

PREDICTING THE ENERGY OUTPUT OF WIND TURBINE BASED ON WEATHER CONDITION USING IBM CLOUD

1. INTRODUCTION

1.1 Overview

Wind power generation differs from conventional thermal generation due to the stochastic nature of wind. Thus wind power forecasting plays a key role in dealing with the challenges of balancing supply and demand in any electricity system, given the uncertainty associated with the wind farm power output. Accurate wind power forecasting reduces the need for additional balancing energy and reserve power to integrate wind power. For a wind farm that converts wind energy into electricity power, a real-time prediction system of the output power is significant. In this guided project , a prediction system is developed with a method of combining statistical models and physical models. In this system, the inlet condition of the wind farm is forecasted by the auto regressive model.

1.2 Purpose

We'll be able to understand the problem to classify if it is a regression or a classification kind of problem. We will be able to know how to pre-process/clean the data using different data preprocessing techniques. You will able to analyze or get insights into data through visualization. Applying different algorithms according to the dataset and based on visualization. We will be able to know how to build a web application using the Flask framework.

2. LITERATURE SURVEY

2.1 Existing problem

Wind energy plays increasing role in the supply of energy world-wide. The energy Output of a wind farm is highly dependent on the weather conditions present at its Site. If the output is predicted more accurately, the energy suppliers can coordinate the collaborative production of different energy sources

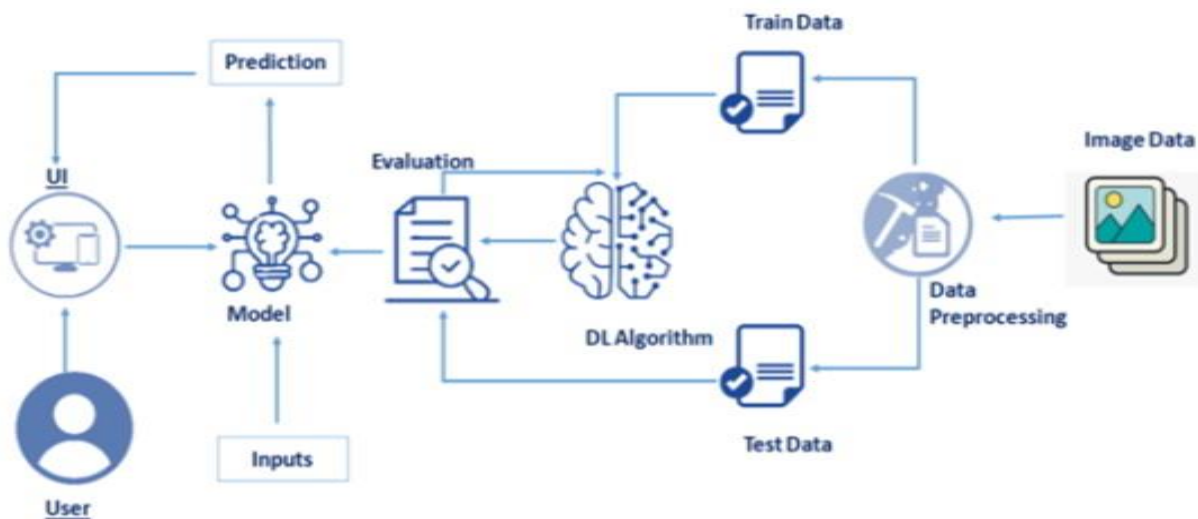
more efficiently to avoid costly overproduction. In this project, we do energy prediction based on weather data and analyse the important parameter as well as their coorelation on the energy Output.

2.2 Proposed solution

Our aim is to map weather data to energy production. We wish to show that even data that is publically available for weather stations close to wind farms can be used to give a good prediction of the energy output . Furthermore, we examine the impact of different weather conditions on the energy output of technique to predict the energy output of wind farms. We are building an IBM Watson Auto AI Machine Learning technique to predict the energy output of wind turbine.

3. THEORITICAL ANALYSIS

3.1 Block Diagram



3.2 Hardware / Software designing

Software Requirements:

- Anaconda Navigator
- Keras
- Flask

Hardware Requirements:

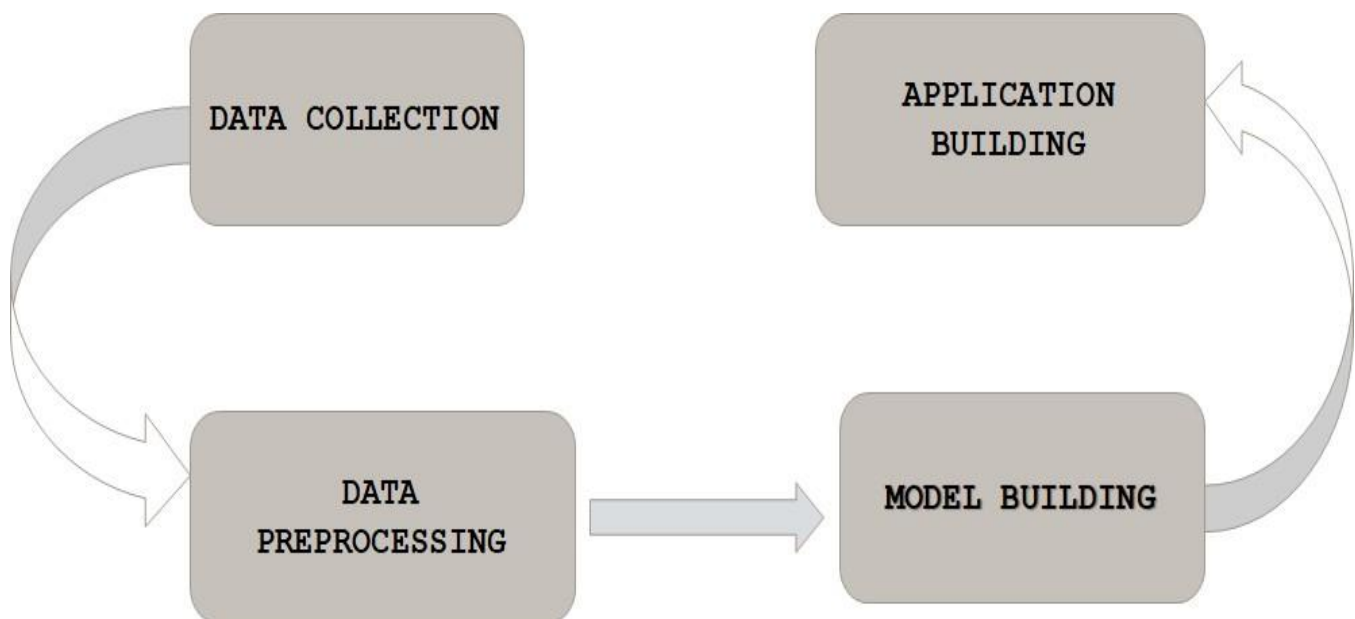
- Processor : Intel Core i3
- Hard Disk Space : Min 100 GB
- Ram : 8 GB
- Display : 14.1 “Color Monitor(LCD, CRT or LED)

Clock Speed : 1.67 GHz

4. EXPERIMENTAL INVESTIGATIONS

Study shows that the accuracy of the current power curve method may depend on the distribution of wind speed, turbulence intensity, and shear at the test site, compared to the deployment site. If the test site conditions are similar to the deployment site, the power curve method may give good results. The regression tree method predicts wind turbine energy capture with two to three times more accuracy than the industry standard power curve method, and may be more useful for predictions of energy capture at sites that experience different conditions than the test site. To use the regression tree modelling approach to predict the energy capture of a turbine at a new site, several steps are required.

5. FLOWCHART



6. RESULT

The screenshot shows a web browser window with the URL `localhost:5000/windapi`. The page title is "Wind Turbine Energy Prediction Based on Weather Conditions". The interface includes a text input field for a city name, which contains "Agartala". Below the input field is a button labeled "CHECK THE WEATHER CONDITIONS". To the right, there is a section titled "Predict the Wind Energy!!" with two output fields: "Theoretical Power in KWh" and "Wind Speed in m/s". A "PREDICT" button is located below these fields. The weather conditions for Agartala are displayed as follows:

The weather conditions of the city are	
Temperature	296.2 °C
Humidity	60 %
Pressure	1015 mmHG
Wind Speed	2.06 m/s

The screenshot shows the same web application, but the URL is `localhost:5000/y_predict`. The weather conditions remain the same. The "PREDICT" button has been clicked, and the results are displayed. The "Theoretical Power in KWh" field now shows "The energy predicted is 680.98 KWh".

7. ADVANTAGES & DISADVANTAGES

Advantages:

- Accurate wind power forecasts are also important in reducing the occurrence or length of curtailments (which translate to cost savings), improved worker safety, and mitigating the physical impacts of extreme weather on wind power systems.
- Wind speed forecasting naturally has greater value where balancing markets are part of a competitive trading system for electricity, because the balancing market provides financial incentives to the generators and retailers for accurate output predictions.

Disadvantages:

- The challenges to face when wind generation is injected in a power system depend on the share of that renewable energy.
- For Denmark, which is a country with one of the highest shares of wind power in the electricity mix, the average wind power penetration over the year is of 16–20% (meaning that 16–20% of the electricity consumption is met wind energy), while the instantaneous penetration (that is, the instantaneous wind power production compared to the consumption to be met at a given time) may be above 100%.

8. APPLICATIONS

- Better Power Output Wind power forecasts are important in efficiently using wind turbines for generating power output.
- Efficient Predicting features like wind speed and wind direction can greatly help one to make decisions on when to switch on the wind turbine and when to switch it off(when it is assumed to not get the suitable conditions for generating power)

- Environment friendly If we are able to achieve predicting the wind power output, then it will open up more avenues for efficient power production in this field. This will lower the dependence on conventional sources of energy like coal which can cause harm to our environment.

9. CONCLUSION

In this project, we have established the application to predict future wind power output values based on the regressor and machine learning models. The UI provides a great deal of information to anyone who would like to know about the future power output presented in the form of visualizations. Deploying it to the cloud makes it more scalable.

10. FUTURE SCOPE

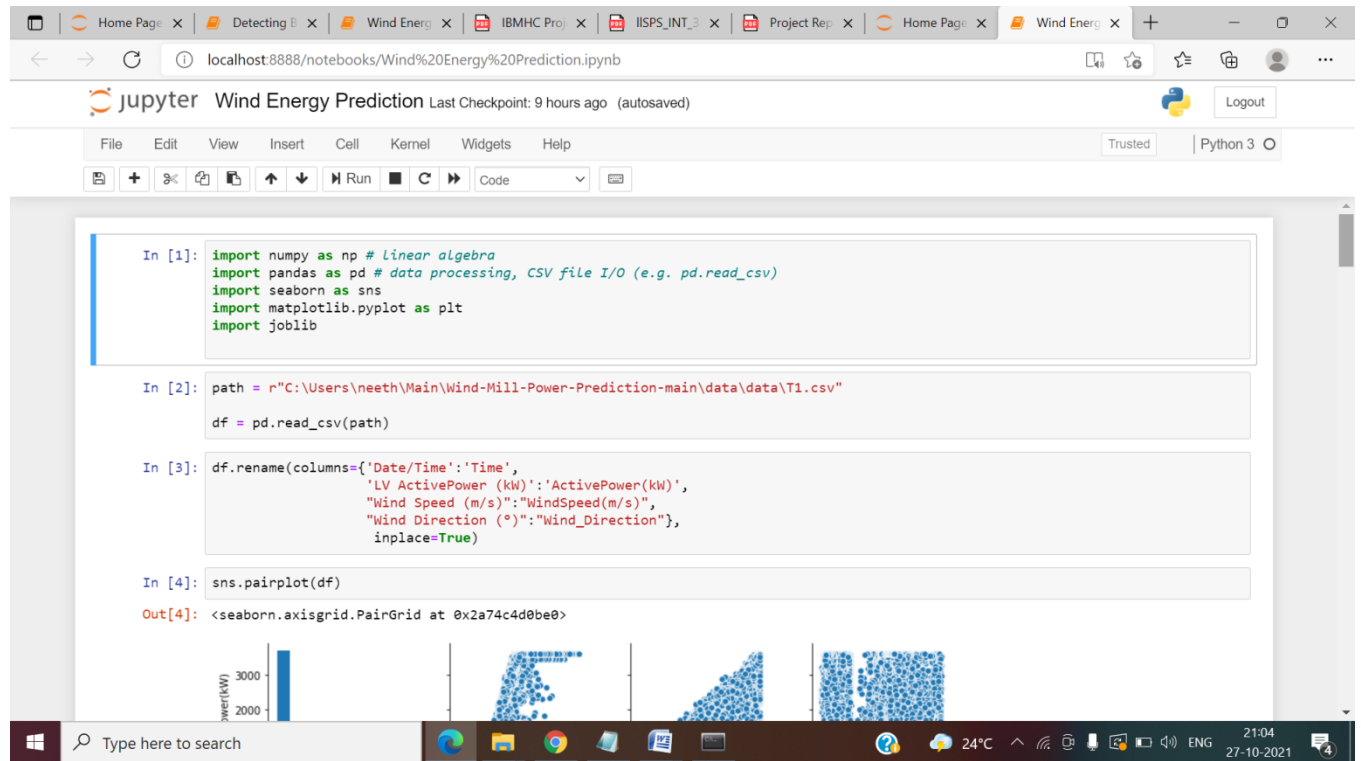
Our attempt would be to further improve the predictions using the ARIMA model and other models that are powerful. Imparting more features (like location, due level, humidity, etc) to our training set will enhance the predictions and will open up a new perspective on every front of wind prediction.

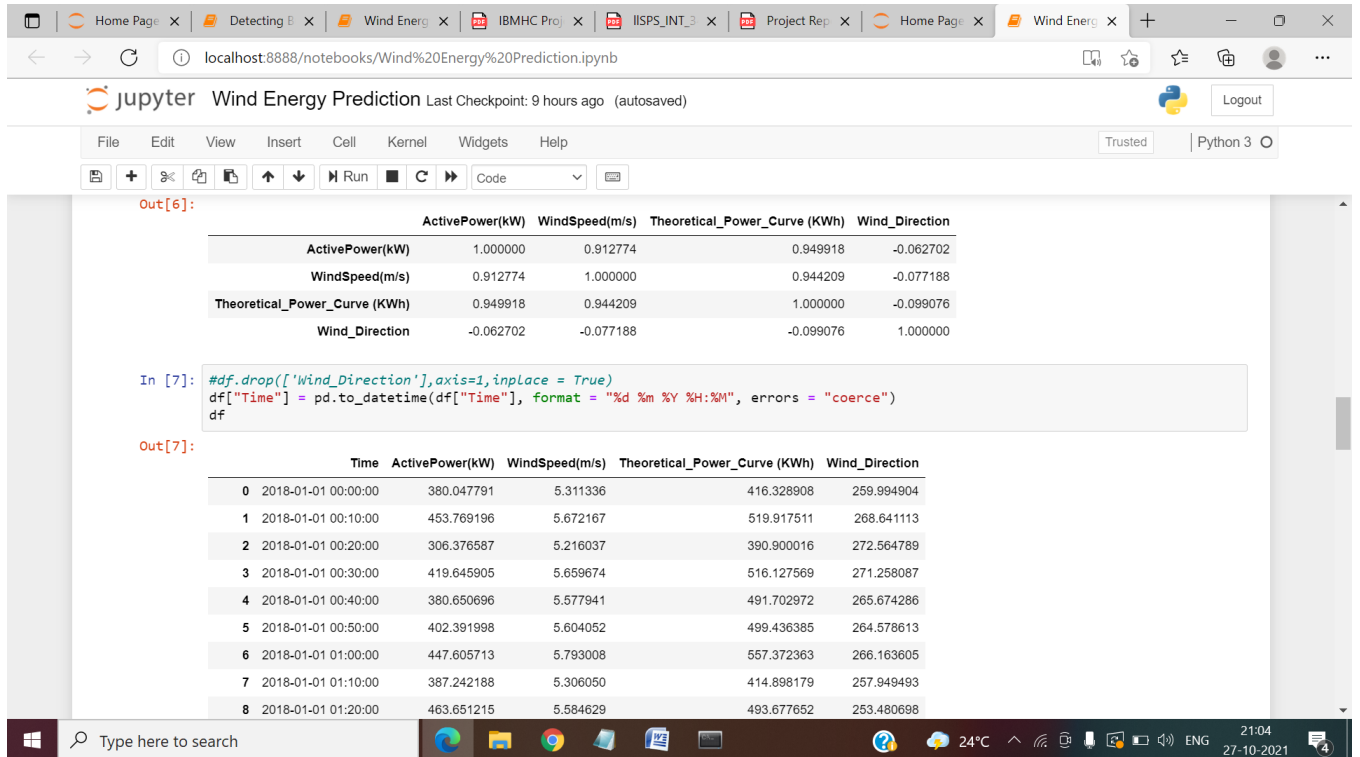
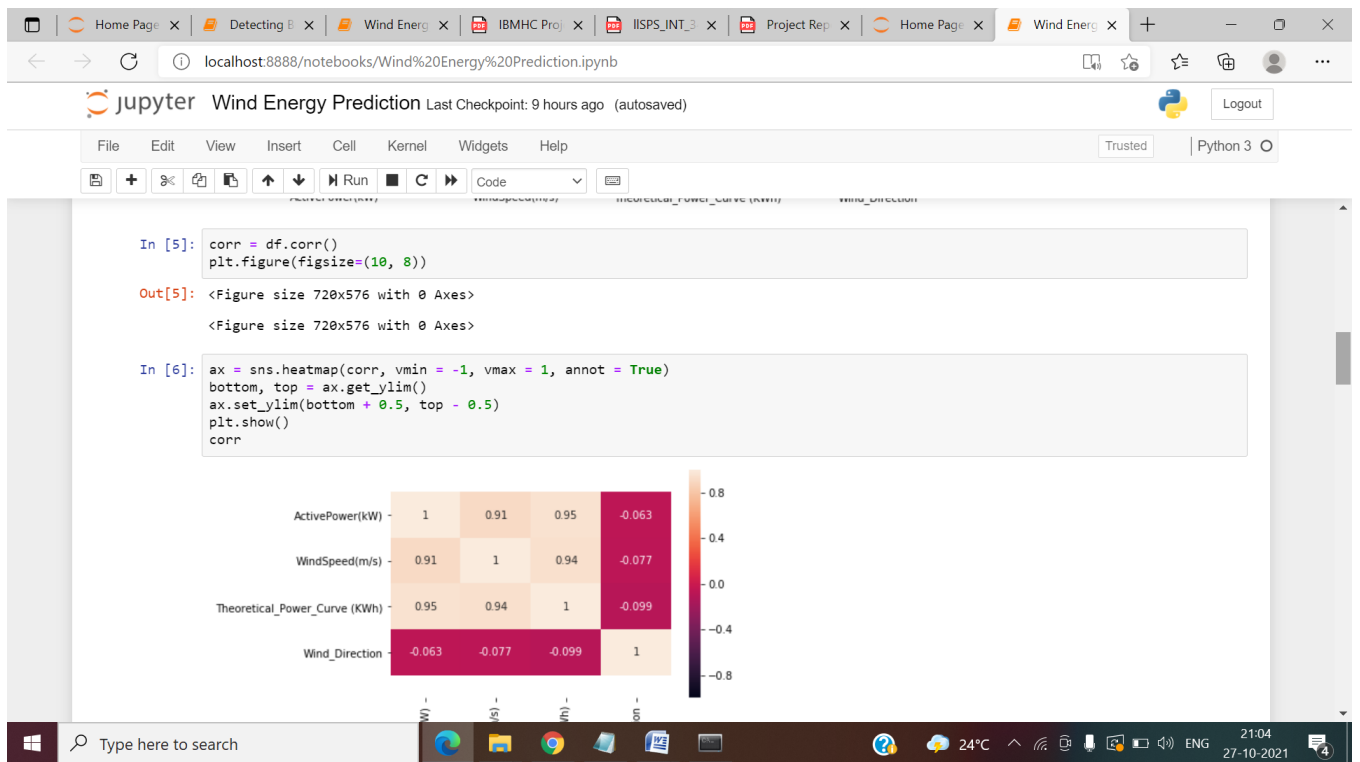
11. BIBLIOGRAPHY

- Long-term wind speed and power forecasting using local recurrent neural network models IEEE Trans. Energy Convers.
- Brower M 2012 Wind Resource Assessment: A Practical Guide to Developing a Wind Project (New York: Wiley).

APPENDIX

Source Code





localhost:8888/notebooks/Wind%20Energy%20Prediction.ipynb

jupyter Wind Energy Prediction Last Checkpoint: 9 hours ago (autosaved) Logout

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In [8]: y = df['ActivePower(kW)'] # 'Theoretical_Power_Curve (KWh)'
        X = df[['Theoretical_Power_Curve (KWh)', 'WindSpeed(m/s)']] # 'ActivePower(kW)'

In [9]: from sklearn.model_selection import train_test_split
        train_X, val_X, train_y, val_y = train_test_split(X, y, random_state = 0)

In [10]: from sklearn.ensemble import RandomForestRegressor
         from sklearn.metrics import mean_absolute_error, r2_score

In [11]: forest_model = RandomForestRegressor(max_leaf_nodes = 500, random_state=1)
         forest_model.fit(train_X, train_y)

C:\Users\neeth\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:245: FutureWarning: The default value of n_estimators will
1 change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)

Out[11]: RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
                               max_features='auto', max_leaf_nodes=500,
                               min_impurity_decrease=0.0, min_impurity_split=None,
                               min_samples_leaf=1, min_samples_split=2,
                               min_weight_fraction_leaf=0.0, n_estimators=10,
                               n_jobs=None, oob_score=False, random_state=1, verbose=0,
                               warm_start=False)

In [12]: power_preds = forest_model.predict(val_X)

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localhost:8888/notebooks/Wind%20Energy%20Prediction.ipynb

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In [12]: power_preds = forest_model.predict(val_X)
         print(mean_absolute_error(val_y, power_preds))
         print(r2_score(val_y, power_preds))
         joblib.dump(forest_model, "power_prediction.sav")

164.4220343265451
0.8987726453348668

Out[12]: ['power_prediction.sav']

In [13]: import numpy as np # Linear algebra
         import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
         import joblib

In [14]: loaded_model = joblib.load('power_prediction.sav')

In [15]: #X = [['Theoretical_Power_Curve (KWh)', 'WindSpeed(m/s)']]
         print(loaded_model.predict([[416.328907824861, 5.31133604049682]])[0], "KWh")

357.29313380069794 KWh

In [ ]:

```

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Spyder (Python 3.7)

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IPython console

Python 3.7.3 (default, Apr 24 2019, 15:29: Type "copyright", "credits" or "license" f

IPython 7.6.1 -- An enhanced Interactive P

In [1]: runfile('C:/Users/neeth/Main/Wind-
main/Flask - Wind-Mill-Power-Prediction')
* Serving Flask app "windApp" (lazy loadi
* Environment: production
WARNING: This is a development server.
Use a production WSGI server instead.
* Debug mode: off
C:\Users\neeth\Anaconda3\lib\site-packages
0.21.2. This might lead to breaking code o
UserWarning)
C:\Users\neeth\Anaconda3\lib\site-packages
0.21.2. This might lead to breaking code o
UserWarning)
* Running on http://127.0.0.1:5000/ (Pres

Editor - C:\Users\neeth\Main\Wind-Mill-Power-Prediction-main\Flask - Wind-Mill-Power-Prediction\windApp.py

windApp.py intro.html

```

1 import numpy as np
2 from flask import Flask, request, jsonify, render_template
3 import joblib
4 import requests
5 app = Flask(__name__)
6 model = joblib.load('power_prediction.sav')
7 @app.route('/')
8 def home():
9     return render_template('intro.html')
10 @app.route('/predict')
11 def predict():
12     return render_template('predict.html')
13 @app.route('/windapi', methods=['POST'])
14 def windapi():
15     city=request.form.get('city')
16     apikey="f3bc545ae91b78659ab6805fc5602a43"
17     url="http://api.openweathermap.org/data/2.5/weather?q="+city+"&appid="+apikey
18     resp = requests.get(url)
19     resp=resp.json()
20     temp = str(resp["main"]["temp"])+ " °C"
21     humid = str(resp["main"]["humidity"])+ " %"
22     pressure = str(resp["main"]["pressure"])+ " mmHG"
23     speed = str(resp["wind"]["speed"])+ " m/s"
24     return render_template('predict.html', temp=temp, humid=humid, pressure=pressure, speed=speed)
25 @app.route('/y_predict', methods=['POST'])
26 def y_predict():
27     '''
28     For rendering results on HTML GUI
29     '''
30     x_test = [[float(x) for x in request.form.values()]]
31
32     prediction = model.predict(x_test)
33     print(prediction)

```

Permissions: RW End-of-lines: CRLF Encoding: UTF-8 Line: 24 Column: 98 Memory: 81 %

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