+ Text

+ Code

Activity 1: Import Necessary Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import seaborn as sns from sklearn
import preprocessing from sklearn
import model selection from sklearn
\verb|import metrics from sklearn|\\
import linear_model from sklearn
import ensemble from sklearn
import tree from sklearn
import svm
import xgboost
import matplotlib.pyplot as plt from IPython.display
import display from time
import time plt.style.use('dark_background')
```

Activity 2: Importing the Dataset

df = pd.read csv('weatherAUS.csv')

Activity 3: Analyse the data

df.head()

Date Location MinTemp MaxTemp Rainfall Evaporation Sunshine WindGustD

	2008-		13.4	22.9	0.6	NaN	NaN	
0		Albury						
	12-01							
	2008-							
1		Albury	7.4	25.1	0.0	NaN	NaN	WN
	12-02	,						
	2008-							
_	2000-		40.0	0==				1440
2		Albury	12.9	25.7	0.0	NaN	NaN	WS
	12-03							
	2008-							
3		Albury	9.2	28.0	0.0	NaN	NaN	N
	12-04	,						
	2008-		17.5	32.3	1.0	NaN	NaN	
4	2000	Albury	11.0	02.0	1.0	rtart	14014	
*	10 OF	Albuly						
	12-05							
5		rows × 23						
,								
		columns						

df.describe()

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGu	
count	143975.000000	144199.000000	142199.000000	82670.000000	75625.000000	13519	
mean	12.194034	23.221348	2.360918	5.468232	7.611178	4	
std	6.398495	7.119049	8.478060	4.193704	3.785483	1	
min	-8.500000	-4.800000	0.000000	0.000000	0.000000		
25%	7.600000	17.900000	0.000000	2.600000	4.800000	3	
50%	12.000000	22.600000	0.000000	4.800000	8.400000	3	
75%	16.900000	28.200000	0.800000	7.400000	10.600000	4	
max	33.900000	48.100000	371.000000	145.000000	14.500000	13	

df.shape

(145460, 23)

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 145460 entries, 0 to 145459 Data columns (total 23 columns):

Non-Null Count # Column Dtype -----_____ Ω Date 145460 non-null object 145460 non-null object

 $https://colab.research.google.com/drive/1FhBKxqFbBcAl_Dr5O4xT-S3JjutL7KQ5\#scrollTo=GiOhhjWtpCBQ\&printMode=true$

142199 non-null object 22 RainTomorrow 142193 non-null object dtypes: float64(16),

143693 non-null float64

141851 non-null float64

RainToday object(7) memory usage: 25.5+ MB

Temp9am

Temp3pm

Activity 4: Handling Missing Values

df.isnull().sum()

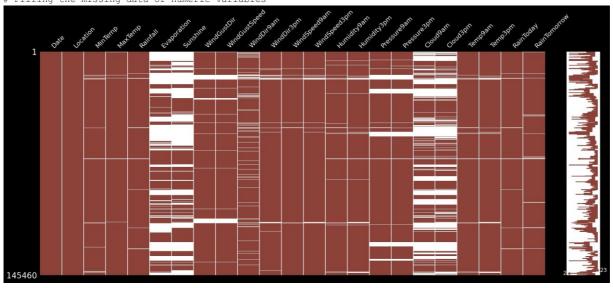
19

20

21

Date	0
Location	0
MinTemp	1485
MaxTemp	1261
Rainfall	3261
Evaporation	62790
Sunshine	69835
WindGustDir	10326
WindGustSpeed	10263
WindDir9am	10566
WindDir3pm	4228
WindSpeed9am	1767
WindSpeed3pm	3062
Humidity9am	2654
Humidity3pm	4507
Pressure9am	15065
Pressure3pm	15028
Cloud9am	55888
Cloud3pm	59358
Temp9am	1767
Temp3pm	3609
RainToday	3261
RainTomorrow	3267
dtype: int64	

import missingno as msno msno.matrix(df, color=(0.55,0.255, 0.225), fontsize=16) <Axes: > # Filling the missing data of numeric variables



Filling NaN values with mean, median and mode using fillna() method.

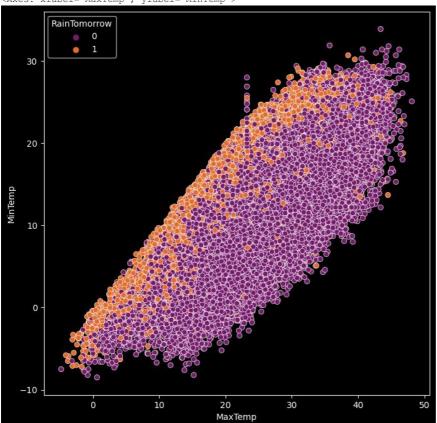
th mean df['MinTemp'].fillna(df['MinTemp'].mean(), inplace=True)

```
df['MaxTemp'].fillna(df['MaxTemp'].mean(), inplace=True)
df['Rainfall'].fillna(df['Rainfall'].mean(), inplace=True)
df['WindGustSpeed'].fillna(df['WindGustSpeed'].mean(), inplace=True)
df['WindSpeed9am'].fillna(df['WindSpeed9am'].mean(), inplace=True)
df['WindSpeed3pm'].fillna(df['WindSpeed3pm'].mean(), inplace=True)
df['Humidity9am'].fillna(df['Humidity9am'].mean(), inplace=True)
df['Humidity3pm'].fillna(df['Humidity3pm'].mean(), inplace=True)
df['Pressure9am'].fillna(df['Pressure9am'].mean(), inplace=True)
df['Pressure3pm'].fillna(df['Pressure3pm'].mean(), inplace=True)
df['Temp9am'].fillna(df['Temp9am'].mean(), inplace=True)
df['Temp3pm'].fillna(df['Temp3pm'].mean(), inplace=True)
df = df.drop(["Evaporation", "Sunshine", "Cloud9am", "Cloud3pm", "Location", "Date"], axis =1)
df.head()
                  MinTemp MaxTemp Rainfall WindGustDir WindGustSpeed WindDir9am WindDir3
            0
                          13.4 22.9
                                                           0.6
                                                                               \٨/
                                                                                                  44 0
                                                                                                                       \//
                                                                                                                                           W/N
                          7.4 25.1 0.0 WNW 44.0 NNW WS 2 12.9 25.7 0.0 WSW 46.0 W WS 3 9.2 28.0 0.0 NE 24.0 SE
            1
            4
                          17.5 32.3
                                                     1.0
                                                                               W
                                                                                                  41.0
                                                                                                                       FNF
df = df.dropna(axis = 0)
df.shape
          (123710.17)
df columns
          Index(['MinTemp', 'MaxTemp', 'Rainfall', 'WindGustDir', 'WindGustSpeed',
                           'WindDir9am', 'WindDir3pm', 'WindSpeed9am', 'WindSpeed3pm',
                          'Humidity9am', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Temp9am',
                          'Temp3pm', 'RainToday', 'RainTomorrow'],
          dtype='object')
from sklearn.preprocessing import LabelEncoder le =
LabelEncoder() df['WindGustDir'] =
le.fit transform(df['WindGustDir']) df['WindDir9am'] =
le.fit transform(df['WindDir9am']) df['WindDir3pm'] =
le.fit transform(df['WindDir3pm']) df['RainToday'] =
le.fit_transform(df['RainToday']) df['RainTomorrow'] =
le.fit_transform(df['RainTomorrow'])
          <ipython-input-13-2e21397e68d0>:3: SettingWithCopyWarning:
          A value is trying to be set on a copy of a slice from a DataFrame.
          Try using .loc[row indexer, col indexer] = value instead
          See the caveats in the documentation: \underline{\texttt{https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html\#returning\_a}
          \texttt{df['WindGustDir']} = \texttt{le.fit\_transform(df['WindGustDir'])} \\ < \texttt{ipython-input-13-2e21397e68d0} > : 4: \\ \texttt{SettingWithCopyWarning: le.fit\_transform(df['WindGustDir'])} \\ < \texttt{le.fit\_transform(df['WindGustDir'])} \\ < \texttt{le.fit\_transform(d
          A value is trying to be set on a copy of a slice from a DataFrame.
          Try using .loc[row indexer,col indexer] = value instead
          See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a
          df['WindDir9am'] = le.fit transform(df['WindDir9am']) <ipython-input-13-2e21397e68d0>:5: SettingWithCopyWarning:
          A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row_indexer,col_indexer] = value instead
          See the caveats in the documentation: \underline{\texttt{https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html\#returning-a}
          \label{eq:df'WindDir3pm']} $$ df'' WindDir3pm'] = le.fit_transform(df''WindDir3pm') < ipython-input-13-2e21397e68d0 >: 6: SettingWithCopyWarning: le.fit_transform(df'''WindDir3pm') < ipython-input-13-2e21397e76d0 >: 6: SettingWithCopyWarning < ipython-input-13-2e21396 >: 6: SettingWithCopyWarning < ipython-input-13
          A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row indexer,col indexer] = value instead
          See the caveats in the documentation: \underline{\texttt{https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html\#returning-a}
          df['RainToday'] = le.fit_transform(df['RainToday']) <ipython-input-13-2e21397e68d0>:7: SettingWithCopyWarning:
          A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row indexer, col indexer] = value instead
          See the caveats in the documentation: \underline{\text{https://pandas.pydata.org/pandas-docs/stable/user\_guide/indexing.html\#returning-a}}
          df['RainTomorrow'] = le.fit_transform(df['RainTomorrow'])
```

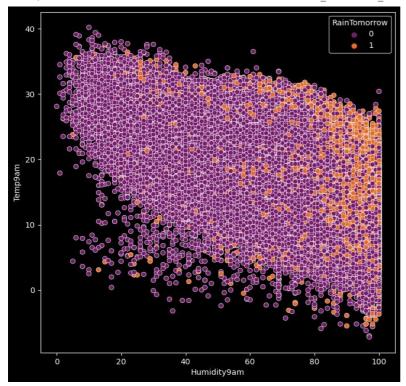
Activity 5: Data Visualisation

 $\texttt{plt.figure} \, (\texttt{figsize} = (8,8)) \, \, \texttt{sns.scatterplot} \, (\texttt{x} = 'MaxTemp', \, \, \texttt{y} = 'MinTemp', \, \, \texttt{hue} = 'RainTomorrow' \, \, , \, \, \\ \texttt{palette} = 'inferno', \, \texttt{data} = \texttt{df})$

<Axes: xlabel='MaxTemp', ylabel='MinTemp'>



plt.figure(figsize = (8,8)) sns.scatterplot(x = 'Humidity9am', y = 'Temp9am', hue = 'RainTomorrow' ,
palette = 'inferno',data = df) <Axes: xlabel='Humidity9am', ylabel='Temp9am'>



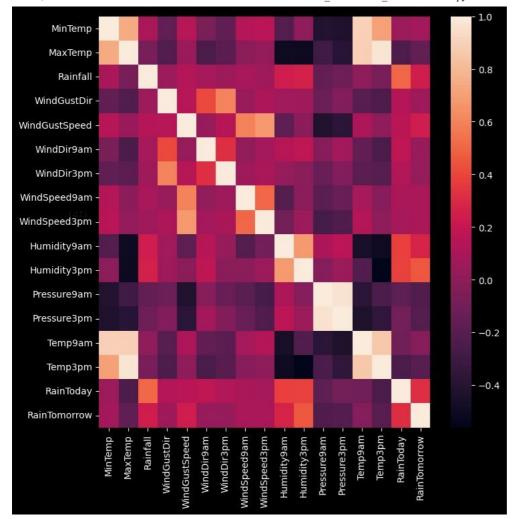
df.corr()

	MinTemp	MaxTemp	Rainfall	WindGustDir	WindGustSpeed	WindDir
MinTemp	1.000000	0.738283	0.099872	-0.166598	0.141259	-0.069
MaxTemp	0.738283	1.000000	-0.079862	-0.226085	0.037297	-0.247
Rainfall	0.099872	-0.079862	1.000000	0.045529	0.131532	0.085
WindGustDir	-0.166598	-0.226085	0.045529	1.000000	0.144093	0.408
WindGustSpeed	0.141259	0.037297	0.131532	0.144093	1.000000	0.035
WindDir9am	-0.069470	-0.247731	0.085228	0.408314	0.035928	1.000
WindDir3pm	-0.170151	-0.187850	0.048898	0.601815	0.144941	0.319
WindSpeed9am	0.138219	-0.015504	0.085619	0.031805	0.591774	0.017
WindSpeed3pm	0.153703	0.024165	0.060373	0.103787	0.675796	0.076
Humidity9am	-0.216681	-0.505146	0.236884	0.066498	-0.176424	0.144
Humidity3pm	-0.000857	-0.508514	0.258590	0.050049	-0.011814	0.173
Pressure9am	-0.415777	-0.297520	-0.164740	-0.132905	-0.424447	-0.027
Pressure3pm	-0.431118	-0.391762	-0.124273	-0.037600	-0.380522	0.066
Temp9am	0.896122	0.887680	0.004099	-0.205309	0.107882	-0.161
Temp3pm	0.706237	0.974990	-0.083480	-0.238315	0.003190	-0.253
RainToday	0.042841	-0.239697	0.501775	0.135595	0.154041	0.172
RainTomorrow	0.076630	-0.168453	0.240838	0.050900	0.236541	0.031

cor=df.corr()

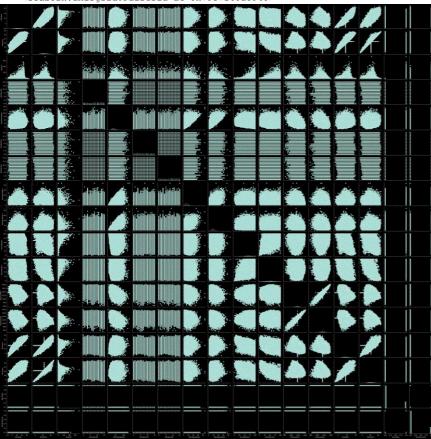
Heatmap

plt.figure(figsize = (8,8))
sns.heatmap(df.corr()) <Axes: >

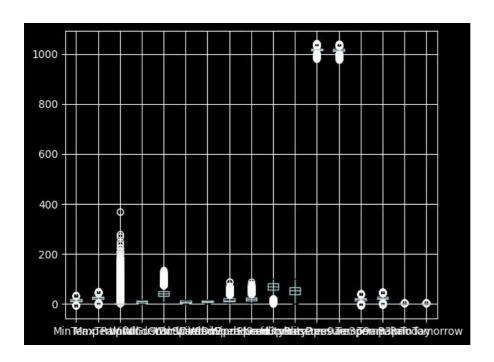


sns.pairplot

<seaborn.axisgrid.PairGrid at 0x7937160a8940>



df.boxplot



Activity 6: Splitting the Dataset into Dependent and Independent variable

SPLITTING THE DATASET y -

- Independant x -
- Dependant

```
x = df.drop(['RainTomorrow'], axis = 1)
y = df['RainTomorrow']
```

x.head()

MinTemp MaxTemp Rainfall WindGustDir WindGustSpeed WindDir9am WindDir3pm WindSpeed9am WindSpeed3pm Humidity9am

0	13.4	22.9	0.6	13	44.0	13	14	20.0	24.0	71.0				
1	1 7.4 25.1 0.0 14 44.0 6 15 4.0 22.0 44.0 2 12.9 25.7 0.0 15 46.0 13 15 19.0 26.0 38.0													
				3	9.2	28.0	0.0	4	24.0	9	0	11.0	9.0	45.0
				4	17.5	32.3	1.0	13	41.0	1	7	7.0	20.0	82.0

Activity 7: Splitting the data into Train and Test

```
from sklearn.model_selection import train_test_split x_train, x_test,
y_train, y_test = train_test_split(x,y, test_size = 0.2)
```

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

Milestone 3: Model Builing

Model building includes the following main tasks

- 1. Import the model building Libraries
- 2. Initializing the model
- 3. Training and testing the model
- 4. Evaluation of Model
- 5. Save the Model

Activity 8: Training and Testing the Model

Decision Tree

Testing on Train and test models respectively

```
Dtree = DecisionTreeClassifier()
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
Dtree.fit(x_train, y_train_encoded) p4 =
Dtree.predict(x_train)
print("Decision Tree:", metrics.accuracy_score(y_train_encoded, p4))
    Decision Tree: 1.0
{\tt from \ sklearn.tree \ import \ DecisionTreeClassifier}
dt = DecisionTreeClassifier()
dt.fit(x_train,y_train) predictions =
dt.predict(x_test) print(confusion_matrix(y_test,
predictions)) print(classification_report(y_test,
predictions)) print(accuracy_score(y_test,
predictions))
    [[16512 2819]
[ 2502 2909]]
                  precision recall f1-score
                                  0.85
                            0.54
                                      0.52
```

```
accuracy 0.78 24742
macro avg 0.69 0.70 0.69 24742
weighted avg 0.79 0.78 0.79 24742
0.7849405868563576
```

Random Forest Classifier

Testing on Train and test models respectively

```
Rand_forest = RandomForestClassifier()
label_encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
Rand_forest.fit(x_train, y_train_encoded) p2 =
Rand_forest.predict(x_train)
print("Random Forest:", metrics.accuracy_score(y_train_encoded, p2))
     Random Forest: 0.999969687171611
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier()
rf.fit(x_train,y_train) predictions =
rf.predict(x test) print(confusion matrix(y test,
predictions)) print(classification report(y test,
predictions)) print(accuracy_score(y_test,
predictions))
     [[18389 942]
     [ 2648 2763]]
                   precision
                                recall f1-score
                                                   support
                               0.95 0.91
                      0.87
                                                      19331
                 0.75 0.51 0.61
                                               5411
         accuracy
                                                  0.85
                             0.85 24742
0.73 0.76 24742 weighted
0.84 24742 0.8549025947781101
                     0.81
              0.85
                      0.85
```

XGBoost Classifier

Testing on Train and test models respectively

```
GBM = GradientBoostingClassifier()
label encoder = LabelEncoder()
y_train_encoded = label_encoder.fit_transform(y_train)
GBM.fit(x_train, y_train_encoded) p5 =
GBM.predict(x_train)
print("Gradient Boosting:", metrics.accuracy_score(y_train_encoded, p5))
    Gradient Boosting: 0.8525280898876404
import xgboost as xgb xgb =
xgb.XGBClassifier() xgb.fit(x_train, y_train)
pred = xgb.predict(x_test)
print('acc',accuracy_score(y_test,pred))
print('f1',classification_report(y_test,pred))
print('matrix',confusion_matrix(y_test,pred))
    acc 0.8555492684504082
    f1
                    precision recall f1-score support
                     0.88 0.94
0.54 0.62
                   0.86
0.54
              0
                                         0.91
                                                19331
                                        5411
           0.73
                                         0.86
       accuracy
                  0.80 0.74
0.85 0.86
                                      0.77
    macro avq
                  0.85
                                       0.85
    weighted avg
    matrix [[18225 1106] [ 2468 2943]]
```

SVM

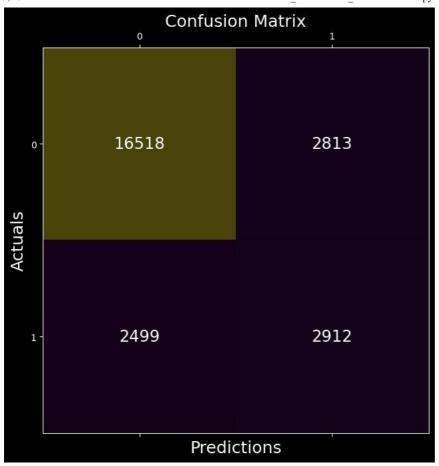
Testing on Train and test models respectively

```
svm = SVC() label_encoder = LabelEncoder()
 y_train_encoded = label_encoder.fit_transform(y_train)
 svm.fit(x train, y train encoded) p3 =
svm.predict(x_train)
print("SVM:", metrics.accuracy_score(y_train_encoded, p3))
              SVM: 0.8388266914558241
from sklearn.svm import SVC from sklearn.metrics import confusion_matrix,
 classification_report, accuracy_score svc = SVC() svc.fit(x_train, y_train)
predictions = svc.predict(x test) print("Confusion Matrix:\n",
 \verb|confusion_matrix(y_test, predictions)|| print("\nClassification Report:\n", or other prediction Report:\n", or other predictions)|| print("\nClassification Report:\n", or other predictions)|| print("\nClassification Report:\n", or other predictions)|| print("\n', or other predi
 classification_report(y_test, predictions)) print("\nAccuracy Score:",
 accuracy_score(y_test, predictions))
              Confusion Matrix:
                 [[18698 633]
                 [ 3261 2150]]
              Classification Report:
                                                                                                                               precision
              recall f1-score support
                                                         0.85 0.97 0.91
0.40 0.52 5411
                                             0
                                                                                                                                   0.91
                                                                                                                                                          19331
                                 0.77
                         accuracy
                                                                                                                                    0.84
                                                                                                                                                                  24742
              macro avg 0.81 0.68 weighted avg 0.83 0.84
                                                                                                                         0.72
                                                                                                                                                         24742
                                                                                                                                  0.82
                                                                                                                                                              24742
              Accuracy Score: 0.8426157950044458
```

Selecting DECISION TREE as our prediction

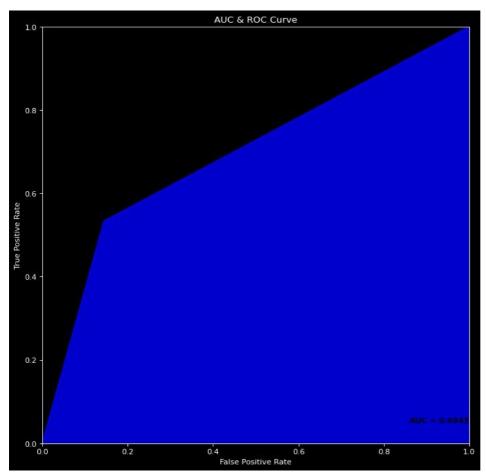
Model Confusion Matrix

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion matrix
import matplotlib.pyplot as plt from
sklearn.tree import DecisionTreeClassifier
dt = DecisionTreeClassifier()
dt.fit(x_train,y_train) predictions =
dt.predict(x_test) print(confusion_matrix(y_test,
predictions)) conf matrix=
confusion matrix(y_test, predictions)
fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(conf_matrix, alpha=0.3)
for i in range(conf matrix.shape[0]):
   for j in range(conf_matrix.shape[1]): # Add the missing closing parenthesis here
ax.text(x=j, y=i, s=conf_matrix[i, j], va='center', ha='center', size='xx-large')
plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
    [[16518 2813]
[ 2499 2912]]
```



Roc-Auc Curve

```
from sklearn.tree import DecisionTreeClassifier from sklearn.metrics import confusion matrix, accuracy score,
precision_score, recall_score, f1_score, roc_auc_score, roc_cur import matplotlib.pyplot as plt
# Create a Decision Tree Classifier instance and fit it to your training data
dt = DecisionTreeClassifier() dt.fit(x_train, y_train)
# Make predictions on the test data
predictions = dt.predict(x_test)
# Calculate the confusion matrix conf_matrix =
confusion_matrix(y_test, predictions)
# Calculate various classification metrics
accuracy = accuracy score(y test, predictions)
precision = precision_score(y_test, predictions)
recall = recall_score(y_test, predictions)
f1_score = f1_score(y_test, predictions)
# Calculate AUC and ROC curve auc =
roc auc score(y test, predictions) fpr, tpr,
thresholds = roc_curve(y_test, predictions)
# Plot the ROC curve plt.figure(figsize=(12, 10), dpi=80) plt.axis('scaled') plt.xlim([0, 1])
plt.ylim([0, 1]) plt.title("AUC & ROC Curve") plt.plot(fpr, tpr, 'b') plt.fill_between(fpr, tpr, facecolor='blue', alpha=0.8) plt.text(1, 0.05, 'AUC = {:.4f}'.format(auc), ha='right', fontsize=10,
weight='bold', color='black') plt.xlabel("False Positive Rate") plt.ylabel("True Positive Rate")
plt.show()
# Print the confusion matrix and other metrics
print("Confusion Matrix:") print(conf_matrix)
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall) print("F1-score:",
f1_score) print("AUC:", auc)
```



SAVING THE MODEL

```
import pickle
# Save your model with a specific name
with open('dt.pkl', 'wb') as model_file:
    pickle.dump(dt, model_file)
from sklearn.impute import SimpleImputer
# Create and train the Imputer
imp_mode = SimpleImputer(strategy='most_frequent')
imp_mode.fit(x_train)
# Save the Imputer
with open('imputer.pkl', 'wb') as imputer file:
    pickle.dump(imp_mode, imputer_file)
from sklearn.preprocessing import StandardScaler
# Create and fit the Scaler
sc = StandardScaler()
sc.fit(x_train)
# Save the ScalerConfusion Matrix: with
[[16537 2794]open('scaler.pkl', 'wb') as
scaler_file:
    pickle.dump [ 2526 2885]](sc, scaler file)
    Accuracy: 0.7849810039608762
    Precision: 0.5080119739390738
    Recall: 0.5331731657734246
importF1-score: 0.5202885482416592
    pickle AUC: 0.6943192402763972
# Assuming you have a Decision Tree model (dt), a LabelEncoder (le), an Imputer (imp mode), and a Scaler (sc) to save.
\ensuremath{\text{\#}} Save the Decision Tree model with
open('dt.pkl', 'wb') as model_file:
pickle.dump(dt, model file)
```

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```
# Save the LabelEncoder with
open('encoder.pkl', 'wb') as le_file:
pickle.dump(le, le file)
# Save the Imputer with open('imputer.pkl',
'wb') as imputer_file:
pickle.dump(imp_mode, imputer_file)
# Save the Scaler with open('scaler.pkl',
'wb') as scaler_file:
   pickle.dump(sc, scaler_file)
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
# Create a TF-IDF vectorizer
tfidf = TfidfVectorizer()
# Create a Multinomial Naive Bayes classifier
mnb = MultinomialNB()
# Fit the classifier with some data (you should have training data)
# For example:
# mnb.fit(X train, y train)
# Save the TF-IDF vectorizer import pickle with
open('vectorizer.pkl', 'wb') as vectorizer file:
pickle.dump(tfidf, vectorizer_file)
# Save the Multinomial Naive Bayes model
with open('dt.pkl', 'wb') as model file:
pickle.dump(mnb, model_file)
```