Analyzing Climate Trends and Predicting Extreme Weather Events in Sri Lanka

Introduction

This presentation will cover the analysis of climate trends and the prediction of extreme weather events in Sri Lanka. The primary purpose of this research is to enhance the understanding of how climate change impacts this region and to develop accurate predictive models that can assist in disaster preparedness and mitigation strategies. The objectives include identifying the main drivers of climate change, analyzing how these changes manifest across different regions and seasons, and employing advanced methodologies to predict extreme weather events.

Background of the Study

Sri Lanka has experienced significant climate variability in recent decades, characterized by irregular rainfall patterns, rising temperatures, and an increased frequency of extreme weather events such as floods, droughts, and cyclones. This section provides the necessary context by discussing the historical climate trends and the developments that have led to these changes. Factors such as natural climate variability and anthropogenic activities, including greenhouse gas emissions and deforestation, are highlighted to provide a comprehensive understanding of the current climate scenario in Sri Lanka.

Literature Review

Topic Title	Author(s)	Problem	Source
Application of Neural Networks in Weather Forecasting	Gyanesh Shrivastava, Sanjeev Karmakar and Manoj Kumar Kowar	Using Bayesian model averaging for forecast ensemble calibration	International Journal of Computer Applications, August 2012
Applying Neural Network Models to Prediction and Data Analysis in Meteorology and Oceanography	Hsieh & Tang	Prediction and data analysis using neural network models	Applying Neural Network Models to Prediction and Data Analysis in Meteorology and Oceanography, 01 Sep 1998
Using Bayesian Model Averaging to Calibrate Forecast Ensembles	Raftery et al.	Using Bayesian model averaging for forecast ensemble calibration	Using Bayesian Model Averaging to Calibrate Forecast Ensembles, vNovember 4, 2003
Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting	Xingjian *SHI* , *Zhourong Chen*, *Hao Wang*	Using convolutional LSTM networks for precipitation nowcasting, Precipitation nowcasting using machine learning	Advances in Neural Information Processing Systems 28 (NIPS 2015)

Cont…..

Using Bayesian Model Averaging to Calibrate Forecast Ensembles	Adrian E. Raftery, Tilmann Gneiting and Fadoua Balabdaoui	forecast ensemble calibration.	Ethical considerations in machine learning, 01 May 2005
Classification, Seasonality and Persistence of Low-Frequency Atmospheric Circulation Patterns	Anthony G. Barnston and Robert E. Livezey	Classification and analysis of low-frequency atmospheric patterns	Classification, Seasonality and Persistence of Low-Frequency Atmospheric Circulation Patterns, 01 Jun 1987
The Quiet Revolution of Numerical Weather Prediction	Peter Bauer, Alan Thorpe and Gilbert Brunet	Advances in numerical weather prediction	quiet revolution of numerical weather prediction, 02 September 2015
Model Cards for Model Reporting	Simone Wu and Margaret Mitchell	Ethical considerations in machine learning	Model Cards for Model Reporting, January 2019

Research Objectives/Questions

1. **How can the implementation of machine learning algorithms be optimized for scalability and efficiency in the context of operational weather forecasting systems?**

2. **What strategies and techniques can be employed to enhance the computational performance and scalability of machine learning models, particularly when deployed in resource-constrained environments?**

3. **To what extent could machine learning models improve temperature and rainfall predictions?**

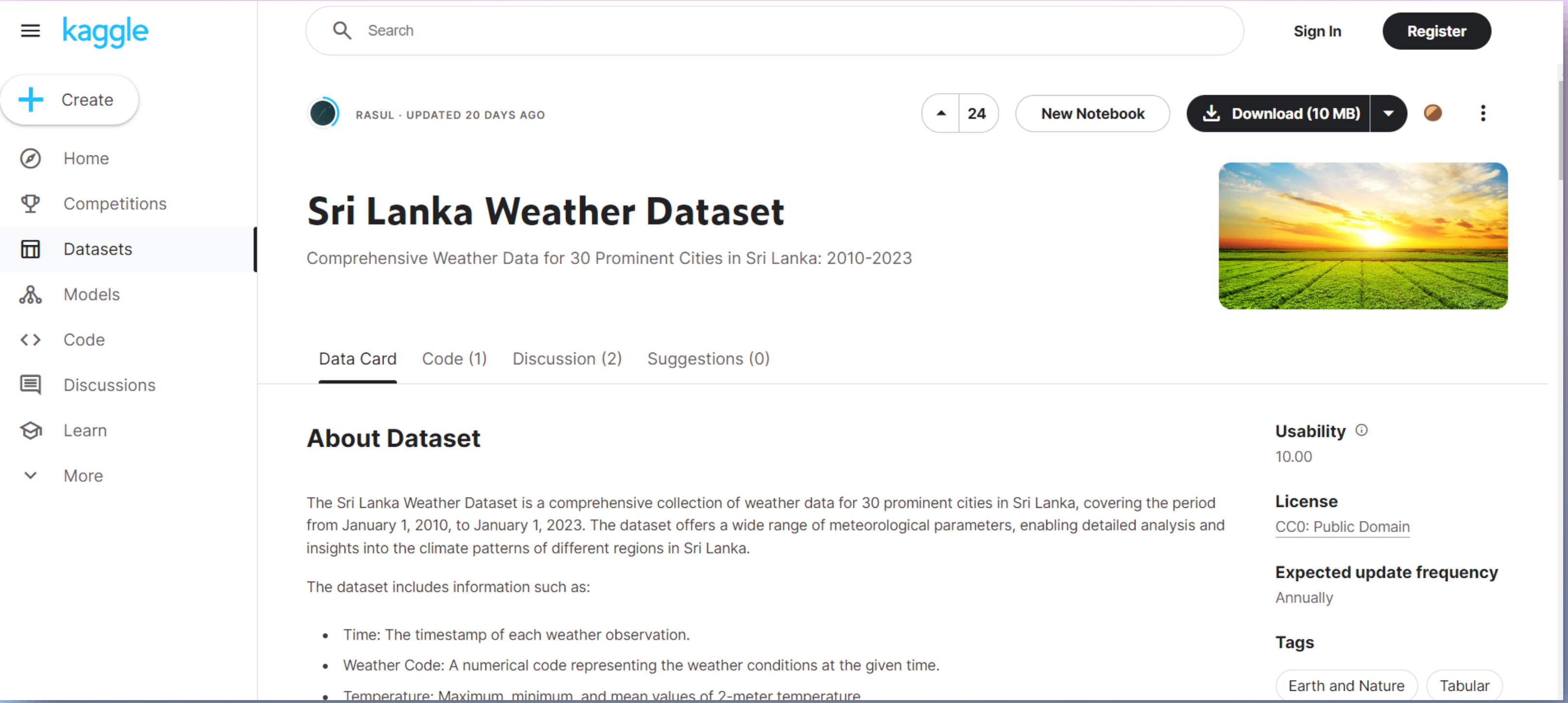
Methodology

- **Research Design**

The study systematically developed and evaluated machine learning models for weather prediction using Python and sci-kit-learn. Key steps included preprocessing raw weather data to handle missing values and normalize features, selecting linear regression models for their effectiveness, training models on split data sets, and evaluating them using mean squared error (MSE). Models were validated with real-world data to ensure robustness and generalizability.

- # Data Collection Methods

Historical weather data was sourced from Kaggle. Python libraries like pandas and NumPy were used for data extraction and preprocessing.



- # Data Preprocessing
  - **Selection of Relevant Features:** Only the columns relevant to the prediction tasks were retained. These included 'apparent_temperature_mean', 'rain_sum', 'temperature_2m_mean', and 'weathercode'.

2. Data Preprocessing

Keep only the selected columns

```
[ ]  data = data[['apparent_temperature_mean', 'rain_sum', 'temperature_2m_mean', 'weathercode']]
```

- **Handling Missing Values:** Any missing values within these selected columns were addressed by removing the incomplete records to maintain data integrity and prevent biases in the model training process.

Handle missing values if any

```
[ ]  data = data.dropna()
```

• Data Preprocessing

- **Correlation Analysis:** A correlation matrix was created to understand the relationships between the variables. This analysis helped in identifying multicollinearity and ensuring the selected features contributed uniquely to the model's predictions

```python
# 4. Display Heatmap of Correlation Matrix
plt.figure(figsize=(10, 6))
correlation_matrix = data.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix Heatmap')
plt.show()

# 5. Display Correlation Coefficients
print("Correlation Matrix:")
print(correlation_matrix)
```

```
Correlation Matrix:
                            apparent_temperature_mean  rain_sum  \
apparent_temperature_mean                    1.000000 -0.091989
rain_sum                                    -0.091989  1.000000
temperature_2m_mean                          0.888324 -0.234696
weathercode                                  0.099155  0.395169

                            temperature_2m_mean  weathercode
apparent_temperature_mean              0.888324     0.099155
rain_sum                              -0.234696     0.395169
temperature_2m_mean                    1.000000    -0.150776
weathercode                           -0.150776     1.000000
```

Model Selection and Training

- **Splitting the Data:** to effectively evaluate the performance of the weather prediction models, the dataset was divided into training and testing sets.

Separate features and target variables

```
X = data[['apparent_temperature_mean', 'rain_sum']]  # Features
y_temp = data['temperature_2m_mean']  # Target variable for temperature prediction
y_weathercode = data['weathercode']  # Target variable for weather code prediction
y_rain = data['rain_sum']  # Target variable for rain prediction
```

Split data into training and testing sets

```
X_train, X_test, y_temp_train, y_temp_test = train_test_split(X, y_temp, test_size=0.2, random_state=42)
_, _, y_weathercode_train, y_weathercode_test = train_test_split(X, y_weathercode, test_size=0.2, random_state=42)
_, _, y_rain_train, y_rain_test = train_test_split(X, y_rain, test_size=0.2, random_state=42)
```

Model Selection and Training

- **Training the Models:** the next step involved training separate Linear Regression models to predict temperature, weather code, and rain sum. Linear Regression was chosen for its simplicity and efficiency in modeling linear relationships.

3. Choose Models

```
[ ] temp_model = LinearRegression()
    weathercode_model = LinearRegression()
    rain_model = LinearRegression()
```

4. Train the Models

```
[ ] temp_model.fit(X_train, y_temp_train)
    weathercode_model.fit(X_train, y_weathercode_train)
    rain_model.fit(X_train, y_rain_train)
```

```
▾ LinearRegression
LinearRegression()
```

• Model Selection and Training

- **Model Evaluation:** Model evaluation is a critical step in the machine learning workflow to ensure that the developed models perform well not only on the training data but also on unseen test data. This involves assessing the models' predictive accuracy and generalizability using various evaluation metrics

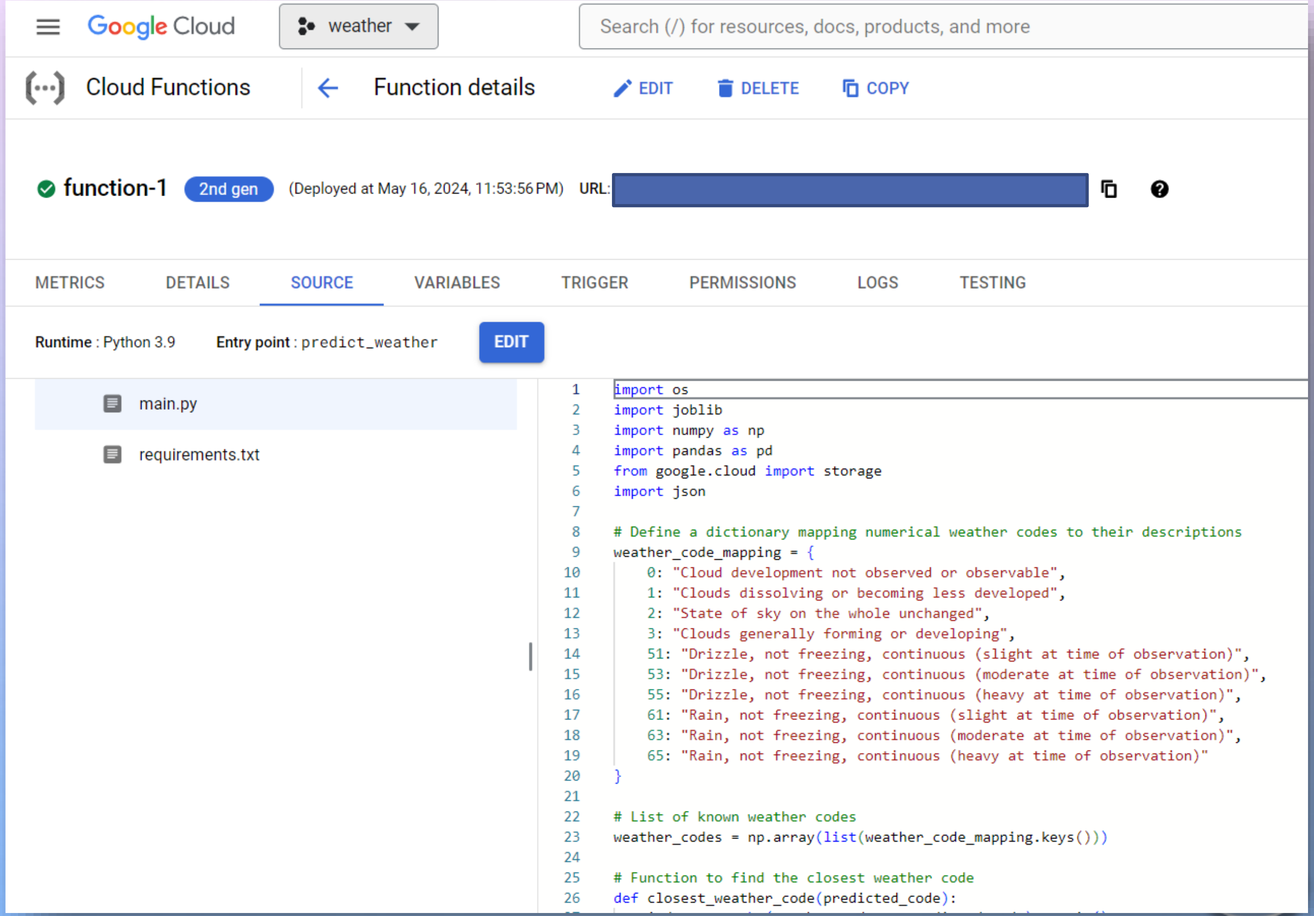
5. Evaluate the Models

```
y_temp_pred = temp_model.predict(X_test)
temp_mse = mean_squared_error(y_temp_test, y_temp_pred)
print("Temperature Mean Squared Error:", temp_mse)

y_weathercode_pred = weathercode_model.predict(X_test)
weathercode_mse = mean_squared_error(y_weathercode_test, y_weathercode_pred)
print("Weather Code Mean Squared Error:", weathercode_mse)

y_rain_pred = rain_model.predict(X_test)
rain_mse = mean_squared_error(y_rain_test, y_rain_pred)
print("Rain Mean Squared Error:", rain_mse)
```

```
Temperature Mean Squared Error: 0.6294819522850056
Weather Code Mean Squared Error: 379.97785175752966
Rain Mean Squared Error: 4.3244541176454146e-29
```

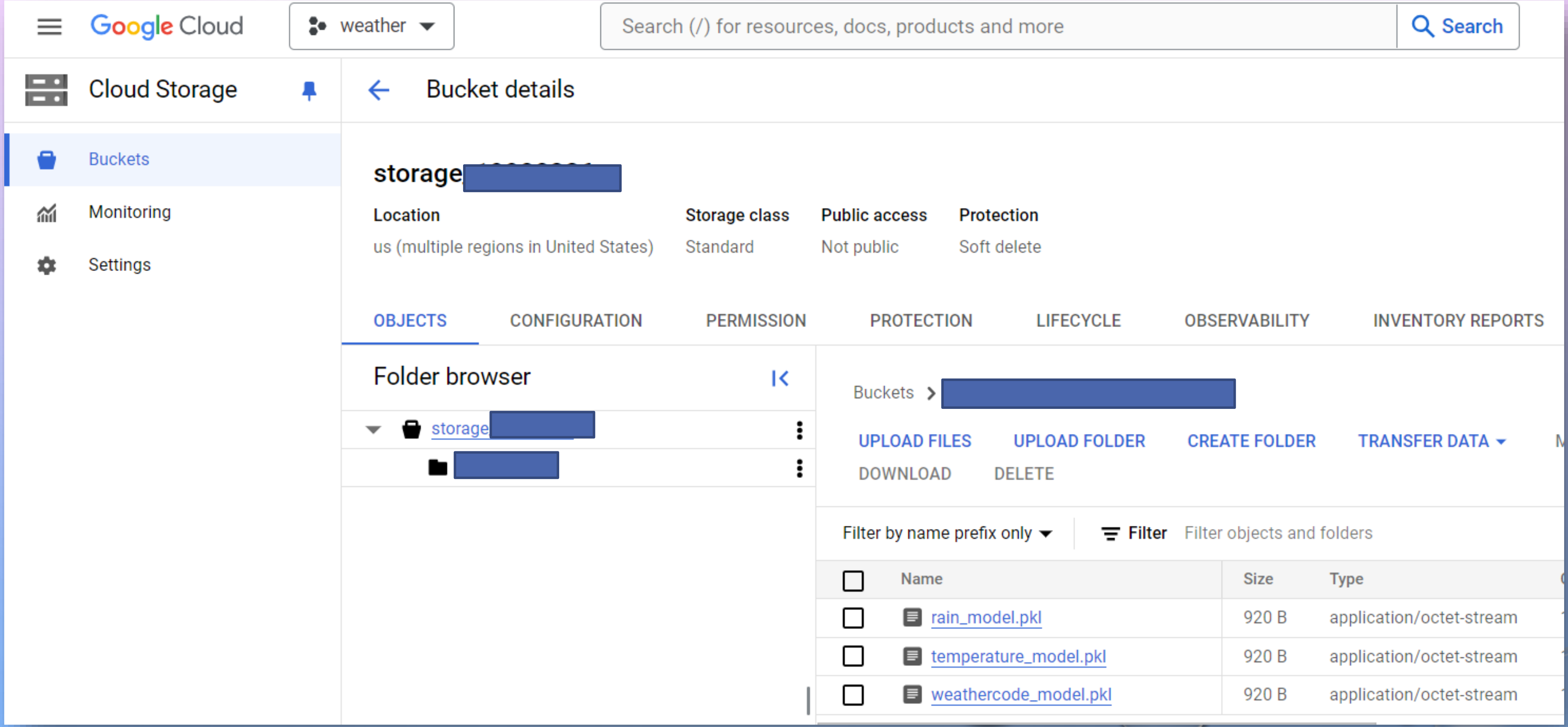
• Cloud Function Development

- **Writing the Cloud Function Code:** the cloud function is responsible for loading the trained machine learning models from Google Cloud Storage, processing incoming data, making predictions, and returning the results.



• Google Blob Storage Deployment

- Google Cloud Storage (GCS) plays a crucial role in this project for storing and managing various artifacts and resources associated with the machine learning models and their deployment.



Testing and Validation

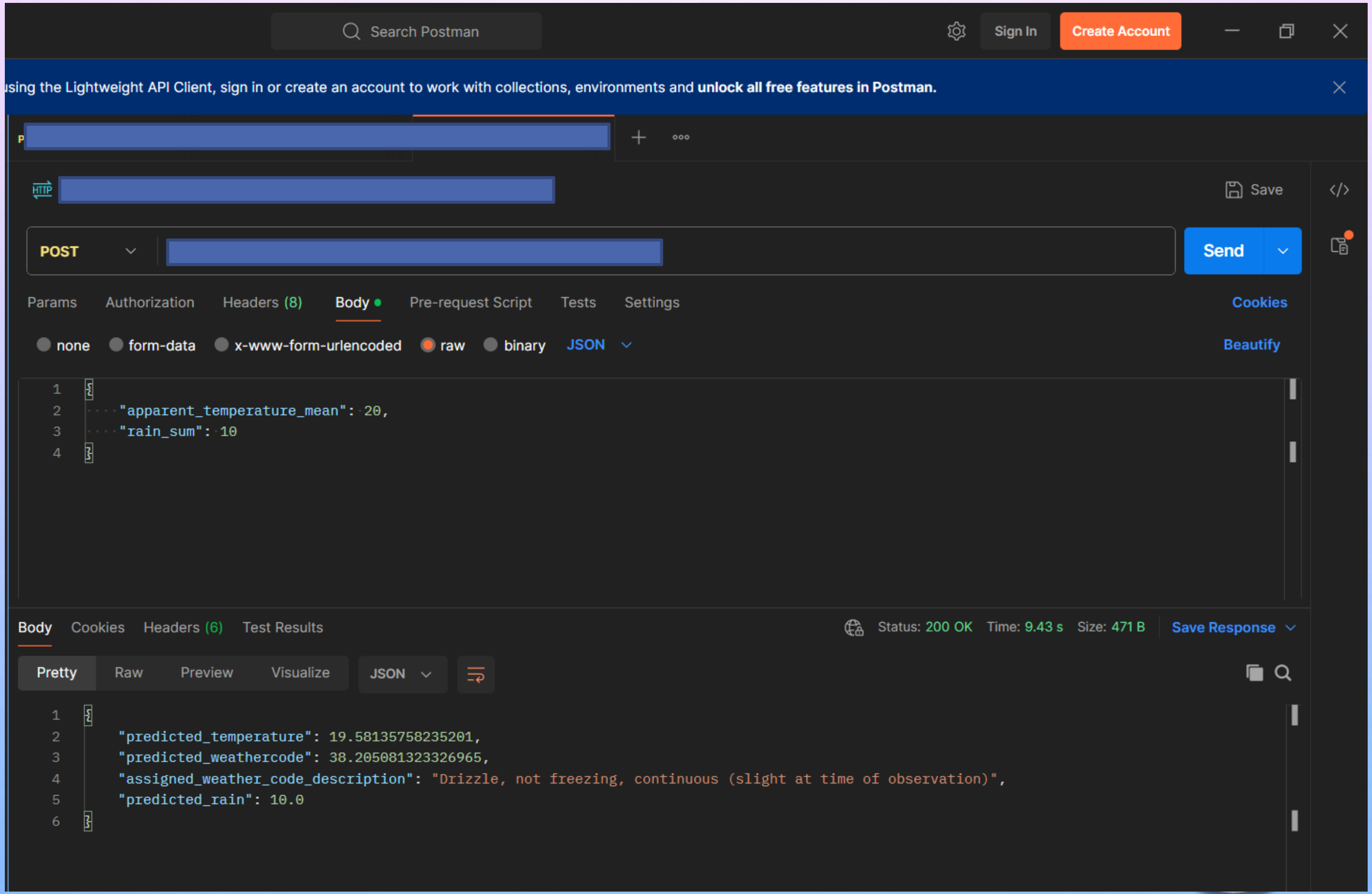
- **Testing the weather prediction model:** The prepared sample inputs are fed into the trained machine-learning model to generate predictions. The model's output is compared against expected outcomes based on ground truth data or domain knowledge. Testing helps identify any discrepancies or inaccuracies in the model's predictions.

```python
# Function to predict with the loaded models
def predict_weather(apparent_temperature_mean, rain_sum):
    # Create a DataFrame for the input features
    input_data = pd.DataFrame({
        'apparent_temperature_mean': [apparent_temperature_mean],
        'rain_sum': [rain_sum]
    })

    # Make predictions using the loaded models
    predicted_temperature = loaded_temp_model.predict(input_data)[0]
    predicted_weathercode = loaded_weathercode_model.predict(input_data)[0]
    predicted_rain = loaded_rain_model.predict(input_data)[0]

    # Find the closest weather code
    closest_code = closest_weather_code(predicted_weathercode)
    predicted_weather_description = weather_code_mapping.get(closest_code, "Unknown weather code")

    # Print the predictions
    print("Predicted Temperature:", predicted_temperature)
    print("Predicted Numerical Weather Code:", predicted_weathercode)
    print("Assigned Weather Code Description:", predicted_weather_description)
    print("Predicted Rain:", predicted_rain)

    return predicted_temperature, closest_code, predicted_rain, predicted_weather_description

# Example usage of the prediction function
apparent_temperature_mean = 38
rain_sum = 5

predicted_temperature, closest_code, predicted_rain, weather_description = predict_weather(apparent_temperature_mean, rain_sum)
```

```
Predicted Temperature: 31.119851939504276
Predicted Numerical Weather Code: 54.60256579947055
Assigned Weather Code Description: Drizzle, not freezing, continuous (heavy at time of observation)
Predicted Rain: 5.000000000000002
```

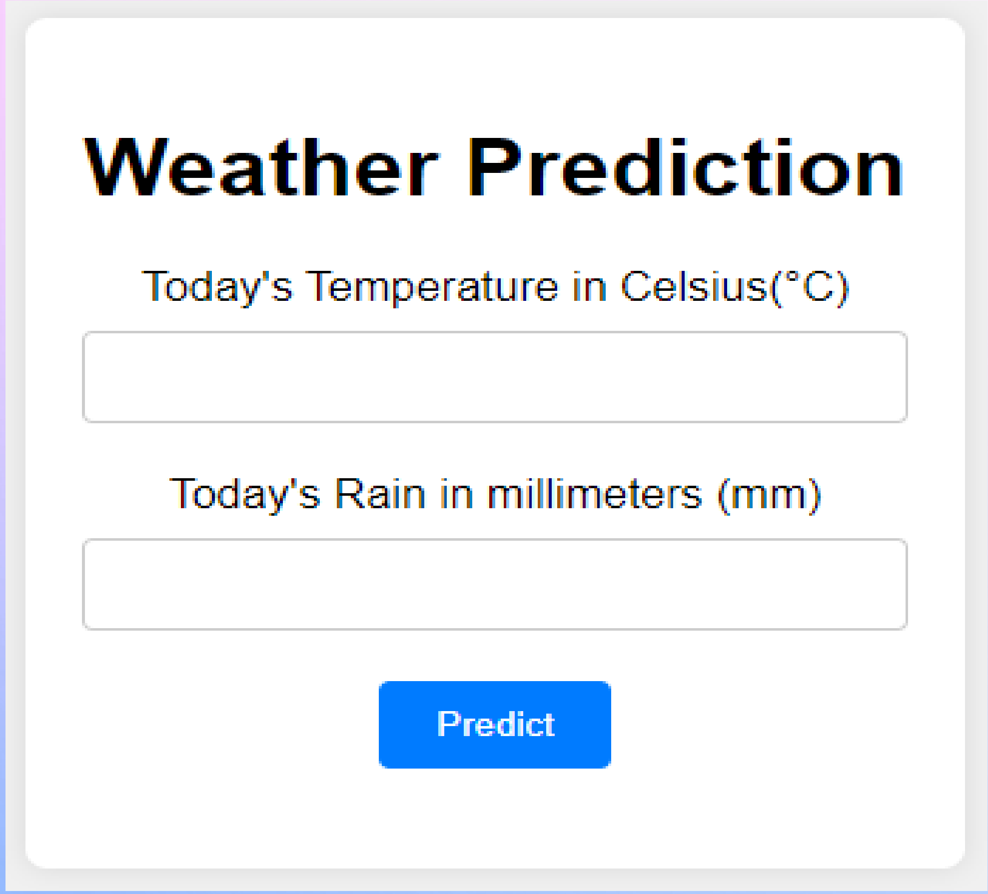
Testing and Validation

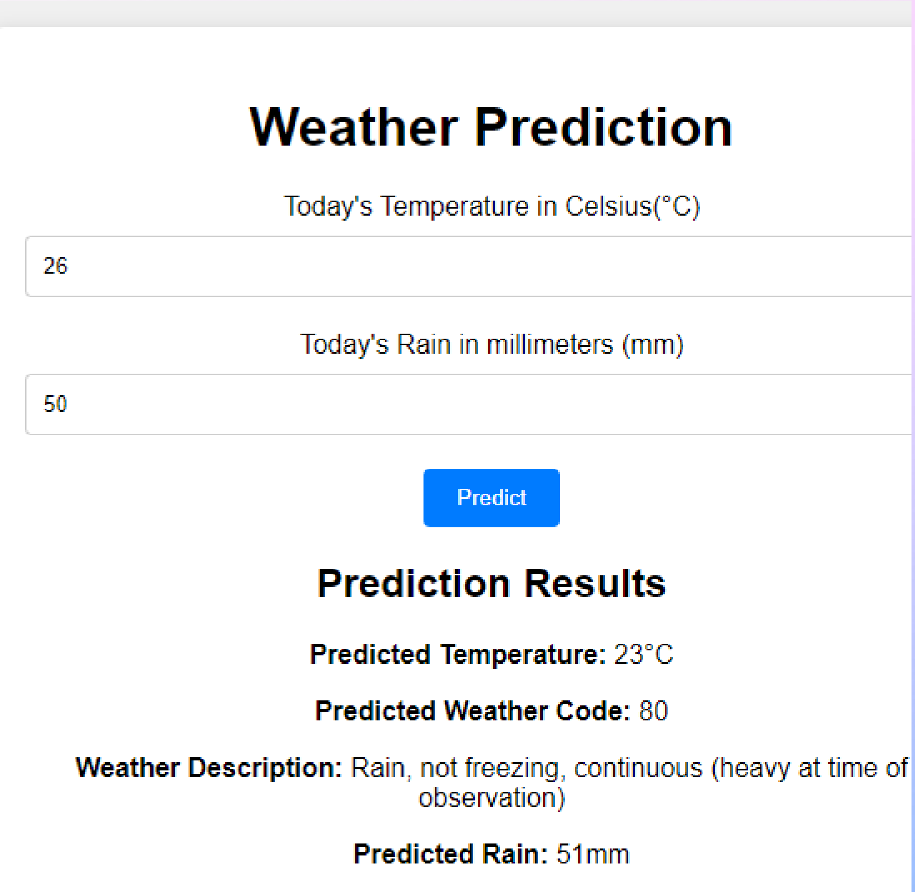
- **Testing the Cloud Function:** cloud function is crucial to ensure that it operates correctly and returns accurate predictions. The primary tool used for this purpose is Postman, a popular API client that allows for the testing of HTTP requests



Results

The implementation of machine learning models for weather prediction was extended to a practical deployment, utilizing both a web interface and cloud-based AI model hosting. The web interface was developed using PHP and HTML and deployed on a free domain and hosting service provided by InfinityFree(https://www.infinityfree.com). Additionally, the machine learning model was deployed using Google Cloud Platform (GCP), specifically through Google Cloud Functions, to ensure scalable and efficient model inference.


Weather Prediction
Today's Temperature in Celsius(°C)
Today's Rain in millimeters (mm)
Predict


Weather Prediction
Today's Temperature in Celsius(°C)
26
Today's Rain in millimeters (mm)
50
Predict
Prediction Results
Predicted Temperature: 23°C
Predicted Weather Code: 80
Weather Description: Rain, not freezing, continuous (heavy at time of observation)
Predicted Rain: 51mm

- **Hosting and domain name**

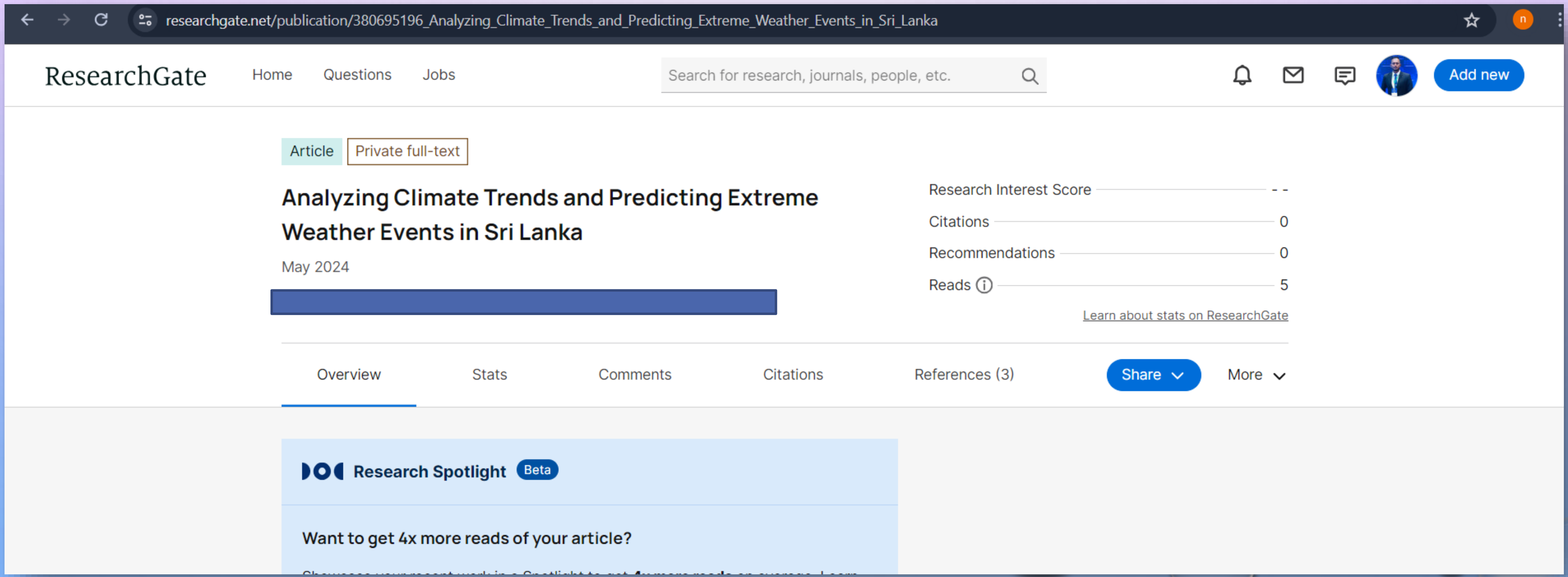
InfinityFree was chosen as the hosting provider due to its free services and robust infrastructure, offering unlimited disk space and bandwidth for the project, free subdomains, custom domain support, MySQL database support, and PHP/HTML compatibility.

http://weather-check.rf.gd/

- # Research Paper publication

By publishing on ResearchGate, the research was positioned to contribute to the broader scientific discourse on the application of machine learning in meteorology, offering valuable insights and methodologies that can be utilized and built upon by other researchers and practitioners in the field.

https://www.researchgate.net/publication/380695196_Analyzing_Climate_Trends_and_Predicting_Extreme_Weather_Events_in_Sri_Lanka



Conclusion

This study demonstrates the significant advancements in weather prediction through machine learning, utilizing Python and sci-kit-learn to enhance forecast accuracy and efficiency. Neural networks, feature engineering, and ensemble learning have shown great promise in capturing complex meteorological patterns. Despite these advancements, challenges such as model generalizability, interpretability, and ethical considerations remain. Future research should focus on improving the robustness and transparency of these models, integrating traditional numerical methods with machine learning to achieve more reliable and equitable weather forecasting systems.

THANK YOU