



# **HINDUSTHAN INSTITUTE OF TECHNOLOGY**

(An Autonomous Institution, Approved by AICTE, New Delhi, Affiliated to Anna University, Chennai, Accredited with "A" Grade by NAAC) Valley Campus, Pollachi Main Road, Coimbatore 641 032.

## **DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING**

### **PROJECT REPORT ON**

**HX 8001 PROFESSIONAL READINESS FOR INNOVATION, EMPLOYABILITY  
AND ENTREPRENEURSHIP  
(Naalaiya Thiran Program)**

### **PROJECT TITLE**

**Exploratory Analysis of Rain Fall Data in India for Agriculture**

**TEAM ID: PNT2022TMID10487**

#### **TEAM MEMBERS:**

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## **EXPLORATORY ANALYSIS OF RAINFAL DATA IN INDIA FOR AGRICULTURE**

### ***PROJECT REPORT***

#### **1.Introduction:**

Rainfall has been a major concern these days. Weather conditions have been changing for time being. Rainfall forecasting is important otherwise, it may lead to many disasters. Irregular heavy rainfall may lead to the destruction of crops, heavy floods that can cause harm to human life. It is important to exactly determine the rainfall for effective use of water resources, crop productivity, and pre-planning of water structures.

This comparative study is conducted concentrating on the following aspects: modeling inputs, Visualizing the data, modeling methods, and preprocessing techniques. The results provide a comparison of various evaluation metrics of these machine learning techniques and their reliability to predict rainfall by analyzing the weather data.

We will be using classification algorithms such as Decision tree, Random forest, KNN, and xgboost. We will train and test the data with these algorithms. From this best model is selected and saved in pkl format. Once the model is saved, we integrate it with flask application and also deploy the model in IBM.

#### **1.1 Project Overview :**



The Indian summer monsoon typically lasts from June-September, with large areas of western and central India receiving more than 90% of their total annual precipitation during the period, and southern and northwestern India receiving 50%-75% of their total annual rainfall. Overall, monthly totals average 200-300 mm over the country as a whole, with the largest values observed during the heart of the monsoon season in July and August.

There was an early start to monsoon conditions during 1996, with monsoonal rains completely covering India by 30 June, 2 weeks earlier than normal. There was also a late finish to the monsoon season, with a complete withdrawal of monsoonal rains from India not seen until 11 October. For the area as a whole, rainfall was above normal during June and July, near normal during August, slightly below normal during September, and then substantially above normal during October. In fact, average October totals nearly equalled those observed during September.

## **1.2 Purpose :**

The main purpose of EDA is to help look at data before making any assumptions. It can help identify obvious errors, as well as better understand patterns within the data, detect outliers or anomalous events, find interesting relations among the variables

One of the primary purposes of exploratory data analysis is to identify issues early on to ensure that the data going into machine learning (ML) models is both accurate and consistent and will provide valid, unbiased results.

This analysis will provide useful information for water resources planner, farmers and urban engineers to assess the availability of water and create the storage accordingly. The mean, standard deviation and coefficient of variation of monthly and annual rainfall was calculated to check the rainfall variability.

## 2.LITERATURE SURVEY

### 2.1 Existing Problem

Weather conditions changes then and often. This can lead to Severe threats to all the living beings including human beings. So predicting weather, especially Irregular heavy rainfall can cause huge floods and economic losses. This also decreases crop productivity and may lead into Food shortage. Collection of previous 10 years data may give us an idea about the pattern of Rainfall. Using all these Datas, Appropriate farming activities can be performed. These datas can help us in predicting Rainfall .We will using lot of algorithms like KNN, XGboost, etc. We will train and test the data using these algorithms and predict the best one.

### 2.2 References

S.NO	Y EAR	AUTHOR	TITLE	CONTENT
1	2017	S. Cramer, M.Kampouridis, A. A. Freitas, and A. K. Alexandridis	An extensive evaluation of seven machine learning methods	Rainfall prediction in weather derivatives.
2	2016	S. Zhang, L. Lu, J. Yu, and H. Zhou	Short-term water level prediction using different artificial intelligent models	Geoinformatics, AgroGeoinformati cs

3	2016	S. Zainudin , D. S. Jasim , and A. A. Bakar	Comparative Analysis of Data Mining Techniques	Rainfall Prediction
4	2013	R. Venkata Ramana, B. Krishna, S. R. Kumar, and N. G. Pandey	Monthly Rainfall Prediction Using Wavelet Neural Network Analysis	Wavelet Neural Network Analysis, Water Resource
5	2013	D. Nayak, A. Mahapatra, and P. Mishra	A Survey on Rainfall Prediction	Artificial Neural Network

**Problem Statement :**

Weather conditions changes then and often. This can lead to Severe threats to all the living beings including human beings. So predicting weather, especially Irregular heavy rainfall, Droughts can cause huge economic losses. This also decreases crop productivity and may lead into Food shortage. Predicting the Rainfall plays a vital role in our life time. Farmers will get benefit due to this and Our country’s GDP will rise. Collection of previous 10 years data may give us an idea about the pattern of Rainfall. Using all these Datas, Appropriate farming activities can be performed. Water is the vital mineral for a life. So, these datas can help us in predicting Rainfall during summer days to save water.

Agriculture definitely requires gallons of waters.



### Customer Problem Statement :

Create a problem statement to understand your customer's point of view. The Customer Problem Statement template helps you focus on what matters to create experiences people will love.

A well-articulated customer problem statement allows you and your team to find the ideal solution for the challenges your customers face. Throughout the process, you'll also be able to empathize with your customers, which helps you better understand how they perceive your product or service.

Problem Statement (PS)	I am (Customer)	I'm trying to	But	Because	Which makes me feel
PS-1	Farmer	Predict the heavy rainfall to take precautionary measures to protect the crops from destruction	Can't predict the heavy rainfall	The climate changes made difficult to make the season as usual	Sad and anxious



PS-2	Department agencies	Make a continuous and good supply of the crops	The crops are destructed and are in shortage.	The heavy rainfall can't be predicted beforehand	Frustrated
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### 3.IDEATION & PROPOSED SOLUTION

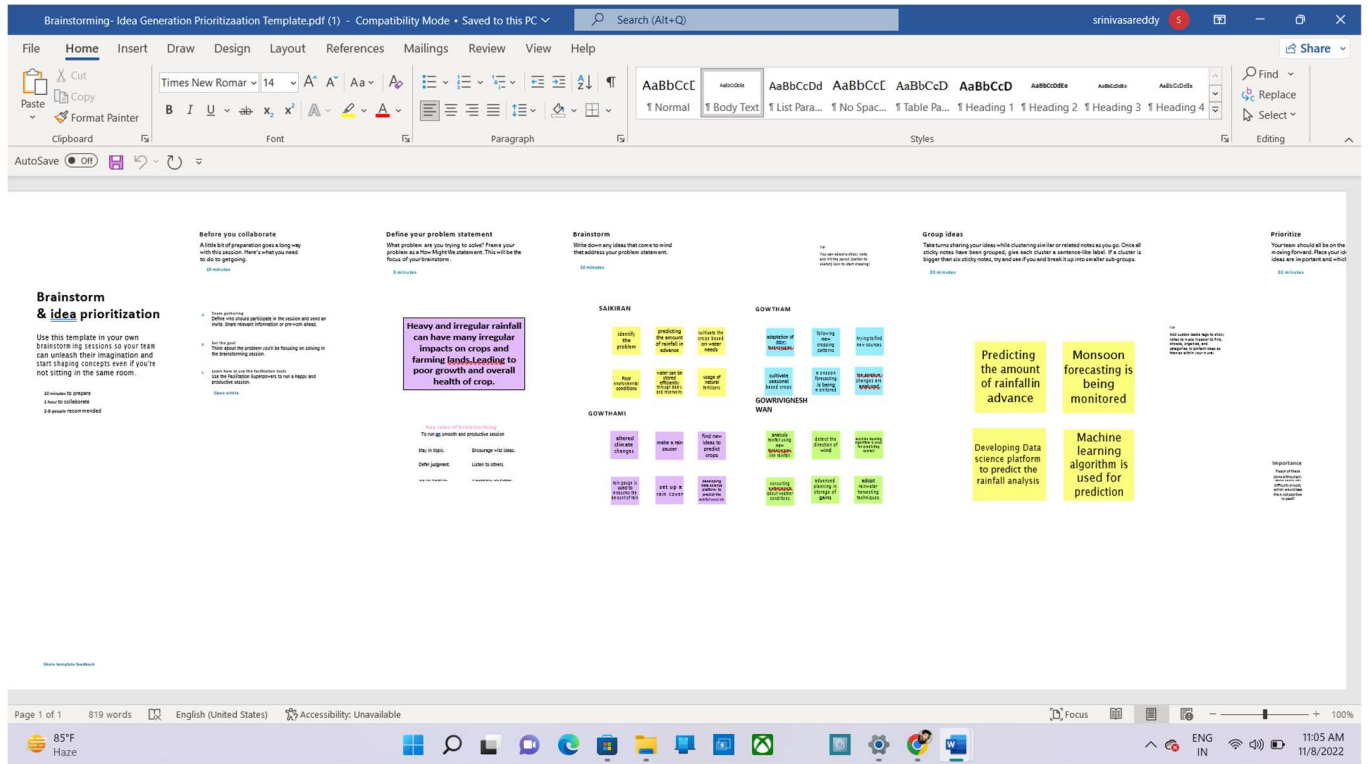
#### 3.1 Empathy Map & Canvas

##### Definition:

An empathy map is a collaborative visualization used to articulate what we know about a particular type of user. It externalizes knowledge about users in order to

- 1) create a shared understanding of user needs.
- 2) aid in decision making.

### 3.2 Ideation & Brainstorming



### 3.3 Proposed Solution

#### Proposed Solution Template:

S.No.	Parameter	Description
-------	-----------	-------------

1.	Problem Statement (Problem to be solved)	<p>1. Climate is a important aspect of human life. So, the Prediction should accurate as much as possible. In this paper we try to deal with the prediction of the rainfall which is also a major aspect of human life and which provide the major resource of human life which is Fresh Water.</p> <p>2. Now climate change is the biggest issue all over the world. Peoples are working on to detect the patterns in climate change as it affects the economy in production to infrastructure</p>
2.	Idea / Solution description	<p>1. In rainfall also making prediction of rainfall is a challenging task with a good accuracy rate. Making prediction on rainfall cannot be done by the traditional way, so scientist is using machine learning and deep learning to find out the pattern for rainfall prediction.</p> <p>2. Provides extra support to maintain the agriculture.</p>

3.	Novelty / Uniqueness	<ol style="list-style-type: none"> <li>1. This application is useful for the beginners in agriculture.</li> <li>2. Seed maturity selection features are available.</li> </ol>
4.	Social Impact / Customer Satisfaction	<ol style="list-style-type: none"> <li>1. Different types of crops can be planted for good health.</li> <li>2. Helps in producing healthy crops and good fields.</li> </ol>
5.	Business Model (Revenue Model)	<ul style="list-style-type: none"> <li>• This comparative study is conducted concentrating on the following aspects: modeling inputs, Visualizing the data, modeling methods, and pre-processing techniques. The results provide a comparison of various evaluation metrics of these machine learning techniques and their</li> </ul>
		<p>reliability to predict rainfall by analyzing the weather data.</p> <p>We will be using classification algorithms such as Decision tree,</p> <p>Random forest, KNN, and</p>

		xgboost.
6.	Scalability of the Solution	<ul style="list-style-type: none"> <li>When we predict rainfall correctly, it helps growth of crop and yielding will be better.</li> </ul>

### 3.4 Problem Solution



## 4. REQUIREMENT ANALYSIS

### 4.1 Func onal Requirements:

Following are the func onal requirements of the proposed solu on.

<b>NFR-1</b>	<b>Usability</b>	The system should be easy to use.
<b>NFR-2</b>	<b>Security</b>	Security is given over the model, so the user can use this with full trust. The system should protect the data and informa on related to the farms.
<b>NFR-3</b>	<b>Reliability</b>	Good connec vity and a suppor ng device . The system should be reliable and not crash when using it.

<b>FR No.</b>	<b>Func onal Requirement (Epic)</b>	<b>Sub Requirement (Story / Sub-Task)</b>
<b>FR-1</b>	Import necessary packages	Impor ng packages like NumPy, pandas, seaborn, etc
<b>FR-2</b>	Download and load dataset	Download the dataset Load the Appropriate dataset
<b>FR-3</b>	Pre-processing of data	Making data suitable for building a good model
<b>FR-4</b>	Building Machine learning model	Choose the best algorithm. Check for the best op mised result.
<b>FR-5</b>	Train the data	Train the model using training data.
<b>FR-6</b>	Test the model	Test the model for the best evalua on and analysing.

### 4.2 Non-func onal Requirements:

Following are the non-func onal requirements of the proposed solu on.

<b>FR No.</b>	<b>Non-Func onal Requirement</b>	<b>Descrip on</b>
---------------	----------------------------------	-------------------

**NFR-4      Performance**

The system should output results of different inputs in a reasonable me..

**NFR-5      Availability**

Any person can use this and this is an open-source model.

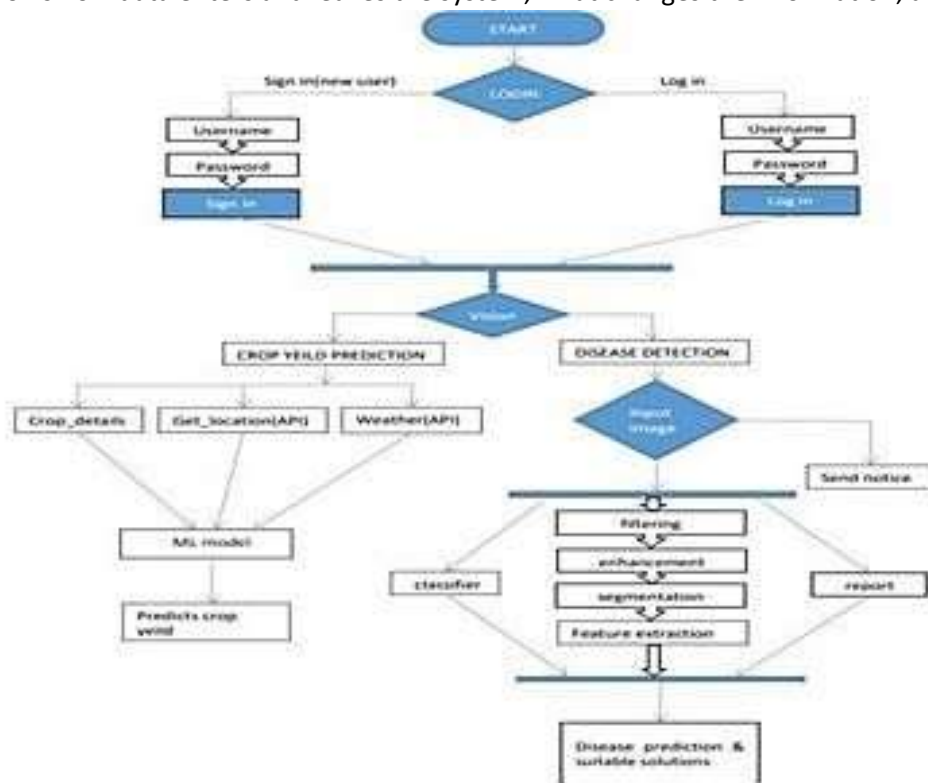
**NFR-6 Scalability** Farmers, Vegetable sellers, ci zens can use this, predic on of data is accurate.

## 5. PROJECT DESIGN

### 5.1 Data Flow Diagrams:

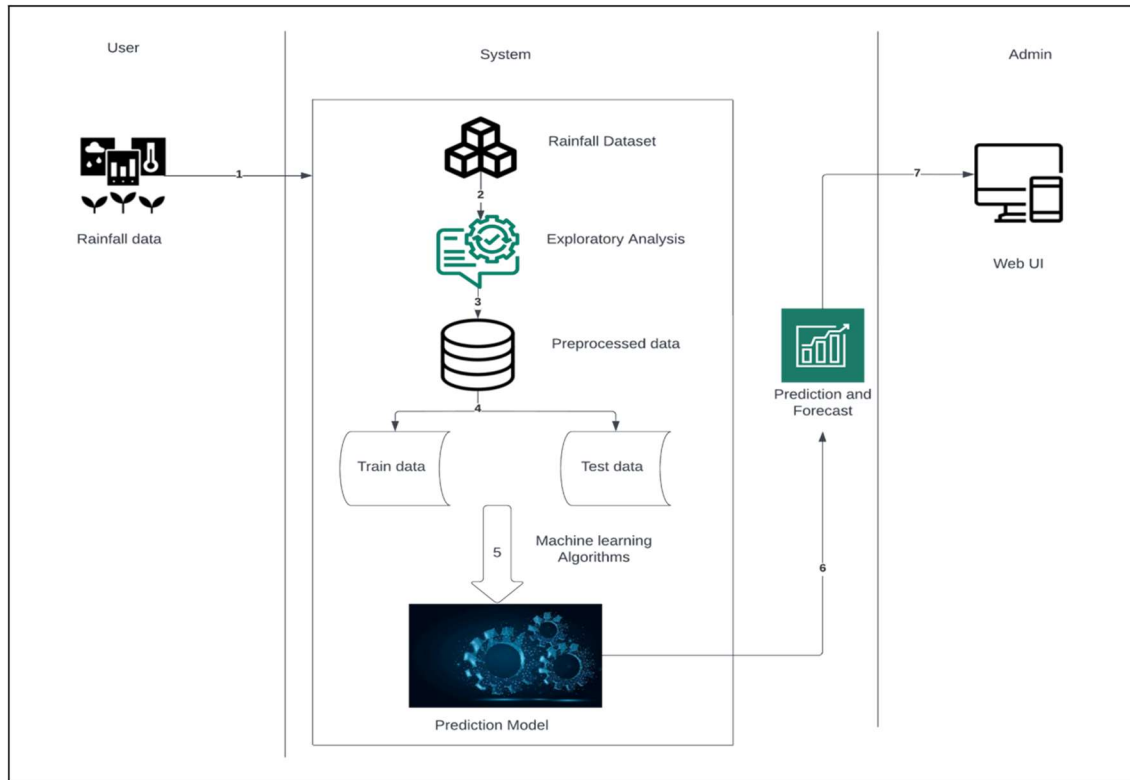
#### Data Flow Diagrams:

A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system. A neat and clear DFD can depict the right amount of the system requirement graphically. It shows how data enters and leaves the system, what changes the information, and where data is stored.



### 5.2 Technical Architecture:





**Table-1 : Components & Technologies:**

S.No	Component	Description	Technology
1.	User Interface	The user interacts with the application through a web UI and a chatbot	HTML, CSS, python, Flask
2.	Application Logic-1	Logic for registration Registration	Python
3.	Application Logic-2	Logic for login to the application	Python
4.	Application Logic-3	Integrating machine learning model and the webpage	Flask
5.	Database	Numeric data	MySQL
6.	File Storage	To store files such as prediction report	Local Filesystem
7.	External API	Allows developers access to critical forecasts, alerts, and observations, along with other weather data.	IBM Weather API
8.	Machine Learning Model	Predictive modeling is a statistical technique using machine learning and data mining to predict and forecast likely future outcomes with the aid of historical and existing data	Predictive modeling
9.	Infrastructure (Server)	Application Deployment on Local System Local Server Configuration: built-in flask web server	Flask web server

**Table-2: Application Characteristics:**

S.No	Characteristics	Description	Technology
1.	Open-Source Frameworks	Flask	Micro web framework written in Python
2.	Security Implementations	Basic HTTP authentication, Session based authentication, User Registration, Login Tracking	Flask Security
3.	Scalable Architecture	Size is everything, and Flask's status as a microframework means that you can use it to grow a tech project such as a web app incredibly quickly. Its simplicity of use and few dependencies enable it to run smoothly even as it scales up and up.	Flask
4.	Availability	Higher compatibility with latest technologies and allows customization	Flask
5.	Performance	<ul style="list-style-type: none"><li>● Integrated support for unit testing.</li><li>● RESTful request dispatching.</li><li>● Uses Jinja templating.</li><li>● Support for secure cookies (client side sessions)</li><li>● 100% WSGI 1.0 compliant.</li></ul>	Flask

### **5.3 User Stories:**

User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Customer (Mobile user)	Registration	USN-1	As a user, I can register for the application by entering my email, password, and confirming my password.	I can access my account / dashboard	High	Sprint-1
		USN-2	As a user, I will receive confirmation email once I have registered for the application	I can receive confirmation email & click confirm	High	Sprint-1
		USN-3	As a user, I can register for the application through Facebook	I can register & access the dashboard with Facebook Login	Low	Sprint-2
		USN-4	As a user, I can register for the application through Gmail		Medium	Sprint-1
	Login	USN-5	As a user, I can log into the application by entering email & password		High	Sprint-1
	Dashboard	USN-6	As a user, I can view the details about the page and navigate through the entire pages	I can navigate through the pages.	Medium	Sprint-1
	Prediction	USN-7	User can search for the area / place where the user wants to know the prediction of rainfall .	Searching for the region within INDIA only be accepted	High	Sprint-1
		USN-8	The prediction or analysis for the desired region for the future or past events respectively		High	Sprint-1
		USN-9	User can see the visualization of the rainfall data for the specific region in INDIA for a specified time period.		High	Sprint-1

	News	USN-10	User can view the latest news articles related to agriculture.	I can view the news articles.	Medium	Sprint-2
Customer (Web user)	Support	USN-11	User can ask queries about the system.	I can rectify my doubts	High	Sprint-3
Customer Care Executive		USN-12	The team must analyse all the queries and debug it in the next update		High	Sprint-3
User Type	Functional Requirement (Epic)	User Story Number	User Story / Task	Acceptance criteria	Priority	Release
Core development team	Core function	USN - 14	Design and develop the application in such a way that the best user interface and maintenance should be taken care of		High	Sprint-1
		USN - 15	The website is responsive on all the devices and the screen sizes. User experience should be good irrespective of the devices or platforms		High	Sprint - 1

## 6.PROJECT PLANNING & SCHEDULING

### 6.1 Sprint Delivery Schedule:

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### Project Planning Phase

Project Planning Template (Product Backlog, Sprint Planning, Stories, Story points)

Date	27 October 2022
Team ID	PNT2022TMD10487
Project Name	Project – EXPLORATORY ANALYSIS OF RAINFALL DATA IN INDIA FOR AGRICULTURE.
Maximum Marks	8 Marks

Product Backlog, Sprint Schedule, and Estimation (4 Marks)

Use the below template to create product backlog and sprint schedule

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Rainfall Prediction ML Model (Dataset)	USN-1	Weather Dataset Collection, Data preprocessing, Data Visualization.	5	High	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint-1		USN-2	Train Model using Different machine learning Algorithms	5	High	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint-1		USN-3	Test the model and give best	10	High	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint-2	Registration	USN-4	As a user, they can register for the application through Gmail. Password is set up.	5	Medium	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint-2	Login	USN-5	As a user, they can log into the application by entering email & password	5	Medium	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN

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Sprint-2		USN-6	Credentials should be used for multiple systems and verified	4	Medium	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint-2	Dashboard	USN-7	Attractive dashboard forecasting live weather	6	Low	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint-3	Rainfall Prediction	USN-8	User enter the location, temperature, humidity	10	High	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint-3		USN-9	Predict the rainfall and display the result	10	High	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-4	Testing	USN-10	Test the application	10	High	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN
Sprint-4	Deploy Model	USN-11	Deploy the model in IBM cloud to make user friendly application	10	High	G.SAIKIRAN,GOWTHAM,GOWTHAMI,GOWRIVIGNESHWARAN

Project Tracker, Velocity & Burndown Chart: (4 Marks)

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	31 Oct 2022	05 Nov 2022	20	05 Nov 2022
Sprint-2	20	6 Days	05 Nov 2022	10 Nov 2022	20	10 Nov 2022
Sprint-3	20	6 Days	10 Nov 2022	15 Nov 2022	20	15 Nov 2022
Sprint-4	20	6 Days	15 Nov 2022	21 Nov 2022	20	21 Nov 2022

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**Velocity:**

Imagine we have a 5-day sprint duration, and the velocity of the team is 20 (points per sprint). Let's calculate the team's average velocity (AV) per iteration unit (story points per day)

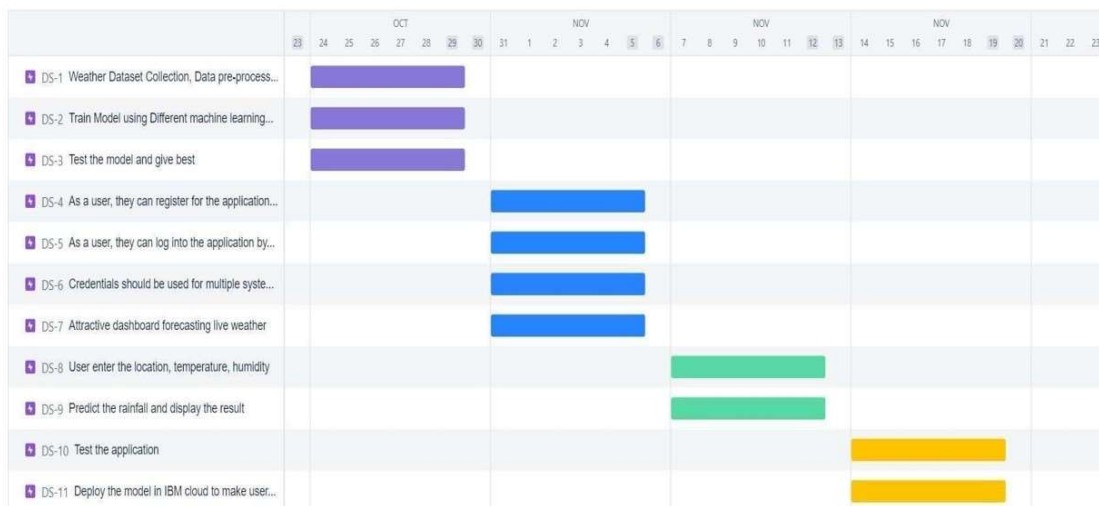
$$AV = \text{Sprint duration} / \text{Velocity} = 20 / 5 = 4$$

Total Average Velocity=4

### **Burndown Chart:**

A burn down chart is a graphical representation of work left to do versus time. It is often used in agile software development methodologies such as Scrum. However, burn down charts can be applied to any project containing measurable progress over time.

**Tool : Jira Software**



## **6.2 Sprint Planning & Es ma on:**

TITLE	DESCRIPTION	DATE
Literature survey & information gathering	Collect the relevant information on project use case, refer the existing solutions, technical papers, research publications etc.	12 SEPTEMBER 2022
Prepare empathy map	Prepare Empathy Map Canvas and List of problem statements	14 SEPTEMBER 2022



Ideation	List the ideas by organizing the brainstorming session and prioritize the top 3 ideas based on the feasibility & importance	22 SEPTEMBER 2022
Proposed solution	Prepare the proposed solution document, which includes the novelty, feasibility of idea, business model, social impact, scalability of solution, etc.	24 SEPTEMBER 2022
Problem solution fit	Prepare problem - solution fit document & Solution Architecture	19 OCTOBER 2022 ( resubmitted)
Solution Architecture	Prepare Solution Architecture document	resubmitted )19 OCTOBER 2022 (

Customer journey	Prepare the customer journey maps to understand the user interactions & experiences with the application	19 OCTOBER 2022
Solution requirement	Prepare the Functional Requirement Document	19 OCTOBER 2022
Data flow diagrams	Prepare the Data Flow Diagrams	19 OCTOBER 2022
Technology architecture	Prepare Technology Architecture of the solution	19 OCTOBER 2022
Prepare Milestone & activity list	Prepare the Milestone & activity list of the project	26 OCTOBER 2022
Project development – delivery of sprint – 1,2,3 & 4	Develop & submit the developed code by testing it	In process ...



## 7.CODING & SOLUTIONING

(Explain the features added in the project along with code)

### 7.1 Feature 1

```
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
import sklearn

data = pd.read_csv("/content/weatherAUS.csv - weatherAUS.csv.csv")
data.head()
```

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation
Sunshine \						
0	2008-12-01	Albury	13.4	22.9	0.6	NaN
NaN						
1	2008-12-02	Albury	7.4	25.1	0.0	NaN
NaN						
2	2008-12-03	Albury	12.9	25.7	0.0	NaN
NaN						
3	2008-12-04	Albury	9.2	28.0	0.0	NaN
NaN						
4	2008-12-05	Albury	17.5	32.3	1.0	NaN
NaN						

	WindGustDir	WindGustSpeed	WindDir9am	...	Humidity9am	Humidity3pm
\						
0	W	44.0	W	...	71.0	22.0
1	WNW	44.0	NNW	...	44.0	25.0
2	WSW	46.0	W	...	38.0	30.0
3	NE	24.0	SE	...	45.0	16.0
4	W	41.0	ENE	...	82.0	33.0

	Pressure9am	Pressure3pm	Cloud9am	Cloud3pm	Temp9am	Temp3pm
RainToday \						
0	1007.7	1007.1	8.0	NaN	16.9	21.8
No						
1	1010.6	1007.8	NaN	NaN	17.2	24.3
No						
2	1007.6	1008.7	NaN	2.0	21.0	23.2

No						
3	1017.6	1012.8	NaN	NaN	18.1	26.5
No						
4	1010.8	1006.0	7.0	8.0	17.8	29.7
No						

	RainTomorrow
0	No
1	No
2	No
3	No
4	No

[5 rows x 23 columns]

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
21  RainToday             142199 non-null object
22  RainTomorrow          142193 non-null object
dtypes: float64(16), object(7)
memory usage: 25.5+ MB
```

data.shape

(145460, 23)

```
print('\nUnique Values: ',data.nunique())
```

```
Unique Values: Date          3436
Location          49
MinTemp          389
MaxTemp          505
Rainfall         681
Evaporation      358
Sunshine         145
WindGustDir       16
WindGustSpeed     67
WindDir9am        16
WindDir3pm        16
WindSpeed9am      43
WindSpeed3pm      44
Humidity9am       101
Humidity3pm       101
Pressure9am       546
Pressure3pm       549
Cloud9am          10
Cloud3pm          10
Temp9am           441
Temp3pm           502
RainToday         2
RainTomorrow      2
dtype: int64
```

```
print('\nMissing Values: ',data.isna().sum())
```

```
Missing Values: 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
```

```
data.describe()
```

	MinTemp	MaxTemp	Rainfall	Evaporation	\
count	143975.000000	144199.000000	142199.000000	82670.000000	
mean	12.194034	23.221348	2.360918	5.468232	
std	6.398495	7.119049	8.478060	4.193704	
min	-8.500000	-4.800000	0.000000	0.000000	
25%	7.600000	17.900000	0.000000	2.600000	
50%	12.000000	22.600000	0.000000	4.800000	
75%	16.900000	28.200000	0.800000	7.400000	
max	33.900000	48.100000	371.000000	145.000000	

	Sunshine	WindGustSpeed	WindSpeed9am	WindSpeed3pm	\
count	75625.000000	135197.000000	143693.000000	142398.000000	
mean	7.611178	40.035230	14.043426	18.662657	
std	3.785483	13.607062	8.915375	8.809800	
min	0.000000	6.000000	0.000000	0.000000	
25%	4.800000	31.000000	7.000000	13.000000	
50%	8.400000	39.000000	13.000000	19.000000	
75%	10.600000	48.000000	19.000000	24.000000	
max	14.500000	135.000000	130.000000	87.000000	

	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	\
count	142806.000000	140953.000000	130395.000000	130432.000000	
mean	68.880831	51.539116	1017.64994	1015.255889	
std	19.029164	20.795902	7.10653	7.037414	
min	0.000000	0.000000	980.50000	977.100000	
25%	57.000000	37.000000	1012.90000	1010.400000	
50%	70.000000	52.000000	1017.60000	1015.200000	
75%	83.000000	66.000000	1022.40000	1020.000000	
max	100.000000	100.000000	1041.00000	1039.600000	

	Cloud9am	Cloud3pm	Temp9am	Temp3pm
count	89572.000000	86102.000000	143693.000000	141851.000000
mean	4.447461	4.509930	16.990631	21.68339
std	2.887159	2.720357	6.488753	6.93665
min	0.000000	0.000000	-7.200000	-5.40000
25%	1.000000	2.000000	12.300000	16.60000
50%	5.000000	5.000000	16.700000	21.10000
75%	7.000000	7.000000	21.600000	26.40000
max	9.000000	9.000000	40.200000	46.70000

```
data.isnull().sum()
```

```
Date      0
Location  0
```



```

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

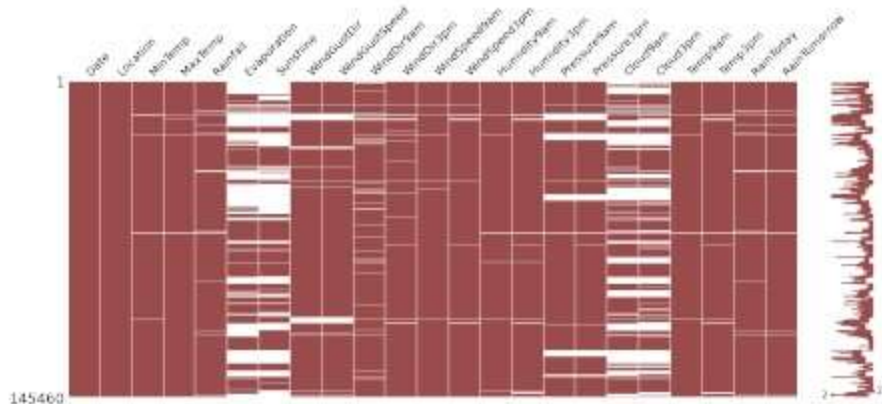
```

```

import missingno as msno
msno.matrix(data,color=(0.60,0.300,0.300),fontsize=20)

<matplotlib.axes._subplots.AxesSubplot at 0x7ff0c1783bd0>

```



```

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)

```

```

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)

cat_names=data_cat.columns
import numpy as np

from sklearn.impute import SimpleImputer
imp_mode= SimpleImputer (missing_values=np.nan, strategy =
'most_frequent')
data_cat= imp_mode.fit_transform(data_cat)
data_cat = pd.DataFrame(data_cat,columns=cat_names)
data = pd.concat([data, data_cat],axis=1)
data.corr()

```

	MinTemp	MaxTemp	Rainfall	WindGustSpeed
WindSpeed9am \				
MinTemp	1.000000	0.733400	0.102706	0.172553
0.173404				
MaxTemp	0.733400	1.000000	-0.074040	0.065895

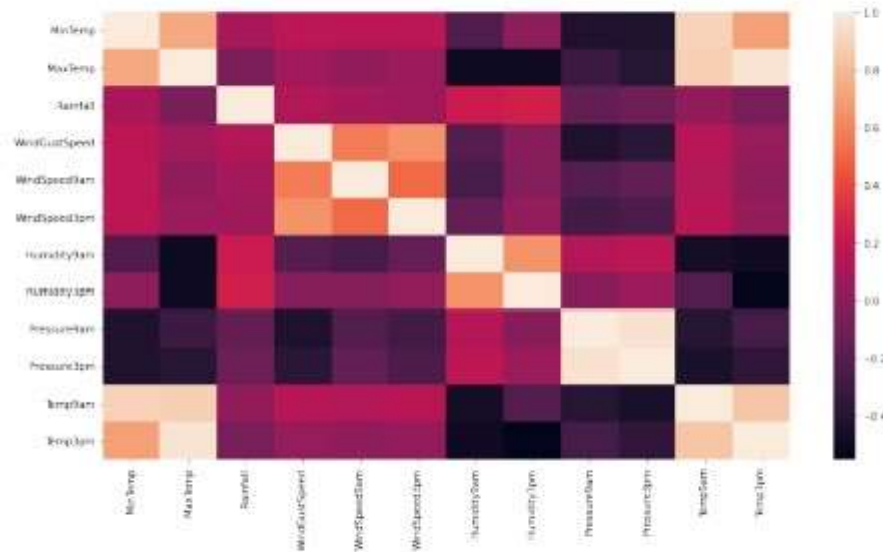
0.014294				
Rainfall	0.102706	-0.074040	1.000000	0.126446
0.085925				
WindGustSpeed	0.172553	0.065895	0.126446	1.000000
0.577319				
WindSpeed9am	0.173404	0.014294	0.085925	0.577319
1.000000				
WindSpeed3pm	0.173058	0.049717	0.056527	0.657243
0.512427				
Humidity9am	-0.230970	-0.497927	0.221380	-0.207964
0.268271				
Humidity3pm	0.005995	-0.498760	0.248905	-0.025355
0.030887				
Pressure9am	-0.423584	-0.308309	-0.159055	-0.425760
0.215339				
Pressure3pm	-0.433147	-0.396622	-0.119541	-0.383938
0.165388				
Temp9am	0.897692	0.879170	0.011069	0.145904
0.127592				
Temp3pm	0.699211	0.968713	-0.077684	0.031884
0.004476				

	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am	\
MinTemp	0.173058	-0.230970	0.005995	-0.423584	
MaxTemp	0.049717	-0.497927	-0.498760	-0.308309	
Rainfall	0.056527	0.221380	0.248905	-0.159055	
WindGustSpeed	0.657243	-0.207964	-0.025355	-0.425760	
WindSpeed9am	0.512427	-0.268271	-0.030887	-0.215339	
WindSpeed3pm	1.000000	-0.143458	0.016275	-0.277604	
Humidity9am	-0.143458	1.000000	0.659072	0.131503	
Humidity3pm	0.016275	0.659072	1.000000	-0.025848	
Pressure9am	-0.277604	0.131503	-0.025848	1.000000	
Pressure3pm	-0.239659	0.176009	0.048695	0.959662	
Temp9am	0.161060	-0.469641	-0.216964	-0.397131	
Temp3pm	0.027587	-0.490709	-0.555608	-0.265532	

	Pressure3pm	Temp9am	Temp3pm
MinTemp	-0.433147	0.897692	0.699211
MaxTemp	-0.396622	0.879170	0.968713
Rainfall	-0.119541	0.011069	-0.077684
WindGustSpeed	-0.383938	0.145904	0.031884
WindSpeed9am	-0.165388	0.127592	0.004476
WindSpeed3pm	-0.239659	0.161060	0.027587
Humidity9am	0.176009	-0.469641	-0.490709
Humidity3pm	0.048695	-0.216964	-0.555608
Pressure9am	0.959662	-0.397131	-0.265532
Pressure3pm	1.000000	-0.441459	-0.360707
Temp9am	-0.441459	1.000000	0.846141
Temp3pm	-0.360707	0.846141	1.000000

```
cor=data.corr()
plt.figure(figsize=(15,8))
sns.heatmap(data=cor,xticklabels=cor.columns.values,yticklabels=cor.columns.values)
```

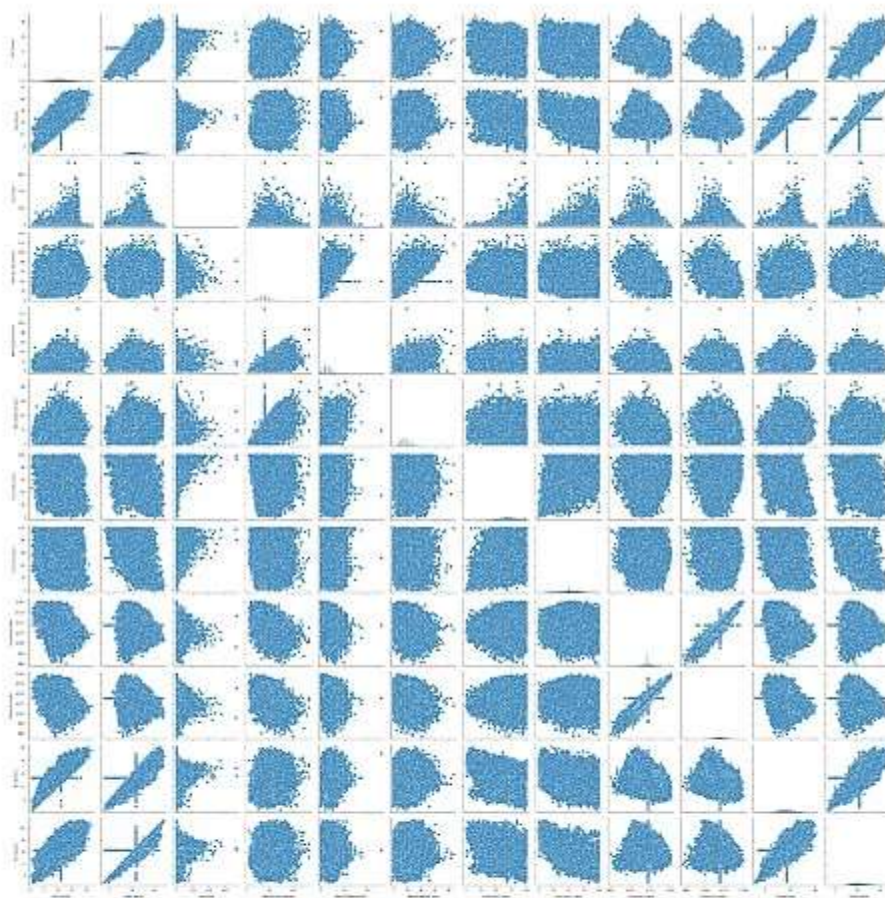
<matplotlib.axes.\_subplots.AxesSubplot at 0x7fb321e2bc10>



```
sns.pairplot(data)
```

<seaborn.axisgrid.PairGrid at 0x7fb31479d610>





```
plt.figure(figsize=(15,8))  
data.boxplot()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb30f56ec50>
```

```

0      W      WNW
1     NNW     WSW
2      W      WSW
3      SE      E
4     ENE     NW

```

```
df.shape
```

```
(142193, 19)
```

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

```
y=df['RainTomorrow']
```

```
x.head()
```

	Date	Location	MinTemp	MaxTemp	Rainfall	WindGustSpeed \
0	2008-12-01	Albury	13.4	22.9	0.6	44.0
1	2008-12-02	Albury	7.4	25.1	0.0	44.0
2	2008-12-03	Albury	12.9	25.7	0.0	46.0
3	2008-12-04	Albury	9.2	28.0	0.0	24.0
4	2008-12-05	Albury	17.5	32.3	1.0	41.0

	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm	Pressure9am \
0	20.0	24.0	71.0	22.0	1007.7
1	4.0	22.0	44.0	25.0	1010.6
2	19.0	26.0	38.0	30.0	1007.6
3	11.0	9.0	45.0	16.0	1017.6
4	7.0	20.0	82.0	33.0	1010.8

	Pressure3pm	Temp9am	Temp3pm	RainToday	WindGustDir	WindDir9am
0	1007.1	16.9	21.8	No	W	W
1	1007.8	17.2	24.3	No	WNW	NNW
2	1008.7	21.0	23.2	No	WSW	W
3	1012.8	18.1	26.5	No	NE	SE
4	1006.0	17.8	29.7	No	W	ENE

```
x_main=x.drop(['Date','Location','WindGustDir','WindDir9am','WindDir3pm'],axis=1)
```

```
x_main.head()
```

4	7.0	20.0	82.0	33.0	1010.8
---	-----	------	------	------	--------

	Pressure3pm	Temp9am	Temp3pm	RainTomorrow	RainToday	WindGustDir	\
0	1007.1	16.9	21.8	No	No	W	
1	1007.8	17.2	24.3	No	No	WNW	
2	1008.7	21.0	23.2	No	No	WSW	
3	1012.8	18.1	26.5	No	No	NE	
4	1006.0	17.8	29.7	No	No	W	

	WindDir9am	WindDir3pm
0	W	WNW
1	NNW	WSW
2	W	WSW
3	SE	E
4	ENE	NW

```
df=data.dropna()
df.head()
```

	Date	Location	MinTemp	MaxTemp	Rainfall	WindGustSpeed	\
0	2008-12-01	Albury	13.4	22.9	0.6	44.0	
1	2008-12-02	Albury	7.4	25.1	0.0	44.0	
2	2008-12-03	Albury	12.9	25.7	0.0	46.0	
3	2008-12-04	Albury	9.2	28.0	0.0	24.0	
4	2008-12-05	Albury	17.5	32.3	1.0	41.0	

	WindSpeed9am	WindSpeed3pm	Humidity9am	Humidity3pm
0	20.0	24.0	71.0	22.0
1	4.0	22.0	44.0	25.0
2	19.0	26.0	38.0	30.0
3	11.0	9.0	45.0	16.0
4	7.0	20.0	82.0	33.0

	Pressure3pm	Temp9am	Temp3pm	RainTomorrow	RainToday	WindGustDir	\
0	1007.1	16.9	21.8	No	No	W	
1	1007.8	17.2	24.3	No	No	WNW	
2	1008.7	21.0	23.2	No	No	WSW	
3	1012.8	18.1	26.5	No	No	NE	
4	1006.0	17.8	29.7	No	No	W	

	WindDir9am	WindDir3pm
--	------------	------------

	MinTemp	MaxTemp	Rainfall	WindGustSpeed	WindSpeed9am
0	13.4	22.9	0.6	44.0	20.0
1	7.4	25.1	0.0	44.0	4.0
2	12.9	25.7	0.0	46.0	19.0
3	9.2	28.0	0.0	24.0	11.0
4	17.5	32.3	1.0	41.0	7.0

	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	Temp9am
0	71.0	22.0	1007.7	1007.1	16.9
1	44.0	25.0	1010.6	1007.8	17.2
2	38.0	30.0	1007.6	1008.7	21.0
3	45.0	16.0	1017.6	1012.8	18.1
4	82.0	33.0	1010.8	1006.0	17.8

	RainToday
0	No
1	No
2	No
3	No
4	No

```
x_p=pd.get_dummies(x_main,columns=['RainToday'])
x_p.head()
```

	MinTemp	MaxTemp	Rainfall	WindGustSpeed	WindSpeed9am
0	13.4	22.9	0.6	44.0	20.0
1	7.4	25.1	0.0	44.0	4.0
2	12.9	25.7	0.0	46.0	19.0
3	9.2	28.0	0.0	24.0	11.0
4	17.5	32.3	1.0	41.0	7.0

	Humidity9am	Humidity3pm	Pressure9am	Pressure3pm	Temp9am
--	-------------	-------------	-------------	-------------	---------



Temp3pm \					
0	71.0	22.0	1007.7	1007.1	16.9
21.8					
1	44.0	25.0	1010.6	1007.8	17.2
24.3					
2	38.0	30.0	1007.6	1008.7	21.0
23.2					
3	45.0	16.0	1017.6	1012.8	18.1
26.5					
4	82.0	33.0	1010.8	1006.0	17.8
29.7					

	RainToday_No	RainToday_Yes
0	1	0
1	1	0
2	1	0
3	1	0
4	1	0

```

from sklearn.preprocessing import LabelEncoder
lb=LabelEncoder()
y_main=pd.DataFrame(lb.fit_transform(y),columns=['RainTomorrow'])
y_main.head()

```

	RainTomorrow
0	0
1	0
2	0
3	0
4	0

```

from sklearn.preprocessing import StandardScaler

names = x.columns

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

sc=StandardScaler()

x_scaled=pd.DataFrame(sc.fit_transform(x_p),columns=x_p.columns)
x_scaled.head()

```

```

    MinTemp    MaxTemp    Rainfall    WindGustSpeed    WindSpeed9am
WindSpeed3pm \
0  0.189949 -0.045963 -0.207770      0.305395      0.677617
0.614796
1  -0.749180  0.263481 -0.279002      0.305395     -1.130078
0.385479
2  0.111688  0.347875 -0.279002      0.457621      0.564636
0.844114
3  -0.467441  0.671385 -0.279002     -1.216867     -0.339212    -
1.105087
4  0.831687  1.276207 -0.160282      0.077056     -0.791135
0.156161

    Humidity9am    Humidity3pm    Pressure9am    Pressure3pm    Temp9am
Temp3pm \
0  0.113867     -1.436005     -1.475400     -1.220931    -0.013524
0.016423
1  -1.312289     -1.289891     -1.045530     -1.116169     0.032829
0.380285
2  -1.629213     -1.046369     -1.490223     -0.981474     0.619960
0.220185
3  -1.259469     -1.728231     -0.007913     -0.367863     0.171886
0.700483
4  0.694893     -0.900255     -1.015884     -1.385559     0.125534
1.166225

    RainToday_No    RainToday_Yes
0      0.532962      -0.532962
1      0.532962      -0.532962
2      0.532962      -0.532962
3      0.532962      -0.532962
4      0.532962      -0.532962

from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test =
train_test_split(x_scaled,y_main,test_size=0.2,random_state=0)

```

## 7.2 Feature 2:

## MODEL BUILDING

### Training And Testing The Model

```
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()
```

```
# Training the every model with Train data
```

```
model1=XGBoost.fit(x_train,y_train)  
model2=Rand_forest.fit(x_train,y_train)  
model3=svm.fit(x_train,y_train)  
model4=Dtree.fit(x_train,y_train)  
model5=GBM.fit(x_train,y_train)  
model6=log.fit(x_train,y_train)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/  
_label.py:98: DataConversionWarning: A column-vector y was passed when  
a 1d array was expected. Please change the shape of y to  
(n_samples, ), for example using ravel().
```

```
    y = column_or_1d(y, warn=True)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/preprocessing/_label.py  
:133: DataConversionWarning: A column-vector y was passed when a 1d  
array was expected. Please change the shape of y to (n_samples, ), for  
example using ravel().
```

```
    y = column_or_1d(y, warn=True)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:  
DataConversionWarning: A column-vector y was passed when a 1d array  
was expected. Please change the shape of y to (n_samples, ), for  
example using ravel().
```

This is separate from the ipykernel package so we can avoid doing  
imports until

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:993  
: DataConversionWarning: A column-vector y was passed when a 1d array  
was expected. Please change the shape of y to (n_samples, ), for  
example using ravel().
```

```
    y = column_or_1d(y, warn=True)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/ensemble/_gb.py:494:  
DataConversionWarning: A column-vector y was passed when a 1d array  
was expected. Please change the shape of y to (n_samples, ), for  
example using ravel().
```

```
    y = column_or_1d(y, warn=True)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:993  
: DataConversionWarning: A column-vector y was passed when a 1d array  
was expected. Please change the shape of y to (n_samples, ), for
```

## 8. TESTING

### TESTING REPORT

Testing of an individual software component or module is termed as Unit Testing. It is typically done by the programmer and not by testers, as it requires detailed knowledge of the internal program design and code.

The Code was developed in 3 separate parts-

1. AI Model developed using Jupyter Notebook
2. Web Front end was developed using VS Code
3. Backend Database was developed using MongoDB

PROJECT NAME	Exploratory Analysis of RainFall Data in India for Agriculture
PROJECT TYPE	APPLIED DATA SCIENCE
DEVELOPER	Praveen
LANGUAGE	PYTHON,HTML,CSS,JAVA SCRIPT
TOTAL NUMBER OF TEST CASES	50
NUMBER OF TEST CASES EXECUTED	49
NUMBER OF TEST CASES PASSED	45
NUMBER OF TEST CASES FAILED	4-DUE TO TECHNICAL ISSUES

### UNIT TESTING:

Unit testing is carried out screen-wise, each screen being identified as an object. Attention is diverted to individual modules, independently to one another to locate errors. This has enabled the detection of errors in coding and logic



.This is the first level of testing. In this, codes are written such that from one module, we can move on to the next module according to the choice we enter.



### SYSTEM TESTING:

In this, the entire system was tested as a whole with all forms, code, modules and class modules. System testing is the stage of implementation, which is aimed at ensuring that the system works accurately and efficiently before live operation commences.

It is a series of different tests that verifies that all system elements have been properly integrated and perform allocated functions.

System testing makes logical assumptions that if all parts of the system are correct, the goal will be successfully achieved. Testing is the process of executing the program with the intent of finding errors.

Testing cannot show the absence of defects, it can only show that software errors are present.



## 9.RESULTS

A screenshot of a web browser window. The browser's address bar shows the file path: C:/Users/prave/OneDrive/Desktop/PAVEEN/template/PRAVEEN.html. The webpage has a dark, cloudy sky background. At the top, the title "Rainfall Prediction" is displayed. Below the title, there is a list of input fields, each with a label and a text box: "Mintemp" (Min temp), "Maxtemp" (Max temp), "Rainfall" (Rainfall), "WindGustSpeed" (WindGustSpeed), "WindSpeed9am" (WindSpeed9am), "WindSpeed3pm" (WindSpeed3pm), "Humidity9am" (Humidity9am), "Humidity3pm" (Humidity3pm), "Pressure9am" (Pressure 9am), "Pressure3pm" (Pressure 9am), "Temp9am" (Temp9am), "Temp3pm" (Temp3pm), "RainToday\_No", and "RainToday\_Yes". At the bottom of the form, there is a "Predict" button. The browser's taskbar at the bottom shows the system clock as 14:10 on 18-11-2022, along with various application icons and a weather widget showing 29°C Haze.

**\*By clicking the referred values in the above html above page then we can get the chance basing on the information stored in the dataset what we have**  
**\*here is the data set value information we have it.**

### Advantages of EDA:

- It gives us valuable insights into the data.
- It helps us with feature selection (i.e using PCA)
- Visualization is an effective way of detecting outliers.

### Disadvantages of EDA:

- If not perform properly EDA can misguide a problem.
- EDA does not effective when we deal with high-dimensional data.

### Applications of Exploratory Data Analysis:

- Let's analyze the applications of Exploratory Data Analysis with a use case of univariate analysis where we will seek the measurement of the central tendency of the data:
- Measurement of central tendency gives us an overview of the univariate variable. Central tendency is the measurement of Mean, Median, and Mode.
- Mean is the simple average where the median is the 50% percentile and Mode is the most frequently occurring value. Suppose we want to get the knowledge about the salary of a data scientist.
- Also, suppose we have carefully collected data of the data scientist with similar expertise and experience range.

Now if we want to get the average it is simply the total salary of all the data scientists of the sample divided by the number of data scientists in the sample or population. But if you think carefully the average salary is not a proper term because in the presence of some extreme values the result will be skewed. Suppose for maximum cases the salary is between 8-10 LPA and for one or two cases it is 32 LPA. Now adding all these the average will be skewed. Median is more suitable for such situations, it is more robust to outliers.

### Conclusion:

In this article, we have discussed the various methodologies involved in exploratory data analysis, the applications, advantages, and disadvantages it. We

also walked through the sample codes to generate the plots in python using seaborn and Matplotlib libraries. EDA is the art part of data science literature which helps to get valuable insights and visualize the data.

### Scope for future work:

Acceptance and use of weather information based farm advisories is likely to occur gradually. Farmers need time to try out new information, experience the benefits, and accept the results. Technology is changing rapidly whereas the mindset of the farmers changes slowly. Experiencing accurate information and beneficial outcomes leads to trust building which certainly will encourage educated farmers to adopt the advisories. The following points may be taken into consideration while planning the future studies.

- Need to make these impact studies an integral part of the Agro advisory services of the country. Need to develop AAS service based decision support system for managing weather variability in reducing the negative impacts on yield.
- Improving package of practices for major crops keeping in view the weather sensitive crop stages and weather sensitive farm operations for reducing cost of cultivation and improving yield and increasing net returns. Need to improve the forecast quality during the sowing operations of kharif crops.
- Studies may be undertaken to quantify the value of medium range weather forecast in Nitrogen fertilizer management in arable crops. The N fertilizer advice may be tested through determining the uptake efficiency. The

changes in N leaching, de-nitrification and crop N uptake due to the forecast quality needs to be assessed.

- Yield and gross profit changes may then be linked to N uptake. 99 Need to integrate Medium Range Weather Forecast with extended range forecast for better planning of the field operations particularly for sowing and mid-season corrections incase of drought.
- The impact studies should be replicated in other crops of the region. Similar studies are also needed in other AAS units in India. The successful implementation of the scientific agro-meteorological forecasts need blending with local technologies like traditional methods so that farmers can readily adopt and be benefited from these scientific forecast.
- There is need to deliver district level weather based advisories through an automated dissemination system. In addition to the agriculture sector there is need to carry out similar studies in other weather sensitive sectors of economy as systematic and reliable data on the scope and dimensions of the relationship of weather and various user sectors is lacking.
- Better understanding of use and value of weather forecast may help substantially reduce the risks to life and property. For example, if there is knowledge about how many people and how much property is actually at risk to floods, one may be able to develop better strategies to reduce that undefined risk.
- In addition to the general lack of knowledge of the societal context of weather events, there is also limited understanding of how decision makers could and actually use weather information. The significance of this study seems to call for a wide range of interests to support the similar efforts on other sectors such as aviation, power etc.
- The power firms like the Power Grid Corporation of India (PGCIL) require location specific quantitative forecast of Maximum/ Minimum Temperatures, Rainfall, Clouds, Wind Speed/direction four days in advance to run their Load Forecast models and the Power Distribution models.

- PGCIL estimates about 5-12 % saving on power equivalent to Rs 110 crore per month through use of weather forecast of higher accuracy (>70%)  
Therefore to undertake work in such spheres, there is urgent need to form a cohesive group of meteorologists (forecasters and researchers), users, and representatives from related fields (economics, policy makers, etc.).
- Although the entire meteorological community ought to be concerned with the outcome of that decision-making process, one should not try to do this in meteorological terms only. Public policy-makers must make difficult economic decisions that include issues of human safety, as well as purely economic factors.
- Decision making in weather sensitive sectors of economy must be made with knowledge of the economic impacts of weather forecasts, rather than without that quantitative information.

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Annexure:

### Annexure-I

Following are the verification scores that have been used for verifying the rainfall and temperature forecasts disseminated to the AAS units on a bi-weekly basis

#### (a) Measures of obtaining skill of Yes/No rainfall

In the following 2×2 contingency table, if Y stands for occurrence of rain and N stands for non-occurrence then

Forecast (Rain)	Observed (Rain)	
	Yes	No
Yes	YY	YN
No	NY	NN

The total number of cases ( $M$ ) is given by:

$$M = YY + YN + NY + NN$$

##### i. Ratio Score

Ratio Score ( $RS$ ), also known as the Hit Rate or Percentage Correct, measures the proportion of correct forecasts. The  $RS$  varies from 0 to 100 with 100 indicating perfect forecasts.

$$RS = \frac{\text{correct forecasts}}{\text{total forecasts}} = \frac{(YY + NN)}{M} \times 100$$

##### ii. Hanssen and Kuipers' Score

Hanssen and Kuipers' Score ( $HKS$ ) (Woodcock, 1976, 1981) is the ratio of economic saving over climatology due to the forecast to that of a set of perfect forecasts. In  $HKS$  the reference hit rate in the denominator is for random forecasts that are constrained to be unbiased.

$$HKS = \frac{\text{correct forecast} - (\text{correct forecast})_{\text{random}}}{M - (\text{correct forecast})_{\text{random, unbiased}}}$$

$$HKS = \frac{(YY * NN - YN * NY)}{(YY + NY)(YN + NN)}$$

That is, the imagined random reference forecasts in the denominator have a marginal distribution that is equal to the (sample) climatology (Wilks, 1995). The value of  $HKS$  varies from -1 to +1. If all forecast are wrong (i.e.  $YY = NN = 0$ ) then it is -1, and if all forecast are perfect (i.e.  $YN = NY = 0$ ) then it is +1, and random forecasts receive a score of 0.



**(b) Criteria for obtaining usability of Quantitative Precipitation (QP)**

Error Structure for verification of Quantitative Precipitation		
	Observed rainfall $\leq 10\text{mm}$	Observed rainfall $> 10\text{mm}$
Correct	$\text{Diff} \leq 0.2 \text{ mm}$	$\text{Diff} \leq 2\% \text{ of obs}$
Usable	$0.2 \text{ mm} < \text{Diff} \leq 2.0\text{mm}$	$2\% \text{ of obs} < \text{Diff} \leq 20\% \text{ of obs}$
Unusable	$\text{Diff} > 2.0 \text{ mm}$	$\text{Diff} > 20\% \text{ of obs}$

where *Diff* stands for Absolute difference of observed and forecasted in mm and *obs* stands for observed rainfall in mm

**(c) Measures of obtaining skill of temperature**

Correlation Coefficient (*r*) and Root Mean Square Error (*RMSE*) are calculated for obtaining the skill of the model in forecasting maximum and minimum temperatures.

(i). Correlation coefficient can be defined as

$$r(f_i, o_i) = \frac{\sum (f_i - \bar{f})(o_i - \bar{o})}{\left[ \sum (f_i - \bar{f})^2 \sum (o_i - \bar{o})^2 \right]^{1/2}}$$

(ii) Root Mean Square Error (*RMSE*): The *RMSE* is the square root of Mean Square Error (*MSE*) which measures the degree of correspondence between the forecasts and observations in terms of the average squared difference between  $f_i$  and  $o_i$ .

Where

$$RMSE = \left( \frac{1}{n} \sum (f_i - o_i)^2 \right)^{1/2}$$

$f_i$  = forecast value

$\bar{f}$  = mean forecast value

$o_i$  = observed value

$\bar{o}$  = mean observed value

$n$  = total no : of observations / forecast

**(d) Criteria for obtaining usability of Temperature forecast**

Error Structure for verification of Temperature Forecast	
<i>Correct</i>	$Diff \leq 1^{\circ}C$
<i>Usable</i>	$1^{\circ}C < Diff \leq 2^{\circ}C$
<i>Unusable</i>	$Diff > 2^{\circ}C$

where *Diff* stands for Absolute difference of observed and forecasted temperatures in  $^{\circ}C$

**GITHUB LINK : <https://github.com/IBM-EPBL/IBM-Project-27822-1660067073>**