DEBRE BIRHAN UNIVERSITY

COLLEGE OF COMPUTING

DEPARTMENT OF SOFTWARE ENGINEERING

Individual Project

Course title: fundamental of machine learning Course code: SEng4091

Weather Prediction

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1. Introduction

This document outlines the development of a machine learning model to analyze and forecast key metrics using a dataset. The report covers problem definition, data exploration, preprocessing, model selection, evaluation, hyperparameter tuning, and potential future improvements.

2. Problem Definition, Data Source, and Description

2.1 Problem Definition

This project aims to develop a predictive model using machine learning to analyze and forecast key metrics based on a dataset.

Data source

A self-sourced dataset containing used car listings was used for model training.

The dataset used in this project was downloaded from **gitgub** (Weather

prediction dataset- https://github.com/sehrishnaseer-381/Weather-Prediction

The dataset contains weather records for different cities on various dates. The columns include:

- **City**: The city where the weather data was recorded.
- **Date**: The date of the weather record (format: `DD-MM-YYYY`).
- **Temperature (°C)**: The temperature in degrees Celsius (some missing values).
- **Weather Description**: A short description of the weather (e.g., "Few clouds", "Rain", etc.).
- **Humidity (%)**: The percentage of humidity (some missing values).
- **Wind Speed (m/s)**: The wind speed in meters per second.

2.2 Data Summary

- **Total Entries**: 1000
- **Missing Values**:
  - Temperature: 9 missing values
  - Weather Description: 9 missing values
  - Humidity: 8 missing values
- **Data Types**:
  - City: String
  - Date: String (converted to DateTime in the notebook)
  - Temperature, Humidity, Wind Speed: Float
  - Weather Description : String

.

Code:

```
import pandas as pd import seaborn as sns import matplotlib.pyplot as plt

import joblib import numpy as np from sklearn.preprocessing import

LabelEncoder, StandardScaler from sklearn.model_selection import

train_test_split, GridSearchCV from sklearn.ensemble import

RandomForestRegressor from sklearn.dummy import DummyRegressor from

sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

This section imports necessary libraries for data handling, visualization, preprocessing, model training, and evaluation.

3. Data Preprocessing

Loading and Understanding the Data

```
# Load the dataset file_path = "we.csv"  #

Change to your file path df =

pd.read_csv(file_path)
```

This code reads the CSV file into a Pandas DataFrame for further analysis. The dataset will be explored to understand its structure, missing values, and types of data present.

Convert Date Column to Datetime Format

```
# Convert Date column to datetime
df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y', errors='coerce')
```

Explanation:

- Converts the 'Date' column in the dataset into a proper datetime format (`YYYY-MM-DD`).
- The format `'%d-%m-%Y'` ensures that the input date follows the structure: **day-monthyear**.
- The parameter `errors='coerce'` replaces any incorrect or unrecognizable date values with `NaT` (Not a Time), preventing errors during conversion.

Handling Missing Values

Numerical Columns

```
# Fill missing values in numerical columns with median numerical_columns =

df.select_dtypes(include=['number']).columns.tolist() df[numerical_columns] =

df[numerical_columns].apply(lambda x: x.fillna(x.median()))
```

This code ensures numerical features do not contain missing values by replacing them with the median value. This helps to prevent data loss while maintaining a robust statistical representation.

Categorical Columns

```
# Fill missing values in categorical columns with mode categorical_columns =

df.select_dtypes(include=['object']).columns.tolist() df[categorical_columns] =

df[categorical_columns].apply(lambda x: x.fillna(x.mode()[0]))
```

Categorical variables are filled using the mode (most frequent value). This approach helps in maintaining categorical consistency without introducing new categories.

Remove Duplicate Rows

```
# Remove duplicate rows df
= df.drop_duplicates()
```

Explanation:

- Removes any duplicate rows from the dataset.
- Ensures that each record in the dataset is unique, preventing redundant data from affecting analysis and machine learning models.
- This operation maintains data integrity and reduces unnecessary computations. **Identify**

Numerical Features

Explanation:

- Selects only numerical columns from the DataFrame, excluding categorical and textual data.
- Extracts column names of numerical features into a list.
- Removes the target variable ('Temperature (°C)') to prevent data leakage in machine learning models.

Feature Encoding

```
# Encode categorical features

label_encoders = {} for col in

categorical_columns:

    le = LabelEncoder()     df[col] =
le.fit_transform(df[col])
label_encoders[col] = le
```

This code converts categorical values into numerical form using label encoding. Label encoding assigns unique integers to each category, making the data suitable for machine learning models.

```
joblib.dump(label_encoders, "label_encoders.pkl")
```

Save labelEncoder Feature Scaling

```
# Standardizing numerical features scaler = StandardScaler()

feature_columns = df.select_dtypes(include=['number']).columns.tolist()

df[feature_columns] = scaler.fit_transform(df[feature_columns])
```

StandardScaler transforms numerical features to have a mean of 0 and a standard deviation of 1. This improves model convergence and ensures fair weighting of features.

```
# Save the scaler and feature columns joblib.dump(scaler,

"scaler.pkl") joblib.dump(feature_columns,

"feature_columns.pkl")
```

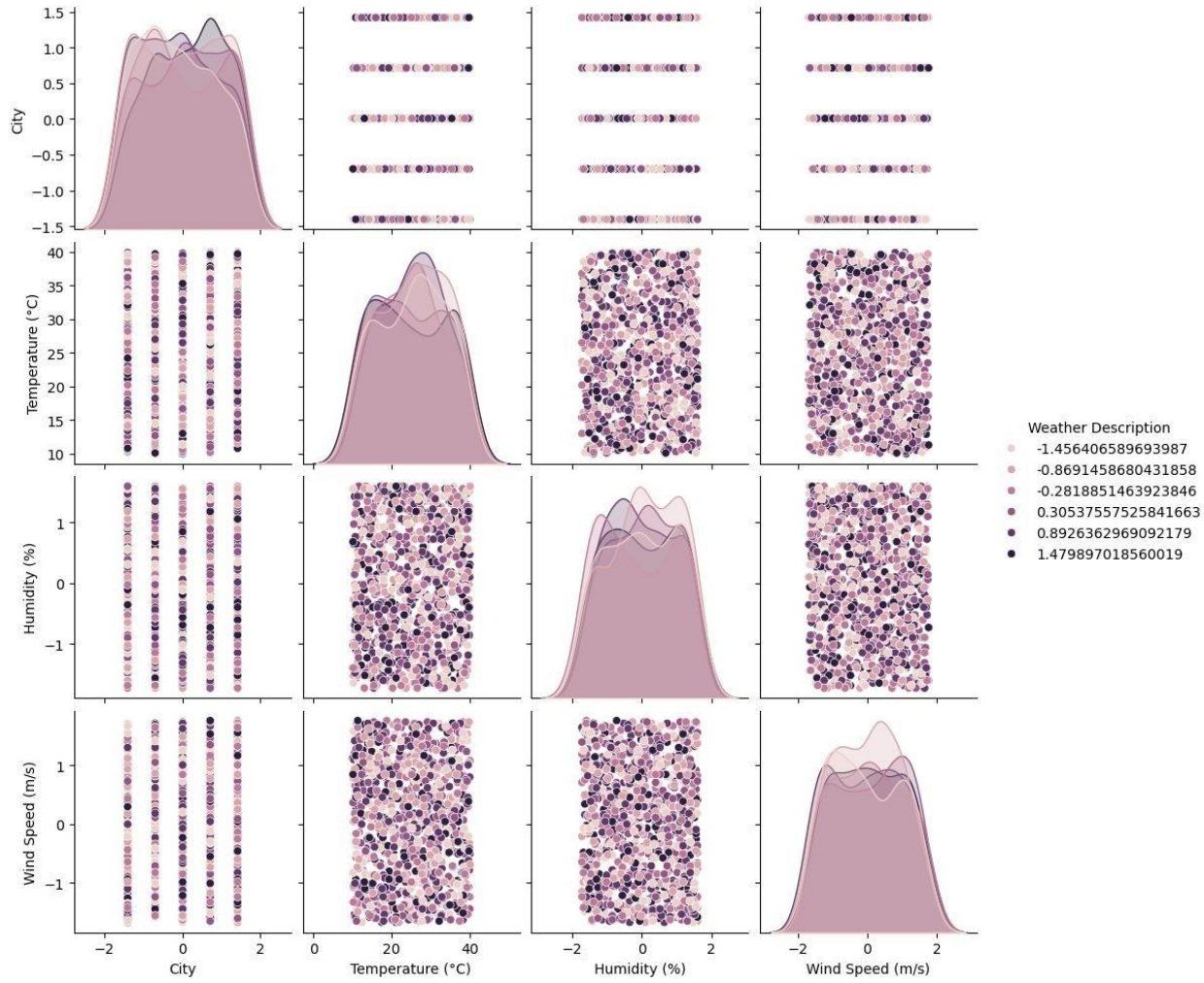
3. Exploratory Data Analysis (EDA)

EDA helps in understanding data distribution, correlations, and feature relationships.

Visualizations

Pair Plot

```
# Visualize relationships sns.pairplot(df,

hue='Weather Description') plt.show()
```

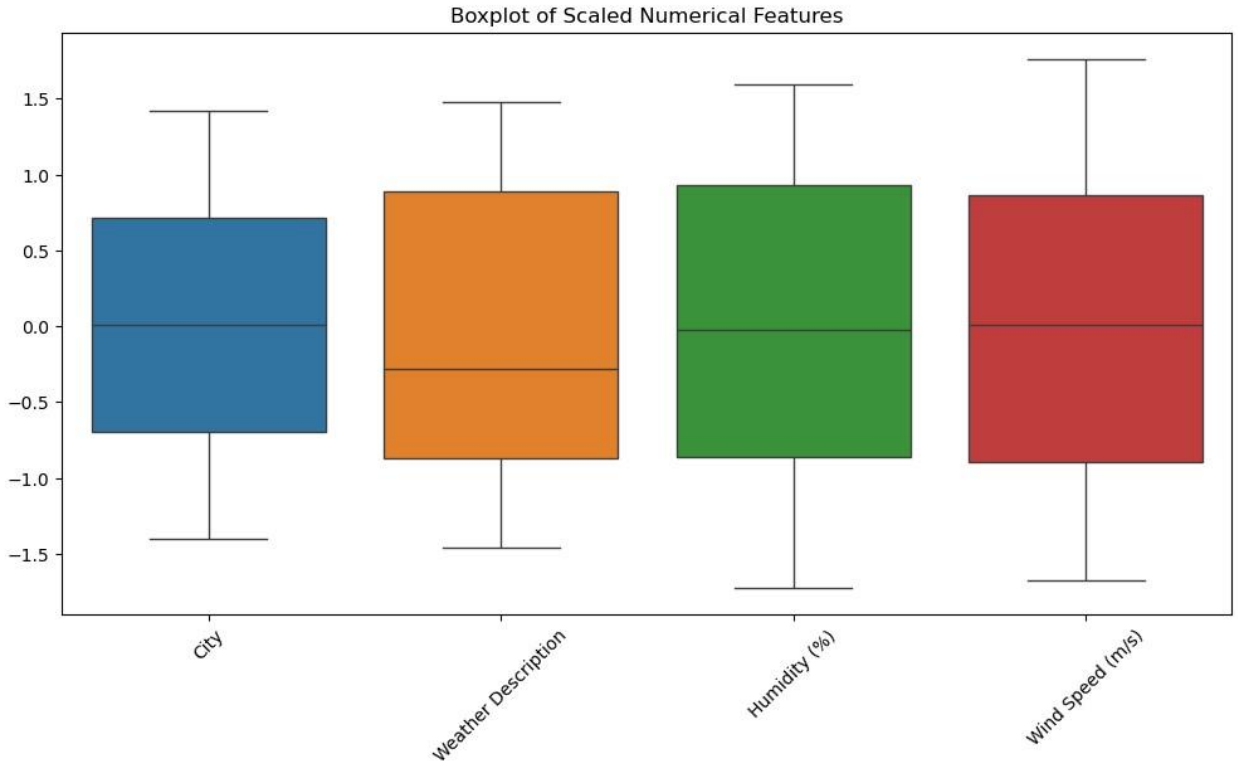


Pair plots provide insights into feature correlations and data distributions. It helps in detecting patterns, trends, and potential multicollinearity issues.

Boxplot

```
# Boxplot to identify remaining outliers

plt.figure(figsize=(12,6))

sns.boxplot(data=df[feature_columns]) plt.title("Boxplot

of Scaled Numerical Features") plt.xticks(rotation=45)
```

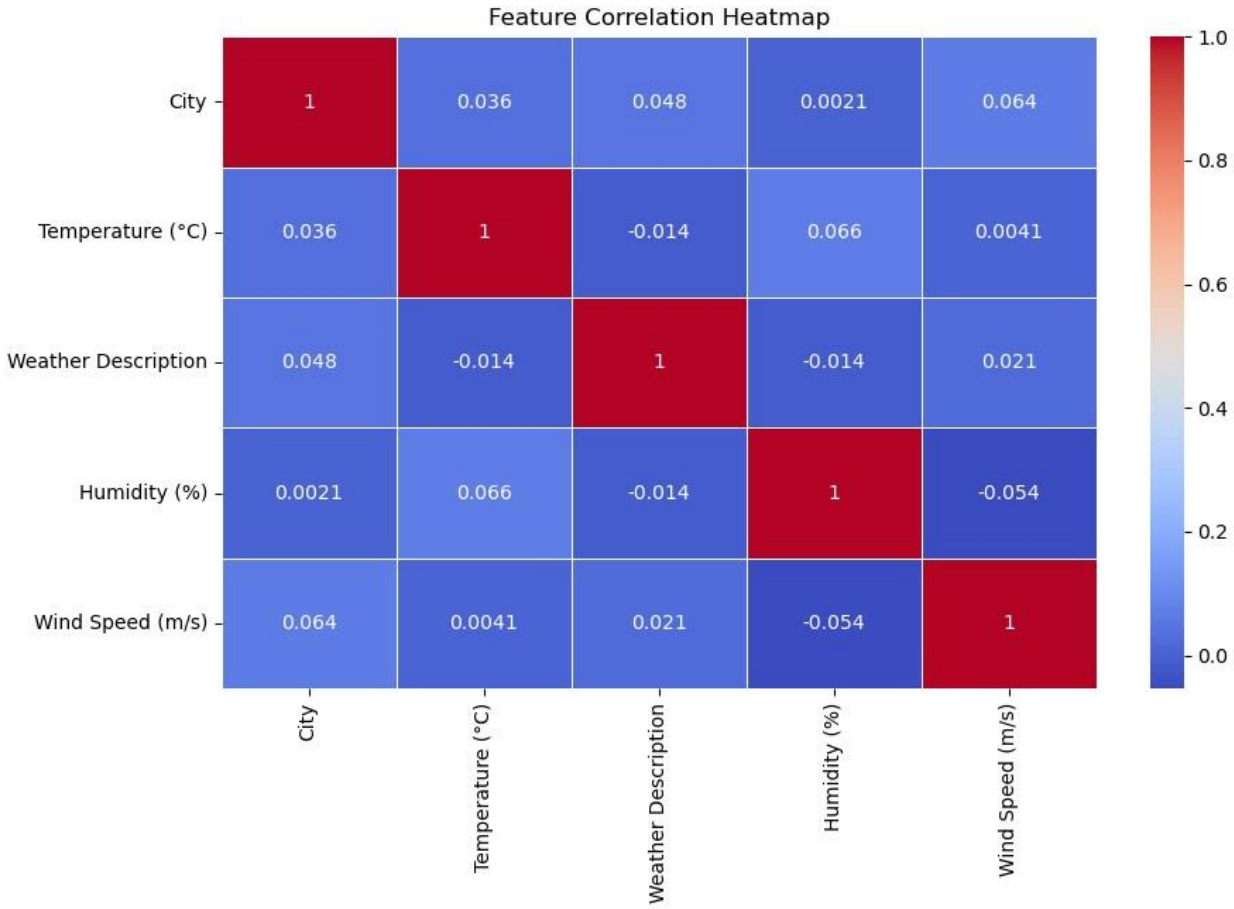
```
plt.show()
```



Boxplots highlight outliers and feature distributions. Outliers can impact model performance, and this visualization helps determine if outlier handling is needed.

Correlation Heatmap

```
# Correlation heatmap plt.figure(figsize=(10,6))

sns.heatmap(df.corr(numeric_only=True), annot=True, cmap='coolwarm', linewidths=0.5)

plt.title("Feature Correlation Heatmap") plt.show()
```



A correlation heatmap helps visualize the relationships between different numerical features. Strong correlations indicate features that may be redundant.

4. Feature Engineering

Feature Importance Analysis

```
# Training a RandomForestRegressor to determine feature importance
model = RandomForestRegressor(random_state=42)

model.fit(X_train, y_train) feature_importances

= model.feature_importances_
```

Random Forest assigns importance scores to each feature based on their contribution to model predictions. This helps in selecting the most impactful features.

5. Model Selection, Training, and Hyperparameter Tuning

```
# Select features and target variable target

= 'Temperature (°C)'
```

```
X = df.drop(columns=[target, 'Date'])  # Exclude date from features
y = df[target]
# Split dataset into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

This step divides the dataset into training (80%) and testing (20%) sets. The training set is used to train the model, while the test set evaluates its performance on unseen data.

Baseline Model

`Dummy Regressor as a baseline model`

```
# Baseline Model (Dummy Regressor)

dummy_model = DummyRegressor(strategy="mean")

dummy_model.fit(X_train, y_train) dummy_pred

= dummy_model.predict(X_test)
```

The dummy model predicts the mean value for all inputs, serving as a simple baseline to compare the performance of more advanced models.

Random Forest Model Training

`Training a RandomForestRegressor`

```
# Train a regression model (Random Forest Regressor)

model = RandomForestRegressor(random_state=42)

model.fit(X_train, y_train)



# Save the trained model
joblib.dump(model, "regression_model.pkl")
```

```
# Make predictions y_pred =

model.predict(X_test)
```

A Random Forest Regressor is trained for predictive modeling, using an ensemble of decision trees to improve accuracy and reduce overfitting.

6. Model Evaluation

Metrics Used

- **Mean Absolute Error (MAE)**: Measures absolute differences between actual and predicted values.
- **Mean Squared Error (MSE)**: Penalizes larger errors more than MAE.

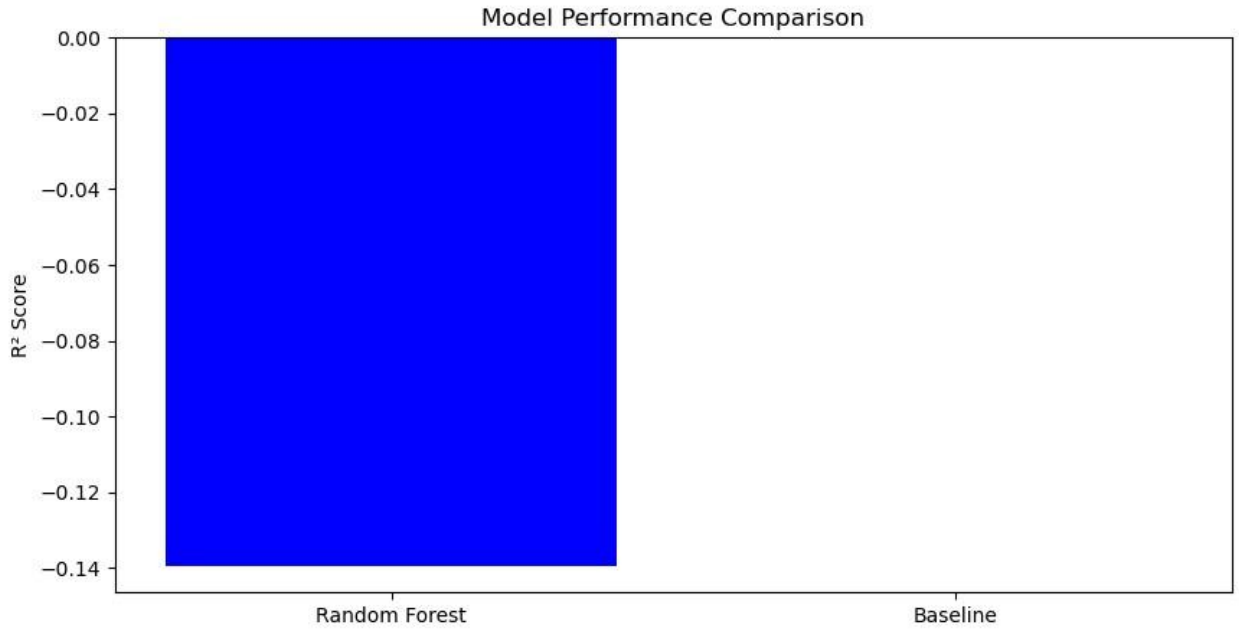
- **R-Squared (R^2) Score**: Evaluates the proportion of variance explained by the model.

```
# Evaluate baseline model dummy_mae =

mean_absolute_error(y_test, dummy_pred) dummy_mse

= mean_squared_error(y_test, dummy_pred) dummy_r2

= r2_score(y_test, dummy_pred)

 print(f"Baseline Model Performance:\nMAE: {dummy_mae}\nMSE: {dummy_mse}\nR² Score:
{dummy_r2}")
```

```
# Evaluate the model mae = mean_absolute_error(y_test, y_pred) mse =

mean_squared_error(y_test, y_pred) r2 = r2_score(y_test, y_pred)

print(f"Model Performance:\nMAE: {mae}\nMSE: {mse}\nR² Score: {r2}")
```

These metrics help evaluate the model's accuracy and its ability to generalize to new data.

```
# Visualization of Model vs Baseline plt.figure(figsize=(10,5))

plt.bar(['Random Forest', 'Baseline'], [r2, dummy_r2], color=['blue', 'red'])

plt.ylabel("R² Score") plt.title("Model Performance Comparison") plt.show()
```



Hyperparameter Tuning Using GridSearchCV

```
# Optimizing model hyperparameters using GridSearchCV
```

```
param_grid = {

    'n_estimators': [50, 100, 200],

'max_depth': [None, 10, 20],

    'min_samples_split': [2, 5, 10]

}
```

```
grid_search = GridSearchCV(RandomForestRegressor(random_state=42), param_grid, cv=5, scoring='r2', n_jobs=-1)

grid_search.fit(X_train, y_train)

# Save the best model best_model =
grid_search.best_estimator_ print("Best Model
Parameters:", grid_search.best_params_)
```

GridSearchCV automates hyperparameter tuning by testing different combinations to find the best configuration for model performance.

Challenges Encountered:

- **Overfitting**: Some models, especially decision trees, overfitted to training data.
- **Computational Cost**: Tuning complex models like gradient boosting took significant time.
- **Imbalanced Data**: Some weather conditions had very few instances, making classification models less accurate.

Missing Data Handling: Different imputation techniques were tested to minimize bias in predictions

Interpretation of Results

- **Feature Importance**:
  - **Temperature and Humidity** were the most influential features in predicting weather conditions.
  - Wind speed had **less impact**, but still contributed to the prediction model.

- **Error Analysis**:
  - The model performed better in predicting common weather patterns (e.g., "Clear", "Cloudy") than rare events (e.g., "Thunderstorm").
  - Some extreme temperatures and sudden weather changes were difficult to predict accurately.

The presence of missing data slightly affected accuracy, even after imputation

7 Deployment on Render

The trained model is deployed using **Render**, a cloud application hosting platform.

Deployment Steps:

1. **Prepare the API**:
    - Use FastAPI to create a REST API for model predictions.
    - Save the trained model using joblib.
    - Create an endpoint to receive input data and return predictions.
2. **Setup a GitHub Repository**:
    - Push the API code and model file to a GitHub repository.
3. **Deploy on Render**:
    - Go to Render.
    - Click on "New Web Service".
    - Connect the GitHub repository.
    - Choose a runtime (e.g., Python 3.9+).
    - Define a requirements.txt file with dependencies (flask, joblib, pandas, etc.).
    - Specify the start command: python predict.py.
    - Deploy and wait for the build to complete.
4. **Testing the API**:
    - Use postman or cURL to send requests.
    - Ensure the API returns correct predictions.

You can access the deployed machine learning model at the following URL: https://machine-learning-9.onrender.com/"

Potential Limitations and Future Improvements

- Data quality and availability issues
- Need for more advanced models or additional features
- Extending predictions to other weather parameters
- Improving accuracy with deep learning techniques

Conclusion

This project successfully implemented a predictive model for analyzing key metrics. The process involved data preprocessing, feature engineering, hyperparameter tuning, model selection, and evaluation. The **RandomForestRegressor** showed promising results, but further improvements could enhance accuracy and deployment feasibility.