A

Mini Project

On

Predicting Rainfall Using Machine Learning Techniques

(Submitted in partial fulfillment of the requirements for the award of Degree)

BACHELOR OF TECHNOLOGY

In

COMPUTER SCIENCE AND ENGINEERING

By

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UNDER THE GUIDANCE OF

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CMR TECHNICAL CAMPUS

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2020-2024

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the project entitled **"PREDICTING RAINFALL USING MACHINE LEARNING TECHNIQUE"** being submitted by **SHEGGARI TEJA SRI (217R5A0519)**in partial fulfillment of the requirements for the award of the degree of B.Tech in Computer Science and Engineering to the Jawaharlal Nehru Technological University Hyderabad, is a record of bonafide work carried out by them under our guidance and supervision during the year 2023-24.

The results embodied in this thesis have not been submitted to any other University or Institute for the award of any degree or diploma.

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Submitted for viva voice Examination held on ________________

ACKNOWLEDGEMENT

Apart from the efforts of us, the success of any project depends largely on the encouragement and guidelines of many others. We take this opportunity to express our gratitude to the people who have been instrumental in the successful completion of this project.

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ABSTRACT

Rainfall prediction is one of the challenging and uncertain tasks which has a significant impact on human society. Timely and accurate predictions can help to proactively reduce human and financial loss. This study presents a set of experiments which involve the use of prevalent machine learning techniques to build models to predict whether it is going to rain tomorrow or not based on weather data for that particular day in major cities of Australia. This comparative study is conducted concentrating on three aspects: modeling inputs, modeling methods, and pre-processing techniques. The results provide a comparison of various evaluation metrics of these machine learning techniques and their reliability to predict the rainfall by analyzing the weather data.

Rainfall prediction is a critical aspect of meteorology with profound implications for agriculture, water resource management, and disaster preparedness. Traditional methods of rainfall prediction often rely on numerical weather models and historical data analysis. However, the increasing complexity of climate patterns demands more sophisticated approaches. This study explores the application of machine learning techniques to predict rainfall with improved accuracy and efficiency.

The proposed model integrates various meteorological parameters, such as temperature, humidity, wind speed, and atmospheric pressure, as input features for the machine learning algorithms. Historical rainfall data, collected from reliable sources, is used to train and validate the model. The study employs a diverse set of machine learning algorithms, including but not limited to decision trees, support vector machines, and neural networks, to compare their performance in rainfall prediction.

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1.INTRODUCTION

1.INTRODUCTION

1.1 PROJECT SCOPE

The project aims to develop a machine learning-based rainfall prediction system.This system will utilize historical weather data, including temperature, humidity, wind speed, and atmospheric pressure, to forecast rainfall events accurately. By employing advanced machine learning techniques such as regression and deep learning, the project intends to provide timely and reliable rainfall predictions, contributing to better preparedness for weather-related events and their potential impacts.

1.2 PROJECT PURPOSE

Predicting rainfall using machine learning techniques aims to leverage data-driven algorithms to enhance weather forecasting accuracy. By analyzing historical and real-time meteorological data, these projects not only assist in anticipating rain events but also contribute to disaster preparedness, agriculture, and scientific research by uncovering complex weather patterns and improving early warning systems for extreme weather events. Ultimately, the goal is to provide timely and precise information to aid decision-making and mitigate the impacts of rainfall-related disasters.

1.3 PROJECT FEATURES

The project features include data collection and preprocessing, feature engineering, model selection and training, and real-time prediction capabilities. It leverages machine learning algorithms to analyze historical weather data, allowing for accurate rainfall forecasts. Additionally, it offers scalability and adaptability for various geographical regions, making it a versatile tool for rainfall prediction across Different enivironments.

2.SYSTEM ANALYSIS

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SYSTEM ANALYSIS

Predicting rainfall through machine learning involves a systematic process. It starts with defining the problem and collecting relevant data, including weather and environmental factors. Preprocessing and feature selection prepare the data, and suitable machine learning models are chosen, trained, and evaluated. The model is then deployed, monitored, and updated for real-time predictions. Ethical considerations, compliance with regulations, and documentation are vital components, ensuring the reliability and usefulness of rainfall predictions in applications such as agriculture and meteorology.

2.1 PROBLEM DEFINITION

In a project aimed at predicting rainfall using machine learning techniques, several essential features must be considered. Firstly, comprehensive data collection from reliable meteorological sources is crucial, encompassing historical rainfall data as well as relevant meteorological variables like temperature, humidity, wind speed, and atmospheric pressure. Geographic features such as latitude, longitude, and elevation also play a vital role. Data preprocessing steps, including handling missing values and outliers, are essential for data quality. Feature engineering is another key aspect, involving the creation of temporal features, rolling averages, and lag variables to capture patterns over time. Model selection involves choosing suitable algorithms like regression models, decision trees, or neural networks, while ensemble methods can enhance predictive accuracy. Proper evaluation metrics and visualization techniques are necessary for assessing model performance, and the deployment of the model, continuous monitoring, and ethical considerations are also integral to a successful project.

2.2 EXISTING SYSTEM

Rainfall prediction is important as heavy rainfall can lead to many disasters. The prediction helps people to take preventive measures and moreover the prediction s hould be accurate. There are two types of prediction short term rainfall prediction and long term rainfall. Prediction mostly short term prediction can gives us the accurate result. The main challenge is to build a model for long term rainfall prediction. Heavy precipitation prediction could be a major drawback for earth science department because it is closely associated with the economy and lifetime of human.

2.2.1 DISADVANTAGES OF EXISTING SYSTEM

- **Lack of data:** Machine learning algorithms require large amounts of data to be trained effectively. In many regions, historical rainfall data may be limited or incomplete, which could limit the accuracy of the predictions.
- **Difficulty in feature selection:** Identifying the most important variables or features that influence rainfall patterns can be challenging, and different machine learning algorithms may yield different results.
- **Data quality:** Machine learning models are only as good as the data they are trained on. Poor quality data, such as incorrect measurements or biases in the data collection process, can negatively impact the accuracy of the predictions

2.3 PROPOSED SYSTEM

It’s a cause for natural disasters like flood and drought that square measure encountered by individuals across the world each year. Accuracy of rainfall statement has nice importance for countries like India whose economy is basically dependent on agriculture. The dynamic nature of atmosphere, applied mathematical techniques fail to provide sensible accuracy for precipitation statement. The prediction of precipitation using machine learning techniques may use regression.

Intention of this project is to offer non-experts easy access to the techniques, approaches utilized in the sector of precipitation prediction and provide a comparative study among the various machine learning techniques.

The following are some of the important financial questions asked during preliminaryinvestigation:

- The costs conduct a full system investigation.
- The cost of the hardware and software.
- The benefits in the form of reduced costs or fewer costly errors.

Since the system is developed as part of project work, there is no manual cost to spend for the proposed system. Also, all the resources are already available, it gives an indication that the system is economically possible for development.

2.3.1 ADVANTAGES OF THE PROPOSED SYSTEM

- **Better accuracy:** Machine learning algorithms can analyze large amounts of data and identify patterns that may not be obvious to human analysts. This can lead to more accurate predictions of rainfall, which can be beneficial for farmers, hydrologists, and other professionals who rely on this information.
- **Timely predictions:** Machine learning algorithms can process data quickly and generate predictions in real-time or near real-time. This can be useful in situations where timely decisions need to be made, such as predicting floods or planning irrigation schedules.
- **Scalability:** Machine learning algorithms can be trained on large datasets and can be easily scaled to accommodate more data as it becomes available. This can help to improve the accuracy of predictions over time.

2.4 FEASIBILITY STUDY

The feasibility of the project is analyzed in this phase and a business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This isto ensure that the proposed system is not a burden to the company. Three key considerations involved in the feasibility analysis:

- Economic Feasibility
- Technical Feasibility
- Social Feasibility

2.4.1 ECONOMIC FEASIBILITY

The developing system must be justified by cost and benefit. Criteria to ensure that effort is concentrated on a project, which will give best, return at the earliest. One of the factors, which affect the development of a new system, is the cost it would require.

The following are some of the important financial questions asked during preliminaryinvestigation:

- The costs conduct a full system investigation.
- The cost of the hardware and software.
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Since the system is developed as part of project work, there is no manual cost to spend for the proposed system. Also, all the resources are already available, it gives an indication that the system is economically possible for development.

2.4.2 TECHNICAL FEASIBILITY

The technical feasibility of predicting rainfall using machine learning techniques is grounded in the availability of comprehensive and high-quality datasets. Meteorological agencies and weather stations routinely collect historical rainfall data, offering a rich source for training and validating machine learning models. Advances in remote sensing technologies, such as satellite imagery and weather radars, provide real-time data that can enhance the accuracy of predictions. Machine learning algorithms, ranging from traditional regression models to more sophisticated deep learning approaches, can effectively capture complex patterns and relationships within the data. However, challenges such as the non-linear nature of atmospheric processes and the need for large and diverse datasets should be considered. Integration with advanced computing infrastructure and parallel processing capabilities enables the efficient training and deployment of complex models. Additionally, ongoing research in meteorology and machine learning continues to refine algorithms and improve prediction accuracy. Overall, the technical feasibility of rainfall prediction through machine learning rests on the collaborative efforts of meteorologists, data scientists, and technologists to harness the power of advanced algorithms and robust data sources.

2.4.3 SOCIAL FEASIBILITY

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

2.5 HARDWARE & SOFTWARE REQUIREMENTS

2.5.1 HARDWARE REQUIREMENTS:

Hardware interfaces specify the logical characteristics of each interface between the software product and the hardware components of the system. The following are some hardware requirements.

- System : minimum i3 processor
- Hard Disk : 120 GB
- Ram : 16 GB

2.5.2 SOFTWARE REQUIREMENTS:

Software Requirements specifies the logical characteristics of each interface and software components of the system. The following are some software requirements.

- Operating System : Windows 8
- Coding Language : Python

3.ARCHITECTURE

3. ARCHITECTURE

3.1 PROJECT ARCHITECTURE

This project architecture shows the procedure followed for classification, starting from input to final prediction.

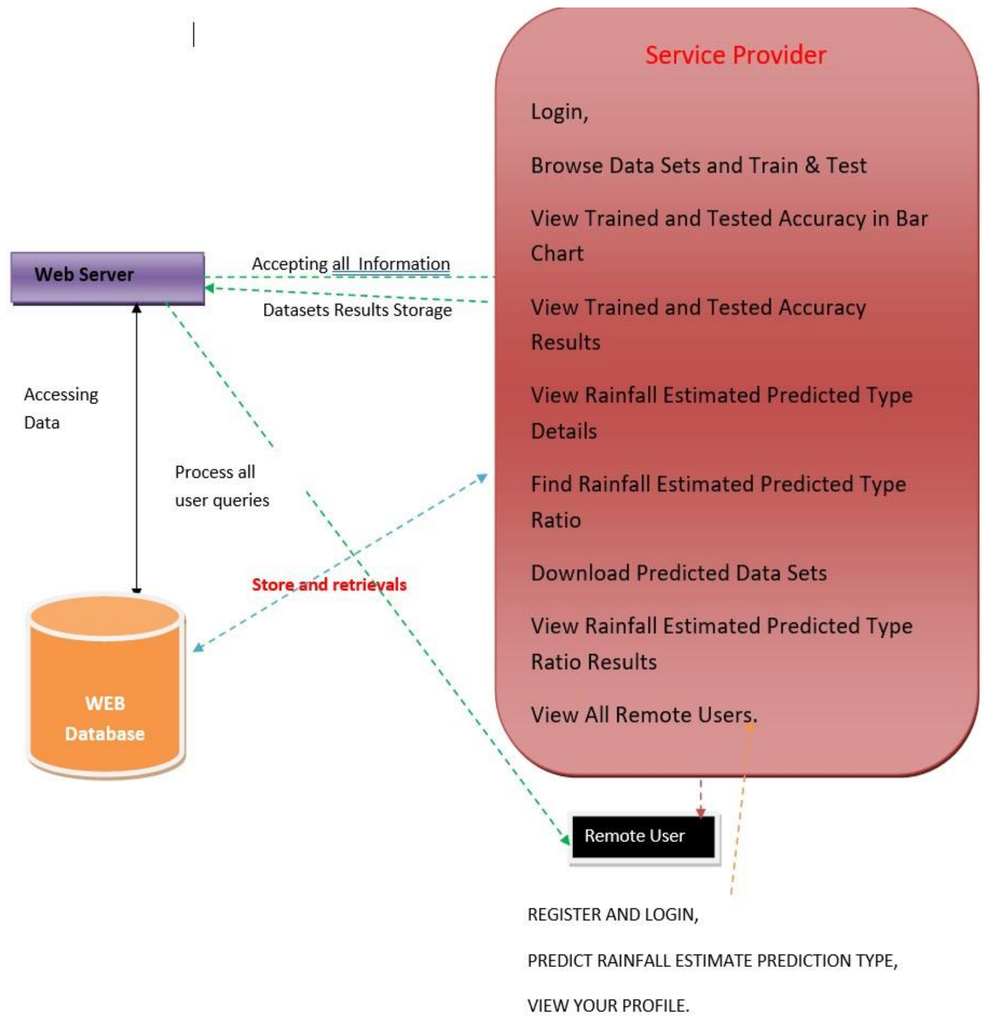


Figure 3.1 System Architecture Of Predicting Rainfall Using Machine Learning Technique

3.2 DESCRIPTION

Predicting rainfall using machine learning techniques is a sophisticated and data-driven approach to gain insights into weather patterns and anticipate rain occurrences. This process hinges on the utilization of historical and current meteorological data, encompassing factors like temperature, humidity, wind speed, and atmospheric pressure, as well as recorded instances of rainfall. This data is meticulously curated and formatted to eliminate inconsistencies and missing values, rendering it suitable for analysis. Feature selection is crucial to pinpoint the most relevant weather variables that influence rainfall. Machine learning models, including decision trees, support vector machines, and stochastic gradient descent classifiers, are then employed to discern intricate relationships between these selected features and the presence or absence of rain. These models undergo rigorous training on historical data, followed by evaluation using performance metrics to gauge their accuracy. Once validated, these models can be deployed to make real-time predictions by inputting current weather data, providing invaluable insights for agriculture, flood prediction, and resource management. Continuous model monitoring and refinement are imperative, given the ever-changing nature of weather, ensuring that these predictive tools remain effective and reliable for decision-makers and researchers alike. In essence, predicting rainfall through machine learning represents a dynamic and data-centric approach that enhances our understanding of weather phenomena, aiding in disaster preparedness and sustainable resource allocation.

3.3 USE CASE DIAGRAM

In the use case diagram, we have basically one actor who is the user in the trained model.A use case diagram is a graphical depiction of a user's possible interactions with a system. A use case diagram shows various use cases and different types of users the system has. The use cases are represented by either circles or ellipses. The actors are often shown as stick figures.

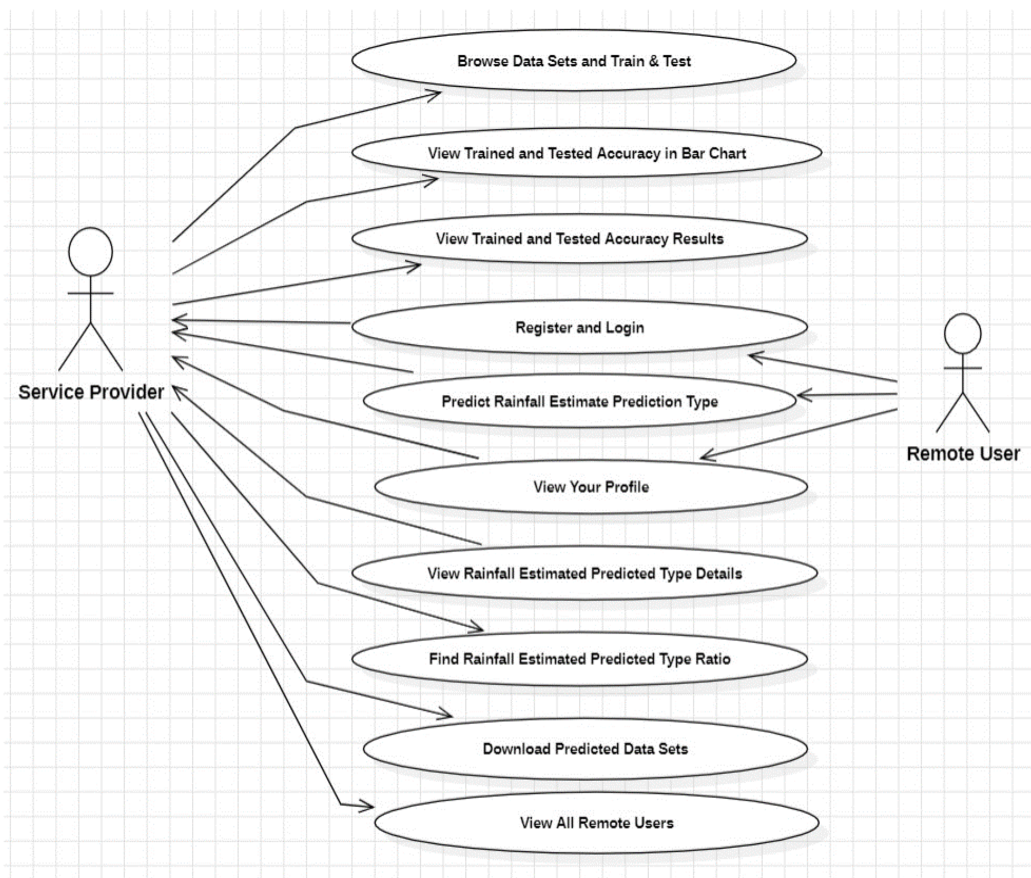


Figure 3.3: Use Case Diagram of Predicting Rainfall Using Machine Learning Technique

3.4 CLASS DIAGRAM

Class diagram is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among objects.

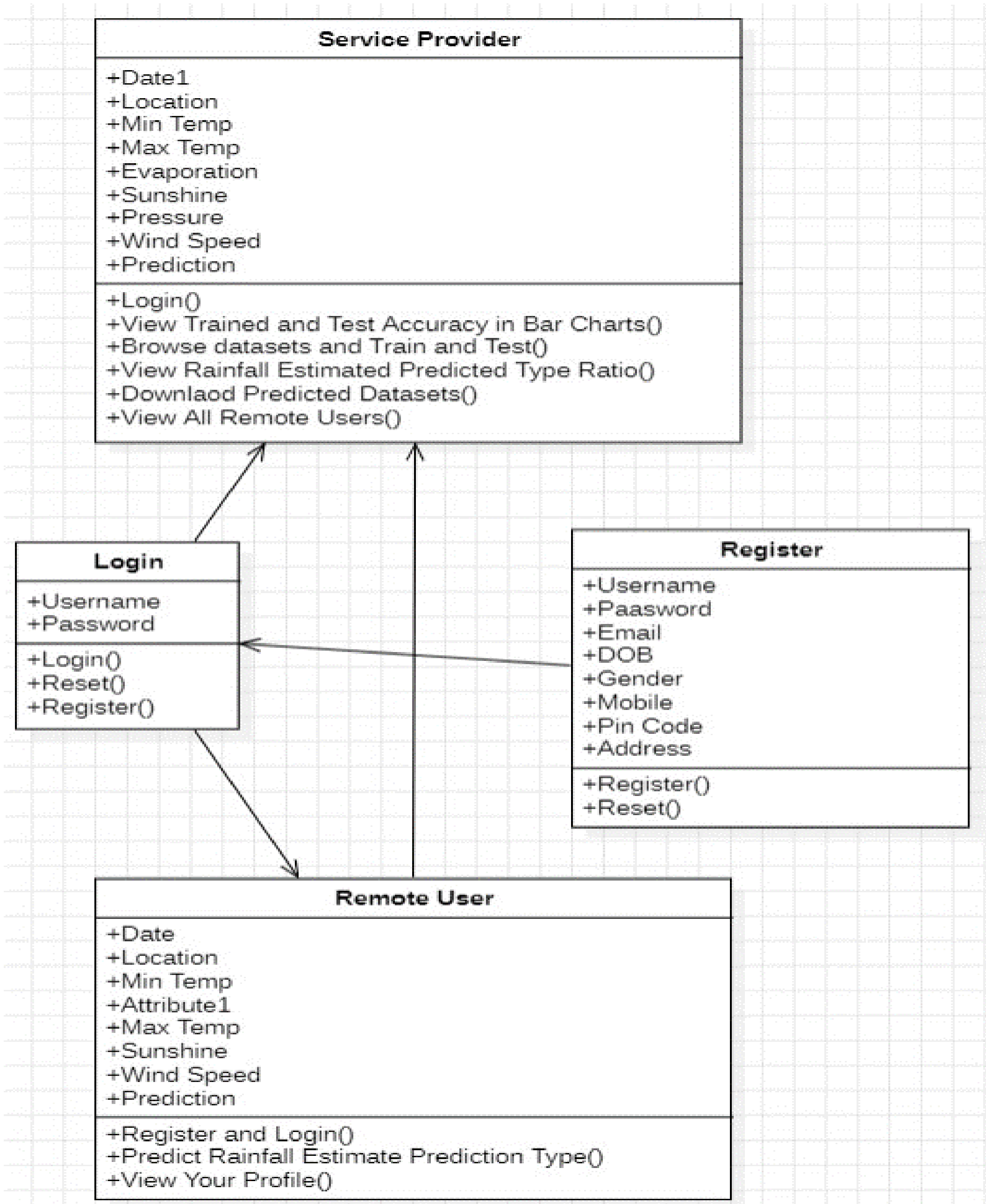


Figure 3.4: Activity Diagram of Predicting Rainfall Using Machine Learning Technique

3.5 SEQUENCE DIAGRAM

A sequence diagram shows object interactions arranged in time sequence. It depicts the objects involved in the scenario and the sequence of messages exchanged between the objects needed to carry out the functionality of the scenario. Sequence diagrams are typically associated with use case realizations in the logical view of the system under development.

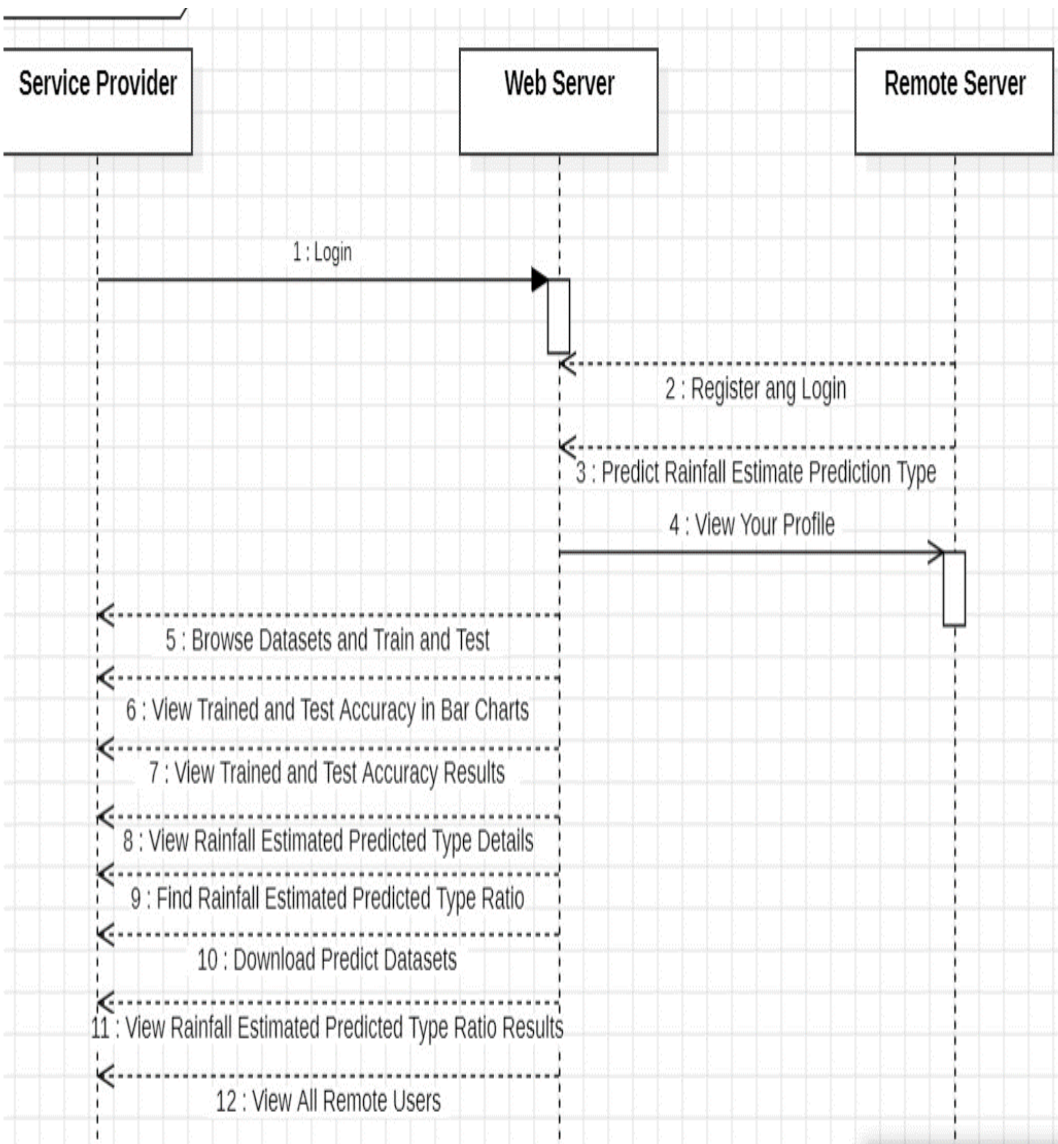


Figure 3.5: Sequence Diagram of Predicting Rainfall Using Machine Learning Technique

3.6 ACTIVITY DIAGRAM

Activity diagrams are graphical representations of workflows of stepwis activities and actions with support for choice, iteration and concurrency. They can also include elements showing the flow of data between activities through one or more datastores.

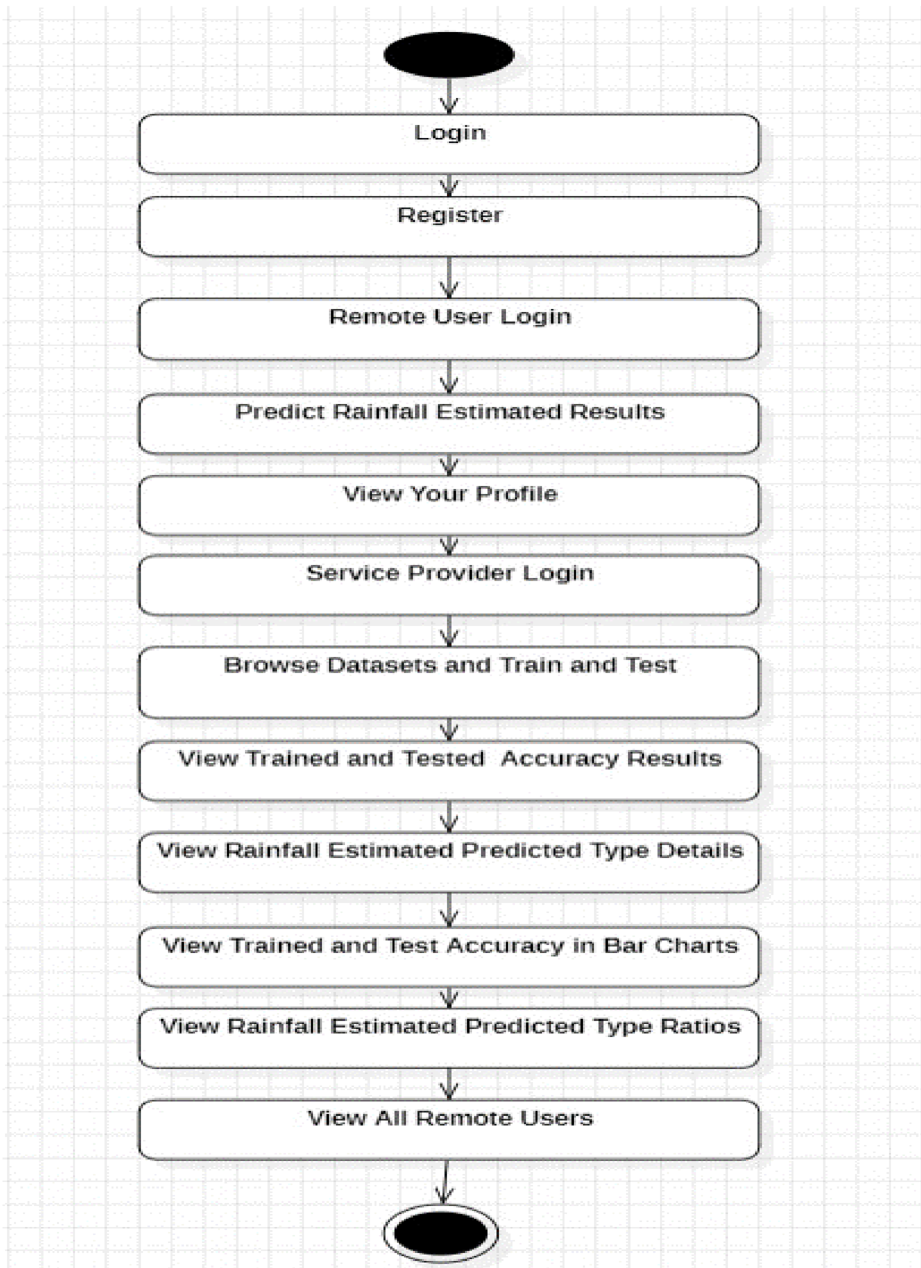


Figure 3.6: Activity Diagram of Predicting Rainfall Using Machine Learning Technique

4.IMPLEMENTATION

4.IMPLEMENTATION

4.1 SAMPLE CODE

```
import numpy as np

import pandas as pd

from sklearn.impute import SimpleImputer

from sklearn.preprocessing import LabelEncoder

from sklearn.preprocessing import StandardScaler

from sklearn.model_selection import train_test_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score

dataset = pd.read_csv('Dataset/weatherAUS.csv',nrows=4000)

X = dataset.iloc[:,[1,2,3,4,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21]].values

Y = dataset.iloc[:,-1].values

print(X)


print(Y)


Y = Y.reshape(-1,1)

#Dealing with invalid Data

imputer = SimpleImputer(missing_values=np.nan,strategy='most_frequent')

X = imputer.fit_transform(X)
```

```
print(X)
 le1 = LabelEncoder()
 X[:,0] = le1.fit_transform(X[:,0])
 le2 = LabelEncoder()
 X[:,4] = le2.fit_transform(X[:,4])
 le3 = LabelEncoder()
 X[:,6] = le3.fit_transform(X[:,6])
 le4 = LabelEncoder()
 X[:,7] = le4.fit_transform(X[:,7])
 le5 = LabelEncoder()
 X[:,-1] = le5.fit_transform(X[:,-1])
 le6 = LabelEncoder()
 Y[:,-1] = le6.fit_transform(Y[:,-1])
 print(X)
 print(Y)

 Y = np.array(Y,dtype=float)
 print(Y)

 #Feature Scaling
 sc = StandardScaler()
 X = sc.fit_transform(X)
  print(X)
```

```
#Splitting Dataset into Training set and Test set
 X_train,X_test,Y_train,Y_testtrain_test_split(X,Y,test_size=0.2,random_state=0)
 print(X_train)
 print(Y_train)

 #Training Model
 classifier = RandomForestClassifier(n_estimators=100,random_state=0)
 classifier.fit(X_train,Y_train)
 print(classifier.score(X_train,Y_train))
 y_pred = le6.inverse_transform(np.array(classifier.predict(X_test),dtype=int))
 Y_test1 = le6.inverse_transform(np.array(Y_test,dtype=int))
 print(y_pred)
 print(Y_test1)

 y_pred = y_pred.reshape(-1,1)
 Y_test1 = Y_test1.reshape(-1,1)
 df = np.concatenate((Y_test1,y_pred),axis=1)
 print(dataframe)
rf_accuracy = accuracy_score(Y_test1,y_pred)
 print("\nRandom Forest Accuracy: "+str(rf_accuracy
```

```
from sklearn.ensemble import BaggingClassifier
dt = BaggingClassifier(n_estimators=250,max_features=12)
dt.fit(X_train,Y_train)
print(dt.score(X_train,Y_train))
y_pred = le6.inverse_transform(np.array(dt.predict(X_test),dtype=int))
Y_test2 = le6.inverse_transform(np.array(Y_test,dtype=int))
 y_pred = y_pred.reshape(-1,1)
Y_test2 = Y_test2.reshape(-1,1)
df = np.concatenate((Y_test2,y_pred),axis=1)
dataframe = pd.DataFrame(df,columns=['Rain on Tommorrow','Prediction of Rain'])
print(dataframe)

dt_accuracy = accuracy_score(Y_test1,y_pred)
print("\nBagging Classifier Accuracy: "+str(dt_accuracy))
 #print(y_pred)
 #print(Y_test)

from sklearn.ensemble import GradientBoostingClassifier
dt = GradientBoostingClassifier(n_estimators=170,max_depth=1)
dt.fit(X_train,Y_train)
print(dt.score(X_train,Y_train))
```

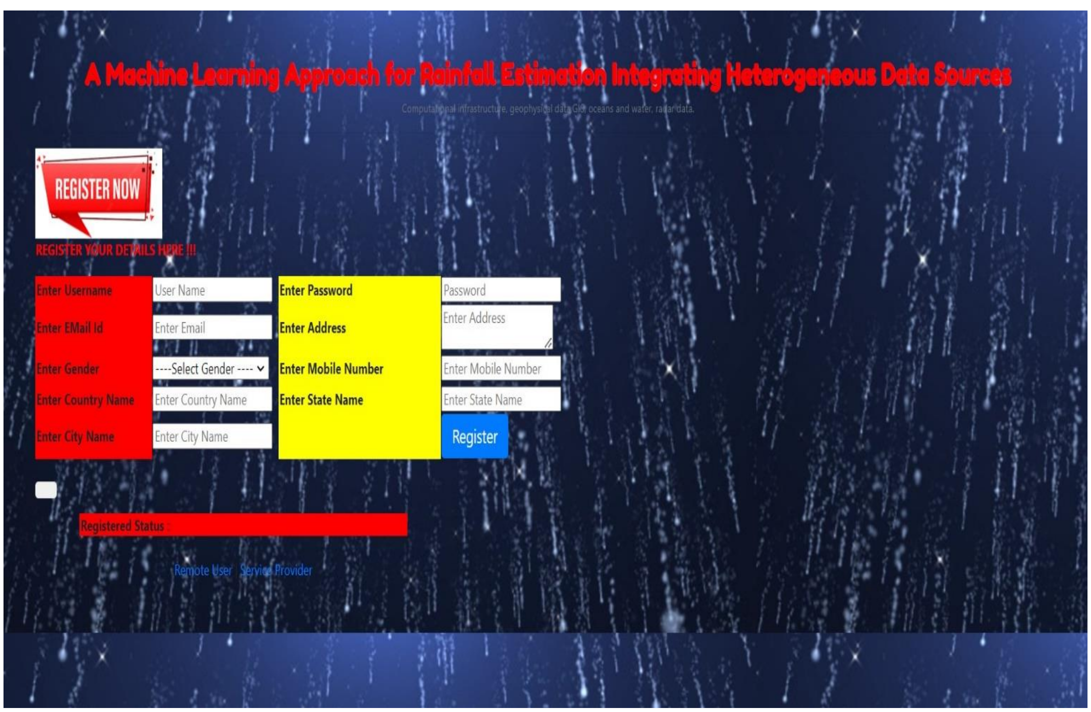
```
y_pred = le6.inverse_transform(np.array(dt.predict(X_test),dtype=int))
Y_test3 = le6.inverse_transform(np.array(Y_test,dtype=int))
y_pred = y_pred.reshape(-1,1)
Y_test3 = Y_test3.reshape(-1,1)
df = np.concatenate((Y_test3,y_pred),axis=1)
dataframe = pd.DataFrame(df,columns=['Rain on Tommorrow','Prediction of Rain'])
print(dataframe)

dt_accuracy = accuracy_score(Y_test1,y_pred)
print("\nGradient Boosting Accuracy: "+str(dt_accuracy))
#print(y_pred)
#print(Y_test)

import xgboost as xgb
xg = xgb.XGBClassifier(n_estimators=140, max_depth=12)
xg.fit(X_train,Y_train)
print(xg.score(X_train,Y_train))

y_pred = le6.inverse_transform(np.array(xg.predict(X_test),dtype=int))
Y_test4 = le6.inverse_transform(np.array(Y_test,dtype=int))
#print(y_pred)
#print(Y_test)
```

```
y_pred = y_pred.reshape(-1,1)

Y_test4 = Y_test4.reshape(-1,1)

df = np.concatenate((Y_test4,y_pred),axis=1)

dataframe = pd.DataFrame(df,columns=['Rain on Tommorrow','Prediction of
    Rain'])

print(dataframe)

dt_accuracy = accuracy_score(Y_test1,y_pred)

prin5t("\nXGBoost Accuracy: "+str(dt_accuracy)
```

5.SCREENSHOTS

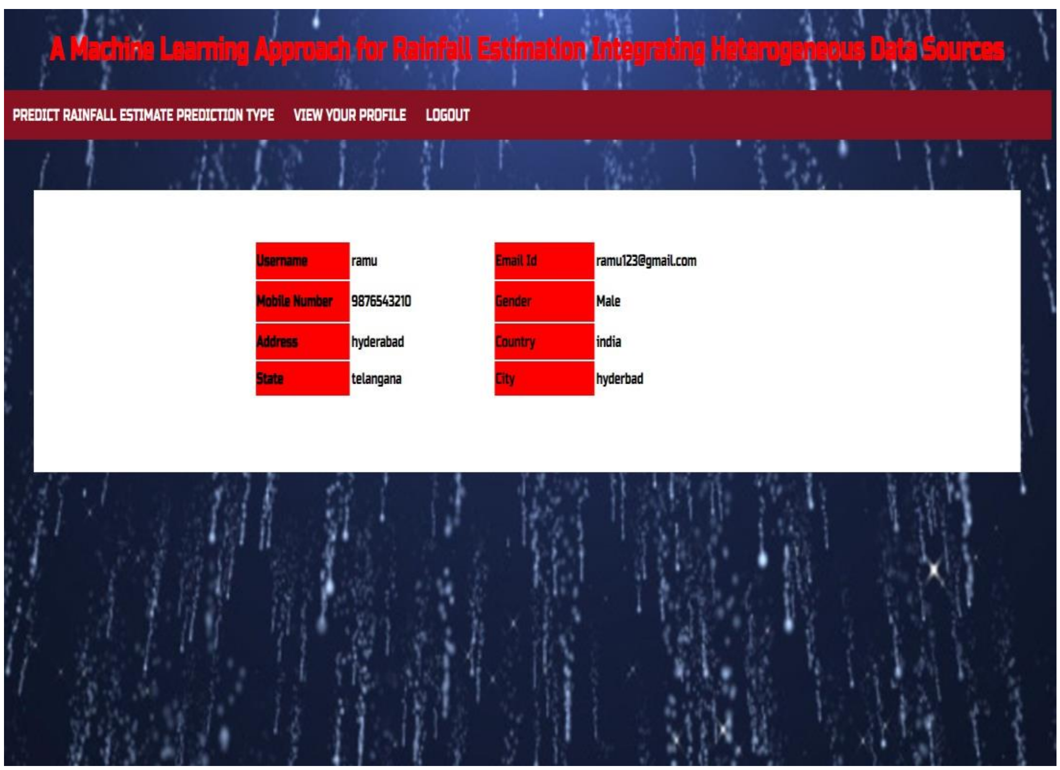
5.SCREENSHOTS

Screenshot No 5.1 : Home page

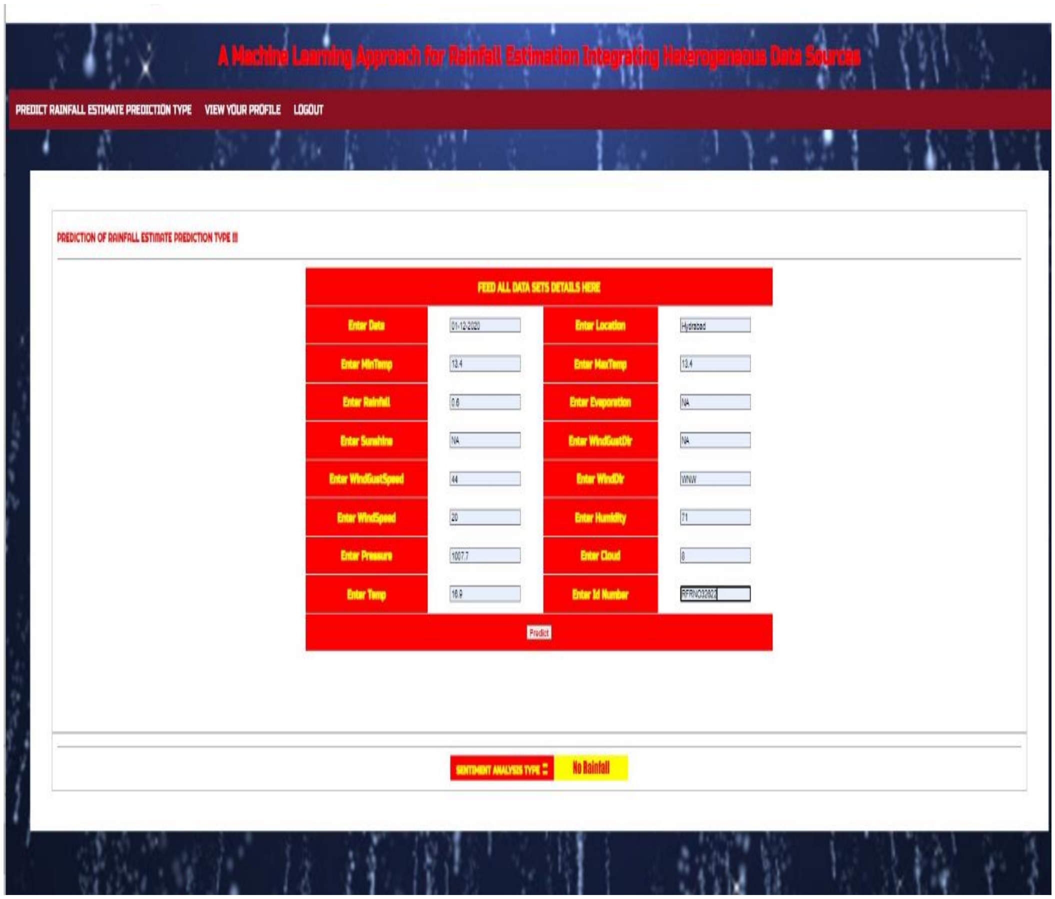


Screenshot No 5.2 : Register page

Screenshot No 5.3 : Login Page



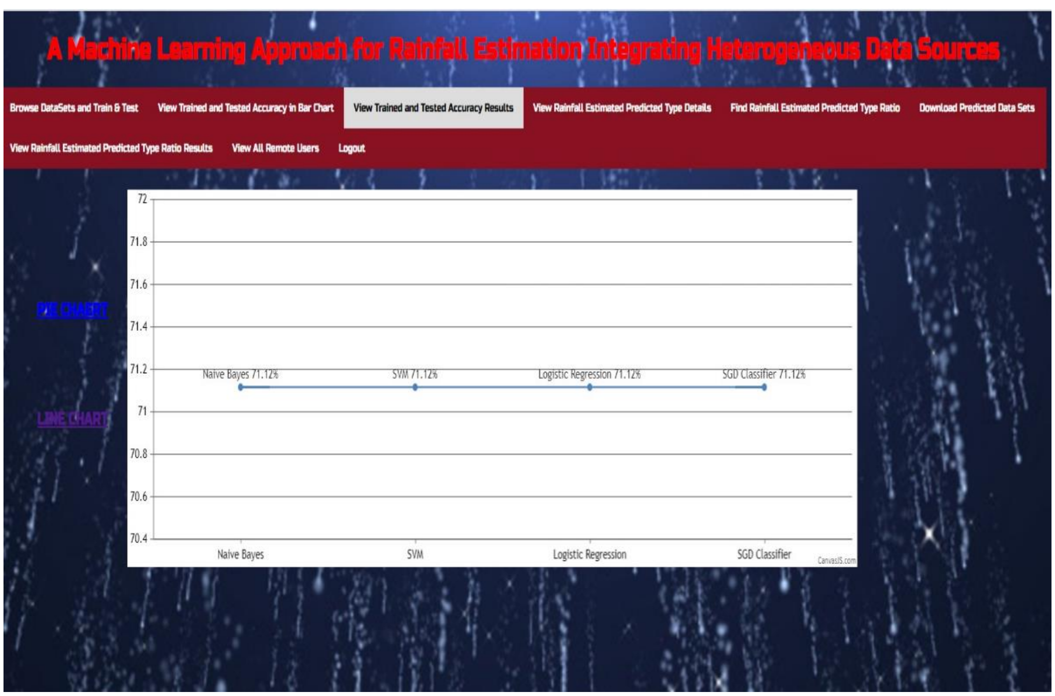
Screenshot No 5.4 : View Your Profile



Screenshot No 5.5 : Predict Rainfall Estimate Predict Type

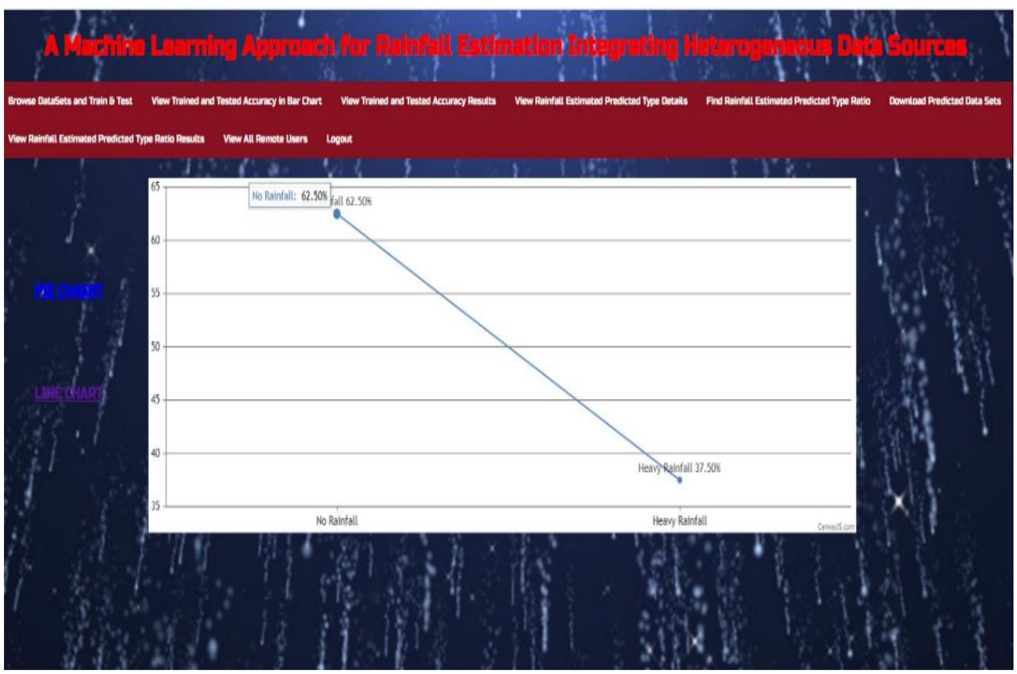
Screenshot No 5.6 : Service Provider Login

Screenshot No 5.7 : View Trained and Tested Accuracy in Bar Chart

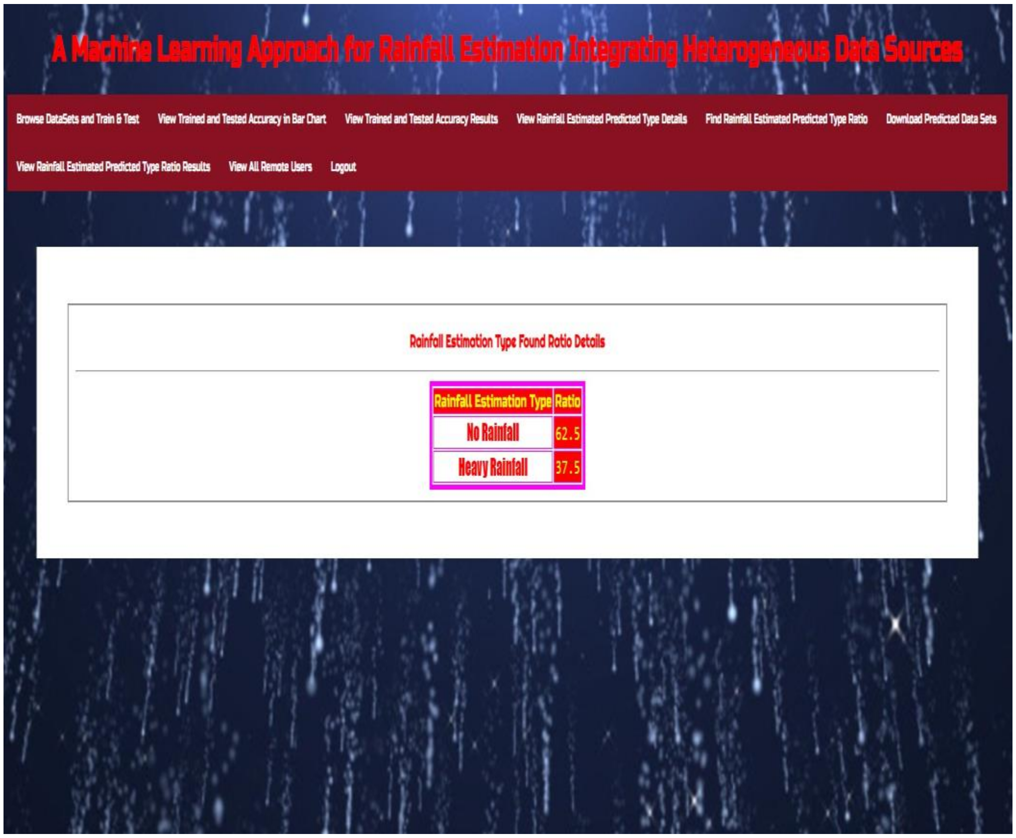


Screenshot No 5.8 : View Trained and Tested Accuracy Results

Screenshot No 5.9 : Rainfall Estimation Datasets Trained and Tested Result



Screenshot No 5.10 : Find Rainfall Estimate Predicted Type Ratio



Screenshot No 5.11 : Rainfall Estimated Type Found Ratio Details

6.TESTING

6.TESTING

6.1 INTRODUCTION TO TESTING

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product. It provides a way to check the functionality of components, sub assemblies, assemblies and/or a finished product It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

6.2 TYPES OF TESTING

6.2.1 UNIT TESTING

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application. It is done after the completion of an individual unit before integration. This is a structural testing that relies on knowledge of its construction and is invasive. Unit tests perform basic tests at component level and test a specific business process, application and/or system configuration. Unit testsensure that each unique path of a business process performs accurately to the documented specifications and contains clearly defined inputs and expected results.

6.2.2 INTEGRATION TESTING

Integration tests are designed to test integrated software components to determine if they actually run as one program. Integration tests demonstrate that although the components were individually satisfactory, as shown by successfully unit testing, the combination of components is correct and consistent. Integration testing is specifically aimed at exposing the problems that arise from the combination of components.

6.2.3 FUNCTIONAL TESTING

Functional tests provide systematic demonstrations that functions tested are available as specified by the business and technical requirements, system documentation, and user manuals.

Functional testing is centered on the following items:

Valid Input: identified classes of valid input must be accepted.

Functions : identified functions must be exercised.

Output : identified classes of application outputsmust be exercised.

Systems/Procedures: interfacing systems or procedures must be invoked.

Organization and preparation of functional tests is focused on requirements, key functions, or special test cases.

6.3 TEST CASES

6.3.1 CLASSIFICATION

S.NO	Min Temperature (°C)	Max Temperature (°C)	Humidity (%)	Wind Speed (km/h)	Cloud Cover (%)	Expected Rainfall
1	13.4	22.9	71	20	8	NO
2	17.5	32.3	82	7	7	YES
3	14.3	25	20	49	1	YES
4	12.9	29.6	7	54	6	NO
5	15.9	21.7	15	89	8	YES

7.CONCLUSION

7.CONCLUSION & FUTURE SCOPE

7.1 PROJECT CONCLUSION

Conclusion of project is predicting rainfall has the potential to significantly improve our ability to forecast weather patterns and prepare for extreme weather events. In conclusion, the application of machine learning techniques for predicting rainfall represents a significant advancement in meteorological science and practical decision-making. These models have demonstrated their capability to analyze vast datasets, extract meaningful patterns, and generate accurate rainfall forecasts, enabling us to better prepare for and respond to weather-related events. This technology has wide-ranging implications, from early warning systems for floods and droughts to optimizing agricultural practices and water resource management. Nevertheless, challenges persist, such as the need for high-quality data, model interpretability, and accounting for climate change effects. As we continue to refine and expand these machine learning approaches, there is a promising path forward to enhancing our ability to predict rainfall, thus contributing to safer and more sustainable communities in an increasingly uncertain climate.

7.2 FUTURE SCOPE

- **Improved Accuracy and Precision**:Future research will likely focus on enhancing the accuracy and precision of rainfall predictions by developing more sophisticated machine learning algorithms and mode.

- **Hydrological Integration**: Coupling rainfall prediction with hydrological models can improve the understanding of how rainfall affects river flow,reservoir levels, and groundwater recharge.

- **Localized Predictions**: Developing models for localized rainfall predictions is essential, as rainfall patterns can vary significantly within a region. High-resolution models that consider topography and land-use characteristics can be beneficial.

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8.2 GITHUB LINK

https://github.com/sheggariTejasri/Predicting-Rainfall-Using-Machine-Learning-Technique.git