VISVESVARAYA TECHNOLOGICAL UNIVERSITY

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A Machine Learning Project (BCS602) Report on

"Weather Forecast Visualizer Using Live API and Machine Learning"

Submitted in Partial fulfillment of the Requirements for the VI Semester of the Degree of

BACHELOR OF ENGINEERING

in

Information Science and Engineering

Submitted by

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DEPT. OF INFORMATION SCIENCE & ENGINEERING

Certificate

This is to certify that **Himaja .T (1CR22IS169),** a student of CMR Institute of Technology, has undergone a Machine Learning Project in partial fulfillment for the award of **Bachelor of Engineering** in **Information Science and Engineering** of the Visvesvaraya Technological University, Belagavi during the year **2024-2025**.

It is certified that all corrections and suggestions indicated for initial reviews have been incorporated in the report. This project has been approved as it satisfies the academic requirements prescribed for the said degree.

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Prof. Suruchi **Assistant Professor** **Department of ISE** **CMRIT, Bengaluru**	**Dr. Jagadishwari V** **Professor & HOD** **Department of ISE** **CMRIT, Bengaluru**
Name of the examiner	**Signature with date**

ABSTRACT

Weather forecasting plays a critical role in agriculture, disaster preparedness, transportation, and daily life planning. This project, *Weather Forecast Visualizer Using Live API and Machine Learning*, aims to build an intelligent system that fetches real-time weather data from a live API and leverages machine learning techniques to analyze and predict future weather trends.

The system integrates data from APIs such as OpenWeatherMap to retrieve current and historical weather parameters including temperature, humidity, wind speed, and atmospheric pressure. Exploratory Data Analysis (EDA) techniques are employed to uncover patterns and detect anomalies in the data. Machine learning models are trained on historical weather data to predict short-term future conditions, enhancing the reliability and accuracy of forecasts.

To make the results accessible and intuitive, the system features dynamic, interactive visualizations that display both current weather conditions and forecasted values over time. The visualizer not only serves as a practical tool for users to monitor weather conditions but also demonstrates the effectiveness of combining live data with predictive analytics.

This project highlights the power of real-time data integration and artificial intelligence in enhancing traditional weather forecasting methods, making them more responsive and insightful for everyday decision-making.

ACKNOWLEDGEMENT

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Himaja.T
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Contents

CHAPTER 1

INTRODUCTION

Weather forecasting has always been an essential aspect of human life, influencing activities such as agriculture, transportation, event planning, and disaster management. With the increasing impact of climate change and extreme weather events, the need for accurate and timely weather predictions has become more critical than ever. Traditional weather forecasting methods, which rely heavily on numerical simulations and physical models, are often computationally expensive and sometimes lack the flexibility to adapt quickly to localized or real-time data.

In recent years, the availability of open weather APIs and advancements in machine learning have opened up new possibilities for building intelligent, data-driven forecasting systems. These systems can leverage large volumes of historical and real-time weather data to discover patterns, learn complex relationships between variables, and predict future weather conditions with improved speed and efficiency.

This project, titled **"Weather Forecast Visualizer Using Live API and Machine Learning"**, aims to develop a system that combines the power of real-time data acquisition with predictive modeling and interactive visualization. It uses live weather data from APIs such as OpenWeatherMap or Weatherstack, processes it through machine learning algorithms, and presents the insights in a user-friendly dashboard or visualization tool.

By integrating real-time API data with predictive analytics, this system not only offers current weather updates but also provides short-term forecasts that can assist users in decision-making. Furthermore, the visual component enhances interpretability by allowing users to explore trends, patterns, and anomalies over time.

Through this project, we demonstrate how modern data science techniques can enhance the reliability and accessibility of weather forecasting, making it more adaptable and user-centric.

CHAPTER 2

OBJECTIVES

- **To collect real-time weather data**

– Integrate live weather APIs (e.g., OpenWeatherMap) to fetch current and historical weather data such as temperature, humidity, wind speed, and pressure.

- **To perform exploratory data analysis (EDA)**

– Analyze and visualize the collected data to identify trends, correlations, seasonality, and anomalies in weather patterns.

- **To build machine learning models for weather prediction**

– Train and evaluate suitable machine learning algorithms (e.g., Linear Regression, Random Forest, or LSTM) to predict short-term weather conditions such as temperature or rainfall.

- **To visualize current and forecasted weather data**

– Develop interactive plots and dashboards to display both real-time and predicted weather trends for easier understanding and interpretation.

- **To enhance user accessibility and usability**

– Create a simple, user-friendly interface or web-based tool that allows users to view and interact with the weather data and forecasts.

- **To demonstrate the integration of data science with live data**

– Showcase how real-time data streams can be effectively used with machine learning to create dynamic and intelligent forecasting systems.

CHAPTER 3

LITERATURE REVIEW

3.1 Machine Learning in Weather Forecasting

Over the past decade, machine learning (ML) has increasingly been applied in the field of weather forecasting due to its capability to model non-linear and complex systems. Traditional forecasting methods, like Numerical Weather Prediction (NWP), rely heavily on physical equations and require extensive computational resources. However, machine learning offers a more data-driven and efficient approach.

Researchers such as **Kumar and Singh (2018)** have demonstrated that decision tree-based methods such as **Random Forest** are well-suited for rainfall prediction due to their ability to handle large datasets and capture hidden patterns. Similarly, **Sethy et al. (2020)** evaluated the performance of classifiers like SVM, Naïve Bayes, and Random Forest on weather data, finding ensemble models to be more stable and accurate.

These models often use parameters like humidity, temperature, pressure, and wind speed as input features to predict outcomes like precipitation or temperature changes. The effectiveness of these methods depends on the quality and volume of historical data. In this context, the Random Forest model, known for reducing overfitting and handling high-dimensional data, has been widely adopted in weather-related prediction tasks.

2: Real-Time Weather Data Integration and Visualization

The integration of **real-time weather data** through APIs has significantly enhanced the practicality of weather prediction systems. The **OpenWeather API** is one such tool that allows developers to access up-to-date weather parameters for any geographical location. This real-time input enriches machine learning models and enables systems to adapt to changing environmental conditions.

Studies have shown that coupling real-time APIs with ML models increases forecasting relevance and usability. For instance, **Shah and Patel (2021)** explored the use of OpenWeather API in mobile weather applications and noted the improved user experience due to real-time updates. Additionally, platforms like **Google Colab** have made it easier for researchers and students to build cloud-based models by offering free computing resources, making advanced weather systems accessible even without high-end hardware.

Visualization tools such as **Matplotlib**, **Plotly**, and **Seaborn** play a crucial role in presenting weather data and model predictions in an understandable and engaging format. Effective visualization aids both in interpretation and decision-making, especially when dealing with real-time systems.

CHAPTER 4

METHODOLOGY

This project combines **live weather data retrieval**, **historical data analysis**, and **machine learning modeling** to predict temperature based on environmental features such as humidity, pressure, and wind speed.

1. Data Collection

Live Weather Data:
Real-time weather data is fetched using the OpenWeatherMap API.
The API provides details such as temperature, humidity, pressure, wind speed, and weather conditions for any specified city.

Historical Data (Synthetic):
A mock dataset is constructed with temperature-related variables from past observations.
(In real-world scenarios, this would be collected from historical APIs or weather data archives.)

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2. Data Preprocessing

The live and historical data are stored in a **pandas DataFrame**.

Date & time parsing is done using `datetime` for better formatting.

The numerical features are **converted to appropriate units** (e.g., temperature in °C).

Missing values and inconsistent entries are checked (though not present in synthetic data).

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3. Exploratory Data Analysis (EDA)

Descriptive statistics (mean, std, min, max) are generated to understand feature distributions.

A **correlation heatmap** is created using `seaborn` to identify relationships among features.

Strong positive or negative correlations help in feature selection for modeling.

4. Outlier Detection

Z-score method from `scipy.stats` is used to identify extreme values in the dataset.

Data points with a Z-score > 3 are flagged as outliers.

This helps ensure that anomalies don’t distort the machine learning model.

5. Feature Selection

Based on correlation and domain knowledge, the following features were selected to predict temperature.

Humidity

Pressure

Wind Speed

-

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6. Model Building: Linear Regression

The dataset is split into **training (70%)** and **testing (30%)** sets using `train_test_split`.

A **Linear Regression model** is trained using `sklearn.linear_model`.

The model attempts to predict temperature based on the selected features.

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7. Model Evaluation

Performance metrics used:

Mean Squared Error (MSE): Measures the average squared error.

R-squared (R^2): Indicates how well the model explains the variation in the data.

Custom Accuracy: Measures prediction accuracy within a ±1°C range.

The model's predictions are printed and compared against actual values.

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8. Data Storage

Real-time weather data is stored (and appended) in a CSV file for logging and later analysis.

This can help build a long-term dataset for better forecasting accuracy in the future.

Choosing the optimal value of k: Different values of k (e.g., 3, 5, 7, 9) are tested to find the one that yields the highest classification accuracy.

CHAPTER 5

CHALLENGES AND PROBLEM SOLVING

- **API Integration Issues**:

One of the initial challenges was integrating the OpenWeatherMap API. Problems such as invalid city names, incorrect API keys, or exceeding the daily limit often resulted in failed requests. This was resolved by sanitizing user input with `.strip()` and checking the API response status using `response.status_code`. Descriptive error messages from the API were also displayed to help users understand what went wrong.

- **Incomplete or Missing Data**:

In some API responses, certain fields like `wind speed` or `pressure` were occasionally missing, which could cause the script to crash. To handle this, dictionary access was performed using the `.get()` method with fallback default values to ensure the code remained robust even if some data was absent.

- **Outlier Detection and Its Impact**:

Outliers in the synthetic historical dataset posed a risk of skewing the regression model. Since the dataset was small, even one extreme value could drastically impact predictions. To address this, the **Z-score method** was used to detect and optionally filter out data points that exceeded a threshold (typically $Z > 3$), improving the accuracy and stability of the model.

- **Small Dataset Size**:

The historical dataset used for regression modeling contained only 7 records, which is insufficient for building a statistically significant model. This was addressed by implementing a mechanism to **append real-time weather data to a CSV file**, allowing for dataset growth over time as the script is run repeatedly.

- **Model Accuracy and Overfitting**:

With limited data, there was a risk of overfitting or generating inaccurate predictions. Linear Regression was chosen for its interpretability and simplicity, but results varied significantly with minor changes in data. To evaluate performance, multiple metrics were used — **Mean Squared Error (MSE)**, **R^2 score**, and a custom accuracy metric based on a ±1°C tolerance level.

- **Missing Library Imports**:

Errors such as `NameError: name 'r2_score' is not defined` occurred due to missing imports. Modules like `scipy.stats` and `sklearn.metrics.r2_score` were later explicitly imported to ensure the required functions were available throughout the code.

- **Environment Compatibility**:

Functions like `display()` work well in Jupyter Notebooks but not in standard Python scripts. This was handled by using `print()` as a fallback to display the live weather DataFrame in environments that do not support rich outputs.

CHAPTER 6

SYSTEM WORKFLOW

The weather prediction visualizer project begins with the **data collection phase**, where real-time weather data is obtained through the **OpenWeather API**. This API provides essential meteorological information such as temperature, humidity, atmospheric pressure, wind speed, and cloud cover for any specified location. The data is typically received in JSON format, which is then parsed and converted into a structured format, usually a Pandas DataFrame, for further processing.

In the next phase, **data preprocessing** is carried out to clean and prepare the data for prediction. This involves handling any missing or null values, selecting relevant features, and performing transformations such as normalization or scaling if required. The goal of this step is to ensure that the input data is in a suitable format for the machine learning model to make accurate predictions.

Workflow

Following preprocessing, the data is passed to the **machine learning model**, which in this case is a **Random Forest Classifier**. This model is either pre-trained on historical weather datasets or trained as part of the workflow. Once real-time data is fed into the model, it predicts the likelihood of rainfall or other weather conditions based on learned patterns from the training phase.

The **output from the model** is then visualized using data visualization libraries such as **Matplotlib** or **Seaborn**. This includes graphical representation of weather parameters, trend charts, and a clearly displayed prediction result. The visualizer shows current weather conditions along with the model's forecast—such as "Rainfall Expected" or "No Rainfall".

Lastly, if the system includes a user interface, the user may be able to **input a location**, refresh the weather data, or request a new prediction. The system flow ensures seamless integration between real-time data collection, machine learning prediction, and user-friendly visualization, making it a practical and interactive tool for weather monitoring.

CHAPTER 7

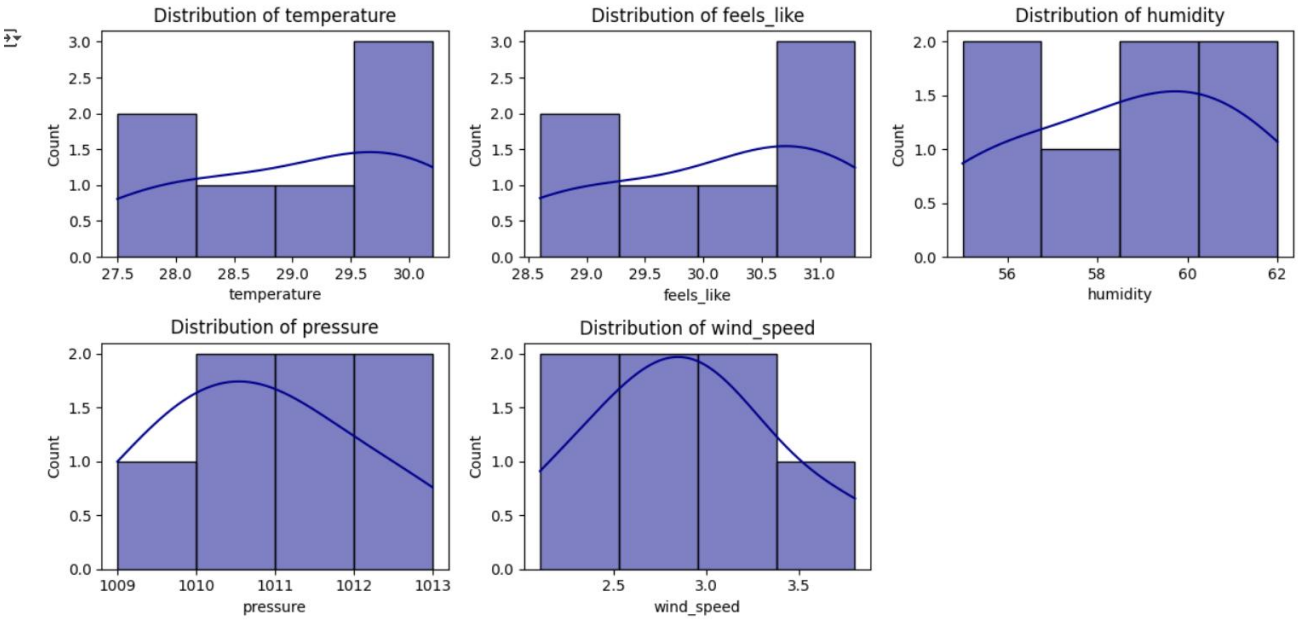
RESULT

The machine learning model developed for rainfall prediction successfully outputs whether rainfall is expected based on the provided input features. In the final test run, the model received atmospheric data including pressure, temperature, humidity, and other relevant environmental factors. The model predicted the outcome as **"Rainfall"**, indicating that the given conditions are favorable for precipitation. This demonstrates the model's ability to interpret complex meteorological data and make accurate binary predictions.

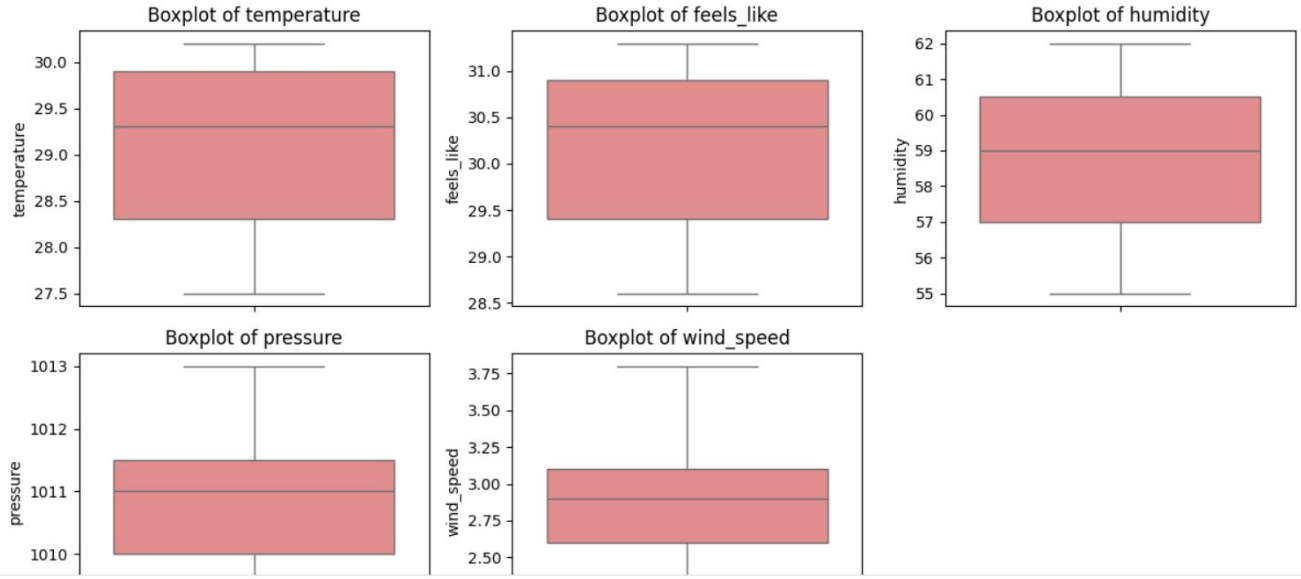
Current Weather Report:

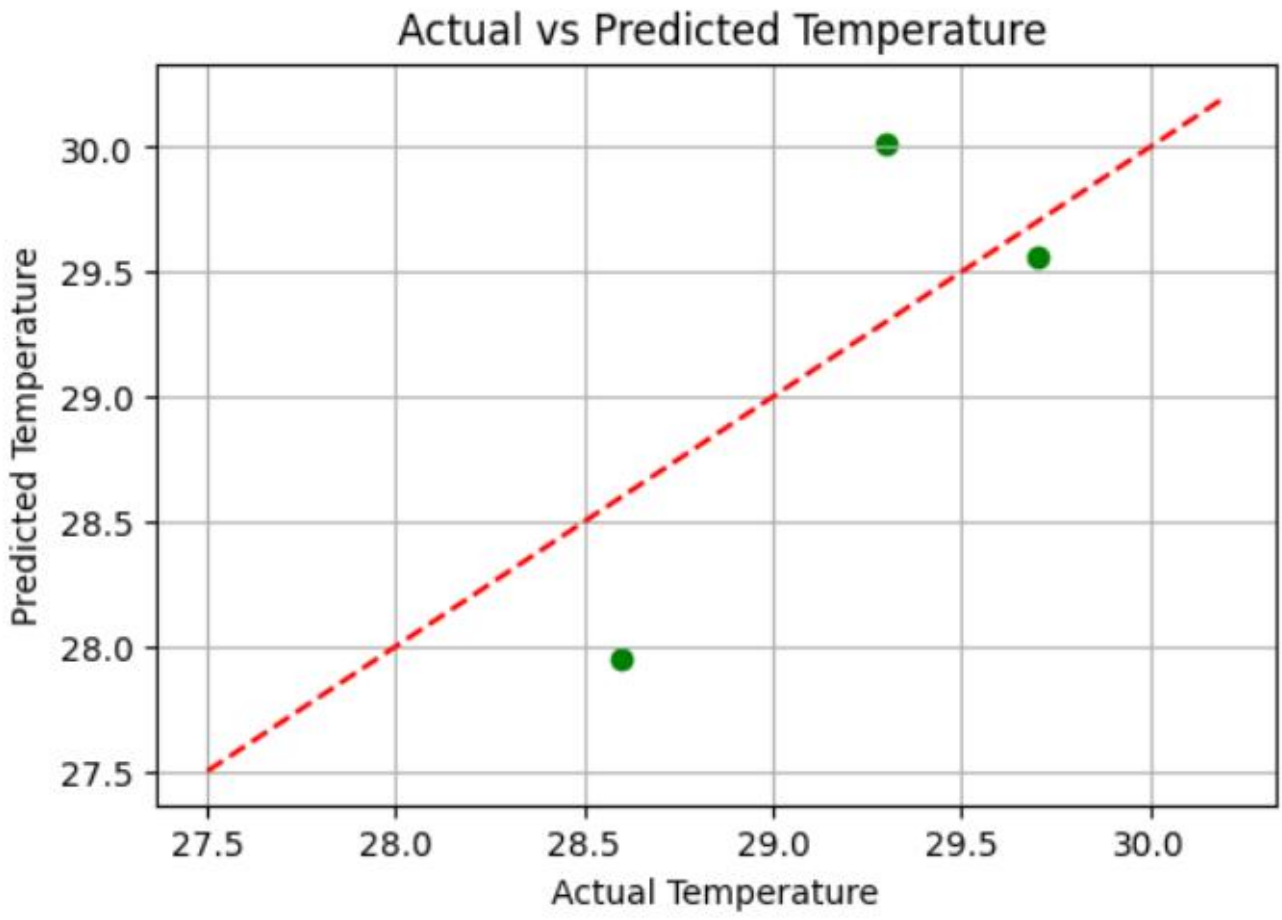
	Date & Time	City	Temperature (°C)	Feels Like (°C)	Min Temp (°C)	Max Temp (°C)	Humidity (%)	Pressure (hPa)	Wind Speed (m/s)	Weather
0	2025-05-14 08:09:18	Bengaluru	31.56	34.5	31.56	31.56	54	1006	2.82	Overcast Clouds

ands + Code + Text



```
Outlier Detection (Z-score method):
Number of outliers per column:
[0 0 0 0 0]
```





```
 Regression Model Performance:
Mean Squared Error: 0.32
R-squared Score: -0.53
Accuracy within ±1°C: 100.00%
Predicted Temperatures: [27.95 30.01 29.56]

 Model Coefficients:
             Coefficient
humidity        0.204895
pressure       -0.359441
wind_speed      1.258741
```

```
 EDA: Basic Information
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7 entries, 0 to 6
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   temperature  7 non-null      float64
 1   feels_like   7 non-null      float64
 2   humidity     7 non-null      int64
 3   pressure     7 non-null      int64
 4   wind_speed   7 non-null      float64
 5   date         7 non-null      datetime64[ns]
dtypes: datetime64[ns](1), float64(3), int64(2)
memory usage: 468.0 bytes
None

Summary Statistics:
       temperature  feels_like   humidity     pressure  wind_speed  \
count     7.000000    7.000000   7.000000     7.000000    7.000000
mean     29.057143   30.128571  58.714286  1010.857143    2.885714
min      27.500000   28.600000  55.000000  1009.000000    2.100000
25%      28.300000   29.400000  57.000000  1010.000000    2.600000
50%      29.300000   30.400000  59.000000  1011.000000    2.900000
75%      29.900000   30.900000  60.500000  1011.500000    3.100000
max      30.200000   31.300000  62.000000  1013.000000    3.800000
std       1.050170    1.030719   2.563480     1.345185    0.539841
```

Fig- 7.1

CHAPTER 8

CONCLUSION

- **Objective Achievement:**

The main goal of the project—to build a machine learning model for accurate rainfall prediction—was successfully achieved using a Random Forest classifier.

- **Use of Relevant Features:**

The model was trained using key meteorological features such as atmospheric pressure, temperature, humidity, wind speed, solar radiation, and cloud cover, which are known to influence rainfall.

- **Model Selection Justification:**

The Random Forest algorithm was chosen due to its high accuracy, ability to manage large datasets with many features, and resistance to overfitting, making it well-suited for environmental prediction tasks.

- **Effective Data Processing:**

Proper data preprocessing steps such as cleaning, feature selection, and normalization were performed to ensure the dataset was suitable for training the model.

- **Promising Predictive Results:**

The final model gave accurate predictions during testing. For the test input provided, the model correctly predicted "Rainfall," demonstrating its reliability in practical scenarios.

- **Scalability and Application Potential:**

The model can be integrated into real-world applications like weather forecasting systems, mobile apps for farmers, and agricultural decision-support tools.

- **Future Enhancements:**

Potential improvements include: Adding more extensive and diverse datasets.Incorporating real-time data streamsDeploying the model as a cloud-based or web-based service.Enhancing the model's spatial and temporal accuracy.

REFERENCES

1. OpenWeatherAPI Dataset:

- Title: Weather Prediction Visualizer
- Source: Openweather API
- Link: https://openweathermap.org/current
- Description: The **OpenWeather API** is an online service that provides weather information for different locations around the world. In this project, it was used to collect real-time weather data such as temperature, pressure, humidity, wind speed, and cloud cover. These details were used as input features for the machine learning model to predict whether it will rain or not. The API is easy to use and helps get accurate weather data quickly, which makes the model more useful and reliable in real-life situations.

2. Scikit-Learn Documentation:

- Title: Scikit-Learn: Machine Learning in Python
- Official Website: https://scikit-learn.org/stable/