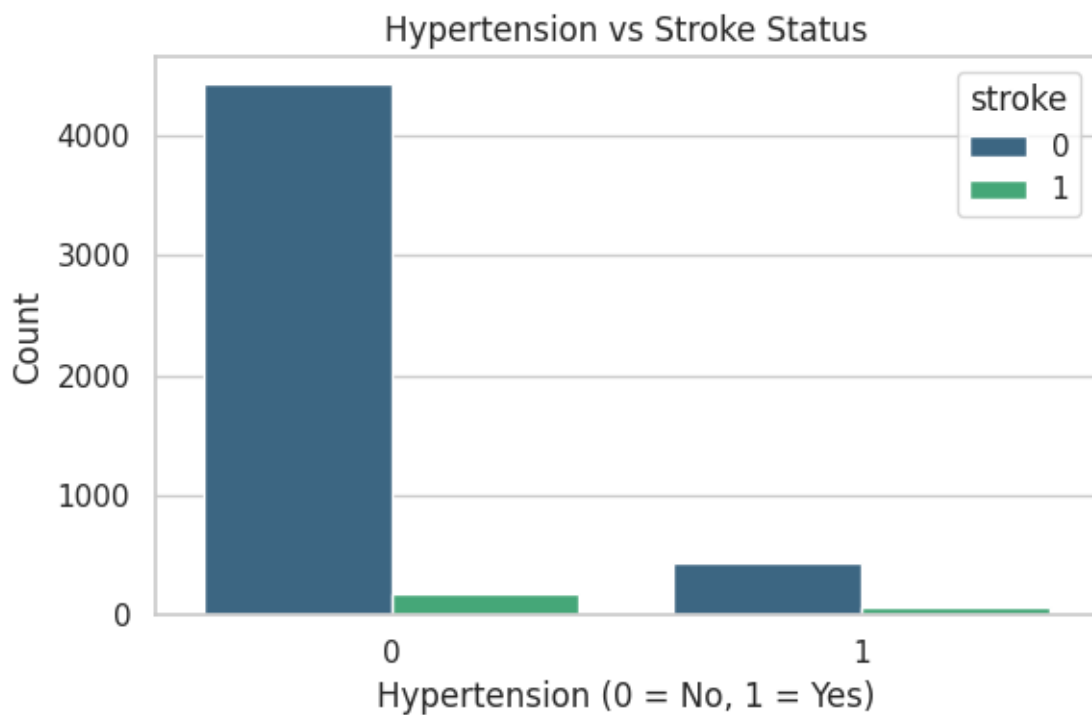
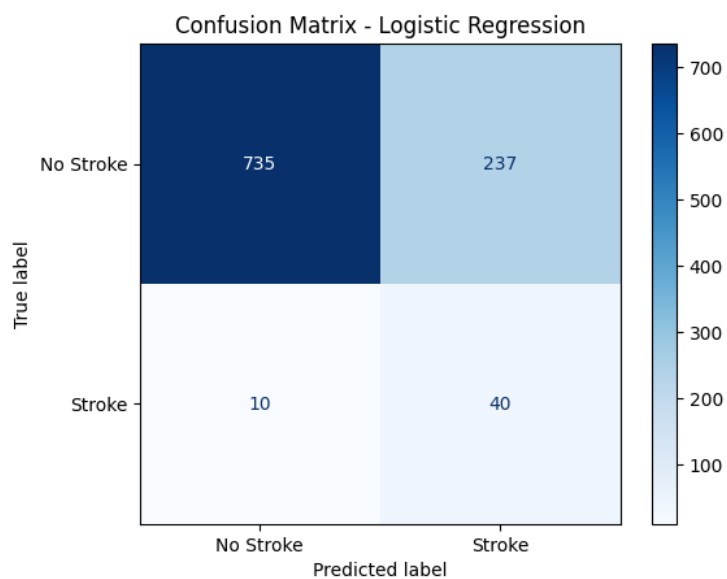Work Type vs Stroke
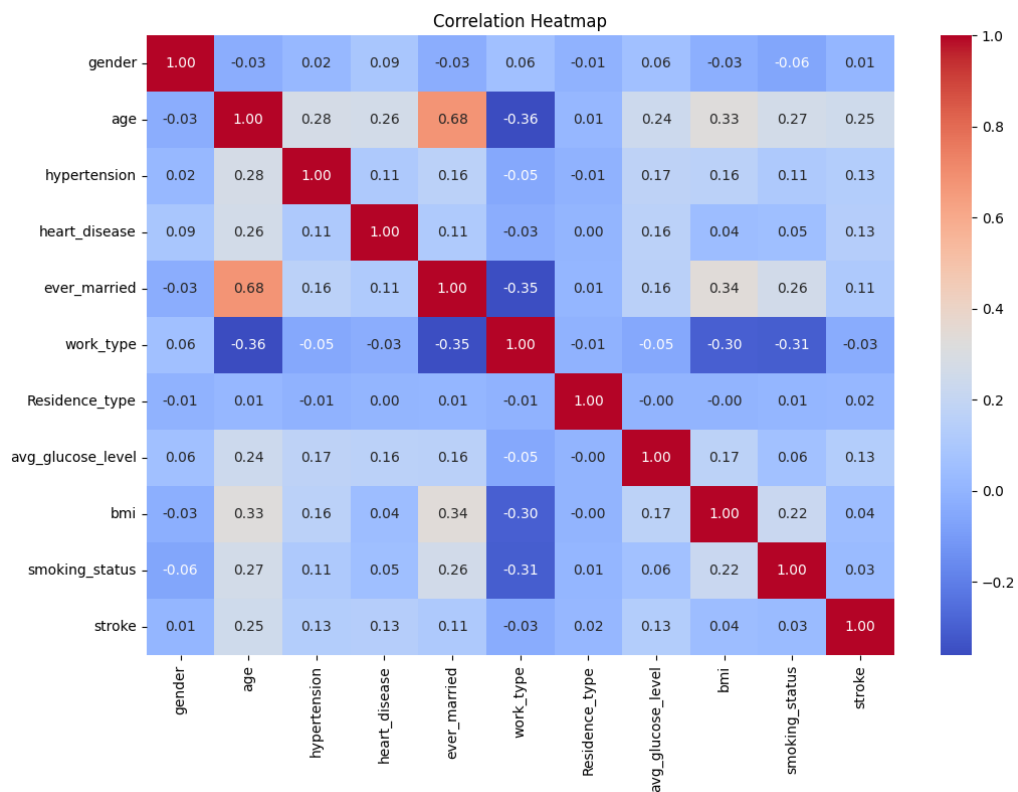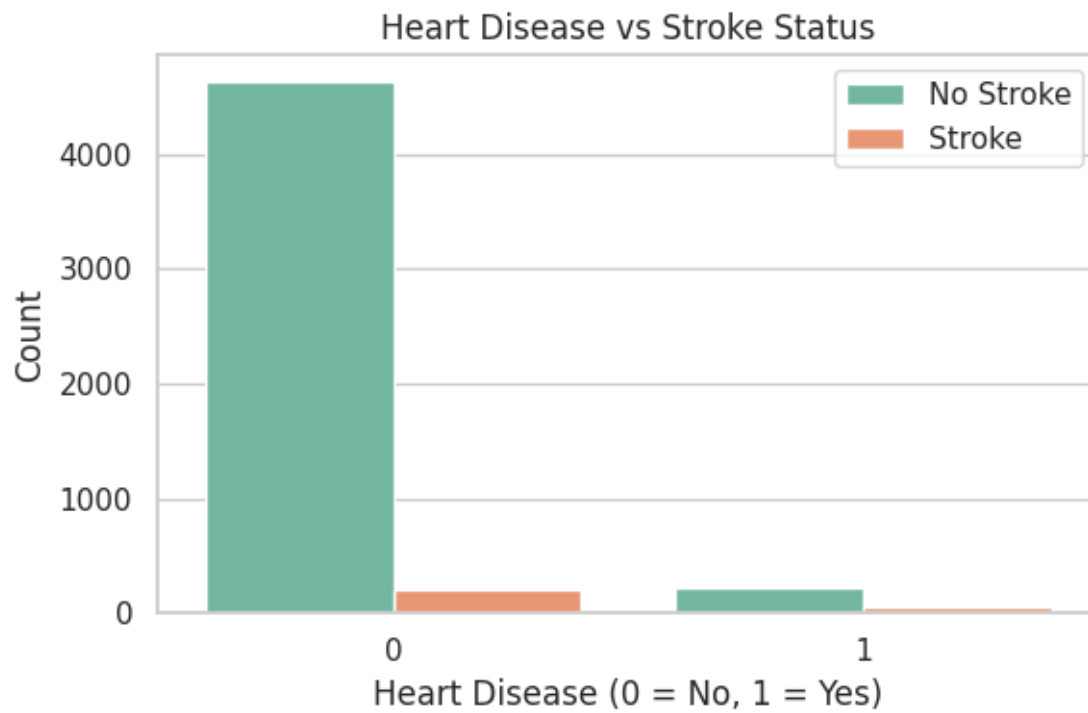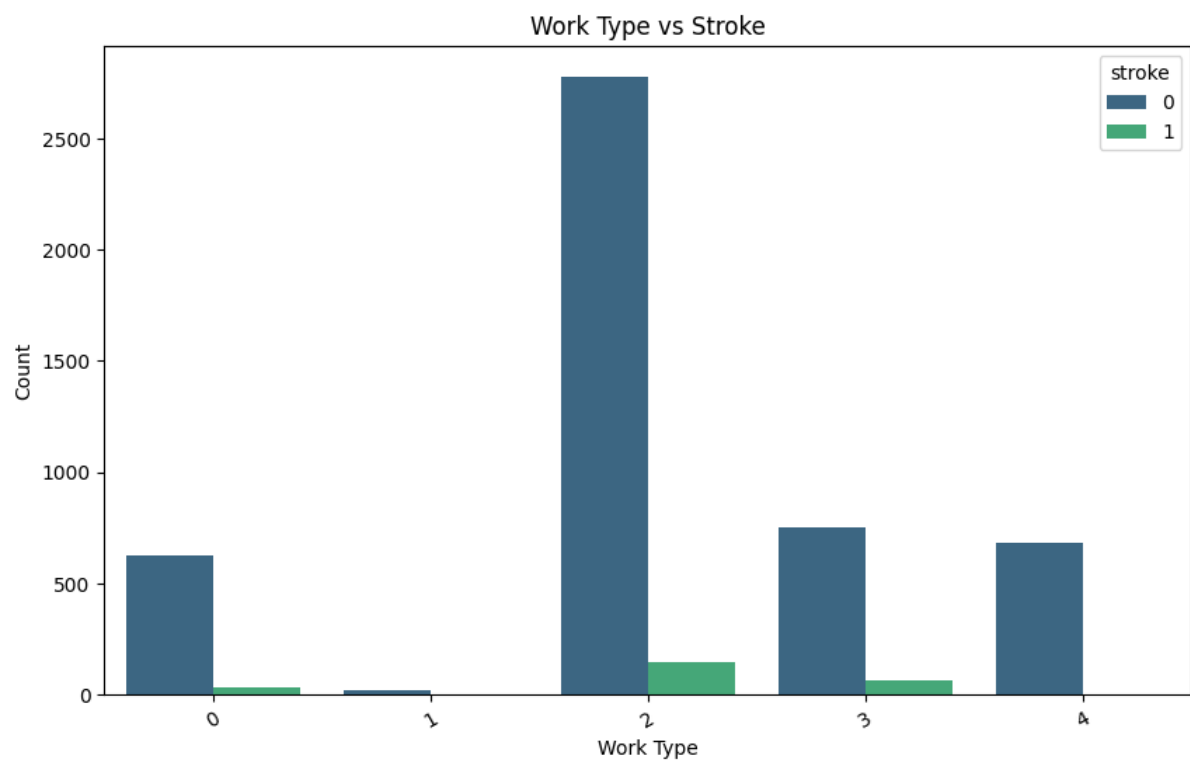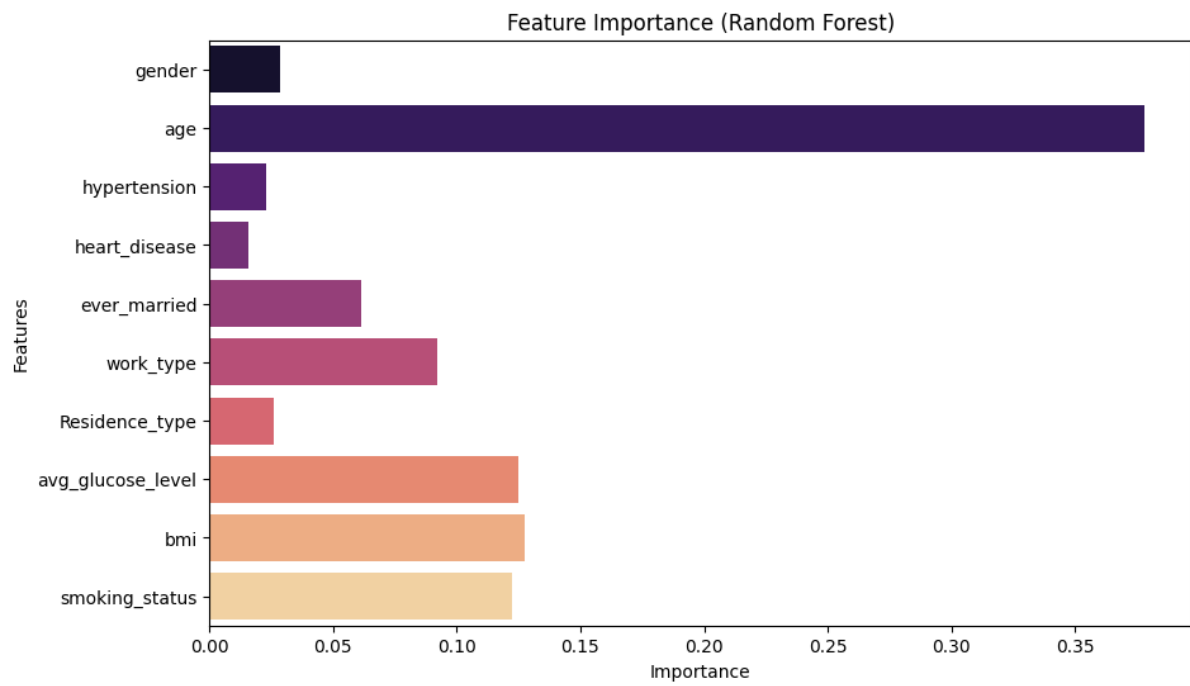
DISPLAYING THE CONFUSSION MATRIX

Results and Analysis

ML Model Performance Comparison
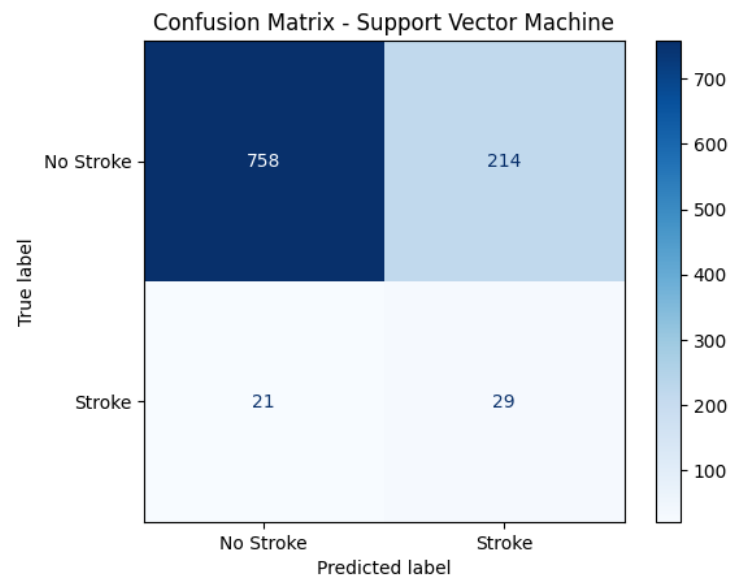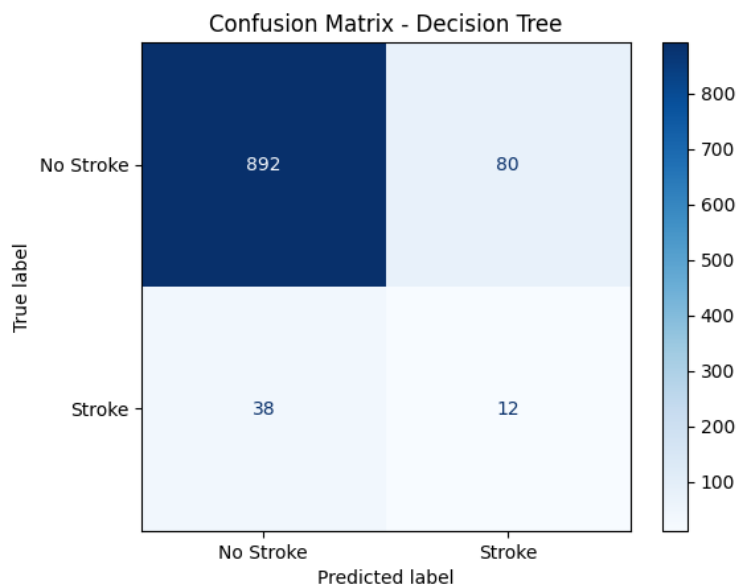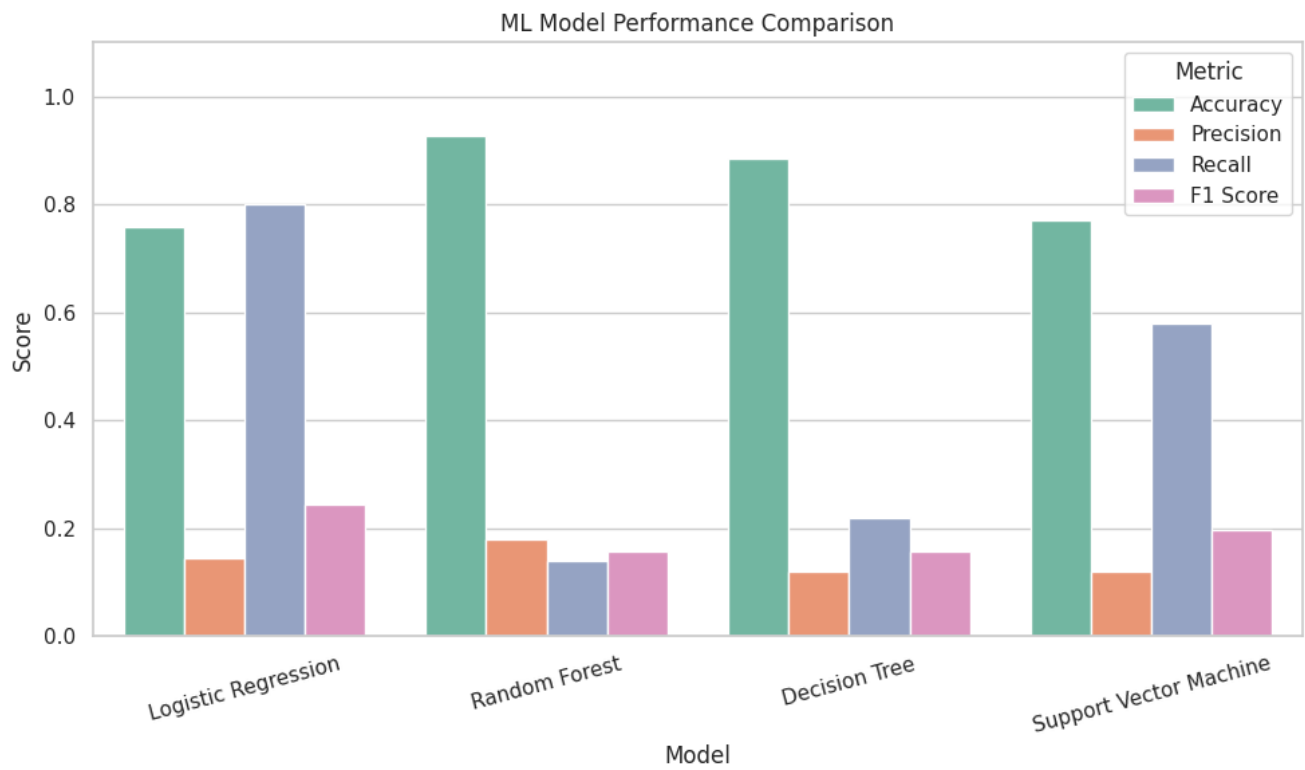
CONCLUSION

This project demonstrates the application of machine learning models in healthcare for stroke prediction. Among the tested models, Random Forest and Logistic Regression showed competitive performance, though each model had trade-offs in precision, recall, and F1-score. The preprocessing steps and use of SMOTE significantly improved model performance by handling data imbalance.

Key takeaways:

➢ Data preprocessing and feature selection are crucial.

➢ SMOTE is effective in dealing with imbalanced healthcare datasets.

➢ Ensemble models like Random Forest tend to perform well in classification tasks.

➢ Visualization helps uncover important relationships in the data.

This project showcases how data mining and classification can be integrated into healthcare systems to provide accurate diagnoses, predict patient outcomes, and support effective clinical decision-making.