Final_Project_1_Diabetes_Prediction_from_Medical_Records

April 28, 2025

1 1. Importing Libraries

[73]:
```
# Basic libraries
import pandas as pd
import numpy as np
from google.colab import drive

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Machine Learning models
from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB

# Metrics
from sklearn.metrics import classification_report
```

2 2. Loading the Dataset

[74]:
```
# Loading the dataset
drive.mount('/content/drive')
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/
↪FP1_Diabetes_prediction.csv')
df.head()
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

[74]:
```
   Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0            1       85             66             29        0  26.6
1            1       89             66             23       94  28.1
```

```
2            5      116             74            0        0  25.6
3           10      115              0            0        0  35.3
4            2      197             70           45      543  30.5

   DiabetesPedigreeFunction  Age  Outcome  Id
0                     0.351   31        0   1
1                     0.167   21        0   3
2                     0.201   30        0   5
3                     0.134   29        0   7
4                     0.158   53        1   8
```

3 3. Exploratory Data Analysis (EDA)

[75]:
```
print(df.info()) ## Basic info, describes the dataset size and outlines␣
↪variables
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550 entries, 0 to 549
Data columns (total 10 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               550 non-null    int64
 1   Glucose                   550 non-null    int64
 2   BloodPressure             550 non-null    int64
 3   SkinThickness             550 non-null    int64
 4   Insulin                   550 non-null    int64
 5   BMI                       550 non-null    float64
 6   DiabetesPedigreeFunction  550 non-null    float64
 7   Age                       550 non-null    int64
 8   Outcome                   550 non-null    int64
 9   Id                        550 non-null    int64
dtypes: float64(2), int64(8)
memory usage: 43.1 KB
None
```

[76]:
```
print(df.describe()) #Quick Stats Mean, Std, Min, Max
```

```
       Pregnancies     Glucose  BloodPressure  SkinThickness     Insulin  \
count   550.000000  550.000000     550.000000     550.000000  550.000000
mean      4.034545  121.560000      69.381818      20.014545   80.141818
std       3.447325   30.551206      19.036147      15.898006  115.429640
min       0.000000    0.000000       0.000000       0.000000    0.000000
25%       1.000000  100.000000      62.000000       0.000000    0.000000
50%       3.000000  119.000000      72.000000      22.000000   22.500000
75%       6.000000  141.000000      80.000000      32.000000  128.750000
max      17.000000  197.000000     122.000000      63.000000  846.000000
```

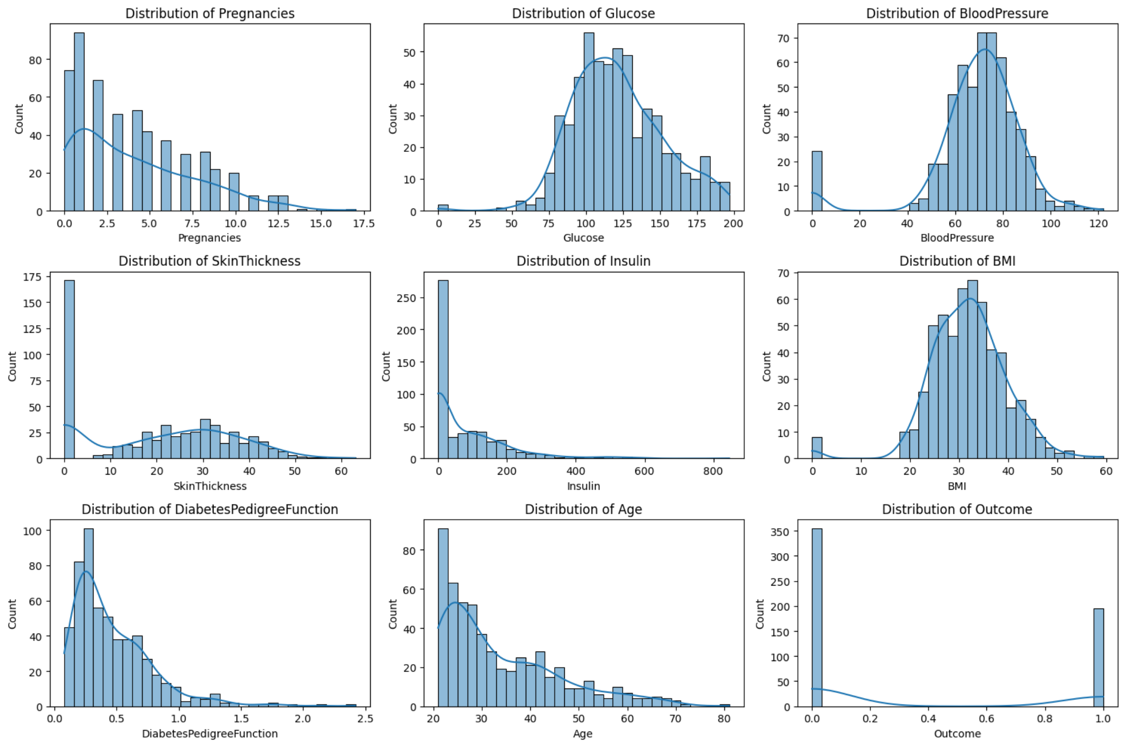
```
             BMI  DiabetesPedigreeFunction         Age     Outcome  \
count  550.000000                550.000000  550.000000  550.000000
mean    31.902000                  0.466582   33.590909    0.354545
std      7.822178                  0.320054   12.054140    0.478811
min      0.000000                  0.078000   21.000000    0.000000
25%     27.200000                  0.239250   24.000000    0.000000
50%     32.000000                  0.375000   29.000000    0.000000
75%     36.500000                  0.628250   41.000000    1.000000
max     59.400000                  2.420000   81.000000    1.000000

              Id
count  550.000000
mean   379.630909
std    222.127731
min      1.000000
25%    187.250000
50%    377.500000
75%    571.500000
max    766.000000
```

[77]:
```
print(df.isnull().sum()) # Check missing values
```

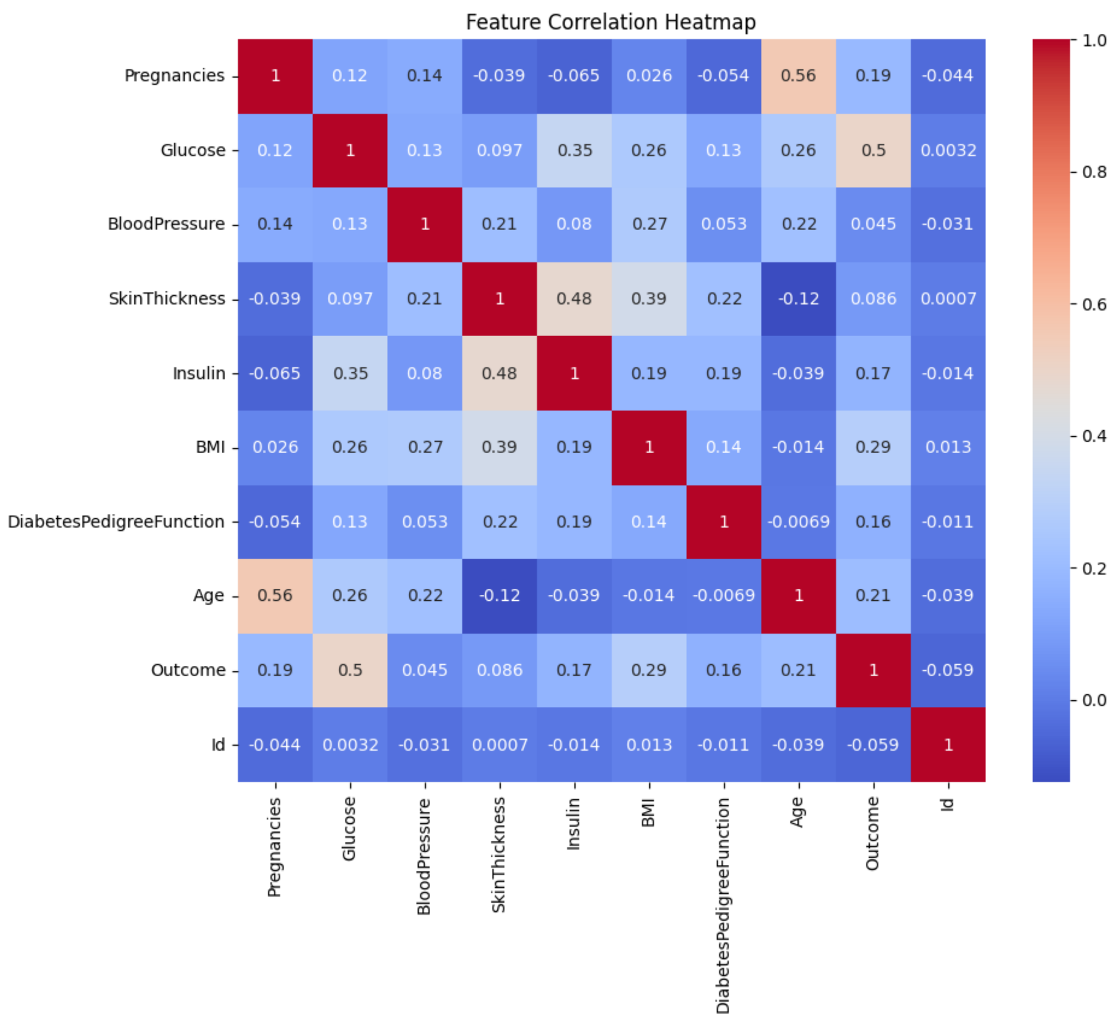
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
Id                          0
dtype: int64
```

4 4. Visualization

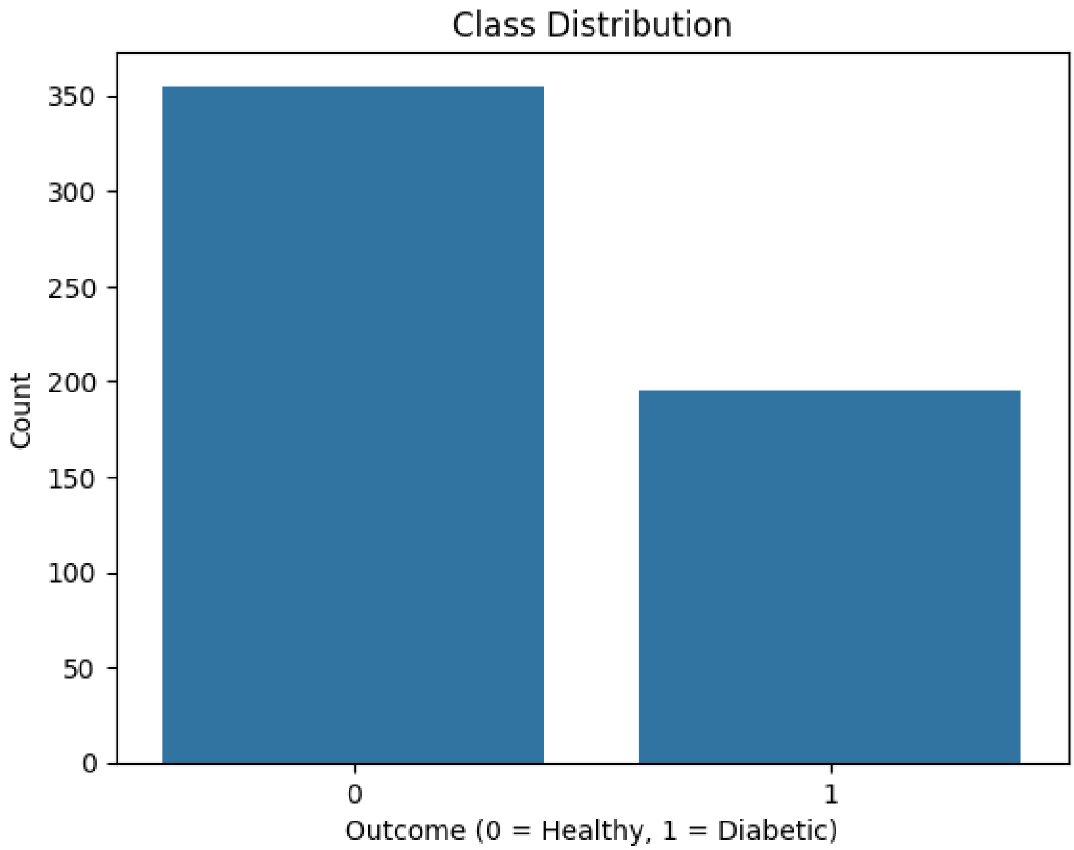
[78]:
```
# 1. Distribution/Histogram of features
plt.figure(figsize=(15, 10))
for i, col in enumerate(df.columns[:-1]):
    plt.subplot(3, 3, i+1)
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(f'Distribution of {col}')
plt.tight_layout()
plt.show()
```



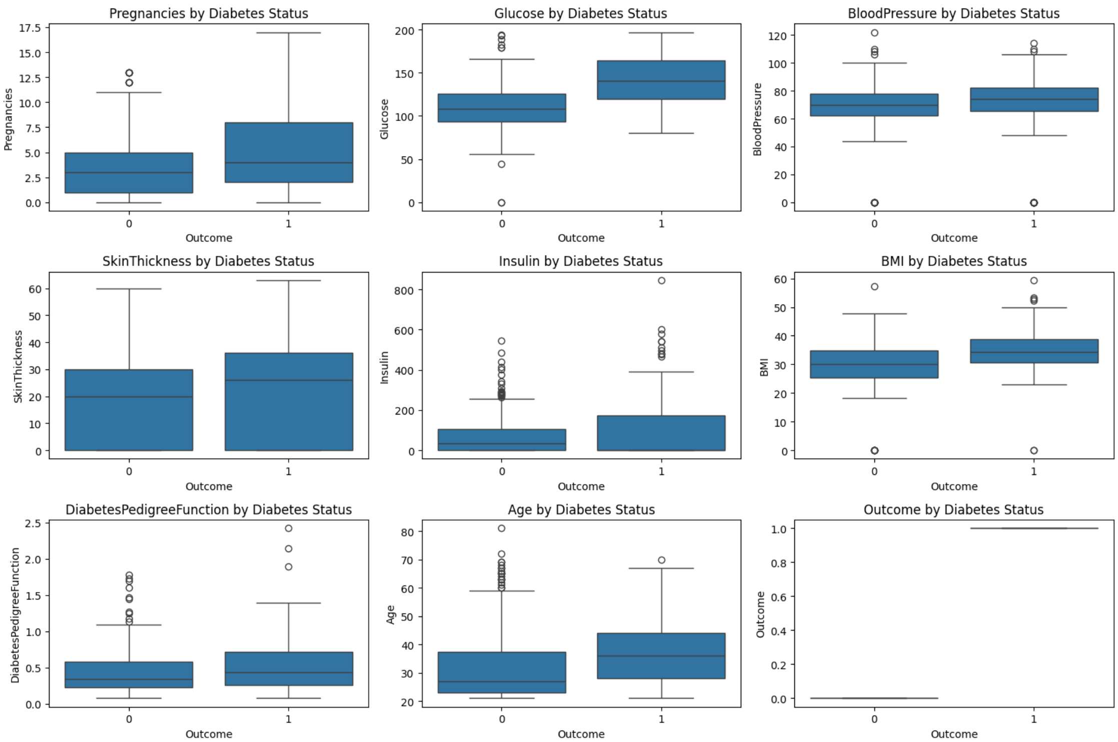
[79]:
```python
#2. Correlation Heatmap
plt.figure(figsize=(10,8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm')
plt.title('Feature Correlation Heatmap')
plt.show()
```



[80]:
```python
#3. Class Balance Plot, visualizes the instances of 0 and 1 for outcome variable
sns.countplot(x='Outcome', data=df)
plt.title('Class Distribution')
plt.xlabel('Outcome (0 = Healthy, 1 = Diabetic)')
plt.ylabel('Count')
plt.show()
```



[81]:
```python
# 4. Boxplots to identify outliers
plt.figure(figsize=(15, 10))
for i, col in enumerate(df.columns[:-1]):
    plt.subplot(3, 3, i+1)
    sns.boxplot(x='Outcome', y=col, data=df)
    plt.title(f'{col} by Diabetes Status')
plt.tight_layout()
plt.show()
```



5 5. Prepare Features and Labels

[82]:
```
# Split data into features and targe
X = df.drop(columns=['Outcome'])
y = df['Outcome']
```

6 6. Standardize Features

[83]:
```
# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

7 7. Initialize Models

[84]:
```
# Initialize models
models = {
    'Support Vector Machine': SVC(kernel='rbf', random_state=42),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42),
    'Logistic Regression': LogisticRegression(max_iter=1000, random_state=42),
    'K-Nearest Neighbors': KNeighborsClassifier(),
    'Naive Bayes': GaussianNB()
```

```
}
```

8 8. 10-Fold Cross-Validation and Evaluation

[85]:
```
# 10-fold cross-validation setup
cv = StratifiedKFold(n_splits=10, shuffle=True, random_state=42)

# Metrics to evaluate
metrics = ['accuracy', 'f1', 'precision', 'recall']

# Evaluate models
results = []
for name, model in models.items():
    scores = {m: cross_val_score(model, X_scaled, y, cv=cv, scoring=m).mean()␣
 ↪for m in metrics}
    results.append([name, scores['accuracy'], scores['f1'],␣
 ↪scores['precision'], scores['recall']])

# Create and display results DataFrame
results_df = pd.DataFrame(results, columns=['Model', 'Accuracy', 'F1-Score',␣
 ↪'Precision', 'Recall'])
results_df = results_df.sort_values('F1-Score', ascending=False).
 ↪reset_index(drop=True)
```

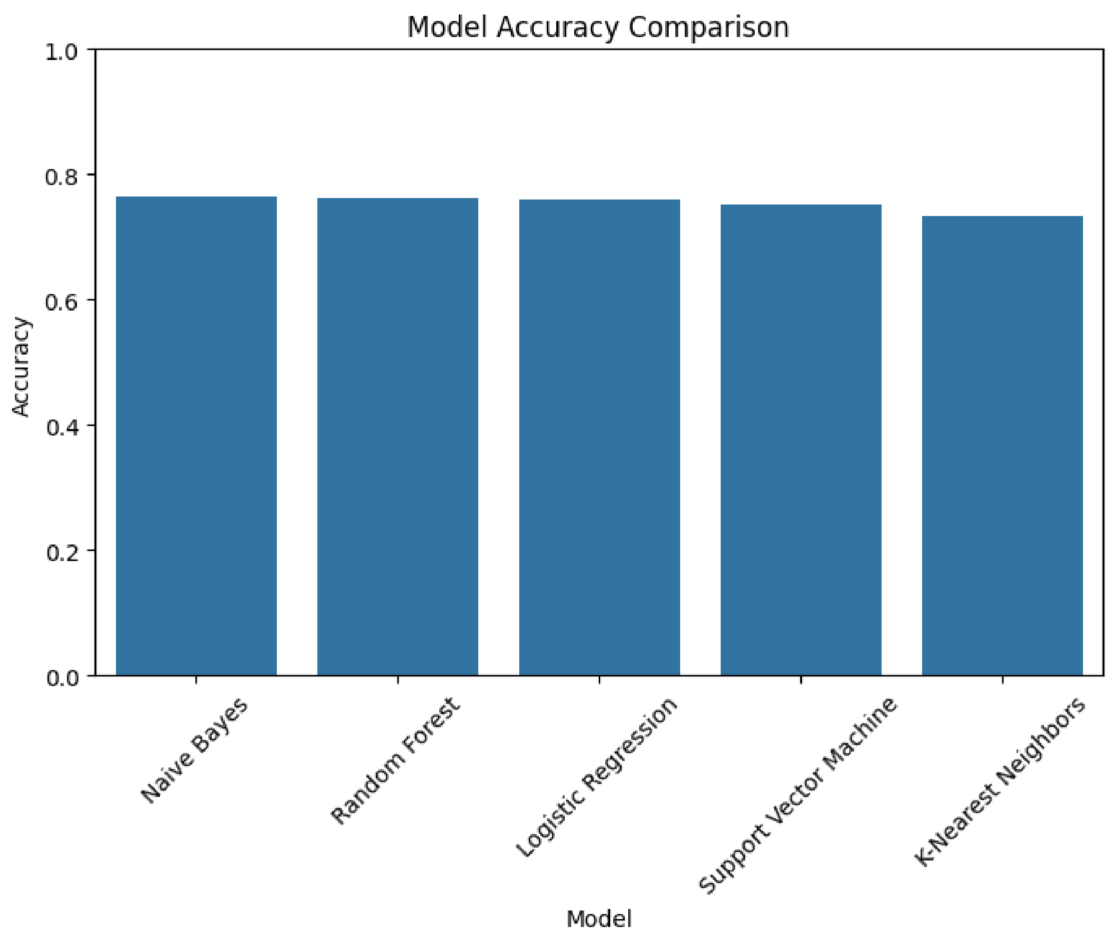
9 9. Display results table

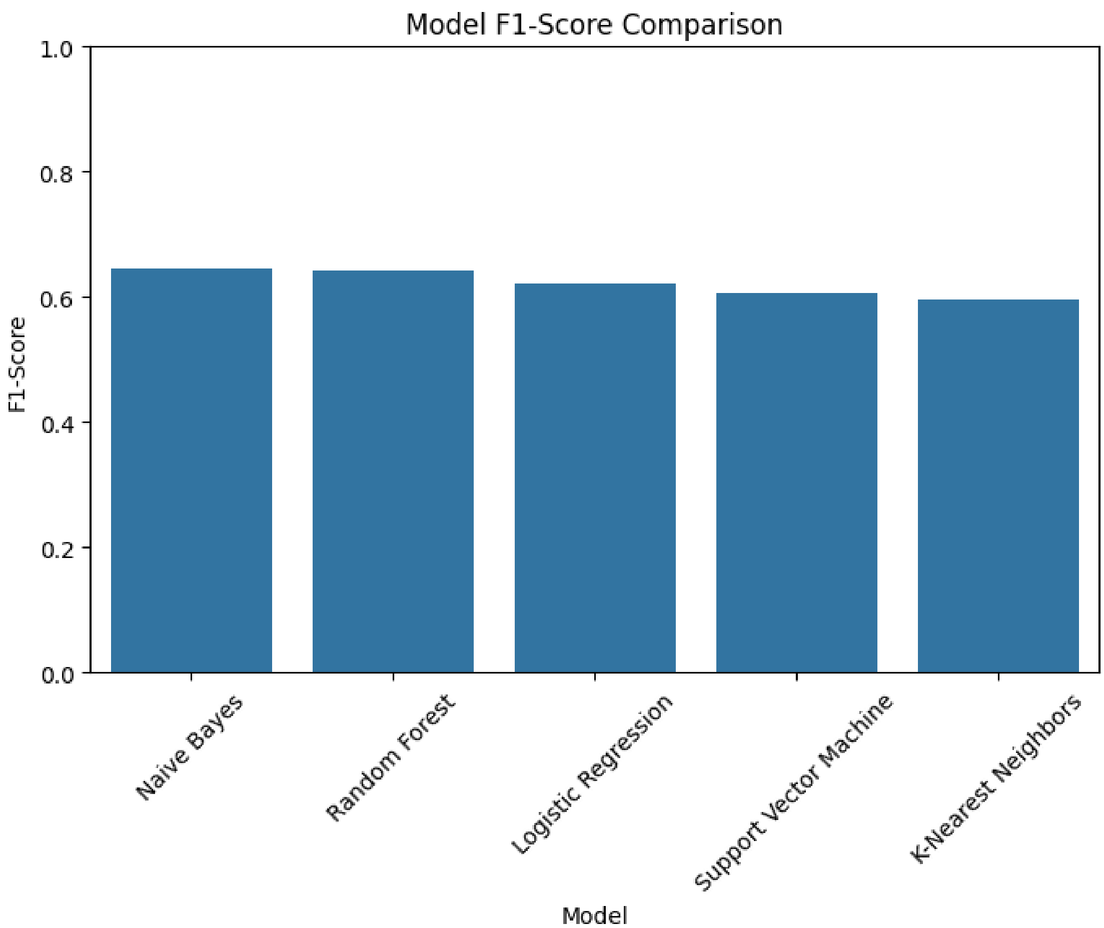
[86]:
```
#Display the result table
print("\nPerformance Comparison:\n")
print(results_df.round(4))
```

```
Performance Comparison:

                    Model  Accuracy  F1-Score  Precision  Recall
0             Naive Bayes    0.7636    0.6455     0.6968  0.6108
1           Random Forest    0.7618    0.6417     0.7005  0.6100
2     Logistic Regression    0.7600    0.6204     0.7098  0.5592
3  Support Vector Machine    0.7509    0.6057     0.6876  0.5487
4     K-Nearest Neighbors    0.7327    0.5952     0.6412  0.5629
```

10 10. Visual Representation of Accuracy and F1 Scores

[87]:
```
# Plot of Accuracy
plt.figure(figsize=(8,5))
sns.barplot(x='Model', y='Accuracy', data=results_df)
plt.title('Model Accuracy Comparison')
plt.xticks(rotation=45)
plt.ylim(0,1)
plt.show()

#Plot of F1 Scores
plt.figure(figsize=(8,5))
sns.barplot(x='Model', y='F1-Score', data=results_df)
plt.title('Model F1-Score Comparison')
plt.xticks(rotation=45)
plt.ylim(0,1)
plt.show()
```





11 11. Classification Reports of All Models on Full Data

[88]:
```
print("Classification Reports (trained on full data):\n")

for name, model in models.items():
    # Fit model on full data
    model.fit(X, y)

    # Predict on full data
    y_pred = model.predict(X)

    # Print classification report
    print(f"Model: {name}")
    print(classification_report(y, y_pred, digits=4))
    print("-" * 60)
```

```
Classification Reports (trained on full data):
```

```
Model: Support Vector Machine
              precision    recall  f1-score   support

           0     0.7183    0.9408    0.8146       355
           1     0.7529    0.3282    0.4571       195

    accuracy                         0.7236       550
   macro avg     0.7356    0.6345    0.6359       550
weighted avg     0.7306    0.7236    0.6879       550

------------------------------------------------------------
Model: Random Forest
              precision    recall  f1-score   support

           0     1.0000    1.0000    1.0000       355
           1     1.0000    1.0000    1.0000       195

    accuracy                         1.0000       550
   macro avg     1.0000    1.0000    1.0000       550
weighted avg     1.0000    1.0000    1.0000       550

------------------------------------------------------------
Model: Logistic Regression
              precision    recall  f1-score   support

           0     0.7908    0.8732    0.8300       355
           1     0.7152    0.5795    0.6402       195

    accuracy                         0.7691       550
   macro avg     0.7530    0.7264    0.7351       550
weighted avg     0.7640    0.7691    0.7627       550

------------------------------------------------------------
Model: K-Nearest Neighbors
              precision    recall  f1-score   support

           0     0.8056    0.8873    0.8445       355
           1     0.7484    0.6103    0.6723       195

    accuracy                         0.7891       550
   macro avg     0.7770    0.7488    0.7584       550
weighted avg     0.7853    0.7891    0.7835       550

------------------------------------------------------------
Model: Naive Bayes
              precision    recall  f1-score   support
```

```
           0     0.8042    0.8563    0.8295       355
           1     0.7035    0.6205    0.6594       195

    accuracy                         0.7727       550
   macro avg     0.7539    0.7384    0.7444       550
weighted avg     0.7685    0.7727    0.7692       550

------------------------------------------------------------
```