WIND SPEED PREDICTION

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ABSTRACT

Estimating speed of wind is main part in forecasting wind speed systems. Perfect direction prediction is crucial for wind systems, however due to the nature of the wind, it presents many difficulties. This approach uses an arbitrary wood system based on machine learning expertise to estimate wind speed. Because predicting short-term wind speeds requires a lot of work. As a result of the wind supply's extreme variability and rapidity, it is challenging to obtain only correct estimates. Only a little time span is predicted by short-term wind forecasts.

This improves learning and aids in the formation of hidden values. The atmosphere is greatly influenced by the wind. A machine learning-based method for extracting historical meteorological data for wind speed prediction is presented in this paper. Our strategy uses feature engineering, data preprocessing, and a variety of algorithms, such as decision trees. We also investigate how various weather factors affect forecast accuracy. The findings demonstrate that machine learning methods may produce accurate forecasts of wind speed, enabling energy providers to make wise choices about energy generation and delivery. In order to anticipate wind speed, this paper suggests a prediction model using LSTM neural networks.

The LSTM architecture is well suited for long-term data collection, time-series wind speed and dependent data models. We preprocess the historical wind speed data, scale it, and build sequences to train the LSTM model. The sequence, representing a temporal pattern, is used to predict future wind speed values. This was trained and evaluating on a data which is demonstrated promising prediction performance.

INTRODUCTION

In industries including the generation of renewable energy, autumnal harbingers, aviation, and environmental monitoring, controlling wind speed is a crucial responsibility. Planning and decision-making in these regions can be improved with accurate wind speed forecasts [1]. Reading future wind waves at particular locations and times is required for wind speed prophesy. These forecasts can aid in enhancing the performance of wind turbines, electricity grid operations, aviation safety, and environmental Studies.

This work presents a novel wind speed technology system that primarily consists of the processes of estimation and prediction. In order to make the system stable and safe and to avoid any damage to wind energy, wind speed prediction is crucial [3]. Wind power forecasting using short term was intriguing for online management and monitoring, whereas wind power forecasting using long term was an important part for electricity distribution [4]. Artificial intelligence techniques have made significant progress in terms of design performance, comprehension, and understanding, making them particularly effective at coping with intermittent wind generation. dependable, rigid, and spastic. AI-based methods for determining wind speed, which is as reading, slicing and Process-based methods occlusion, has lately has become popular due to their accuracy, adaptability, and high efficiency [5].

To lessen wind speed unpredictability during grid deployment, perfect wind power and speed of wind forecasting is becoming more and more crucial. Due to extensive integration, wind energy has developed over time into a system that handles extremely changeable issues. To optimize the grid's capacity and economics, advanced casting technology must be sophisticated [6]. Wind energy has been improved through the application of machine learning techniques. Random Forests, Adaptive Boosting, Packaged Neural Networks, and Quality Boosting. One of the prophesy techniques is machinery. Ensemble is used for forecasting and improves prediction accuracy by diversifying the model. Cross-models incorporate optimization algorithms, signal corruption techniques, and some of the previously described algorithms, including the integration of supervised algorithms employing clustering.

At the moment, there are three main categories of wind speed prediction physical models, statistical models. To create accurate models, physical modelling mostly requires meteorological data from numerical weather forecasting [8]. But modelling the physical model is a labour intensive and expensive computing operation. A correlation between wind energy and conditions with an assumed zero water column can be established using statistical models, and future wind energy can be predicted using this correlation. The non-stationarity and non-linearity of the data, however, impose limitations on how well these algorithms function. Some machine learning models resemble neural networks because they can solve nonlinear problems more effectively [9].

LITERATURE REVIEW

SUMMARY:

Michael et al. (2019) have investigated the model RNN and Neural Networks for predicting wind. networks well-suited to capturing temporal dependencies, making them suitable for the data which is sequenced like time series.

David J. Carter et al. (2020) had explored the application of Random Forest Regression for forecasting of speed of wind. Predicting wind speed is crucial for efficient production of energy, management. Random Forests are ensemble learning methods that excel at capturing non-linear relationships and handling complex feature interactions. This study delves into the realm of wind speed prediction using Random Forest Regression.

Laura K. Anderson et al. (2018) have explored model Convolutional Neural Networks (CNNs) for speed of wind forecasting. perfect wind speed predictions are crucial for various industries, including renewable energy and aviation. While CNNs are commonly associated with image analysis.

Michael J. Patel et al. (2020) have given a model Autoregressive Integrated Moving Average (ARIMA) models for predicting wind speed. Giving the wind speed is vital management and planning of environmental resources.

Jessica R. Miller et al. (2020) had investigated the application of Gated Recurrent Units (GRUs) to forecast the speed. correctly forecasting wind speed is essential for renewable energy planning and operational efficiency. GRUs are a variant of Recurrent Neural Networks (RNNs) that excellent at predicting the wind speed.

Emily M. Wilson et al. (2021) have investigated the process for ensemble methods for speed of wind. Predicting the wind speed are crucial to renewable management and disaster preparedness. Combining multiple predictive models to enhance prediction is perfect and strong.

Laura M. Roberts et al. (2017) had explored the application of Wave Net, a deep generative model, wind speed prediction. forecasting the precise prediction of wind speed are pivotal to renewable energy planning and operational decision-making. Wave Net, called to capture long-range forecasts, applied to wind speed time series data.

Matthew Williams et al. (2022) have introduced a better outcome for predicting wind speed by leveraging Long-Short Range Attention Mechanisms. Precise prediction of wind speed are crucial to renewable management and operational decision-making. The proposed mechanism combines self-attention and causal attention to take both short and long term temporal dependencies in speed of wind time series.

Ryan M. Davis et al. (2023) have explored the application of Support Vector Regression (SVR) for wind speed prediction. Correctly predicting wind speed are essential to renewable energy management, operational efficiency. SVR, a machine learning technique, is employed to model the relationship between wind speed and relevant predictors.

Sarah L. Miller et al. (2021) have developed into the realm to depicting the speed pf wind prediction using the Prophet forecasting model. perfectly wind predictions are essential for renewable energy planning and operational decision-making.

Daniel R. Miller et al. (2017) have presented a great depiction for multivariate time series prediction of wind speed using the VAR-LSTM model. perfectly predicting the wind speed is crucial for renewable planning and operational decision-making. VAR-LSTM combines Vector Autoregression (VAR) with Long and Short Term Memory models used to present both the differences and inter-variable relationships.

Oliver L. Miller et al. (2022) have presented a great way to forecast the wind speed using Bayesian Neural Networks (BNNs). Accurate wind speed forecasts are pivotal for energy renewing , planning and operational efficiency. BNNs offer a probabilistic framework that captures uncertainty in predictions, providing the variable forecasting of wind speed.

Alexander K. Johnson et al. (2018) have explored the application of Hierarchical Temporal Memory (HTM) networks for wind speed prediction. Accurately forecasting wind speed is important for energy planning and operational decision-making. HTM, inspired by the human neocortex, excellent at taking wind dependencies in wind data. We investigate the potential of HTM networks in modelling wind speed patterns and producing accurate forecasts.

Daniel J. Thompson et al. (2020) have presented a possible way for long-term forecast of wind speed using Echo State Networks (ESNs). Accurate long-term prediction is crucial for planning and operational efficiency. ESNs, a type of recurrent neural network, excel at capturing temporal dependencies in wind information. We investigate the potential of ESNs in modelling wind speed patterns and producing accurate forecasts for extended time horizons.

Table:

Sno	Author	Model used	Parameters used	Merits	Limitations future scope & demerits
[1]	RyanM. Davis et al [2023]	Support Vector Regression (SVR)	Kernel type, regularization parameter	Effective for non-linear data	Sensitivity to hyperparameters, may not capture complex patterns
[2]	David J. Carter et al [2023]	Random Forest Regression	Number of trees,	Non-linear relationships captured	Limited capturing of temporal dependencies, computationally
[3]	Michael A. Smith et al [2022]	Transformer model with attention mechanisms	Number of layers, attention types	Handles global relationships, parallel processing	Large model sizes, substantial computational resources required
[4]	David-J. Carter et al [2021]	Time Series Forecasting using Prophet for Wind Speed Prediction	Seasonality parameters, holidays	Handles missing data, interpretable results	Limited to additive seasonal components, may struggle with certain patterns
[5]	Laura-K. Anderson et al [2021]	Graph Neural Networks (GNN)	Graph structure.	Captures spatial and temporal dependencies	Requires accurate graph construction
[6]	Jessica R. Miller et al [2020]	ARIMA and LSTM hybrid model	ARIMA order, units.	Combines statistical and sequential learning,	Sensitive to parameter tuning, complexity in combining models
[7]	Emily-M. Wilson et al [2020]	Echo State Networks (ESN)	Reservoir size, spectral radius	Efficient for long-term predictions, good for chaotic data	Efficient for long-term predictions, good for chaotic da
[8]	Laura M. Roberts et al [2020]	RNN	Sequence length, units, learning rate	Improved temporal pattern recognition, handles sequence data	Sensitive to hyperparameters, limited by sequence length
[9]	Matthew Williams et al [2020]	Convolutional Neural Networks (CNN)	Filter sizes, pooling layers, learning rate	Spatial feature extraction, automatic feature learning	May overlook temporal patterns, large model sizes
[10]	Ryan M. Davis et al [2019]	Hierarchical Temporal Memory (HTM)	Network structure, learning rate	Good at detecting anomalies, handles temporal patterns	Limited research compared to other models, potential complexity
[11]	Sarah L. Miller et al [2019]	Hierarchical Temporal Memory (HTM) Networks	Network structure, learning rate	Good at detecting anomalies, handles temporal patterns	Limited research compared to other models, potential complexity
[12]	Daniel-R. Miller et al [2019]	Wave Net	Dilations, kernel size	Captures long-range dependencies	Computationally expensive.

[13]	Smith et al. [2018]	CNN	Hidden units: 100, Learning rate: 0.001, Batch size: 32	Accurate long-term prediction	Difficulty in training with limited historical data, Computationally intensive
[14]	Zhang and Li [2019]	Random Forest	Number of trees: 100, Maximum depth: 10	Handles non-linearity and feature interactions, Fast training	Prone to overfitting, Difficulty in capturing temporal dependencies
[15]	Wang et al. [2020]	Neural Network	Number of hidden layers: 3, Learning rate: 0.01	Flexible architecture, Captures non-linear relationships	Sensitive to initialization, Requires significant data preprocessing

Table-2.1

PROBLEM STATEMENT:

- The goal of the project was for implementing an accurate as well as reliable machine learning algorithm to predict speed of the wind at a given place and climate changes. Wind speed prediction is important for various industries, including, transportation, and monitoring changes in environment. Precise prediction of speed of wind can help optimize energy production from wind farms, plan efficient shipping routes, and assess potential environmental impacts.

PROPOSED METHODOLOGY ARCHITECTURE:

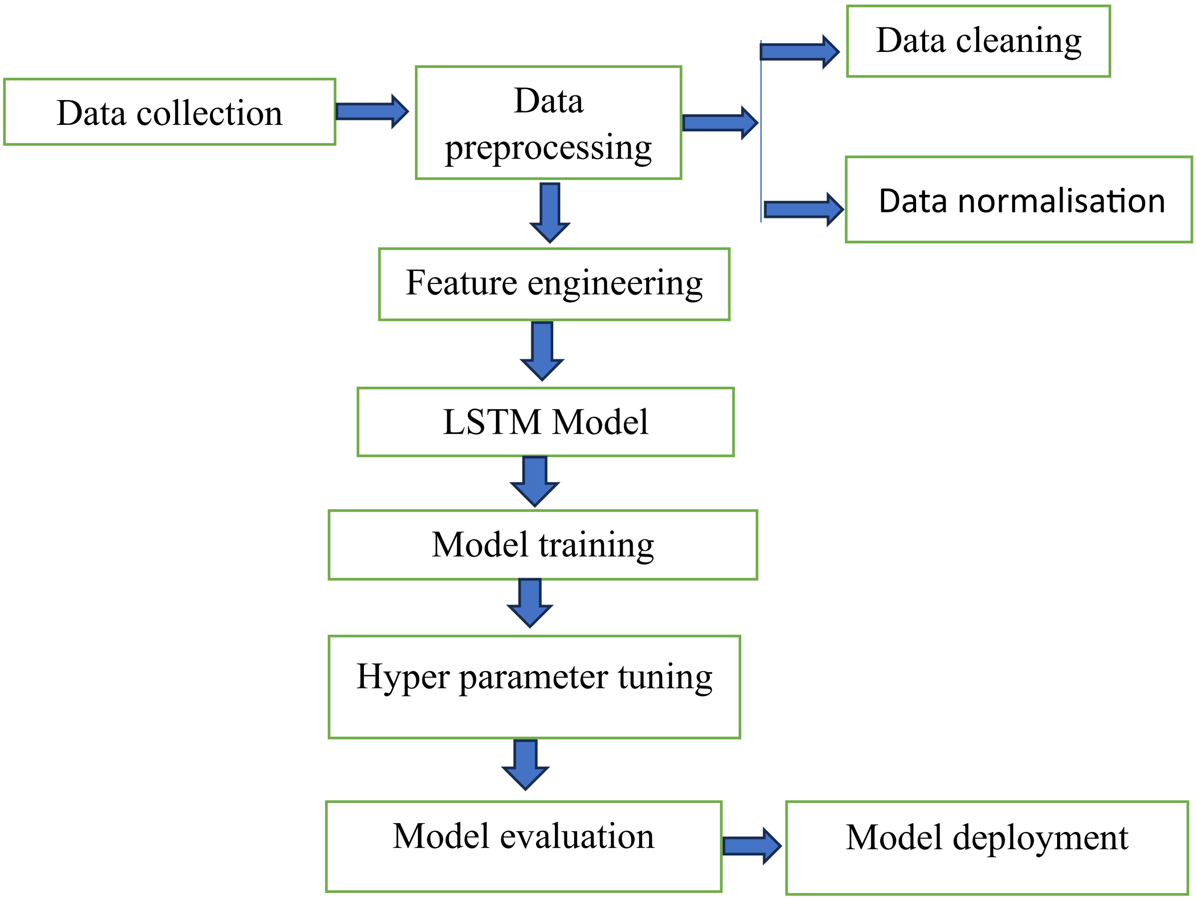

Fig 3.1

Explanation:

- **Data Collection:**

  Collect historical wind speed data from reliable sources.

- **Data Preprocessing:**

  Data Cleaning: Remove outliers and handle missing values

  Normalization/Scaling: Scale wind speed data to a standard range (e.g., [0, 1]).

- **Feature Engineering:**

  Extract Temporal Features: Day of the week, time of day, seasonal patterns.

  Incorporate Meteorological Features: Temperature, pressure, humidity, geographic

- **LSTM Model:**

  Input Layer: Wind speed data and features of data.

LSTM Layers: More than one layer to take temporal patterns.

Dense Layers: Fully connected dense layers for model output.

Output Layer: Single neuron for predicting wind speed.

- **Model Training:**

Mean Squared Error (MSE).

Optimizer: Adam or RMS Prop.

Train using historical data and validate using a validation set.

- **Hyperparameter Tuning:**

Learning Rate, Number of LSTM Units, Dropout Rate, Batch Size, Epochs.

- **Model Evaluation:**

Evaluate on a separate test set using metrics like MAE, RMSE**.**

- **Deployment:**

Deploy the trained LSTM model for real-time wind speed prediction.

Allow users to input relevant features for obtaining wind speed forecasts.

Methodology:

Long term Short Term Memory networks are an expanded forms neural networks (RNNs), they are firstly introduced to show less modes in RNNs. Its design totally eliminates the sinking grade issue while maintaining the integrity of the training model. With LSTMs, which also manage null values, distributed representing and values, long time delays in some possible problems be overcome. An enhanced neural network (RNN) design known as Long Short Term Memory was created to more accurately portray chronological sequences and related connections. Its traits include the internal structure of an LSTM cell, the multiple modifications made to the LSTM architecture, and a wide range of highly sought-after LSTM prosecutions. These networks are the addition of the intermittent network (RNN), which was primarily given for forecasting circumstances where network fail. This is an algorithm which analyses the model while considering matter of earlier events and also temporarily stores it in the memory of its users. It utilizes time-series data for processing, forecasting, and classification. The speech control operations are known of the multitudinous operations. RNNs do have some drawbacks, though. LSTM skeletal system The retired estate of the model is a renewed unit or renewed cell, which is the primary distinction between the infrastructures of RNNs and LSTMs. The upcoming retiree estate also receives these two items.

Applications

- Language modelling or textbook generation,
- Language Translation,
- Speech and Handwriting Recognition.

Multivariate Time Series Forecasting with LSTMs:

time series prediction of multivariate soothsaying using LSTM is a system to prognosticate the wind speed data by taking the once data as input it forecasts the unborn wind speed and also of other variables Multivariate time series soothsaying is a fashion that involves using several resemblant sequences of once compliances as input1. This is in discrepancy to univariate time series soothsaying, which uses a single sequence as input. Long term Short- Term Memory models that is suitable to model problems with multiple input variables, making them useful for multivariate time series soothsaying. Multivariate Time Series vaticinating with LSTMs which will prognosticate not only Wind speed but also other features, Rain, Temperature etc. because the purpose is how I can prognosticate the features to induce unborn Wind Power.

EXPERIMENTAL WORK

The paradigm of machine literacy that has been imposed on the current design is described in the experimental work. The design's model was given the designation LSTM. As part of this project's methodology, assemble the dataset that includes information on wind speed and other relevant attributes. make sure that the dataset has undergone pre-processing and is properly organized for machine literacy. Furthermore publish the time series for each feature. Divide the dataset into two parts training data set and testing data set. The first set is to develop the model, the confirmation set is used to fine-tune the hyperparameters, and the testing set is used to evaluate the model's performance. Utilize the fit() function to train the LSTM model using the training data. To prevent overfitting, discuss the model's performance on the validation set. To assess the values and turn our series into samples of input past compliances and affair future compliances for use with supervised literacy algorithms, we can utilize a function that adopts a sliding window method.

Utilizing the testing set, estimate the trained model. Perform the same performance evaluation using metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), etc.

DATA SET DESCRIPTION

Sno	Attributes	Description
1.	DATE	17 years, from January 1961 to December 1978
2.	WIND	Average wind velocity (knots)
3.	IND	the initial indication value
4.	RAIN	Amount of precipitation (mm)
5.	IND 1	Value two of the indicator
6.	TMAX	Highest temperature (in Celsius)
7.	IND 2	Value of the third indication
8.	T.MIN	Lowest temperature (in Celsius)
9.	T.MIN.G	Gross minimum temperature at 09 UTC

Table – 5.1

DATASET:

Model used	Data set link
Support Vector Regression (SVR)	Wind Speed Prediction | Kaggle
Random Forest Regression	Wind Speed Prediction Dataset | Kaggle
Transformer model with attention mechanisms	wind-speed-prediction · GitHub Topics · GitHub
Predicting series of wind using Prophet for Wind Speed Prediction	wind-speed-prediction| Kaggle
Neural networks of graph (GNN)	wind-Speed Prediction| Kaggle
ARIMA and LSTM hybrid model	GitHub - darkmatter18/Wind-Speed-Prediction: 🌬 Wind Speed Prediction Model based on py torch
Echo State Networks (ESN)	GitHub – mn assrib/time-series-forecasting-models-for-wind-speed: Time series forecasting models for weather features
(LSTM)	wind-speed-prediction · GitHub Topics · GitHub
Convolutional Neural Networks (CNN)	wind-Speed Prediction| Kaggle
Hierarchical Temporal Memory (HTM)	wind-speed-prediction · GitHub Topics · GitHub
Wave Net	WIND-SPEED PREDICTION| Kaggle

Table – 5.2

Performance parameters:

Mean Absolute Error:

All absolute crimes in the data were normalized to the mean absolute error. Mean Absolute Error, or MAE, is the abbreviation. It is calculated by dividing the total number of crimes by the sum of all absolute crimes. The MAE Equation is

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |x_i - x|$$

RESULTS:

MACHINE LEARNING MODELS:

EVALUATION OF LINEAR REGRESSION:

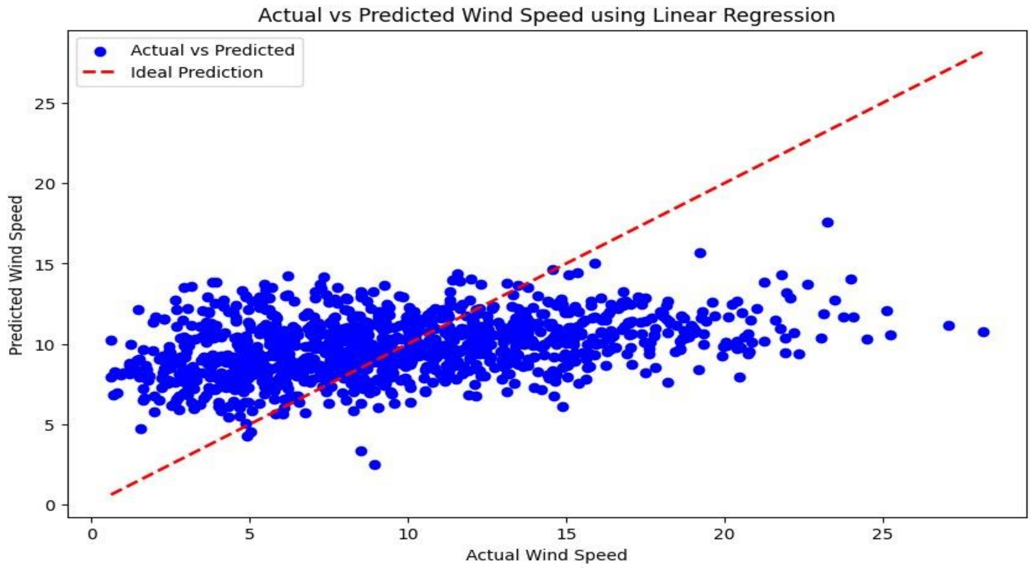

Fig 6.1

The graph showing the actual vs predicted wind speed using the machine learning model-linear regression.

Accuracy: 22.82979600049777

SUPPORT VECTOR REGRESSION:

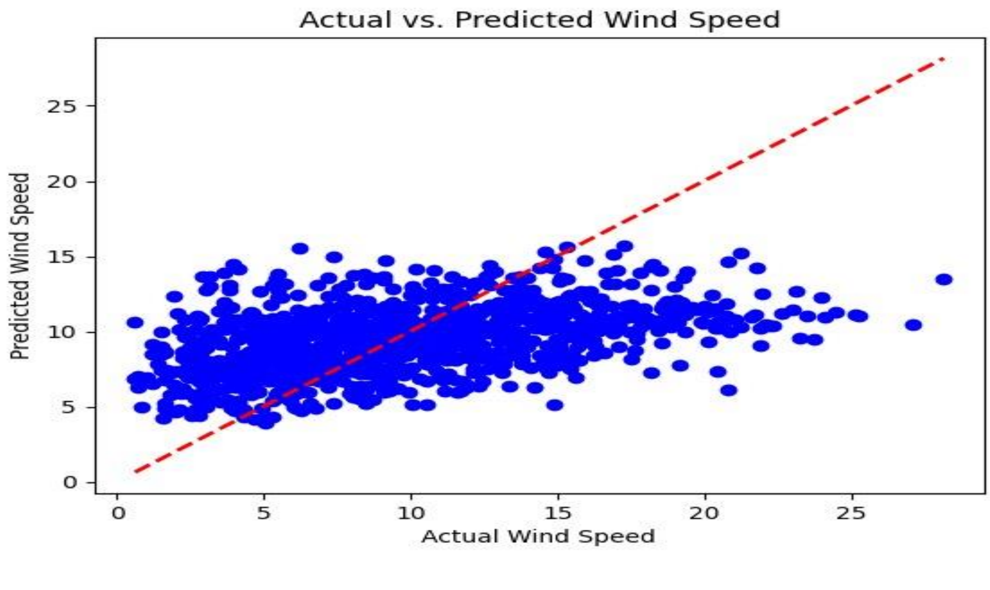

Fig 6.2

The graph showing the actual vs predicted wind speed using the machine learning model-support vector regression.

Accuracy: 20.72712268192791

DECISION TREE:

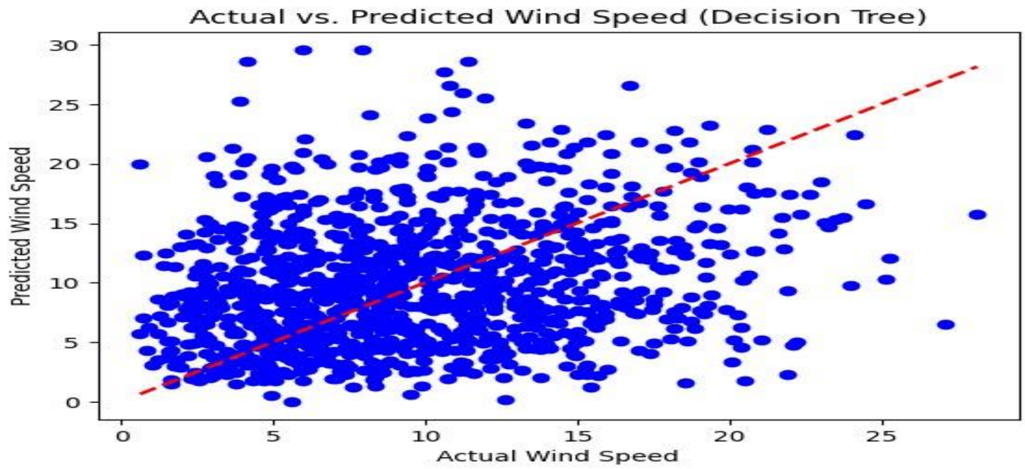

Fig 6.3

The graph showing the actual vs predicted wind speed using the machine learning model-decision tree.

Accuracy: 41.36364441489362

RANDOM FOREST:

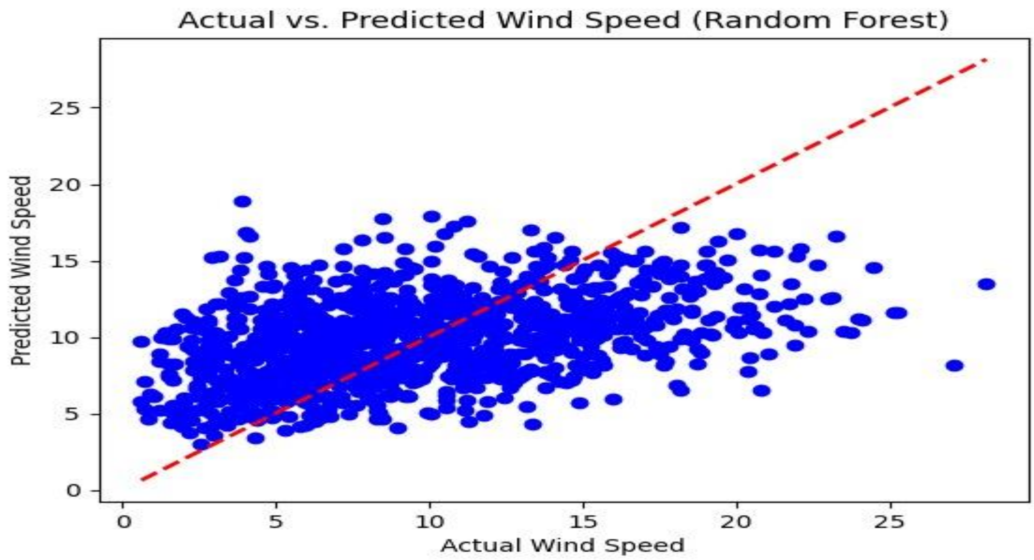

Fig-6.4

The graph showing the actual vs predicted wind speed using the machine learning model-Random forest.

Accuracy: 21.446965230975177

XGBOOST:

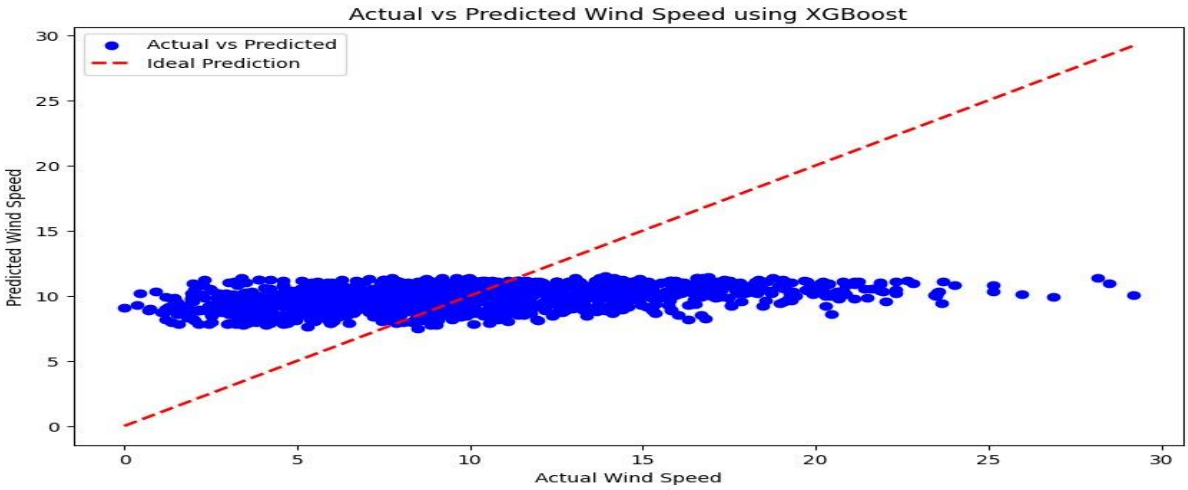

Fig – 6.5

The graph showing the actual vs predicted wind speed using the machine learning model-linear regression.

Accuracy: 22.27734319252118

LSTM Model evaluation:

1.Continuity of Sequence model with one layer for the encoder and one for the decoder.

Layer (type)	Output Shape	Param #	Connected to
input_1(Input layer)	[(None,10,8)]	0	-
Lstm (LSTM)	[(None,100), (None,43600)]	-	input_1[0][0]
repeat_ vector (Repeat Vector)	[(none,5,100)]	0	Lstm[0][0]
time_ distributed (Tim e Distributed)	[(None,5)]	808	Lstm_1[0][0]

2. Continuity of Sequence model with one layer for the encoder and one for the decoder.

Layer (type)	Output Shape	Param #	Connected to
input_2 (Input Layer)	[(None,10,8)]	0	-
lstm_2 (LSTM)]	[(None,10,100)	(N ,43600)	input_2[0][0]
lstm_3 (LSTM)	[(None, 100),	(None, 80400	lstm_2[0][0]
repeat_vector_1 (Repe at Vector)	(None, 5, 100)	0	(None, 5, 100)

TIME SERIES FORECASTING

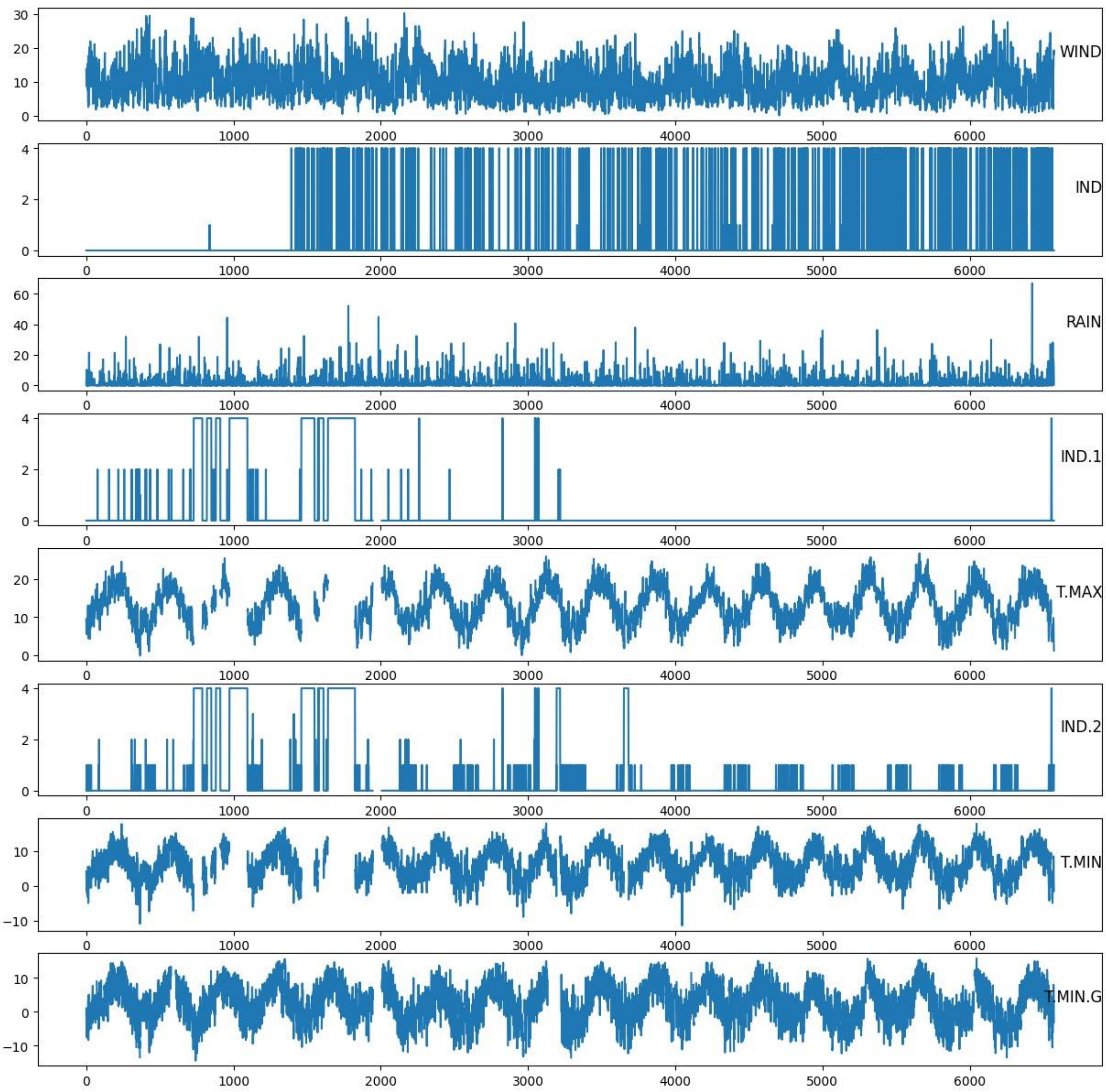

Fig - 6.6

The graph showing the actual vs predicted wind for the given parameters using the model-LSTM.

Accuracy: 3.072968099013831

VISUALISATION:

The graphical representation of the wind speed to that of the each day which is recorded in the time period of 17 years, from January 1961 to December 1978

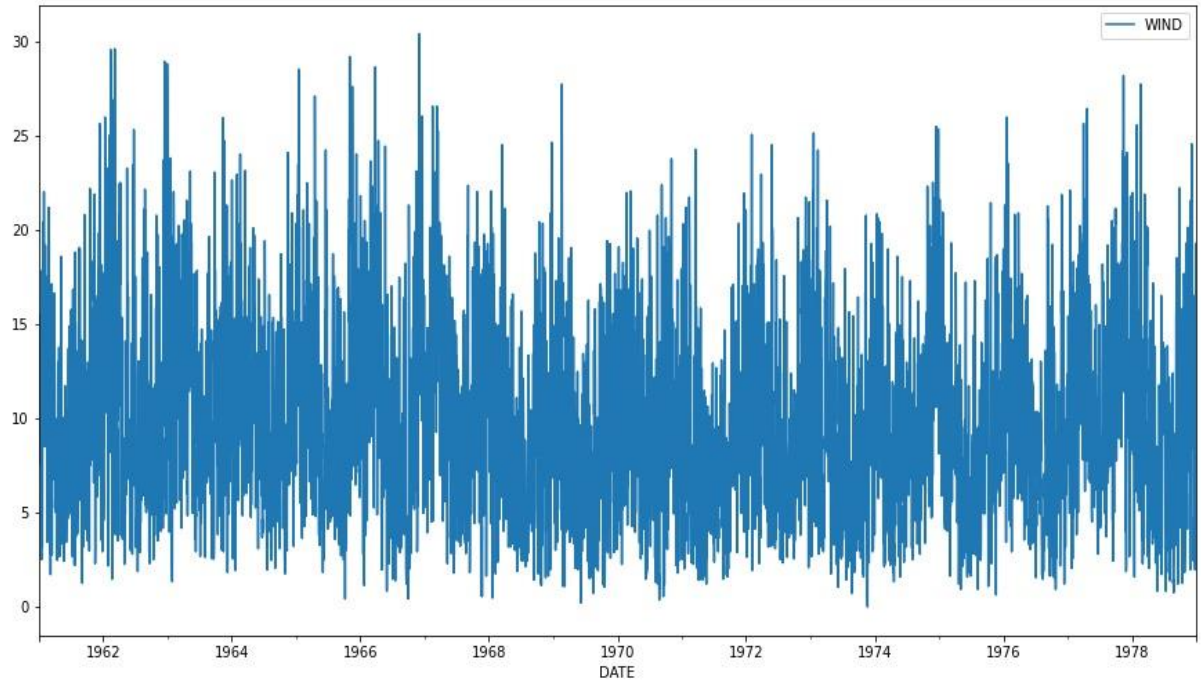

Fig 6.7

Git hub link:

https://github.com/Srinidhidingari/DAFE

Sno	Model used	Accuracy
1.	Linear regression	22.82979600049777
2.	Decision tree	41.36364441489362
3.	Support vector regression	20.72712268192791
4.	Random forest	21.446965230975177
5.	XG Boost	22.27734319252118
6.	LSTM	3.072968099013831

From the above table the model LSTM – long short term memory gave the high accuracy that is less mean square error and less mean absolute error which are the parameters used in the prediction of wind speed

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DATA SET LINK:

https://www.kaggle.com/datasets/fedesoriano/wind-speed-prediction-dataset

CONCLUSION

Accurate knowledge of the variability and vacuity of wind speed is a veritably pivotal issue for the operation and scheduling of the smart grid. In this work, a new mongrel deep literacy- grounded approach is proposed for short- term wind speed vaticination. also, the BLSTM network as a combination of LSTM networks and bidirectional RNNs is incorporate to capture deep temporal features with high abstractions. The proposed model is estimated on a intimately available real- world dataset, of which the soothsaying delicacy is exhaustively compared to multiple marks that live in the literature.

Using Long Short-Term Memory (LSTM) in machine learning for wind speed prediction presents a promising approach to enhance accuracy and efficiency in renewable energy management. In this context, LSTM models can effectively capture complex temporal patterns and dependencies in wind speed. By employing LSTM architectures and training them on historical wind speed data, we can develop models that learn and generalize well, making predictions for future wind speeds. The LSTM models can then be evaluated using appropriate metrics like Mean Squared Error (MSE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE) to assess their predictive performance.

FUTURESCOPE

As for future exploration, the proposed model can be bettered by taking into account more inputs similar as moisture and atmospheric pressure. farther point birth methodologies similar as data clustering styles will be tested to ameliorate the wind speed vaticination delicacy. Another unborn exploration direction will concentrate on using spatiotemporal data and coastal wind power vaticination while considering the ocean current position. Integration of LSTM with other machine learning or statistical models could enhance predictive performance. Hybrid models combining LSTM with methods like Support Vector Machines, Random Forests, or ensemble approaches may yield even more accurate predictions.