Brain Stroke Model

Author: Annbellah Nduta Mbungu

Business Understanding

The title of this dataset is called "Brain Stroke dataset" from kaggle.com

Number of records: 4981 Number of columns: 11 Target variable: churn

Stakeholder

Healthcare Providers.Including hospitals, clinics, and individual healthcare practitioners who will use the predictive model to identify and manage patients at high risk of stroke.

Importance of the Project

Strokes are a major cause of morbidity and mortality worldwide, leading to significant long-term disabilities and healthcare expenses. Early identification and intervention for high-risk individuals can significantly reduce the incidence of strokes and the severity of their consequences. This project aims to provide a data-driven approach to enhance preventive healthcare measures.

Project Objective

The primary goal of this project is to develop a predictive model that can accurately identify individuals at high risk of having a stroke based on various health and demographic factors. By leveraging this model, healthcare providers can proactively manage and mitigate stroke risks, ultimately improving patient outcomes and reducing healthcare costs associated with stroke-related treatments and complications.

Models

Baseline model: Logistic regression Model 2: Decision tree Model 3: Knn Model 4: Random forest

Evaluation Metric

I have decided to use Recall as the evaluation metric for this project. Recall is calculated by dividing the number of true positives by the sum of true positives and false negatives. It measures the proportion of actual positive instances that are correctly identified. I selected this metric because our goal is to identify as many positive instances as possible, making it the most suitable choice when dealing with imbalanced data.

Import Libraries

Firstly, we import the necessary libraries to be used in this project

```
#Importing the necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import cross_val_score
from sklearn.metrics import confusion_matrix,classification_report
```

Loading the Data

The next step is to extract the data and put in a pandas dataframe, and to print the first 5 rows to see if the data was imported correctly.

```
stroke_df = pd.read_csv('brain_stroke.csv')
stroke_df.head()
```

```
   gender   age  hypertension  heart_disease ever_married
work_type  \
0    Male  67.0             0              1          Yes
Private
1    Male  80.0             0              1          Yes
Private
2  Female  49.0             0              0          Yes
Private
3  Female  79.0             1              0          Yes  Self-
employed
4    Male  81.0             0              0          Yes
Private

  Residence_type  avg_glucose_level   bmi   smoking_status  stroke
0          Urban             228.69  36.6  formerly smoked       1
1          Rural             105.92  32.5     never smoked       1
2          Urban             171.23  34.4           smokes       1
3          Rural             174.12  24.0     never smoked       1
4          Urban             186.21  29.0  formerly smoked       1
```

Exploring and Cleaning of the data

Below I am exploring the data, and checking what the data types of each columns, the descriptive statistics and finally I will check for any duplicates and missing data.

```
stroke_df.shape
```

```
(4981, 11)
```

```
stroke_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4981 entries, 0 to 4980
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   gender             4981 non-null   object
 1   age                4981 non-null   float64
 2   hypertension       4981 non-null   int64
 3   heart_disease      4981 non-null   int64
 4   ever_married       4981 non-null   object
 5   work_type          4981 non-null   object
 6   Residence_type     4981 non-null   object
 7   avg_glucose_level  4981 non-null   float64
 8   bmi                4981 non-null   float64
 9   smoking_status     4981 non-null   object
 10  stroke             4981 non-null   int64
```

```
dtypes: float64(3), int64(3), object(5)
memory usage: 428.2+ KB
```

```
stroke_df.describe()
```

```
               age  hypertension  heart_disease  avg_glucose_level  \
count  4981.000000   4981.000000    4981.000000        4981.000000
mean     43.419859      0.096165       0.055210         105.943562
std      22.662755      0.294848       0.228412          45.075373
min       0.080000      0.000000       0.000000          55.120000
25%      25.000000      0.000000       0.000000          77.230000
50%      45.000000      0.000000       0.000000          91.850000
75%      61.000000      0.000000       0.000000         113.860000
max      82.000000      1.000000       1.000000         271.740000

               bmi       stroke
count  4981.000000  4981.000000
mean     28.498173     0.049789
std       6.790464     0.217531
min      14.000000     0.000000
25%      23.700000     0.000000
50%      28.100000     0.000000
75%      32.600000     0.000000
max      48.900000     1.000000
```

```
stroke_df.columns
```

```
Index(['gender', 'age', 'hypertension', 'heart_disease',
'ever_married',
       'work_type', 'Residence_type', 'avg_glucose_level', 'bmi',
       'smoking_status', 'stroke'],
      dtype='object')
```

```
stroke_df.duplicated().sum()
```

```
0
```

```
stroke_df.isnull().sum()
```

```
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
```

```
stroke_df['stroke'].value_counts()
```

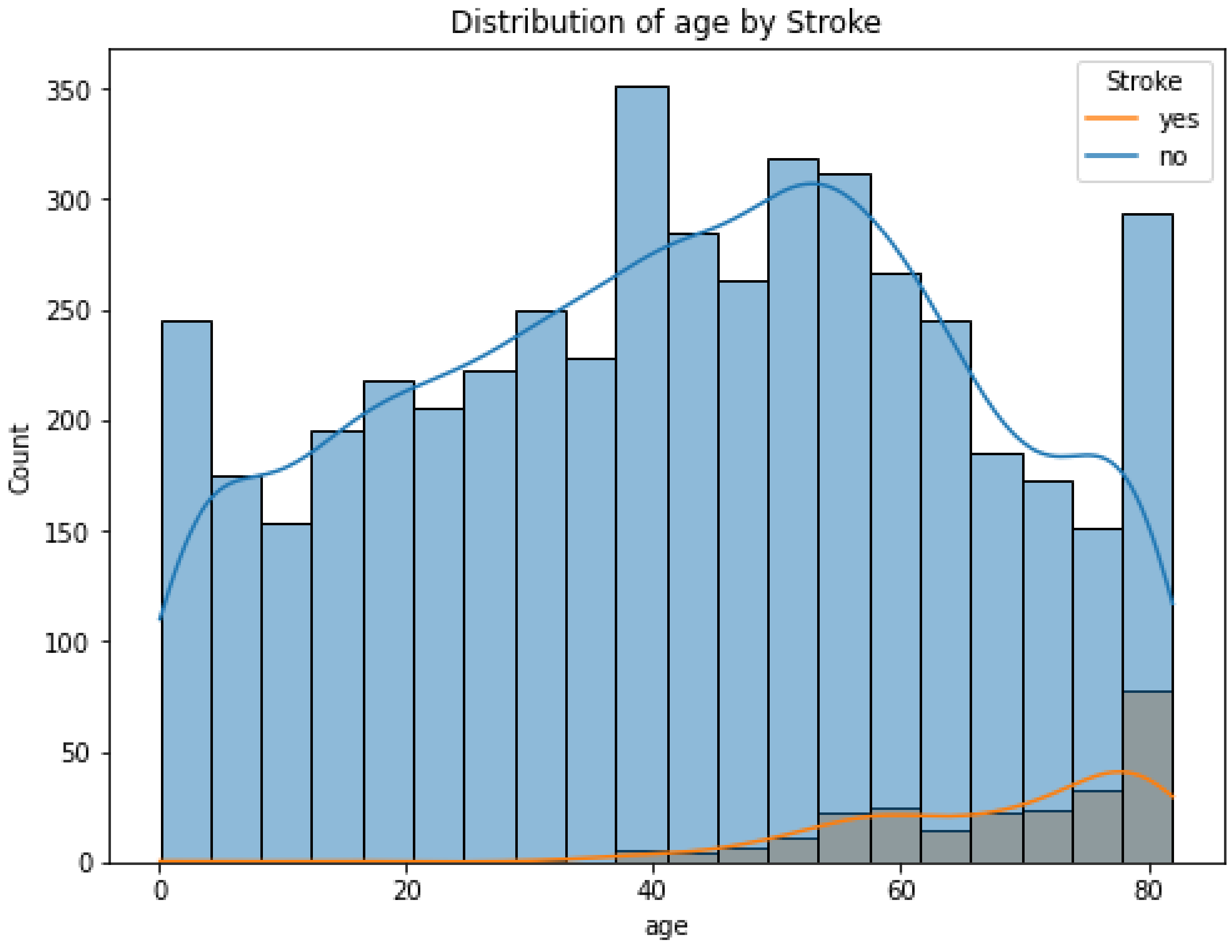
```
0    4733
1     248
Name: stroke, dtype: int64
```

The dataset has no null values or duplicates but its imbalanced which we will deal with later. The columns on gender and smoking status need to be encoded which I will also do later.

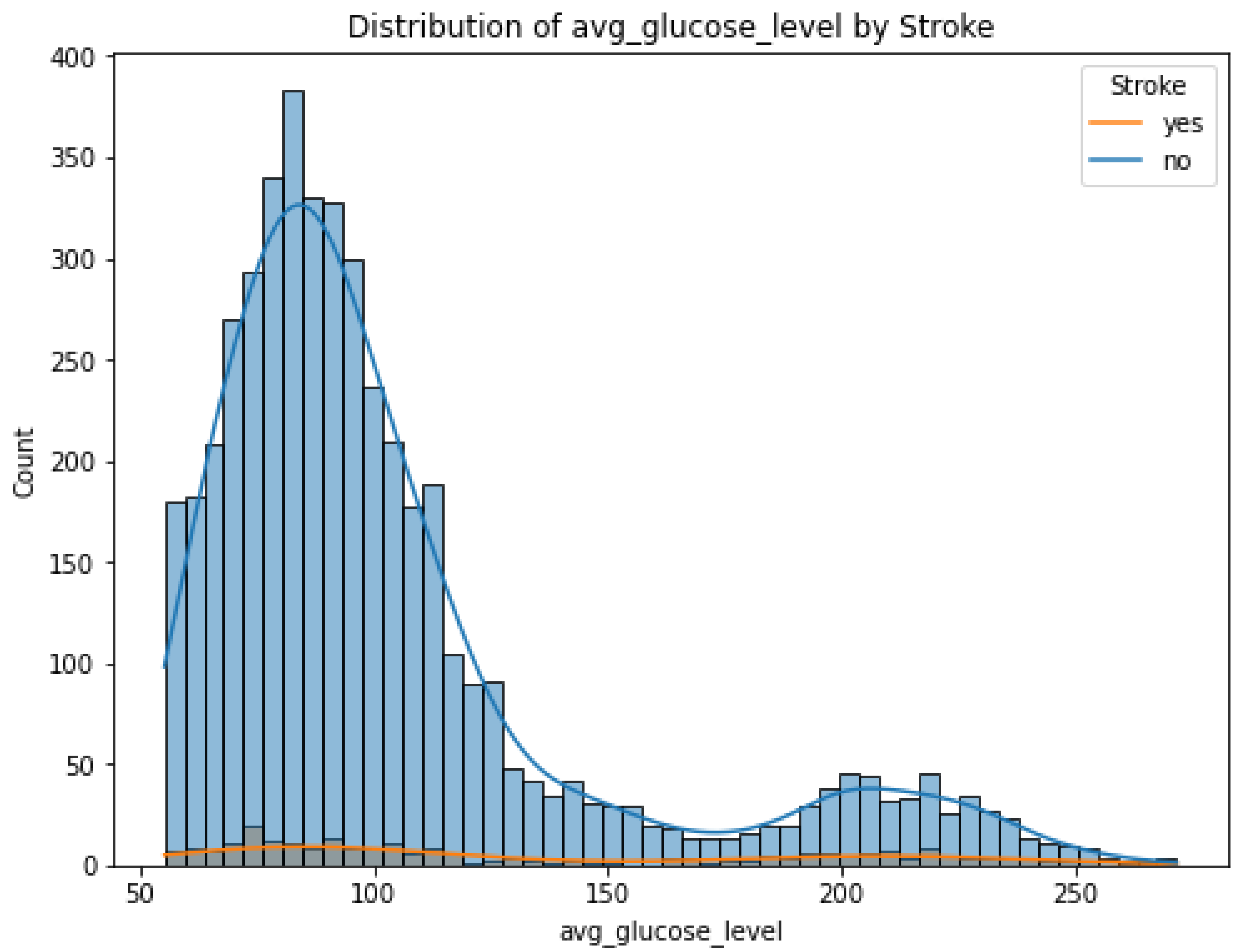
Data Visualization

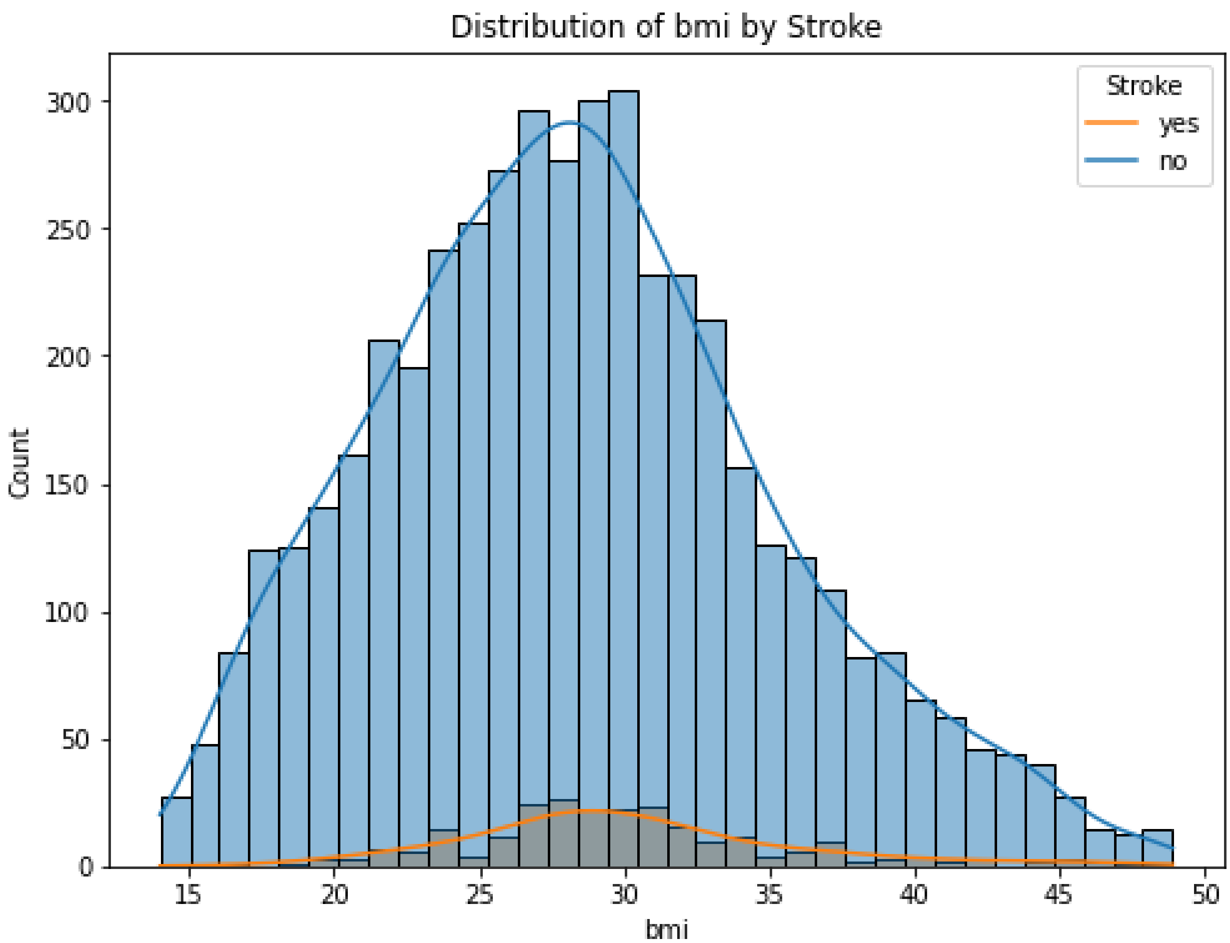
We will start with checking the relationship between the dependent variable and the numerical variables.

```
numerical_columns = ['age', 'avg_glucose_level', 'bmi']
stroke_df_num = stroke_df[numerical_columns + ['stroke']]

# Plot histograms for numerical columns
for col in numerical_columns:
    plt.figure(figsize=(8, 6))
    sns.histplot(data=stroke_df_num, x=col, hue='stroke', kde=True)
    plt.title(f'Distribution of {col} by Stroke')
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.legend(title='Stroke', labels=['yes', 'no'])
    plt.show()
```



Distribution of age by Stroke
Stroke
yes
no
Count
age
0
50
100
150
200
250
300
350
0
20
40
60
80


Distribution of avg_glucose_level by Stroke
Stroke
yes
no
Count
avg_glucose_level
0
50
100
150
200
250
300
350
400
50
100
150
200
250



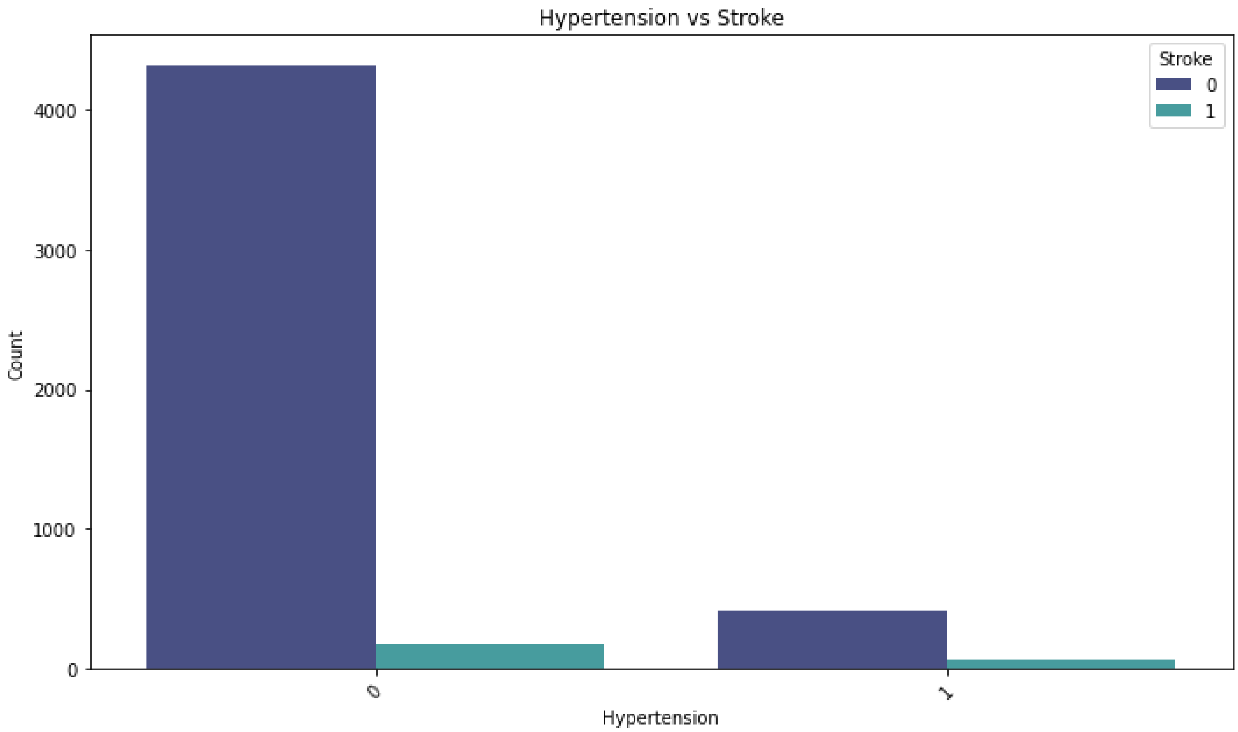
From the above visualizations, its evident that people from the age between 60-80, people with bmis between 26-32 are more likely to get a stroke.

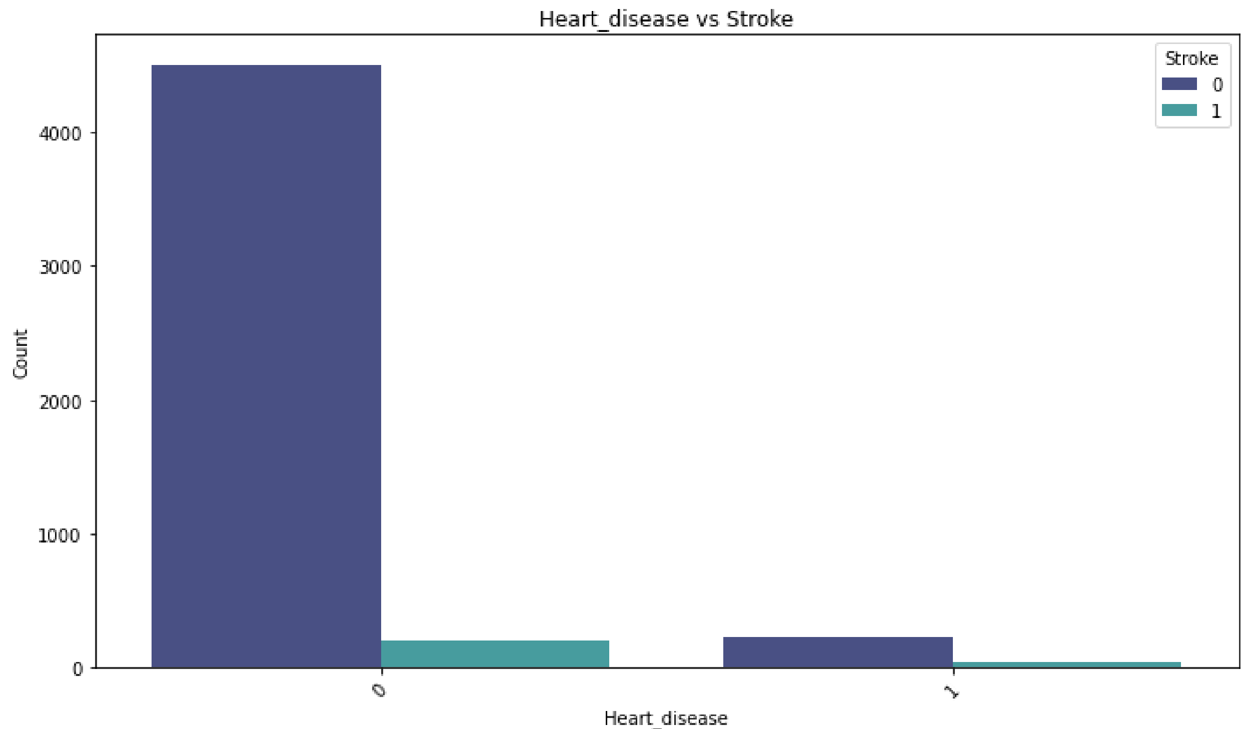
Categorical Variables

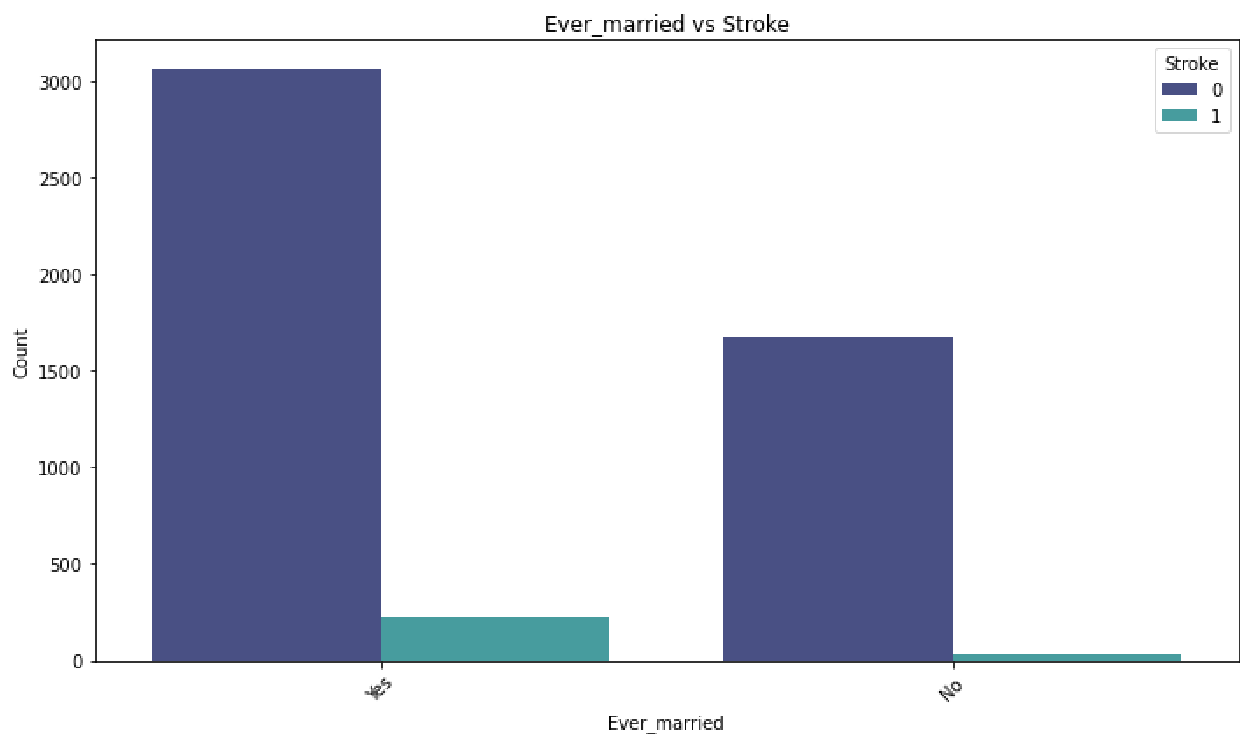
We will check how the categorical variables relate with the dependent variable

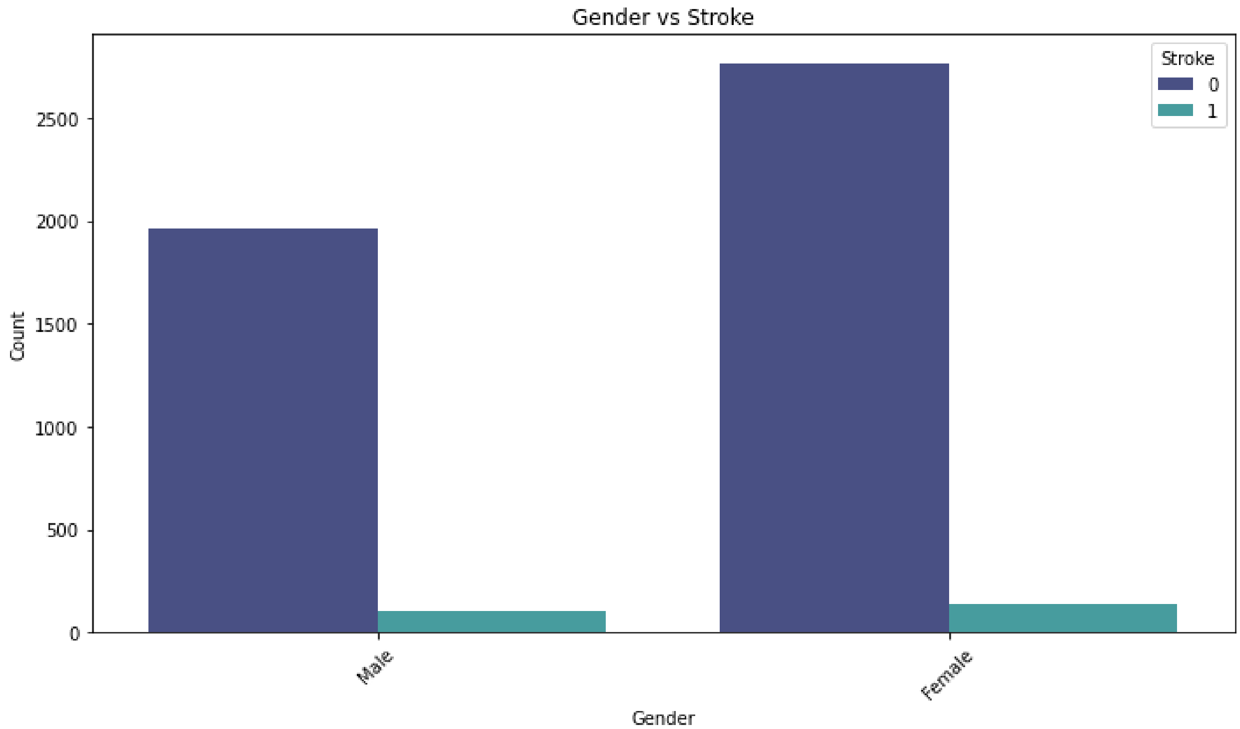
```
categorical_columns = ['hypertension', 'heart_disease',
'ever_married', 'gender', 'smoking_status', 'work_type',
'Residence_type']



# Loop through each categorical column and create a count plot with
specified colors
for column in categorical_columns:
    plt.figure(figsize=(10, 6))
    sns.countplot(x=column, hue='stroke', data=stroke_df,
palette='mako')
    plt.title(f'{column.capitalize()} vs Stroke')
    plt.xlabel(column.capitalize())
```

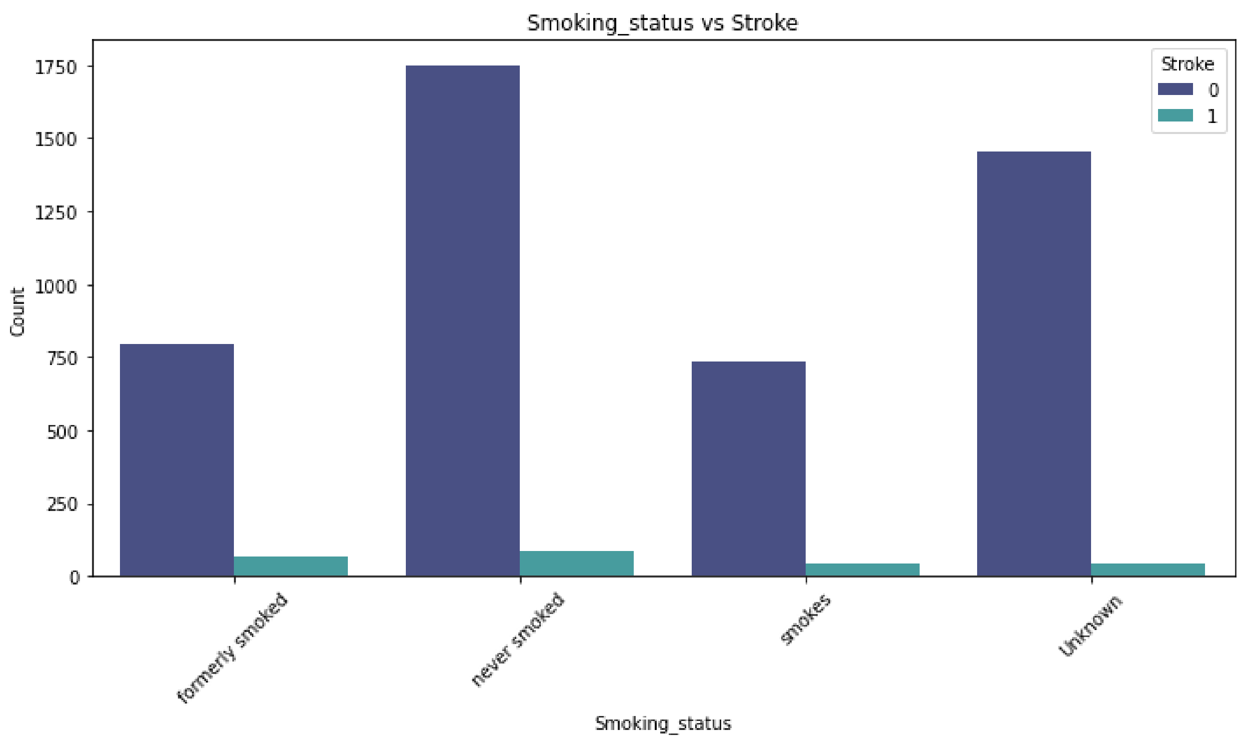
```
    plt.ylabel('Count')
    plt.legend(title='Stroke', loc='upper right')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

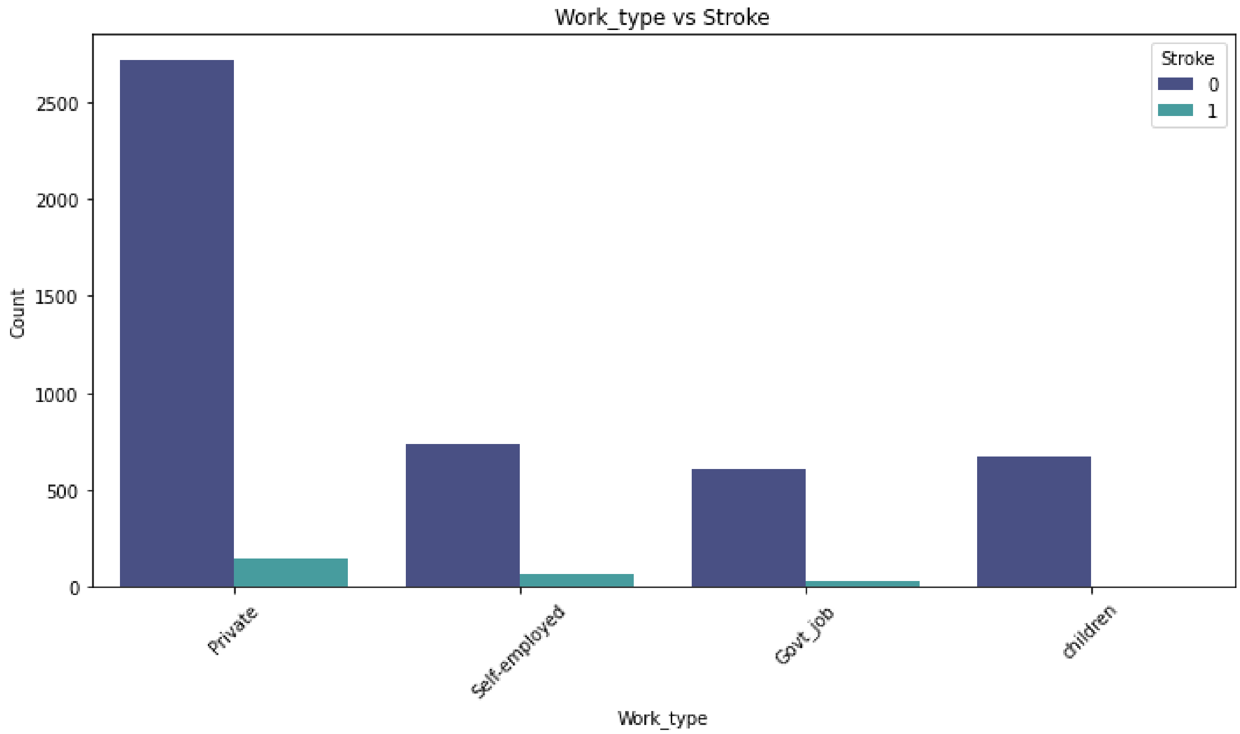


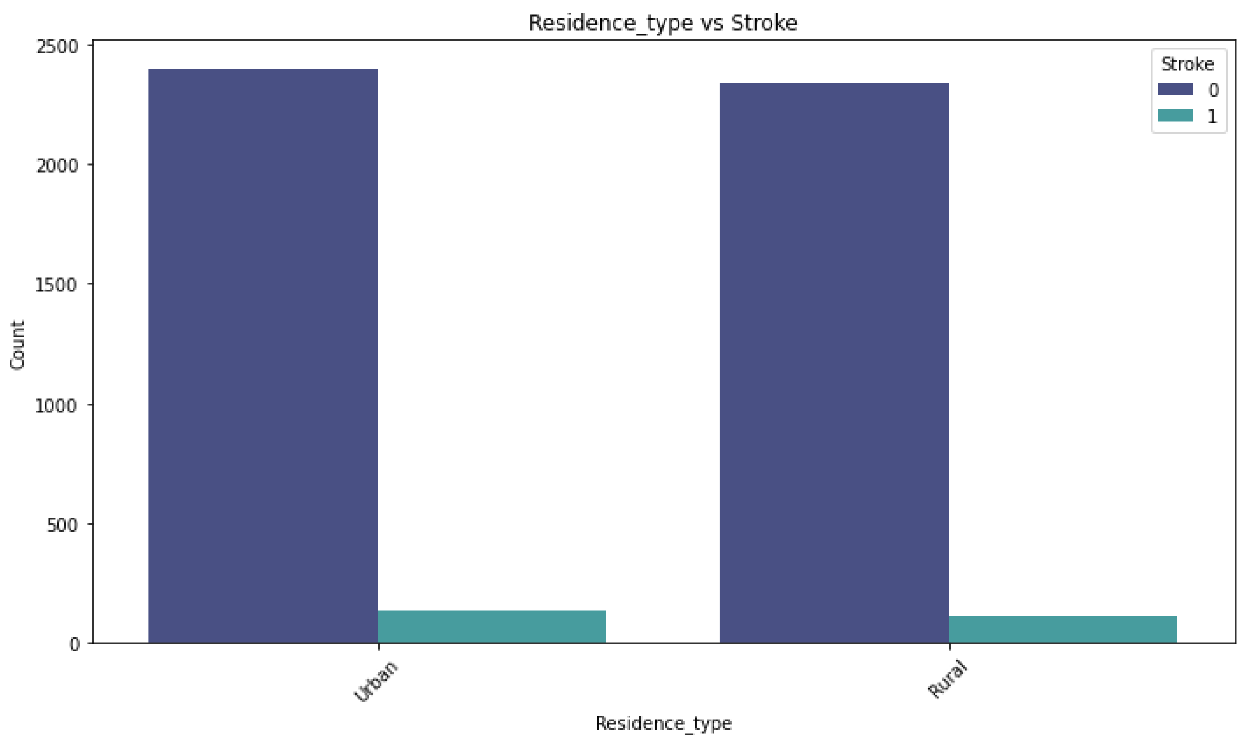

Heart_disease vs Stroke
Stroke
0
1
Count
0
1000
2000
3000
4000
Heart_disease
0
1


Ever_married vs Stroke
Stroke
0
1
Count
0
500
1000
1500
2000
2500
3000
Ever_married
Yes
No


Gender vs Stroke
Stroke
0
1
2500
2000
1500
1000
500
0
Count
Male
Female
Gender


Smoking_status vs Stroke
Stroke
0
1
1750
1500
1250
1000
750
500
250
0
Count
formerly smoked
never smoked
smokes
Unknown
Smoking_status

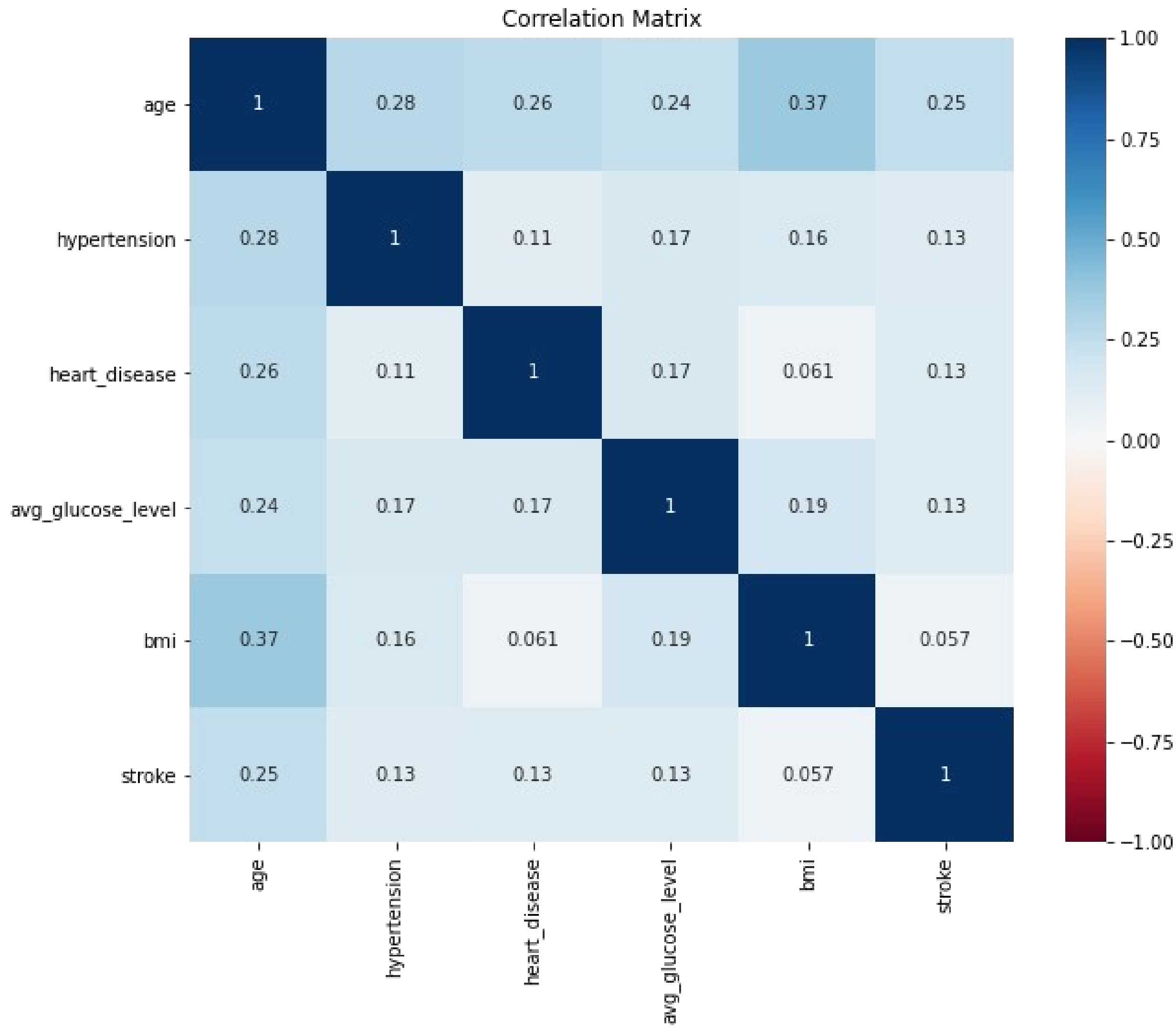





```
stroke_df.corr()

                        age  hypertension  heart_disease
avg_glucose_level  \
age                1.000000      0.278120       0.264852
```

```
0.236763
hypertension        0.278120      1.000000       0.111974
0.170028
heart_disease       0.264852      0.111974       1.000000
0.166847
avg_glucose_level  0.236763      0.170028       0.166847
1.000000
bmi                 0.373703      0.158762       0.060926
0.186348
stroke              0.246478      0.131965       0.134610
0.133227

                         bmi    stroke
age                 0.373703  0.246478
hypertension        0.158762  0.131965
heart_disease       0.060926  0.134610
avg_glucose_level  0.186348  0.133227
bmi                 1.000000  0.056926
stroke              0.056926  1.000000
```

```
correlation_matrix = stroke_df.corr()


plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='RdBu', center=0,
vmin = -1, vmax = 1)
plt.title('Correlation Matrix')
plt.show()
```



Feature Engineering

```
#Onehot Encoding for the smoking status column
stroke_df = pd.get_dummies(stroke_df, columns=['smoking_status'])

# Turning the categorical columns into numerical columns
label_encoder = LabelEncoder()
stroke_df['ever_married'] =
label_encoder.fit_transform(stroke_df['ever_married'])
stroke_df['gender'] = label_encoder.fit_transform(stroke_df['gender'])
```

Now I will drop the variables that don't seem relevant

```
stroke_df=stroke_df.drop(['work_type'],axis=1)
stroke_df=stroke_df.drop(['Residence_type'],axis=1)

stroke_df.head()
```

```
   gender   age  hypertension  heart_disease  ever_married
avg_glucose_level  \
0       1  67.0             0              1             1
228.69
1       1  80.0             0              1             1
105.92
2       0  49.0             0              0             1
171.23
3       0  79.0             1              0             1
174.12
4       1  81.0             0              0             1
186.21

    bmi  stroke  smoking_status_Unknown  smoking_status_formerly
smoked  \
0  36.6       1                       0
1
1  32.5       1                       0
0
2  34.4       1                       0
0
3  24.0       1                       0
0
4  29.0       1                       0
1

   smoking_status_never smoked  smoking_status_smokes
0                            0                      0
1                            1                      0
2                            0                      1
3                            1                      0
4                            0                      0
```

Train Test Split

```
X = stroke_df.drop(['stroke'],axis=1)
y = stroke_df['stroke']

X_train, X_test, y_train, y_test = train_test_split(X,
y,test_size=0.2, random_state=1)

mm_scaler = MinMaxScaler()
X_train = mm_scaler.fit_transform(X_train)
X_test = mm_scaler.transform(X_test)
```

Baseline Model

Logistic Regression

I will be using the logistic regression as my baseline model.

```
#Initialize the logistic regression
logreg = LogisticRegression()

#fit the model
logreg.fit(X_train, y_train)
```

```
LogisticRegression()
```

```
#Get predictions
y_pred_log_train = logreg.predict(X_train)
y_pred_log_test = logreg.predict(X_test)
```

Classification report of the training data

```
display(confusion_matrix(y_train, y_pred_log_train))
print(classification_report(y_train, y_pred_log_train))
```

```
array([[3798,    0],
       [ 186,    0]], dtype=int64)

              precision    recall  f1-score   support

           0       0.95      1.00      0.98      3798
           1       0.00      0.00      0.00       186

    accuracy                           0.95      3984
   macro avg       0.48      0.50      0.49      3984
weighted avg       0.91      0.95      0.93      3984


c:\Users\NDUTA\anaconda3\envs\learn-env\lib\site-packages\sklearn\
metrics\_classification.py:1221: UndefinedMetricWarning: Precision and
F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this
behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Classification report for the testing data

```
display(confusion_matrix(y_test, y_pred_log_test))
print(classification_report(y_test, y_pred_log_test))
```

```
array([[935,   0],
       [ 62,   0]], dtype=int64)

              precision    recall  f1-score   support

           0       0.94      1.00      0.97       935
           1       0.00      0.00      0.00        62

    accuracy                           0.94       997
```

```
   macro avg       0.47      0.50      0.48       997
weighted avg       0.88      0.94      0.91       997
```

After running the first classification report on the training data, our baseline model had a recall score of 0%. This is not good and leaves a lot of room for improvement.

I'll try balancing the dataset to see the impact but before splitting for indexing purposes

```
from sklearn.utils import resample

# Separate majority and minority classes
df_majority = stroke_df[stroke_df.stroke == 0]
df_minority = stroke_df[stroke_df.stroke == 1]

# Undersample the majority class
df_majority_undersampled = resample(df_majority,
                                    replace=False,    # sample without
replacement
                                    n_samples=248,    # to match
minority class
                                    random_state=42)  # reproducible
results

# Combine minority class with undersampled majority class
df_undersampled = pd.concat([df_minority, df_majority_undersampled])

# Display the new class counts
print(df_undersampled.stroke.value_counts())

1    248
0    248
Name: stroke, dtype: int64

df_undersampled.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 496 entries, 0 to 1798
Data columns (total 12 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   gender                          496 non-null    int32
 1   age                             496 non-null    float64
 2   hypertension                    496 non-null    int64
 3   heart_disease                   496 non-null    int64
 4   ever_married                    496 non-null    int32
 5   avg_glucose_level               496 non-null    float64
 6   bmi                             496 non-null    float64
 7   stroke                          496 non-null    int64
 8   smoking_status_Unknown          496 non-null    uint8
```

```
 9   smoking_status_formerly smoked  496 non-null    uint8
 10  smoking_status_never smoked     496 non-null    uint8
 11  smoking_status_smokes           496 non-null    uint8
dtypes: float64(3), int32(2), int64(3), uint8(4)
memory usage: 32.9 KB
```

```
X = df_undersampled.drop(['stroke'],axis=1)
y = df_undersampled['stroke']
X_train, X_test, y_train, y_test = train_test_split(X,
y,test_size=0.2, stratify=y,random_state=1)
```

```
logreg2 = LogisticRegression()
logreg2.fit(X_train, y_train)
y_pred_log2_train = logreg2.predict(X_train)
y_pred_log2_test = logreg2.predict(X_test)
```

```
c:\Users\NDUTA\anaconda3\envs\learn-env\lib\site-packages\sklearn\
linear_model\_logistic.py:762: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(
```

```
display(confusion_matrix(y_train, y_pred_log2_train))
print(classification_report(y_train, y_pred_log2_train))
```

```
array([[139,  59],
       [ 40, 158]], dtype=int64)
```

```
              precision    recall  f1-score   support

           0       0.78      0.70      0.74       198
           1       0.73      0.80      0.76       198

    accuracy                           0.75       396
   macro avg       0.75      0.75      0.75       396
weighted avg       0.75      0.75      0.75       396
```

```
display(confusion_matrix(y_test, y_pred_log2_test))
print(classification_report(y_test, y_pred_log2_test))
```

```
array([[32, 18],
       [ 9, 41]], dtype=int64)
```

```
              precision    recall  f1-score   support

           0       0.78      0.64      0.70        50
           1       0.69      0.82      0.75        50

    accuracy                           0.73       100
   macro avg       0.74      0.73      0.73       100
weighted avg       0.74      0.73      0.73       100
```

Before undersampling, the model's accuracy was high(94%) but the recall for the minority class was low(0%) and this being a medical field model thats not good, But after undersampling even if the accuracy dropped to 73%, at least the recall went higher (83%)for the minority class meaning it got better at predicting the ones with a risk of getting a brain stroke.

Decision Tree

```
#Initialize the decision tree
clf = DecisionTreeClassifier(max_depth = 5, min_samples_leaf = 2,
min_samples_split = 5, random_state=42)
#fit the model
dec_clf = clf.fit(X_train,y_train)
```

Decision trees require some pruning to become more accurate. For this model I used min_samples_split, and min_samples_leaf.

```
#Get predictions
y_pred_dec_train = dec_clf.predict(X_train)
y_pred_dec_test = dec_clf.predict(X_test)
```

Classification report of the training set

```
print(classification_report(y_train, y_pred_dec_train))
display(confusion_matrix(y_train, y_pred_dec_train))

              precision    recall  f1-score   support

           0       0.81      0.81      0.81       198
           1       0.81      0.81      0.81       198

    accuracy                           0.81       396
   macro avg       0.81      0.81      0.81       396
weighted avg       0.81      0.81      0.81       396


array([[160,  38],
       [ 38, 160]], dtype=int64)
```

We have a much better recall score on our training data using the decision tree model. We slightly improved from our baseline model from 80% previously, to 81% with the decision tree model.

Classification report of the testing set

```
print(classification_report(y_test, y_pred_dec_test))
display(confusion_matrix(y_test, y_pred_dec_test))
```

```
              precision    recall  f1-score   support

           0       0.73      0.72      0.73        50
           1       0.73      0.74      0.73        50

    accuracy                           0.73       100
   macro avg       0.73      0.73      0.73       100
weighted avg       0.73      0.73      0.73       100


array([[36, 14],
       [13, 37]], dtype=int64)
```

We have gotten a slightly lower recall score on our test data, but still scored the same with our baseline model. Also, our false negative number was increased.

KNN

```
model = KNeighborsClassifier()
Knn = model.fit(X_train,y_train)
y_pred_knn_train = Knn.predict(X_train)
y_pred_knn_test = Knn.predict(X_test)

print(classification_report(y_train,y_pred_knn_train))
display(confusion_matrix(y_train, y_pred_knn_train))
```

```
              precision    recall  f1-score   support

           0       0.85      0.72      0.78       198
           1       0.75      0.87      0.81       198

    accuracy                           0.79       396
   macro avg       0.80      0.79      0.79       396
weighted avg       0.80      0.79      0.79       396


array([[142,  56],
       [ 26, 172]], dtype=int64)
```

```
print(classification_report(y_test,y_pred_knn_test))
display(confusion_matrix(y_test,y_pred_knn_test))
```

```
              precision    recall  f1-score   support

           0       0.76      0.70      0.73        50
           1       0.72      0.78      0.75        50

    accuracy                           0.74       100
   macro avg       0.74      0.74      0.74       100
weighted avg       0.74      0.74      0.74       100


array([[35, 15],
       [11, 39]], dtype=int64)
```

KNN with GridSearchCv

I am now performing GridSearchCV on the knn model, to see what hypertuning should be taken place in order to get the best performing knn model

```
# Define the parameter grid for GridSearchCV
param_grid = {
    'n_neighbors': [3, 5, 7],       # Number of neighbors to consider
    'weights': ['uniform', 'distance'],  # Weighting strategy for
neighbors
    'algorithm': ['auto', 'ball_tree', 'kd_tree', 'brute'],  #
Algorithm to compute nearest neighbors
    'p': [1, 2]  # Distance metric: 1 for Manhattan distance, 2 for
Euclidean distance
}

# Instantiate GridSearchCV
grid_search = GridSearchCV(estimator=model, param_grid=param_grid,
cv=3, n_jobs=-1, verbose=2)

# Fit the grid search to the data
grid_search.fit(X_train, y_train)

# Get the best model from GridSearchCV
best_knn = grid_search.best_estimator_

# Predict using the best model
y_pred_knn_train2 = best_knn.predict(X_train)
y_pred_knn_test2 = best_knn.predict(X_test)
# Evaluate the best model
print("Best parameters found:", grid_search.best_params_)
print(classification_report(y_train, y_pred_knn_train2))
display(confusion_matrix(y_train, y_pred_knn_train2))

Fitting 3 folds for each of 48 candidates, totalling 144 fits
```

```
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent
workers.
[Parallel(n_jobs=-1)]: Done  38 tasks      | elapsed:    2.7s

Best parameters found: {'algorithm': 'auto', 'n_neighbors': 7, 'p': 2,
'weights': 'uniform'}
              precision    recall  f1-score   support

           0       0.82      0.68      0.74       198
           1       0.73      0.85      0.78       198

    accuracy                           0.77       396
   macro avg       0.77      0.77      0.76       396
weighted avg       0.77      0.77      0.76       396


[Parallel(n_jobs=-1)]: Done 144 out of 144 | elapsed:    3.0s finished

array([[135,  63],
       [ 30, 168]], dtype=int64)

print(classification_report(y_test, y_pred_knn_test2))
display(confusion_matrix(y_test, y_pred_knn_test2))

              precision    recall  f1-score   support

           0       0.82      0.72      0.77        50
           1       0.75      0.84      0.79        50

    accuracy                           0.78       100
   macro avg       0.78      0.78      0.78       100
weighted avg       0.78      0.78      0.78       100


array([[36, 14],
       [ 8, 42]], dtype=int64)
```

The KNN model seems to improve compared to our baseline model and decision tree model. The accuracy is higher (78%), the recall is also higher and the false negatives have reduced to 8.

Random Forest

```
rand = RandomForestClassifier(n_estimators=10, max_depth=5,
random_state=42)
model = rand.fit(X_train,y_train)
y_pred_rand_train = model.predict(X_train)
y_pred_rand_test = model.predict(X_test)

print(classification_report(y_train, y_pred_rand_train))
display(confusion_matrix(y_train, y_pred_rand_train))
```

```
              precision    recall  f1-score   support

           0       0.89      0.77      0.82       198
           1       0.80      0.90      0.85       198

    accuracy                           0.84       396
   macro avg       0.84      0.84      0.84       396
weighted avg       0.84      0.84      0.84       396


array([[152,  46],
       [ 19, 179]], dtype=int64)
```

```python
print(classification_report(y_test, y_pred_rand_test))
display(confusion_matrix(y_test, y_pred_rand_test))
```

```
              precision    recall  f1-score   support

           0       0.81      0.68      0.74        50
           1       0.72      0.84      0.78        50

    accuracy                           0.76       100
   macro avg       0.77      0.76      0.76       100
weighted avg       0.77      0.76      0.76       100


array([[34, 16],
       [ 8, 42]], dtype=int64)
```

Random Forest with GridSearchCV

I will try to hypertune to see if it will be better than the previous models

```python
# Create the parameter grid based on the results of random search
param_grid = {'criterion':['gini','entropy'],
              'max_depth':[3,6,9,12],
              'min_samples_leaf': [5,10,12],
              'n_estimators': [10, 12, 15, 20]
             }


# Instantiate the grid search model
grid_search =GridSearchCV(rand, param_grid, cv=5, scoring='accuracy')
# Fit the grid search to the data
grid_search.fit(X_train, y_train)

print(f"Best parameters: {grid_search.best_params_}")
best_rf = grid_search.best_estimator_

# Predict using the best model
```

```
y_pred_rand_train2 = best_rf.predict(X_train)
y_pred_rand_test2 = best_rf.predict(X_test)

# Evaluate the model
print(classification_report(y_train, y_pred_rand_train2))
display(confusion_matrix(y_train, y_pred_rand_train2))
```

```
Best parameters: {'criterion': 'gini', 'max_depth': 9,
'min_samples_leaf': 5, 'n_estimators': 15}
              precision    recall  f1-score   support

           0       0.89      0.80      0.85       198
           1       0.82      0.90      0.86       198

    accuracy                           0.85       396
   macro avg       0.86      0.85      0.85       396
weighted avg       0.86      0.85      0.85       396
```

```
array([[159,  39],
       [ 19, 179]], dtype=int64)
```

```
print(classification_report(y_test, y_pred_rand_test2))
display(confusion_matrix(y_test, y_pred_rand_test2))
```

```
              precision    recall  f1-score   support

           0       0.80      0.70      0.74        50
           1       0.73      0.82      0.77        50

    accuracy                           0.76       100
   macro avg       0.76      0.76      0.76       100
weighted avg       0.76      0.76      0.76       100
```

```
array([[35, 15],
       [ 9, 41]], dtype=int64)
```

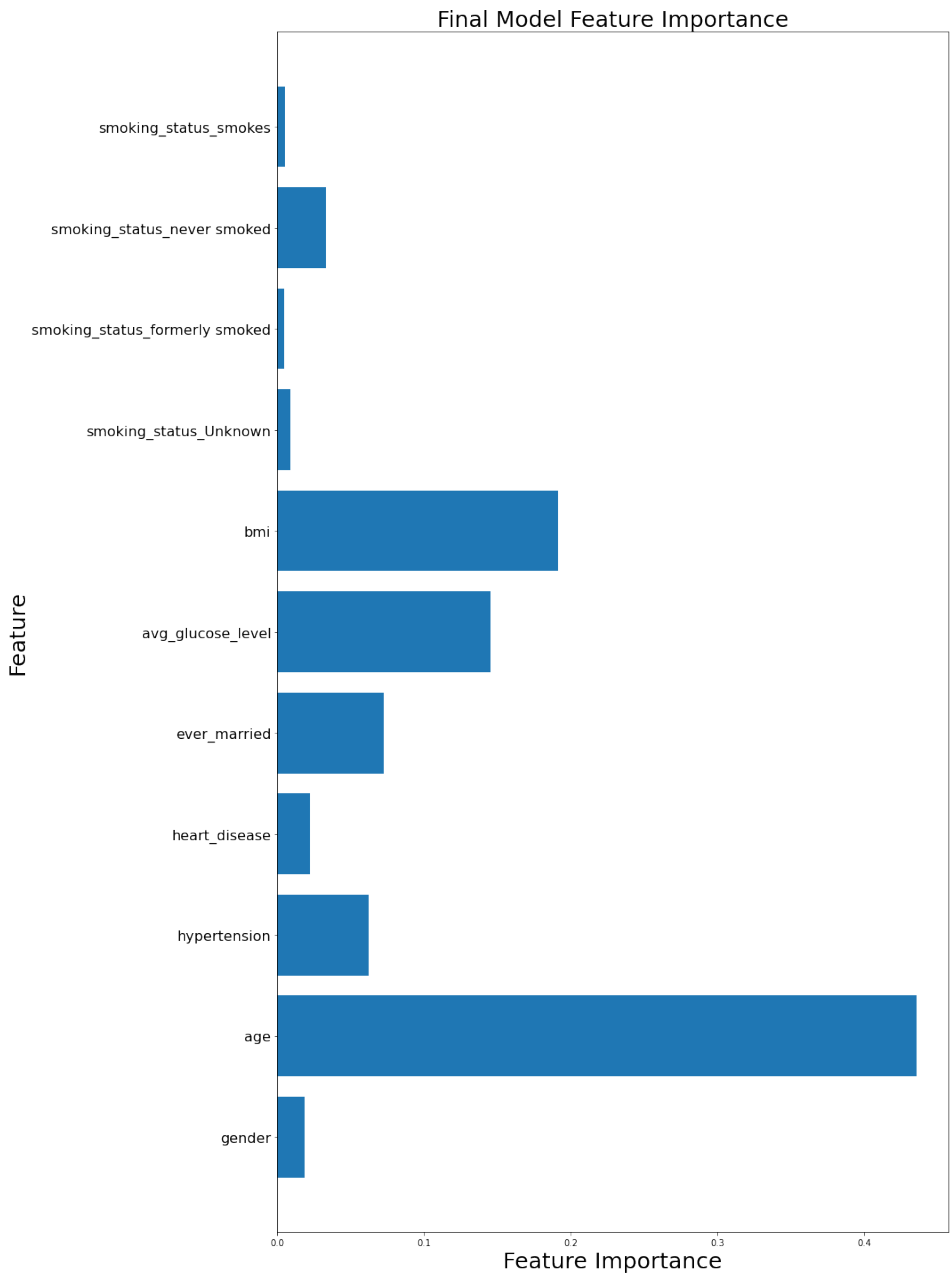
Certainly the random forest with gridsearchCV didn't improve compare to the knn model.The false negatives increased slightly from 8 to 9, the recall also reduced from 84% to 82%

```
model.feature_importances_
```

```
array([0.01850418, 0.43545357, 0.06248769, 0.02230103, 0.07256894,
       0.14546653, 0.19109151, 0.00889573, 0.00461138, 0.03321568,
       0.00540376])
```

```
def plot_features_importances(model):
    n_features = X_test.shape[1]
    plt.figure(figsize=(15,20))
```

```
    plt.barh(range(n_features), model.feature_importances_,
align='center')
    plt.yticks(np.arange(n_features), X_test.columns.values, fontsize
= 16)
    plt.xlabel('Feature Importance', fontsize = 25)
    plt.ylabel('Feature', fontsize = 25)
    plt.title('Final Model Feature Importance', fontsize = 25)
    plt.tight_layout()

plot_features_importances(model)
```



Final Model Feature Importance
smoking_status_smokes
smoking_status_never smoked
smoking_status_formerly smoked
smoking_status_Unknown
bmi
avg_glucose_level
ever_married
heart_disease
hypertension
age
gender
Feature
0.0
0.1
0.2
0.3
0.4
Feature Importance

We can see from this feature importance graph that there are three features that the model is weighing more heavily.

- Age
- BMI
- Avg_glucose_levels

Results

Logistic Regression

Recall Score (Train): 80%

Recall Score (Test): 82%

Decision Tree

Recall Score (Train): 81%

Recall Score (Test):74%

KNN

Recall Score (Train):87%

Recall Score (Test):78%

KNN With GridSearchCV

Recall Score (Train):85%

Recall Score (Test):84%

Random Forest

Recall Score (Train):90%

Recall Score (Test):84%

Random Forest with GridSearchCV:

Recall Score (Train):90%

Recall Score (Test):82%

Best Model Selection

Considering both the recall on the training and test sets, the KNN with GridSearchCV and Random Forest (without GridSearchCV) models are the top contenders:

- KNN with GridSearchCV: 85% recall on training, 84% recall on test.
- Random Forest: 90% recall on training, 84% recall on test.

Both models perform equally well on the test set. However, the KNN with GridSearchCV has a smaller gap between training and test recall, suggesting it might generalize slightly better without as much overfitting compared to the Random Forest.

Recommendations

- Deploy the KNN with GridSearchCV model due to its balanced and high recall scores.
- Continuously monitor and update the model with new data to maintain performance.
- Analyze feature importance and collect additional data to enhance model accuracy.
- Use resampling techniques and cost-sensitive learning to handle imbalanced data.
- Develop a user-friendly interface and provide training for healthcare providers.
- Regularly evaluate the model for biases and ensure data privacy and security.