Mehran University Research Journal of Engineering and Technology

https://doi.org/10.22581/muet1982.3246

2024, 43(4) 170-181

Analyzing convolutional neural networks and linear regression models for wind speed forecasting in sustainable energy provision

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Received: 28 April 2024, Accepted: 15 September 2024, Published: 01 October 2024

KEYWORDS

Sustainable Energy Source

Wind Energy Conservation

Renewable Energy

Linear Regression Model

Convolutional Neural Network

Wind Speed Forecasting

ABSTRACT

Wind energy's significance lies in its contribution to electricity production. Accurate wind speed prediction is crucial for precisely forecasting electricity generation, enhancing its overall importance. For the wind speed prediction two methods are developed in this paper that are the Linear Regression Method and Convolutional Neural Networks (CNNs). Linear regression makes a linear relation between input and output which are used to predict continuous outcomes. The second proposed leverage hierarchical feature extraction through convolutional layers, enabling them to excel at tasks like pattern recognition by capturing spatial patterns and hierarchies of information. Hyperparameter tuning is applied on both the models to minimize the errors. Then both the model's performances are compared under different error matrices including MAE, RMSE, MSE and MAPE. The observations indicate that both the Linear Regression Model and CNN models are capable of forecasting wind speed However, the Linear Regression Model after Hyperparameter tuning performs better in terms of the calculated errors.

1. Introduction

Today, the world relies extensively on electricity mainly at home, industries and offices. The electrical equipment's need continuous supply of electricity, which renders them usable. Thus, how well people utilize these equipment and do everyday chores is directly impacted by the generation and delivery of power [1]. Additionally, the availability and reliability of electricity are crucial for our performance and productivity as it powers a variety of processes, machinery, and communication systems, promoting efficiency and economic progress [2]. Ultimately, everyone needs access to a steady supply of energy to run our appliances, maintain our daily routines, and advance civilization as a whole [3]. Meanwhile this should be kept in view that the operation and maintenance of the power system may all benefit greatly from an accurate load prediction [4]. So, there must be a proper balance between energy production and consumption because energy cannot be stored in large quantities [5].

As a result of rising energy demands and the limited availability of fossil fuels in our expanding world, the world has begun to shift towards sustainable alternatives [6]. Renewable energy sources including solar energy [7], wind energy, hydro power, tidal energy, geothermal energy, and bio-fuel energy are viewed as feasible possibilities since they provide an almost limitless supply of energy. Renewable resources utilize the power of unrestricted, plentiful natural components like sunshine and wind as opposed to fossil fuels, which are limited and non-renewable [8]. Utilizing renewable energy sources shift to a more ecologically responsible and sustainable energy system [9]. In Pakistan there is a lot of potentials to produce solar and wind energy [10]. Countries may lessen their reliance on fossil fuels, cut carbon emissions, and increase their energy security by depending on these sources. Electricity can be generated locally by using natural renewable energy, making energy independence [11].

Due to several major reasons, the wind energy is observed as the best source of renewable energy [12, 13]. It can be used on both onshore and offshore making them accessible for more people, also it is safe and clean energy without any pollution [14]. When wind turbines run they do not produce any smoke or air pollution as compared to the energy produced by burning coal etc. Moreover it is cheaper source of energy which needs one time investment [15, 16]. For the creation of renewable energy, it is a preferred option because of its affordability, environmental advantages, and employment-generating potential [17].

There is a direct correlation between wind speed and the energy produced by wind energy installations [18]. Increased wind speeds result in greater kinetic energy, which improves power production efficiency and raises the amount of electricity produced.

The ability to predict wind speed gives wind farm operators the ability to maximize energy output and optimize turbine performance [19, 20]. The most effective use of wind resources and dependable electricity production are ensured by accurate predictions, which aid in effective resource allocation, maintenance planning, and grid integration [21].

Numerous machine learning methods have been used in conjunction with artificial intelligence (AI) to estimate wind speed [22, 23]. Some of them are Artificial Neural Networks (ANN), Regression Models, Neural Networks, Hybrid Approaches, K-Nearest Neighbours (KNN). These techniques, such as empirical mode decomposition (EMD), were first used to convert wind speed into simple and steady sub-series [24], wavelet transform (WT) [25], wavelet packet decomposition (WPD) [26], etc. In the realm of energy and power production, where the pursuit of sustainable solutions drives innovation, this paper unveils a pioneering approach at the crossroads of AI technology and renewable energy systems. With a keen focus on sustainable energy infrastructures and system reliability, this study delves into the convergence of two potent AI models, harnessed to predict wind speeds—a vital parameter in the efficient functioning of wind mills. As the world stands at the juncture of conventional energy and burgeoning renewable resources, the integration of predictive AI models into wind energy technology represents a pivotal stride towards enhancing energy efficiency and conservation. In the following pages, the synthesis of these cutting-edge paradigms unfolds, poised to shape the future of energy landscapes while resonating with the diverse facets encapsulated within the ambit of energy-related discourse.

Traditional methods are often based on simple models or historical analysis and therefore may be problematic for handling the complex and changeable nature of the weather. For example, these classical methods, persistence models or time series models, like AR, MA, ARMA, lack flexibility and cannot capture the nonlinear dependencies satisfactorily, if at all, into the forecasts or adjust to the environment.

Accurate wind speed estimates are important for a variety of applications, but traditional methods often fail in terms of accuracy and scalability. These methods rely heavily on complex models or historical data, which cannot be attributed to abrupt climate change or local factors.

This paper presents a novel AI-based method for wind speed forecasting that uses machine learning algorithms to provide real-time forecast accuracy. Unlike traditional models, our method evolves for changing climate models and reduce errors caused by outdated data or conservative-models.

Implementing Machine Learning techniques, on the contrary, is best done to big data because it is able to discover hidden patterns or relationships within the data which other conventional methods may not. The conventional ML, or Machine Learning approach can utilize ANNs or Support Vector Machines, learns from data, and gradually becomes better. This flexibility in addition to the potential to learn complex relationships makes most ML methods to be stronger and efficient than traditional methods. Hence by stating the inefficiency of traditional methods, we can explain the reason for the preference of ML methods over other methods in estimating wind speed.

This research paper examines a comparative analysis done between CNN and Linear Regression for wind speed prediction. The investigation is conducted specifically for the wind turbine installation at Gharo, Pakistan. Each wind speed reading was recorded with a time stamp of 10 minutes, making up the 2400 data samples that made up the data-set utilized to apply the model. The access to the whole dataset is limited by the University Ethics Committee. Nevertheless, it is understood that in some instances the database may be released for research purposes. These 2400 samples were split into the train prediction, validation prediction, and test prediction groups in order to achieve a thorough examination which is discussed in the section 3 and 4. The concluding segment of the paper succinctly encapsulates the outcomes of the study.

2. Related Work

Wind speed forecasting has been the subject of extensive investigation. Previously, these time-series studies were conducted using conventional statistical analytic approaches.

In paper [27], Convolutional neural networks (CNN) and LSTM can be used to make 2-D forecasting of the wind speed. In [28], on the basis of feature analysis, the prediction of wind is offered. Comparative analysis revealed that the suggested model's MAE and RMSE are, respectively, 7.51% and 0.70%, allowing for the effective utilisation of spatiotemporal feature information in wind speed forecasting.

In paper [29] a comparison of different models is done for wind speed prediction. Authors conclude that non- linear models like neural networks are better than linear regression.

Recent study shows that CNN and LSTM can be used separately and in hybrid to predict wind speed but one drawback is that in hybrid model, forecasting uncertainties are unpredictable. So in [13] a new model CNN-bidirectional LSTM is proposed to solve this problem. The results exhibit high accuracy and best ability in uncertainty estimation.

In the paper [30] different methods to forecast the wind speed have been reviewed. Physical models require large amounts of data and contend with complex terrain and rapidly changing weather conditions. Statistical models such as RMA make only short-term forecasts and cannot account for abrupt wind changes, while sustainability models are simpler though less practical in long-term forecasting the original neural networks were often overfitting and lacked generalizability, making them inappropriate for dynamic environments. Overall, these methods could not provide accurate long-term wind forecasts.

The above study suggests that the traditional methods to forecast the wind speed have many drawbacks, that's why AI models have been adopted in this paper.

In [31] a hybrid model combining LSTM, CNN and CEEMDEN is proposed for multi-step wind speed prediction. The results demonstrate that each of the three components of the proposed model enhances performance in predicting the wind speed.

In [32] the main goal of this work was to ascertain how effectively the network architecture can foresee using historical data. They also contrast the outcomes of predictions generated by these networks with those of a fully connected neural network.

Their analysis's findings demonstrate how employing LSTM and 1D-CNN greatly enhances temporal alignment and prediction accuracy. With a dimensionality of three, the LSTM only accepts the current value as input because it was particularly made to employ temporal sequences.

Two methods are developed for wind speed prediction: ANNs and MLR [33]. Finding the factors that have the most effects on wind speed is the creation of regression model. In the second proposed method, back- propagation (BP) is employed for training ANNs. When it comes to statistical errors the ANNs outperform.

Wind speed forecasting is challenging in high-altitude, complex terrains where wind fluctuations cause typical methods to fail [34]. Their bespoke solution includes advanced RNNs and dynamic neural networks (DNNs), in addition to standard linear regression models. By precisely estimating wind speeds in the challenging Andean terrain, they hope to locate possible locations for wind energy harvesting. Two meteorological stations are first deployed by the research within the mountainous study region in order to gather data in 2018. Next, measurable variables are examined to determine relevant parameters.

According to the research, the multivariable LSTM network produces the most accurate findings, demonstrating its skill in forecasting wind speed over challenging terrains and emphasising the need of include observed factors. The predicted wind speeds also reach levels that are suitable for producing significant wind energy.

In a paper [35], five machine learning algorithms were employed using daily wind speed data to perform long- term wind power projection. They presented a machine learning-driven approach for efficient wind power forecasting, and they used numerous case studies to assess algorithm performance. This demonstrates how machine learning might be used to develop models from reference sites and pre-assess the sustainability of wind farms in uncharted areas.

3. Using CNN And Linear Regression For The Prediction Of Wind Speed

Wind speed is predicted using Linear Regression and CNN (Convolutional Neural Network) models. The data collection contains measurements of wind speed which are taken after every ten minutes.

3.1 The Applicability of Convolutional Neural Networks (CNNs) For Wind Speed Prediction

CNNs is a type of deep learning model which excel at processing grid-like inputs such as time series and images. CNN uses multiple convolutional and pooling layers. The convolutional layers use filters or kernels. The pooling layers minimise the dimensions.

Estimating wind speed involves using both complex patterns in the collected data and wind speed measurements collected from several locations throughout time. CNNs for wind speed prediction also have fully connected associations. These additional layers aid in accurate prediction-making by creating fake time patterns and wind speed variations.

Considering all this CNNs proves to be perfect for wind speed prediction. Their utility in predicting and forecasting wind speed patterns has been proved by their actual application in meteorology and weather forecasting jobs.

3.2 Architecture of The Employed CNN Model

CNN models are made up of convolutional, pooling, as well as fully connected layers. Use of the VGGNet architecture is made for wind prediction.

1) The first layer in the VGGNet architecture represents the input picture or data that the CNN will process.
2) Convolutional Layers: These layers are in charge of sifting through the incoming data and extracting features. There are generally 16 or 19 convolutional layers in a VGGNet. Learnable filters are used in a sequence of convolutions performed by each convolutional layer to capture regional patterns or characteristics. These filters traverse the data input and generate feature maps.
3) Activation Function: To provide non-linearity to the model after each convolutional layer.
4) Pooling Layers: through it the feature maps' spatial dimensions are reduced. The maximum value contained inside a pooling window is preserved by VGGNet, with the remaining values being discarded.
5) Fully Connected Layers: These layers analyse the data from the preceding levels and generate predictions from it. These layers are connected to every neuron in the preceding layer, which aids in the data's high-level relationship capturing. The final layers of a VGGNet generally have one or two completely linked layers.
6) Activation Function and Output Layer: Like the convolutional layers, the layers also use an activation function.

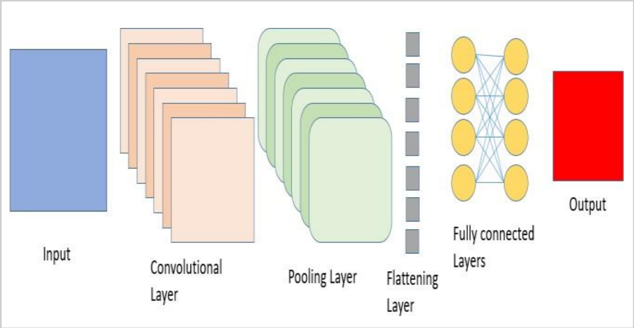

Fig. 1. CNN Architecture

Each wind speed reading was recorded with a time stamp of 10 minutes, making up the 2400 data samples that made up the data-set utilized to apply the model. These 2400 samples were split into the train prediction, validation prediction, and test prediction groups in order to achieve a thorough examination. The validation and test prediction subsets each included 350 data samples, whereas the train prediction subset contained 1600 data samples. This split produced a ratio of 1600:350:350, enabling efficient training, validation, and performance testing of the model. A CNN model is trained by repeatedly feeding input data batches into the network, modifying the model's parameters depending on the computed loss, and then optimizing the model's performance. In this instance, during training, two distinct batch sizes—namely, 16 and 32—were taken into consideration. Hundred different epochs were also used. The model learns pattern and evolve over time by varying the batch size.

Hyperparameter is used to change the standard CNN architecture. Hyperparameters are the controls that are supplied by the trainer that is these parameters are not pick up during the training of model. The hyperparameters that were tuned to optimize the model's performance blanketed the getting to know price, batch size, and community architecture. These hyper-parameters are used to change the CNN model's performance. The goal is to determine which combination of hyperparameters yields the best results in terms of accuracy, speed of convergence, and ability to generalise.

3.3 Linear Regression Model and Its Suitability For Wind Speed Prediction

It is among the simplest and most often applied techniques in machine learning. By using linear regression, prediction is done and the relationship between variables can also be found.

Wind speed forecasting is a challenging issue that goes beyond the scope of straightforward linear regression since it necessitates the capture of temporal patterns, seasonal changes, and weather dependencies.

3.4 Architecture of the employed Linear Regression Model

For regression jobs (for example, forecasting the price of a property, wind speed, or temperature) based on input data, linear regression is a straightforward, single-layer model. There are no secret layers or intricate modifications used in linear regression. A straight-line equation serves as the model's representation. The formula for Linear Regression Model can be given by Eq. (1):

$$Z = \beta 0 + \beta 1Xa + \beta 2Xb + \ldots + \beta nXn + \varepsilon \quad (1)$$

Here, Z represents the variable which is the outcome we aim to predict or explain. Xa, Xb… Xn are the terms which are the predictors or factors that influence Z. The parameter β0 indicates the expected value of Y when all independent variables are zero. The coefficients β1,β2,…,βn are assigned to each respective independent variable, representing the change in Z for a one-unit change in the corresponding X, assuming all other variables remain constant. Lastly, ϵ is the error term, capturing the variation in Z that cannot be explained by the independent variables in the model.

The available data, the study's objective, and the resources allocated for model development can all have an impact on the model's design and degree of sophistication. As previously mentioned, the stages involved in developing a wind power density WPD model include data collection, pre-processing, statistical analysis, wind speed frequency analysis, wind power density computation, geographical interpolation, mapping/visualization, and so on.

These methods focus on assessing past wind speed and direction data to determine the potential wind resource at a certain location or across a larger area. Many crucial steps were taken to construct an effective model for the study that used linear regression to anticipate wind power density (WPD):

1) Feature Selection:

- A number of potential factors were carefully considered and analysed, accounting for variables such as wind speed, air density, and temperature.
- Use of feature engineering techniques allowed for the extraction of important data and the creation of relevant predictors, which improved the predictive power of the model.
- Only the most significant traits were included; the less significant ones were left out.

2) Regularization:

- To make the model more robust, regularisation techniques like Ridge and Lasso Regression were studied.
- Through testing and cross-validation, the regularisation strength parameter was adjusted.

3) Data Pre-processing:

- Scaling and normalising the features were done as the pre-processing processes.

4) Model Evaluation:

- The assessment measures were carefully chosen, with
- A focus on capturing the precision and prognostication capabilities of the model for WPD estimation.

5) Regularization Strength:

- To achieve the ideal balance between under fitting and over-fitting in the case of Ridge or Lasso Regression, the appropriate regularization strength (lambda or alpha) was established after extensive experimentation.

These meticulous methods were followed throughout the investigation to ensure that the linear regression model employed for WPD prediction was well- optimized.

4. Experiment and Results

4.1 Performance Evaluation of the Trained CNN Model

The data-set is split into 3 parts. Second, pre-processing techniques like as normalisation, scaling, or augmentation are applied to identify meaningful patterns. After then, the model learns how to recognise relevant characteristics and provide accurate predictions.

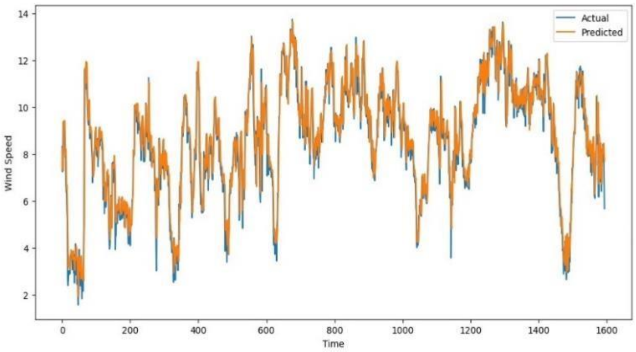

Fig. 2. Train Prediction By CNN Model Without Hyperparameter

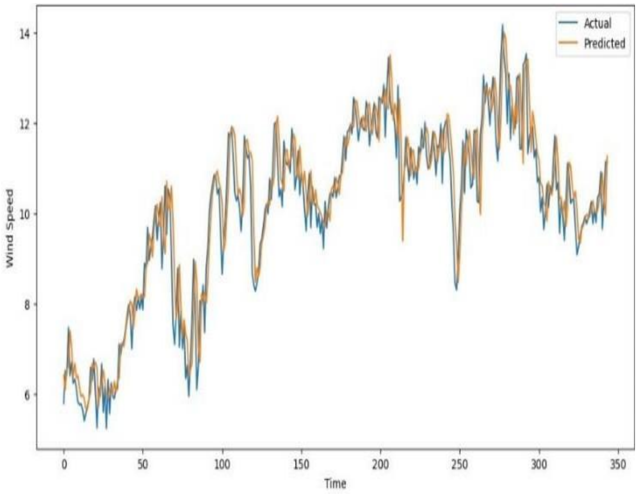

Fig. 3. Validation Prediction By CNN Model Without Hyperparameter

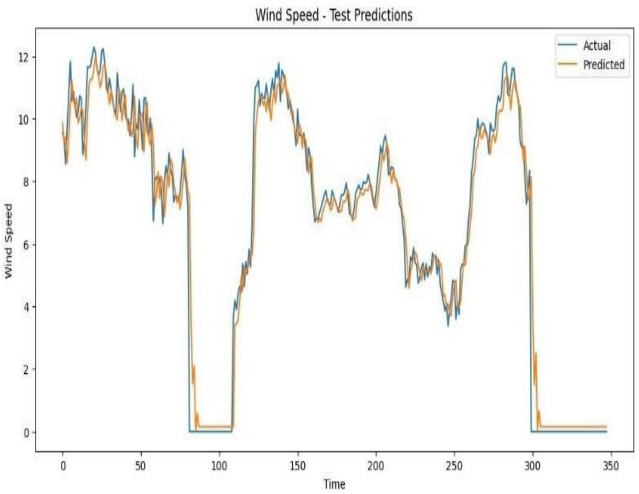

Fig. 4. Test Prediction By CNN Model Without Hyperparameter

After training, hyper-parameter tweaking is carried out to optimize model performance-related factors including learning rate, batch size, and network architecture. All of these procedures of the CNN model's performance and generalizability. The results after simply applying CNNs are shown below (see Fig. 1 and 3) and the results after applying hyperparameter are sown afterwards (see Fig. 4 and 6).

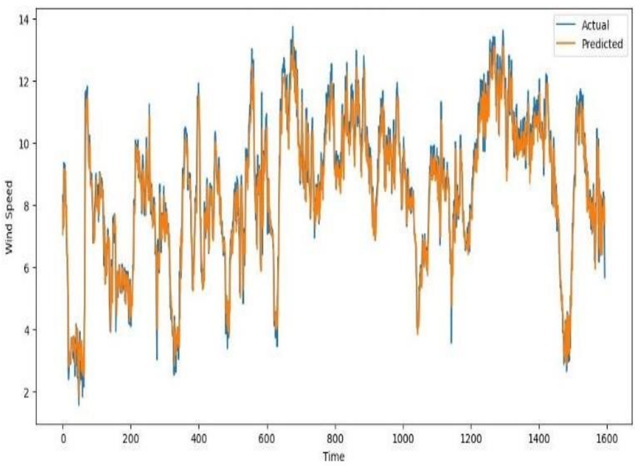

Fig. 5. Train Prediction By CNN Model With Hyperparameter

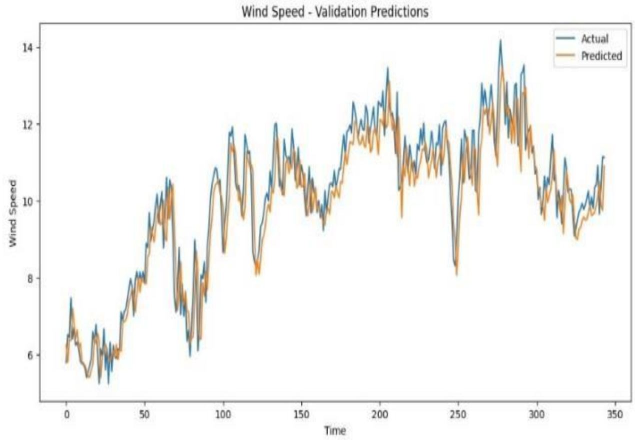

Fig. 6. Validation Prediction By CNN Model With Hyperparameter

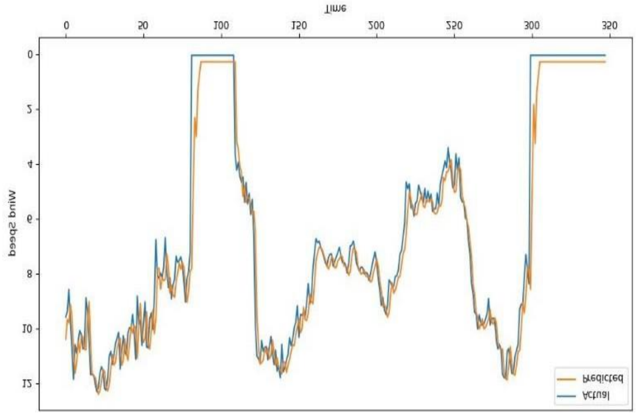

Fig. 7. Test Prediction By CNN Model With Hyperparameter

4.2 Evaluation Metrics To Assess The Performance Of The CNN Model

Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE) are utilized to assess the model's performance.

RMSE is the root mean square error. It's used error metric for regression models. Its formula can be taken from [36].

MSE is the mean square error which gives the average of the square of the error. Its formula is taken from [37].

MAE is the mean absolute error values. Its formula is taken from [36].

MAPE calculates the mean average percentage error. It's often used in forecasting and demand prediction. Its formula is given in [38]

The commonplace absolute mistakes had been assessed by means of using MAE, imparting a clear indication of prediction accuracy without disproportionate penalization of huge deviations. The common percentage mistakes were calculated by the use of MAPE, helping in gauging regular average overall performance in phrases of relative errors.

Collectively, those metrics furnished a entire assessment of the model's predictive accuracy and generalizability to new statistics.

Note that the absolute value bars |·| ensure that the percentage differences are positive. Also, avoid using MAPE when actual values ( ) are very close to zero, as it can result in division by zero or extremely large percentages.

Table 1

Error metrics of CNN model without hyper-parameter tuning

Without Hyper-parameter	MSE	RMSE	MAE	MAPE
Training Metrics	0.58784	0.76670	0.58686	39.8992
Validation Metrics	0.49886	0.70630	0.53755	24.7765
Test Metrics	1.01054	1.00525	0.56433	inf

Table 2

Error metrics of CNN model with hyper-parameter tuning

With Hyper-parameter	MSE	RMSE	MAE	MAPE
Training Metrics	0.5534	0.7439	0.5676	38.5046
Validation Metrics	0.5282	0.7267	0.5410	23.9639
Test Metrics	0.8520	0.9230	0.5172	inf

These metrics provide insights into the model's performance. MAPE is indicated as "inf," which typically signifies that there might be zero or close to zero values in the actual data, leading to an undefined percentage error.

4.3 Performance Evaluation Of The Trained Linear Regression Model

A trained Linear Regression model's effectiveness is typically evaluated at many key points. The data is pre- processed to improve the model's capacity to discover important patterns and correlations. Operations like feature scaling and normalization may be used in pre- processing. Hyperparameter tweaking is carried out after the training phase to improve model performance-related elements like the learning rate or regularization strength.

The results after simply applying Linear Regression Model are shown below (see Fig. 8 and 10) and the results after applying hyperparameter are sown afterwards (see Fig. 11 and 13).

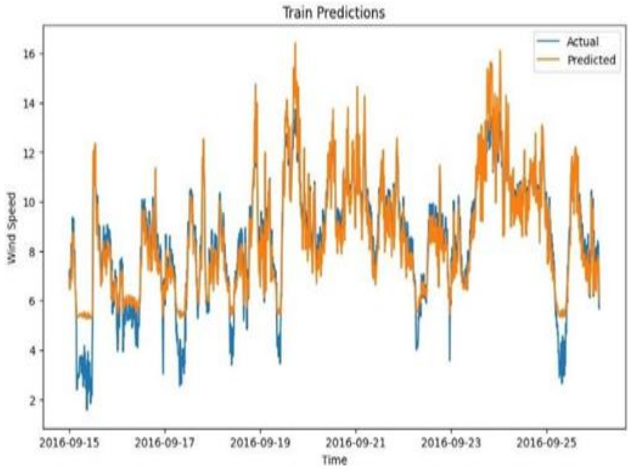

Fig. 8. Train Prediction By Linear Regression Model Without Hyperparameter

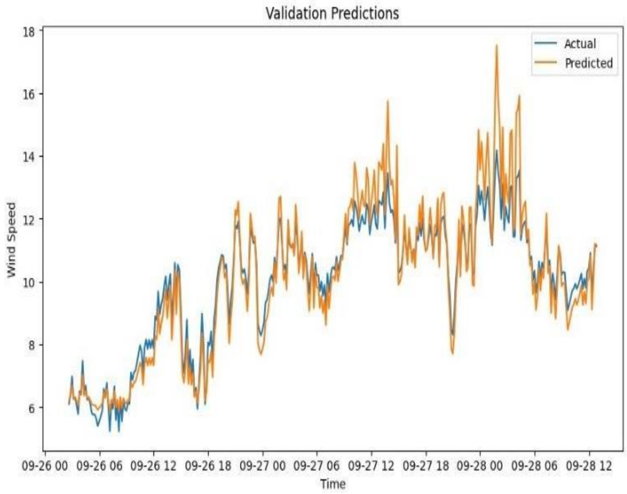

Fig. 9. Validation Prediction By Linear Regression Model Without Hyperparameter

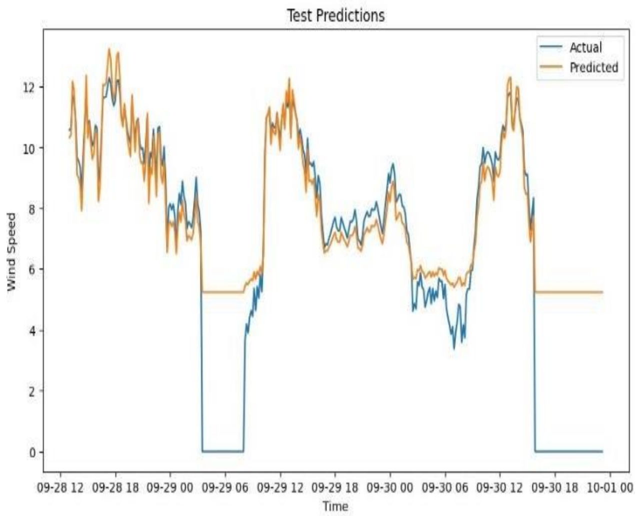

Fig. 10. Test Prediction By Linear Regression Model Without Hyperparameter

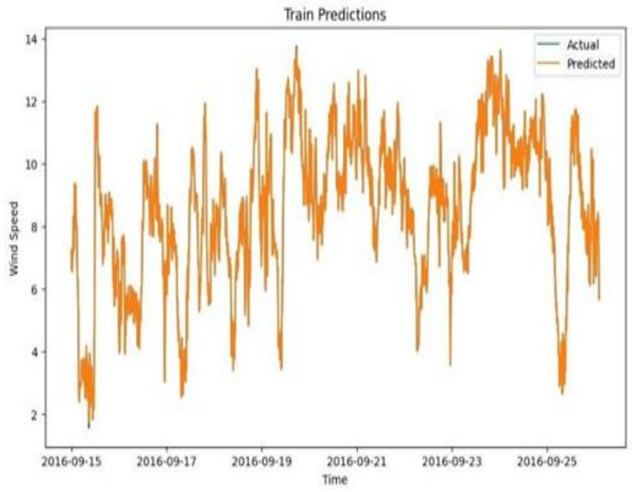

Fig. 11. Train Prediction By Linear Regression Model With Hyperparameter

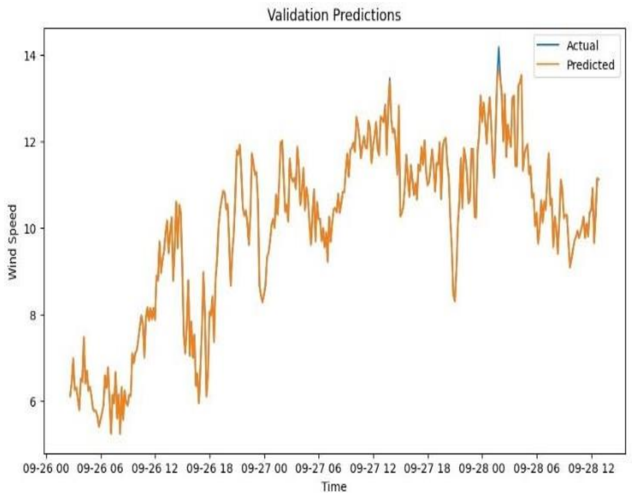

Fig. 12. Validation Prediction By Linear Regression Model With Hyperparameter

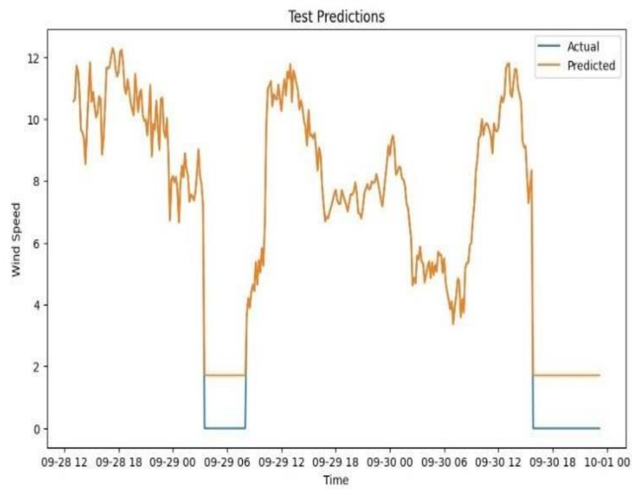

Fig. 13. Test Prediction By Linear Regression Model With Hyperparameter

4.4 Evaluation Metrics To Assess The Performance Of The Linear Regression Model

A number of indicators are evaluated in order to judge the model's performance. These metrics offer numerical measurements that make it possible to assess how well the model is doing on a particular job. These measures can be examined to learn more about the model's recall, accuracy, and other critical performance factors, enabling deft conclusions to be made about the model's efficacy and room for development. The formulae to find these error matrices are specified in Eqs. (2) - (5)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

$$RMSE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100 \tag{5}$$

Table 3

Error metrics of linear regression model without hyper-parameter tuning

Without Hyper-parameter	MSE	RMSE	MAE	MAPE
Training Metrics	0.6258	0.7910	0.6025	10.028
Validation Metrics	0.4126	0.6423	0.4768	4.6222
Test Metrics	6.0070	2.4509	1.4894	inf

Table 4

Error metrics of linear regression model with hyper-parameter tuning

With Hyper-parameter	MSE	RMSE	MAE	MAPE
Training Metrics	1.9698	0.0044	0/0012	0.0243
Validation Metrics	0.0008	0.0286	0.0043	0.0392
Test Metrics	0.6105	0.7813	0.3588	inf

These tells about the model's performance, indicating the level of accuracy achieved in predicting the target variable.

The use of normalization, scaling, and data enhancement plays an important role in the CNN model's ability to predict. Models were quantitatively evaluated for analytical metrics such as MSE, RMSE, MAE, and MAPE with better generalization and error in validation-test sets, which showed that the linear regression model outperformed CNN, especially in terms of error value occurrence lower and higher accuracy in wind speed prediction although CNN after hyperparameter tuning Improvements were shown, but its performance lagged after Linear Regression, possibly due to the smooth, linear nature of the dataset Higher error rates in MAPE, in particular, meaning "inf", emphasizes difficulty with near zero handling values, and suggests a more dramatic choice of metric While tuning has its advantages, sometimes simple examples such as linear regression can provide more reliable performance, especially in domains with linear trends.

In the paper [39] Bayesian prediction is used for forecasting the wind speed. For different instances the RMSE value ranges from 0.9593 to 0.8821 which is greater than the RMSE value obtained by Linear Regression model in this paper i.e 0.7813.

Comparing the overall performance of CNN and Linear Regression with different state-of-the-art methods, including Bayesian prediction and superior gadget studying methods, it's miles clean that every technique has its strengths and boundaries. In this regard, they surpassed their overall performance so by means of linear regression The linear regression model exhibited exact accuracy and occasional mistakes metrics notwithstanding its simplicity, that is consistent with its effectiveness in capturing linear trends in the dataset with winds. This evaluation specializing in them effectiveness in forecasting velocity confirms that although CNNs have the energy to version complex data, easier techniques inclusive of linear regression or Bayesian strategies can on occasion outperform them, mainly in conditions where the underlying records relationships are more trustworthy or whilst the dimensions of the statistics set is small.

In our previous research [40], wind speed was predicted using Lazy prophet and RNN models. The metrics values are given in the table below. The results clearly shows that in comparison to Lazy prophet and RNN models the CNN outperforms and predicts wind speed with far more accuracy.

Table 5

Error metrics of LazyProphet model without hyper-parameter tuning

LazyProphet	MSE	RMSE	MAE
Training Metrics	2.13	1.46	1.17
Validation Metrics	31.30	5.59	4.83
Test Metrics	35.23	5.94	5.30

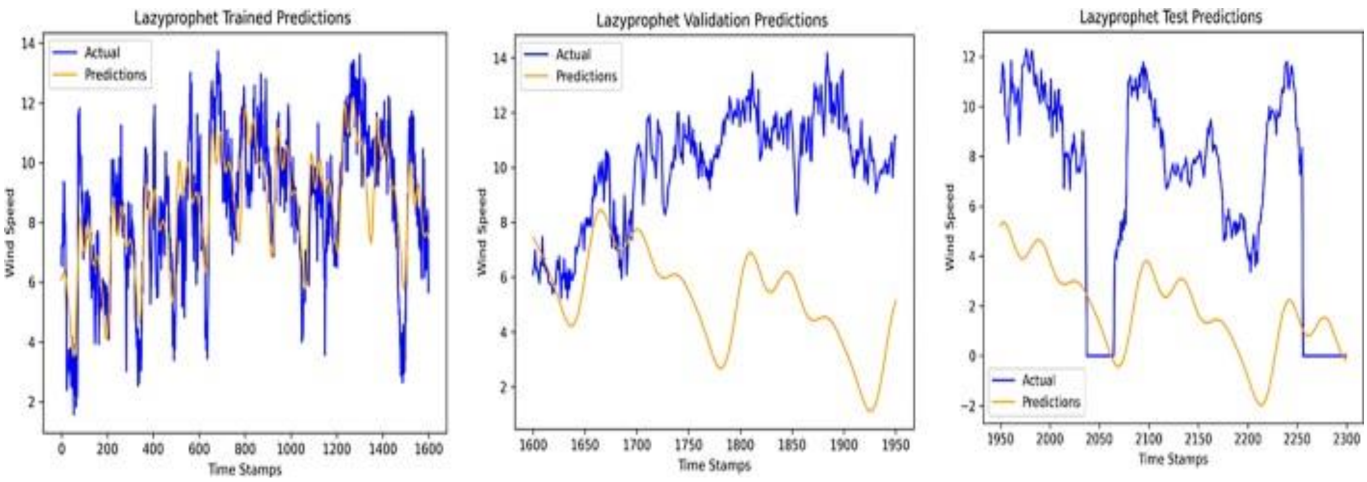

Fig. 14. Prediction By Lazyprophet Model Without Hyperparameter

Table 6

Error metrics of RNN model without hyper-parameter tuning

RNN	MSE	RMSE	MAE
Training Metrics	1.22	1.11	0.87
Validation Metrics	1.18	1.39	1.00
Test Metrics	1.34	1.31	0.81

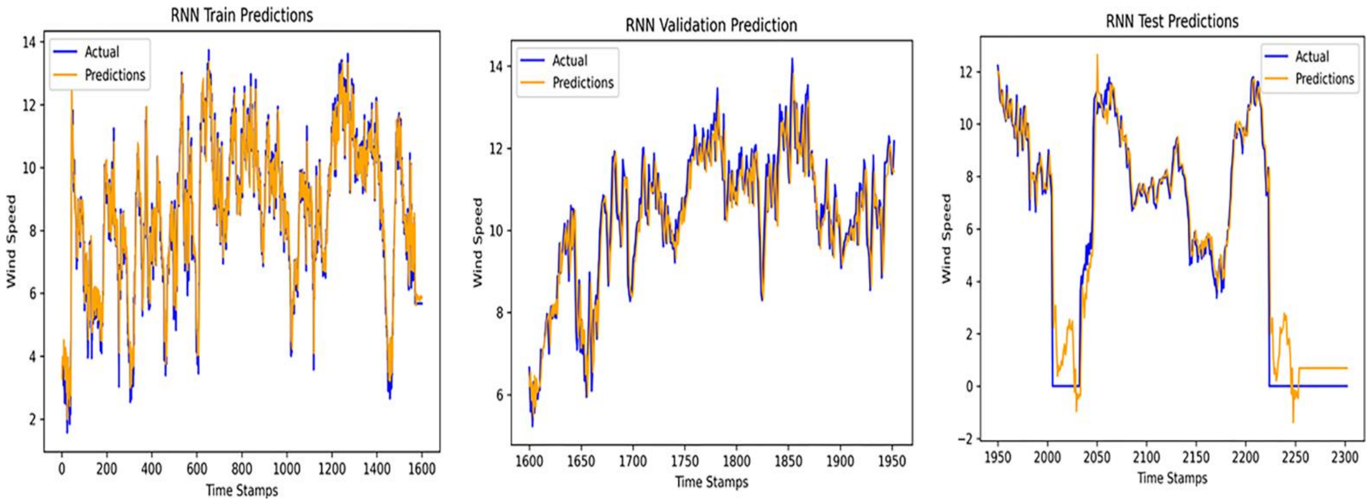

Fig. 15. Prediction By RNN Model Without Hyperparameter

5. Conclusion

The research findings derived from the analysis of the CNN model and the linear regression model demonstrate that the results obtained through linear regression exhibit higher accuracy and display lower error matrix values. Nonetheless, the outcomes achieved after applying hyperparameter tuning to both models are highly promising, showcasing near-perfect results in most cases.

6. Acknowledgment

The dataset records the wind speed measurements on time and date basis sourced from Gharo wind mill. Because the information came from the efforts and activities of the company itself, access is limited by the University Ethics Committee. Nevertheless, it is understood that in some instances the database may be released for research purposes, after obtaining the consent of the chairman of the Ethics Committee. Any such request for data access should be directed to the committee at dir-rnd@pnec.nust.edu.pk.

7. References

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