Disease Predition from Medical Data

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.linear model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score
from sklearn.pipeline import Pipeline
from google.colab import drive
# Mount Google Drive
drive.mount('/content/drive')

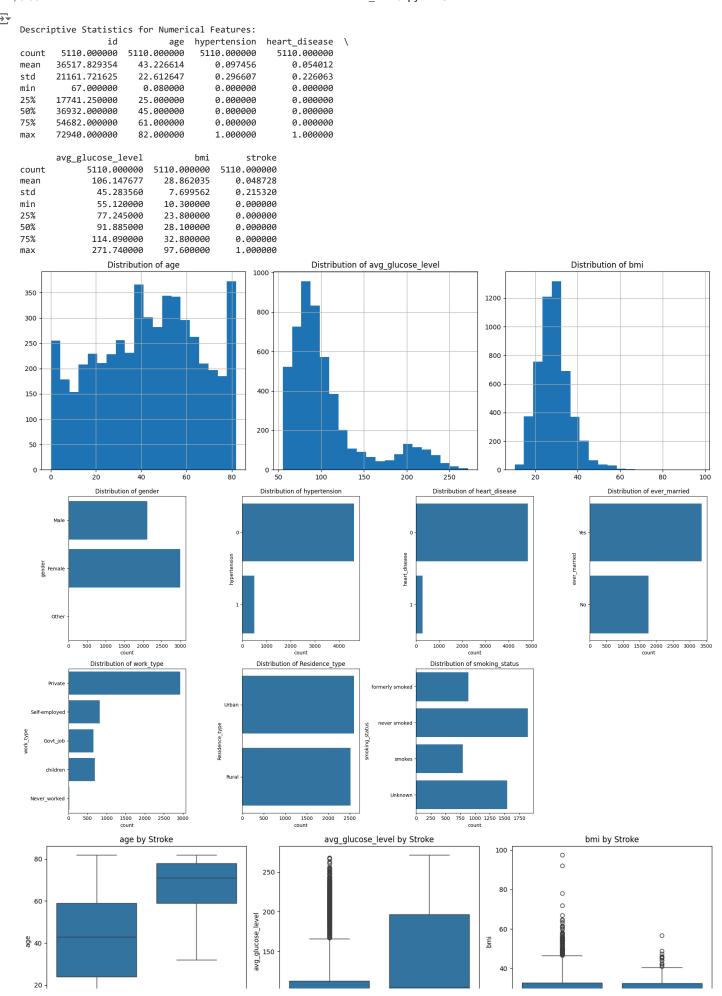
→ Mounted at /content/drive

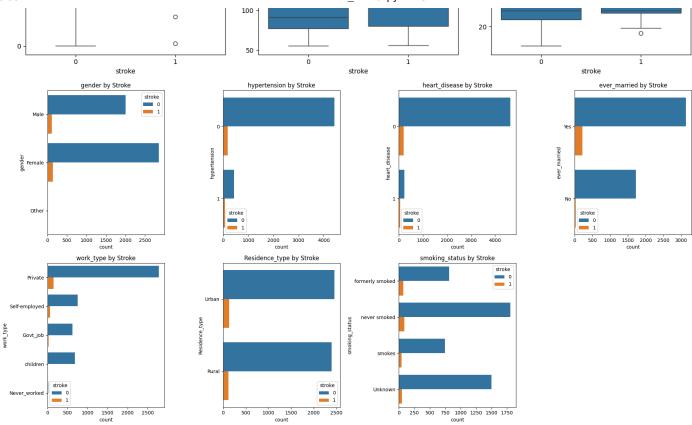
# Load the dataset
data = pd.read_csv("drive/My Drive/ML_internship/ML_Task03/healthcare-dataset-stroke-data.csv")
# Display basic information about the dataset
print("Basic Information about the Dataset:")
print(data.info())
# Display the first few rows of the dataset
print("\nFirst few rows of the dataset:")
print(data.head())

→ Basic Information about the Dataset:
     <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 5110 entries, 0 to 5109
    Data columns (total 12 columns):
                      Non-Null Count Dtype
     # Column
                           -----
     0 id
                          5110 non-null
                                           int64
     1
         gender
                           5110 non-null
                                           object
                           5110 non-null
                                           float64
     2
         age
         hypertension
                          5110 non-null
     3
                                           int64
     4
         heart_disease
                            5110 non-null
                                           int64
         ever_married
                            5110 non-null
                                           object
     6
         work_type
                            5110 non-null
                                           object
         Residence_type
                            5110 non-null
         avg_glucose_level 5110 non-null
                                           float64
                            4909 non-null
                                           float64
         bmi
     10 smoking_status
                            5110 non-null
                                           object
                            5110 non-null
    dtypes: float64(3), int64(4), object(5)
    memory usage: 479.2+ KB
    First few rows of the dataset:
          id gender age hypertension heart_disease ever_married \
        9046
                Male
                      67.0
                                      0
                                                     1
                                                                Yes
       51676 Female 61.0
                                      0
    1
                                                     0
                                                                Yes
    2
       31112
               Male 80.0
                                      0
                                                     1
                                                                Yes
              Female 49.0
                                      0
                                                     0
       60182
                                                                Yes
        1665 Female 79.0
                                                                Yes
           work_type Residence_type avg_glucose_level bmi
                                                              smoking_status
    0
             Private
                              Urban
                                           228.69 36.6 formerly smoked
       Self-employed
                              Rural
                                               202.21 NaN
                                                                never smoked
    1
    2
             Private
                              Rural
                                               105.92 32.5
                                                                never smoked
    3
             Private
                              Urban
                                               171.23 34.4
                                                                 smokes
      Self-employed
    4
                              Rural
                                               174.12 24.0
                                                                never smoked
       stroke
    0
            1
    1
            1
    2
            1
    3
            1
    4
            1
```

Data Preprocess

```
# Handling missing values for 'bmi'
median_bmi = data['bmi'].median()
data['bmi'].fillna(median_bmi, inplace=True)
🚁 <ipython-input-6-eee5454a4cf6>:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignme
     The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting value.
     For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].me
       data['bmi'].fillna(median_bmi, inplace=True)
# Descriptive statistics for numerical variables
print("\nDescriptive Statistics for Numerical Features:")
print(data.describe())
# Plotting histograms for the numerical variables
numerical_features = ['age', 'avg_glucose_level', 'bmi']
plt.figure(figsize=(15, 5))
for i, feature in enumerate(numerical_features, 1):
   plt.subplot(1, 3, i)
   data[feature].hist(bins=20)
   plt.title(f'Distribution of {feature}')
plt.tight_layout()
plt.show()
# Visualizing the distribution of categorical variables
categorical_features = ['gender', 'hypertension', 'heart_disease', 'ever_married',
                         work_type', 'Residence_type', 'smoking_status']
plt.figure(figsize=(20, 10))
for i, feature in enumerate(categorical_features, 1):
   plt.subplot(2, 4, i)
   sns.countplot(y=feature, data=data)
   plt.title(f'Distribution of {feature}')
plt.tight_layout()
plt.show()
# Visualizing the relationship between different variables and stroke occurrence
# For numerical features
plt.figure(figsize=(15, 5))
for i, feature in enumerate(numerical_features, 1):
   plt.subplot(1, 3, i)
    sns.boxplot(x='stroke', y=feature, data=data)
   plt.title(f'{feature} by Stroke')
plt.tight_layout()
plt.show()
# For categorical features
plt.figure(figsize=(20, 10))
for i, feature in enumerate(categorical_features, 1):
   plt.subplot(2, 4, i)
    sns.countplot(y=feature, hue='stroke', data=data)
   plt.title(f'{feature} by Stroke')
plt.tight_layout()
plt.show()
```





Encoding Categorical Variables

```
# Features and target variable
X = data.drop(['id', 'stroke'], axis=1)
y = data['stroke']

# Encoding categorical variables using OneHotEncoder
categorical_features = ['gender', 'ever_married', 'work_type', 'Residence_type', 'smoking_status']
numerical_features = ['age', 'hypertension', 'heart_disease', 'avg_glucose_level', 'bmi']

# Preprocessing pipelines for both numerical and categorical data
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_features),
        ('cat', OneHotEncoder(), categorical_features)
])

Splitting the Data into Training and Test Sets
```

```
# Split the dataset into training and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, stratify=y, random_state=42)
```

Model Training and Evaluation

```
# Evaluate the model performance on test data
test_accuracy = lr_model.score(X_test, y_test)
print(f'Test Accuracy: {test_accuracy:.2f}')
# Classification report and confusion matrix
y_test_pred = lr_model.predict(X_test)
print("\nClassification Report for Test Data:")
print(classification_report(y_test, y_test_pred))
print("Confusion Matrix for Test Data:")
print(confusion_matrix(y_test, y_test_pred))
# ROC-AUC score
test_roc_auc = roc_auc_score(y_test, lr_model.predict_proba(X_test)[:, 1])
print(f'Test ROC-AUC Score: {test_roc_auc:.2f}')
     Training Accuracy: 0.95
     Test Accuracy: 0.95
     Classification Report for Test Data:
                   precision
                                 recall f1-score
                                                     support
                0
                                             0.98
                                                         972
                         0.95
                                   1.00
                1
                         1.00
                                   0.02
                                             0.04
                                                          50
                                             0.95
                                                        1022
         accuracy
        macro avg
                         0.98
                                   0.51
                                             0.51
                                                        1022
                         0.95
                                             0.93
                                                        1022
     weighted avg
                                   0.95
     Confusion Matrix for Test Data:
     [[972 0]
      [ 49
             1]]
     Test ROC-AUC Score: 0.84
# Visualizing the ROC curve
from sklearn.metrics import roc_curve
fpr, tpr, _ = roc_curve(y_test, lr_model.predict_proba(X_test)[:, 1])
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {test_roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic Curve')
plt.legend(loc="lower right")
plt.show()
<del>_</del>
                        Receiver Operating Characteristic Curve
         1.0
         0.8
      Frue Positive Rate
         0.6
         0.4
         0.2
                                                       ROC curve (area = 0.84)
         0.0
               0.0
                           0.2
                                                   0.6
                                       0.4
                                                               0.8
                                                                            1.0
                                      False Positive Rate
```