```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
```

```
df = pd.read_excel('/content/Karachi.xlsx')
```

# 1. Data source:

We were able to get Karachi's weather data of the year 2022 from Pakistan Meteorological Department for research and educational purposes.

## Data Description:

1. Wind_direction: Measured in degrees
2. Wind_speed: Measured in (km/h)
3. Air Pressure: Measured in hPa
4. Humidity: Measured in percentage (converted from g.m-^3, which is units of grams of water vapour per cubic metre of air)
5. Clouds: Measured in oktas (from 0-8, with 0 meaning sky is clear, and 8 meaning sky is completey covered.
6. Rainfall: Measured in milimeters (mm)

# 2. Data Pre-processing

```
df.head()
```

| | Date | Min_temp | Max_temp | Wind_speed | Wind_direction | Rainfall | Air Pressure | Humidity | C |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 2022-01-01 | 12.9 | 23.8 | 4 | 23 | 0 | 1021.2 | 57 | |
| **1** | 2022-01-02 | 13.5 | 25.4 | 6 | 23 | 0 | 1019.5 | 46 | |
| **2** | 2022-01-03 | 16.0 | 25.5 | 6 | 23 | 0 | 1017.8 | 40 | |

```
df.tail()
```

| | Date | Min_temp | Max_temp | Wind_speed | Wind_direction | Rainfall | Air Pressure | Hum |
|---|---|---|---|---|---|---|---|---|
| **360** | 2022-12-27 | 12.5 | 26.5 | 2 | 45 | 0 | 1020.4 | |
| **361** | 2022-12-28 | 13.0 | 27.0 | 4 | 68 | 0 | 1018.5 | |
| **362** | 2022-12-29 | 14.5 | 27.1 | 0 | 0 | 0 | 1017.3 | |

**2.1:** Converting our date column to pandas datetime, because it is easier to use.

```
# convert the 'Date' column to a datetime data type
df['Date'] = pd.to_datetime(df['Date'])
```

```
#some rainfall data has "trace", changing to numeric values
df["Rainfall"] = pd.to_numeric(df["Rainfall"], errors='coerce')
```

```
df.columns
```

```
Index(['Date', 'Min_temp', 'Max_temp', 'Wind_speed', 'Wind_direction',
       'Rainfall', 'Air Pressure', 'Humidity', 'Clouds'],
      dtype='object')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 365 entries, 0 to 364
Data columns (total 9 columns):
 #   Column          Non-Null Count  Dtype         
---  ------          --------------  -----         
 0   Date            365 non-null    datetime64[ns]
 1   Min_temp        365 non-null    float64       
 2   Max_temp        365 non-null    float64       
 3   Wind_speed      365 non-null    int64         
 4   Wind_direction  365 non-null    int64         
 5   Rainfall        348 non-null    float64       
 6   Air Pressure    365 non-null    float64       
 7   Humidity        365 non-null    int64         
 8   Clouds          365 non-null    int64         
dtypes: datetime64[ns](1), float64(4), int64(4)
memory usage: 25.8 KB
```

```
df.isna().sum()
```

```
Date              0
Min_temp          0
Max_temp          0
Wind_speed        0
Wind_direction    0
Rainfall         17
Air Pressure      0
Humidity          0
Clouds            0
dtype: int64
```

**2.2:** displaying frequency and unique values for each column in our dataset

```
for column in df.columns:
    print("Unique values for column '{}':".format(column))
    print(df[column].unique())
    print("\nValue counts for column '{}':".format(column))
    print(df[column].value_counts())
    print("\n")
```

```
'2022-02-26T00:00:00.000000000' '2022-02-27T00:00:00.000000000'
'2022-02-28T00:00:00.000000000' '2022-03-01T00:00:00.000000000'
'2022-03-02T00:00:00.000000000' '2022-03-03T00:00:00.000000000'
'2022-03-04T00:00:00.000000000' '2022-03-05T00:00:00.000000000'
'2022-03-06T00:00:00.000000000' '2022-03-07T00:00:00.000000000'
'2022-03-08T00:00:00.000000000' '2022-03-09T00:00:00.000000000'
'2022-03-10T00:00:00.000000000' '2022-03-11T00:00:00.000000000'
'2022-03-12T00:00:00.000000000' '2022-03-13T00:00:00.000000000'
'2022-03-14T00:00:00.000000000' '2022-03-15T00:00:00.000000000'
'2022-03-16T00:00:00.000000000' '2022-03-17T00:00:00.000000000'
```

```
'2022-05-15T00:00:00.000000000' '2022-05-16T00:00:00.000000000'
'2022-05-17T00:00:00.000000000' '2022-05-18T00:00:00.000000000'
'2022-05-19T00:00:00.000000000' '2022-05-20T00:00:00.000000000'
'2022-05-21T00:00:00.000000000' '2022-05-22T00:00:00.000000000'
'2022-05-23T00:00:00.000000000' '2022-05-24T00:00:00.000000000'
'2022-05-25T00:00:00.000000000' '2022-05-26T00:00:00.000000000'
'2022-05-27T00:00:00.000000000' '2022-05-28T00:00:00.000000000'
'2022-05-29T00:00:00.000000000' '2022-05-30T00:00:00.000000000'
'2022-05-31T00:00:00.000000000' '2022-06-01T00:00:00.000000000'
'2022-06-02T00:00:00.000000000' '2022-06-03T00:00:00.000000000'
'2022-06-04T00:00:00.000000000' '2022-06-05T00:00:00.000000000'
'2022-06-06T00:00:00.000000000' '2022-06-07T00:00:00.000000000'
'2022-06-08T00:00:00.000000000' '2022-06-09T00:00:00.000000000'
'2022-06-10T00:00:00.000000000' '2022-06-11T00:00:00.000000000'
'2022-06-12T00:00:00.000000000' '2022-06-13T00:00:00.000000000'
'2022-06-14T00:00:00.000000000' '2022-06-15T00:00:00.000000000'
'2022-06-16T00:00:00.000000000' '2022-06-17T00:00:00.000000000'
'2022-06-18T00:00:00.000000000' '2022-06-19T00:00:00.000000000'
```

## 3. Feature Engineering

**3.1:** Dewpoint calculation

- Dewpoint is caclulated by the Magnus Formula, which takes into account the temperature, humidity and air pressure.
- We have created a function, which calculates dewpoint based on these parameters, and created a new column as Dew_point in our dataset
- We also only had min and max temperatures, so we calculated the average temperature for each day and used it for dewpoint calculation.

$$\text{Dew Point} = \frac{243.12 \times \left\{ \ln\left(\frac{RH}{100}\right) + \frac{17.62 \times T}{243.12 + T} \right\}}{17.62 - \left\{ \ln\left(\frac{RH}{100}\right) + \frac{17.62 \times T}{243.12 + T} \right\}}$$

Formula for dewpoint is as follows:

```
from numpy import log, e

def calculate_dewpoint(temperature, humidity):
    dewpoint = (243.12 * ((log((humidity/100) * (6.112 * (e ** ((17.62 * temperature) / (243.04 + temperature)))))))) / (17.62 - log((humidit
    return dewpoint

#calculate average temperature because we have min and max
df["Temperature"] = (df["Min_temp"] + df["Max_temp"])/2

#calculate dewpoint
df["Dew_point"] = calculate_dewpoint(df["Temperature"], df["Humidity"])
```

```
df.head()
```

| | Date | Min_temp | Max_temp | Wind_speed | Wind_direction | Rainfall | Air Pressure | Humidity | Clouds | Temperature | Dew_point |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2022-01-01 | 12.9 | 23.8 | 4 | 23 | 0 | 1021.2 | 57 | 2 | 18.35 | 39.919259 |
| **1** | 2022-01-02 | 13.5 | 25.4 | 6 | 23 | 0 | 1019.5 | 46 | 0 | 19.45 | 37.219492 |
| **2** | 2022-01-03 | 16.0 | 25.5 | 6 | 23 | 0 | 1017.8 | 40 | 3 | 20.75 | 36.134650 |
| **3** | 2022-01-04 | 17.0 | 25.5 | 4 | 45 | 0 | 1016.9 | 49 | 7 | 21.25 | 40.453937 |
| **4** | 2022-01-05 | 14.8 | 23.5 | 0 | 0 | 20.7 | 1015.5 | 95 | 8 | 19.15 | 50.810661 |

**3.2:** Conditions classification

- We are going to classify each day in our dataset into 5 different weather conditions.
- The weather conditions include **"Sunny", "Windy", "Rainy", "Cloudy" and "Stormy".**
- We are classifying our days based on the values of "Rainfall", "Wind_speed", "Clouds" and "Air Pressure".

```
# Create a new column 'Conditions'
df['Conditions'] = ''

# Classify each day as one of the conditions
for i in range(len(df)):
    if (df['Rainfall'][i] > 0):
```

```
        df.at[i, 'Conditions'] = 'Rainy'
    elif (df['Wind_speed'][i] > 15):
        df.at[i, 'Conditions'] = 'Windy'
    elif (df['Clouds'][i] > 6):
        df.at[i, 'Conditions'] = 'Cloudy'
    elif (df['Air Pressure'][i] < 1000):
        df.at[i, 'Conditions'] = 'Stormy'
    else:
        df.at[i, 'Conditions'] = 'Sunny'

df.head()
```

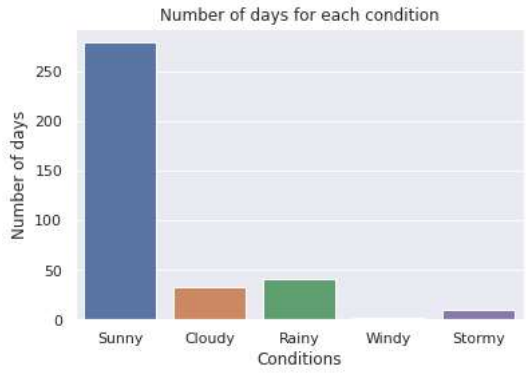
| | Date | Min_temp | Max_temp | Wind_speed | Wind_direction | Rainfall | Air Pressure | Humidity | Clouds | Temperature | Dew_point | Conditions |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 2022-01-01 | 12.9 | 23.8 | 4 | 23 | 0.0 | 1021.2 | 57 | 2 | 18.35 | 39.919259 | Sunny |
| 1 | 2022-01-02 | 13.5 | 25.4 | 6 | 23 | 0.0 | 1019.5 | 46 | 0 | 19.45 | 37.219492 | Sunny |
| 2 | 2022-01-03 | 16.0 | 25.5 | 6 | 23 | 0.0 | 1017.8 | 40 | 3 | 20.75 | 36.134650 | Sunny |

# 4. Data Visualization

**4.1:** Weather conditions over count of days

```
import seaborn as sns

sns.countplot(df['Conditions'])
plt.xlabel("Conditions")
plt.ylabel("Number of days")
plt.title("Number of days for each condition")
plt.savefig("conditions.png", dpi = 300)
plt.show()
```

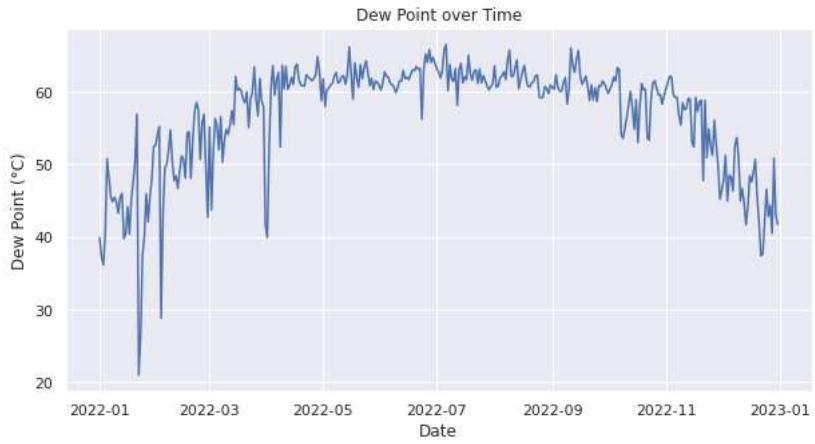
```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From v
  warnings.warn(
```




**Observation**: In the year 2022, majority of the days were sunny.

**4.2:** Dewpoint over time

```
#set date as the index
df.set_index("Date", inplace=True)

plt.figure(figsize=(10,5))
plt.plot(df["Dew_point"])
plt.xlabel("Date")
plt.ylabel("Dew Point (°C)")
plt.title("Dew Point over Time")
plt.savefig('dewpoint_over_time.png', dpi = 300)
plt.show()
```

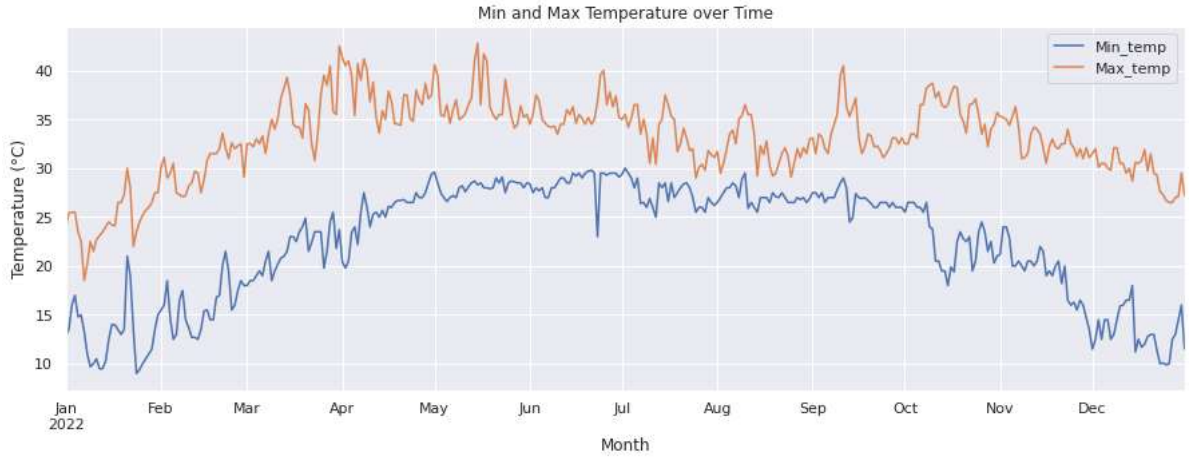



**Observation**:

- The sudden drop in dew point readings between January and March, and between March and May that we are observing in our graph could indicate a change in weather patterns during those periods.
- Dew point temperature is a measure of the amount of moisture in the air, so a drop in dew point temperature typically indicates that the air is becoming drier.

**4.3:** Min and Max temperatures during all 12 months of 2022

```
# plot the time series of 'Min_temp' and 'Max_temp'
df[['Min_temp', 'Max_temp']].plot(figsize=(15,5))
plt.xlabel('Month')
plt.ylabel('Temperature (°C)')
plt.title('Min and Max Temperature over Time')
plt.savefig("min_max.png", dpi=300)
plt.show()
```

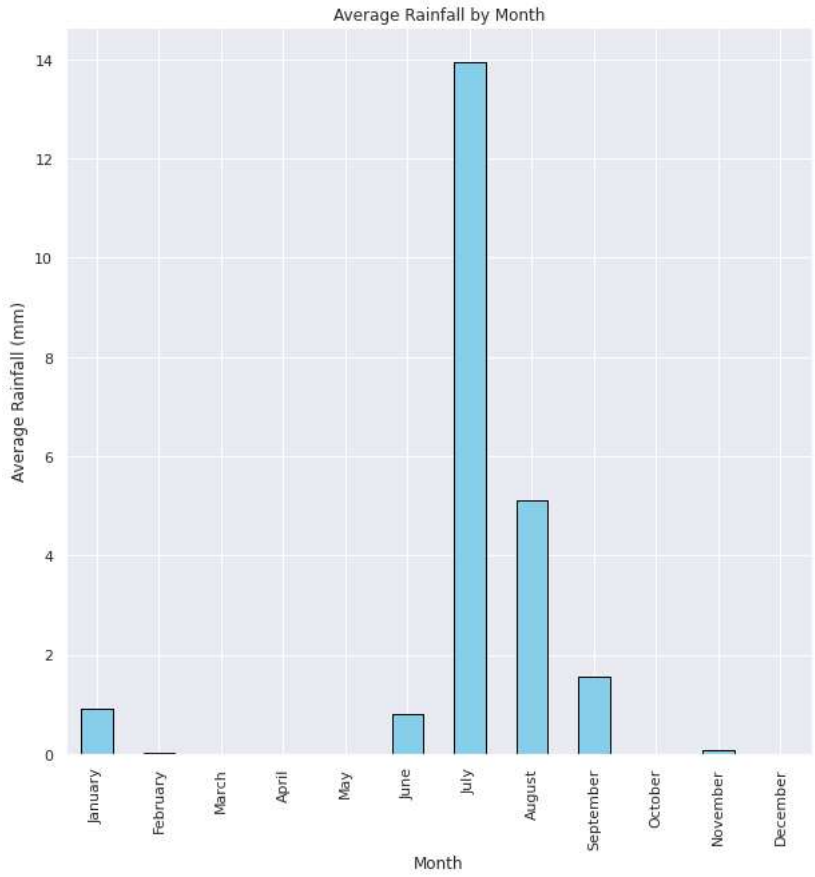



**Observation**: April and June were the warmest months of 2022

**4.4:** Average rainfall by each month

```
import calendar #for getting month names

#reading in dataset again, with dates
df = pd.read_excel("/content/Karachi.xlsx", parse_dates=['Date'])

#some rainfall data has "trace", changing to numeric values
df["Rainfall"] = pd.to_numeric(df["Rainfall"], errors='coerce')


df_monthly = df.groupby(df['Date'].dt.month)['Rainfall'].mean()
df_monthly.index = [calendar.month_name[i] for i in df_monthly.index]

# plot the bar chart
```

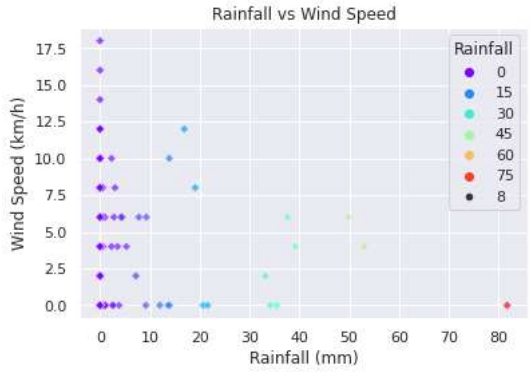
```
plt.figure(figsize=(10,10))
df_monthly.plot(kind='bar', color='skyblue', edgecolor='black')
plt.xticks(range(0,12))
plt.xlabel('Month')
plt.ylabel('Average Rainfall (mm)')
plt.title('Average Rainfall by Month')
plt.savefig("avg_rainfall.png", dpi=300)
plt.show()
```




**Observation**: July had the most amount of rainfall in 2022.

**4.5:** Comparison of rainfall to windspeed

```
sns.scatterplot(x="Rainfall", y="Wind_speed", data=df,
                alpha=0.7, size=8, sizes=(20, 200),
                hue="Rainfall", legend="brief",
                palette="rainbow", marker="D")
plt.xlabel('Rainfall (mm)')
plt.ylabel('Wind Speed (km/h)')
plt.title('Rainfall vs Wind Speed')
plt.savefig("scatterplot.png", dpi=300)
```



**Observation**: As rainfall increases, wind decreases. Hence, we can say that wind speed is inversely proportional to rainfall

## 5. Building a Rainfall Prediction Model

**5.1** Handling values before feeding them into our model

Some of our days have trace values. replacing all "trace" values in rainfall to 0

```
df = pd.read_excel('/content/Karachi.xlsx')
```

```
# convert the 'Date' column to a datetime data type
df['Date'] = pd.to_datetime(df['Date'])
```

```
df['Rainfall'] = df['Rainfall'].replace('Trace', 0)
```

Label encoding our conditions column

```
from sklearn.preprocessing import LabelEncoder

# create an instance of the label encoder
le = LabelEncoder()

# fit and transform the 'Conditions' column
df['Conditions'] = le.fit_transform(df['Conditions'])
```

```
# Get the label encoding mapping
mapping = dict(zip(le.classes_, le.transform(le.classes_)))
print(mapping)
```

```
{'Cloudy': 0, 'Rainy': 1, 'Stormy': 2, 'Sunny': 3, 'Windy': 4}
```

```
df.head()
```

| | Date | Min_temp | Max_temp | Wind_speed | Wind_direction | Rainfall | Air Pressure | Humidity | Clouds | temperature | Dew_point | Conditions |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 2022-01-01 | 12.9 | 23.8 | 4 | 23 | 0.0 | 1021.2 | 57 | 2 | 18.35 | 39.919259 | 3 |
| **1** | 2022-01-02 | 13.5 | 25.4 | 6 | 23 | 0.0 | 1019.5 | 46 | 0 | 19.45 | 37.219492 | 3 |
| **2** | 2022-01-03 | 16.0 | 25.5 | 6 | 23 | 0.0 | 1017.8 | 40 | 3 | 20.75 | 36.134650 | 3 |

**5.2** Training a LR model

```
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error

# define the predictor and target variables
X = df[['Min_temp', 'Max_temp', 'Wind_speed', 'Wind_direction', 'Air Pressure', 'Humidity', 'Clouds', 'Dew_point', 'Conditions']]
y = df['Rainfall']

# 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=31)

# fit a linear regression model to the training data
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)

# make predictions on the test data
y_pred = lin_reg.predict(X_test)

# calculate the mean absolute error of the model
mae = mean_absolute_error(y_test, y_pred)
```

```
print("Mean Absolute Error: {:.2f}".format(mae))
```

```
Mean Absolute Error: 3.49
```

### 5.3 Training a Random Forest Regressor model

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
# define the predictor and target variables
X = df[['Min_temp', 'Max_temp', 'Wind_speed', 'Wind_direction', 'Air Pressure', 'Humidity', 'Clouds', 'Dew_point', 'Conditions']]
y = df['Rainfall']


# 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=32)

# fit a random forest regressor model to the training data
rf_reg = RandomForestRegressor(n_estimators=100)
rf_reg.fit(X_train, y_train)

# make predictions on the test data
y_pred = rf_reg.predict(X_test)

# calculate the mean absolute error of the model
mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error: {:.2f}".format(mae))
```

```
Mean Absolute Error: 1.11
```

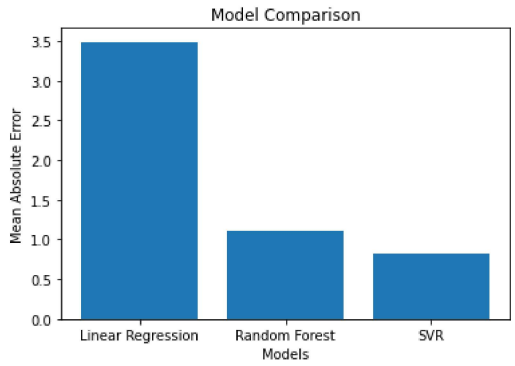
### 5.4 Training a Support Vector Regressor model

```
from sklearn.svm import SVR
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# define the predictor and target variables
X = df[['Min_temp', 'Max_temp', 'Wind_speed', 'Wind_direction', 'Air Pressure', 'Humidity', 'Clouds', 'Dew_point', 'Conditions']]
y = df['Rainfall']

# 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)

# fit a SVM model to the training data
svm = SVR(kernel='poly', degree=2)
svm.fit(X_train, y_train)

# make predictions on the test data
y_pred = svm.predict(X_test)

# calculate the mean squared error of the model
mae = mean_absolute_error(y_test, y_pred)
print("Mean Absolute Error: ", mae)
```

```
Mean Absolute Error:  0.8346566766734576
```

## ML Models Performance Evaluation

```
# Define the models and their corresponding errors
models = ['Linear Regression', 'Random Forest', 'SVR']
errors = [3.49, 1.11, 0.83]

plt.bar(models, errors)

# Add labels and title
plt.xlabel('Models')
plt.ylabel('Mean Absolute Error')
plt.title('Model Comparison')
plt.show()
```




- The linear regression model has a mean absolute error of 3.36, which means each prediction is off by 3.36 units
- The random forest regressor model has a mean absolute error of 1.15, which is much better.
- The Support Vector Regressor has a mean absolute error of 0.83, which is our best performing model.

## 6. Predicting July 2023 Rainfall

- Now, using our random forest regressor model, we will predict the rainfall in July 2023.

> Rainfall depends on the following variables:
>
> 1. 'Min_temp'
> 2. 'Max_temp'
> 3. 'Wind_speed'
> 4. 'Wind_direction'
> 5. 'Air Pressure'
> 6. 'Humidity'
> 7. 'Clouds'
> 8. 'Dew_point'
> 9. 'Conditions'

- By giving certain values, we can predict the amount of rainfall in the month of July 2023.
- Label encoded values for the conditions are {'Cloudy': 0, 'Rainy': 1, 'Stormy': 2, 'Sunny': 3, 'Windy': 4}

```
#support vector regressor object
svm = SVR(kernel='poly', degree=2)


#fit the model with our previous data
svm.fit(X_train, y_train)

#create a new dataset for July 2023
july_2023 = pd.DataFrame({'Min_temp': [30], 'Max_temp': [40], 'Wind_speed': [15],
'Wind_direction': [270], 'Air Pressure': [1009], 'Humidity': [60],
'Clouds': [4], 'Dew_point': [15], 'Conditions': [1]})


#using the trained model to make predictions
july_2023_pred = rf_reg.predict(july_2023)

print("With these variables, the rainfall in july 2023 will be",july_2023_pred,"(mm)")

     With these variables, the rainfall in july 2023 will be [7.529] (mm)


df.head()
```

| | Date | Min_temp | Max_temp | Wind_speed | Wind_direction | Rainfall | Air Pressure | Humidity | Clouds | Temperature | Dew_point | Conditions |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | |

```
df.to_excel("Karachi_Cleaned_2022.xlsx")
```

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 01 | 12.9 | 23.8 | 4 | 23 | 0.0 | 1021.2 | 57 | 2 | 18.35 | 39.919259 | 3 |
| 1 | 2022-01-02 | 13.5 | 25.4 | 6 | 23 | 0.0 | 1019.5 | 46 | 0 | 19.45 | 37.219492 | 3 |
| 2 | 2022-01-03 | 16.0 | 25.5 | 6 | 23 | 0.0 | 1017.8 | 40 | 3 | 20.75 | 36.134650 | 3 |

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