

# Time Series Forecasting of Wind Speed for Wind Power Production using Machine Learning

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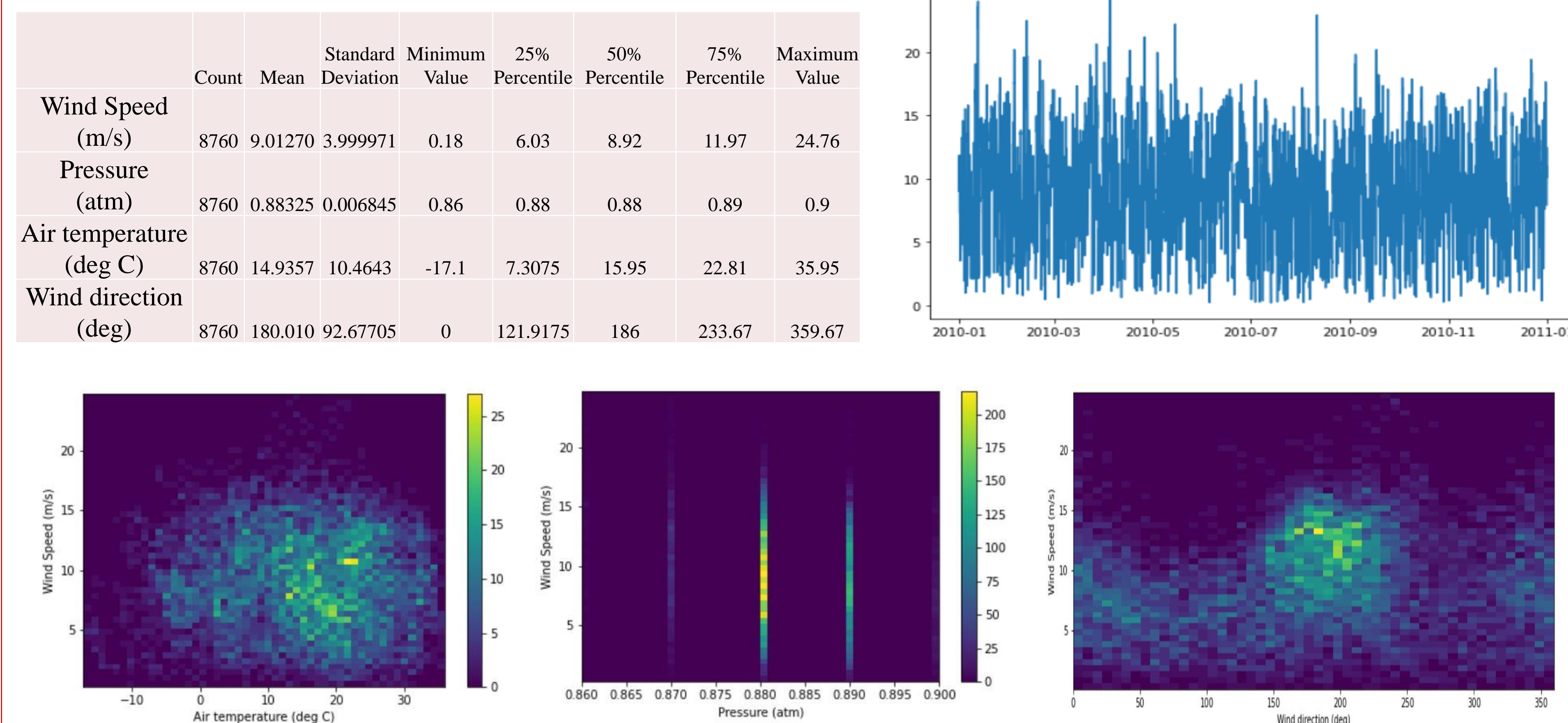
## Abstract

Wind speed prediction in a given location is crucial for the evaluation of the wind power project. The accurate prediction of the wind speed improves the planning, reduce the cost and improve the use of resources for a wind power generation. There has been growing interest in the field of deep learning and neural networks for the prediction of wind speed as it can overcome the issue of accurately forecasting the nonlinear patterns of wind speed data using classical time series methods. In this study, a weather data set provided by National Oceanic and Atmospheric Administration of South Plains Region of Texas is investigated to forecast the wind speed for multiple time steps. At first, simple linear model is applied for wind speed prediction. Then, various advanced deep learning models such as Convolutional and Recurrent Neural Networks (CNNs and RNNs) are built and applied to predict the wind speed. Unlike other machine learning algorithms, long short-term memory recurrent neural networks (LSTM) are capable of automatically learning features from sequence data, support multi-variate data, and can output a variable length sequences that can be used for multi-step forecasting. The performance of nine different models used in this study are compared using different method to evaluate the accuracy such as Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Based on the accuracy the best model is chosen and proposed for the wind speed prediction of the region. The study shows the superiority of Encoder-Decoder LSTM other machine learning methods. .

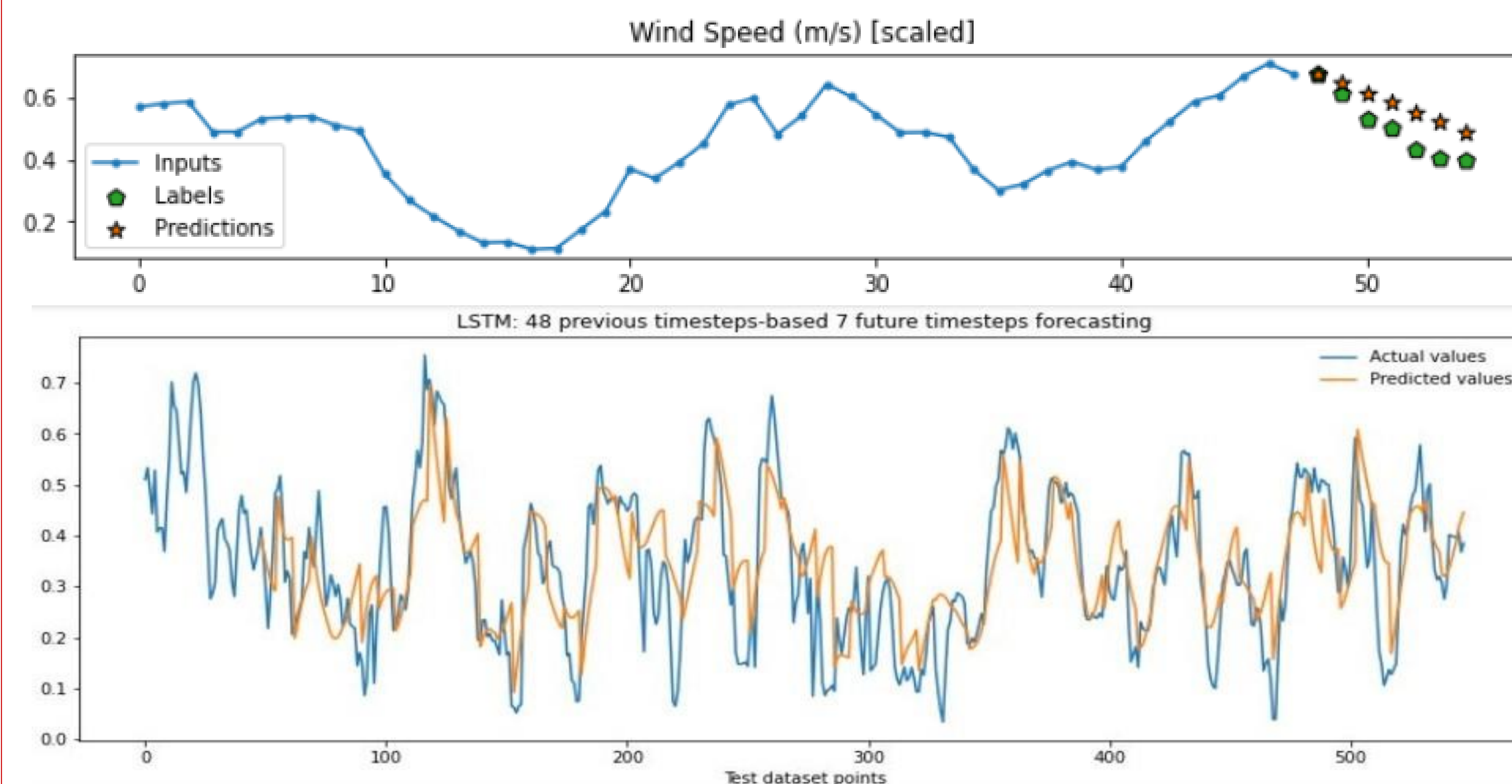
## Introduction and Objective

Wind energy is a variable renewable energy source [1], the power produced by the wind turbine hence, fluctuates with the variation of wind speed ; therefore, in the wind farm, unexpected variation of wind power output may increase the operating costs of the electricity system. So, intermittency of wind is the biggest challenge of a wind farm to implement wind-energy as a reliable autonomous source of electric power. Moreover, wind speed forecasting (WSF) system based on accurate model that reflecting the variation of wind speed is critical to the effective harvesting of energy from wind, integration of available wind power to the electrical power grid, and analyze the efficiency and performance of wind turbine based electrical generation system. Various methods have been developed so far for WSF specially using deep learning method as there is still a challenge in precision forecasting of wind speed. There are not any single best technique to solve wind time series forecasting. In order to deal with wind time-series forecasting, each problem might be solved with a different approach and comparing the different methods available is the only way to find the best method [2]. Hence, in this research, we compare the various deep learning method used for the wind speed forecasting

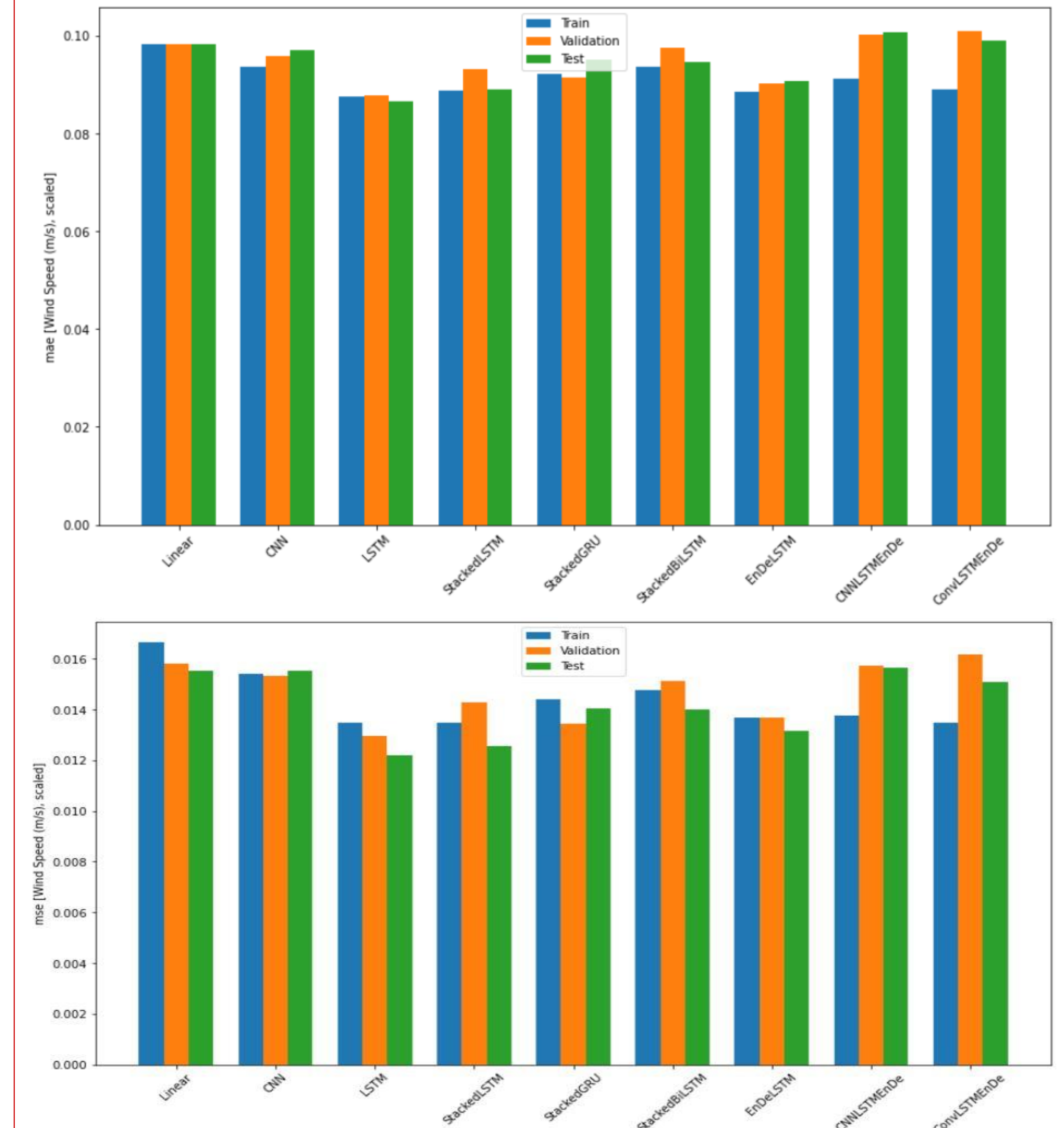
## Data Visualization



## Forecasting and Validation



## Evaluation of Model



## Conclusion

- It is essential to know which model can produce better results because accurate estimation of the future wind speed is essential for the turbine power control, energy trading and also power system planning.
- The result of this comparative study shows that the LSTM and stacked LSTM method is superior over other hybrid LSTM and CNN based method of WSF.
- Moreover, the CNN method alone does not show better performance as it is mostly used for image recognition but hybrid method

## References:

1. S. R. Sinsel, R. L. Riemke, and V. H. Hoffmann, "Challenges and solution technologies for the integration of variable renewable energy sources—a review," renewable energy, vol. 145, pp. 2271-2285, 2020.
2. Zhang, G. P., & Kline, D. M. (2007). Quarterly time-series forecasting with neural networks. IEEE transactions on neural networks, 18(6), 1800-1814.



## Methodology

