```python
import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, accuracy_score
from sklearn.cluster import KMeans
from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt
import seaborn as sns

# Load the dataset

# drive.mount('/content/drive')

# file_path = '/content/drive/MyDrive/healthcare_dataset.csv'

file_path = "healthcare_ds.csv"
df = pd.read_csv(file_path)

# Display the shape of the data and first few rows
print(f"Dataset shape: {df.shape}")
df.head()
```

```
Dataset shape: (55500, 15)
```

```
            Name  Age  Gender Blood Type Medical Condition Date of
Admission  \
0  Bobby JacksOn   30    Male         B-            Cancer
2024-01-31
1   LesLie TErRy   62    Male         A+           Obesity
2019-08-20
2    DaNnY sMitH   76  Female         A-           Obesity
2022-09-22
3   andrEw waTtS   28  Female         O+          Diabetes
2020-11-18
4  adrIENNE bEll   43  Female        AB+            Cancer
2022-09-19

             Doctor                    Hospital Insurance Provider  \
0     Matthew Smith             Sons and Miller        Blue Cross
1   Samantha Davies                     Kim Inc          Medicare
2  Tiffany Mitchell                    Cook PLC             Aetna
3       Kevin Wells  Hernandez Rogers and Vang,          Medicare
4    Kathleen Hanna                 White-White             Aetna

   Billing Amount  Room Number Admission Type Discharge Date
Medication  \
0    18856.281306          328         Urgent     2024-02-02
Paracetamol
```

```
1    33643.327287          265       Emergency     2019-08-26
Ibuprofen
2    27955.096079          205       Emergency     2022-10-07
Aspirin
3    37909.782410          450        Elective     2020-12-18
Ibuprofen
4    14238.317814          458          Urgent     2022-10-09
Penicillin

   Test Results
0        Normal
1  Inconclusive
2        Normal
3      Abnormal
4      Abnormal
```

Drop unnecessary columns (Name, Doctor, Hospital), encode categorical variables, and handle missing data

```
# Drop columns that are not needed for ML models
df_cleaned = df.drop(['Name', 'Doctor', 'Hospital'], axis=1)

# Convert date columns to datetime and create "Length of Stay"
df_cleaned['Date of Admission'] = pd.to_datetime(df_cleaned['Date of
Admission'])
df_cleaned['Discharge Date'] = pd.to_datetime(df_cleaned['Discharge
Date'])
df_cleaned['Length of Stay'] = (df_cleaned['Discharge Date'] -
df_cleaned['Date of Admission']).dt.days

# Handle missing values (e.g., replace NaN with mean or mode)
df_cleaned['Billing Amount'].fillna(df_cleaned['Billing
Amount'].mean(), inplace=True)
df_cleaned['Medication'].fillna('Unknown', inplace=True)
df_cleaned['Test Results'].fillna('Unknown', inplace=True)

# Encode categorical variables
label_encoder = LabelEncoder()

# Encode 'Gender', 'Blood Type', 'Medical Condition', 'Admission
Type', 'Test Results'
df_cleaned['Gender'] =
label_encoder.fit_transform(df_cleaned['Gender'])
df_cleaned['Blood Type'] =
label_encoder.fit_transform(df_cleaned['Blood Type'])
df_cleaned['Medical Condition'] =
label_encoder.fit_transform(df_cleaned['Medical Condition'])
df_cleaned['Admission Type'] =
label_encoder.fit_transform(df_cleaned['Admission Type'])
```

```
df_cleaned['Test Results'] =
label_encoder.fit_transform(df_cleaned['Test Results'])

# Display first few rows after preprocessing
df_cleaned.head()
```

```
C:\Users\roshan\AppData\Local\Temp\ipykernel_1600\2971295002.py: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
original object.


  df_cleaned['Billing Amount'].fillna(df_cleaned['Billing
Amount'].mean(), inplace=True)
C:\Users\roshan\AppData\Local\Temp\ipykernel_1600\2971295002.py:11:
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
original object.


  df_cleaned['Medication'].fillna('Unknown', inplace=True)
C:\Users\roshan\AppData\Local\Temp\ipykernel_1600\2971295002.py:12:
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
original object.


  df_cleaned['Test Results'].fillna('Unknown', inplace=True)
```

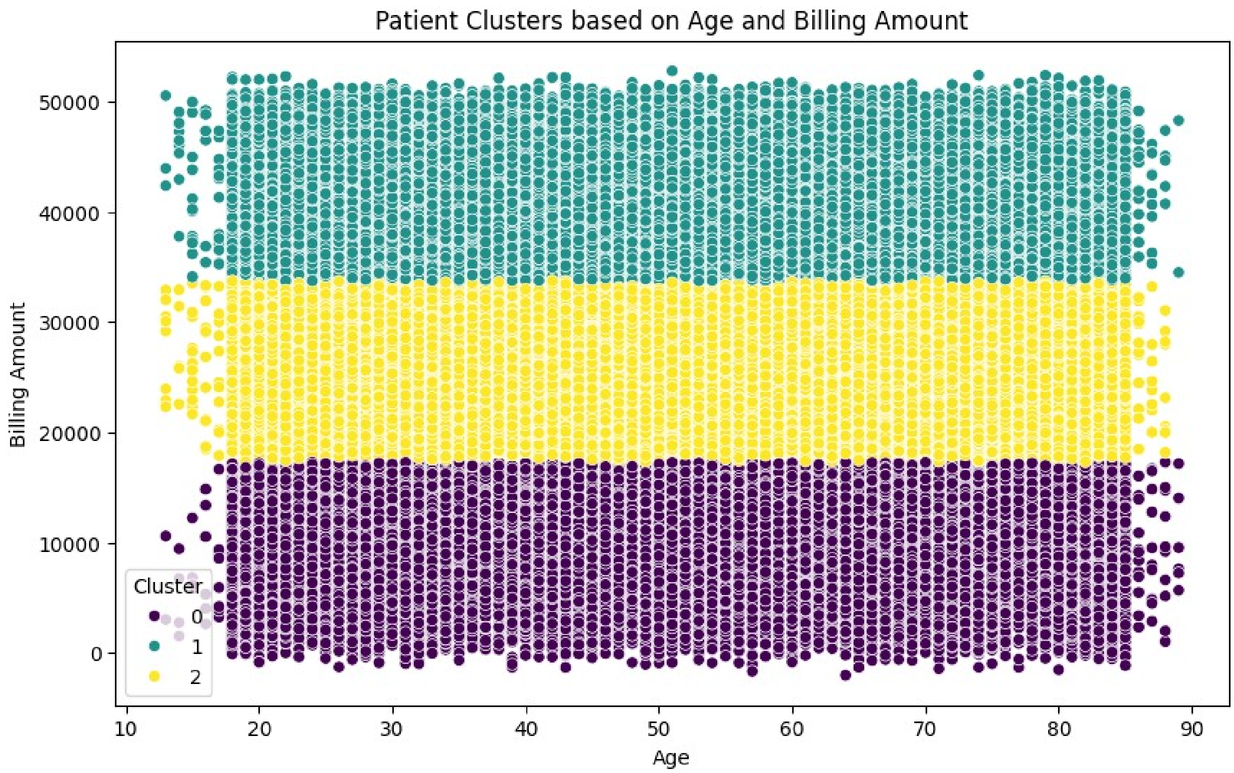
```
   Age  Gender  Blood Type  Medical Condition Date of Admission  \
0   30       1           5                  2        2024-01-31
1   62       1           0                  5        2019-08-20
2   76       0           1                  5        2022-09-22
3   28       0           6                  3        2020-11-18
4   43       0           2                  2        2022-09-19

  Insurance Provider  Billing Amount  Room Number  Admission Type  \
0         Blue Cross    18856.281306          328               2
1           Medicare    33643.327287          265               1
2              Aetna    27955.096079          205               1
3           Medicare    37909.782410          450               0
4              Aetna    14238.317814          458               2

  Discharge Date   Medication  Test Results  Length of Stay
0     2024-02-02  Paracetamol             2               2
1     2019-08-26    Ibuprofen             1               6
2     2022-10-07      Aspirin             2              15
3     2020-12-18    Ibuprofen             0              30
4     2022-10-09   Penicillin             0              20

# Predict 'Medical Condition' using Random Forest Classifier

# Features (X) and Target (y)
X = df_cleaned.drop(['Medical Condition'], axis=1)
y = df_cleaned['Medical Condition']

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Initialize RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators=100,
random_state=42)

# Convert 'Date of Admission' and 'Discharge Date' to numerical
features
X_train['Date of Admission'] = X_train['Date of
Admission'].dt.dayofyear
X_train['Discharge Date'] = X_train['Discharge Date'].dt.dayofyear

X_test['Date of Admission'] = X_test['Date of Admission'].dt.dayofyear
X_test['Discharge Date'] = X_test['Discharge Date'].dt.dayofyear

# Convert 'Insurance Provider' and 'Medication' to numerical using
Label Encoding
# Create a LabelEncoder instance
insurance_encoder = LabelEncoder()
medication_encoder = LabelEncoder() # Create a new encoder for
'Medication'
```

```
# Fit and transform on training data
X_train['Insurance Provider'] =
insurance_encoder.fit_transform(X_train['Insurance Provider'])
X_train['Medication'] =
medication_encoder.fit_transform(X_train['Medication']) # Encode
'Medication'

# Transform test data using the same encoders
X_test['Insurance Provider'] =
insurance_encoder.transform(X_test['Insurance Provider'])
X_test['Medication'] =
medication_encoder.transform(X_test['Medication'])  # Encode
'Medication'


# Train the model
rf_classifier.fit(X_train, y_train)

# Predict on test set
y_pred = rf_classifier.predict(X_test)

# Evaluate the model
print(f"Accuracy: {accuracy_score(y_test, y_pred)}")
print("Classification Report:")
print(classification_report(y_test, y_pred))
```

```
Accuracy: 0.2919819819819982
Classification Report:
              precision    recall  f1-score   support

           0       0.30      0.30      0.30      1915
           1       0.29      0.30      0.29      1847
           2       0.28      0.29      0.29      1871
           3       0.29      0.29      0.29      1822
           4       0.29      0.28      0.28      1788
           5       0.32      0.29      0.30      1857

    accuracy                           0.29     11100
   macro avg       0.29      0.29      0.29     11100
weighted avg       0.29      0.29      0.29     11100
```

```
# Use KMeans clustering to segment patients into clusters
kmeans = KMeans(n_clusters=3, random_state=42)

# Instead of converting 'Date of Admission' and 'Discharge Date'
again,
# create a copy of df_cleaned with the necessary preprocessing for
KMeans
# Exclude 'Cluster' from drop as it doesn't exist yet. It will be
```

```
created later
X_kmeans = df_cleaned.drop(['Medical Condition'], axis=1)

# Convert 'Date of Admission' and 'Discharge Date' to numerical
features
X_kmeans['Date of Admission'] = X_kmeans['Date of
Admission'].dt.dayofyear
X_kmeans['Discharge Date'] = X_kmeans['Discharge Date'].dt.dayofyear

# Convert 'Insurance Provider' and 'Medication' to numerical using
Label Encoding
# Create a LabelEncoder instance for 'Insurance Provider'
insurance_encoder = LabelEncoder()
# Create a LabelEncoder instance for 'Medication'
medication_encoder = LabelEncoder()

# Fit and transform on X_kmeans
X_kmeans['Insurance Provider'] =
insurance_encoder.fit_transform(X_kmeans['Insurance Provider'])
X_kmeans['Medication'] =
medication_encoder.fit_transform(X_kmeans['Medication'])

# Fit the KMeans model
df_cleaned['Cluster'] = kmeans.fit_predict(X_kmeans)

# Visualize clusters using Age and Billing Amount
plt.figure(figsize=(10,6))
sns.scatterplot(x='Age', y='Billing Amount', hue='Cluster',
data=df_cleaned, palette='viridis')
plt.title('Patient Clusters based on Age and Billing Amount')
plt.show()
```

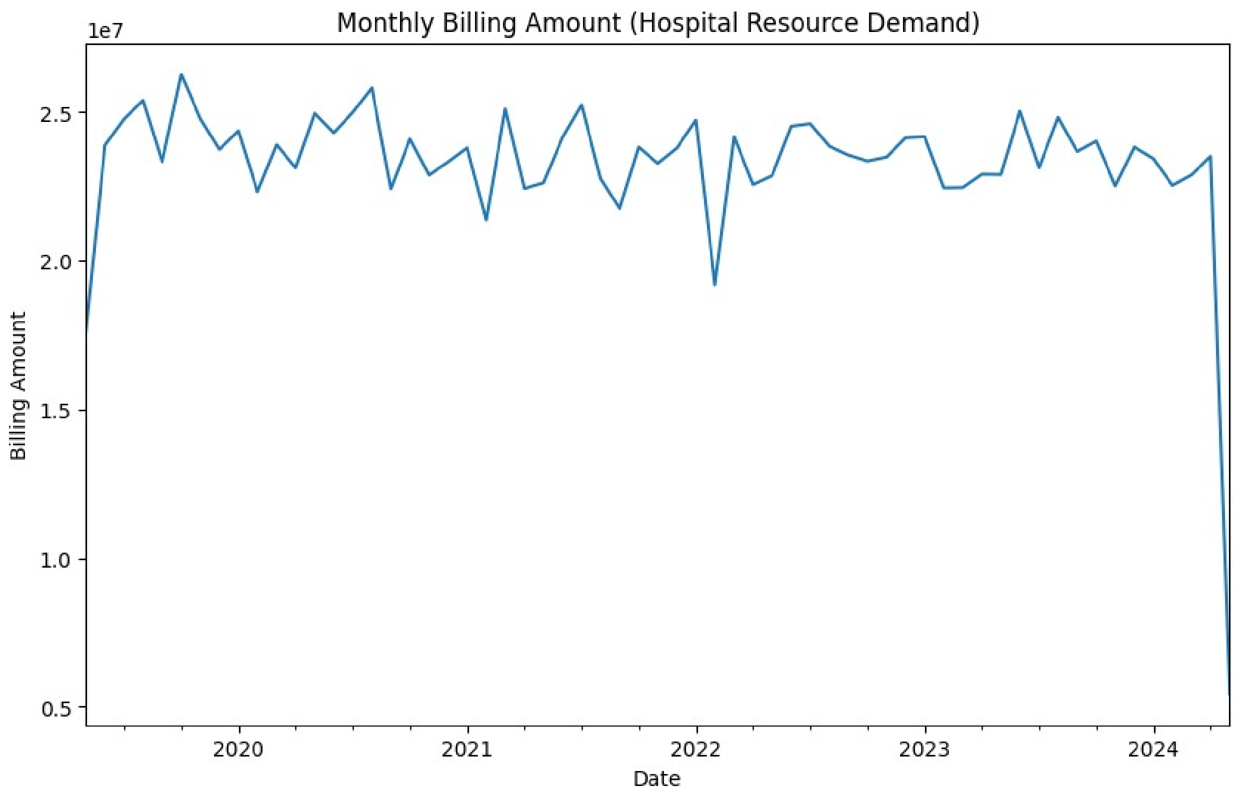


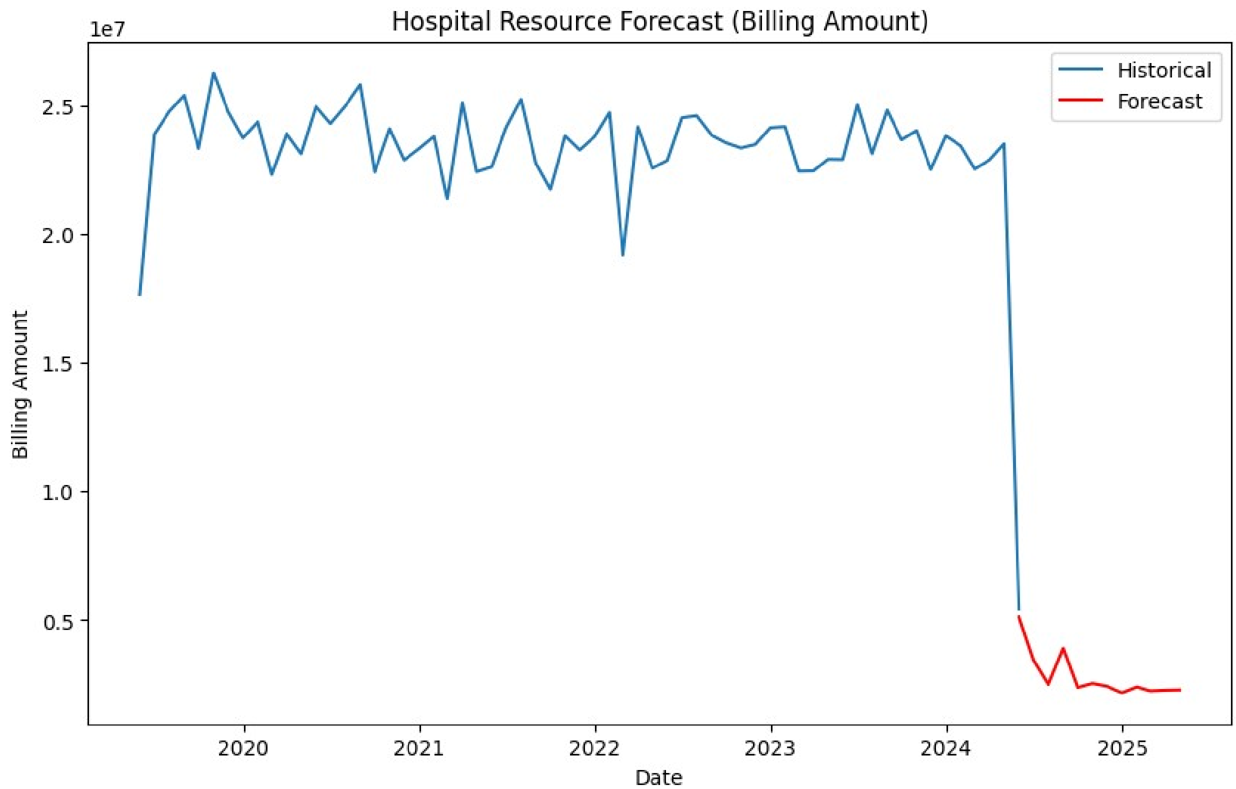
Step 5: Resource Forecasting (Time-Series Analysis)

We'll use ARIMA to forecast hospital resource demand (e.g., room occupancy).

```
# Forecasting: Use 'Length of Stay' and 'Billing Amount' for time-
series prediction

# Resample the data by month for hospital resource demand prediction
df_cleaned['Date of Admission'] = pd.to_datetime(df_cleaned['Date of
Admission'])
df_monthly = df_cleaned.resample('ME', on='Date of
Admission').agg({'Billing Amount': 'sum'})

# Plot the total billing amount over time (as an indicator of hospital
resource use)
plt.figure(figsize=(10,6))
df_monthly['Billing Amount'].plot()
plt.title('Monthly Billing Amount (Hospital Resource Demand)')
plt.xlabel('Date')
plt.ylabel('Billing Amount')
plt.show()

# Fit ARIMA model (order may need tuning based on data
characteristics)
arima_model = ARIMA(df_monthly['Billing Amount'], order=(5, 1, 0))  #
Example order
```

```
arima_fit = arima_model.fit()

# Forecast next 12 months
forecast = arima_fit.forecast(steps=12)
forecast_index = pd.date_range(df_monthly.index[-1], periods=12,
freq='ME')

# Plot forecast
plt.figure(figsize=(10,6))
plt.plot(df_monthly.index, df_monthly['Billing Amount'],
label='Historical')
plt.plot(forecast_index, forecast, label='Forecast', color='red')
plt.title('Hospital Resource Forecast (Billing Amount)')
plt.xlabel('Date')
plt.ylabel('Billing Amount')
plt.legend()
plt.show()
```



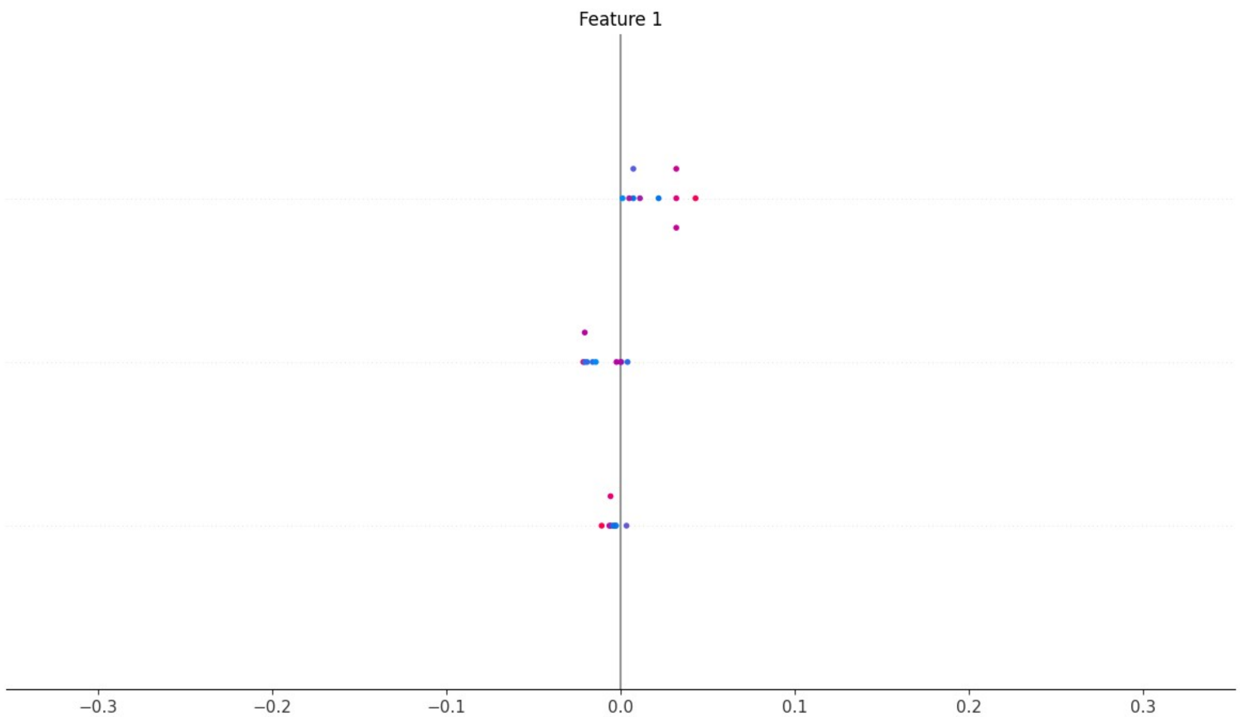


Step 7: Model Explainability with SHAP For interpretability, SHAP (Shapley Additive Explanations) helps us understand how each feature contributes to the model's predictions. We'll focus on the RandomForestClassifier.

For interpretability, SHAP (Shapley Additive Explanations) helps us understand how each feature contributes to the model's predictions. We'll focus on the RandomForestClassifier.

```
import shap
from sklearn.datasets import load_iris
from sklearn.ensemble import RandomForestClassifier

# Load sample data
X, y = load_iris(return_X_y=True)
rf = RandomForestClassifier().fit(X, y)

# SHAP explanation
explainer = shap.TreeExplainer(rf)
shap_values = explainer.shap_values(X[:10])  # Small sample
shap.summary_plot(shap_values, X[:10])
```

```
<Figure size 640x480 with 0 Axes>
```



Step 8: Hyperparameter Tuning for RandomForestClassifier

You can further improve the Random Forest Classifier by tuning the hyperparameters using GridSearchCV.

```
from sklearn.model_selection import GridSearchCV

# Define the parameter grid for RandomForest
param_grid = {
    'n_estimators': [50, 100],  # Reduced the n_estimators options
    'max_depth': [10, 20],       # Reduced the max_depth options
    'min_samples_split': [2, 5]  # Reduced the min_samples_split
options
}

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=rf_classifier,
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)

# Best parameters from GridSearchCV
print(f"Best parameters: {grid_search.best_params_}")

# Evaluate the best model on test data
best_rf_classifier = grid_search.best_estimator_
y_pred_best = best_rf_classifier.predict(X_test)
```

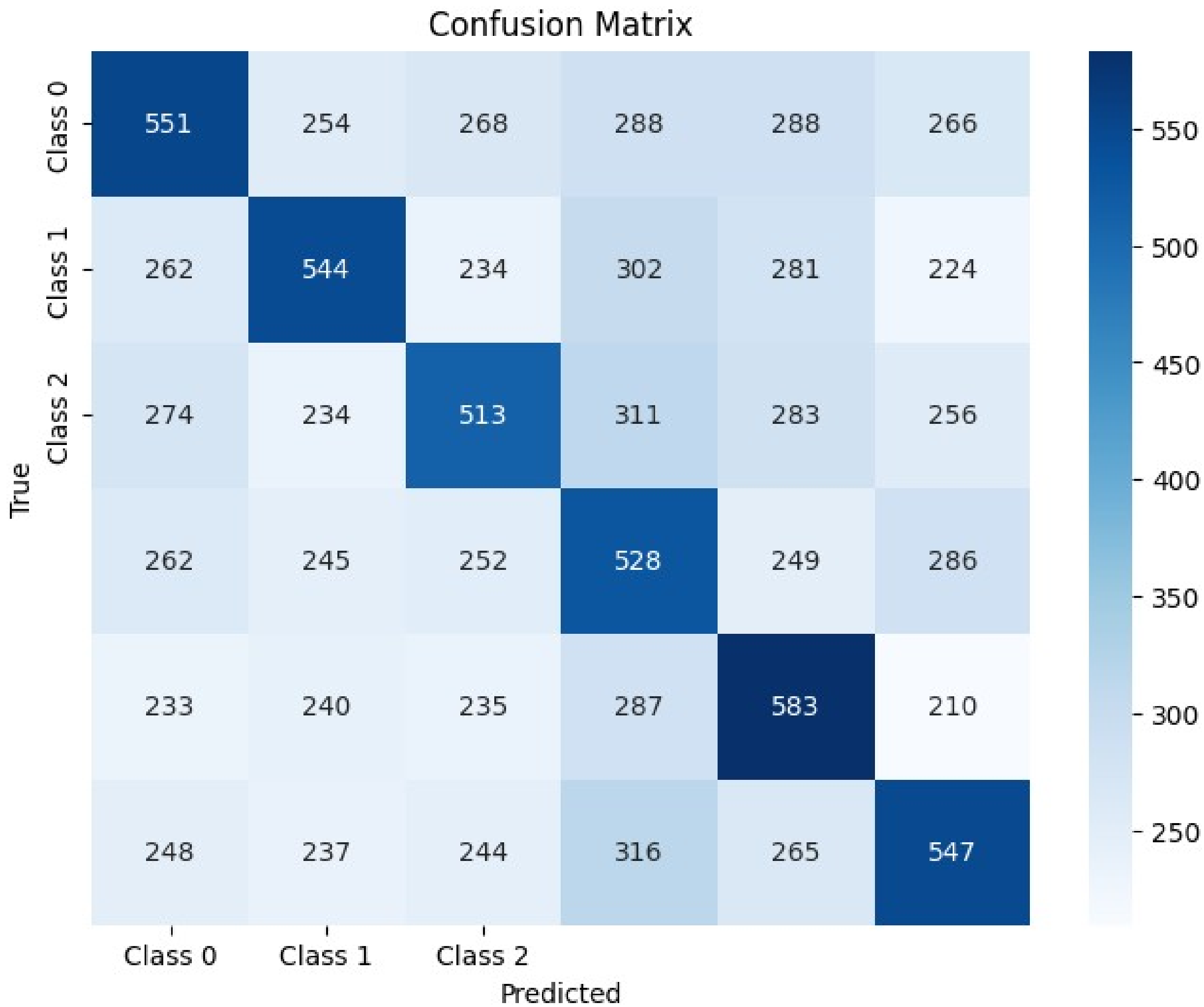
```
# Evaluate performance of the tuned model
print(f"Accuracy of tuned model: {accuracy_score(y_test,
y_pred_best)}")
print("Classification Report for tuned model:")
print(classification_report(y_test, y_pred_best))
```

```
Fitting 3 folds for each of 8 candidates, totalling 24 fits
Best parameters: {'max_depth': 20, 'min_samples_split': 5,
'n_estimators': 100}
Accuracy of tuned model: 0.2942342342342342
Classification Report for tuned model:
              precision    recall  f1-score   support

           0       0.30      0.29      0.29      1915
           1       0.31      0.29      0.30      1847
           2       0.29      0.27      0.28      1871
           3       0.26      0.29      0.27      1822
           4       0.30      0.33      0.31      1788
           5       0.31      0.29      0.30      1857

    accuracy                           0.29     11100
   macro avg       0.29      0.29      0.29     11100
weighted avg       0.30      0.29      0.29     11100
```

Step 9: Final Model Evaluation

After tuning the model, you should assess the performance again using different metrics and analyze the results. For instance, you can use Confusion Matrix to see how well the model performs.

```
from sklearn.metrics import confusion_matrix
import seaborn as sns

# Compute confusion matrix
cm = confusion_matrix(y_test, y_pred_best)

# Plot confusion matrix
plt.figure(figsize=(8,6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Class
0', 'Class 1', 'Class 2'], yticklabels=['Class 0', 'Class 1', 'Class
2'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



Confusion Matrix
Class 0
Class 1
Class 2
True
Predicted
551
254
268
288
288
266
262
544
234
302
281
224
274
234
513
311
283
256
262
245
252
528
249
286
233
240
235
287
583
210
248
237
244
316
265
547
550
500
450
400
350
300
250