1. Dataset Download

```
def install_and_download_dataset():
    import kagglehub
    path = kagglehub.dataset_download("jillanisofttech/brain-stroke-dataset")
    return path

dataset_path = install_and_download_dataset()
print("Dataset path:", dataset_path)
```

```
Dataset path: /kaggle/input/brain-stroke-dataset
```

2. Data Loading

```
def load_dataset(path):
    import pandas as pd
    csv_path = path + "/brain_stroke.csv"
    dataframe = pd.read_csv(csv_path)
    return dataframe

df = load_dataset(dataset_path)
print(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
```

3. Initial Data Exploration

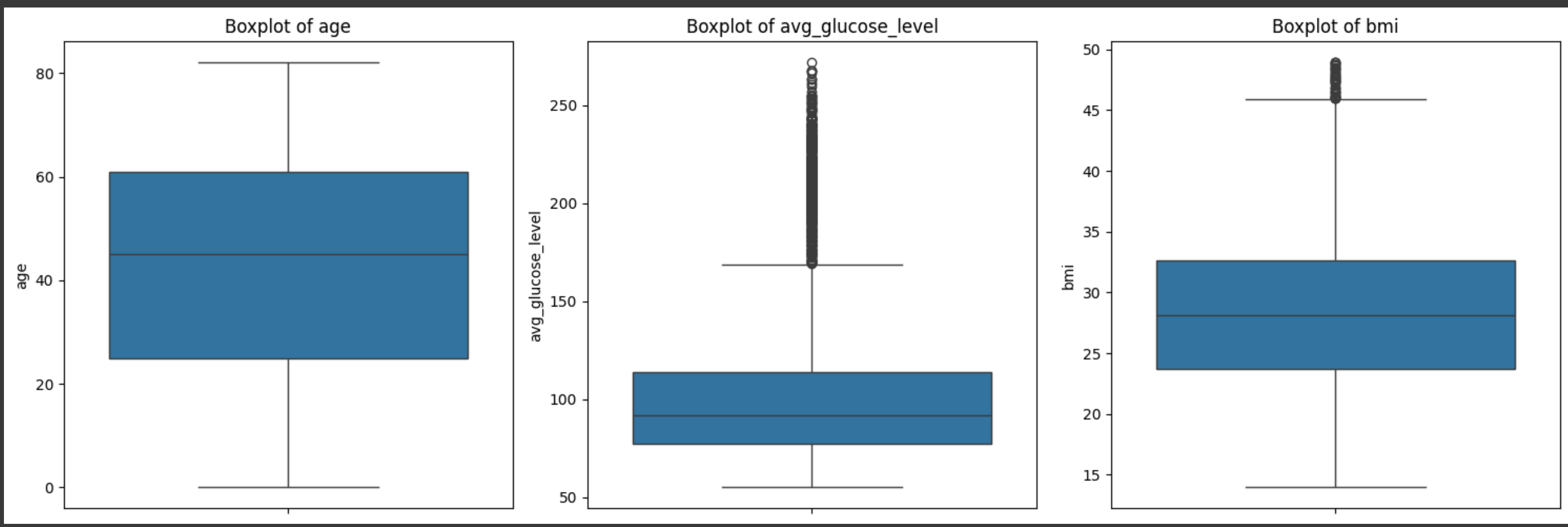
```
def explore_dataset(df):
    print("Data Info:")
    print(df.info())

    print("\nMissing Values:")
    print(df.isnull().sum())

    print("\nStatistical Summary:")
    print(df.describe(include='all'))

explore_dataset(df)
```

```
 10  stroke             4981 non-null   int64
dtypes: float64(3), int64(3), object(5)
memory usage: 428.2+ KB
None

Missing Values:
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

Statistical Summary:
        gender          age  hypertension  heart_disease ever_married  \
count     4981  4981.000000   4981.000000    4981.000000         4981
unique       2          NaN           NaN            NaN            2
top     Female          NaN           NaN            NaN          Yes
freq      2907          NaN           NaN            NaN         3280
mean       NaN    43.419859      0.096165       0.055210          NaN
std        NaN    22.662755      0.294848       0.228412          NaN
min        NaN     0.080000      0.000000       0.000000          NaN
25%        NaN    25.000000      0.000000       0.000000          NaN
50%        NaN    45.000000      0.000000       0.000000          NaN
75%        NaN    61.000000      0.000000       0.000000          NaN
max        NaN    82.000000      1.000000       1.000000          NaN

       work_type Residence_type  avg_glucose_level          bmi  \
count       4981           4981        4981.000000  4981.000000
unique         4              2                NaN          NaN
top      Private          Urban                NaN          NaN
freq        2860           2532                NaN          NaN
mean         NaN            NaN         105.943562    28.498173
std          NaN            NaN          45.075373     6.790464
min          NaN            NaN          55.120000    14.000000
25%          NaN            NaN          77.230000    23.700000
50%          NaN            NaN          91.850000    28.100000
75%          NaN            NaN         113.860000    32.600000
max          NaN            NaN         271.740000    48.900000

       smoking_status       stroke
count            4981  4981.000000
unique              4          NaN
top      never smoked          NaN
freq             1838          NaN
mean              NaN     0.049789
std               NaN     0.217531
min               NaN     0.000000
25%               NaN     0.000000
50%               NaN     0.000000
75%               NaN     0.000000
max               NaN     1.000000
```

4. Data Visualizations

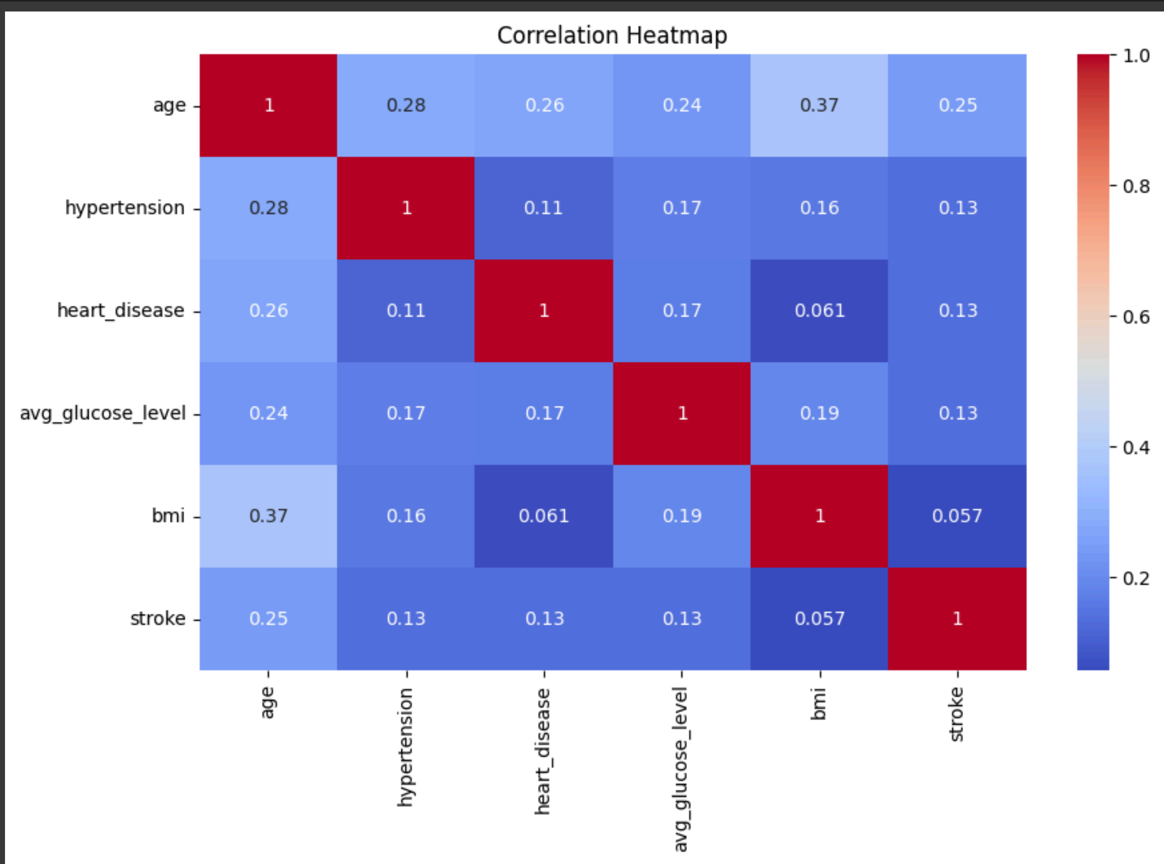
4.1 Box Plots for Numeric Variables

```
def plot_boxplots(df):
    import matplotlib.pyplot as plt
    import seaborn as sns

    numeric_cols = ['age', 'avg_glucose_level', 'bmi']
    plt.figure(figsize=(15, 5))
    for i, col in enumerate(numeric_cols):
        plt.subplot(1, 3, i+1)
        sns.boxplot(data=df, y=col)
        plt.title(f'Boxplot of {col}')
    plt.tight_layout()

plot_boxplots(df)
```



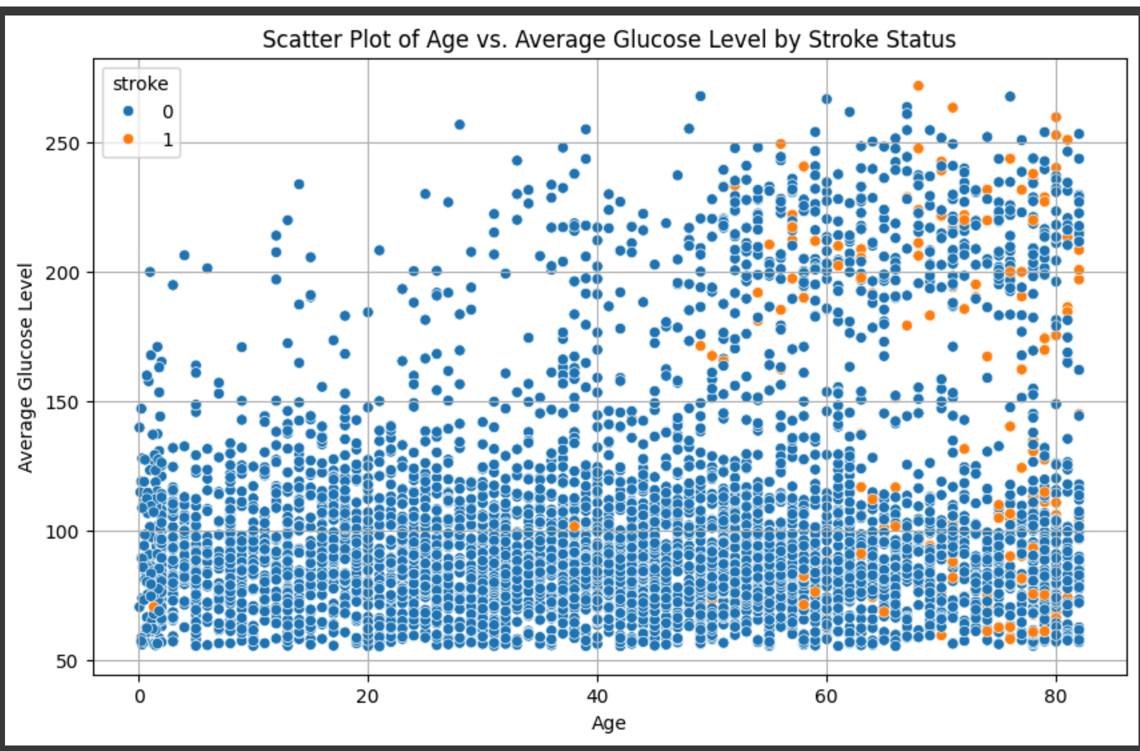
4.2 Correlation Heatmap

```
def plot_correlation_heatmap(df):
    import matplotlib.pyplot as plt
    import seaborn as sns

    plt.figure(figsize=(10, 6))
    correlation = df.corr(numeric_only=True)
    sns.heatmap(correlation, annot=True, cmap='coolwarm')
    plt.title("Correlation Heatmap")
    plt.show()

plot_correlation_heatmap(df)
```



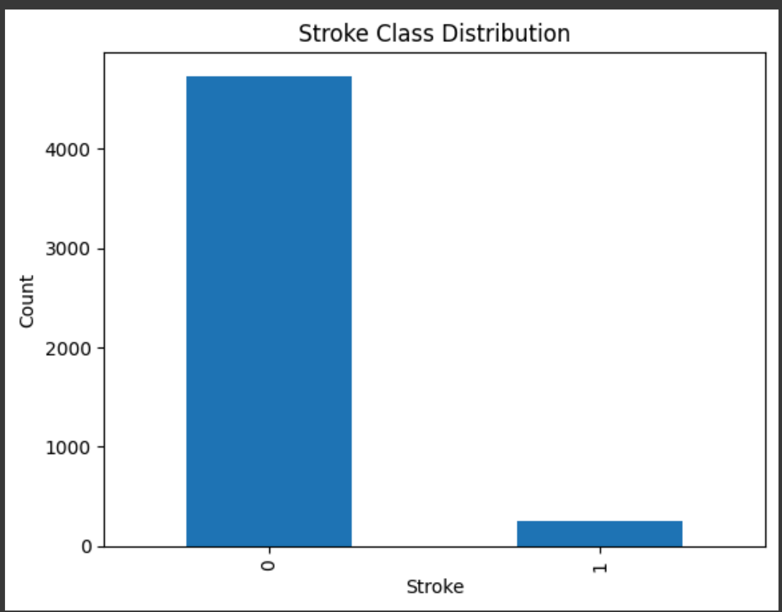
4.3 Scatter Plot

```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(10, 6))
sns.scatterplot(data=df, x='age', y='avg_glucose_level', hue='stroke')
plt.title('Scatter Plot of Age vs. Average Glucose Level by Stroke Status')
plt.xlabel('Age')
plt.ylabel('Average Glucose Level')
plt.grid(True)
plt.show()
```



4.4 Stroke Class Distribution

```
def plot_stroke_distribution(df):
    import matplotlib.pyplot as plt

    stroke_counts = df['stroke'].value_counts()
    stroke_counts.plot(kind='bar', title='Stroke Class Distribution')
    plt.xlabel('Stroke')
    plt.ylabel('Count')
    plt.show()

plot_stroke_distribution(df)
```



5. Preprocessing

```
def preprocess_data(df):
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import LabelEncoder, StandardScaler
    from imblearn.over_sampling import SMOTE
    import pandas as pd # Import pandas here

    if 'id' in df.columns:
        df.drop('id', axis=1, inplace=True)

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

    binary_columns = ['gender', 'ever_married', 'Residence_type']
    for column in binary_columns:
        if df[column].dtype == 'object':
            encoder = LabelEncoder()
            df[column] = encoder.fit_transform(df[column])

    df = pd.get_dummies(df, columns=['work_type', 'smoking_status'])

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

    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)

    smote = SMOTE(random_state=42)
    X_resampled, y_resampled = smote.fit_resample(X_scaled, y)

    X_train, X_test, y_train, y_test = train_test_split(
        X_resampled, y_resampled, test_size=0.2, random_state=42
    )

    return X, y, X_resampled, y_resampled, X_train, X_test, y_train, y_test

X, y, X_resampled, y_resampled, X_train, X_test, y_train, y_test = preprocess_data(df)

print("Original dataset shape:", X.shape)
print("Resampled dataset shape:", X_resampled.shape)
print("Training set shape:", X_train.shape)
print("Test set shape:", X_test.shape)
```

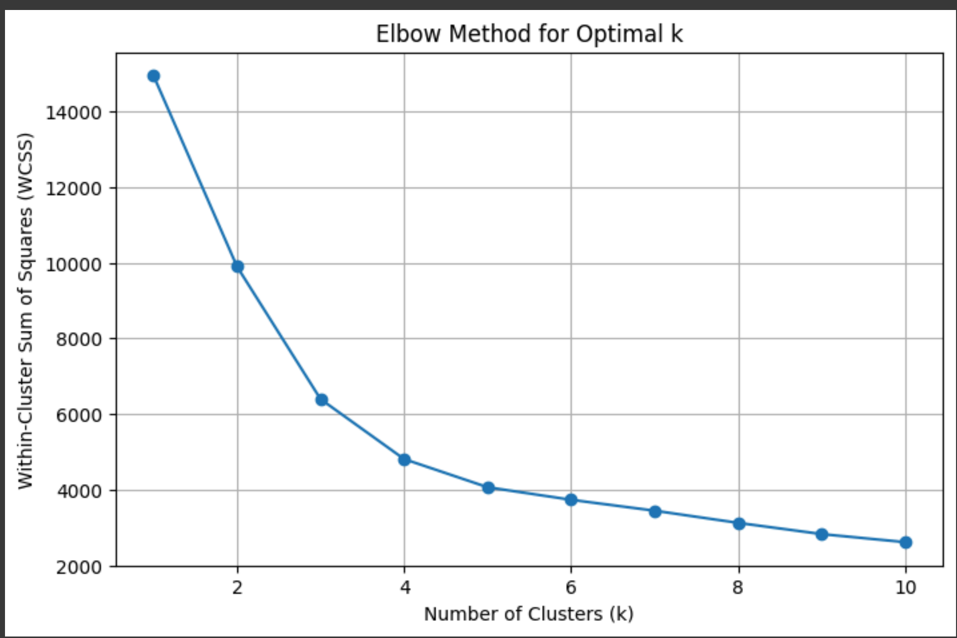
```
Original dataset shape: (4981, 16)
Resampled dataset shape: (9466, 16)
Training set shape: (7572, 16)
```

```
Test set shape: (1894, 16)
```

Elbow Method

```
from sklearn.preprocessing import StandardScaler

X = df[['age', 'avg_glucose_level', 'bmi']].dropna()
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

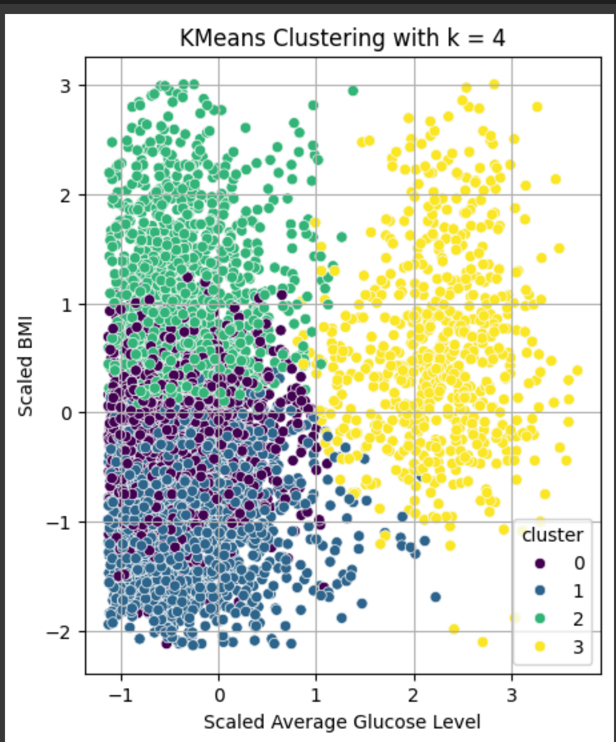
```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

wcss = []
K = range(1, 11)

for k in K:
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)

plt.figure(figsize=(8, 5))
plt.plot(K, wcss, marker='o')
plt.title('Elbow Method for Optimal k')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Within-Cluster Sum of Squares (WCSS)')
plt.grid(True)
plt.show()
```



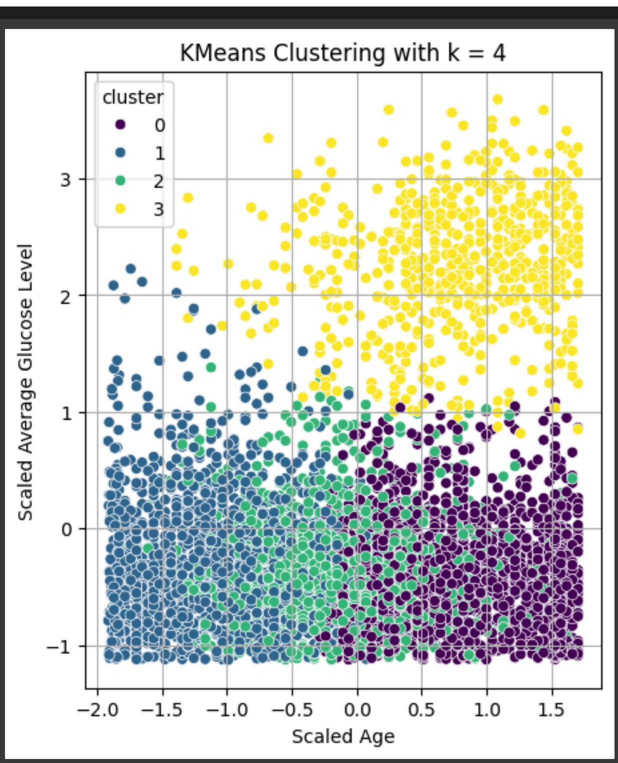
KMeans

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
k_values_to_visualize = [2, 3, 4]
for k in k_values_to_visualize:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    clusters = kmeans.fit_predict(X_scaled)
    X_scaled_df = pd.DataFrame(X_scaled, columns=['age', 'avg_glucose_level', 'bmi'])
    X_scaled_df['cluster'] = clusters
```

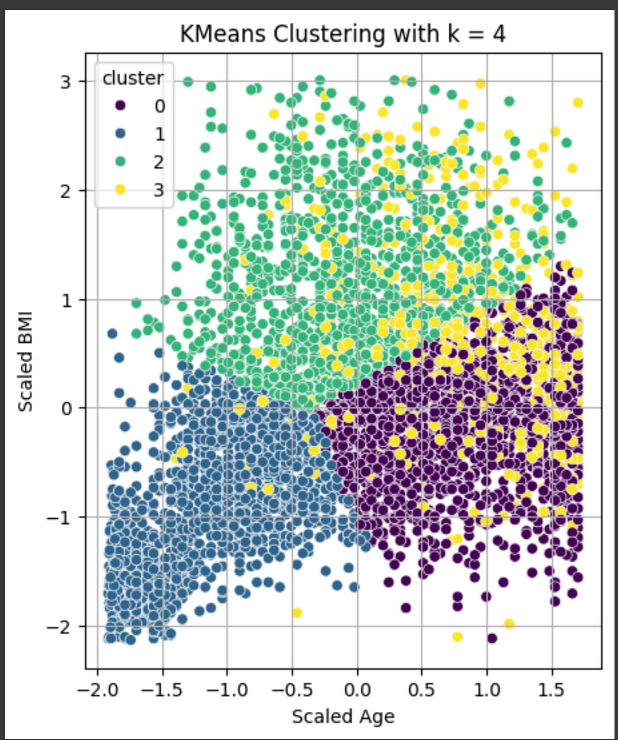
```
    plt.figure(figsize=(5, 6))
    sns.scatterplot(data=X_scaled_df, x='avg_glucose_level', y='bmi', hue='cluster', palette='viridis', legend='full')
    plt.title(f'KMeans Clustering with k = {k}')
    plt.xlabel('Scaled Average Glucose Level')
    plt.ylabel('Scaled BMI')
    plt.grid(True)
    plt.show()
```




```
    plt.figure(figsize=(5, 6))
    sns.scatterplot(data=X_scaled_df, x='age', y='avg_glucose_level', hue='cluster', palette='viridis', legend='full')
    plt.title(f'KMeans Clustering with k = {k}')
    plt.xlabel('Scaled Age')
    plt.ylabel('Scaled Average Glucose Level')
    plt.grid(True)
    plt.show()
```



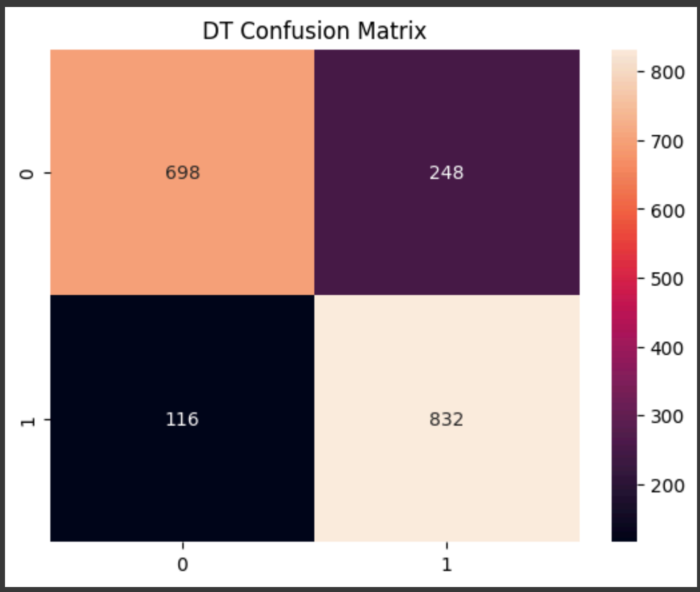

```
    plt.figure(figsize=(5, 6))
    sns.scatterplot(data=X_scaled_df, x='age', y='bmi', hue='cluster', palette='viridis', legend='full')
    plt.title(f'KMeans Clustering with k = {k}')
    plt.xlabel('Scaled Age')
    plt.ylabel('Scaled BMI')
    plt.grid(True)
    plt.show()
```



6. Decision Tree Classifier

```
def decision_tree_classifier(X_train, X_test, y_train, y_test):
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.metrics import accuracy_score, f1_score, classification_report, confusion_matrix
    import seaborn as sns
    import matplotlib.pyplot as plt

    model = DecisionTreeClassifier(max_depth=5, random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    print("Decision Tree Classifier")
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("F1 Score:", f1_score(y_test, y_pred))
    print("Classification Report:\n", classification_report(y_test, y_pred))

    matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(matrix, annot=True, fmt='d')
    plt.title("DT Confusion Matrix")
    plt.show()

    return y_pred

y_pred_dt = decision_tree_classifier(X_train, X_test, y_train, y_test)
```

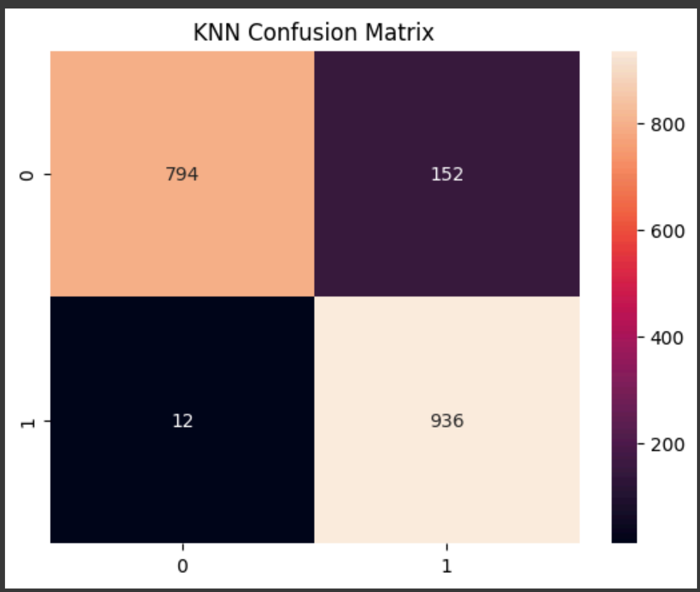
```
Decision Tree Classifier
Accuracy: 0.8078141499472017
F1 Score: 0.8205128205128205
Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.74      0.79       946
           1       0.77      0.88      0.82       948

    accuracy                           0.81      1894
   macro avg       0.81      0.81      0.81      1894
weighted avg       0.81      0.81      0.81      1894
```



7. K-Nearest Neighbors Classifier

```
def knn_classifier(X_train, X_test, y_train, y_test):
    from sklearn.neighbors import KNeighborsClassifier
    from sklearn.metrics import accuracy_score, f1_score, classification_report, confusion_matrix
    import seaborn as sns
    import matplotlib.pyplot as plt

    model = KNeighborsClassifier(n_neighbors=5)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)

    print("K-Nearest Neighbors Classifier")
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("F1 Score:", f1_score(y_test, y_pred))
    print("Classification Report:\n", classification_report(y_test, y_pred))

    matrix = confusion_matrix(y_test, y_pred)
    sns.heatmap(matrix, annot=True, fmt='d')
    plt.title("KNN Confusion Matrix")
    plt.show()

    return y_pred

y_pred_knn = knn_classifier(X_train, X_test, y_train, y_test)
```

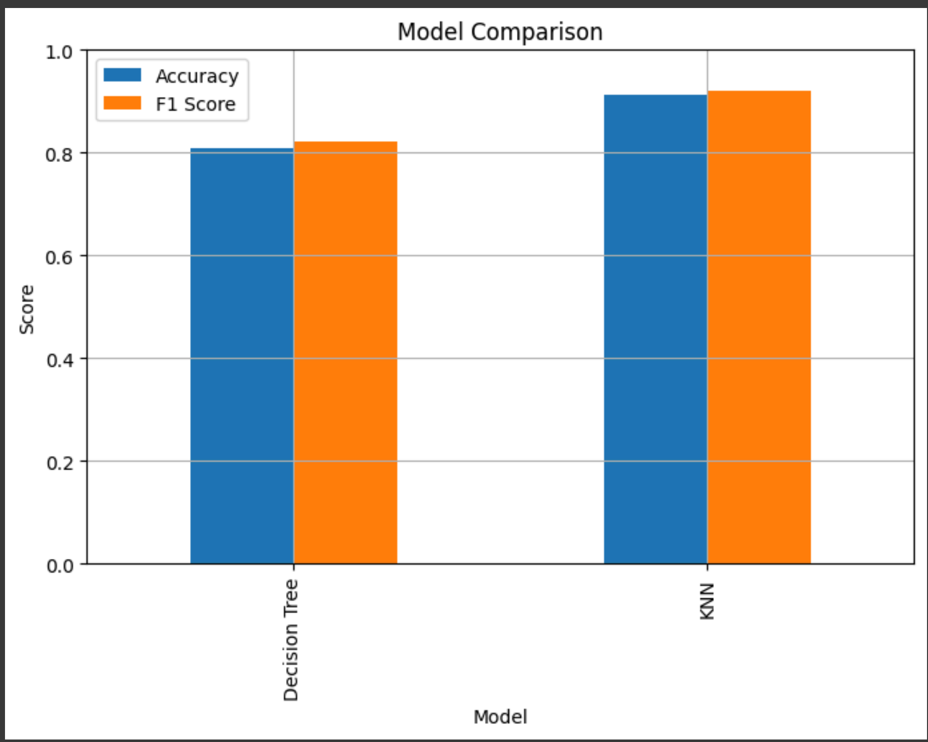
```
K-Nearest Neighbors Classifier
Accuracy: 0.9134107708553326
F1 Score: 0.9194499017681729
Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.84      0.91       946
           1       0.86      0.99      0.92       948

    accuracy                           0.91      1894
   macro avg       0.92      0.91      0.91      1894
weighted avg       0.92      0.91      0.91      1894
```



8. Model Comparison

```
def compare_models(y_test, y_pred_dt, y_pred_knn):
    from sklearn.metrics import accuracy_score, f1_score
    import pandas as pd
    import matplotlib.pyplot as plt

    accuracy_dt = accuracy_score(y_test, y_pred_dt)
    f1_dt = f1_score(y_test, y_pred_dt)

    accuracy_knn = accuracy_score(y_test, y_pred_knn)
    f1_knn = f1_score(y_test, y_pred_knn)

    results_df = pd.DataFrame({
        'Model': ['Decision Tree', 'KNN'],
        'Accuracy': [accuracy_dt, accuracy_knn],
```

```
        'F1 Score': [f1_dt, f1_knn]
    })

    results_df.set_index('Model').plot(kind='bar', figsize=(8, 5), legend=True, title="Model Comparison")
    plt.ylabel("Score")
    plt.ylim(0, 1)
    plt.grid(True)
    plt.show()

compare_models(y_test, y_pred_dt, y_pred_knn)
```

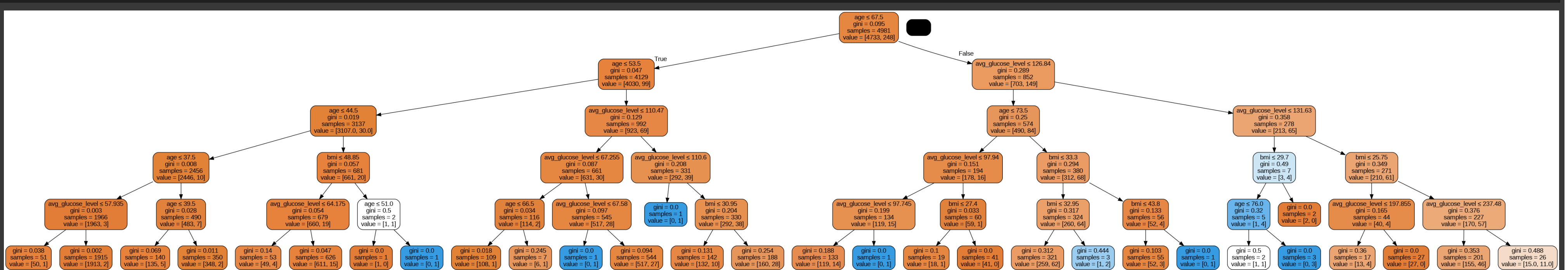


9. Decision Trees

```
!apt-get install -y graphviz
!pip install graphviz
```

```
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
graphviz is already the newest version (2.42.2-6ubuntu0.1).
0 upgraded, 0 newly installed, 0 to remove and 35 not upgraded.
Requirement already satisfied: graphviz in /usr/local/lib/python3.11/dist-packages (0.20.3)
```

```
#  Train the model
from sklearn.tree import DecisionTreeClassifier
clf_tree = DecisionTreeClassifier(max_depth=5, random_state=42)
clf_tree.fit(X, y)

# Export to PNG using pydotplus
import pydotplus
from sklearn.tree import export_graphviz

def tree_graph_to_png(tree, feature_names, png_file_to_save):
    """
    Generate a PNG image of the decision tree.
    Requires pydotplus and Graphviz installed.
    """
    dot_data = export_graphviz(
        tree, feature_names=feature_names,
        filled=True, rounded=True, special_characters=True,
        out_file=None
    )
    graph = pydotplus.graph_from_dot_data(dot_data)
    graph.write_png(png_file_to_save)

# Save the tree to a PNG file
tree_graph_to_png(
    tree=clf_tree,
    feature_names=X.columns.tolist(),
    png_file_to_save="stroke_decision_tree.png"
)

# Step 6: Display PNG
from IPython.display import Image
Image(filename="stroke_decision_tree.png")
```



10. ROC Curve

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

df = pd.read_csv(install_and_download_dataset() + "/brain_stroke.csv")
```

```
df.drop('id', axis=1, inplace=True, errors='ignore')
df['bmi'].fillna(df['bmi'].median(), inplace=True)
for col in ['gender', 'ever_married', 'Residence_type']:
    df[col] = LabelEncoder().fit_transform(df[col])
df = pd.get_dummies(df, columns=['work_type', 'smoking_status'])
X = StandardScaler().fit_transform(df.drop('stroke', axis=1))
y = df['stroke']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

m = LogisticRegression(max_iter=1000).fit(X_train, y_train)
fpr, tpr, _ = roc_curve(y_test, m.predict_proba(X_test)[:, 1])
plt.plot(fpr, tpr, label=f"AUC={auc(fpr, tpr):.2f}"); plt.plot([0,1],[0,1],'k--')
plt.xlabel("False Positive Rate"); plt.ylabel("True Positive Rate")
plt.title("ROC Curve"); plt.legend(); plt.grid(); plt.show()
```

```
<ipython-input-20-2ae6f036df00>:10: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the

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