

## **1. PREDICTING HOUSE PRICES**

<b>EX.N0 : 1</b>	<b>Predicting House Prices</b>
<b><u>DATE : 24/07/2024</u></b>	

**PROBLEM STATEMENT:** Build a regression model to predict house prices based on features like location, size, and amenities.

**PYTHON CONCEPTS:** Functions, classes, numeric types, sequences.

**VISUALIZATION:** Plotting regression line, residual plots.

**MULTIVARIATE ANALYSIS:** Multiple regression.

**DATASET:** Kaggle House Prices

### **ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

### **PROGRAM:**

```
import pandas as pd
```

```
from sklearn.preprocessing import LabelEncoder
```

```
from sklearn.model_selection import train_test_split
```

```

from sklearn.linear_model import LinearRegression

from sklearn.metrics import r2_score, mean_absolute_error

import matplotlib.pyplot as plt

file_path = 'C:/Users/APPU/Downloads/Housing.csv'

housing_data = pd.read_csv(file_path)

categorical_features = ['mainroad', 'guestroom', 'basement', 'hotwaterheating', 'airconditioning',
'prefarea', 'furnishingstatus']

le = LabelEncoder()

for feature in categorical_features:
    housing_data[feature] = le.fit_transform(housing_data[feature])

X = housing_data.drop('price', axis=1) y = housing_data['price']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = LinearRegression()

model.fit(X_train, y_train)

y_pred = model.predict(X_test)

r2 = r2_score(y_test, y_pred)

mae = mean_absolute_error(y_test, y_pred)

plt.figure(figsize=(10, 6))

plt.scatter(y_test, y_pred, alpha=0.7, color='b')

plt.plot([y_test.min(), y_test.max()],
[y_test.min(), y_test.max()], 'k--', lw=2)

plt.xlabel('Actual Price')

plt.ylabel('Predicted Price')

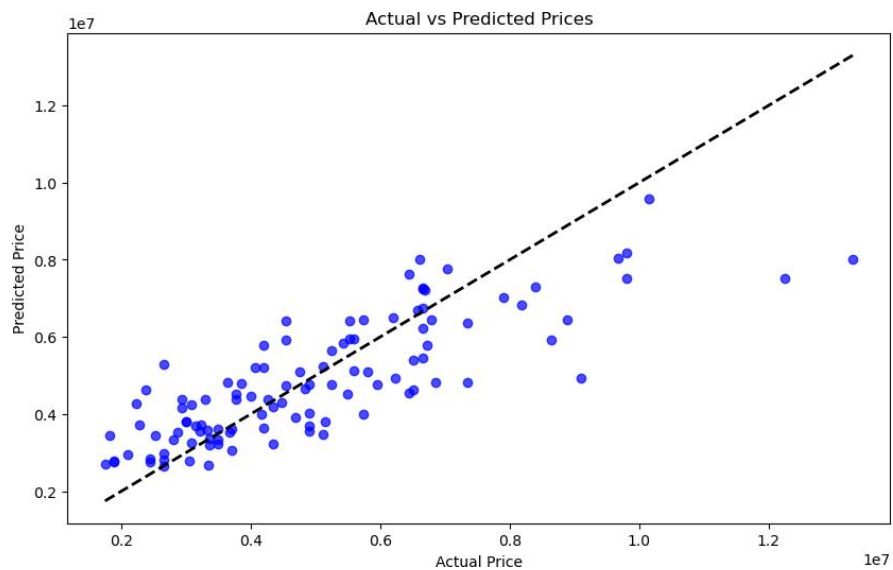
plt.title('Actual vs Predicted Prices')

plt.show()

```

```
print(f'R-squared (R²): {r2}')
```

```
print(f'Mean Absolute Error (MAE): {mae}')
```



```
import numpy as np
test=np.array([ 7420,4,2,3,1,0,0,0,1,2,1,0]).reshape(-12,12)
model.predict(test)

array([8004072.41154001])
```

## **RESULT:**

Thus, the program for house price prediction is executed successfully.

## **2. CUSTOMER SEGMENTATION FOR AN E-COMMERCE COMPANY**

<b>EX.N0 : 2</b>	<b>Customer Segmentation for an E-commerce Company</b>
<b><u>DATE : 05/08/2024</u></b>	

**PROBLEM STATEMENT:** Perform cluster analysis to segment customers based on purchasing behaviour.

**PYTHON CONCEPTS:** Data structures, file reading/writing.

**VISUALIZATION:** Cluster plots.

**MULTIVARIATE ANALYSIS:** Cluster analysis with k-means, hierarchical clustering.

**DATASET:** Online Retail Dataset

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

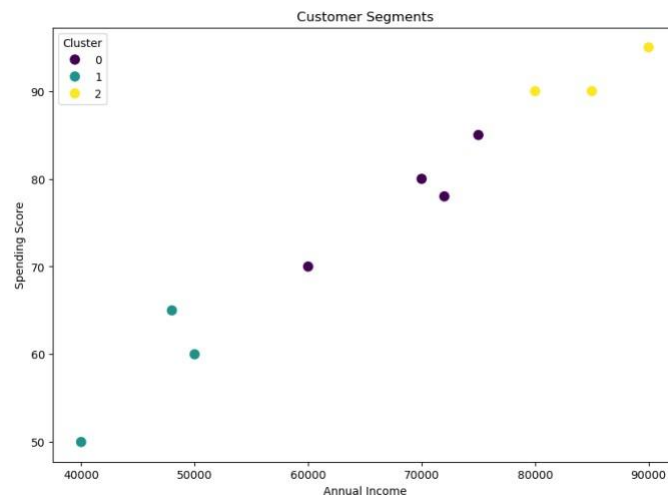
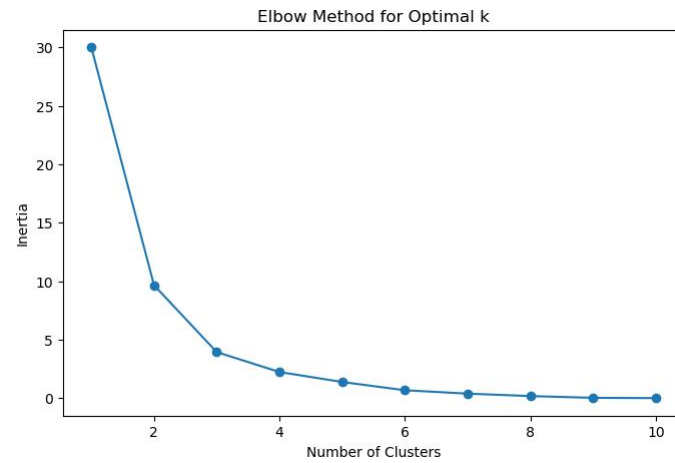
```
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
import seaborn as sns
import os
```

```

os.environ['OMP_NUM_THREADS'] = '1'
data = {'CustomerID': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
'Age': [25, 45, 35, 50, 23, 33, 43, 36, 29, 55],
'AnnualIncome': [50000, 60000, 70000, 80000, 40000, 75000, 85000, 72000, 48000, 90000],
'SpendingScore': [60, 70, 80, 90, 50, 85, 90, 78, 65, 95] }
df = pd.DataFrame(data)
features = df[['Age', 'AnnualIncome', 'SpendingScore']]
scaler = StandardScaler()
scaled_features = scaler.fit_transform(features) inertia = []
k_range = range(1, 11) for k in k_range:
kmeans = KMeans(n_clusters=k, n_init=10, random_state=0)
kmeans.fit(scaled_features)
inertia.append(kmeans.inertia_) plt.figure(figsize=(8, 5))
plt.plot(k_range, inertia, marker='o')
plt.xlabel('Number of Clusters') plt.ylabel('Inertia')
plt.title('Elbow Method for Optimal k') plt.show() optimal_k = 3
kmeans = KMeans(n_clusters=optimal_k, n_init=10, random_state=0)
df['Cluster'] = kmeans.fit_predict(scaled_features)
plt.figure(figsize=(10, 7))
sns.scatterplot(data=df, x='AnnualIncome', y='SpendingScore', hue='Cluster', palette='viridis',
s=100)
plt.title('Customer Segments')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.legend(title='Cluster')
plt.show()
print(df)

```

## **OUTPUT:**



	CustomerID	Age	AnnualIncome	SpendingScore	Cluster
0	1	25	50000	60	1
1	2	45	60000	70	0
2	3	35	70000	80	0
3	4	50	80000	90	2
4	5	23	40000	50	1
5	6	33	75000	85	0
6	7	43	85000	90	2
7	8	36	72000	78	0
8	9	29	48000	65	1
9	10	55	90000	95	2

## **RESULT:**

Thus, the program for Customer Segmentation for an E-commerce Company is executed successfully.

### **3. SENTIMENT ANALYSIS OF MOVIE REVIEWS**

<b>EX.NO : 3</b>	<b>SENTIMENT ANALYSIS OF MOVIE REVIEWS</b>
<b><u>DATE : 07/08/2024</u></b>	

**PROBLEM STATEMENT:** Classify movie reviews as positive or negative using text Data.

**PYTHON CONCEPTS:** Text files, sequences, flow controls.

**VISUALIZATION:** Word cloud, bar plots.

**MULTIVARIATE ANALYSIS:** PCA for text data, logistic regression.

**DATASET:** IMDB Movie Reviews.

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

```
import pandas as pd
import matplotlib.pyplot as plt
from wordcloud import WordCloud
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.decomposition import PCA
```

```

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer
import seaborn as sns
nltk.download('punkt')
nltk.download('stopwords')
df = pd.read_csv('C:/Users/AI_LAB/Downloads/IMDB Dataset.csv')
stop_words = set(stopwords.words('english'))
stemmer = PorterStemmer()
def preprocess_text(text):
    tokens = word_tokenize(text.lower())
    tokens = [stemmer.stem(word) for word in tokens if word.isalpha() and word not in stop_words]
    return ' '.join(tokens)
df['cleaned_review'] = df['review'].apply(preprocess_text)
vectorizer = TfidfVectorizer(max_features=5000)
X = vectorizer.fit_transform(df['cleaned_review']).toarray()
encoder = LabelEncoder()
y = encoder.fit_transform(df['sentiment'])
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
plt.figure(figsize=(8, 6))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='coolwarm', alpha=0.5)
plt.title('PCA of Movie Reviews')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Sentiment')
plt.show()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)

```

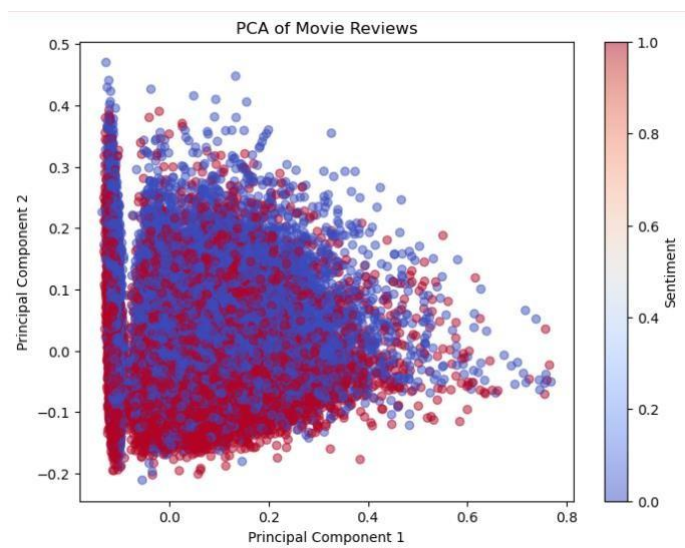


```

y_pred = model.predict(X_test)
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
positive_reviews = ' '.join(df[df['sentiment'] == 1]['cleaned_review'])
negative_reviews = ' '.join(df[df['sentiment'] == 0]['cleaned_review'])
plt.figure(figsize=(12, 6))
if len(positive_reviews.strip()) > 0:
plt.subplot(1, 2, 1)
plt.imshow(WordCloud(width=800, height=400,
background_color='white').generate(positive_reviews), interpolation='bilinear')
plt.title('Positive Reviews')
plt.axis('off')
else: print("No content available for positive reviews.")
if len(negative_reviews.strip()) > 0:
plt.subplot(1, 2, 2)
plt.imshow(WordCloud(width=800, height=400,
background_color='white').generate(negative_reviews), interpolation='bilinear')
plt.title('Negative Reviews')
plt.axis('off') else:
print("No content available for negative reviews.")
plt.show()
sns.countplot(x='sentiment', data=df)
plt.title('Sentiment Distribution')
plt.xlabel('Sentiment')
plt.ylabel('Count')
plt.show()

```

**OUTPUT:**



Confusion Matrix:

```
[[4306 655]
 [ 511 4528]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.89	0.87	0.88	4961
1	0.87	0.90	0.89	5039
accuracy			0.88	10000
macro avg	0.88	0.88	0.88	10000
weighted avg	0.88	0.88	0.88	10000

**RESULT:**

Thus, the program for sentiment analysis of movie reviews is executed successfully.

#### **4. STOCK MARKET ANALYSIS**

<b>EX.N0 : 4</b>	<b>STOCK MARKET ANALYSIS</b>
<b><u>DATE : 14/08/2024</u></b>	

**PROBLEM STATEMENT:** Analyse stock market data to predict future stock prices.

**PYTHON CONCEPTS:** Data structures, file reading/writing, functions.

**VISUALIZATION:** Line plots, candlestick charts.

**MULTIVARIATE ANALYSIS:** Time series analysis, regression.

**DATASET:** Yahoo Finance Stock Data.

#### **ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

#### **PROGRAM:**

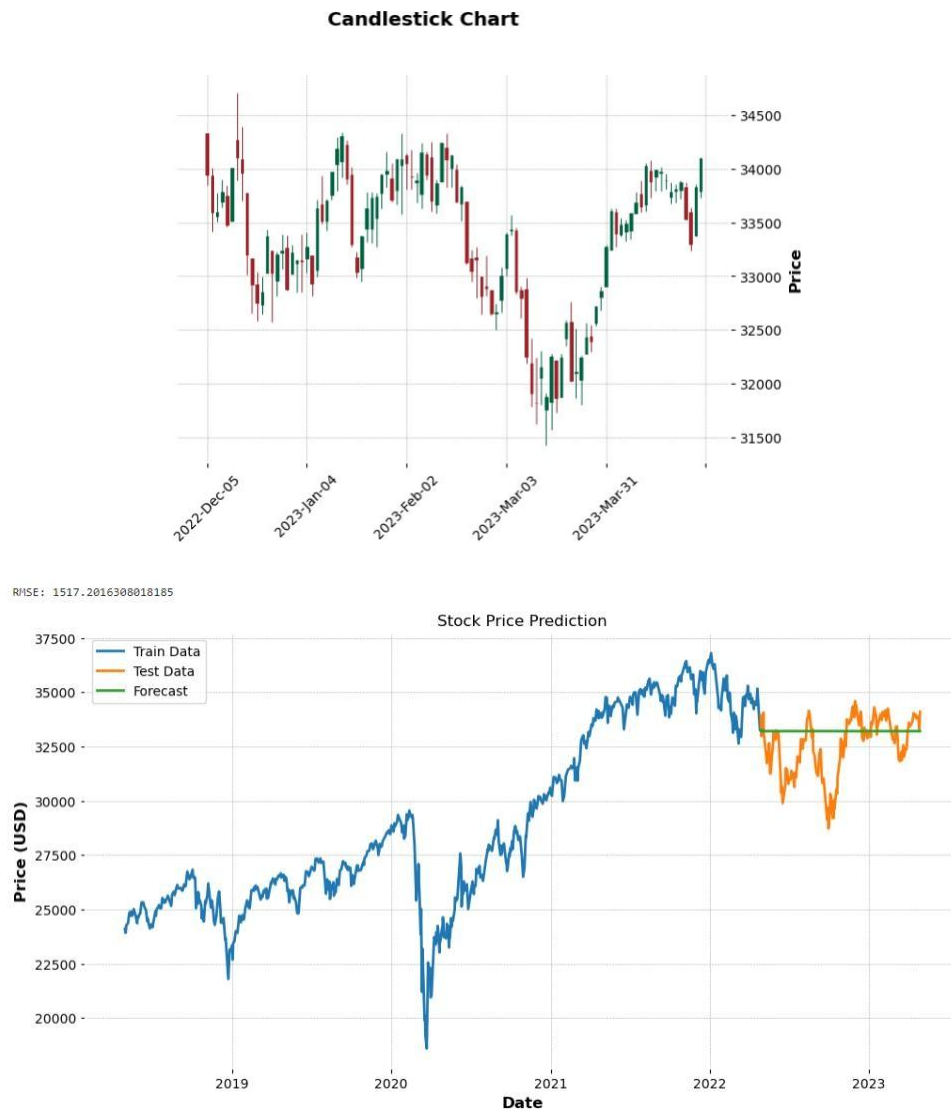
```
import pandas as pd
import matplotlib.pyplot as plt
import mplfinance as mpf
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
import numpy as np
```

```

file_path = r'C:\Users\APPU\Downloads\yahoo_data.xlsx'
data = pd.read_excel(file_path, index_col='Date', parse_dates=True)
data.rename(columns={'Close*': 'Close', 'Adj Close*': 'Adj Close'}, inplace=True)
data.sort_index(inplace=True)
data.ffmpeg(inplace=True)
if 'Adj Close' in data.columns:
plt.figure(figsize=(12, 6))
plt.plot(data['Adj Close'], label='Adjusted Close Price')
plt.title('Adjusted Close Price Over Time')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.legend()
plt.show()
reduced_data = data[-100:] # Reduce data points for candlestick chart
mpf.plot(reduced_data, type='candle', style='charles', title='Candlestick Chart')
train_data, test_data = data['Adj Close'][:int(len(data)*0.8)], data['Adj Close'][int(len(data)*0.8):]
model = ARIMA(train_data, order=(5, 1, 0))
model_fit = model.fit()
forecast = model_fit.forecast(steps=len(test_data))
mse = mean_squared_error(test_data, forecast)
rmse = np.sqrt(mse)
print(f'RMSE: {rmse}')
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data, label='Train Data')
plt.plot(test_data.index, test_data, label='Test Data')
plt.plot(test_data.index, forecast, label='Forecast')
plt.title('Stock Price Prediction')
plt.xlabel('Date')
plt.ylabel('Price (USD)')
plt.legend()
plt.show()

```

## **OUTPUT:**



## **RESULT:**

Thus, the program for stock market analysis is executed successfully.

## **5. LOAN DEFAULT PREDICTION**

<b>EX.N0 : 5</b>	<b>LOAN DEFAULT PREDICTION</b>
<b><u>DATE : 21/08/2024</u></b>	

**PROBLEM STATEMENT:** Predict loan default probability based on borrower information.

**PYTHON CONCEPTS:** Classes, functions, sequences.

**VISUALIZATION:** ROC curve, bar plots.

**MULTIVARIATE ANALYSIS:** Logistic regression, factor analysis.

**DATASET:** Lending Club Loan Data

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

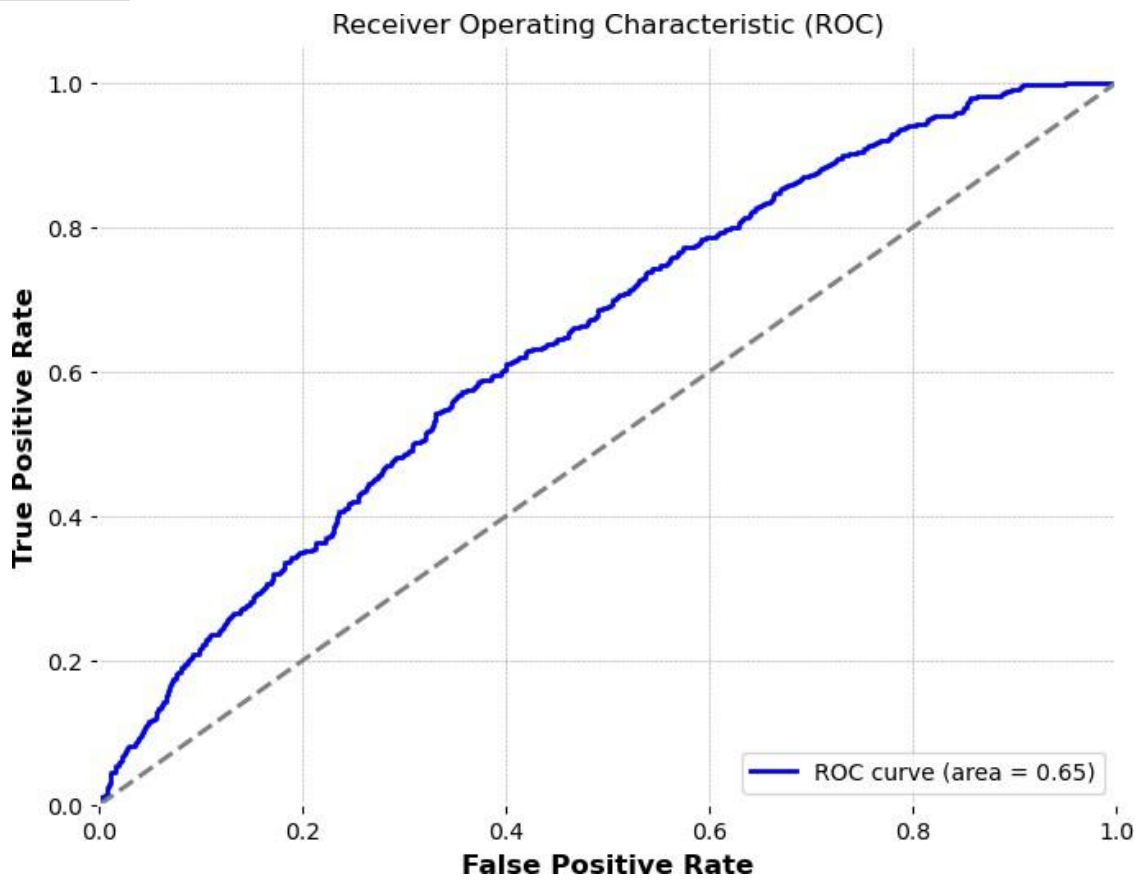
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
import os
```

```

file_path = 'C:/Users/APPU/Downloads/loan_data.csv' # Update path accordingly
if os.path.exists(file_path):
    df = pd.read_csv(file_path)
    print("Data loaded successfully.") else:
    print(f"File not found: {file_path}")
    dummies = pd.get_dummies(df['purpose'], drop_first=True)
    df = pd.concat([df, dummies], axis=1)
    df.drop('purpose', inplace=True, axis=1)
    X = df.drop(['not.fully.paid'], axis=1)
    y = df['not.fully.paid']
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    pca = PCA(n_components=2)
    X_pca = pca.fit_transform(X_scaled)
    X_train, X_test, y_train, y_test = train_test_split(X_pca, y, test_size=0.33, random_state=42)
    model = LogisticRegression()
    model.fit(X_train, y_train)
    y_pred_prob = model.predict_proba(X_test)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC)')
    plt.legend(loc='lower right')
    plt.show()

```

### **OUTPUT:**



### **RESULT:**

Thus, the program for loan default prediction is executed successfully.



## **6. IMAGE CLASSIFICATION**

<b>EX.N0 : 6</b>	<b>IMAGE CLASSIFICATION</b>
<b><u>DATE : 04/09/2024</u></b>	

**PROBLEM STATEMENT:** Classify images into categories using various features.

**PYTHON CONCEPTS:** File handling, classes.

**VISUALIZATION:** Image plots, feature importance plots.

**MULTIVARIATE ANALYSIS:** PCA, clustering.

**DATASET:** CIFAR-10 Dataset

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

```
import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import matplotlib.pyplot as plt
import numpy as np
```

```

(X_train, y_train), (X_test, y_test) = tf.keras.datasets.cifar10.load_data()
X_train, X_test = X_train / 255.0, X_test / 255.0
class_names = ['airplane', 'automobile', 'bird', 'cat', 'deer',
'dog', 'frog', 'horse', 'ship', 'truck']
plt.figure(figsize=(10,10))
for i in range(25): plt.subplot(5,5,i+1)
plt.xticks([]) plt.yticks([]) plt.grid(False)
plt.imshow(X_train[i], cmap=plt.cm.binary)
plt.xlabel(class_names[y_train[i][0]])
plt.show()
model = models.Sequential([
layers.Conv2D(32, (3, 3), activation='relu', input_shape=(32, 32, 3)),
layers.MaxPooling2D((2, 2)),
layers.Conv2D(64, (3, 3), activation='relu'),
layers.MaxPooling2D((2, 2)),
layers.Conv2D(64, (3, 3), activation='relu'),
layers.Flatten(), layers.Dense(64, activation='relu'),
layers.Dense(10) ]) model.compile(optimizer='adam',
loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
metrics=['accuracy'])
history = model.fit(X_train, y_train, epochs=10,
validation_data=(X_test, y_test))
test_loss, test_acc = model.evaluate(X_test, y_test, verbose=2)
print(f"\nTest accuracy: {test_acc}")
plt.figure(figsize=(8, 4))
plt.subplot(1, 2, 1) plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.ylabel('Accuracy') plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.subplot(1, 2, 2) plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss') plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Test'], loc='upper left')
plt.tight_layout() plt.show()

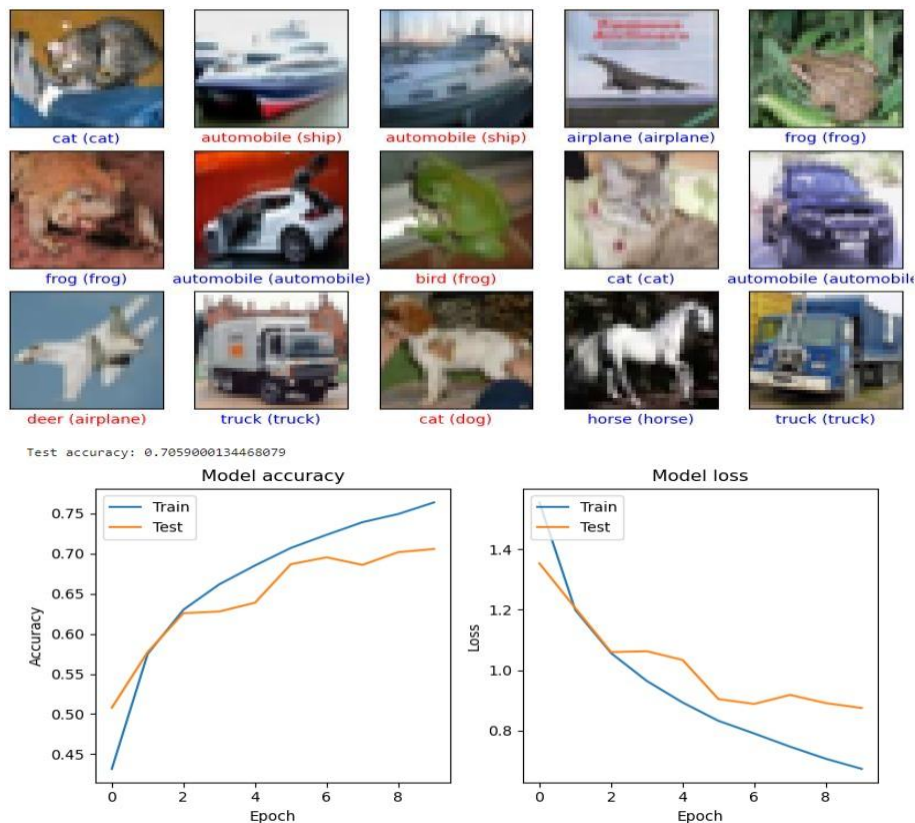
```

```

predictions = model.predict(X_test)
plt.figure(figsize=(10, 10))
for i in range(25): plt.subplot(5, 5, i+1)
plt.xticks([]) plt.yticks([]) plt.grid(False)
plt.imshow(X_test[i], cmap=plt.cm.binary)
predicted_label = np.argmax(predictions[i])
true_label = y_test[i][0]
color = 'blue' if predicted_label == true_label else 'red'
plt.xlabel(f'{class_names[predicted_label]} ({class_names[true_label]})', color=color)
plt.show()

```

### **OUTPUT:**



### **RESULT:**

Thus, the program for Image Classification is executed successfully.

## **7. PREDICTING DIABETES**

<b>EX.N0 : 7</b>	<b>PREDICTING DIABETES</b>
<b><u>DATE : 11/09/2024</u></b>	

**PROBLEM STATEMENT:** Predict the onset of diabetes based on medical measurements.

**PYTHON CONCEPTS:** Data structures, numeric types, functions.

**VISUALIZATION:** Scatter plots, heatmaps.

**MULTIVARIATE ANALYSIS:** Logistic regression, LDA.

**DATASET:** Pima Indians Diabetes Database

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
url = https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians-diabetes.data.csv
columns = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI',
'DiabetesPedigreeFunction', 'Age', 'Outcome']
```

```

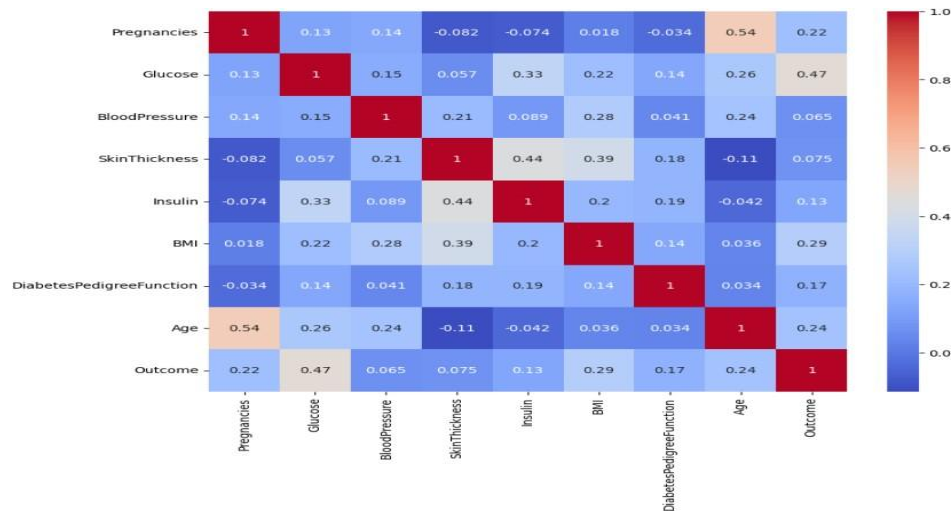
data = pd.read_csv(url, header=None, names=columns)
print("First 5 records:\n", data.head())
print("\nStatistical Summary:\n", data.describe())
print("\nDataset Info:\n")
print(data.info())
sns.pairplot(data, hue='Outcome')
plt.show()
correlation_matrix = data.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.show()
X = data.drop('Outcome', axis=1)
y = data['Outcome']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
accuracy = accuracy_score(y_test, y_pred)
print(f"\nModel Accuracy: {accuracy * 100:.2f}%")
sample = X_test.iloc[0].values.reshape(1, -1)
sample_prediction = model.predict(sample)
print(f"\nPrediction for sample case (1 = Diabetes, 0 = No Diabetes): {sample_prediction[0]}")

```

## OUTPUT:

First 5 records:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	\
0	6	148	72	35	0	33.6	
1	1	85	66	29	0	26.6	
2	8	183	64	0	0	23.3	
3	1	89	66	23	94	28.1	
4	0	137	40	35	168	43.1	



Confusion Matrix:

```
[[120 31]
 [ 30 50]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.80	0.79	0.80	151
1	0.62	0.62	0.62	80
accuracy			0.74	231
macro avg	0.71	0.71	0.71	231
weighted avg	0.74	0.74	0.74	231

Model Accuracy: 73.59%

Prediction for sample case (1 = Diabetes, 0 = No Diabetes): 0

## RESULT:

Thus, the program for predicting diabetes is executed successfully.

## **8. WINE QUALITY PREDICTION**

<b>EX.N0 : 8</b>	<b>WINE QUALITY PREDICTION</b>
<b><u>DATE : 18/09/2024</u></b>	

**PROBLEM STATEMENT:** Predict the quality of wine based on various chemical properties.

**PYTHON CONCEPTS:** Classes, sequences, file handling.

**VISUALIZATION:** Histograms, box plots.

**MULTIVARIATE ANALYSIS:** Multiple regression, factor analysis.

**DATASET:** Wine Quality Dataset

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

```

from sklearn.metrics import mean_squared_error, r2_score
class WineQualityPredictor:
def __init__(self, num_samples=1000):
self.num_samples = num_samples
self.data = None
self.model = None
def generate_data(self):
np.random.seed(42)
quality = np.random.randint(3, 9, self.num_samples) # Quality scores between 3 and 8
fixed_acidity = np.random.uniform(4.6, 15.9, self.num_samples)
volatile_acidity = np.random.uniform(0.12, 1.58, self.num_samples)
citric_acid = np.random.uniform(0, 1, self.num_samples)
residual_sugar = np.random.uniform(1.9, 15.5, self.num_samples)
chlorides = np.random.uniform(0.012, 0.1, self.num_samples)
free_sulfur_dioxide = np.random.uniform(1, 72, self.num_samples)
total_sulfur_dioxide = np.random.uniform(6, 289, self.num_samples)
density = np.random.uniform(0.99007, 1.00369, self.num_samples)
pH = np.random.uniform(2.74, 4.01, self.num_samples)
sulfur_dioxide = np.random.uniform(10, 60, self.num_samples)
alcohol = np.random.uniform(8.0, 14.9, self.num_samples)
self.data = pd.DataFrame({
'fixed acidity': fixed_acidity, 'volatile acidity': volatile_acidity, 'citric acid': citric_acid,
'residual sugar': residual_sugar, 'chlorides': chlorides, 'free sulfur dioxide': free_sulfur_dioxide,
'total sulfur dioxide': total_sulfur_dioxide, 'density': density, 'pH': pH,
'sulphur dioxide': sulfur_dioxide, 'alcohol': alcohol, 'quality': quality })
print(f'Synthetic Data Generated: {self.data.shape[0]} rows and {self.data.shape[1]} columns')
def visualize_data(self):
self.data.hist(bins=15, figsize=(15, 10))
plt.suptitle('Histograms of Wine Quality Features')
plt.show() plt.figure(figsize=(10, 6))
sns.boxplot(x='quality', y='fixed acidity', data=self.data)
plt.title('Box Plot of Fixed Acidity by Quality')
plt.show() def preprocess_data(self):
X = self.data.drop('quality', axis=1)
y = self.data['quality']

```

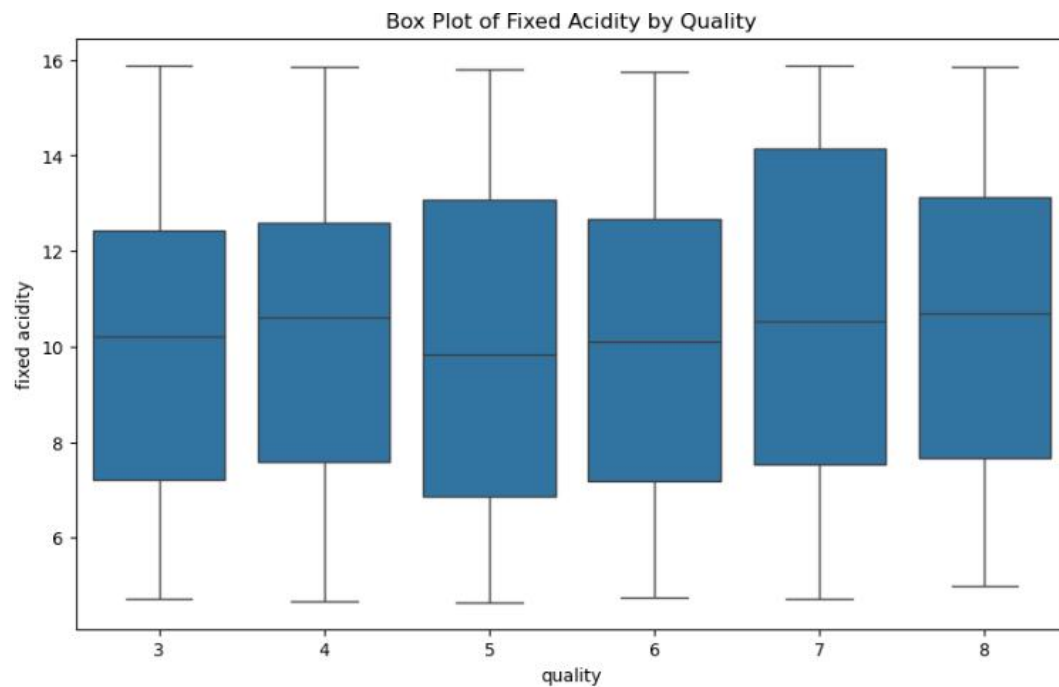
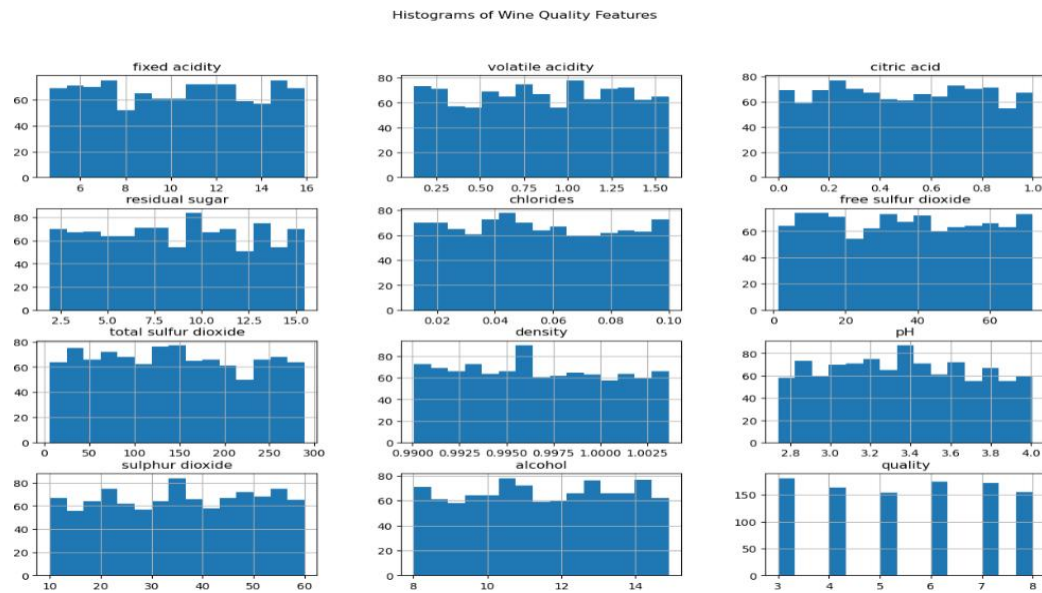


```

return X, y
def train_model(self, X, y):
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
    self.model = LinearRegression()
    self.model.fit(X_train, y_train)
    y_pred = self.model.predict(X_test)
    return y_train, y_test, y_pred
def evaluate_model(self, y_test, y_pred):
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    print(f'Mean Squared Error: {mse}')
    print(f'R^2 Score: {r2}')
def predict_quality(self, input_features):
    input_df = pd.DataFrame([input_features], columns=self.data.columns[:-1])
    prediction = self.model.predict(input_df)
    return prediction[0]
def run(self):
    self.generate_data()
    self.visualize_data()
    X, y = self.preprocess_data()
    y_train, y_test, y_pred = self.train_model(X, y)
    self.evaluate_model(y_test, y_pred)
if __name__ == "__main__":
    wine_predictor = WineQualityPredictor(num_samples=1000)
    wine_predictor.run()
    example_features = {
        'fixed acidity': 7.4, 'volatile acidity': 0.7, 'citric acid': 0.0,
        'residual sugar': 1.9, 'chlorides': 0.076, 'free sulfur dioxide': 11.0,
        'total sulfur dioxide': 34.0, 'density': 0.9978, 'pH': 3.51,
        'sulphur dioxide': 45.0, 'alcohol': 9.4 }
    predicted_quality = wine_predictor.predict_quality(example_features)
    print(f'Predicted Wine Quality: {predicted_quality:.2f}')

```

## OUTPUT:



Mean Squared Error: 2.8525212491984275  
R<sup>2</sup> Score: -0.0010251435985495494  
Predicted Wine Quality: 5.51

## RESULT:

Thus, the program for wine quality prediction is executed successfully.

## **9. HEART DISEASE PREDICTION**

<b>EX.N0 : 9</b>	<b>HEART DISEASE PREDICTION</b>
<b><u>DATE : 07/10/2024</u></b>	

**PROBLEM STATEMENT:** Predict heart disease based on clinical parameters

**PYTHON CONCEPTS:** Functions, data structures.

**VISUALIZATION:** Pair plots, ROC curve.

**MULTIVARIATE ANALYSIS:** Logistic regression, PCA.

**DATASET:** Heart Disease Dataset

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
np.random.seed(42) # For reproducibility
num_samples = 1000
age = np.random.randint(30, 80, num_samples)
sex = np.random.randint(0, 2, num_samples)
cp = np.random.randint(0, 4, num_samples)
trestbps = np.random.randint(90, 200, num_samples)
chol = np.random.randint(150, 300, num_samples)
fbs = np.random.randint(0, 2, num_samples)
restecg = np.random.randint(0, 2, num_samples)
thalach = np.random.randint(60, 200, num_samples)
exang = np.random.randint(0, 2, num_samples)
oldpeak = np.random.uniform(0, 6, num_samples)
slope = np.random.randint(0, 3, num_samples)
ca = np.random.randint(0, 4, num_samples)
thal = np.random.randint(1, 4, num_samples)
target = np.random.randint(0, 2, num_samples)
data = pd.DataFrame({
    'age': age, 'sex': sex, 'cp': cp,
    'trestbps': trestbps, 'chol': chol,
    'fbs': fbs, 'restecg': restecg, 'thalach': thalach, 'exang': exang,
    'oldpeak': oldpeak, 'slope': slope, 'ca': ca,
    'thal': thal, 'target': target})
X = data.drop('target', axis=1)
y = data['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

```

```

class_report = classification_report(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print('Confusion Matrix:')
print(conf_matrix)
print('Classification Report:')
print(class_report)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No Disease', 'Disease'],
yticklabels=['No Disease', 'Disease'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
importance = model.coef_[0]
features = X.columns
importance_df = pd.DataFrame({'Feature': features, 'Importance': importance})
importance_df = importance_df.sort_values(by='Importance', ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(data=importance_df, x='Importance', y='Feature', palette='viridis')
plt.title('Feature Importance')
plt.xlabel('Coefficient Value')
plt.ylabel('Features')
plt.axvline(0, color='red', linestyle='--') # Adding a vertical line at 0
plt.show()

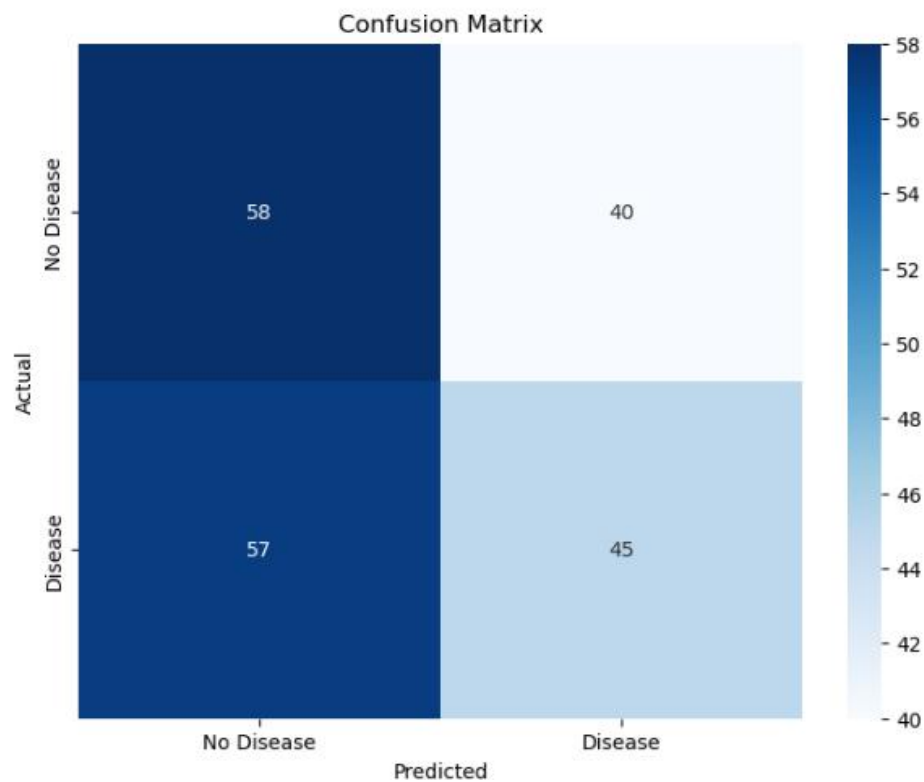
```

## **OUTPUT:**

```
Accuracy: 0.52
Confusion Matrix:
[[58 40]
 [57 45]]
Classification Report:
      precision    recall  f1-score   support

     0       0.50      0.59      0.54        98
     1       0.53      0.44      0.48       102

 accuracy          0.52          200
 macro avg         0.52          200
 weighted avg      0.52          200
```



## **RESULT:**

Thus, the program for heart disease prediction is executed successfully.

## **10. BREAST CANCER DIAGNOSIS**

<b>EX.NO : 10</b>	<b>Breast Cancer Diagnosis</b>
<b><u>DATE : 09/10/2024</u></b>	

**PROBLEM STATEMENT:** Classify tumors as benign or malignant based on features.

**PYTHON CONCEPTS:** Classes, sequences.

**VISUALIZATION:** Confusion matrix, bar plots.

**MULTIVARIATE ANALYSIS:** LDA, logistic regression.

**DATASET:** Breast Cancer Wisconsin Dataset

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
np.random.seed(42) # For reproducibility
num_samples = 1000
age = np.random.randint(30, 80, num_samples)
sex = np.random.randint(0, 2, num_samples)
cp = np.random.randint(0, 4, num_samples)
trestbps = np.random.randint(90, 200, num_samples)
chol = np.random.randint(150, 300, num_samples)
fbs = np.random.randint(0, 2, num_samples)
restecg = np.random.randint(0, 2, num_samples)
thalach = np.random.randint(60, 200, num_samples)
exang = np.random.randint(0, 2, num_samples)
oldpeak = np.random.uniform(0, 6, num_samples)
slope = np.random.randint(0, 3, num_samples)
ca = np.random.randint(0, 4, num_samples)
thal = np.random.randint(1, 4, num_samples)
target = np.random.randint(0, 2, num_samples)
data = pd.DataFrame({
    'age': age, 'sex': sex, 'cp': cp,
    'trestbps': trestbps, 'chol': chol,
    'fbs': fbs, 'restecg': restecg, 'thalach': thalach, 'exang': exang,
    'oldpeak': oldpeak, 'slope': slope, 'ca': ca,
    'thal': thal, 'target': target})
X = data.drop('target', axis=1)
y = data['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
model = LogisticRegression()
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)

```



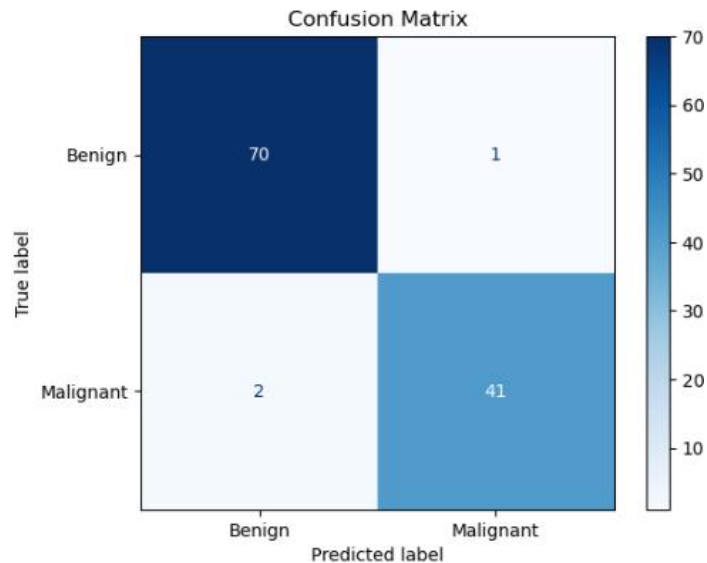
```

class_report = classification_report(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
print('Confusion Matrix:')
print(conf_matrix)
print('Classification Report:')
print(class_report)
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['No Disease', 'Disease'],
yticklabels=['No Disease', 'Disease'])
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
importance = model.coef_[0]
features = X.columns
importance_df = pd.DataFrame({'Feature': features, 'Importance': importance})
importance_df = importance_df.sort_values(by='Importance', ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(data=importance_df, x='Importance', y='Feature', palette='viridis')
plt.title('Feature Importance')
plt.xlabel('Coefficient Value')
plt.ylabel('Features')
plt.axvline(0, color='red', linestyle='--') # Adding a vertical line at 0
plt.show()

```

## OUTPUT:

	precision	recall	f1-score	support
0	0.97	0.99	0.98	71
1	0.98	0.95	0.96	43
accuracy			0.97	114
macro avg	0.97	0.97	0.97	114
weighted avg	0.97	0.97	0.97	114



```
Enter the following features for prediction: compactness_se: 0.03
radius_mean: 14.5 concavity_se: 0.03
texture_mean: 20.0 concave points_se: 0.02
perimeter_mean: 90.0 symmetry_se: 0.02
area_mean: 560.0 fractal_dimension_se: 0.003
smoothness_mean: 0.1 radius_worst: 16.0
compactness_mean: 0.15 texture_worst: 25.0
concavity_mean: 0.2 perimeter_worst: 100.0
concave points_mean: 0.1 area_worst: 800.0
symmetry_mean: 0.18 smoothness_worst: 0.14
fractal_dimension_mean: 0.06 compactness_worst: 0.25
radius_se: 0.6 concavity_worst: 0.3
texture_se: 1.2 concave points_worst: 0.15
perimeter_se: 10.0 symmetry_worst: 0.25
area_se: 40.0 fractal_dimension_worst: 0.08
smoothness_se: 0.007
```

The tumor is predicted to be: Malignant  
Based on the symptoms provided, the person may be at risk.

## RESULT:

Thus, the program for breast cancer diagnosis is executed successfully.

## **11. PREDICTING FLIGHT DELAYS**

<b>EX.N0 : 11</b>	<b>PREDICTING FLIGHT DELAYS</b>
<b><u>DATE : 16/10/2024</u></b>	

**PROBLEM STATEMENT:** Predict flight delays based on historical data.

**PYTHON CONCEPTS:** File reading/writing, functions.

**VISUALIZATION:** Line plots, scatter plots.

**MULTIVARIATE ANALYSIS:** Regression, clustering.

**DATASET:** Flight Delay Dataset

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

```

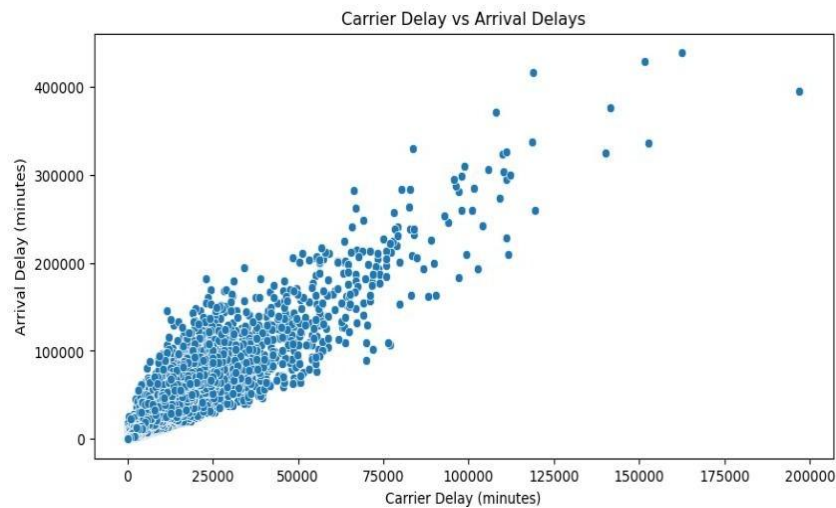
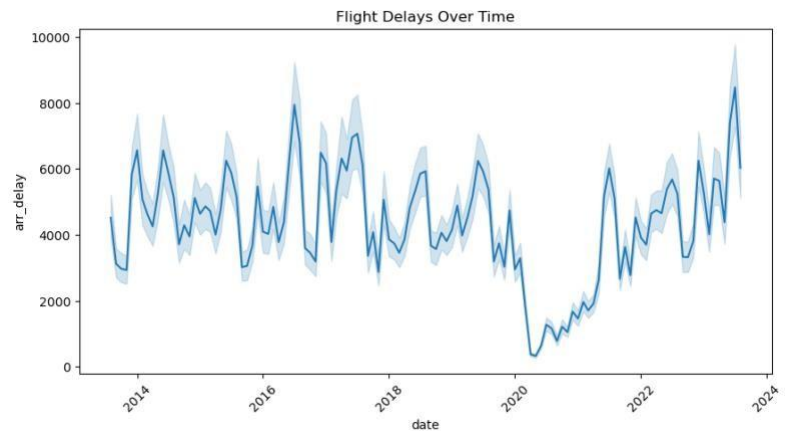
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
df = pd.read_csv('C:/Users/APPU/Downloads/Airline_Delay_Cause.csv')
print(df.columns)
print(df.isnull().sum())
df.dropna(inplace=True) # or df.fillna(method='ffill', inplace=True)
if 'year' in df.columns and 'month' in df.columns:
df['date'] = pd.to_datetime(df[['year', 'month']].assign(day=1))
plt.figure(figsize=(10, 5))
sns.lineplot(data=df, x='date', y='arr_delay') # Adjust if necessary
plt.title('Flight Delays Over Time')
plt.xticks(rotation=45)
plt.show()
delay_column = 'arr_delay' # Using 'arr_delay' for now
if 'carrier_delay' in df.columns and delay_column in df.columns:
plt.figure(figsize=(10, 5))
sns.scatterplot(data=df, x='carrier_delay', y=delay_column) # Adjust as needed
plt.title('Carrier Delay vs Arrival Delays') plt.xlabel('Carrier Delay (minutes)')
plt.ylabel('Arrival Delay (minutes)') plt.show()
else: print("Check the delay columns: 'carrier_delay' or 'arr_delay' do not exist in the
DataFrame.")
df['day_of_week'] = df['date'].dt.dayofweek # Monday=0, Sunday=6
features = ['day_of_week', 'arr_flights', 'carrier_ct'] # Modify as needed
X = df[features] y = df[delay_column]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
model = LinearRegression()
model.fit(X_train, y_train)
predictions = model.predict(X_test)
print('Mean Absolute Error:', mean_absolute_error(y_test, predictions))
print('Mean Squared Error:', mean_squared_error(y_test, predictions))
print('R-squared:', r2_score(y_test, predictions))
plt.figure(figsize=(10, 5)) plt.scatter(y_test, predictions)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linewidth=2) # Line
of equality
plt.title('Predictions vs Actual Delays') plt.xlabel('Actual Delays')
plt.ylabel('Predicted Delays') plt.show()

```

## **OUTPUT:**

```
Index(['year', 'month', 'carrier', 'carrier_name', 'airport', 'airport_name',  
      'arr_flights', 'arr_del15', 'carrier_ct', 'weather_ct', 'nas_ct',  
      'security_ct', 'late_aircraft_ct', 'arr_cancelled', 'arr_diverted',  
      'arr_delay', 'carrier_delay', 'weather_delay', 'nas_delay',  
      'security_delay', 'late_aircraft_delay'],  
      dtype='object')
```

```
year          0  
month         0  
carrier       0  
carrier_name  0  
airport       0  
airport_name  0  
arr_flights   240  
arr_del15     443  
carrier_ct    240  
weather_ct    240  
nas_ct        240  
security_ct   240  
late_aircraft_ct 240  
arr_cancelled 240  
arr_diverted  240  
arr_delay     240  
carrier_delay 240  
weather_delay 240  
nas_delay     240  
security_delay 240  
late_aircraft_delay 240  
dtype: int64
```



Mean Absolute Error: 1592.2201262853362  
Mean Squared Error: 25524907.35571326  
R-squared: 0.8439698040165798

## **RESULT:**

Thus, the program for predicting flight delays is executed successfully.

## **12. ENERGY CONSUMPTION FORECASTING**

<b>EX.N0 : 12</b>	<b>ENERGY CONSUMPTION FORECASTING</b>
<b><u>DATE : 23/10/2024</u></b>	

**PROBLEM STATEMENT:** Forecast energy consumption based on historical data.

**PYTHON CONCEPTS:** Functions, numeric types.

**VISUALIZATION:** Line plots, heatmaps.

**MULTIVARIATE ANALYSIS:** Time series analysis, regression.

**DATASET:** Energy Consumption Dataset

**ALGORITHM:**

Step 1: Start the program.

Step 2: Import necessary libraries.

Step 3: Load the dataset.

Step 4: Encode categorical variable, define feature & testing set.

Step 5: Split the dataset into training & testing set, create trained model.

Step 6: Print equal metric & test the cell.

**PROGRAM:**

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_squared_error
data = pd.read_csv('C:/Users/APPU/Downloads/energy_consumption_dataset.csv',
parse_dates=['Timestamp'], index_col='Timestamp')
print(data.head()) print(data.info())
```

```

data = data.fillna(method='ffill')
plt.figure(figsize=(14, 6))
plt.plot(data['EnergyConsumption'], color='blue', label='Energy Consumption')
plt.title('Energy Consumption Over Time')
plt.xlabel('Date') plt.ylabel('Consumption')
plt.legend() plt.show()

numeric_data = data.select_dtypes(include=[np.number])
plt.figure(figsize=(10, 8))
sns.heatmap(numeric_data.corr(), annot=True, cmap='coolwarm')
plt.title('Correlation Matrix') plt.show()

from statsmodels.tsa.seasonal import seasonal_decompose
result = seasonal_decompose(data['EnergyConsumption'], model='additive', period=24) # Adjust
period based on your data's frequency
result.plot() plt.show()

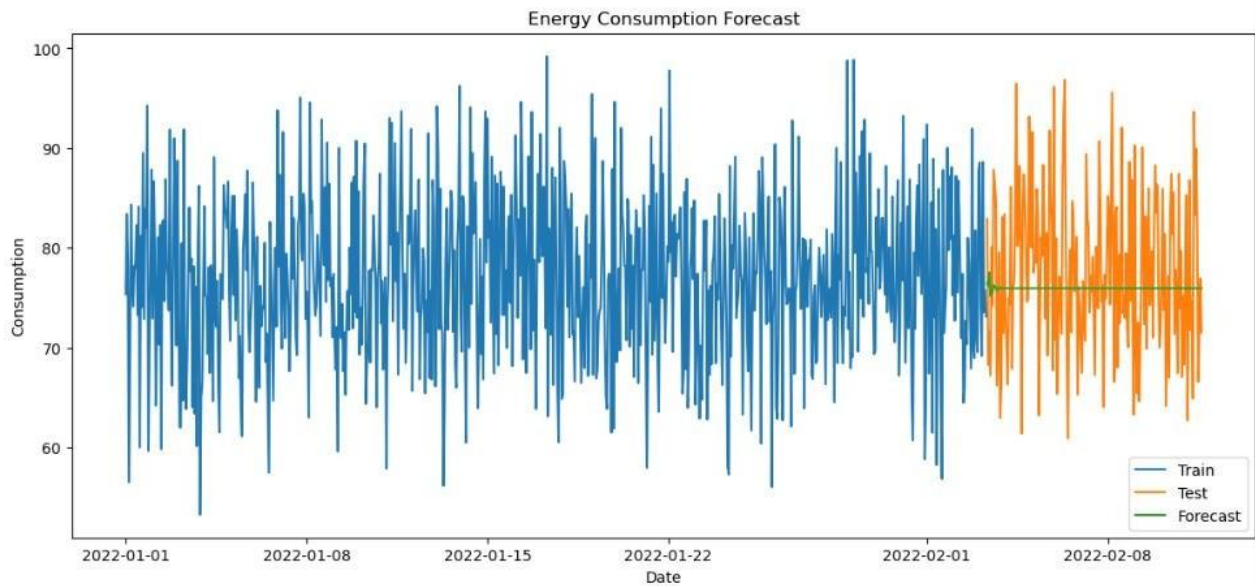
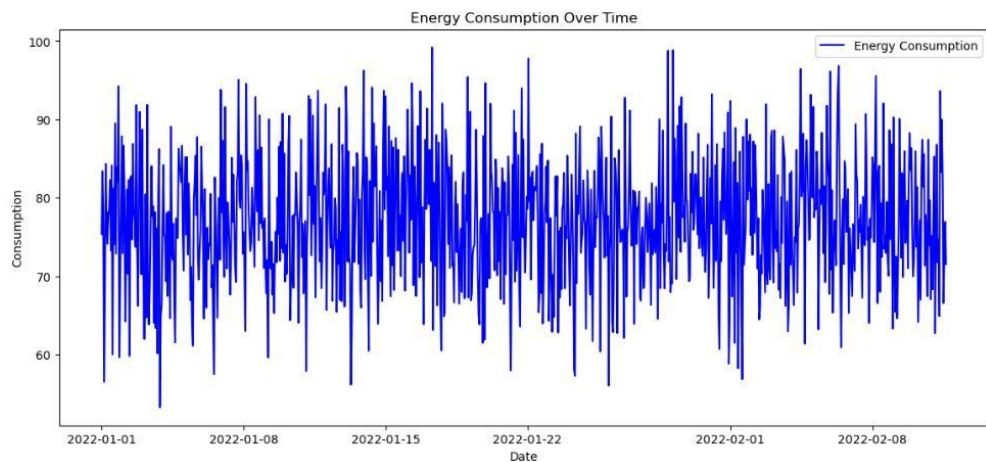
train_size = int(len(data) * 0.8)
train, test = data['EnergyConsumption'][:train_size], data['EnergyConsumption'][train_size:]
model = ARIMA(train, order=(5, 1, 0)) # Adjust (p,d,q) based on your data's behavior
fitted_model = model.fit()
forecast = fitted_model.forecast(steps=len(test))
forecast_index = test.index
mse = mean_squared_error(test, forecast)
rmse = np.sqrt(mse)
print(f'RMSE: {rmse}')

plt.figure(figsize=(14, 6))
plt.plot(train, label='Train')
plt.plot(test, label='Test')
plt.plot(forecast_index, forecast, label='Forecast')
plt.title('Energy Consumption Forecast')
plt.xlabel('Date')
plt.ylabel('Consumption')
plt.legend()
plt.show()

```

## **OUTPUT:**

Timestamp	Temperature	Humidity	SquareFootage	Occupancy \	Timestamp	HVACUsage	LightingUsage	RenewableEnergy	DayOfWeek
2022-01-01 00:00:00	25.139433	43.431581	1565.693999	5	2022-01-01 00:00:00	On	Off	2.774699	Monday
2022-01-01 01:00:00	27.731651	54.225919	1411.064918	1	2022-01-01 01:00:00	On	On	21.831384	Saturday
2022-01-01 02:00:00	28.704277	58.907658	1755.715009	2	2022-01-01 02:00:00	Off	Off	6.764672	Sunday
2022-01-01 03:00:00	20.080469	50.371637	1452.316318	1	2022-01-01 03:00:00	Off	On	8.623447	Wednesday
2022-01-01 04:00:00	23.097359	51.401421	1094.130359	9	2022-01-01 04:00:00	On	Off	3.071969	Friday



## **RESULT:**

Thus, the program for energy consumption forecasting is executed successfully.