STROKE PATIENT HEALTHCARE USING DEEP LEARNING

An overview of data preprocessing, visualization, and modeling.

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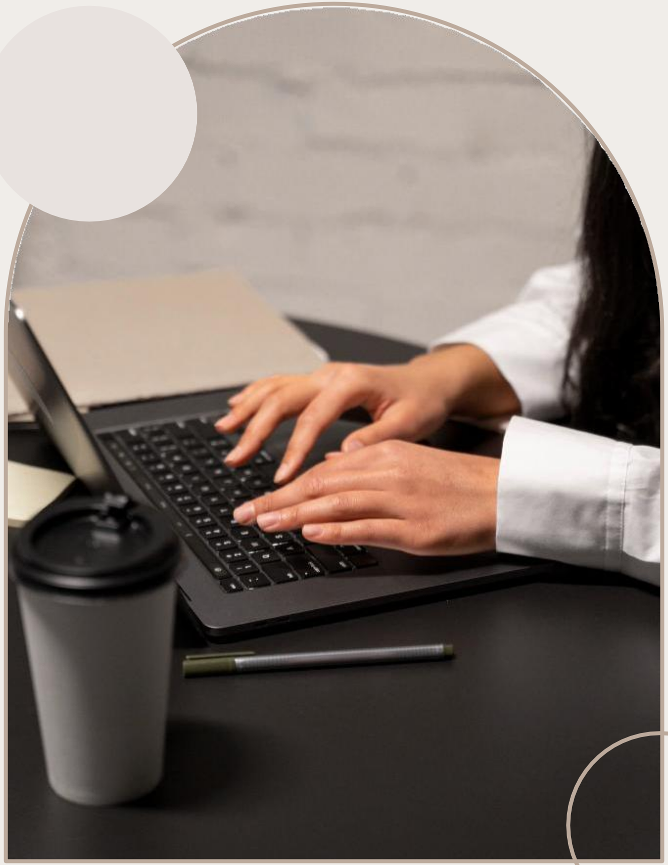
Objective of the project:

The central aim of this project is to conduct a comprehensive analysis of healthcare data to uncover significant patterns and develop a high-accuracy predictive model to assess the likelihood of health conditions, such as stroke. By leveraging robust data exploration, insightful visualizations, and machine learning techniques, this project aims to derive actionable insights and reliable predictions.



Our aim

To analyze the dataset and build a machine learning model that predicts stroke occurrence based on patient health data.

The goal

To derive meaningful insights from the data through preprocessing and visualization, and to evaluate the performance of various models to identify the most effective one for accurate predictions.

Project Overview

The project focuses on analyzing healthcare data to uncover patterns and build a high-accuracy predictive model for assessing stroke risk. It encompasses four milestones that systematically progress from data exploration to model development.

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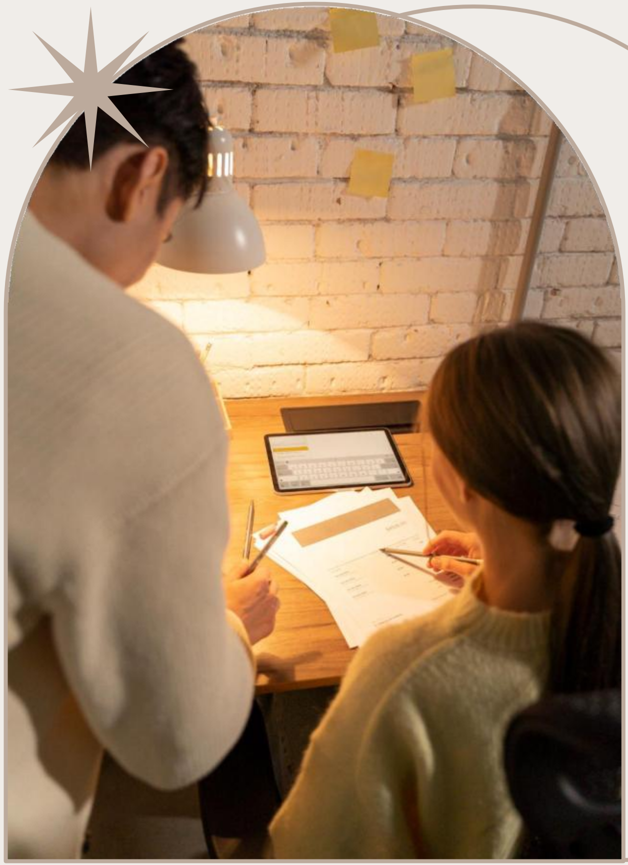


01

Data Preparation

Dataset Characteristics

- ★ The dataset consists of 5110 entries across 12 attributes, incorporating both numerical and categorical features.
- ★ Key columns include age, gender, hypertension, heart_disease, work_type, avg_glucose_level, bmi, and the target variable stroke.

Exploratory Analysis:

Analysis	Definition	Observation
df.shape()	Returns a tuple representing the number of rows and columns in the dataset.	The dataset contains 5110 rows and 12 columns, indicating sufficient data for analysis and modeling.
df.info()	Displays a concise summary of the DataFrame, including non-null counts and data types.	Identified bmi as the only column with missing values. Other columns are complete, with data types categorized as int, float, or object.

df.describe()	Provides statistical summary (mean, std, min, max, etc.) for numerical columns.	Key numerical features like age, avg_glucose_level, and bmi were analyzed. The values show a wide range, with notable outliers in glucose levels and BMI.
df.describe (include=object)	Provides statistical summary for categorical columns (e.g., count, unique values, top category, frequency).	The dataset has higher representation of females (2,994 occurrences) and married individuals (3,353 occurrences). Private employment is the most common work type, urban areas are slightly more prevalent (2,596 occurrences), and the majority of participants have never smoked (1,892 occurrences).
df.smoking_status.unique()	Displays unique values in the smoking_status column.	The unique values are: ['formerly smoked', 'never smoked', 'smokes', 'Unknown']. These categories will need encoding for model compatibility.
df.isnull().sum()	Counts the number of missing values for each column.	Only bmi has 201 missing values. These were handled by imputing the median, ensuring no missing data remained.

(Q) Is it good to have null values in dataset ?

No, null values can hinder data analysis and model performance. They represent missing or incomplete information, which can lead to inaccuracies, biases, or errors if not properly handled. Addressing null values ensures the dataset is clean and reliable for analysis or model training.

Handling Null Values

```
df['bmi'] = df['bmi'].fillna(df['bmi'].median())
```

```
df.isnull().sum()

id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                  201
smoking_status         0
stroke                 0
dtype: int64
```

```
df.isnull().su

id                     0
gender                 0
age                    0
hypertension           0
heart_disease          0
ever_married           0
work_type              0
Residence_type         0
avg_glucose_level      0
bmi                    0
smoking_status         0
stroke                 0
dtype: int64
```

02

Data Visualization

This part focuses on exploring the dataset visually to uncover meaningful patterns and relationships between variables. Through graphs and plots, we analyze trends and distributions, helping identify key insights related to stroke prediction. Additionally, data encoding ensures that categorical variables are transformed into a format suitable for machine learning models.

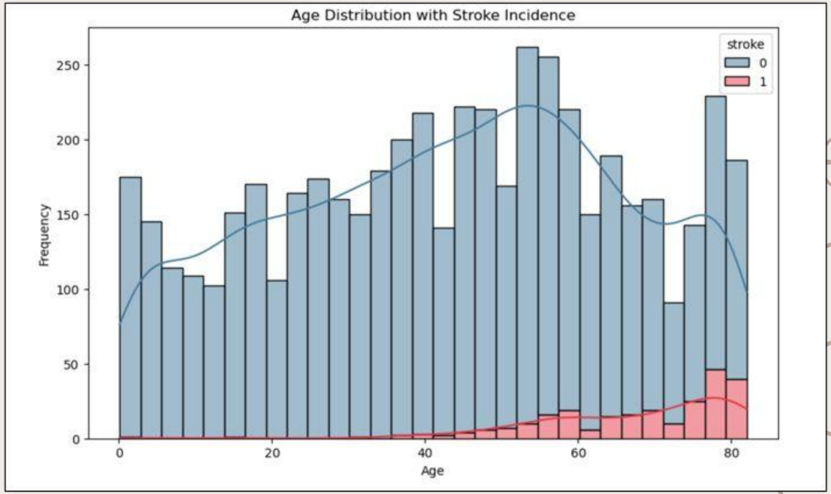
Age Distribution with Stroke Incidence

Visualization: A histogram with KDE overlay showing the distribution of age with stroke incidence.

Observation:

★ Stroke incidence increases significantly in older age groups.

★ Younger individuals have a relatively low frequency of strokes.



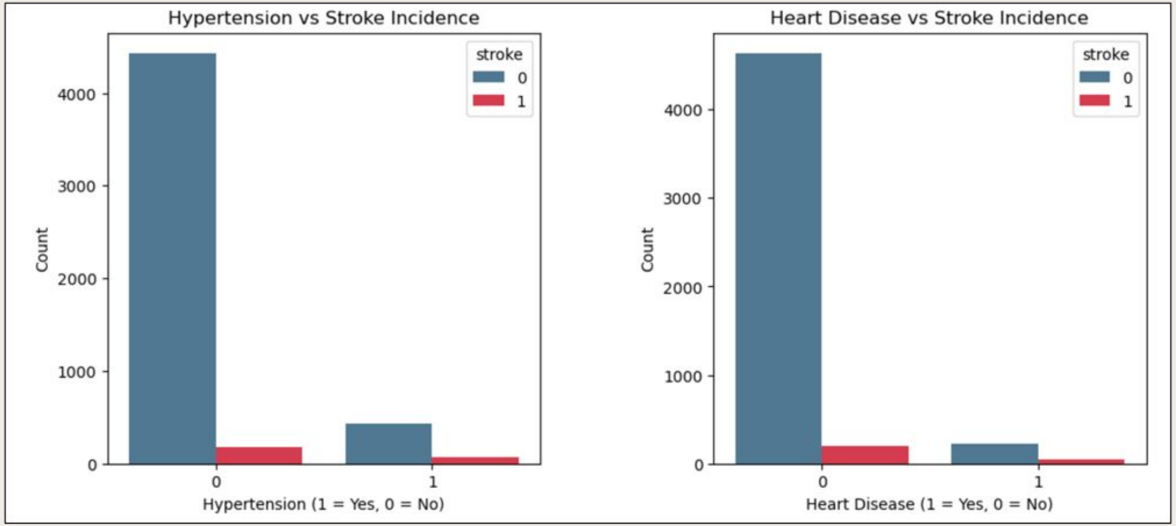
Hypertension and Heart Disease vs Stroke Incidence

Visualization: Two side-by-side bar plots depicting the correlation of hypertension and heart disease with stroke incidence.

Observation:

★ Hypertension and heart disease are strong predictors of stroke.

★ Individuals with either condition have a higher likelihood of experiencing a stroke.

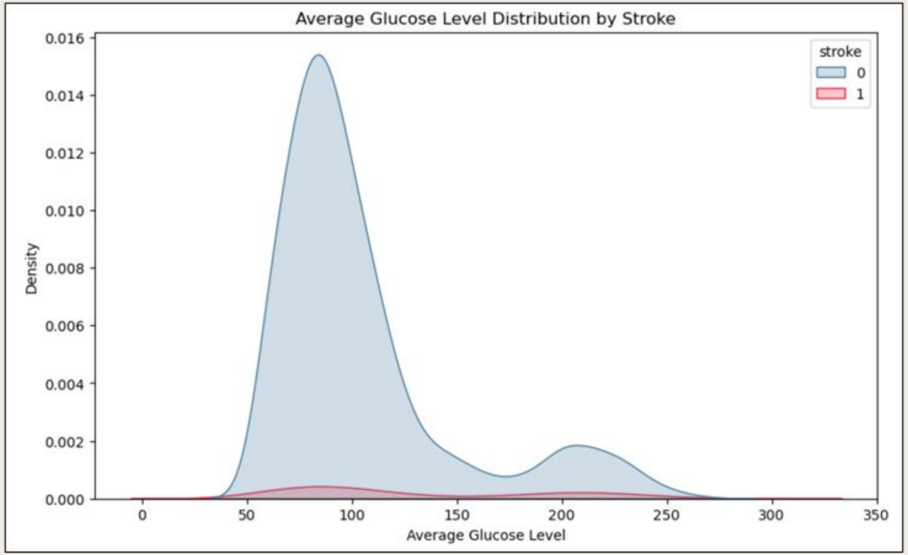


Average Glucose Level Distribution by Stroke

Visualization: A KDE plot illustrating the distribution of average glucose levels for stroke and non-stroke cases.

Observation:

- ★ Higher average glucose levels are associated with increased stroke incidence
- ★ A clear separation in glucose levels exists between stroke and non-stroke groups.



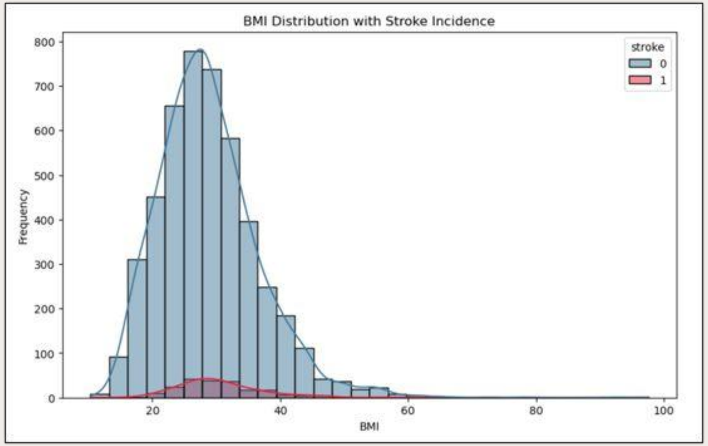
BMI Distribution with Stroke Incidence

Visualization: A histogram with KDE overlay depicting BMI distribution for stroke and non-stroke cases.

Observation:

★ Stroke cases are slightly more frequent among individuals with higher BMI.

★ BMI alone does not show a strong correlation with stroke.

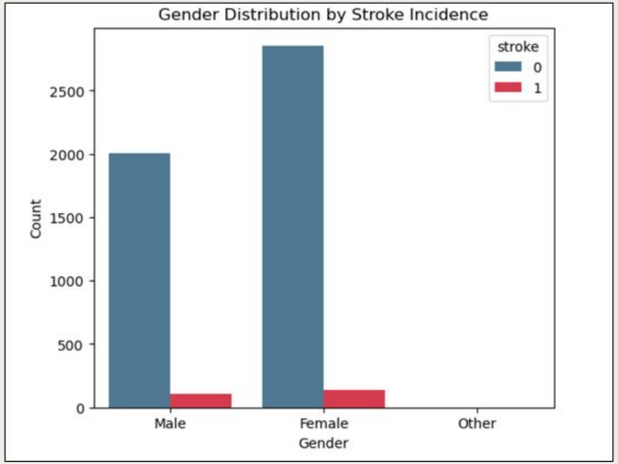


Gender Distribution by Stroke Incidence

Visualization: A count plot showing the distribution of stroke cases by gender.

Observation:

★ Both genders show comparable stroke incidence rates, though slight variations exist.

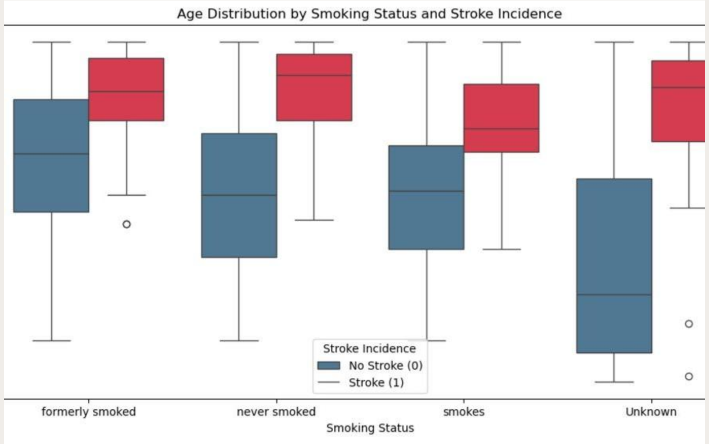


Age Distribution by Smoking Status and Stroke Incidence

Visualization: A boxplot showing age distribution across different smoking statuses with stroke incidence.

Observation:

- ★ Stroke is more prevalent among older individuals, regardless of smoking status.
- ★ Smoking does not directly correlate to stroke in younger age groups but shows an impact in older populations.

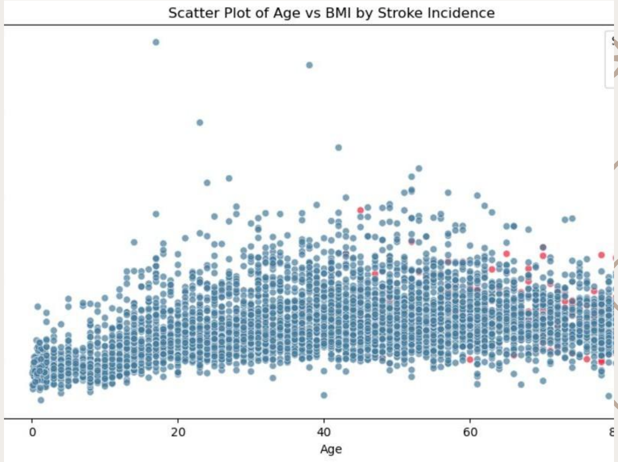


Scatter Plot of Age vs BMI by Stroke Incidence

Visualization: A scatter plot showing the relationship between age, BMI, and stroke incidence.

Observation:

- ★ Most stroke cases cluster in older individuals with a range of BMI values.
- ★ No distinct pattern emerges in BMI but age is a significant factor.

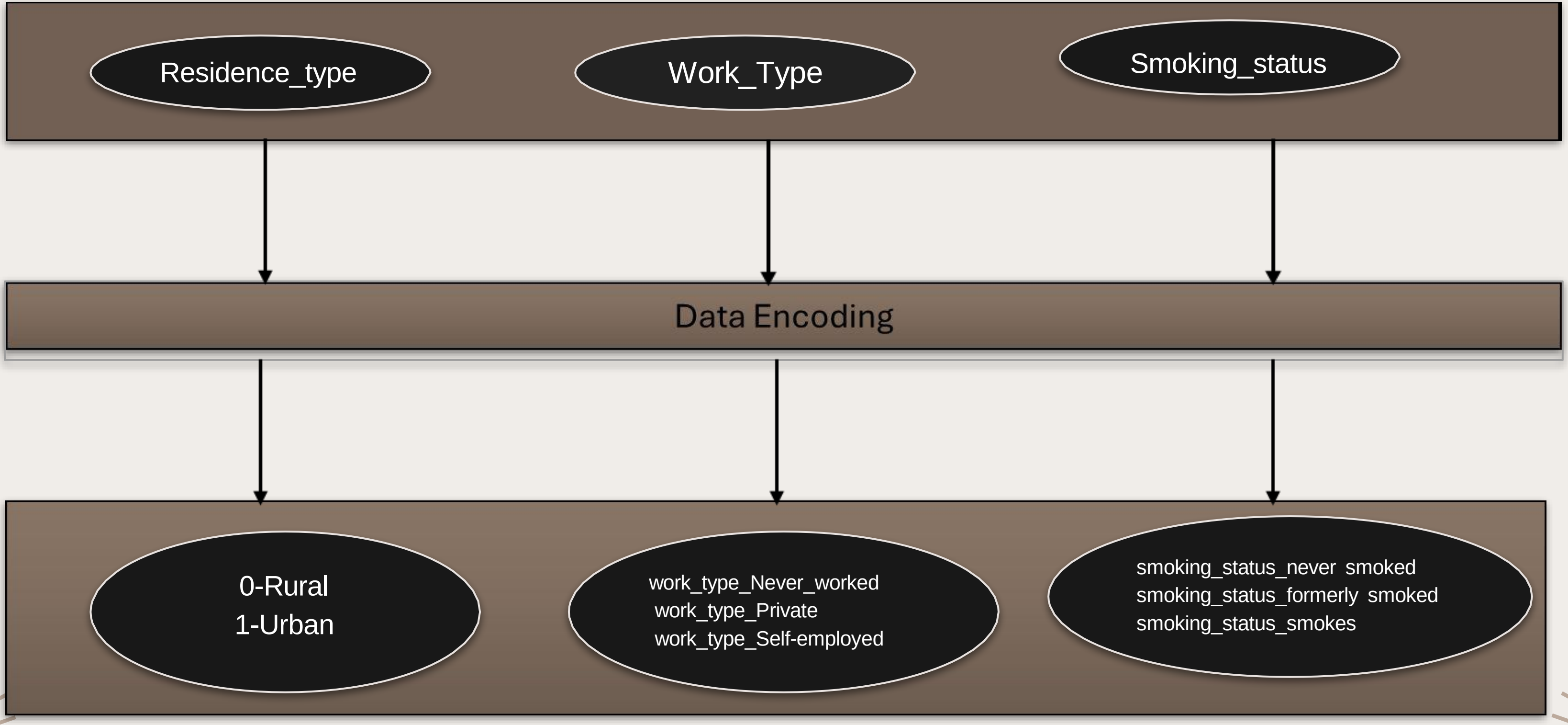


03

Data Encoding

Data Encoding

Data encoding is the process of converting categorical data into numerical formats so that machine learning algorithms can interpret it.



04

Machine Learning Models

Machine Learning (ML) models are algorithms that enable computers to learn patterns from data and make predictions or decisions without being explicitly programmed. Common models are :

Linear Regression

Ridge Regression

Logistic Regression

Lasso Regression

Preprocessing and Data Preparation for Regression Models

- Handling Missing Values
- Encoding Categorical Variables
- Feature Selection
- Standardization
- Train-Test Split

Maths Behind Ridge Regression Model

In a Ridge Regression model, the relationship between the dependent variable y and the independent variables x1,x2,x3....xp is also assumed to be linear, similar to linear regression. However, Ridge Regression introduces a regularization term to prevent overfitting by penalizing large coefficients, which helps improve the model's generalization.

The model can be expressed mathematically as:

$$\min_{\beta}\left\{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2+\lambda\sum_{j=1}^{p}\beta_j^2\right\}$$

- yi: Actual value of the target variable for the ith observation
- yi^: Predicted value for the ith observation
- n: Number of observations
- p: Number of features
- Bj: Coefficient for each feature
- sigma(yi-yi^)^2: Residual sum of squares
- sigma Bj^2: Penalty term

Maths Behind Ridge Regression

Root Mean Squared Error (RMSE): RMSE is a commonly used metric to evaluate the accuracy of a regression model. It measures the average magnitude of the error between predicted values and actual values.

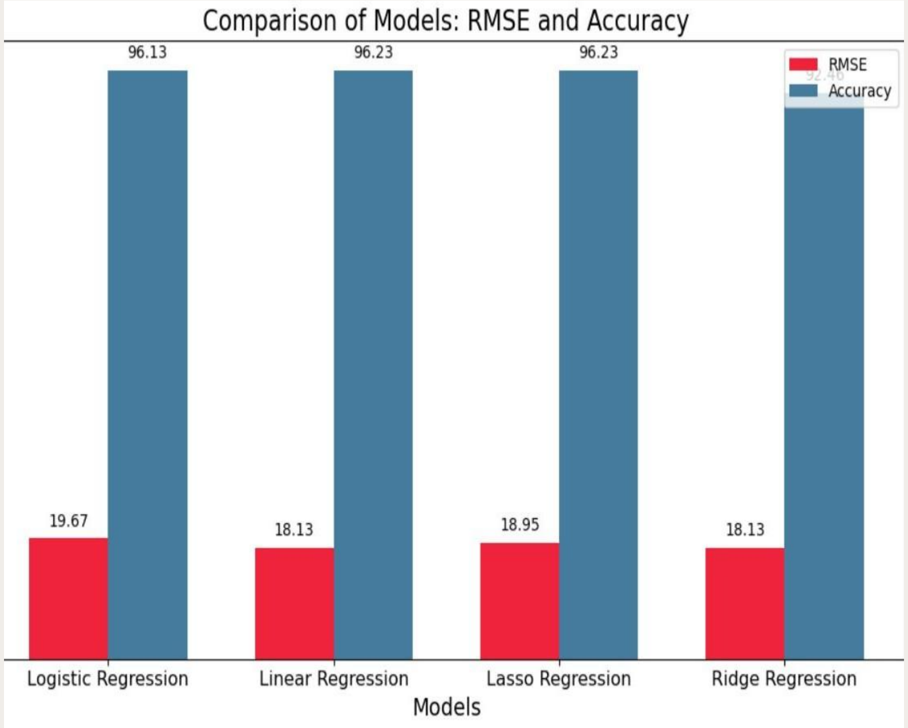
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

- n: is the number of data points
- yi: is the actual value for the i-th data point
- yi^: is the predicted value for the i-th data point.

Model Performance Summary: RMSE and Accuracy

Model	Accuracy	RSME
Ridge Regression	92.5	18.128
Logistic Regression	96.13	19.67
Linear Regression	96.23	18.12
Lasso Regression	96.23	18.95

Visualizing Different Models



Key observations

RMSE Insights: Linear and Ridge models have the lowest RMSE, indicating the most accurate predictions, while Lasso has slightly higher errors, and Logistic Regression performs the worst with the highest RMSE.

Accuracy Insights: All models show high accuracy (above 92%), with Linear and Lasso achieving 96.23%, Ridge at 92.46%, and Logistic Regression slightly behind at 96.13%.

Precision, Recall, F1 Score, and Accuracy Across Models

★ **Precision** (P): Measures how many predicted "Stroke" cases are correct.

P= TP/[TP+FP]

★ **Recall** (R): Measures how many actual "Stroke" cases are correctly identified.

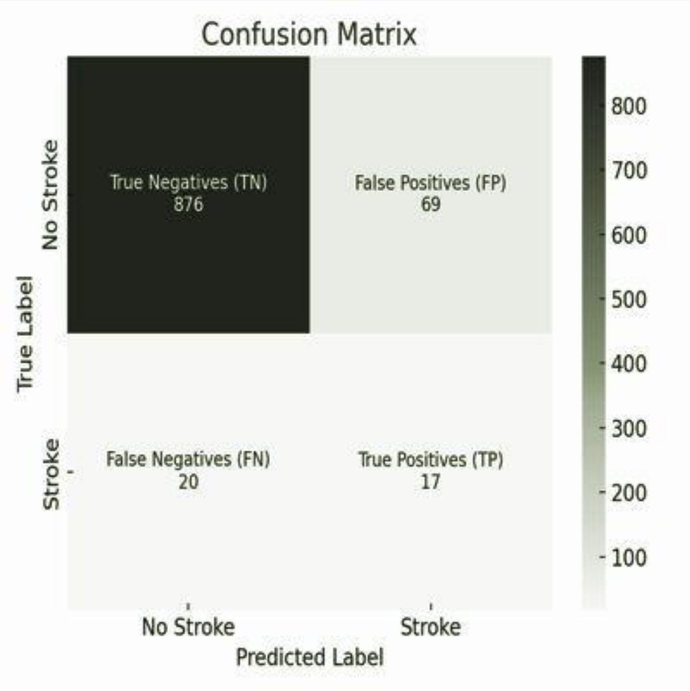
R=TP/[TP+FN]

★ **F1 Score**: Harmonic mean of Precision and Recall, providing a balance between both.

F1 Score= 2*(P x R/P+R)

★ **Accuracy:** Overall correctness of the predictions.

Accuracy=(TP+TN)/(TP+TN+FP+FN)



Observations

Model	Precision	Recall	F1 Score	Accuracy
Ridge Regression	0.253	0.513	0.339	0.92
Linear Regression	0.333	0.054	0.093	0.96
Lasso Regression	0.197	0.459	0.276	0.90
Logistic Regression	0.333	0.0270	0.05	0.96

Ridge Regression: Best recall with balanced performance overall.
Linear Regression: High accuracy but poor recall, struggles with the minority class.
Lasso & Logistic Regression: High accuracy but very low recall and F1 scores, indicating poor minority class detection.

Is accuracy a factor for model performance?

Accuracy alone is not a reliable metric for evaluating model performance, especially in cases of class imbalance. While high accuracy values (e.g., Logistic Regression: 96.13%, Linear Regression: 96.02%) might seem impressive, they can be misleading when the minority class is poorly identified.

For instance:

- Ridge Regression, despite having lower accuracy (92.46%), achieves the highest recall (51.35%), making it more effective at detecting the minority class.
- Logistic Regression has the highest accuracy (96.13%) but extremely low recall (2.7%), failing to identify most minority cases.

Is the dataset biased?

- **Class 0 (No Stroke):** 95.74%
- **Class 1 (Stroke):** 4.26%
  This severe imbalance skews the model toward predicting the majority class, leading to poor detection of the minority class.
- **Steps to mitigate bias:**
  - Changing random state
  - Threshold tuning
  - Adjusting class weights
  - Resampling

Ridge Regression Model Evaluation

Strengths:

- **High Recall (51.35%)**: Ridge effectively identifies positive cases (true positives).
- **Good Accuracy (92.46%)**: Performs well overall in correct predictions.

Weaknesses:

- **Low Precision (25.33%)**: Many false positives, reducing precision.
- **Moderate F1 Score (33.93%)**: Indicates an imbalance between precision and recall.

Conclusion:

Ridge Regression excels in recall but requires improvement in precision to balance performance.

Final Insights

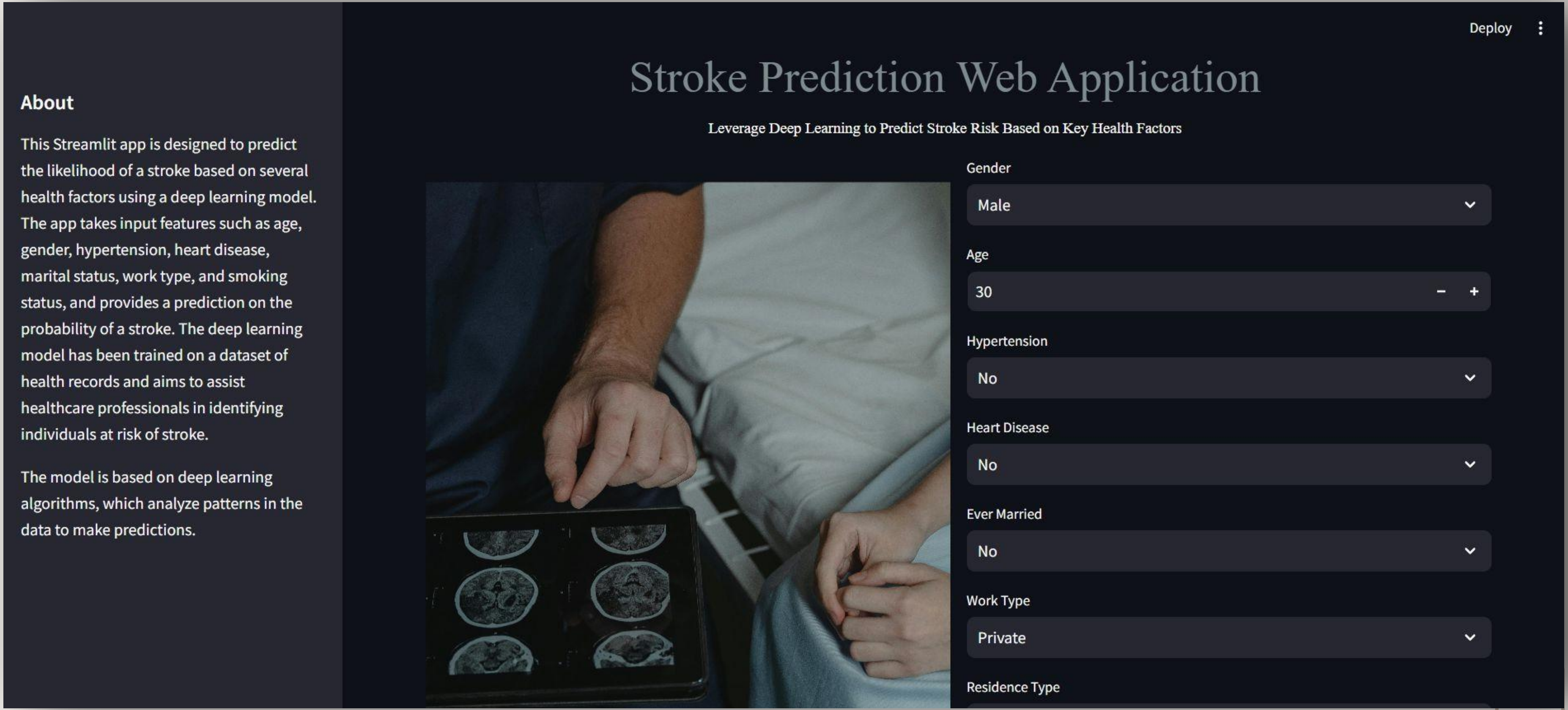
Class Imbalance: Dataset is heavily skewed (95% "No Stroke", 5% "Stroke"), causing bias towards the majority class.

Impact on Performance: High accuracy but poor detection of strokes due to the imbalance.

Evaluation Metrics: Metrics like recall and F1-score are more reliable than accuracy for evaluating minority class detection.

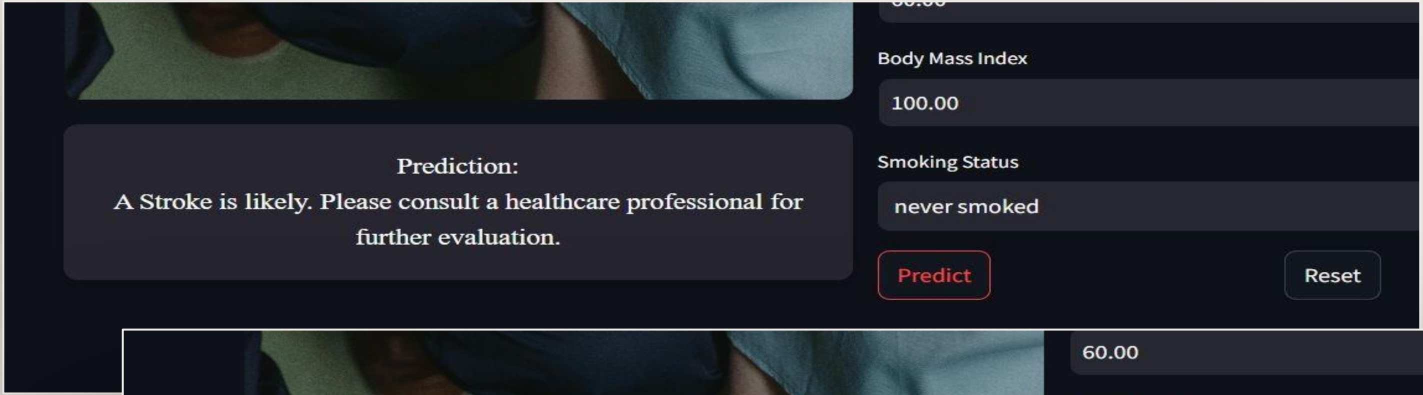
Analysis Conducted: Data preprocessing, visualizations, and modeling plays significant role in this project.

Building a Stroke Prediction Model with Streamlit

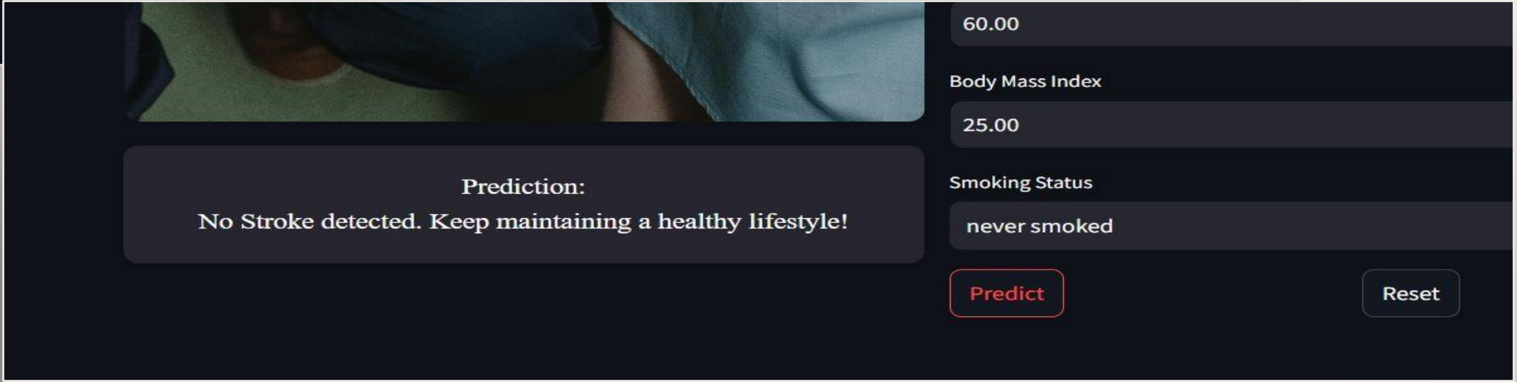


Building a Stroke Prediction Model with Streamlit

It displays the prediction after the user provides the input and clicks the predict button.



Stroke Detected



No Stroke

Code

```python
...el_selection import train_...
...linear_model import Ridge
...earn.linear_model import LogisticRegress...
...klearn.linear_model import LinearRegression
... sklearn.linear_model import Lasso
...om sklearn.preprocessing import StandardScaler
...rom sklearn.metrics import mean_squared_error
from sklearn.metrics import accuracy_score
import numpy as np

# Step 1: Data Preparation
X = df.drop(columns='stroke')  # Drop the 'stroke' column f...
y = df['stroke'].values  # Target variable

# Handle missing values (if any)
df = df.dropna()  # Drop rows with missing values (if any)
X = df.drop(columns='stroke')  # Re-define X after dropping...
y = df['stroke'].values  # Re-define y after dropping NaNs

# Step 2: Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, t...

# Step 3: Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Step 4: Define and train the Ridge Regression model
ridge_model = Ridge(alpha=0.5)  # Set alpha (regularizatio...
ridge_model.fit(X_train_scaled, y_train)

# Step 5: Make predictions
y_pred = ridge_model.predict(X_test_scaled)
```

```python
for column in df.columns:
    # Check if column is categorical
    if df[column].dtype == 'object':
        # If it has only two unique values, use binary encoding
        if df[column].nunique() == 2:
            # Map the values directly to 0 and 1
            df[column] = df[column].map({df[column].unique()[0]: 1, df[column].unique()[1...
        # If it has more than two unique values, use one-hot encoding
        else:
            df = pd.get_dummies(df, columns=[column], drop_first=True)

# Convert any boolean columns to integers (True/False to 1/0)
df = df.applymap(lambda x: int(x) if isinstance(x, bool) else x)

# Check the transformed DataFrame
print("\nEncoded DataFrame:")
display(df.head())
```

✓ 0.0s

```python
# Calculate metrics
precision = precision_score(y_test, y_pred_class)
recall = recall_score(y_test, y_pred_class)
f1 = f1_score(y_test, y_pred_class)
accuracy = accuracy_score(y_test, y_pred_class)

# Print results
print("Precision:", precision)
print("Recall:", recall)
print("F1 Score:", f1)
print("Accuracy:", accuracy)
# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred_class)

# Plot confusion matrix
```

Thanks!