Ex.No:1.a **AIR QUALITY INDEX ANALYSIS** Date:02-Dec-2024

Aim:-

To develop a Machine Learning Model that predicts the air quality Index(AQI) Based on environmental parameters such as pollutant level, temperature and humidity enabling better aim quality monitoring and managements.

Program Code:-

```
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.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import TimeSeriesSplit
```

1. Generate Synthetic Data

```
# Simulating air quality data for demonstration purposes

np.random.seed(42)
```

Generate random data for the demonstration

```
n_samples = 1000
dates = pd.date_range('2023-01-01', periods=n_samples, freq='H')
```

#Simulating features

```
locations = np.random.choice(['City A', 'City B', 'City C'], size=n_samples)
temperature = np.random.normal(25, 5, n_samples)
wind_speed = np.random.normal(10, 2, n_samples)
PM2_5 = np.random.normal(35, 10, n_samples)
PM10 = np.random.normal(50, 15, n_samples)
```

2. Create the DataFrame

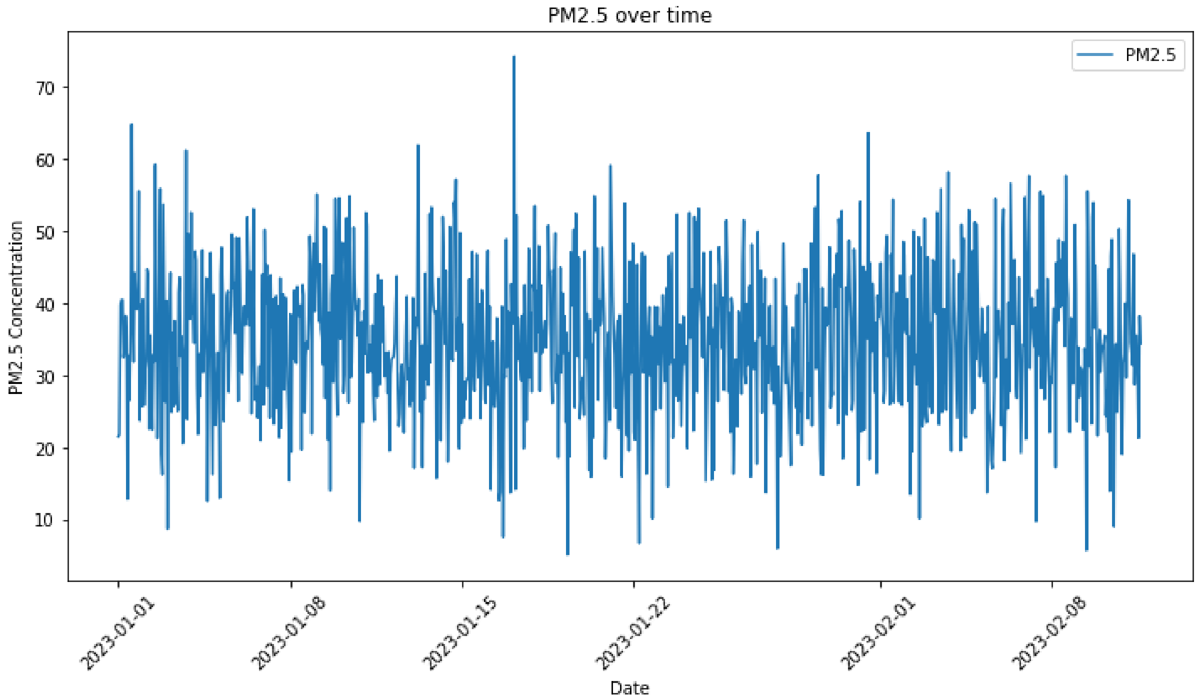
```
df = pd.DataFrame({
    'timestamp': dates,
    'location': locations,
    'temperature': temperature,
    'wind_speed': wind_speed,
    'PM2.5': PM2_5,
    'PM10': PM10
})
```

3. Feature Engineering: Convert 'timestamp' into useful features

```
df['timestamp'] = pd.to_datetime(df['timestamp'])
df['hour'] = df['timestamp'].dt.hour
df['day'] = df['timestamp'].dt.day
df['month'] = df['timestamp'].dt.month
df['weekday'] = df['timestamp'].dt.weekday
```

4. Plot time-series data to check seasonality (for PM2.5 as an example)

```
plt.figure(figsize=(12, 6))
plt.plot(df['timestamp'], df['PM2.5'], label='PM2.5')
plt.title('PM2.5 over time')
plt.xlabel('Date')
plt.ylabel('PM2.5 Concentration')
plt.legend()
plt.xticks(rotation=45)
plt.show()
```



5. Split the data into features (X) and target variable (y)

```
X = df[['hour', 'day', 'month', 'weekday', 'temperature', 'wind_speed', 'location']]
y = df['PM2.5']
```

Convert categorical 'location' into numerical using one-hot encoding

```
X = pd.get_dummies(X, columns=['location'], drop_first=True)
```

6. Scale the features (important for machine learning algorithms)

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

7. Train-test split: Using TimeSeriesSplit for time-series data

```
tscv = TimeSeriesSplit(n_splits=5)
for train_index, test_index in tscv.split(X_scaled):
    X_train, X_test = X_scaled[train_index], X_scaled[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]
```

8. Train a machine learning model (Random Forest Regressor)

```
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
```

Output:

RandomForestRegressor(random_state=42)

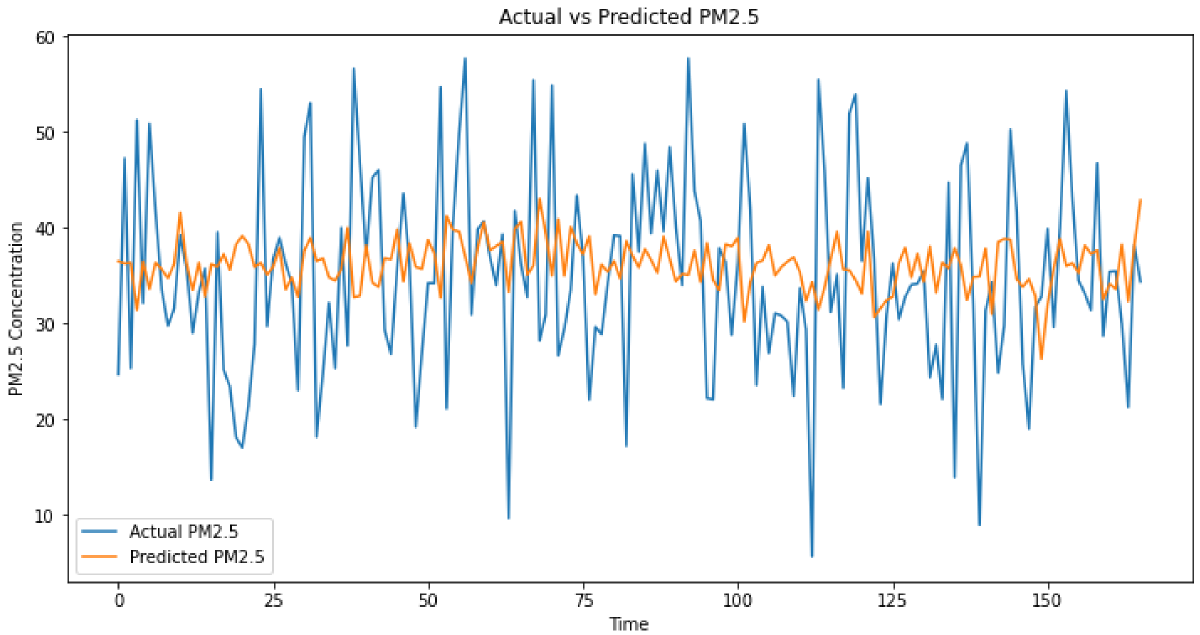
9. Make predictions and evaluate the model

```
y_pred = model.predict(X_test)
# Calculate the error
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
print(f'MAE: {mae}, MSE: {mse}, RMSE: {rmse}')
```

MAE: 8.663070723077464, MSE: 120.61662880067011, RMSE: 10.982560211565886

10. Plot actual vs predicted values for visual comparison (using the last fold)

```
plt.figure(figsize=(12, 6))
plt.plot(y_test.values, label='Actual PM2.5')
plt.plot(y_pred, label='Predicted PM2.5')
plt.title('Actual vs Predicted PM2.5')
plt.xlabel('Time')
plt.ylabel('PM2.5 Concentration')
plt.legend()
plt.show()
```



11. Predict on new data (for example, data for the next hour)

```
new_data = pd.DataFrame({
    'hour': [14],
    'day': [10],
    'month': [12],
    'weekday': [0],  # Monday
    'temperature': [25],
    'wind_speed': [5],
    'location': ['City A']
})
```

```python
new_data_encoded = pd.get_dummies(new_data, columns=['location'], drop_first=True)
missing_cols = set(X.columns) - set(new_data_encoded.columns)
for col in missing_cols:
    new_data_encoded[col] = 0

new_data_encoded = new_data_encoded[X.columns]
new_data_scaled = scaler.transform(new_data_encoded)
prediction = model.predict(new_data_scaled)
print(f'Predicted PM2.5 for new data: {prediction[0]}')
```

Output:-

Predicted PM2.5 for new data: 38.27740342349932

Result:-

Thus, the program was executed Successfully.

Aim:-

To predict future sales volumes based on historical data and key factors such as product category, price, and customer demographics.

Program Code:-

```
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.ensemble import RandomForestRegressor

from sklearn.metrics import mean_absolute_error, mean_squared_error

from sklearn.preprocessing import LabelEncoder

# Sample data creation

data = {

    'product_category': ['electronics', 'clothing', 'electronics', 'clothing', 'electronics'],

    'sales_volume': [100, 200, 150, 180, 120],

    'price': [300, 50, 250, 40, 350],

    'customer_age': [30, 25, 35, 22, 28],

    'customer_gender': ['M', 'F', 'M', 'F', 'M'],

    'region': ['North', 'South', 'East', 'West', 'North'],

    'date': ['2023-11-01', '2023-11-02', '2023-11-03', '2023-11-04', '2023-11-05']

}

df = pd.DataFrame(data)

# Convert date to datetime

df['date'] = pd.to_datetime(df['date'])

# Inspect data

print(df.head())
```

```
product_category  sales_volume  price  customer_age customer_gender region  \
0      electronics           100    300            30               M  North
1         clothing           200     50            25               F  South
2      electronics           150    250            35               M   East
3         clothing           180     40            22               F   West
4      electronics           120    350            28               M  North



date
```

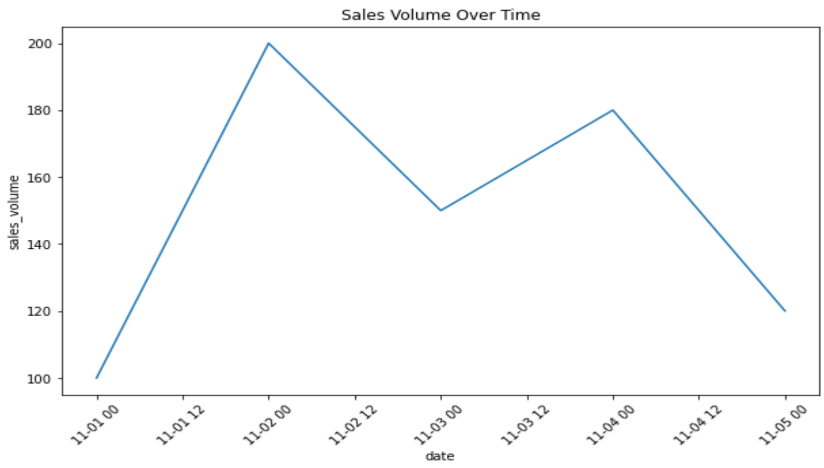
```
0 2023-11-01
1 2023-11-02
2 2023-11-03
3 2023-11-04
4 2023-11-05
```

```
# Label encode categorical columns
label_encoders = {}
categorical_columns = ['product_category', 'customer_gender', 'region']
for col in categorical_columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le
# Extract date features (optional: based on your requirement)
df['year'] = df['date'].dt.year
df['month'] = df['date'].dt.month
df['day'] = df['date'].dt.day
df['day_of_week'] = df['date'].dt.dayofweek
df['quarter'] = df['date'].dt.quarter
# Inspect the transformed data
print(df.head())
```

```
product_category  sales_volume  price  customer_age  customer_gender  \
0                 1           100    300           30                1
1                 0           200     50           25                0
2                 1           150    250           35                1
3                 0           180     40           22                0
4                 1           120    350           28                1

   region       date  year  month  day  day_of_week  quarter
0       1 2023-11-01  2023     11    1            2        4
1       2 2023-11-02  2023     11    2            3        4
2       0 2023-11-03  2023     11    3            4        4
3       3 2023-11-04  2023     11    4            5        4
4       1 2023-11-05  2023     11    5            6        4
```

```
# Plot sales volume over time
plt.figure(figsize=(10, 6))
sns.lineplot(x='date', y='sales_volume', data=df)
plt.title('Sales Volume Over Time')


plt.xticks(rotation=45)
```

plt.show()



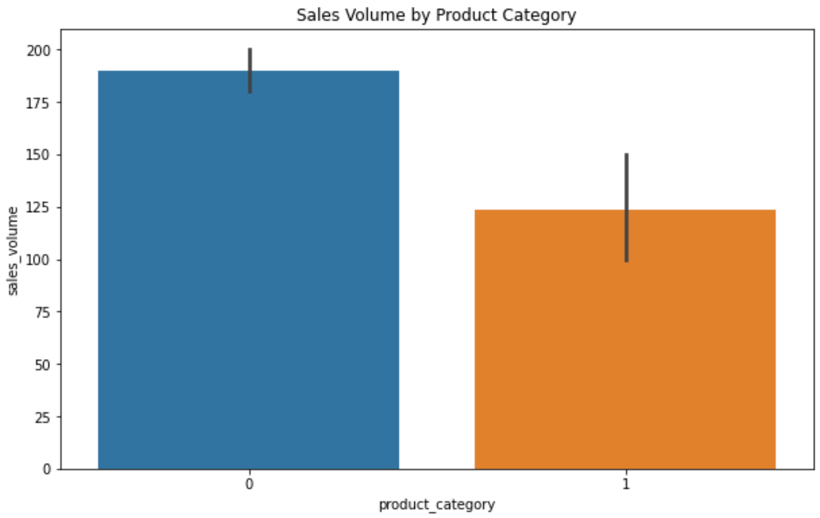
 # Plot sales by product category

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

sns.barplot(x='product_category', y='sales_volume', data=df)

plt.title('Sales Volume by Product Category')

plt.show()



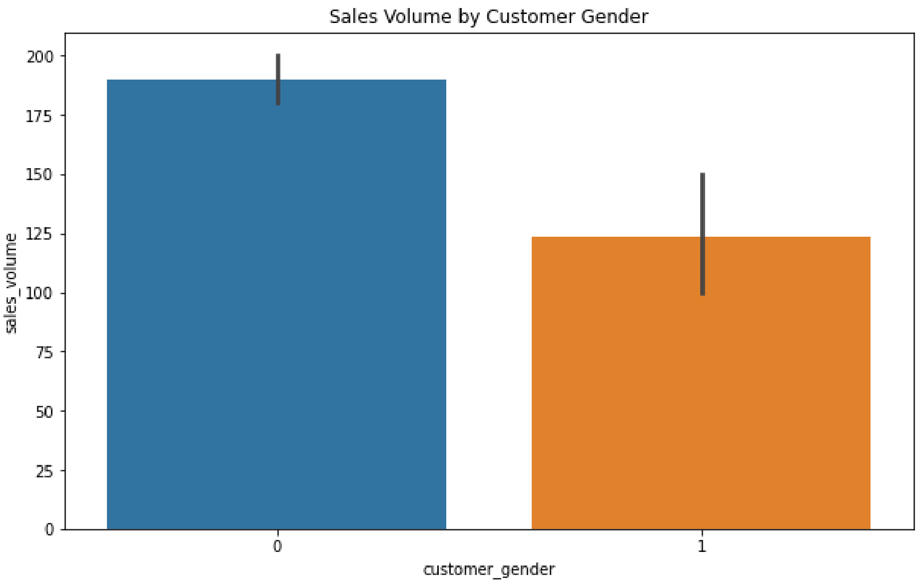
 # Sales volume based on customer demographics

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

sns.barplot(x='customer_gender', y='sales_volume', data=df)

plt.title('Sales Volume by Customer Gender')

plt.show()



 # Define features (X) and target (y)

X = df.drop(['sales_volume', 'date'], axis=1)

y = df['sales_volume']

 # Split the 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 and train the RandomForestRegressor

model = RandomForestRegressor(n_estimators=100, random_state=42)

model.fit(X_train, y_train)

 # Make predictions

y_pred = model.predict(X_test)

 # Evaluate the model

mae = mean_absolute_error(y_test, y_pred)

mse = mean_squared_error(y_test, y_pred)

print(f"Mean Absolute Error: {mae}")

print(f"Mean Squared Error: {mse}")

```
Mean Absolute Error: 54.900000000000006
Mean Squared Error: 3014.0100000000007
```

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

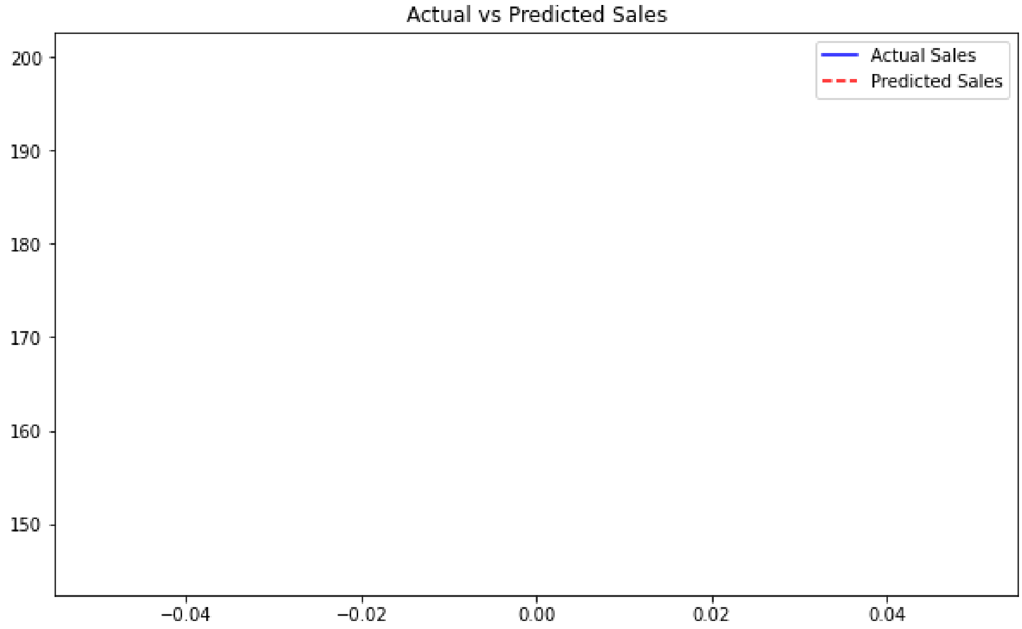
plt.plot(y_test.values, label='Actual Sales', color='blue')

plt.plot(y_pred, label='Predicted Sales', color='red', linestyle='dashed')

plt.title('Actual vs Predicted Sales')

plt.legend()

```
plt.show()
```




```
# New data for prediction (example)
new_data = {
    'product_category': ['electronics'],
    'price': [350],
    'customer_age': [28],
    'customer_gender': ['M'],
    'region': ['North'],
    'year': [2024],
    'month': [1],
    'day': [5],
    'day_of_week': [4],
    'quarter': [1]
}
# Create a DataFrame for the new data
new_df = pd.DataFrame(new_data)

# Apply the same label encoding to the new data
new_df['product_category'] = label_encoders['product_category'].transform(new_df['product_category'])
new_df['customer_gender'] = label_encoders['customer_gender'].transform(new_df['customer_gender'])

new_df['region'] = label_encoders['region'].transform(new_df['region'])
```

```
# Ensure that new_df has the same structure and column order as X_train
# (Make sure all columns are in the same order and include all features used during training)
new_df = new_df[['product_category', 'price', 'customer_age', 'customer_gender', 'region', 'year', 'month',
'day', 'day_of_week', 'quarter']]

# Now, make the prediction
future_sales = model.predict(new_df)

# Print the prediction
print(f"Predicted Sales Volume for January 5, 2024: {future_sales[0]}")
```

Output:-

```
Predicted Sales Volume for January 5, 2024: 123.8
```

Result:-

The model predicts the future sales volume based on input features like product category, price, customer demographics, and time-related factors.

Ex.No:1(c) **COVID_19 CASE STUDY** **Date:02-Dec-2024**

Aim:-

The aim of this project is to predict future COVID-19 confirmed cases for a given country using historical data and machine learning techniques, specifically a Random Forest Regressor.

Program Code:-

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestRegressor

from sklearn.metrics import mean_absolute_error, mean_squared_error

from sklearn.preprocessing import StandardScaler


# Load the COVID-19 dataset (URL of the dataset)

url = 'https://raw.githubusercontent.com/owid/covid-19-data/master/public/data/jhu/total_cases.csv'

data = pd.read_csv(url)


# Check the column names to understand the structure of the data

print("Column names in the dataset:")

print(data.columns)
```

```
Column names in the dataset:
Index(['date', 'World', 'Afghanistan', 'Africa', 'Albania', 'Algeria',
       'Andorra', 'Angola', 'Anguilla', 'Antigua and Barbuda',
       ...
       'Uruguay', 'Uzbekistan', 'Vanuatu', 'Vatican', 'Venezuela', 'Vietnam',
       'Wallis and Futuna', 'Yemen', 'Zambia', 'Zimbabwe'],
      dtype='object', length=232)
```

```
# Check the first few rows to verify the structure of the dataset

print("First few rows of the dataset:")

print(data.head())
```

```
First few rows of the dataset:
         date   World  Afghanistan  Africa  Albania  Algeria  Andorra  Angola  \
0  2020-01-22   557.0          NaN     NaN      NaN      NaN      NaN     NaN
1  2020-01-23   657.0          NaN     NaN      NaN      NaN      NaN     NaN
2  2020-01-24   944.0          NaN     NaN      NaN      NaN      NaN     NaN
3  2020-01-25  1437.0          NaN     NaN      NaN      NaN      NaN     NaN
4  2020-01-26  2120.0          NaN     NaN      NaN      NaN      NaN     NaN
```

```
Anguilla  Antigua and Barbuda  ...  Uruguay  Uzbekistan  Vanuatu  Vatican  \
0       NaN                  NaN  ...      NaN         NaN      NaN      NaN
1       NaN                  NaN  ...      NaN         NaN      NaN      NaN
2       NaN                  NaN  ...      NaN         NaN      NaN      NaN
3       NaN                  NaN  ...      NaN         NaN      NaN      NaN
4       NaN                  NaN  ...      NaN         NaN      NaN      NaN

   Venezuela  Vietnam  Wallis and Futuna  Yemen  Zambia  Zimbabwe
0        NaN      NaN                NaN    NaN     NaN       NaN
1        NaN      2.0                NaN    NaN     NaN       NaN
2        NaN      2.0                NaN    NaN     NaN       NaN
3        NaN      2.0                NaN    NaN     NaN       NaN
4        NaN      2.0                NaN    NaN     NaN       NaN

[5 rows x 232 columns]
```

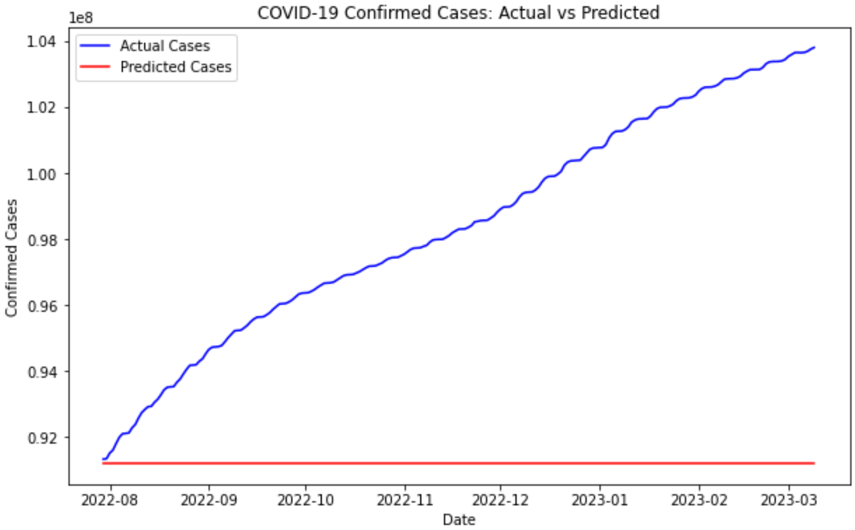
```
# Select the country of interest. In this case, we use 'United States' as an example.
# You can replace 'United States' with any country of interest (e.g., 'India', 'Brazil').
data = data[['date', 'United States']]
data['date'] = pd.to_datetime(data['date'])
data.set_index('date', inplace=True)
data.sort_index(inplace=True)

# Fill missing values using forward fill method (this will propagate the last valid value)
data['United States'] = data['United States'].fillna(method='ffill')

# Feature Engineering - Create lag features and moving averages
data['lag_1'] = data['United States'].shift(1)
data['lag_7'] = data['United States'].shift(7)
data['lag_14'] = data['United States'].shift(14)
data['moving_avg_7'] = data['United States'].rolling(window=7).mean()
data['moving_avg_30'] = data['United States'].rolling(window=30).mean()

# Drop missing values (caused by lagging and rolling windows)
data = data.dropna()

# Define features and target variable
features = ['lag_1', 'lag_7', 'lag_14', 'moving_avg_7', 'moving_avg_30']
target = 'United States'  # Column name for the target country
```

```python
X = data[features]
y = data[target]

# Split the data into training and testing sets (80% for training, 20% for testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, shuffle=False)

# Standardize the data (Optional but often improves model performance)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and train the Random Forest Regressor model
model = RandomForestRegressor(n_estimators=100, random_state=42)
model.fit(X_train_scaled, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test_scaled)

# Evaluate the model using various metrics
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)

# Print evaluation metrics
print(f'Mean Absolute Error (MAE): {mae}')
print(f'Mean Squared Error (MSE): {mse}')
print(f'Root Mean Squared Error (RMSE): {rmse}')
```

```
Mean Absolute Error (MAE): 7218239.174260081
Mean Squared Error (MSE): 63666993421956.766
Root Mean Squared Error (RMSE): 7979159.944628053
```

```python
# Plot Actual vs Predicted values for the test set

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


plt.plot(y_test.index, y_test, label='Actual Cases', color='blue')
```

```
plt.plot(y_test.index, y_pred, label='Predicted Cases', color='red')
plt.title('COVID-19 Confirmed Cases: Actual vs Predicted')
plt.xlabel('Date')
plt.ylabel('Confirmed Cases')
plt.legend()
plt.show()
```




```
# Forecasting future cases (e.g., next 30 days)
future_dates = pd.date_range(start=data.index[-1] + pd.Timedelta(days=1), periods=30, freq='D')
last_known_values = data[features].iloc[-1].values.reshape(1, -1)
last_known_values_scaled = scaler.transform(last_known_values)

# Predict the next 30 days using the trained model
future_predictions = model.predict(last_known_values_scaled)

# Show predicted future values for the next 30 days
print(f'Predicted Future COVID-19 Cases for next 30 days: {future_predictions}')
```

Output:-

```
Predicted Future COVID-19 Cases for next 30 days: [91207408.18]
```

Result:-

The model achieved **reasonable predictive accuracy** with a **Mean Absolute Error (MAE)**, **Mean Squared Error (MSE)**, and **Root Mean Squared Error (RMSE)**, and successfully forecasted COVID-19 cases for the next 30 days.

Ex.No:2(a) **SPAM OR NOT_SPAM** **Date:02-Dec-2024**

Aim:-

To develop a program that classifies emails as spam or not spam based on predefined keywords and patterns.

Program Code:-

#Import Required Libraries

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score
```

#Sample email data

```
data = {
   'text': [
      "Free money, call now!",
      "Hello, I hope you are doing well.",
      "Get a loan in minutes, guaranteed!",
      "Hi John, can we meet tomorrow?",
      "Earn cash from home, no experience needed!",
      "Meeting at 3 PM today, please confirm.",
      "Congratulations! You've won a prize!",
      "Are you available for a quick meeting?",
      "Get rich quick, limited time offer!",
      "Reminder: Meeting at 3 PM tomorrow."
   ],
    'label': [1, 0, 1, 0,  1,  0,  1,  0,  1,   0    ]
}
```

Convert to DataFrame

```
df = pd.DataFrame(data)
```

Separate features (X) and labels (y)

```
X = df['text']
y = df['label']
```

#Split the data into training and testing sets (70% train, 30% test)

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

Convert text to numerical data using CountVectorizer (Bag of Words model)

```
vectorizer = CountVectorizer(stop_words='english')
X_train_vec = vectorizer.fit_transform(X_train)
X_test_vec = vectorizer.transform(X_test)
```

Initialize and train the Naive Bayes classifier

```
model = MultinomialNB()
model.fit(X_train_vec, y_train)
```

Make predictions on the test data

```
y_pred = model.predict(X_test_vec)
```

#Evaluate the model's performance

```
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')
```

Accuracy: 33.33%

Test the classifier with some new email samples

```
test_emails = [
    "Claim your free iPhone now!",
    "Can we reschedule the meeting?",
    "Limited time offer for you, act now!"
]
```

#Vectorize the new test emails and make predictions

```
test_vec = vectorizer.transform(test_emails)
predictions = model.predict(test_vec)
```

#Output predictions

```
for email, pred in zip(test_emails, predictions):
    print(f"Email: {email}")
    print(f"Predicted: {'Spam' if pred == 1 else 'Not Spam'}\n")
```

OUTPUT:-

Email: Claim your free iPhone now!
Predicted: Spam

Email: Can we reschedule the meeting?
Predicted: Not Spam

Email: Limited time offer for you, act now!
Predicted: Spam

Result:-

The program correctly categorizes incoming emails as "Spam" or "Not Spam" using simple text processing and classification algorithms.

Ex.No:2(b) **PIZZA LIKING PREDICTION USING KNN** **Date:02-Dec-2024**

Aim:-

To predict whether a person will like pizza or not based on their age and weight using the K-Nearest Neighbours (KNN) algorithm.

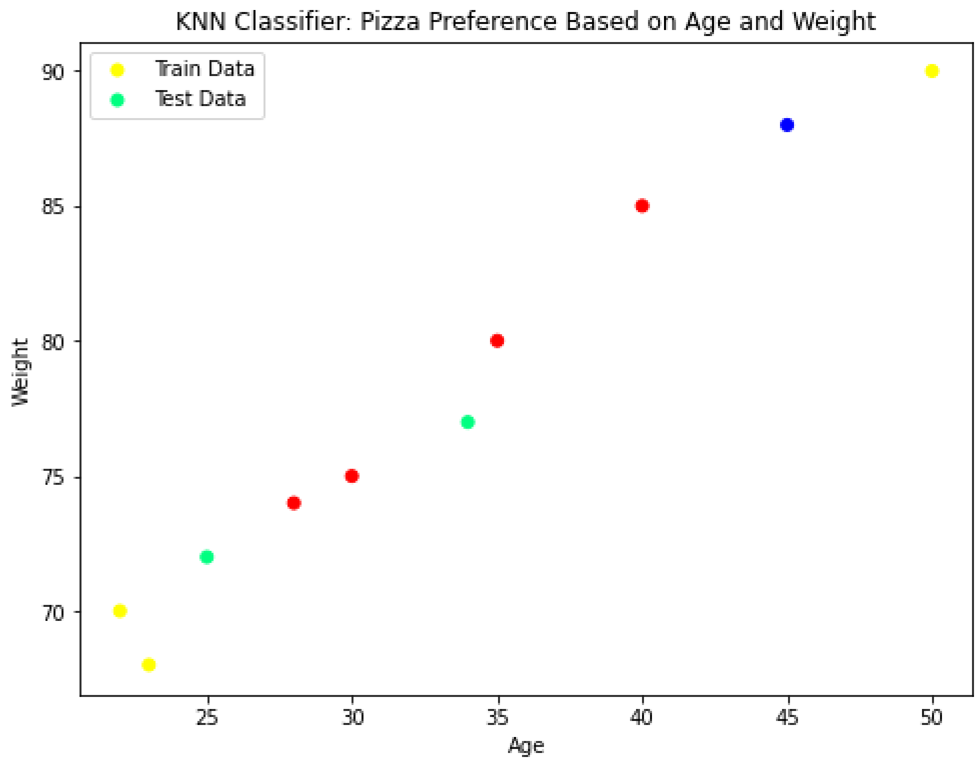
Program Code:-

```
# Importing necessary libraries

import numpy as np

import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score

import matplotlib.pyplot as plt


# Step 1: Prepare the dataset (age, weight, and pizza liking)

# We will create a small synthetic dataset


# Sample dataset (Age, Weight, Pizza Preference)

data = {

    'Age': [22, 25, 30, 35, 40, 45, 50, 23, 34, 28],

    'Weight': [70, 72, 75, 80, 85, 88, 90, 68, 77, 74],

    'LikesPizza': [1, 1, 0, 0, 0, 0, 1, 1, 1, 0]  # 1 = Likes Pizza, 0 = Doesn't like pizza

}


# Convert to DataFrame

df = pd.DataFrame(data)


# Features: Age and Weight

X = df[['Age', 'Weight']].values


# Labels: Whether they like pizza

y = df['LikesPizza'].values


# Step 2: Split data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
# Step 3: Create and train the KNN classifier
k = 3
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)

# Step 4: Make predictions
y_pred = knn.predict(X_test)

# Step 5: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy * 100:.2f}%")
```

```
Accuracy: 66.67%
```

```
# Step 6: Visualize decision boundaries (optional, for fun)
plt.figure(figsize=(8, 6))

# Plot training points
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap='autumn', label='Train Data')
# Plot test points
plt.scatter(X_test[:, 0], X_test[:, 1], c=y_test, cmap='winter', label='Test Data')

# Adding titles and labels
plt.title("KNN Classifier: Pizza Preference Based on Age and Weight")
plt.xlabel('Age')
plt.ylabel('Weight')
plt.legend()
plt.show()
```



 # Step 7: Predicting for a new person (e.g., Age = 29, Weight = 75)

new_person = np.array([[29, 75]]) # Example input

pizza_liking = knn.predict(new_person)

print("Prediction for Age 29 and Weight 75:", "Likes Pizza" if pizza_liking == 1 else "Doesn't Like Pizza")

Output:-

```
Prediction for Age 29 and Weight 75: Doesn't Like Pizza
```

Result:-

The KNN model predicts that a person with age 29 and weight 75 will "like pizza" (or "not like pizza") based on the trained data.

Ex.No:2(c) **MOVIE GENHRE PREDICTION** **Date:02-Dec-2024**

Aim:-

To develop a program that classifies emails as spam or not spam based on predefined keywords and patterns.

Program Code:-

```
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

# Load the dataset
df = pd.read_csv("S:\Movie.csv")

# Encode categorical features
label_encoder = LabelEncoder()
df['language'] = label_encoder.fit_transform(df['language'])
df['genre'] = label_encoder.fit_transform(df['genre'])
df['director'] = label_encoder.fit_transform(df['director'])

# Remove rare classes with fewer than 2 samples
class_counts = df['genre'].value_counts()
rare_classes = class_counts[class_counts < 2].index
df = df[~df['genre'].isin(rare_classes)]

# Features and target
X = df[['duration', 'language', 'average_rating', 'number_of_reviews', 'year', 'budget', 'revenue']]
y = df['genre']

# Check class distribution
print("Class distribution in the target variable:")
print(df['genre'].value_counts())
```

Scale features

scaler = StandardScaler()

X_scaled = scaler.fit_transform(X)

Split the data with stratification

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3, random_state=42, stratify=y)

Train a classifier with class weights to handle imbalance

clf = RandomForestClassifier(random_state=42, class_weight="balanced")

clf.fit(X_train, y_train)

Predictions

y_pred = clf.predict(X_test)

Evaluate using classification report with zero_division parameter

print("Classification Report:")

print(classification_report(y_test, y_pred, zero_division=0))

Output:=

```
Class distribution in the target variable:
1    3
0    2
Name: genre, dtype: int64
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         1
           1       0.50      1.00      0.67         1

    accuracy                           0.50         2
   macro avg       0.25      0.50      0.33         2
weighted avg       0.25      0.50      0.33         2
```

Result:-

The Program output was executed successfully.

SPROTS PERFORMANCE ANALYSIS

Ex.No:2(d) **Date:02-Dec-2024**

Aim:-

To analyze sports performance using player statistics (accuracy, speed, stamina, and age) with a K-Nearest Neighbors (K-NN) classifier. Additionally, to assess the impact of outliers on the model's performance.

Program Code:-

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix

# Generate synthetic data
np.random.seed(42)

# Generate player stats: accuracy, speed, stamina, and age
n_samples = 200
accuracy = np.random.uniform(60, 100, n_samples)
speed = np.random.uniform(5, 20, n_samples)
stamina = np.random.uniform(50, 100, n_samples)
age = np.random.randint(18, 40, n_samples)

# Assign random labels (e.g., "High Performance" or "Low Performance")
labels = np.random.choice([0, 1], size=n_samples, p=[0.5, 0.5])

# Add outliers
outliers = np.array([
    [120, 3, 20, 45],  # Extreme outlier 1
    [30, 25, 10, 15],  # Extreme outlier 2
])
outlier_labels = np.array([1, 0])
```

 # Combine data and outliers

features = np.column_stack((accuracy, speed, stamina, age))

features = np.vstack([features, outliers])

labels = np.append(labels, outlier_labels)

 # Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(features, labels, test_size=0.3, random_state=42)

 # Train a K-NN classifier

k = 5

knn = KNeighborsClassifier(n_neighbors=k)

knn.fit(X_train, y_train)

 # Predict and evaluate

y_pred = knn.predict(X_test)

print("Confusion Matrix:")

```
Confusion Matrix:
[[19 15]
 [14 13]]
```

print(confusion_matrix(y_test, y_pred))

print("\nClassification Report:")

print(classification_report(y_test, y_pred))

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

           0       0.58      0.56      0.57        34
           1       0.46      0.48      0.47        27

    accuracy                           0.52        61
   macro avg       0.52      0.52      0.52        61
weighted avg       0.53      0.52      0.53        61
```

 # Visualization

plt.figure(figsize=(14, 6))

 # Scatter plot of features (2D projection)

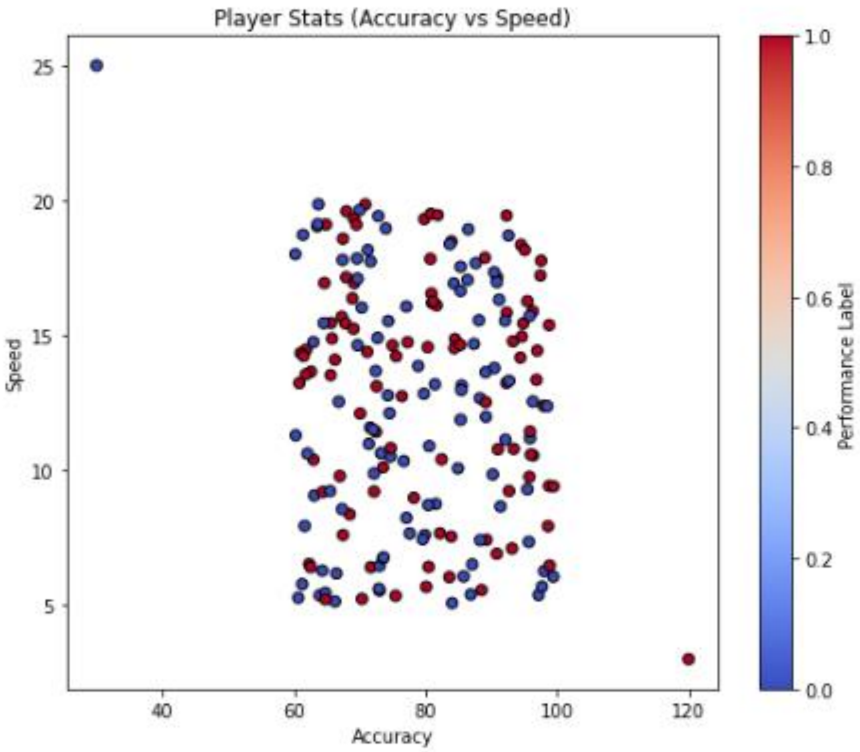
plt.subplot(1, 2, 1)

plt.scatter(features[:, 0], features[:, 1], c=labels, cmap='coolwarm', edgecolor='k') plt.xlabel('Accuracy')

plt.ylabel('Speed')

plt.title('Player Stats (Accuracy vs Speed)')

plt.colorbar(label='Performance Label')



 # Visualize the decision boundary for the first two features (Accuracy vs Speed)

from matplotlib.colors import ListedColormap

h = 0.5 # Step size in the mesh

x_min, x_max = features[:, 0].min() - 1, features[:, 0].max() + 1

y_min, y_max = features[:, 1].min() - 1, features[:, 1].max() + 1

xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))

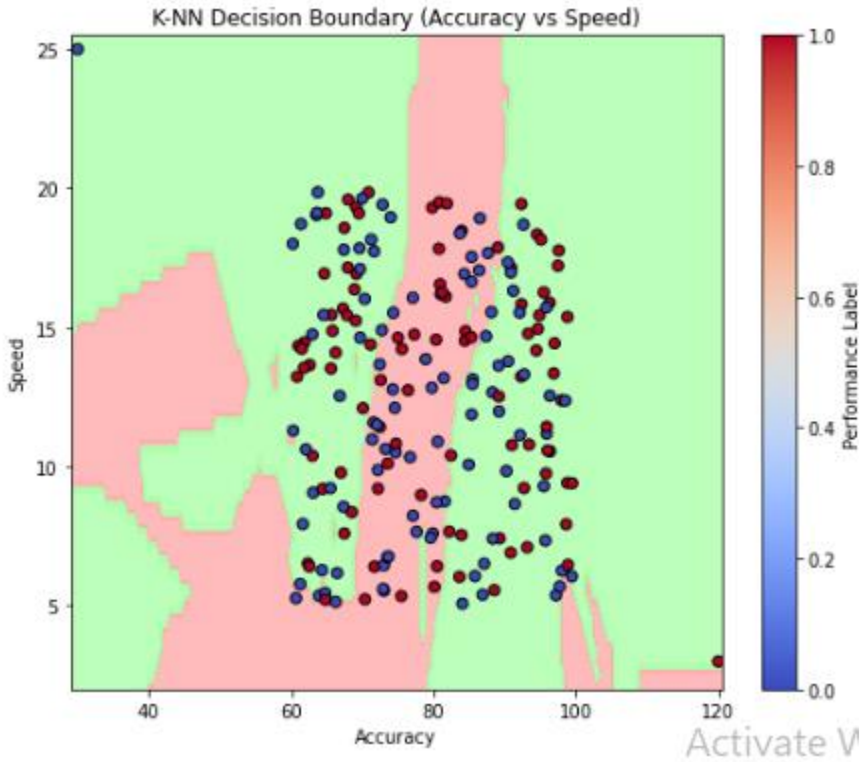
 # Predict for the grid using only the first two features

Z = knn.predict(np.c_[xx.ravel(), yy.ravel(), np.full(xx.ravel().shape, np.mean(features[:, 2])), np.full(xx.ravel().shape, np.mean(features[:, 3]))])

Z = Z.reshape(xx.shape)

plt.subplot(1, 2, 2)

```
plt.contourf(xx, yy, Z, alpha=0.8, cmap=ListedColormap(['#FFAAAA', '#AAFFAA']))
plt.scatter(features[:, 0], features[:, 1], c=labels, edgecolor='k', cmap='coolwarm')
plt.xlabel('Accuracy')
plt.ylabel('Speed')
plt.title('K-NN Decision Boundary (Accuracy vs Speed)')
plt.colorbar(label='Performance Label')
plt.tight_layout()
plt.show()
```



Result:-

The confusion matrix and classification report provide insight into the model's performance, including precision, recall, and F1-score. Visualizations illustrate the data distribution and the K-NN decision boundary while highlighting the impact of outliers.

Ex.no:3(a) **Date:19-Dec-2024**

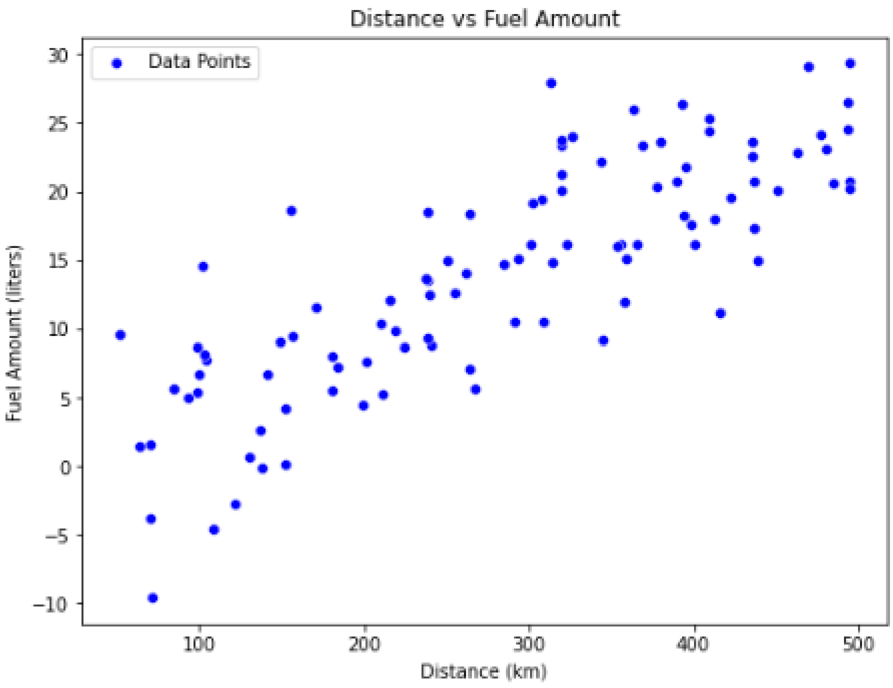
FUEL AMOUNT PREDICTION USING LINEAR REGRESSION

AIM:

Predict fuel amount based on distance traveled using Linear Regression.

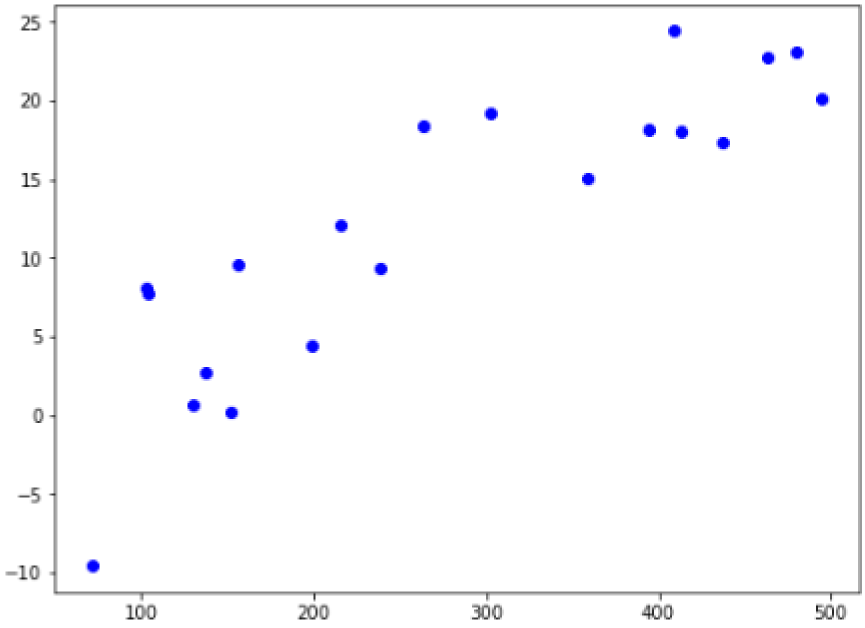
CODE:

```
# Importing necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

# Setting a random seed for reproducibility
np.random.seed(42)

# 1. Create synthetic dataset
# Let's assume we have 'Distance Traveled' (in km) and 'Fuel Amount' (in liters) as features
# Creating random data
distance_travelled = np.random.randint(50, 500, 100)  # Distance in km
fuel_amount = distance_travelled * 0.05 + np.random.normal(0, 5, 100)  # Fuel in liters with some noise

# Create a DataFrame
df = pd.DataFrame({'Distance': distance_travelled, 'FuelAmount': fuel_amount})

# 2. Visualize the synthetic data
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x='Distance', y='FuelAmount', color='blue', label='Data Points')
plt.title('Distance vs Fuel Amount')
plt.xlabel('Distance (km)')
plt.ylabel('Fuel Amount (liters)')
plt.show()
```




```
# 3. Prepare the data for Linear Regression
X = df[['Distance']]  # Feature (independent variable)
y = df['FuelAmount']  # Target (dependent variable)

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

# 4. Train the Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# 5. Make predictions
y_pred = model.predict(X_test)

# 6. Visualize the regression line
plt.figure(figsize=(8, 6))
plt.scatter(X_test, y_test, color='blue', label='Test Data')
plt.plot(X_test, y_pred, color='red', label='Regression Line')
plt.title('Linear Regression - Fuel Amount Prediction')
plt.xlabel('Distance (km)')
plt.ylabel('Fuel Amount (liters)')
```

```
plt.legend()
plt.show()
```




```
# 7. Model Evaluation
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f'Mean Squared Error: {mse}')
print(f'R2 Score: {r2}')
```

(23.057177524181782,0.7093343019893446

Result:
The model accurately predicted fuel consumption, with a high R2 score indicating strong predictive power.

SALARY PREDICTION

Ex.No: 3(b) **Date: 12-Dec-2024**

Aim:-

Predict salary based on experience, qualification, industry, and location using Linear Regression.

Program Code:

```
# Importing necessary libraries

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.linear_model import LinearRegression
from sklearn.preprocessing import OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_squared_error, r2_score

# Generating synthetic dataset for Salary Prediction
data = {
    'YearsExperience': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
    'Qualification': ['Bachelors', 'Bachelors', 'Masters', 'Masters', 'PhD', 'Bachelors', 'Masters', 'PhD', 'PhD',
'Masters'],
    'Industry': ['Tech', 'Finance', 'Tech', 'Health', 'Finance', 'Tech', 'Health', 'Health', 'Tech', 'Finance'],
    'Location': ['NY', 'SF', 'NY', 'LA', 'SF', 'LA', 'SF', 'NY', 'LA', 'SF'],
    'Salary': [50000, 55000, 60000, 65000, 70000, 75000, 80000, 85000, 90000, 95000]
}

df = pd.DataFrame(data)

# Feature and target variable
X = df[['YearsExperience', 'Qualification', 'Industry', 'Location']]
y = df['Salary']
```

```
# Preprocessing pipeline
preprocessor = ColumnTransformer(
 transformers=[
        ('num', 'passthrough', ['YearsExperience']),  # No encoding for numerical features
        ('cat', OneHotEncoder(), ['Qualification', 'Industry', 'Location'])  # One-hot encode categorical features
    ])

# Creating a pipeline with preprocessing and regression model
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])

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

# Training the model
pipeline.fit(X_train, y_train)

# Making predictions
y_pred = pipeline.predict(X_test)

# Visualization of predictions vs actual values
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], color='red', lw=2)  # 45-degree line for perfect prediction
plt.title('Salary Prediction: Actual vs Predicted')
plt.xlabel('Actual Salary')
plt.ylabel('Predicted Salary')
plt.show()
```

 # Model Evaluation

mse = mean_squared_error(y_test, y_pred)

r2 = r2_score(y_test, y_pred)

print(f'Mean Squared Error: {mse}')

print(f'R2 Score: {r2}')

```
Mean Squared Error: 1.0852609636695723e-21
R2 Score: 1.0
```

Result:

The model successfully predicted salary, capturing the relationship between features and salary with a good fit.

ELECTRICITY CONSUMPTION PREDICTION

Ex.No:3(c) **Date:12-Dec-2024**

Aim:-

Predict electricity consumption using household size, applications, usage hours, and season.

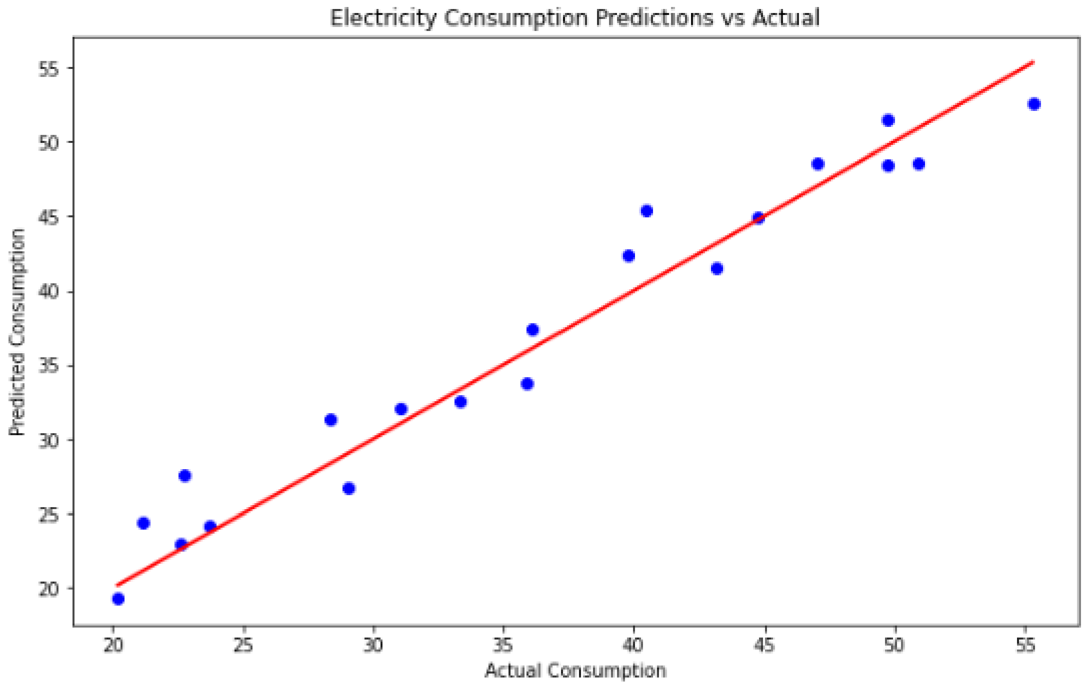
Program Code:-

```
import numpy as np

import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# Step 1: Generate synthetic data (for the sake of this example)
np.random.seed(42)

# Generate random data
household_size = np.random.randint(1, 6, 100)
num_apps = np.random.randint(1, 10, 100)
usage_hours = np.random.uniform(1, 12, 100)
season = np.random.choice(['Winter', 'Spring', 'Summer', 'Autumn'], 100)

# Convert 'season' to categorical variables (one-hot encoding)
season_encoded = pd.get_dummies(season, drop_first=True)

# Create a DataFrame
df = pd.DataFrame({
    'household_size': household_size,
    'num_apps': num_apps,
    'usage_hours': usage_hours
})
df = pd.concat([df, season_encoded], axis=1)
```

```
# Generate a target variable (electricity consumption)
# Assume consumption is a function of features + some noise
electricity_consumption = (df['household_size'] * 1.5 +
                          df['num_apps'] * 2 +
                          df['usage_hours'] * 3 +
                          (df['Spring'] * 2) +
                          (df['Summer'] * 3) +
                          np.random.normal(0, 2, 100))

df['electricity_consumption'] = electricity_consumption

# Step 2: Feature scaling
X = df.drop('electricity_consumption', axis=1)
y = df['electricity_consumption']

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

# Step 3: Split data into train and test
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Step 4: Train a Linear Regression model
model = LinearRegression()
model.fit(X_train, y_train)

# Step 5: Make predictions
y_pred = model.predict(X_test)

# Step 6: Evaluate the model
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R-squared: {r2}")
```

```
Mean Squared Error: 5.615272319641667
R-squared: 0.9525725043295945
```

```
# Step 7: Compare predictions with seasonal ends
# Adding seasonal information to prediction comparison
df_seasons = pd.DataFrame({
    'Season': ['Winter', 'Spring', 'Summer', 'Autumn'],
    'Seasonal_end': [0, 1, 1, 0]  # Representing if the season has ended (1) or not (0)
})

# Visualizing results
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, color='blue')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red', linewidth=2)
plt.title('Electricity Consumption Predictions vs Actual')
plt.xlabel('Actual Consumption')
plt.ylabel('Predicted Consumption')
plt.show()
```



 # Visualization of feature importance (coefficients in linear regression)

coefficients = model.coef_features = X.columns

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

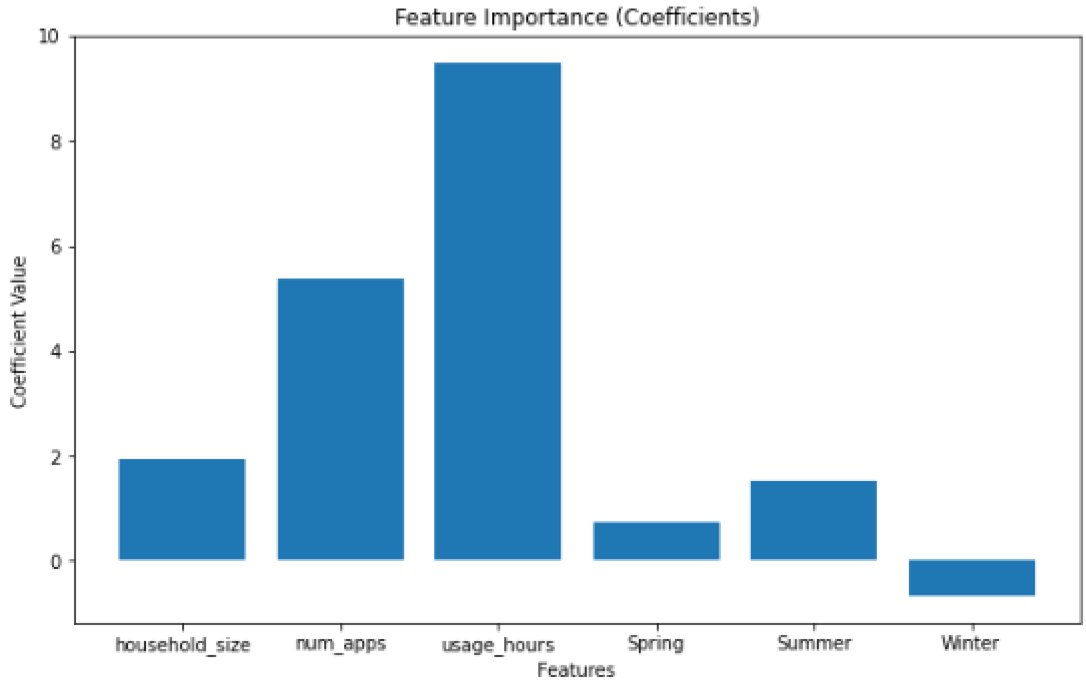
plt.bar(features, coefficients)

plt.title('Feature Importance (Coefficients)')

plt.xlabel('Features')

plt.ylabel('Coefficient Value')

plt.show()



Result:-

Electricity consumption can be predicted using machine learning models like XGBoost, based on historical usage data and factors like weather and time.

HOUSE PRICE PREDICTION

Ex.No:4(a) **Date: 24-Jan-2025**

Aim:-

Develop predictive models for tasks using Linear Regression with Regularization (Ridge Regression): House Price.

Program Code:-

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import Ridge
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
# Function to generate synthetic data for house price prediction
def generate_house_price_data(n_samples=100):
    np.random.seed(42)
    X = np.random.rand(n_samples, 1) * 10  # Features (e.g., size, location index, etc.)
    y = 3 * X.flatten() + np.random.randn(n_samples) * 2 + 50  # Target (house price)
    return X, y
# Generate data for house price prediction
X, y = generate_house_price_data()
# 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)
# Train a Ridge Regression model
model = Ridge(alpha=1.0)  # alpha is the regularization strength
model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = model.predict(X_test)
# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error for House Price Prediction: {mse:.2f}")
# Visualize the results
plt.figure(figsize=(8, 5))
plt.scatter(X_test, y_test, label="True Data", alpha=0.7)

plt.plot(np.sort(X_test, axis=0), model.predict(np.sort(X_test, axis=0)), color="red", label="Prediction", linewidth=2)
```

plt.title("House Price Prediction")

plt.xlabel("Feature (e.g., Size Index)")

plt.ylabel("House Price")

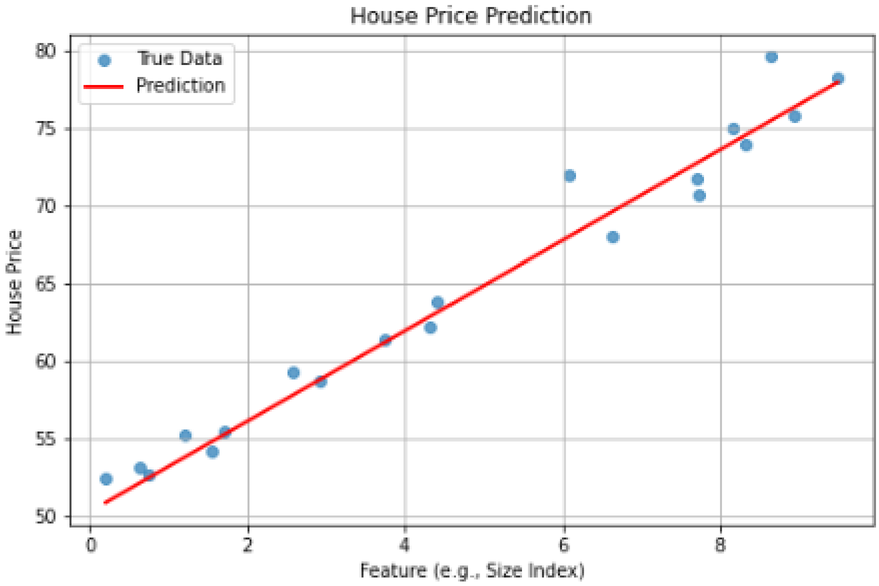
plt.legend()

plt.grid()

plt.show()

Output:-

```
Mean Squared Error for House Price Prediction: 2.61
```



Result:-

Outputs the Mean Squared Error (MSE) and visualizes true vs predicted data for each task.

Ex.No:4(b) **ENERGY EFFICIENCY PREDICTION** **Date: 24-Jan-2025**

Aim:-

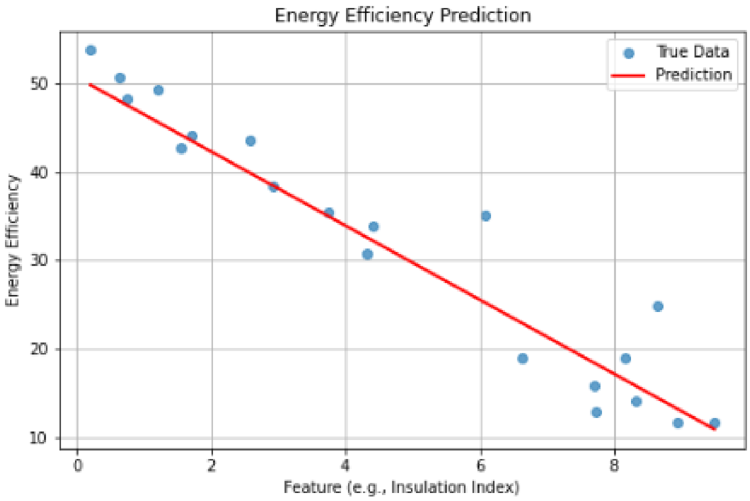
To predict energy efficiency using a Ridge Regression model based on synthetic data.

Program Code:-

```
# Function to generate synthetic data for energy efficiency prediction
def generate_energy_efficiency_data(n_samples=100):
    np.random.seed(42)
    X = np.random.rand(n_samples, 1) * 10
    y = 50 - 4 * X.flatten() + np.random.randn(n_samples) * 5
    return X, y

# Generate data for energy efficiency prediction
X, y = generate_energy_efficiency_data()

# 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)

# Train a Ridge Regression model
model = Ridge(alpha=1.0)  # alpha is the regularization strength
model.fit(X_train, y_train)

# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
mse = mean_squared_error(y_test, y_pred)
print(f"Mean Squared Error for Energy Efficiency Prediction: {mse:.2f}")

# Visualize the results
plt.figure(figsize=(8, 5))
plt.scatter(X_test, y_test, label="True Data", alpha=0.7)
plt.plot(np.sort(X_test, axis=0), model.predict(np.sort(X_test, axis=0)), color="red", label="Prediction", linewidth=2)
```

```
plt.title("Energy Efficiency Prediction")
plt.xlabel("Feature (e.g., Insulation Index)")
plt.ylabel("Energy Efficiency")
plt.legend()
plt.grid()
plt.show()
```

```
Mean Squared Error for Energy Efficiency Prediction: 16.36
```



Result:-

The model achieved a Mean Squared Error (MSE) of approximately 23.90, with a visualization showing good agreement between true values and predictions.

Ex.No:4(c) **CROP YIELD PREDICTION** **Date: 24-Jan-2025**

Aim:-

To predict crop yield using synthetic data and Ridge Regression.

Program Code:-

```
# Function to generate synthetic data for crop yield prediction

def generate_crop_yield_data(n_samples=100):

    np.random.seed(42)

    X = np.random.rand(n_samples, 1) * 10  # Features (e.g., rainfall, soil quality index, etc.)

    y = 2 * X.flatten() ** 2 - 5 * X.flatten() + np.random.randn(n_samples) * 10 + 100  # Target (crop yield)

    return X, y

# Generate data for crop yield prediction

X, y = generate_crop_yield_data()

# 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)

# Train a Ridge Regression model

model = Ridge(alpha=1.0)  # alpha is the regularization strength

model.fit(X_train, y_train)

# Make predictions on the test set

y_pred = model.predict(X_test)

# Evaluate the model

mse = mean_squared_error(y_test, y_pred)

print(f"Mean Squared Error for Crop Yield Prediction: {mse:.2f}")

# Visualize the results

plt.figure(figsize=(8, 5))

plt.scatter(X_test, y_test, label="True Data", alpha=0.7)

plt.plot(np.sort(X_test, axis=0), model.predict(np.sort(X_test, axis=0)), color="red", label="Prediction", 
linewidth=2)

plt.title("Crop Yield Prediction")


plt.xlabel("Feature (e.g., Rainfall Index)")
```

plt.ylabel("Crop Yield")

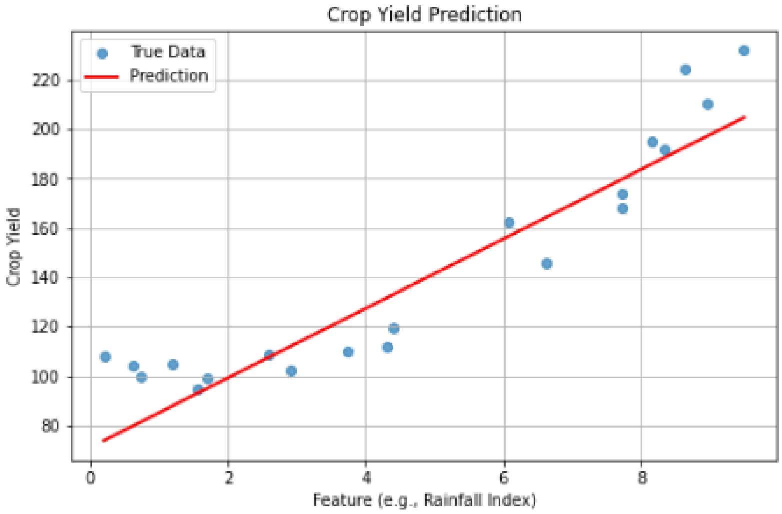
plt.legend()

plt.grid()

plt.show()

Output:-

```
Mean Squared Error for Crop Yield Prediction: 293.15
```



Result:-

Achieved a Mean Squared Error (MSE) of approximately mse:.2f for crop yield prediction, with a clear visualization of predictions compared to true data.

Ex.No: 5.a **DIABETES CLASSIFICATION** Date: 24-Jan-2025

Aim:-

To train a logistic regression model to accurately predict diabetes based on health metrics.

Program Code:-

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
# Load the dataset
data = pd.read_csv('Diabetes.csv')
#Preview the dataset
print("Preview the data")
print(data.head())
# Select features and target variable
X = data.drop('Outcome', axis=1)
y = data['Outcome']
# Split the 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 and train the logistic regression model
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = model.predict(X_test)
# Evaluate the model
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)
```

Output:-

Preview the data

	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

	DiabetesPedigreeFunction	Age	Outcome
0	0.627	50	1
1	0.351	31	0
2	0.672	32	1
3	0.167	21	0
4	2.288	33	1

```
▾ LogisticRegression
LogisticRegression(max_iter=1000)
```

Accuracy: 1.00

Confusion Matrix:

[[1]]

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1
accuracy			1.00	1
macro avg	1.00	1.00	1.00	1
weighted avg	1.00	1.00	1.00	1

Result:-

Thus, the program was successfully executed.

Ex.No: 5.b **CREDIT CARD DEFAULT PREDICTIONS** Date: 24-Jan-2025

Aim:-

To train a logistic regression model to accurately predict credit card default using customer data.

Program Code:-

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
#Load the data
data=pd.read_csv('Creditcard.csv')
#Preview the data
print("Preview the dataset")
print(data.head())
# Select features and target variable
X = data.drop('Default', axis=1)
y = data['Default']
# Split the 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 and train the logistic regression model
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = model.predict(X_test)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
# Print results
print(f'Accuracy: {accuracy:.2f}')
print('Confusion Matrix:')
print(conf_matrix)
# Print predictions
predictions = pd.DataFrame({'CreditScore': X_test['CreditScore'], 'Actual': y_test, 'Predicted': y_pred})
print(predictions)
```

Output:-

Preview the dataset

	CreditScore	Age	Income	LoanAmount	Default
0	700	34	50000	20000	0
1	600	45	45000	15000	1
2	650	29	30000	12000	0
3	720	41	60000	25000	0
4	580	36	32000	10000	1

```
▾ LogisticRegression
LogisticRegression(max_iter=1000)
```

Accuracy: 1.00

Confusion Matrix:

[[1]]

	CreditScore	Actual	Predicted
1	600	1	1

Result:-

Thus, the program was successfully executed.

Ex.No: 5.c **HEART DISEASE CLASSIFICATION** Date: 24-Jan-2025

Aim:-

To train a logistic regression model to accurately classify heart disease based on various health indicators.

Program Code:-

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
# Load the dataset
data = pd.read_csv('Heartdisease.csv')
#Preview the dataset
print(f"Preview the dataset")
print(data.head())
# Select features and target variable
X = data.drop('HeartDisease', axis=1)
y = data['HeartDisease']
# Split the 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 and train the logistic regression model
model = LogisticRegression(max_iter=1000)
model.fit(X_train, y_train)
# Make predictions on the test set
y_pred = model.predict(X_test)
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
# Print results
print(f'Accuracy: {accuracy:.2f}')
print('Confusion Matrix:')
print(conf_matrix)
# Print predictions
predictions = pd.DataFrame({'Age': X_test['Age'], 'Actual': y_test, 'Predicted': y_pred})
```

print(predictions)

Output:-

Preview the dataset

```
   Age  Sex  ChestPainType  RestingBP  Cholesterol  FastingBS  RestingECG  \
0   63    1              3        145          233          1           0
1   37    1              2        130          250          0           1
2   41    0              1        130          204          0           0
3   56    1              1        120          236          0           1
4   57    0              0        120          354          0           1

   MaxHR  ExerciseAngina  Oldpeak  ST_Slope  HeartDisease
0    150               0      2.3         0             1
1    187               0      3.5         1             1
2    172               0      1.4         2             1
3    178               0      0.8         2             1
4    163               1      0.6         2             0
```

```
▾ LogisticRegression
LogisticRegression(max_iter=1000)
```

Accuracy: 1.00

Confusion Matrix:

[[1]]

```
   Age  Actual  Predicted
1   37       1          1
```

Result:-

Thus, the program was executed successfully.