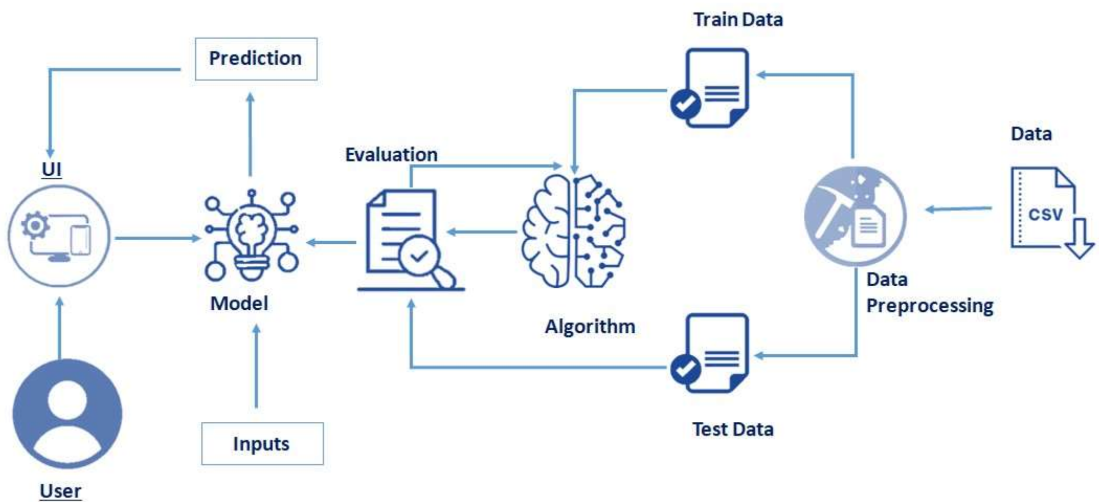
Rainfall Prediction -Project Manual

Date	21 Nov 2023
Team ID	591647
Project Name	Project - **Machine Learning Approach For Predicting The Rainfall**
Maximum Marks	10 Marks

Project Description:

Particularly during the torrential rainfall event. Moreover, one of the major focuses of Climate change study is to understand whether there are extreme changes in the occurrence and frequency of heavy rainfall events. The accuracy level of the ML models used in predicting rainfall based on historical data has been one of the most critical concerns in hydrological studies. An accurate ML model could give early alerts of severe weather to help prevent natural disasters and destruction. Hence, there is needs to develop ML algorithms capable in predicting rainfall with acceptable level of precision and in reducing the error in the dataset of the projected rainfall from climate change model with the expected observable rainfall.

Technical Architecture:



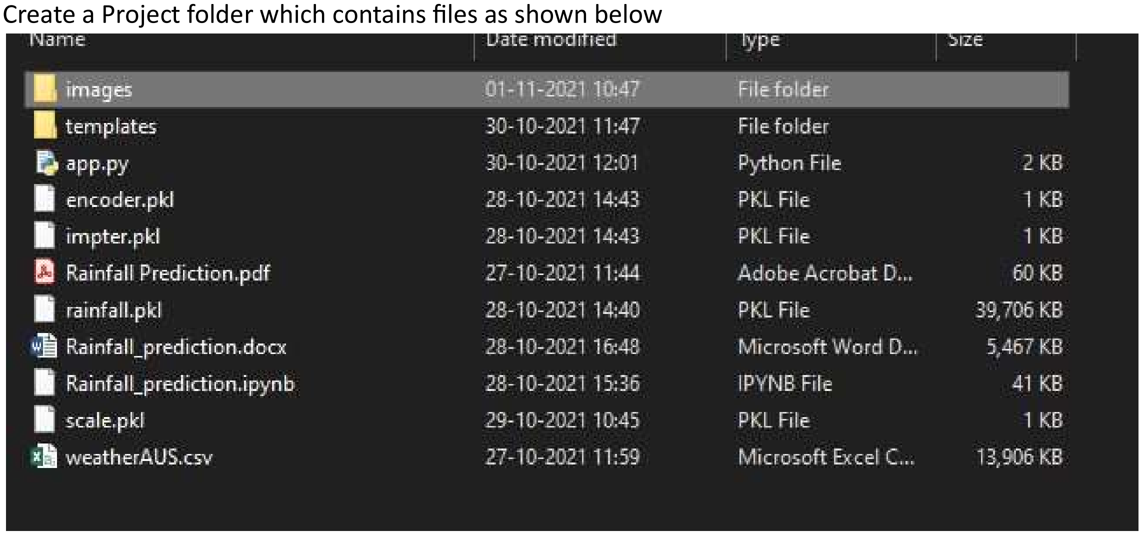
Project Flow:

- User interacts with the UI (User Interface) to enter the input values ● Entered input values are analyzed by the model which is integrated
- Once model analyses the input the prediction is showcased on the UI To accomplish this, we have to complete all the activities and tasks listed below

- Data Collection.
- Collect the dataset
- Data Preprocessing.
- Import the Libraries.
- Importing the dataset.
- Checking for Null Values.
- Data Visualization.
- Taking care of Missing Data.
- Feature Scaling.
- Splitting Data into Train and Test.
- Model Building
- Import the model building Libraries
- Initializing the model
- Training and testing the model
- Evaluation of Model
- Save the Model
- Application Building

Project Structure:

Create a Project folder which contains files as shown below



Name	Date modified	Type	Size
images	01-11-2021 10:47	File folder	
templates	30-10-2021 11:47	File folder	
app.py	30-10-2021 12:01	Python File	2 KB
encoder.pkl	28-10-2021 14:43	PKL File	1 KB
impter.pkl	28-10-2021 14:43	PKL File	1 KB
Rainfall Prediction.pdf	27-10-2021 11:44	Adobe Acrobat D...	60 KB
rainfall.pkl	28-10-2021 14:40	PKL File	39,706 KB
Rainfall_prediction.docx	28-10-2021 16:48	Microsoft Word D...	5,467 KB
Rainfall_prediction.ipynb	28-10-2021 15:36	IPYNB File	41 KB
scale.pkl	29-10-2021 10:45	PKL File	1 KB
weatherAUS.csv	27-10-2021 11:59	Microsoft Excel C...	13,906 KB

- A python file called app.py for server side scipting.
- We need the model which is saved and the saved model in this content is **Rainfall.pkl** ● Templates folder which contains index.HTML file, chance.HTML file, noChance.HTML file.
- Scale.pkl for scaling,encoder.pkl file for encoding the categorical data,imputer.pkl file for filling out the missing values

Milestone 1: Data Collection:

ML depends heavily on data, without data, it is impossible for an "AI" to learn. It is the most crucial aspect that makes algorithm training possible. In Machine Learning projects, we need a training **data set.** It is the actual **data set** used to train the model for performing various actions.

Activity1: Download The dataset

Dataset is collected from the following link:

https://docs.google.com/spreadsheets/d/1RA2OO0LZTeQykI_mvnensAjp6LM4YzWI1Tz0SUG5-Ao/edit#gid=121883362

Milestone 2: Data Preprocessing

Data Pre-processing includes the following main tasks

- Import the Libraries.
- Importing the dataset.
- Checking for Null Values.
- Data Visualization.
- Feature Scaling.
- Splitting Data into Train and Test.

Activity 1: Import Necessary Libraries

- It is important to import all the necessary libraries such as pandas, numpy, matplotlib.
- **Numpy**- It is an open-source numerical Python library. It contains a multi-dimensional array and matrix data structures. It can be used to perform mathematical operations on arrays such as trigonometric, statistical, and algebraic routines.
- **Pandas**- It is a fast, powerful, flexible and easy to use open source data analysis and manipulation tool, built on top of the Python programming language.
- **Seaborn**- Seaborn is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics.
- **Matplotlib**- Visualisation with python. It is a comprehensive library for creating static,animated, and interactive visualizations in Python
- **Sklearn** – which contains all the modules required for model building

```
# Libraries required
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import preprocessing
from sklearn import model_selection
from sklearn import metrics
from sklearn import linear_model
from sklearn import ensemble
from sklearn import tree
from sklearn import svm
import xgboost
```

Activity 2: Importing the Dataset

- You might have your data in .csv files, .excel files

- Let's load a .csv data file into pandas using **read_csv() function.**We will need to locate the directory of the CSV file at first (it's more efficient to keep the dataset in the same directory as your program).

- If your dataset is in some other location ,Then

  Data=pd.read_csv(r"File_location/datasetname.csv")

  Note:r stands for "raw" and will cause backslashes in the string to be interpreted as actual backslashes rather than special characters.

- If the dataset in same directory of your program, you can directly read it, without giving raw as r.

- Our Dataset weatherAus.csv contains following Columns
- Location, MinTemp, MaxTemp, Rainfall, WindGustSpeed,
- WindSpeed9am, WindSpeed3pm, Humidity9am, Humidity3pm
- Pressure9am, Pressure3pm, Temp9am, Temp3pm, RainToday,
- WindGustDir, WindDir9am, WindDir3pm,date
- Raintommorrow – output column

The output column to be predicted is **RainTommorow** .Based on the input variables we predict the chance of rain. The predicted output gives them a fair idea about it will rain or not.

Activity 3: Analyse the data

- head() method is used to return top n (5 by default) rows of a DataFrame or series.

```
n [2]: data = pd.read_csv("C:\\Users\\SmartbridgePC\\Desktop\\AIML\\Guided projects\\rainfall_prediction\\weatherAUS.csv")

n [3]: data.head()

ut[3]:
```

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSpeed	WindDir9am	...	Humidity9am	Humidity3pm	Pressure9
0	2008-12-01	Albury	13.4	22.9	0.6	NaN	NaN	W	44.0	W	...	71.0	22.0	100
1	2008-12-02	Albury	7.4	25.1	0.0	NaN	NaN	WNW	44.0	NNW	...	44.0	25.0	101
2	2008-12-03	Albury	12.9	25.7	0.0	NaN	NaN	WSW	46.0	W	...	38.0	30.0	100
3	2008-12-04	Albury	9.2	28.0	0.0	NaN	NaN	NE	24.0	SE	...	45.0	16.0	101
4	2008-12-05	Albury	17.5	32.3	1.0	NaN	NaN	W	41.0	ENE	...	82.0	33.0	101

5 rows × 23 columns

- describe() method computes a summary of statistics like count, mean, standard deviation, min, max and quartile values.

```
data.describe()
```

The output is as shown below

```
]: data.describe() # gives the descriptive statistics of the data
]:
```

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3p
count	143975.000000	144199.000000	142199.000000	82670.000000	75625.000000	135197.000000	143693.000000	142398.000000	142806.000000	140953.0000
mean	12.194034	23.221348	2.360918	5.468232	7.611178	40.035230	14.043426	18.662657	68.880831	51.5391
std	6.398495	7.119049	8.478060	4.193704	3.785483	13.607062	8.915375	8.809800	19.029164	20.7959
min	-8.500000	-4.800000	0.000000	0.000000	0.000000	6.000000	0.000000	0.000000	0.000000	0.0000
25%	7.600000	17.900000	0.000000	2.600000	4.800000	31.000000	7.000000	13.000000	57.000000	37.0000
50%	12.000000	22.600000	0.000000	4.800000	8.400000	39.000000	13.000000	19.000000	70.000000	52.0000
75%	16.900000	28.200000	0.800000	7.400000	10.600000	48.000000	19.000000	24.000000	83.000000	66.0000
max	33.900000	48.100000	371.000000	145.000000	14.500000	135.000000	130.000000	87.000000	100.000000	100.0000

From the data we infer that there are only decimal values and no categorical values

- info() gives information about the data

```
: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 23 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   Date           145460 non-null  object
 1   Location       145460 non-null  object
 2   MinTemp        143975 non-null  float64
 3   MaxTemp        144199 non-null  float64
 4   Rainfall       142199 non-null  float64
 5   Evaporation    82670 non-null   float64
 6   Sunshine       75625 non-null   float64
 7   WindGustDir    135134 non-null  object
 8   WindGustSpeed  135197 non-null  float64
 9   WindDir9am     134894 non-null  object
 10  WindDir3pm     141232 non-null  object
 11  WindSpeed9am   143693 non-null  float64
 12  WindSpeed3pm   142398 non-null  float64
 13  Humidity9am    142806 non-null  float64
 14  Humidity3pm    140953 non-null  float64
 15  Pressure9am    130395 non-null  float64
 16  Pressure3pm    130432 non-null  float64
 17  Cloud9am       89572 non-null   float64
 18  Cloud3pm       86102 non-null   float64
 19  Temp9am        143693 non-null  float64
 20  Temp3pm        141851 non-null  float64
```

Activity 4: Handling Missing Values

1. After loading it is important to check the complete information of data as it can indication many of the hidden information such as null values in a column or a row

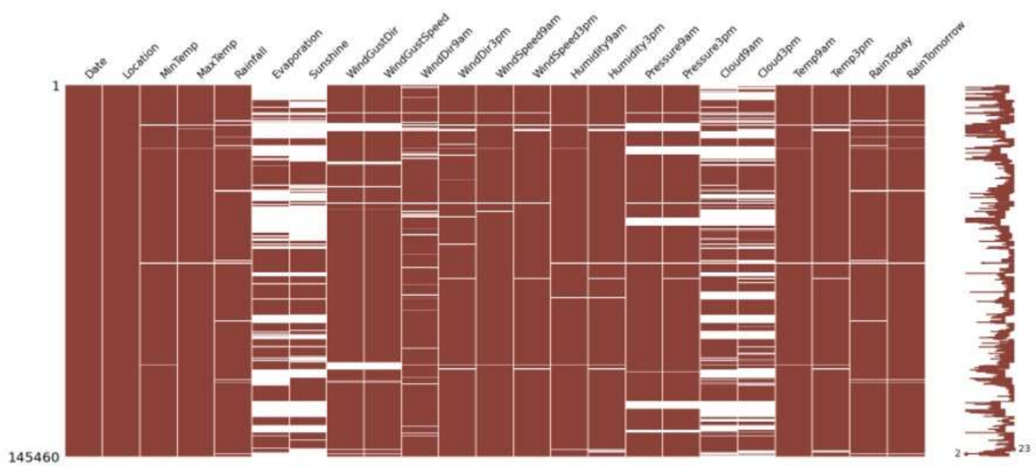
2.Check whether any null values are there or not. if it is present then following can be done,

```
5]: data.isnull().sum()

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

3. Missing matrix: It is way of representing the data in 2-D form. It gives coloured visual summary of the data

Dealing with missing values

```
In [25]: import missingno as msno
         msno.matrix(data,color=(0.55, 0.255, 0.225), fontsize=16)

Out[25]: <AxesSubplot:>
```



4.Imputing data using Imputation method in sklearn.Simpleimputer

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

```
[5]: # removing columns with more than 20% missing values and segregatting cat and num variables
data_cat = data[['RainToday','WindGustDir','WindDir9am','WindDir3pm']]
data.drop(columns=['Evaporation','Sunshine','Cloud9am','Cloud3pm'],axis=1,inplace=True)
data.drop(columns=['RainToday','WindGustDir','WindDir9am','WindDir3pm'],axis=1,inplace=True)
```

```
[6]: # filling the missing data of numeric variables with mean
data['MinTemp'].fillna(data['MinTemp'].mean(),inplace=True)
data['MaxTemp'].fillna(data['MaxTemp'].mean(),inplace=True)
data['Rainfall'].fillna(data['Rainfall'].mean(),inplace=True)
data['WindGustSpeed'].fillna(data['WindGustSpeed'].mean(),inplace=True)
data['WindSpeed9am'].fillna(data['WindSpeed9am'].mean(),inplace=True)
data['WindSpeed3pm'].fillna(data['WindSpeed3pm'].mean(),inplace=True)
data['Humidity9am'].fillna(data['Humidity9am'].mean(),inplace=True)
data['Humidity3pm'].fillna(data['Humidity3pm'].mean(),inplace=True)
data['Pressure9am'].fillna(data['Pressure9am'].mean(),inplace=True)
data['Pressure3pm'].fillna(data['Pressure3pm'].mean(),inplace=True)
data['Temp9am'].fillna(data['Temp9am'].mean(),inplace=True)
data['Temp3pm'].fillna(data['Temp3pm'].mean(),inplace=True)
```

```
[7]: # loading the names of categorical columns
cat_names = data_cat.columns
```

```
[8]: # intializing the simple imputer for missing categorical values
import numpy as np
from sklearn.impute import SimpleImputer
imp_mode = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
```

```
[9]: # fitting and transforming the missing data
data_cat = imp_mode.fit_transform(data_cat)
```

```
10]: # converting array to dataframe
data_cat = pd.DataFrame(data_cat,columns=cat_names)
```

```
11]: # concatinating the categorical and numeric data
data = pd.concat([data,data_cat],axis=1)
```

From the heatmap, we see that there are missing values in the dataset

Activity 5: Data Visualisation

- Data visualization is where a given data set is presented in a graphical format. It helps the detection of patterns, trends and correlations that might go undetected in text-based data.
- Understanding your data and the relationship present within it is just as important as any algorithm used to train your machine learning model. In fact, even the most sophisticated machine learning models will perform poorly on data that wasn't visualized and understood properly.
- To visualize the dataset we need libraries called Matplotlib and Seaborn.
- The Matplotlib library is a Python 2D plotting library which allows you to generate plots, scatter plots, histograms, bar charts etc.

Let's visualize our data using Matplotlib and searborn library.

Before diving into the code, let's look at some of the basic properties we will be using when plotting.

xlabel: Set the label for the x-axis. **ylabel:**

Set the label for the y-axis.

title: Set a title for the axes.

Legend: Place a legend on the axes.

1. data.corr() gives the correlation between the columns

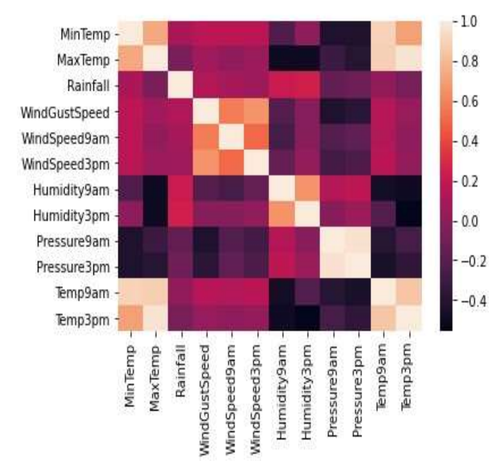
```
data.corr()
```

	Location	MinTemp	MaxTemp	Rainfall	WindGustSpeed	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	Pressur
Location	1.000000	-0.006195	-0.020490	-0.003456	0.069158	0.077025	0.064150	-0.002063	0.011040	0.036480	0.0
MinTemp	-0.006195	1.000000	0.733919	0.103315	0.173361	0.174938	0.174187	-0.232382	0.005930	-0.424336	-0.4
MaxTemp	-0.020490	0.733919	1.000000	-0.074204	0.066298	0.014580	0.050374	-0.499789	-0.499714	-0.309077	-0.3
Rainfall	-0.003456	0.103315	-0.074204	1.000000	0.127263	0.085981	0.056766	0.221395	0.249617	-0.159677	-0.1
WindGustSpeed	0.069158	0.173361	0.066298	0.127263	1.000000	0.577790	0.658334	-0.209226	-0.025751	-0.426586	-0.3
WindSpeed9am	0.077025	0.174938	0.014580	0.085981	0.577790	1.000000	0.513067	-0.269031	-0.031001	-0.215159	-0.1
WindSpeed3pm	0.064150	0.174187	0.050374	0.056766	0.658334	0.513067	1.000000	-0.144264	0.015782	-0.277469	-0.2
Humidity9am	-0.002063	-0.232382	-0.499789	0.221395	-0.209226	-0.269031	-0.144264	1.000000	0.659865	0.131593	0.1
Humidity3pm	0.011040	0.005930	-0.499714	0.249617	-0.025751	-0.031001	0.015782	0.659865	1.000000	-0.025781	0.0
Pressure9am	0.036480	-0.424336	-0.309077	-0.159677	-0.426586	-0.215159	-0.277469	0.131593	-0.025781	1.000000	0.9
Pressure3pm	0.046338	-0.434021	-0.397412	-0.120366	-0.384622	-0.165038	-0.239725	0.176164	0.048554	0.959878	1.0
Temp9am	-0.015597	0.897998	0.880085	0.011385	0.146761	0.128769	0.162143	-0.471141	-0.217573	-0.397746	-0.4
Temp3pm	-0.022712	0.699824	0.969733	-0.077555	0.032245	0.005023	0.028444	-0.492441	-0.555778	-0.266291	-0.3
RainToday	-0.004911	0.055644	-0.226474	0.500279	0.148264	0.100563	0.078361	0.348843	0.370561	-0.179226	-0.1
WindGustDir	-0.005055	-0.136317	-0.212210	0.044855	0.137914	0.009762	0.084012	0.067956	0.063964	-0.120630	-0.0
WindDir9am	-0.004434	-0.029638	-0.212589	0.085140	0.074638	0.109916	0.111072	0.088842	0.148893	-0.050314	0.0
WindDir3pm	0.008325	-0.158958	-0.181344	0.047905	0.136674	0.050200	0.089824	0.026077	-0.007182	-0.133633	-0.0

```
In [12]: cor = data.corr()
```

```
In [13]: sns.heatmap(data=cor,xticklabels=cor.columns.values,yticklabels=cor.columns.values)
```

```
Out[13]: <AxesSubplot:>
```



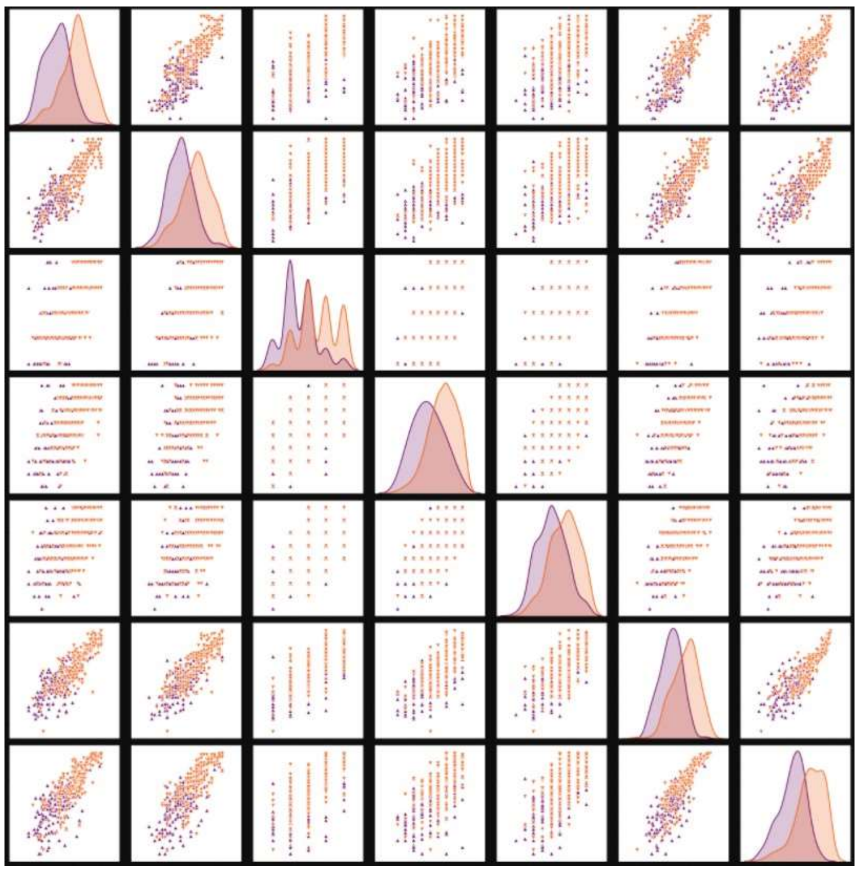
- Correlation strength varies based on colour, lighter the colour between two variables, more the strength between the variables, darker the colour displays the weaker correlation ● We can see the correlation scale values on left side of the above image

2.Pair Plot: Plot pairwise relationships in a dataset.

- By default, this function will create a grid of Axes such that each numeric variable in data will by shared across the y-axes across a single row and the x-axes across a single column. The diagonal plots are treated differently: a univariate distribution plot is drawn to show the marginal distribution of the data in each column.
- We implement this using the below code

Code:- sns.pairplot(data)

The output is as shown below



Pair plot usually gives pair wise relationships of the columns in the dataset

From the above pairplot we infer that

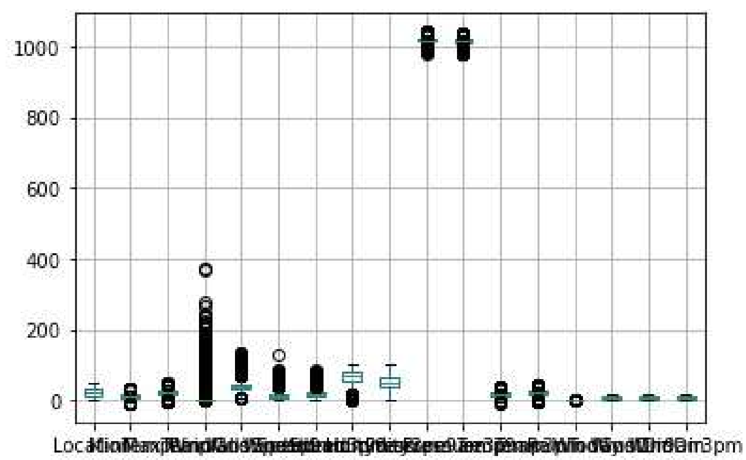
1.from the above plot we can draw inferences such as linearity and strength between the variables

2.how features are correlated(positive, neutral and negative)

3.Box Plot: jupyter has a built-in function to create boxplot called boxplot(). A boxplot plot is a type of plot that shows the spread of data in all the quartiles

```
data.boxplot()
```

```
<AxesSubplot:>
```



From the above box plot we infer how the datapoints are spread and the existence of the outliers

Activity 6: Splitting the Dataset into Dependent and Independent variable

- In machine learning, the concept of dependent variable (y) and independent variables(x) is important to understand. Here, Dependent variable is nothing but output in dataset and independent variable is all inputs in the dataset.
- With this in mind, we need to split our dataset into the matrix of independent variables and the vector or dependent variable. Mathematically, Vector is defined as a matrix that has just one column.

To read the columns, we will use **iloc** of pandas (used to fix the indexes for selection) which takes two parameters — [row selection, column selection].

Let's split our dataset into independent and dependent variables.

y = data['RainTomorrow'] - independent x = data.drop('RainTomorrow',axis=1)

Activity 7: Feature Scaling

There is huge disparity between the x values so let us use feature scaling.
Feature scaling is a method used to normalize the range of independent variables or features of data.

standardizing the data

```
from sklearn.preprocessing import StandardScaler
```

```
#splitting x and y values
y = data['RainTomorrow']
x = data.drop('RainTomorrow',axis=1)
```

```
names = x.columns # loading the names of the x_features
```

```
names
```

```
Index(['Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'WindGustSpeed',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Temp9am', 'Temp3pm', 'RainToday',
       'WindGustDir', 'WindDir9am', 'WindDir3pm', 'year', 'month', 'day'],
      dtype='object')
```

```
sc = StandardScaler() # initializing the standardscaler
```

```
x = sc.fit_transform(x) # fitting an transforming the data into standard
```

```
x = pd.DataFrame(x,columns=names) #scaled data turns into array format,converting them into dataframe
```

- After scaling the data will be converted into array form
- Loading the feature names before scaling and converting them back to dataframe after standard scaling is applied

Activity 8: Splitting the data into Train and Test

- When you are working on a model and you want to train it, you obviously have a dataset. But after training, we have to test the model on some test dataset. For this, you will a dataset which is different from the training set you used earlier. But it might not always be possible to have so much data during the development phase. In such cases, the solution is to split the dataset into two sets, one for training and the other for testing.
- But the question is, how do you split the data? You can’t possibly manually split the dataset into two sets. And you also have to make sure you split the data in a random manner. To help

us with this task, the Scikit library provides a tool, called the Model Selection library. There is a class in the library which is,**‘train_test_split.’** Using this we can easily split the dataset into the training and the testing datasets in various proportions.

- The train-test split is a technique for evaluating the performance of a machine learning algorithm.
- **Train Dataset**: Used to fit the machine learning model.
- **Test Dataset**: Used to evaluate the fit machine learning model.
- In general you can allocate 80% of the dataset to training set and the remaining 20% to test set.We will create 4 sets— X_train (training part of the matrix of features), X_test (test part of the matrix of features), Y_train (training part of the dependent variables associated with the X train sets, and therefore also the same indices), Y_test (test part of the dependent variables associated with the X test sets, and therefore also the same indices.
- There are a few other parameters that we need to understand before we use the class:
- **test_size** — this parameter decides the size of the data that has to be split as the test dataset. This is given as a fraction. For example, if you pass 0.5 as the value, the dataset will be split 50% as the test dataset
- **train_size** — you have to specify this parameter only if you’re not specifying the test_size. This is the same as test_size, but instead you tell the class what percent of the dataset you want to split as the training set.
- **random_state** — here you pass an integer, which will act as the seed for the random number generator during the split. Or, you can also pass an instance of the Random_state class, which will become the number generator. If you don’t pass anything, the Random_state instance used by np.random will be used instead.
- Now split our dataset into train set and test using train_test_split class from scikit learn library.

```
from sklearn import model_selection
x_train,x_test,y_train,y_test=model_selection.train_test_split(x,y,test_size=0.2,ran
dom_state =0)
```

Milestone 3: Model Buiding:

Model building includes the following main tasks

- Import the model building Libraries
- Initializing the model
- Training and testing the model
- Evaluation of Model
- Save the Model

Activity 1: Training and Testing the Model

- Once after splitting the data into train and test, the data should be fed to an algorithm to build a model.
- There are several Machine learning algorithms to be used depending on the data you are going to process such as images, sound, text, and numerical values. The algorithms that you can

choose according to the objective that you might have it may be Classification algorithms are Regression algorithms. 1.Logistic Regression

2.Decision Tree Classifier

3.Random Forest Classifier

4.KNN

5.svm

5.xgboost

Steps in Building the model:-

- Initialize the model
- Fit the models with x_train and y_train
- Predict the y_train values and calculate the accuracy
- Predict the y_test values and calculate the accuracy

initializing all the models and predicting for better accuracy

```
[ ]: #Models intilization of the models
XGBoost = xgboost.XGBRFClassifier()
Rand_forest = sklearn.ensemble.RandomForestClassifier()
svm = sklearn.svm.SVC()
Dtree = sklearn.tree.DecisionTreeClassifier()
GBM = sklearn.ensemble.GradientBoostingClassifier()
log = sklearn.linear_model.LogisticRegression()
```

```
[ ]: # fitting the model
XGBoost.fit(x_train,y_train)
Rand_forest.fit(x_train,y_train)
svm.fit(x_train,y_train)
Dtree.fit(x_train,y_train)
GBM.fit(x_train,y_train)
log.fit(x_train,y_train)
```

```
[ ]: # predicting the train  values
p1 = XGBoost.predict(x_train)
p2 = Rand_forest.predict(x_train)
p3 = svm.predict(x_train)
p4 = Dtree.predict(x_train)
p5 = GBM.predict(x_train)
p6 = log.predict(x_train)
```

```
[ ]: #checking the accuraccy score
print("xgboost:",metrics.accuracy_score(y_train,p1))
print("Rand_forest:",metrics.accuracy_score(y_train,p2))
print("svm:",metrics.accuracy_score(y_train,p3))
print("Dtree:",metrics.accuracy_score(y_train,p4))
print("GBM:",metrics.accuracy_score(y_train,p5))
print("log:",metrics.accuracy_score(y_train,p6))
```

We're going to use x_train and y_train obtained above in train_test_split section to train our decision tree regression model. We're using the fit method and passing the parameters as shown below.

We are using the algorithm from Scikit learn library to build the model as shown below,

Once the model is trained, it's ready to make predictions. We can use the **predict** method on the model and pass **x_test** as a parameter to get the output as **y_pred.**

Notice that the prediction output is an array of real numbers corresponding to the input array.

Activity 2: Model Evaluation

After training the model, the model should be tested by using the test data which is been separated while splitting the data for checking the functionality of the model.

Regression Evaluation Metrics:

These model evaluation techniques are used to find out the accuracy of models built in classification type of machine learning models. We have three types of evaluation methods.

- Accuracy_score
- Confusion matrix
- Roc- Auc Curve

1. Accuracy_score

It is the ratio of number of correct predictions to the total number of input samples.

$$Accuracy = \frac{Number\ of\ Correct\ predictions}{Total\ number\ of\ predictions\ made}$$

```
[40]: print("xgboost:",metrics.accuracy_score(y_test,t1))
      print("Rand_forest:",metrics.accuracy_score(y_test,t2))
      print("svm:",metrics.accuracy_score(y_test,t3))
      print("Dtree:",metrics.accuracy_score(y_test,t4))
      print("GBM:",metrics.accuracy_score(y_test,t5))
      print("log:",metrics.accuracy_score(y_test,t6))

      xgboost: 0.8420478919793242
      Rand_forest: 0.8569218326945391
      svm: 0.8525967861035901
      Dtree: 0.7837476704525476
      GBM: 0.8499947255529379
      log: 0.8418369140968388
```

Select the model,which gives the best accuracy of all,and generate predictions and find the accuracy with training and testing data

2. Confusion Matrix

It is a matrix representation of the results of any binary testing

```
In [61]: conf_matrix = metrics.confusion_matrix(y_test,y_pred)
```

```
In [63]: fig, ax = plt.subplots(figsize=(7.5, 7.5))
ax.matshow(conf_matrix, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center', size='xx-large')

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix', fontsize=18)
plt.show()
```

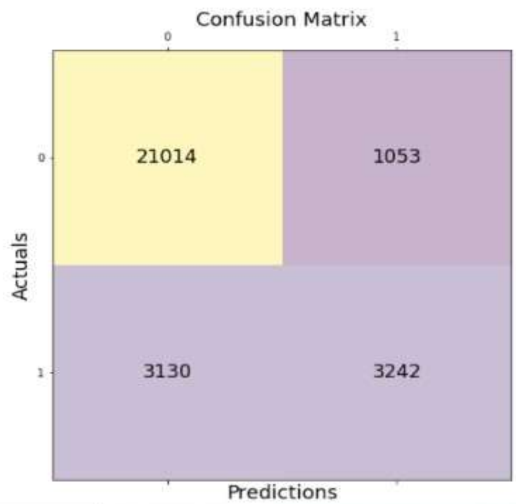


Fig: Confusion Matrix of prediction of rainfall

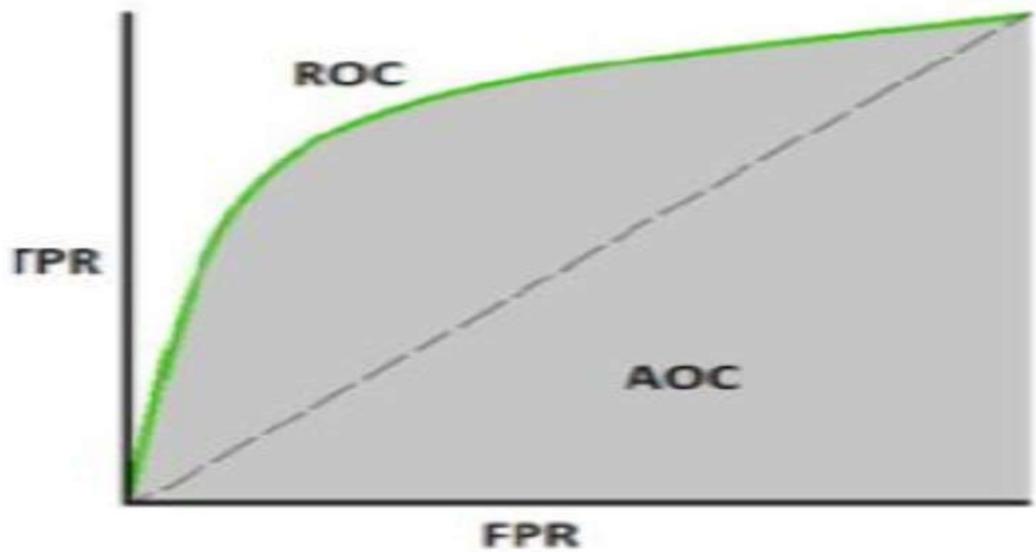
1. True Positive: 3242 (You have predicted the positive case correctly!)
2. True Negative: 21014 (You have predicted negative case correctly!)
3. False Positive: 1053 (You have predicted it will rain, but in actual it will not rain)
4. False Negative: 3130 (Wrong predictions)

3. Roc-Auc Curve

- AUC is the area under the ROC curve. AUC ROC indicates how well the probabilities from the positive classes are separated from the negative classes.
- AUC - ROC curve is a performance measurement for classification problem at various thresholds settings
- ROC is a probability curve and AUC represents degree or measure of separability.
- Higher the AUC, better the model is at predicting 0s as 0s and 1s as 1sThe ROC curve is plotted with TPR against the FPR where TPR is on y-axis and FPR is on the x-axis. ● Code for Roc and performance metrics

```
print(conf_matrix)
print("Accuracy:",Accuracy)
print("Precesion:",Precesion)
print("Recall:",Recall)
print("F1-score:",F1_score)
```

```
auc = metrics.roc_auc_score(y_test,y_pred)

fpr, tpr, thresolds = metrics.roc_curve(y_test,y_pred)

plt.figure(figsize=(12, 10), dpi=80)
plt.axis('scaled')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.title("AUC & ROC Curve")
plt.plot(fpr, tpr, 'v')
plt.fill_between(fpr, tpr, facecolor='blue', alpha=0.8)
plt.text(1, 0.05, 'AUC = %0.4f' % auc, ha='right', fontsize=10, weight='bold', color='black')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.show()
```



For testing the model we use the below method,

Activity 3: Save the Model

After building the model we have to save the model.

Pickle in **Python** is primarily **used** in serializing and deserializing a **Python** object structure. In other words, it's the process of converting a **Python** object into a byte stream to store it in a file/database, maintain program state across sessions, or transport data over the network. wb indicates write method and rd indicates read method.

This is done by the below code

saving the model

```
[29]: import pickle
```

```
[ ]: pickle.dump(model,open('rainfall.pkl','wb')) # model
     pickle.dump(le,open('encoder.pkl','wb'))     # encoder saving
     pickle.dump(imp_mode,open('impter.pkl','wb'))# imputer saving
     pickle.dump(sc,open('scale.pkl','wb'))       # scaling the data
```

Milestone 4 : Application Building

In this section, we will be building a web application that is integrated to the model we built. A UI is provided for the uses where he has to enter the values for predictions. The enter values are given to the saved model and prediction is showcased on the UI.

This section has the following tasks

- Building HTML Pages
- Building server side script

Activity 1: Build HTML Code

In this HTML page, we will create the front end part of the web page. In this page we will accept input from the user and Predict the values.

In our project we have 3 HTML files ,they are

1.inex.html

2.chance.html

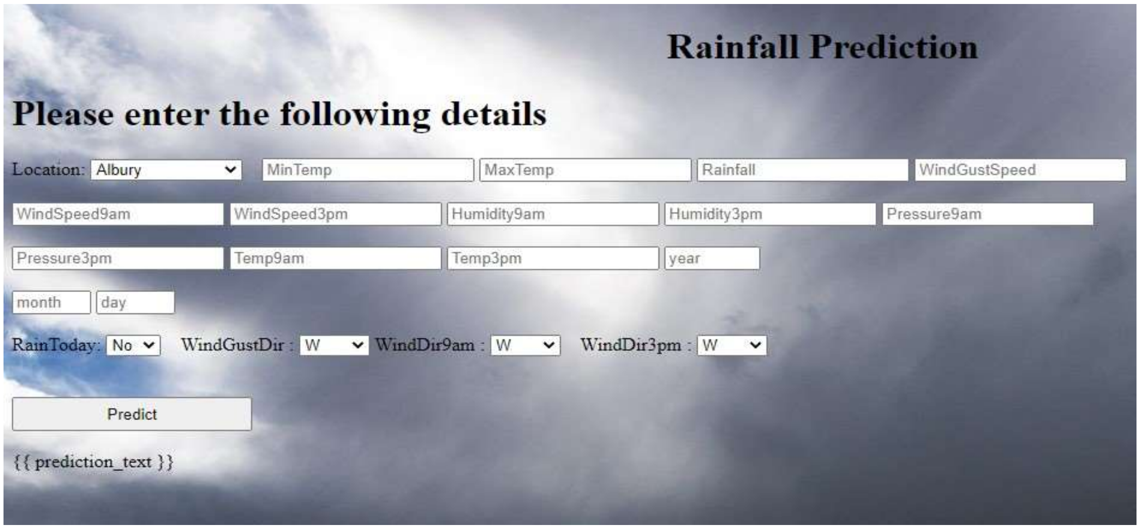
3.noChance.html

index.html

```html
<!DOCTYPE html>
<html >
<head>
  <meta charset="UTF-8">
  <title>Rainfall prediction</title>
</head>


<body background="https://wallpaperaccess.com/full/701614.jpg" text="black">

 <div class="login">
    <center><h1>Rainfall Prediction</h1></center>

     <!-- Main Input For Receiving Query to our ML -->
    <form action="{{ url_for('predict')}}"method="post">


</style></head>

        <label for="Location">Location:</label>
          <select id="Location" name="Location">
                <option value=2>Albury</option>
                <option value=4>BadgerysCreek</option>
                <option value=10>Cobar</option>
                <option value=11>CoffsHarbour</option>
                <option value=21>Moree</option>
                <option value=24>Newcastle</option>
                <option value=26>NorahHead</option>
                <option value=27>NorfolkIsland</option>
                <option value=30>Penrith</option>
                <option value=34>Richmond</option>
                <option value=37>Sydney</option>
                <option value=38>SydneyAirport</option>
                <option value=42>WaggaWagga</option>
                <option value=45>Williamtown</option>
                <option value=47>Wollongong</option>
                <option value=9>Canberra</option>
                <option value=40>Tuggeranong</option>
                <option value=23>MountGinini</option>
                <option value=5>Ballarat</option>
                <option value=6>Bendigo</option>
                <option value=35>Sale</option>
                <option value=19>MelbourneAirport</option>
                <option value=18>Melbourne</option>
                <option value=20>Mildura</option>
                <option value=25>Nhil</option>
                <option value=33>Portland</option>
                <option value=44>Watsonia</option>
```

```html
        <select id="WindDir3pm" name="WindDir3pm">
                <option value=14>W<option>
                <option value=15>WNW<option>
                <option value=0>WSW<option>
                <option value=7>NE<option>
                <option value=13>NNW<option>
                <option value=10>N<option>
                <option value=2>NNE<option>
                <option value=1>SW<option>
                <option value=6>ENE<option>
                <option value=11>SSE<option>
                <option value=12>S<option>
                <option value=9>NW<option>
                <option value=3>SE<option>
                <option value=8>ESE<option>
                <option value=5>E<option>
                <option value=4>SSW<option>
        </select>   


<br>

<br><br>


<button type="submit" class="btn btn-primary btn-block btn-large" style="height:30px;width:200px">Predict</button>

    </form>
<br>


   {{ prediction_text }}


  <br>
  <br>
  <img src="data:image/png;base64,{{url_3}}" alt="Submit Form" height="180" width="233" onerror="this.style.display='none'"/>
  <img src="data:image/png;base64,{{url_1}}" alt="Submit Form" height="180" width="233" onerror="this.style.display='none'"/>
  <img src="data:image/png;base64,{{url_4}}" alt="Submit Form" height="180" width="233" onerror="this.style.display='none'"/>
  <br>
  <br>
  <img src="data:image/png;base64,{{url_2}}" alt="Submit Form" height="150" width="711" onerror="this.style.display='none'"/>

 </div>


</body>
</html>
```

The html page looks like



noChance.html

```
<!DOCTYPE html>
<html >
<head>
  <meta charset="UTF-8">
  <title>Rainfall prediction</title>
</head>


<body background="https://cdn.tourradar.com/s3/tour/1500x800/139566_d97baf8c.jpg" text="black">

 <div class="login">
  <center><h1>No chances of rain today,enjoy your outing.</h1></center>
</body>
</html>
```

The html page looks like

chance.html

```html
<!DOCTYPE html>
<html >
<head>
  <meta charset="UTF-8">
  <title>Rainfall prediction</title>
</head>


<body background="https://wnavprd.blob.core.windows.net/images/guide/chris-seufert-cape-cod-rain-beach-1400-110-1.jpg" text="black">

 <div class="login">
  <center><h1>chances of rain today.</h1></center>
</body>
</html>
```

The html page looks like

Activity 2: Main Python Script Let us build app.py flask file which is a web framework written in python for server-side scripting. Let's see step by step procedure for building the backend application.

In order to develop web api with respect to our model, we basically use Flask framework which is written in python.

Line 1-3 We are importing necessary libraries like Flask to host our model request

Line 4 Initialise the Flask application

Line 5 Loading the model using pickle

Line 7 Routes the api url

Line 9 Rendering the template. This helps to redirect to home page. In this home page ,we give our input and ask the model to predict

Line 19 we are taking the inputs from the form

Line 21-23 Feature Scaling the inputs

Line 24 Predicting the values given by the user

Line 27-30 If output is false render noChance template

If output is True render chance template

Line 31 The value of __name__ is set to __main__ when module run as main program other wise it is set to name of the module

app.py

```python
import numpy as np
import pickle
import joblib
import matplotlib
import matplotlib.pyplot as plt
import time
import pandas
import os
from flask import Flask, request, jsonify, render_template


app = Flask(__name__)
model = pickle.load(open('C:/Users/SmartbridgePC/Desktop/AIML/Guided projects/rainfall_prediction/Rainfall.pkl', 'rb'))
scale = pickle.load(open('C:/Users/SmartbridgePC/Desktop/AIML/Guided projects/rainfall_prediction/scale.pkl','rb'))

@app.route('/')# route to display the home page
def home():
    return render_template('index.html') #rendering the home page

@app.route('/predict',methods=["POST","GET"])# route to show the predictions in a web UI
def predict():
    #  reading the inputs given by the user
    input_feature=[x for x in request.form.values() ]
    features_values=[np.array(input_feature)]
    names = [['Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'WindGustSpeed',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Temp9am', 'Temp3pm', 'RainToday',
       'WindGustDir', 'WindDir9am', 'WindDir3pm', 'year', 'month', 'day']]
    data = pandas.DataFrame(features_values,columns=names)
    data = scale.fit_transform(data)
    data = pandas.DataFrame(data,columns = names)
     # predictions using the loaded model file
    prediction=model.predict(data)
    pred_prob = model.predict_proba(data)
    print(prediction)
    if prediction == "Yes":
         return render_template("chance.html")
    else:
        return render_template("nochance.html")
     # showing the prediction results in a UI
if __name__=="__main__":
```

Activity 3: Run the App

- Open anaconda prompt from the start menu
- Navigate to the folder where your python script is.
- Now type "python app.py" command
- Navigate to the localhost where you can view your web page, Then it will run on local host:5000

Anaconda Prompt (anaconda3) - app.py

```
(base) C:\Users\SmartbridgePC>cd C:\Users\SmartbridgePC\Desktop\AIML\Guided projects\rainfall_prediction

(base) C:\Users\SmartbridgePC\Desktop\AIML\Guided projects\rainfall_prediction>app.py
 * Serving Flask app "app" (lazy loading)
 * Environment: production
   WARNING: This is a development server. Do not use it in a production deployment.
   Use a production WSGI server instead.
 * Debug mode: on
 * Running on http://127.0.0.1:5000/ (Press CTRL+C to quit)
```

Activity 4:

- Copy the http link and paste it in google link tab,it will display the form page
- Enter the values as per the form and click on predict buttion
- It will redirect to the page based on prediction outpu