

Exploratory Analysis of Rain Fall Data in India for Agriculture

**An internship report submitted in partial fulfillment of the requirements
for the award of degree of**

**BACHELOR OF TECHNOLOGY
In
COMPUTER SCIENCE AND ENGINEERING**



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1. Introduction

Agriculture in India largely depends on rainfall, making its analysis crucial for improving crop productivity and resource management. This project focuses on exploring historical rainfall data across different regions to identify patterns, seasonal trends, and variability. Using data visualization, statistical techniques, and machine learning methods, the study provides meaningful insights into rainfall behavior. The findings help farmers make better crop planning decisions and assist experts in efficient irrigation management. Additionally, the analysis supports policymakers in assessing agricultural risks such as droughts and floods. Overall, the project promotes data-driven decision-making for sustainable agriculture.

2. Problem Statement

Rainfall variability is a major challenge for agriculture in India. Predicting rainfall manually is difficult due to multiple influencing factors such as:

- Historical rainfall trends
- Seasonal variations (monsoon patterns)
- Temperature levels
- Humidity
- Wind speed and direction
- Atmospheric pressure
- Geographic location and regional climate differences

The goal of this project is:

To build a predictive system that analyzes historical weather data and forecasts rainfall patterns using machine learning techniques to support agricultural planning and risk management.

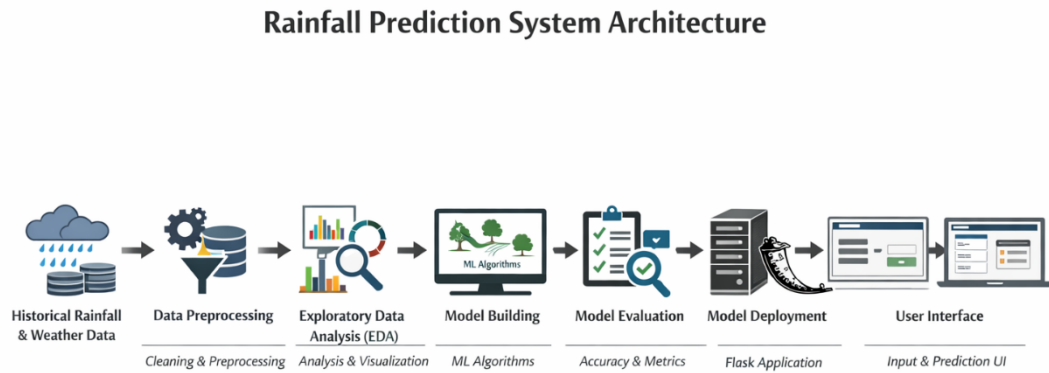
3. Objectives

The primary objectives of this rainfall prediction project are:

1. To analyze the historical rainfall and weather dataset.
2. To clean and preprocess the data (handling missing values, encoding, scaling).
3. To perform Exploratory Data Analysis (EDA) to identify patterns and trends.
4. To build a machine learning model for rainfall prediction (e.g., Random Forest).
5. To evaluate the model performance using appropriate metrics.
6. To deploy the trained model using Flask.
7. To develop a user-friendly web interface for rainfall prediction.

4. System Architecture

Architecture Flow:



Components:

- ☐ Dataset (CSV file – Historical Weather Data)
- ☐ Python (Pandas, NumPy)
- ☐ Scikit-learn
- ☐ Random Forest Algorithm
- ☐ Flask Web Framework
- ☐ HTML (Frontend)
- ☐ Joblib (Model Saving)

5. Dataset Description

The dataset contains weather-related features such as:

| Feature | Description |
|--------------|----------------------|
| Location | City/Region |
| MinTemp | Minimum temperature |
| MaxTemp | Maximum temperature |
| Humidity | Humidity level |
| WindSpeed | Wind speed |
| Pressure | Atmospheric pressure |
| RainToday | Rain today (Yes/No) |
| RainTomorrow | Target variable |

Target Variable:

- 1 → Rain
- 0 → No Rain

6. Data Preprocessing

6.1 Handling Missing Values

- Checked null values using:
`data.isnull().sum()`
- Imputed missing values using mean/median.

6.2 Encoding Categorical Variables

Columns like:

- Location
- Wind Direction

Were encoded using:

`pd.get_dummies()`

6.3 Feature Scaling

Used `StandardScaler` to normalize numerical features.

7. Exploratory Data Analysis (EDA)

7.1 Rainfall Distribution

Analyzed rain vs no-rain cases using count plots.

7.2 Temperature vs Rain

Compared temperature trends during rainy and non-rainy days.

7.3 Humidity Analysis

Observed higher humidity correlation with rainfall.

7.4 Correlation Heatmap

Used:

```
sns.heatmap(corr, cmap='coolwarm', annot=True)
```

To identify feature relationships.

8. Model Selection

Selected:

Random Forest Classifier

Why Random Forest?

- Handles non-linear relationships
- Reduces overfitting
- Works well with large datasets
- High accuracy
- Robust to noise

9. Model Training

9.1 Splitting Dataset

```
X = data_encoded.drop('RainTomorrow', axis=1)
```

```
y = data_encoded['RainTomorrow']
```

```
x_train, x_test, y_train, y_test = train_test_split(
```

```
    X, y, test_size=0.3, random_state=0
```

```
)
```

9.2 Training Model

```
model = RandomForestClassifier()  
model.fit(x_train, y_train)
```

10. Model Evaluation

Metrics Used:

- Accuracy Score
- Confusion Matrix
- Classification Report

```
accuracy_score(y_test, y_pred)
```

```
classification_report(y_test, y_pred)
```

Observations:

- Training Accuracy: High
- Testing Accuracy: Good
- Slight overfitting observed

11. Model Saving

Used Joblib to save the trained model:

```
joblib.dump(model, 'rainfall_model.pkl')
```

This allows the trained rainfall prediction model to be reused without retraining every time the application runs.

12. Web Application Development

Framework Used:

Flask

app.py Structure:

1. Load the trained rainfall model
2. Create route for homepage (/)
3. Accept user weather input
4. Convert input values into required format
5. Predict rainfall using the model
6. Display prediction result

13. Frontend Design

Created using:

- HTML
- Bootstrap (for styling)

Input Fields:

- Temperature
- Humidity
- Wind Speed
- Pressure
- Location (if used)

Prediction Button:

Sends input data to Flask backend and displays rainfall prediction result.

14. Results

The system successfully:

- Accepts weather parameters
- Predicts whether rainfall will occur
- Displays the result instantly

Example:

Input:

- Location: Sydney
- Min Temperature: 16°C
- Max Temperature: 30°C
- Humidity: 85%
- Wind Direction: SW

Output:

Rain is likely Today.

15. Advantages

- Quick prediction
- Easy to use interface
- Good classification accuracy
- Helpful for farmers and planners
- Supports irrigation and crop planning

16. Limitations

- Model depends on historical weather data
- Weather conditions are naturally unpredictable
- Limited feature set
- Possible overfitting

17. Future Enhancements

- Deploy on cloud (AWS / Heroku)
- Add rainfall probability percentage
- Improve UI design
- Add weather data visualization dashboard
- Use advanced models (XGBoost)
- Integrate real-time weather API

18. Technologies Used

| Technology | Purpose |
|--------------|----------------------|
| Python | Programming |
| Pandas | Data analysis |
| NumPy | Numerical operations |
| Scikit-learn | Machine learning |
| Seaborn | Visualization |
| Matplotlib | Visualization |
| Flask | Web backend |
| HTML/CSS | Frontend |
| Joblib | Model saving |

19. Images of Task

Backend:

```
: import pandas as pd
import numpy as np
import joblib

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score

df = pd.read_csv("weatherAUS.csv")
df = df[['Location', 'MinTemp', 'MaxTemp', 'Humidity3pm', 'WindDir3pm', 'RainTomorrow']]
df = df[df['RainTomorrow'].notna()]
df['RainTomorrow'] = df['RainTomorrow'].map({'Yes':1, 'No':0})

X = df.drop("RainTomorrow", axis=1)
y = df["RainTomorrow"]

num_cols = ['MinTemp', 'MaxTemp', 'Humidity3pm']
cat_cols = ['Location', 'WindDir3pm']

num_imputer = SimpleImputer(strategy='mean')
X[num_cols] = num_imputer.fit_transform(X[num_cols])

cat_imputer = SimpleImputer(strategy='most_frequent')
X[cat_cols] = cat_imputer.fit_transform(X[cat_cols])

encoder_dict = {}
for col in cat_cols:
    le = LabelEncoder()
    X[col] = le.fit_transform(X[col])
    encoder_dict[col] = le
```

```
1 from flask import Flask, render_template, request
2 import pandas as pd
3 import joblib
4 import numpy as np
5
6 app = Flask(__name__)
7
8 model = joblib.load("Rainfall.pkl")
9 scaler = joblib.load("scale.pkl")
10 num_imputer = joblib.load("imputer.pkl")
11 encoder_dict = joblib.load("encoder.pkl")
12 FEATURE_ORDER = ['Location', 'MinTemp', 'MaxTemp', 'Humidity3pm', 'WindDir3pm']
13 NUM_COLS = ['MinTemp', 'MaxTemp', 'Humidity3pm']
14
15 Tabnine | Edit | Test | Explain | Document
16 @app.route("/")
17 def home():
18     return render_template("index.html")
19
20 Tabnine | Edit | Test | Explain | Document
21 @app.route("/predict", methods=["POST"])
22 def predict():
23     try:
24         input_data = request.form.to_dict()
25         df = pd.DataFrame([input_data])
26
27         for col, encoder in encoder_dict.items():
28             if col in df.columns:
29                 val = df[col][0]
30                 if val not in encoder.classes_:
31                     return f"Error: Unknown value '{val}' for {col}"
32                 df[col] = encoder.transform(df[col])
33
34         for col in NUM_COLS:
35             df[col] = pd.to_numeric(df[col], errors='coerce')
```

```
<html>
<head>
<style>
</style>
</head>

<body
style="
background-image: url("/static/images/cloudy.jpg");
background-size: cover;
color: black;
">
<div class="login">
<center>
<h1>Rainfall Prediction</h1>
</center>
<form action="{url for ('predict')}" method="post">
<table style="width: 100%">
<tr>
<td>
<label for="Location"><b>Location:</b></label>
</td>
<td>
<select
id="Location"
name="Location"
required
style="width: 100%"
>
<option value="">Select Location</option>
<option value="Albury">Albury</option>
<option value="BadgerysCreek">BadgerysCreek</option>
<option value="Cobar">Cobar</option>
<option value="CoffsHarbour">CoffsHarbour</option>
<option value="Moree">Moree</option>
```

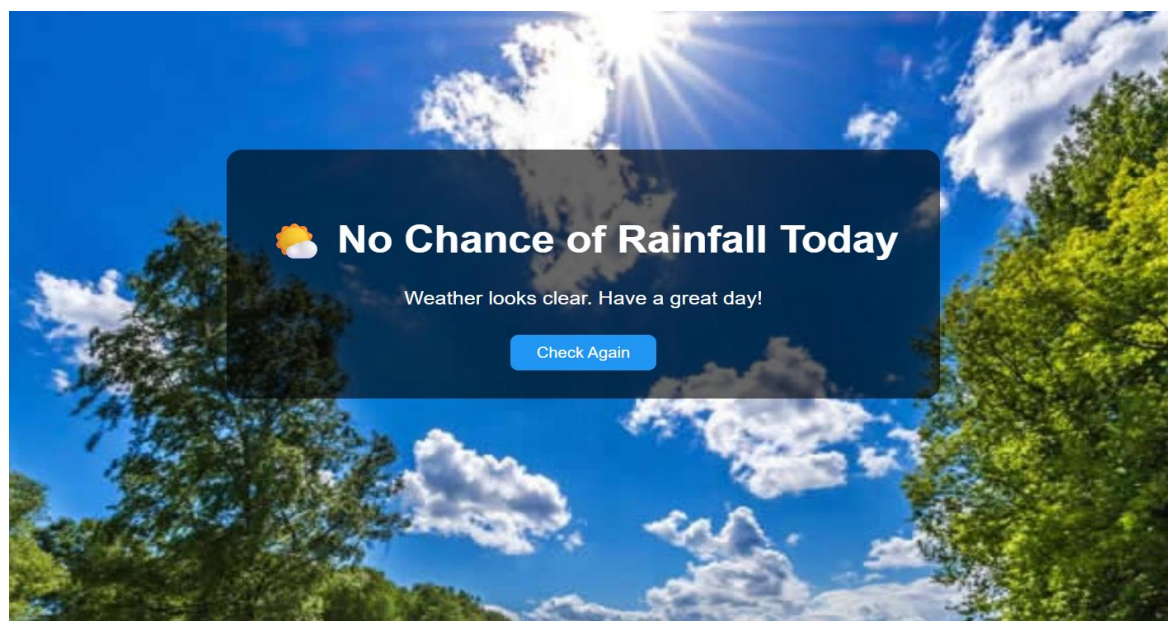
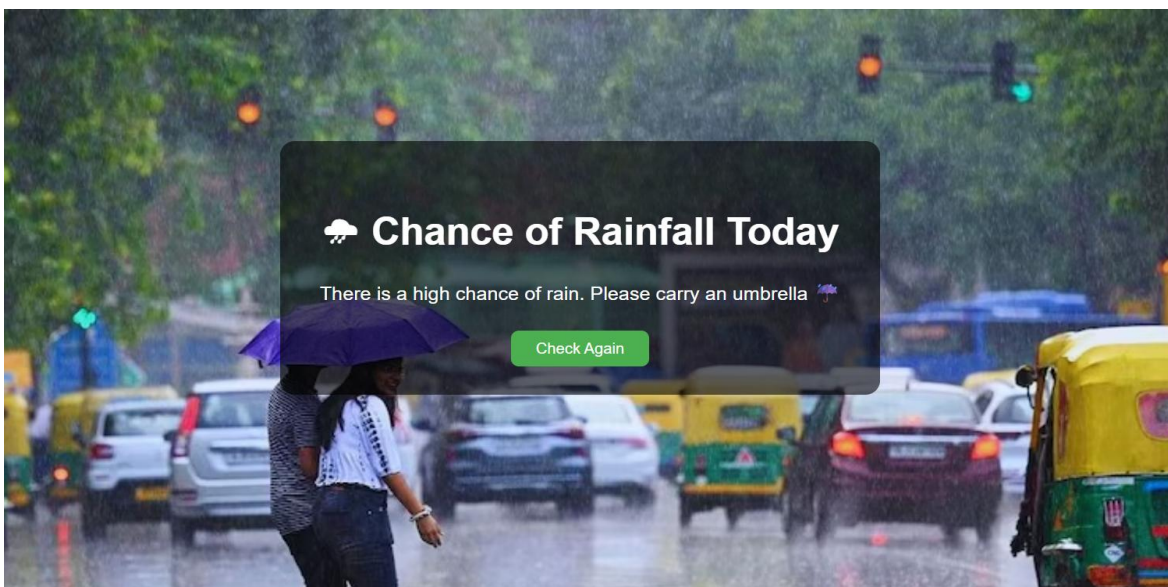
Frontend:



A screenshot of a web application titled "Rainfall Prediction". The form is centered on a background image of a dramatic, cloudy sky with sunlight breaking through. The form contains the following fields:

- Location:** A dropdown menu with the text "Select Location" and a downward arrow.
- Wind Direction:** A dropdown menu with the text "Select Direction" and a downward arrow.
- Min Temperature:** A text input field.
- Max Temperature:** A text input field.
- Humidity :** A text input field.

Below the input fields is a dark button labeled "Predict".



20. Conclusion

This project demonstrates how machine learning can be applied to predict rainfall using historical weather data. The Random Forest classifier provided reliable prediction performance, and deployment using Flask created a practical web-based application.

The system can assist farmers, agricultural experts, and policymakers in making informed decisions related to crop planning and water resource management.