```
In [30]: import pandas as pd
          import numpy as np
          from sklearn.linear_model import LogisticRegression
          from sklearn.model selection import train test split
          from sklearn.preprocessing import StandardScaler
          from sklearn.pipeline import make_pipeline
          from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
          #This means that the target variable is STROKE which has only two classes as 0 - No Stroke and 1 -
          data = pd.read csv('stroke-dataset.csv')
          # Display the first few and last few rows of the dataset.
Out[30]:
                                               heart_disease ever_married
                                                                         work_type residence_type avg_glucose_level
                    id gender
                              age hypertension
              0
                   67
                       Female
                              17.0
                                             0
                                                          0
                                                                      Nο
                                                                             Private
                                                                                           Urban
                                                                                                             92.97
                                                                                                                  NaN
              1
                   77 Female 13.0
                                             0
                                                          0
                                                                      No
                                                                            children
                                                                                            Rural
                                                                                                             85.81 18.6
              2
                   84
                         Male 55.0
                                             0
                                                          0
                                                                     Yes
                                                                             Private
                                                                                            Urban
                                                                                                             89.17 31.5
              3
                       Female 42.0
                                             0
                                                          0
                                                                      No
                                                                             Private
                                                                                            Urban
                                                                                                             98.53 18.5
              4
                   99
                       Female 31.0
                                             0
                                                          0
                                                                      Nο
                                                                             Private
                                                                                           Urban
                                                                                                            108.89
                                                                                                                   52.3
           5105 72911
                       Female 57.0
                                             1
                                                          0
                                                                     Yes
                                                                             Private
                                                                                            Rural
                                                                                                            129.54 60.9
           5106 72914 Female
                             19.0
                                             0
                                                          0
                                                                      No
                                                                             Private
                                                                                            Urban
                                                                                                             90.57 24.2
           5107 72915 Female 45.0
                                             0
                                                          n
                                                                     Yes
                                                                             Private
                                                                                            Urban
                                                                                                            172.33 45.3
                                                          0
           5108
                72918 Female 53.0
                                             1
                                                                     Yes
                                                                             Private
                                                                                            Urban
                                                                                                             62.55 30.3
           5109 72940 Female
                               2.0
                                             n
                                                                      No
                                                                            children
                                                                                            Urban
                                                                                                            102.92 17.6
          5110 rows × 12 columns
In [61]: print(data.shape)
          print(data.columns)
          print(data.dtypes)
          (5110, 12)
          Index(['id', 'gender', 'age', 'hypertension', 'heart_disease', 'ever_married',
                  'work_type', 'residence_type', 'avg_glucose_level', 'bmi',
                  'smoking_status', 'stroke'],
                 dtype='object')
          id
                                   int64
          gender
                                  object
                                 float64
          age
          hypertension
                                   int64
          heart_disease
                                   int64
          ever_married
                                  object
          work_type
                                  object
          residence_type
                                  object
                                 float64
          avg_glucose_level
                                 float64
          bmi
                                  object
          smoking_status
                                   int64
          stroke
          dtype: object
```

```
In [111]: #df.plot(x='stroke', y='age', kind='bar')
import matplotlib.pyplot as plt

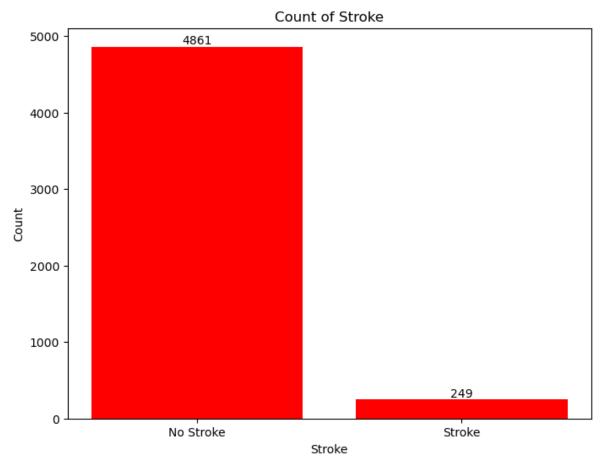
stroke_counts = data['stroke'].value_counts()

plt.figure(figsize=(8, 6))
bars = plt.bar(stroke_counts.index, stroke_counts.values, color='red')

plt.xlabel('Stroke')
plt.ylabel('Count')
plt.title('Count of Stroke')

plt.xticks([0, 1], ['No Stroke', 'Stroke'])

for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 2), va='bottom', ha='center', colo
plt.show()
```



```
In [62]: #Without Solving Class Imbalance problem
         X = data[['heart_disease', 'hypertension', 'avg_glucose_level', 'age']]
         y = data[ 'stroke']
         X_train, X_test, y_train, y_test= train_test_split(X, y, test_size=0.2, random_state=40)
         log_reg = make_pipeline(StandardScaler(), LogisticRegression())
         log reg.fit(X train, y train)
         y pred = log reg.predict (X test)
         print('Accuracy:', accuracy_score(y_test, y_pred))
        print('Confusion Matrix: \n', confusion matrix(y test, y pred))
         Accuracy: 0.9579256360078278
         Confusion Matrix:
          [[979 0]
          [ 43 0]]
In [64]: pip install imblearn
         Collecting imblearn
           Downloading imblearn-0.0-py2.py3-none-any.whl (1.9 kB)
         Collecting imbalanced-learn
           Downloading imbalanced learn-0.11.0-py3-none-any.whl (235 kB)
              ----- 235.6/235.6 kB 4.8 MB/s eta 0:00:00
         Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\bhave\anaconda3\lib\site-packages
         (from imbalanced-learn->imblearn) (1.0.2)
         Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\bhave\anaconda3\lib\site-packages
         (from imbalanced-learn->imblearn) (2.2.0)
         Requirement already satisfied: numpy>=1.17.3 in c:\users\bhave\anaconda3\lib\site-packages (from
         imbalanced-learn->imblearn) (1.24.2)
         Collecting joblib>=1.1.1
           Downloading joblib-1.3.2-py3-none-any.whl (302 kB)
              ----- 302.2/302.2 kB 9.1 MB/s eta 0:00:00
         Requirement already satisfied: scipy>=1.5.0 in c:\users\bhave\anaconda3\lib\site-packages (from i
         mbalanced-learn->imblearn) (1.9.1)
         Installing collected packages: joblib, imbalanced-learn, imblearn
           Attempting uninstall: joblib
             Found existing installation: joblib 1.1.0
             Uninstalling joblib-1.1.0:
              Successfully uninstalled joblib-1.1.0
         Successfully installed imbalanced-learn-0.11.0 imblearn-0.0 joblib-1.3.2
         Note: you may need to restart the kernel to use updated packages.
```

```
In [76]: missing_values = df.isna().sum()
         print(missing_values)
         df = df.dropna()
         df.count()
         id
                               0
         gender
                               0
                               0
         age
         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
Out[76]: id
                               4909
         gender
                               4909
         age
                               4909
         hypertension
                               4909
         heart_disease
                               4909
         ever_married
                               4909
         work_type
                               4909
         residence_type
                               4909
         avg_glucose_level
                               4909
         bmi
                               4909
         smoking\_status
                               4909
                               4909
         stroke
         dtype: int64
```

To Resolve the issue of "Class Imbalance" I prformed - Synthetic Minority Over-sampling Technique (SMOTE) to create synthetic samples for the minority class. SMOTE generates new samples that are combinations of existing ones, helping balance the class distribution.

```
In [92]: from imblearn.over sampling import SMOTE
         df_encoded = pd.get_dummies(df, columns=['gender', 'ever_married', 'work_type', 'residence_type',
         X = df_encoded.drop('stroke', axis=1)
         y = df encoded['stroke']
         X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=43)
         # Apply SMOTE to balance classes
         smote = SMOTE(random state=42)
         X resampled, y resampled = smote.fit resample(X train, y train)
         model = LogisticRegression()
         model.fit(X_resampled, y_resampled)
         y_pred = model.predict(X_test)
         accuracy = accuracy_score(y_test, y_pred)
         report = classification_report(y_test, y_pred)
         conf matrix = confusion matrix(y test, y pred)
         print("Confusion Matrix:")
         print(conf_matrix)
         print(f'Accuracy: {accuracy}\n')
         print(f'Classification Report:\n{report}')
         Confusion Matrix:
         [[886 53]
          [ 27 16]]
         Accuracy: 0.9185336048879837
         Classification Report:
                       precision
                                    recall f1-score
                                                        support
                                      0.94
                                                 0.96
                                                            939
                    0
                            0.97
                                      0.37
                                                 0.29
                                                             43
                    1
                            0.23
                                                0.92
                                                            982
             accuracy
                                                0.62
                                                            982
                            0.60
                                      0.66
            macro avg
         weighted avg
                            0.94
                                      0.92
                                                 0.93
                                                            982
         C:\Users\bhave\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:814: ConvergenceWarn
         ing: 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 (https://scikit-learn.org/stable/m
         odules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit
         -learn.org/stable/modules/linear model.html#logistic-regression)
           n iter i = check optimize result(
         Confusion Matrix
         True Negatives (TN): 886
         False Positives (FP): 53
         False Negatives (FN): 27
```

```
True Positives (TP): 16
In [108]: | from imblearn.over_sampling import SMOTE
          df_encoded = pd.get_dummies(df, columns=['gender', 'ever_married', 'work_type', 'residence_type',
          df_encoded = pd.concat([df_encoded, df[['age', 'hypertension', 'heart_disease', 'avg_glucose_level
          X = df_encoded.drop('stroke', axis=1)
          y = df_encoded['stroke']
          X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=43)
          # Apply SMOTE to balance classes
          smote = SMOTE(random state=42)
          X resampled, y resampled = smote.fit resample(X train, y train)
          model = LogisticRegression()
          model.fit(X resampled, y resampled)
          y pred = model.predict(X test)
          accuracy = accuracy score(y test, y pred)
          report = classification_report(y_test, y_pred)
          conf_matrix = confusion_matrix(y_test, y_pred)
          print("Confusion Matrix:")
          print(conf_matrix)
          print(f'Accuracy: {accuracy}\n')
          print(f'Classification Report:\n{report}')
          Confusion Matrix:
          [[1322 84]
           [ 50 17]]
          Accuracy: 0.9090291921249152
          Classification Report:
                                     recall f1-score
                         precision
                                                         support
                     0
                              0.96
                                        0.94
                                                  0.95
                                                            1406
                     1
                              0.17
                                        0.25
                                                  0.20
                                                              67
                                                  0.91
                                                            1473
              accuracy
             macro avg
                              0.57
                                        0.60
                                                  0.58
                                                            1473
                                                  0.92
          weighted avg
                              0.93
                                        0.91
                                                            1473
```

C:\Users\bhave\anaconda3\lib\site-packages\sklearn\linear_model_logistic.py:814: ConvergenceWarn
ing: 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 (https://scikit-learn.org/stable/m
odules/preprocessing.html)

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit
-learn.org/stable/modules/linear_model.html#logistic-regression)
n iter i = check optimize result(

```
Confustion Matrix:

True Negatives (TN): 1322
False Positives (FP): 84
```

False Negatives (FN): 50 True Positives (TP): 17

The model is performing well in correctly identifying cases of "No Stroke", as indicated by the high number of True Negatives (1322) and the relatively low number of False Positives (84).

However, the model is struggling with identifying cases of "Stroke", as indicated by the low number of True Positives (17) and the moderate number of False Negatives (50). So there is room for improvement in detecting strokes.