

PREDICTING THE ENERGY OUTPUT OF WIND TURBINE BASED ON WEATHER CONDITION USING MACHINE LEARNING

Developed By : U.Arpitha , V.Saivikas , J.Sandhya, K.Vinay

CONTENTS

CHAPTERS	PAGE NO'S
1. INTRODUCTION	02-03
a. Overview	
b. Purpose	
2. LITERATURE SURVEY	03-04
a. Existing Problem	
b. Proposed Solution	
3. THEORETICAL ANALYSIS	04-06
a. Block Diagram	
b. Hardware and Software Design	
4. EXPERIMENTAL INVESTIGATIONS	06
5. FLOWCHART	07-08
6. RESULT	08-11
7. ADVANTAGES AND DISADVANTAGES	11-12
8. APPLICATIONS	12
9. CONCLUSION AND FUTURESCOPE	13
10. BIBILOGRAPHY	13-14
11. APPENDIX	14-15

CHAPTER 1

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.

Wind speed/power has received increasing attention around the earth due to its renewable nature as well as environmental friendliness. With the global installed wind power capacity rapidly increasing, the wind industry is growing into a large-scale business. Reliable short-term wind speed forecasts play a practical and crucial role in wind energy conversion systems, such as the dynamic control of wind turbines and power system scheduling. A precise forecast needs to overcome problems of variable energy production caused by fluctuating weather conditions. Power generated by wind is highly dependent on the wind speed. Though it is highly non-linear, wind speed follows a certain pattern over a certain period of time. We exploit this time series pattern to gain useful information and use it for power prediction.

1.2 PURPOSE

Wind energy plays an 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 can be predicted more accurately, energy suppliers can coordinate the collaborative production of different energy sources more efficiently to avoid costly overproduction. In this paper, we predict energy prediction based on weather data and analyse the important parameters as well as their correlation on the energy output.

CHAPTER 2

LITERATURE SURVEY

2.1 EXISTING PROBLEM

Wind energy plans 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 paper, we do energy prediction based on weather data and analyse the important parameters as well as their correlation on the energy output.

2.2 PURPOSED SOLUTION

Our aim is to map weather data to energy production. We wish to show that even data that is publicly 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 techniques to predict the energy output of wind farms. We are building web app to predict the energy output of wind turbine and weather condition of a city.

To build Machine learning models you must require the following packages

Sklearn : Scikit-learn is a library in Python that provides many unsupervised and supervised learning algorithms.

NumPy : NumPy is a Python package that stands for 'Numerical Python'. It is the core library for scientific computing, which contains a powerful n-dimensional array object

Pandas : pandas is a fast, powerful, flexible, and easy to use open source data analysis and manipulation tool,built on top of the Python programming language._

Matplotlib : It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits

CHAPTER 3

THEORETICAL ANALYSIS

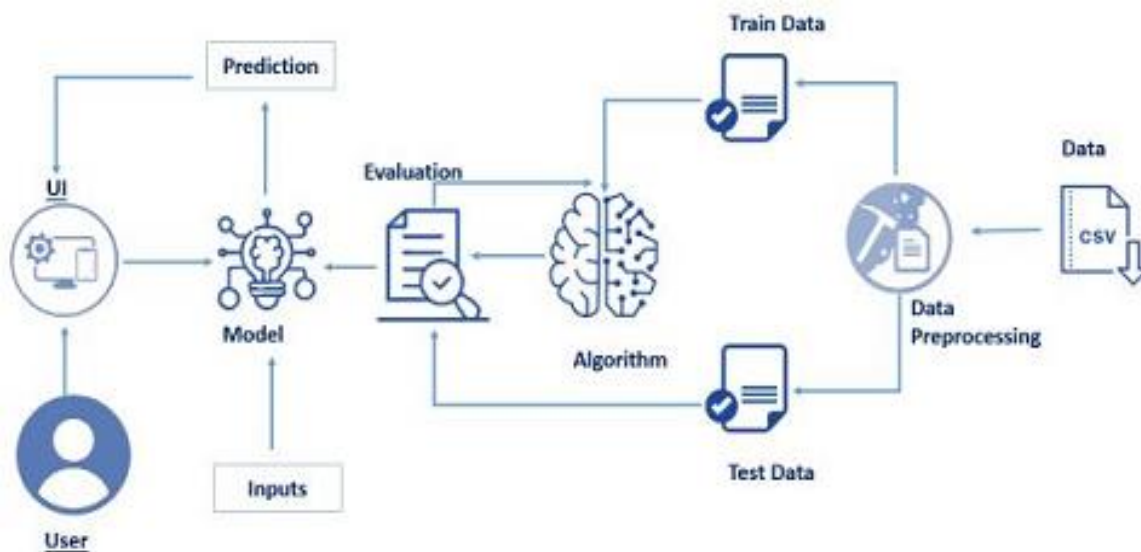
Wind Power Forecasting (WPF) has applications in generation and transmission maintenance planning, energy optimization as well as in energy trading. WPF models exist at different scales and they can be used to predict the production for a single WT to a whole Wind Farm(WF).WPF models are generally divided into two main groups physical and statistical, but hybrids state-of-the-art methods are also common. The physical approach physical aspects into the model, such as information about surrounding terrain and properties of the WT. These models try to get as good estimate of local wind speed as possible before finally reducing the remaining error with some form of MOS. Statistical approaches, relies more on the historical observation and their statistical relation to meteorological predictions as well as measurements from Supervisory Control And Data Acquisition(SCADA).

SCADA is a control system that is used in industrial processes and is the main tool to evaluate the state of power plants.As the name indicated,it is not a full control system,but

rather a system for supervision. In the case of wind turbines it allows remote access to online data that has been gathered by sensors inside and around the plant. Variables accessible through these systems are those directly related to the wind flow as the produced power generated by the plants. i.e. things like rotor wind speed, nacelle position, pitch angle, active ,etc.

Forecast models that use SCADA data as their primary input source usually have a good forecast accuracy at least for first few hours but they tend to be less useful for longer prediction horizons. SCADA data can also be used to detect problems in WT something that can be helpful to improve the reliability of WT.

3.1 BLOCK DIAGRAM



Project Work Flow:

1. Install required packages and libraries
2. Understanding the data.
3. Model Building

4. Application Building

5. Final UI

3.2 HARDWARE / SOFTWARE DESIGNING

For running a machine learning model on the system you need a system with minimum of 16 GB RAM in it and you require a good processor for high performance of the model.

In the list of **Software requirements** you must have:

- i. Jupyter Notebook for programming, which can be installed by Anaconda IDE.
- ii. Python packages.
- iii. A better software for running the html and css files for application building phase e.g. spyder.

CHAPTER 4

EXPERIMENTAL INVESTIGATION

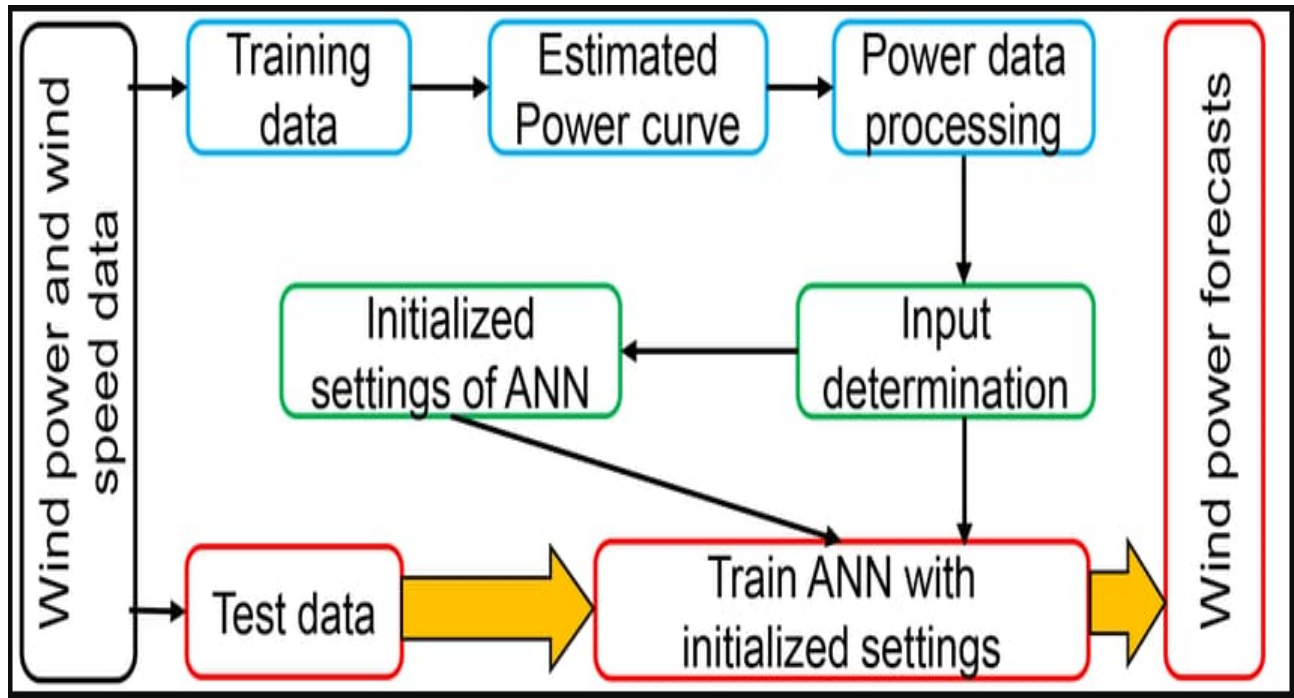
Data Pre-Processing

In this milestone, we will be preprocessing the dataset that is collected. Preprocessing includes:

1. Processing the dataset.
2. Handling the null values.
3. Handling the categorical values if any.
4. Normalize the data if required.
5. Identify the dependent and independent variables.
6. Split the dataset into train and test sets.

CHAPTER 5

FLOWCHART



Project Flow

You will go through all the steps mentioned below to complete the project.

- User interacts with the UI (User Interface) to enter Data
- The entered data is analyzed by the model which is integrated
- Once model analyses the input the prediction is showcased on the UI

To accomplish this, we have to complete all the activities and tasks listed below

1. Data Collection.
 - Collect the dataset or Create the dataset

2. Data Preprocessing.

- Import the Libraries.
- Importing the dataset.
- Checking for Null Values.
- Data Visualization.
- Taking care of Missing Data.
- Label encoding.
- One Hot Encoding.
- Feature Scaling.
- Splitting Data into Train and Test.

3. Model Building

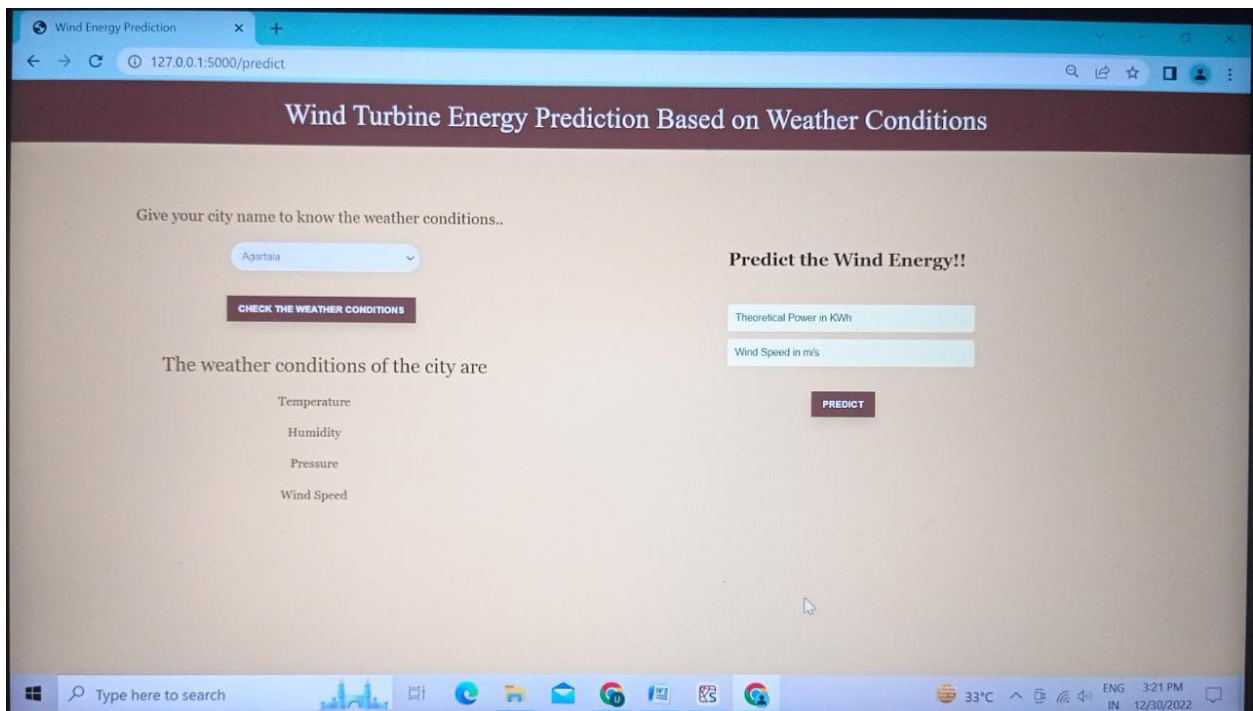
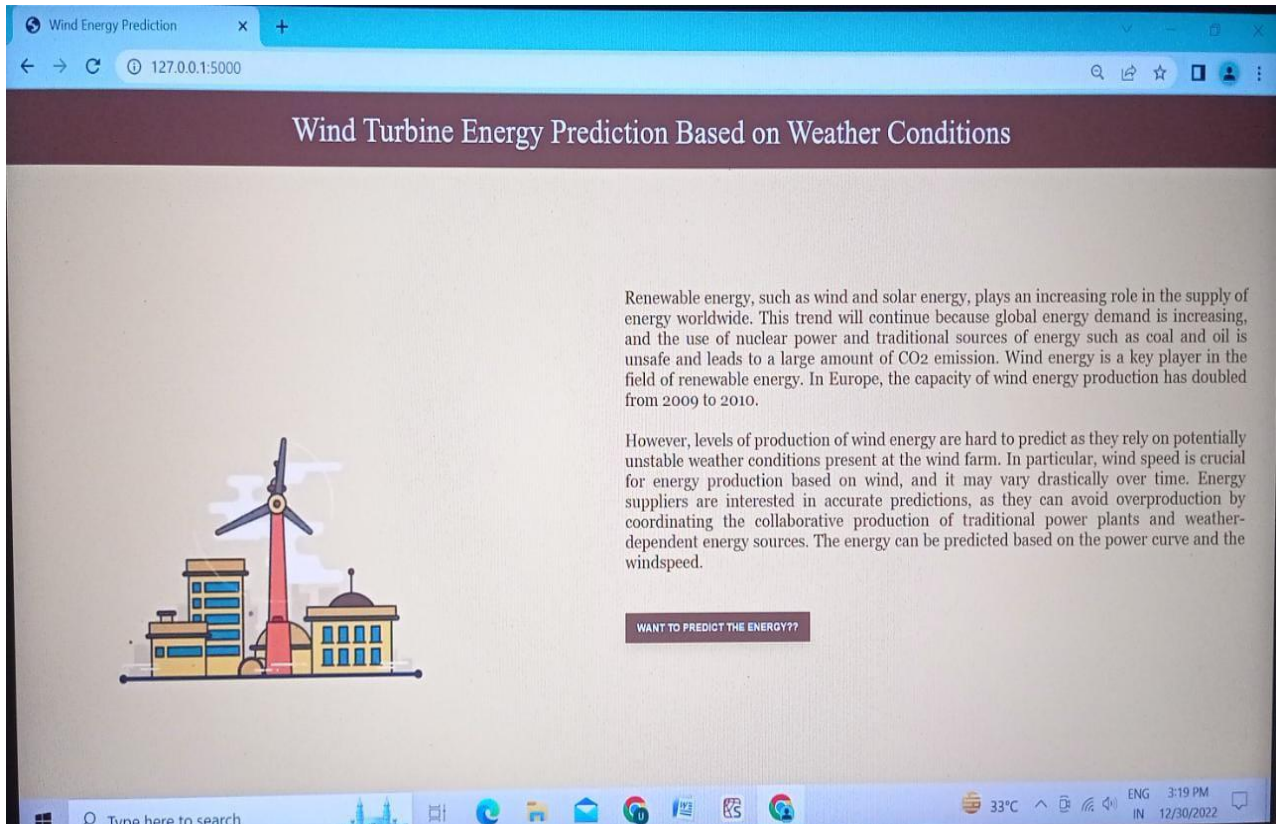
- Training and testing the model
- Evaluation of Model

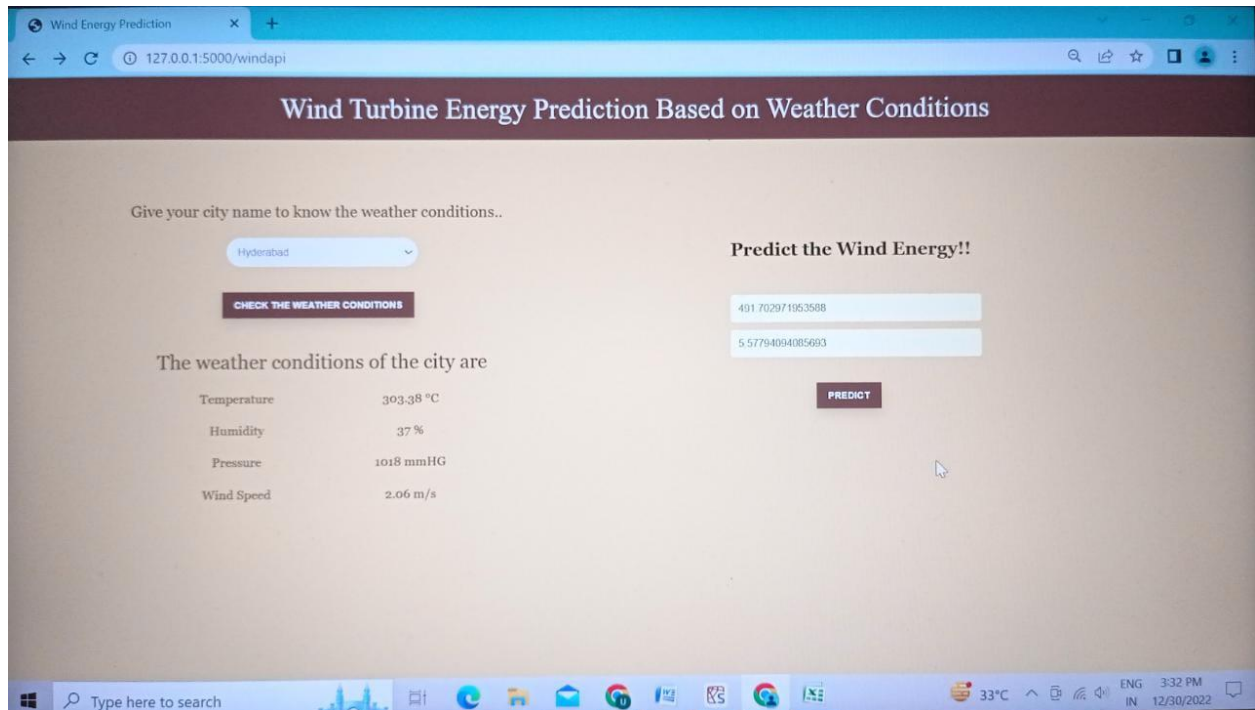
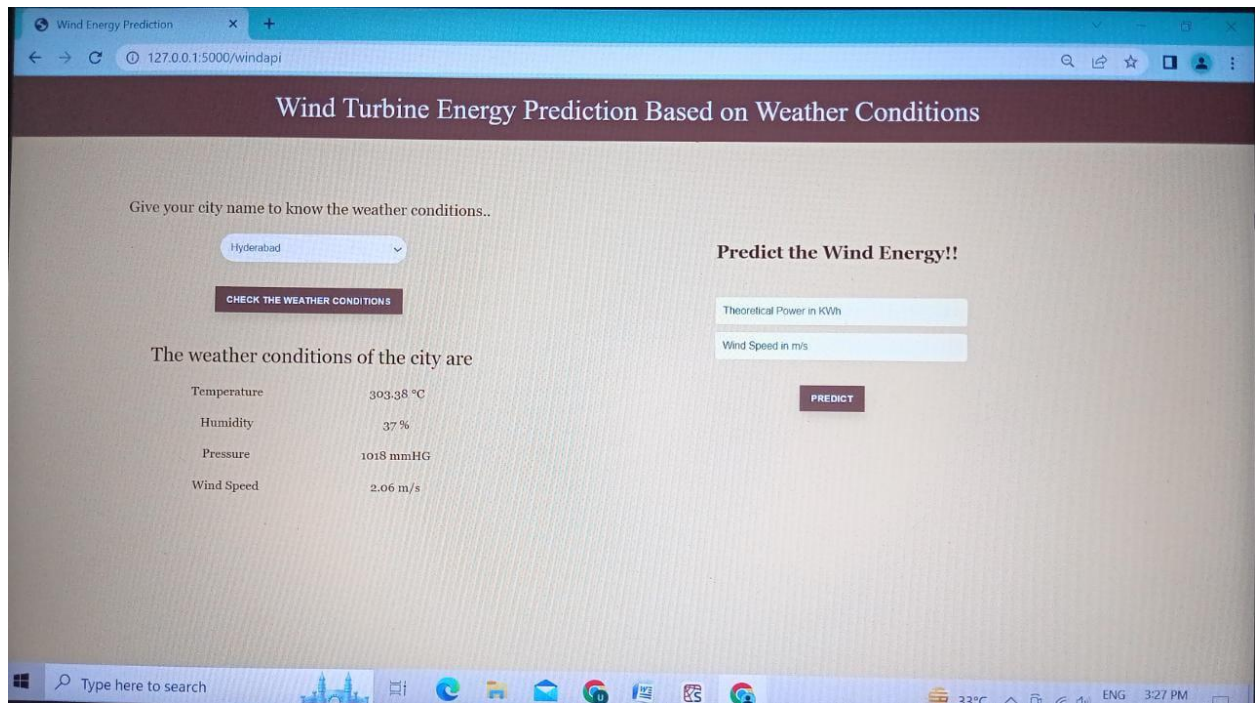
4. Application Building

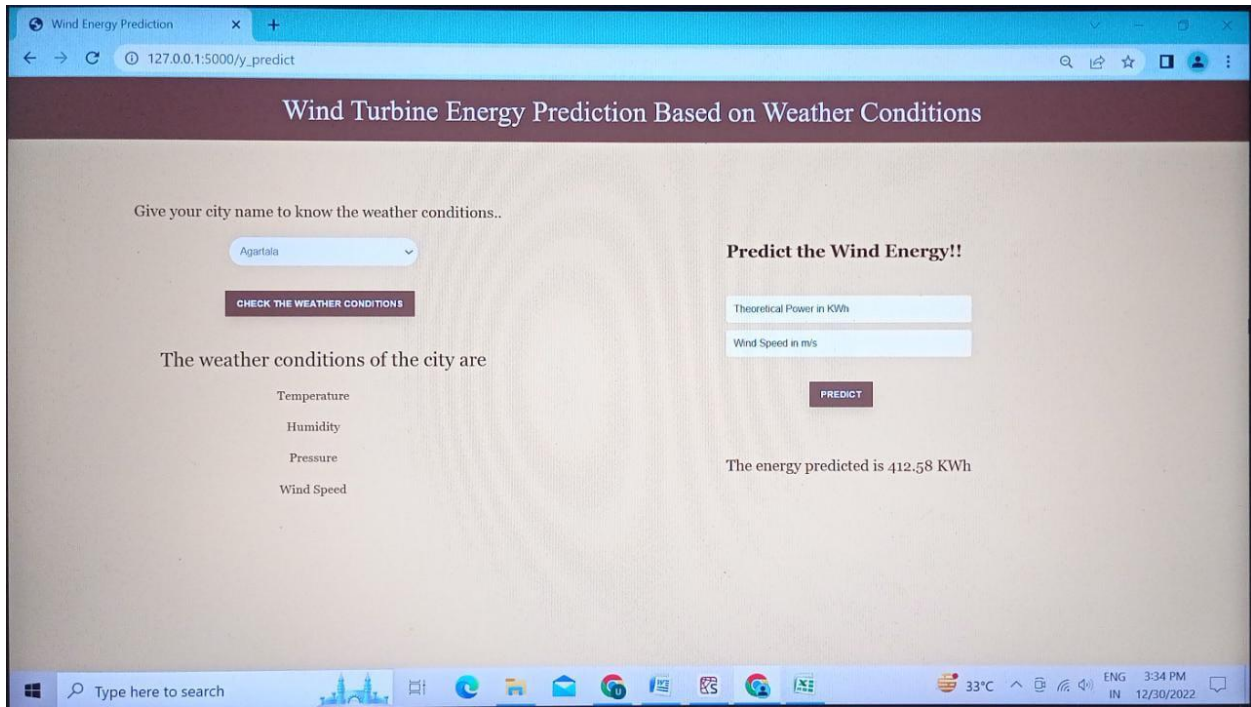
- Create an HTML file
- Build a Python Code

CHAPTER 6

RESULT







CHAPTER 7

ADVANTAGES AND DISADVANTAGES

ADVANTAGES

1. It only requires wind to work.
2. It is considered to be a green source of energy. It does not pollute itself.
3. It is a domestic source of energy.
4. It is a renewable resource with huge potential.
5. Wind turbines only require periodic maintenance, unlike other power sources.

DISADVANTAGES

1. Wind energy is not considered to be reliable. It is a fluctuating source of energy.
2. Electricity from wind energy must be stored.
3. Wind turbines are a potential threat to wildlife such as birds and bats.
4. Deforestation to setup a wind farm creates an environment impact.
5. Noise is a complaint with many wind farms that are close to communities.

CHAPTER 8

APPLICATIONS

1. Better Power Output

Wind power forecasts are important in efficiently using wind turbines for generating power output.

2. 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)

3. Environment friendly

If we are 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.

CHAPTER 9

CONCLUSION AND FUTURESCOPE

In this study, we showed that wind energy output can be predicted from publicly available weather data with accuracy up to 80% R^2 on the training range and up to 85, 5% on the unseen test data. We identified the smallest space of input variables where reported accuracy can be achieved, and provided clear trade-offs in prediction accuracy when decreasing the input space to the wind speed variable.

We are pleased that the presented framework is so simple that it can be used by literally everybody for predicting Theoretical power based on wind energy production —for individual wind turbines on private farms or urban buildings, or for small wind farms. For future work, we are planning further study of the possibilities for longer-term wind energy forecasting.

Several forecasting models were discussed and a lot of researches on the models, which have their own characteristics, were presented. The major focus was on emphasizing the diversity of various forecasting methods available and also on providing a comparison of present mechanisms to determine the best available.

CHAPTER 10

BIBLIOGRAPHY

- [1] O. Kramer and F. Gieseke. Short-term wind energy forecasting using support vector regression. In International Conference on Soft Computing Models in Industrial and Environmental Applications, pages 271–280. Springer, 2011.
- [2] A. Kusiak, H. Zheng, and Z. Song. Short-term prediction of wind farm Power: A data mining approach. IEEE Transactions on Energy Conversion, 24(1):125 – 136, 2009.
- [3] R. Poli, W. B. Langdon, and N. F. McPhee. A Field Guide to Genetic Programming. lulu.com, 2008. ISBN 978-1-4092-0073-4.
- [4] M. Schmidt and H. Lipson. Age-fitness Pareto optimization. In Genetic Programming Theory and Practice VIII, Genetic and Evolutionary Computation, chapter 8, pages 129–146. Springer, 2010.
- [5] I. Sanchez. Short- term prediction of wind energy production. International Journal of Forecasting, 22(1):43 – 56, 2006.

[6] M. Webb and S. Scuglia. Wind power: A favored climate change response. Global Economic Research: Fiscal Pulse (Scotia bank), 2007.

APPENDIX

A Source Code of Flask:

```
import numpy as np
from flask import Flask, request, jsonify, render_template
import joblib
import requests

app = Flask(__name__)

model=joblib.load('C:/Users/HLC/Downloads/MAJORPROJECT/Training/power_prediction.pkl')

@app.route('/')
def home():
    return render_template('intro.html')

@app.route('/predict')
def predict():
    return render_template('predict.html')

@app.route('/windapi',methods=['POST'])
def windapi():
    city=request.form.get('city')
    apikey="27482473161ff3fccd89b5265854fcea"
    url="http://api.openweathermap.org/data/2.5/weather?q="+city+"&appid="+apikey
    resp = requests.get(url)
```

```

print(resp)
resp=resp.json()
print(resp)
temp = str(resp["main"]["temp"])+ " °C"
humid = str(resp["main"]["humidity"])+ " %"
pressure = str(resp["main"]["pressure"])+ " mmHG"
speed = str(resp["wind"]["speed"])+ " m/s"

return render_template('predict.html', temp=temp, humid=humid,
pressure=pressure,speed=speed)

@app.route('/y_predict',methods=['POST'])
def y_predict():
    """
    For rendering results on HTML GUI
    """
    x_test = [[float(x) for x in request.form.values()]]

    prediction = model.predict(x_test)
    print(prediction)
    output=prediction[0]

    return render_template('predict.html', prediction_text='The energy predicted is {:.2f}
    KWh'.format(output))

if __name__ == "__main__":
    app.run(debug=False)

```