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Derin Öğrenme ile Kısa Vadeli Rüzgar Hız Tahmini

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Öz

Rüzgar hızı, yenilenebilir rüzgar enerjisine yatırım yapılması ve planlanmasında rüzgar hızının tahmin edilmesi hayati önem taşımaktadır. Ayrıca mevcut rüzgar santrallerinin üretimi ve iletim hatlarının kapasitelerinin artırılmasında da rüzgar hızının tahmin edilmesi oldukça önem arz etmektedir. Fakat rüzgar hızının aralıklı ve stokastik dalgalanmaları, yüksek kaliteli rüzgar hızı tahmini için önemli bir sorun oluşturmaktadır. Bu çalışmada, rüzgar santrallerinin planlanması ve uygulanabilirlik çalışmaları için rüzgar hız tahminini daha kolay sağlayabilecek derin öğrenme temelli bir yaklaşım önerilmiştir. Bu yaklaşımda öncelikle rüzgar hız zaman verileri sürekli dalgacık dönüşümü ile renkli görüntüye dönüştürüldü. Elde edilen görüntüler, önceden eğitilmiş AlexNet CNN modeline uygulanarak rüzgar hız tahmini gerçekleştirilmektedir. Çalışma, Elazığ meteoroloji bölge müdürlüğünden alınan 2018-2019 yılları arasındaki saatlik hız verileri kullanılmıştır. Yapılan deneysel çalışmalarda, 1-saat, 2-saat ve 3-saat olmak üzere üç farklı ileri ufuk tahmini yapılmıştır. Önerilen tahmin modelinin modelin performans değerlendirilmesi için ortalama mutlak hata (MAE), ortalama karekök hatası (RMSE) ve korelasyon katsayısı (R) metrikleri kullanılmıştır. Deneysel çalışmalarda, tüm veri seti görüntüleri transfer öğrenimi için rastgele bir şekilde sırasıyla %70, %10 ve %20 oranlarında eğitim, doğrulama ve test olmak üzere üç bölüme ayrılmıştır. 1-saat ileri tahminde RMSE, MAE ve R metrikleri için sırasıyla 0,0335, 0,0275 ve 0,9517 deneysel sonuçlar ile en iyi rüzgar hız tahmini gerçekleştirilmiştir. Bu bakımdan önerilen AlexNet modelinde, 1 saat ileri tahmininde, daha güvenilir ve doğru tahmin gerçekleştirdiğinden rüzgar hız tahmininde etkili bir model olduğunu göstermektedir.

Anahtar kelimeler: Rüzgar hız tahmini, Sürekli dalgacık dönüşümü, Evrişimli sinir ağları, Derin öğrenme

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Short-Term Wind Speed Forecasting With Deep Learning

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Abstract
Wind speed forecasting is crucial for planning and investing in renewable wind energy. In addition, Wind speed forecasting is essential for planning renewable wind energy, optimizing wind power production, and enhancing transmission line capacities. However, intermittent and stochastic fluctuations of wind speed pose a significant problem for high quality wind speed forecasting. In this study, a deep learning-based approach is proposed for wind power plant planning and feasibility studies that can provide wind speed prediction more easily. In this approach, firstly, wind speed time data were converted into color images using continuous wavelet transform. The obtained images were applied to the pre-trained AlexNet CNN model and wind speed prediction was performed. In the study, hourly speed data from the Elazig meteorology regional directorate between 2018-2019 were used. In the experimental studies, three different horizon forecasts were made: 1-hour, 2-hour and 3-hour. Metrics like correlation coefficient (R), mean absolute error (MAE), and root means square error (RMSE) were utilized to assess the proposed forecasting models performance. In the experimental studies, the whole dataset images were randomly divided into three parts as training, validation and test at the rates of 70%, 10% and 20% respectively for transfer learning. In the 1-hour horizon forecast, the best wind speed prediction was achieved with experimental results of 0.0335, 0.0275 and 0.9517 for RMSE, MAE and R metrics, respectively. In this respect, the proposed AlexNet model shows that it is an effective model in wind speed forecast since the 1-hour horizon forecast is more reliable and accurate.

Keywords: Wind speed forecasting, Continuous wavelet transform, Convolutional neural networks, Deep learning

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1. Introduction

Global energy consumption is rising significantly due to population growth and technological and economic developments. With the increase in energy demands and the overuse of existing fossil resources, serious environmental problems such as global warming and climate change have been searched for new energy sources [1].

Electrical energy is the most used type of energy in daily life. Among low-carbon generation technologies, wind energy is one of the most important Renewable Energy Sources (RES) in many countries [2]. In this environment, the installed capacity of wind energy is growing annually on a global scale, reaching 650 GW in 2019 [3]. However, wind speed represents a significant variable in the reliability of the electricity grid [4]. Accurate and efficient forecasting of wind energy is of great importance in ensuring the safe and efficient operation of the electricity grid.

Many approaches to wind energy forecasting have been suggested and applied, initially traditional statistical models, physical models and more recently machine learning based models [5]. In wind energy forecasting with physical models, atmospheric flow is simulated using numerical weather forecasts for several locations in each geographical region. Despite the high computational cost, this model demonstrates satisfactory performance in medium- period and long-period wind forecasting. In contrast, traditional-statistical models refer to the data matching among the historical-data and the output of the wind farm. It is a time series approach where traditional statistical models are generally effective in short-term forecasting.

Advances in computer technology has facilitated the wider adoption of machine learning-based methods in the field of wind forecasting [6]. In the literature, there are many works using various deep learning approaches for wind forecasting.

Yildiz et al. [5] improved an enhanced residual-based convolutional neural network for the prediction of wind energy. Although the developed network is less complex and requires less computational resources, it is important to note that some features in the data may be lost due to the residual connection approach. Azimi et al. [7] proposed an approach for feature extraction that combines discrete wavelet transform, harmonic time series analysis, and k-means. For feature extraction, they adopted the decomposition of historical air temperature, wind speed and power data. They then trained a Multi-layer Perceptron Neural Network (MLN) with these extracted features to perform wind forecasting.

Jaseena and Kovoor [8], empirical model decomposition (EMD), ensemble-EMD, wavelet transform (WT) and empirical wavelet transform (EWT) methods combined the features obtained in data decomposition. They then applied these features to a Bidirectional Long-Sort Time Memory (Bi-LSTM) deep learning model for wind speed forecasting. They tested the performance evaluation of the proposed hybrid model with the Dhanushkodi and Melamandai dataset. The experimental results demonstrated that it outperforms other data decomposed-based models in terms of accuracy and stability. Li et al. [9] examined the effect of time resolution in wind energy forecasting. To minimize these effects, they proposed an artificial neural network (ANN)-based wind forecasting model.

Noman et al. [10] proposed the use of multivariate exogenous input variables to improve model performance in wind forecasting. Using the suggested approach features, eight transfer learning techniques, and four neural networks, they were able to predict the wind. They conducted experimental studies with two years of wind speed data averaging over 10-minute intervals. Experimental outcomes showed that the nonlinear auto-regressive exogenous model is more performant than other methods. Zameer et al. [11] developed a genetic programming-based ANN model for short-term wind power forecasting. This developed model was tested with data from five different wind farms. They showed that the model has higher performance than some artificial intelligence-based models. Altan et al. [12] developed a non-linear hybrid model based on gray wolf optimizer decomposition and LSTM deep learning for more accurate and reliable wind speed prediction. With this model, the features obtained from the combination of parsing and LSTM model were combined. They then improved the performance of the wind speed prediction model by optimizing the weighted coefficients of the intrinsic mode function output with gray wolf optimization. Emeksiz and Tan [13] proposed a method based on combining deep learning and mode separation approaches for wind speed estimation. In the proposed model, the signals obtained from adaptive noise reduction and EMD methods are converted into images by continuous wavelet transform in the pre-processing of the data. These images have been applied to various CNN models for effective wind speed forecasting. A multistep wind speed prediction model based on a transformer is proposed, and the multistep wind speed prediction problem is recognized as a sequence-to-sequence mapping problem [14].

In this work, a two-stage transfer learning-based model is proposed for wind speed prediction. In the first stage, hourly wind speed data were converted into images with Continuous Wavelet Transform (CWT). Then, these images were applied to the pre-trained AlexNet model and wind speed prediction was performed. Experimental studies were carried out with hourly wind speed data of Elazig center for the years 2018-2019. The study's contributions are assessed in the manner listed below.

- To overcome the stochastic and unstable features of wind data and reach higher accuracy capacity, RGB color space image sensitive to CWT changes of wind data is provided,
- With the color images derived from wind speed data, the training reliability of the pre-trained convolutional neural network (CNN) improved, and wind forecasting performance is increased.

2. Material and Methods

In this study, a CNN-based model for wind speed forecasting was proposed, and its structure is shown in Figure 1. First, in the suggested model, hourly wind speed data were converted into a two-dimensional image by CWT transformation and then colored and converted into a 3D image. Then, the image size was resized from 368×160 to 227×227 for the input of the AlexNet model. In the final stage, the classification layer of the pre-trained ESA model AlexNet was replaced with a regression layer to predict deep features, enabling automatic wind speed forecasting.

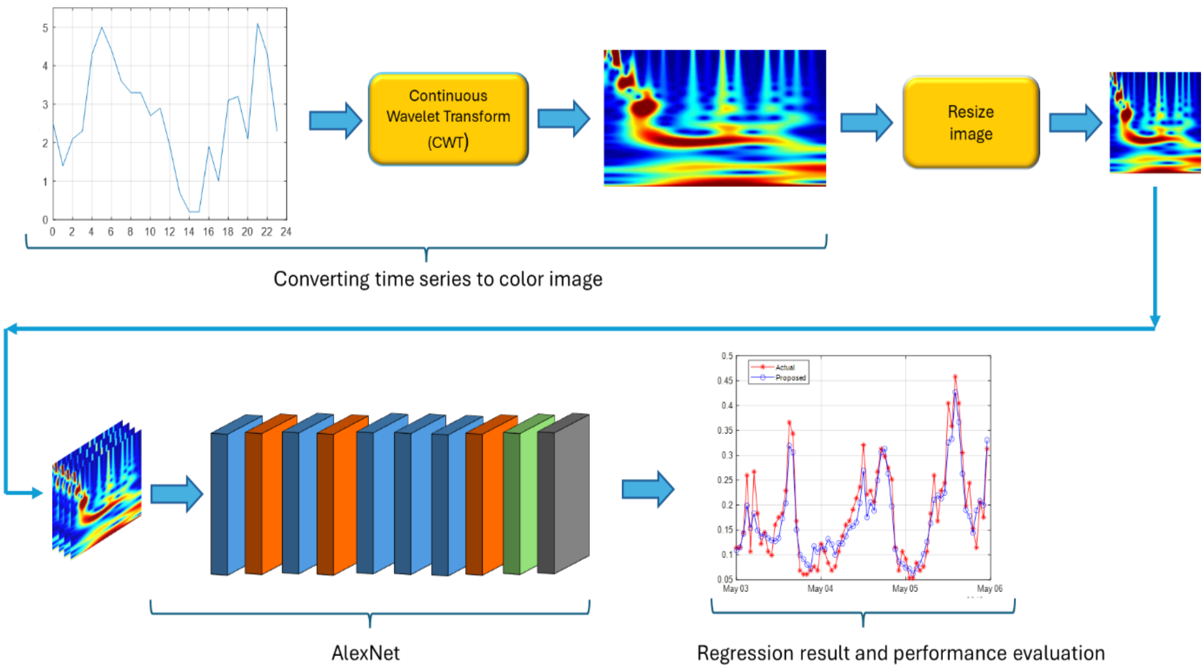

Figure 1. Proposed model chart

2.1. Dataset

The experimental studies used hourly wind direction and speed data (2018–2019) from the Meteorology Directorate's Central/Elazig station (No. 17201). The details of the dataset used in the experimental studies are presented in Figure 2. As seen in figure 2, the columns show the hourly time changes, and the rows show the changes in wind speeds (m/s) against the hourly changes during the day. There is a total of 17448 hours of wind data in the dataset for two years.

Date	0:00:00	1:00:00	2:00:00	3:00:00	4:00:00	5:00:00	6:00:00	7:00:00	8:00:00	9:00:00	10:00:00
January 1, 2018	2.5	1.4	2.1	2.3	4.3	5.0	4.4	3.6	3.3	3.3	2.7
January 2, 2018	0.7	0.3	0.7	0.9	0.7	1.4	0.8	1.5	4.0	5.2	5.2
January 3, 2018	1.8	1.9	1.8	1.8	1.5	1.3	0.9	1.0	1.8	2.2	2.0
January 4, 2018	5.5	4.2	3.8	4.4	4.6	4.0	4.4	6.0	6.0	6.9	5.2
January 5, 2018	5.4	4.9	5.6	5.7	6.3	5.2	4.5	5.0	6.1	5.0	3.0
January 6, 2018	1.8	1.8	1.6	1.6	1.8	1.7	1.2	0.5	1.6	1.8	2.3
January 7, 2018	2.3	1.8	0.9	1.5	2.4	2.0	0.6	0.9	0.7	1.5	2.3
January 8, 2018	1.8	1.6	2.0	1.6	1.5	1.5	0.8	0.4	1.3	2.0	1.7
January 9, 2018	1.7	0.1	1.5	0.8	1.3	1.2	0.7	0.7	1.6	2.2	1.9
January 10, 2018	2.6	2.7	2.8	2.0	2.2	1.6	1.3	0.6	0.6	2.1	2.2
January 11, 2018	0.2	0.2	0.2	0.2	0.5	1.0	0.7	0.5	1.8	1.9	1.6
January 12, 2018	1.4	0.8	0.3	1.0	0.9	1.3	1.3	1.0	0.8	2.3	2.4
January 13, 2018	0.8	0.7	1.5	1.0	0.5	0.8	0.3	1.6	1.1	1.6	2.0
January 14, 2018	0.9	2.5	1.5	1.6	3.8	1.0	1.6	3.2	4.0	5.0	4.4
January 15, 2018	0.5	0.6	1.8	1.9	2.0	2.0	2.0	1.9	1.2	1.3	1.5

Figure 2. Dataset details

2.2. Continuous wavelets transform

The Continuous Wavelet Transform (CWT) is one of the most advanced signal processing techniques available for analyzing time-series data due to its ability to handle non-stationary signals, which are common in real-world applications such as weather patterns, financial data, and physiological signals [13]. CWT allows for the simultaneous analysis of both time and frequency content of a signal, which is particularly important for non-stationary time series where the frequency characteristics change over time. In contrast, traditional methods like the Fourier Transform provide only frequency information and fail to capture the temporal variations within the signal [13-15] Furthermore, CWT enables the signal to be analyzed at multiple scales, providing insights into different frequency components at various time points. This multi-scale analysis offers significant advantages in detecting patterns such as peaks, trends, or anomalies at different resolutions [14, 15].

The basic principle of CWT is based on decomposing a continuous-time function into a set of wavelet functions. The wavelets are derived by applying a shift and scaling operation to the mother wavelet function. Accordingly, CWT can be defined by Equation 1.

$$CWT_f(a,\tau) = \left[f(t), \psi_{a,\tau}(t)\right] = \frac{1}{\sqrt{a}} \int f(t)\psi^* \left(\frac{t-\tau}{a}\right) dt,\ a > 0 \tag{1}$$

Where, ψ is the main wavelet function, a is the scale factor of the wavelet and expands the wavelet length and frequency, τ is the delay factor and controls the delay position on the time axis, and $\psi^*$is the complex conjugate of the wavelet master function. A should be chosen small for the high-frequency features of the signal in the given time series, and a should be chosen large for the low-frequency features of the signal.

Scalograms, which visualize the output of the wavelet transform, show the intensity of different frequencies over time. When displayed in grayscale, it can be difficult to perceive important details [16,17]. Therefore, gray images are often converted to color images to enhance clarity. The choice of color mapping in these images is critical, as it influences how well human observers can detect important patterns, anomalies, or features. For instance, a heat map-style color scheme with a gradient from cool to warm colors (blue to red), such as the "jet" color map, can clearly distinguish between low- and high-energy regions. This clear contrast between low- and high-energy areas makes it easier to identify significant features in the data, such as spikes or frequency shifts [18].

2.3. AlexNet

The AlexNet CNN model was introduced by Alex Krizhevesky at all. in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) competition to contribute to image classification problems [19]. This CNN model broke new ground in computer vision applications, surpassing all previous techniques [20]. AlexNet is a complex neural network consisting of 60 million parameters and trained with more than 1.2 million high-resolution images to classify 1000 different objects, and unlike previous models, it uses the ReLU activation function [21, 22]. As can be seen in the architecture in Figure 3, it consists of 5 convolution layers (Conv), three pooling layers (Max pool) and three fully connected layers (FC). There is also a ReLU activation layer after each convolution layer [23]. In the experimental studies, AlexNet was preferred due to its lighter weights compared to other popular CNN models such as GoogLeNet, VGG, and ResNet.

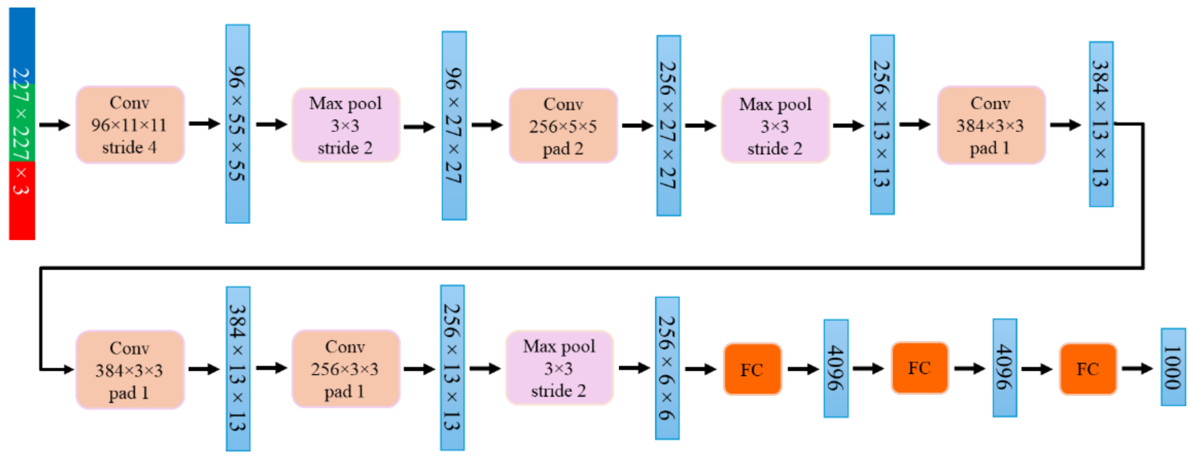

Figure 3. AlexNet architecture

Transfer learning is the reuse of any pre-trained machine learning model with different data with some fine-tuning [24]. The fine-tuning approach is based on optimizing certain parameters of a pre-trained model with a small subset of target data. Its widespread use by researchers is due to its advantages such as simplicity, ease of implementation and efficient use of computational resources [25].

In addition to exploiting prior knowledge in the source domain, this approach allows for more adaptive results by making localized adjustments for target domain-specific tasks. The main aim of transfer learning is to save training time and provide better performance without requiring too much data [26]. AlexNet transfer learning, which will be used in experimental studies, is shown in Figure 4. In experimental studies, the classifier layer connected to the last FC layer of the AlexNet model, details of which are given in Figure 3, was replaced with a regression layer.

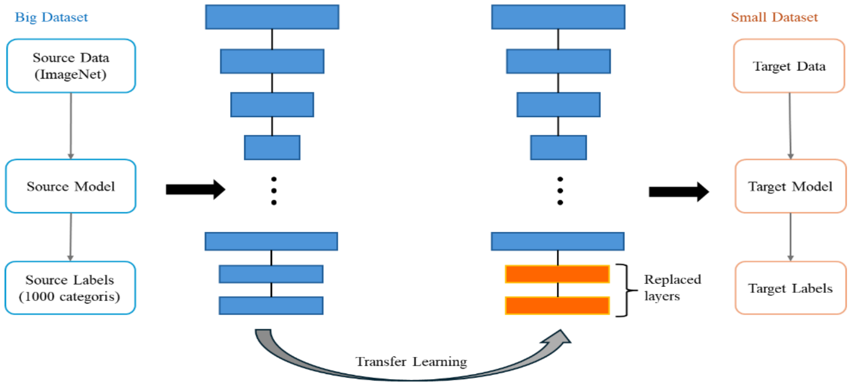

Figure 4. The schematic of AlexNet with transfer learning

2.4. Performance evaluation metrics

Three quantitative evaluation criteria were selected to assess the performance of the proposed method. These are the correlation coefficient (R), the mean absolute error (MAE), and the root mean square error (RMSE).

- RMSE indicates the amount of error between the values predicted by a model and the observed results. A smaller RMSE indicates better performance of the prediction model.
- MAE is a widely used measure for assessing the accuracy of a forecasted model. It is particularly used in regression analysis and determines the average magnitude of errors in predictions. A smaller MAE means higher prediction accuracy.
- R is a measure of the relationship between inputs and outputs [6].

Equations (2-4) of these metrics are given below [27].

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_k - x_k)^2} \tag{2}$$

$$MAE = \frac{1}{n}\sum_{k=1}^{n}|y_k - x_k| \tag{3}$$

$$R = \frac{\sum_{k=1}^{n}(x_k - \overline{x}_k)(y_k - \overline{y}_k)}{\sqrt{\sum_{i=1}^{n}(y_k - \overline{y}_k)^2 \sum_{k=1}^{n}(x_k - \overline{y}_k)^2}} \tag{4}$$

Where n is the total number of test data, x_k is the actual data values, y_k represent the anticipated data values and $\overline{y}_k$, $\overline{x}_k$are the mean values of the data.

3. Experimental Studies and Results

This section presents a concise overview of the experimental setup, and the results obtained in the prediction of wind speed. The experimental studies were conducted on a computer with the following specifications: MATLAB (2021b) installed, quad-core Intel i7 processor, NVIDIA GTX 850M GPU, and 16GB memory.

In the first stage of the experimental studies, time series were converted into images with CWT. For this purpose, the time series signals containing hourly wind speeds between 2018-2019 were first converted into a grey image with dimensions of 168×360 as shown in Figure 5. Subsequently, the changes in pixel brightness and contrast values within the grey image were assigned a jet128 color map of uniform distribution, resulting in a 168×360×3 color scalogram image. This image was then resized to 227×227×3 in accordance with the proposed AlexNet model input. All images were also normalized by mean subtraction.

In the first stage of the experimental studies, the whole dataset was randomly divided into three parts, namely training, validation and test, with 70%, 10% and 20% of the images, respectively, for transfer learning. The training dataset was used in the learning process of the proposed model, while the validation dataset was used as a part of the training set to build the model. The model parameters were also modified using the validation dataset. The performance evaluation was conducted using the test dataset.

The experiments were repeated several times to determine the best parameters of the model during the AlexNet training process. In the initial stages of the training process, the learning rate was adjusted to 0.0001, the mini-batch size was adjusted to 32, and the maximum number of epochs was adjusted to 40, with a drop factor of 0.5 applied every 10 epochs. Moreover, the adaptive moment prediction (Adam) algorithm was used to optimize the whole cost function for the AlexNet model to eliminate convolutional kernels during the back-propagation phase.

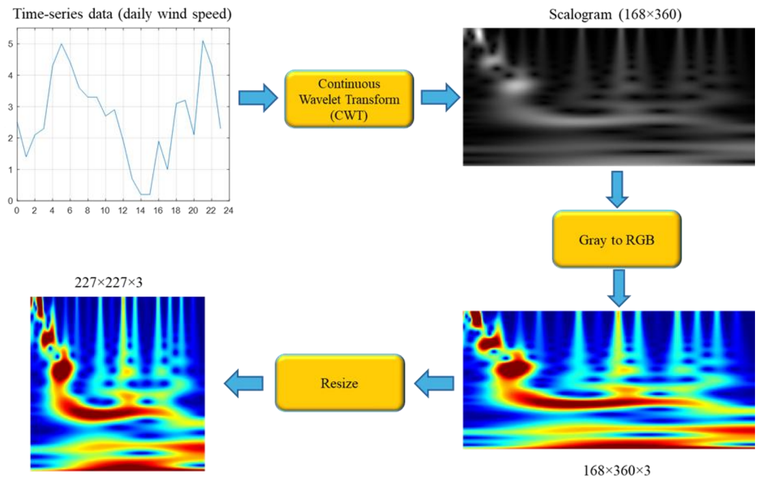

Figure 5. Convert to scalogram images from time series

The experiments were grouped by different forecast horizons to assess the proposed methods precision. The R, MAE and RMSE values for the one-hour, two-hour, and three-hour horizon forecasts of the suggested AlexNet model are presented in Table 1.

Table 1. Performance metrics of 1-hour, 2-hour and 3-hour horizon forecasting for AlexNet

Method	Horizon	Metrics		
		RMSE	MAE	R
AlexNet	1-hour	0.0335	0.0275	0.9517
	2-hour	0.0443	0.0357	0.8908
	3-hour	0.0505	0.0346	0.8365

The proposed AlexNet model has R, MAE and RMSE values of 0.0335, 0.0275 and 0.9517 for 1-hour horizon forecasts, respectively. Similarly, RMSE, MAE and R values for 2-hour horizon forecasts are 0.0443, 0.0357 and 0.8908, respectively. For 3-hour horizon forecasts, RMSE is 0.0505, MAE is 0.0346 and R is 0.8365.

The proposed model performs best for one-hour horizon wind speed forecasting. Therefore, in the proposed The AlexNet model, when utilized in conjunction with a one-hour forecast, can be regarded as a highly effective tool for the generation of more reliable and accurate forecast responses.

In addition, the visualization of certain time intervals to show the validity of the actual and normalized results of the one-hour, two-hour and three-hour horizon forecasts are shown in Figure 6 respectively. As can be seen from the graphs in Figure 6, the wind speed is better predicted in the actual and normalized curves of the 1-hour forecast.

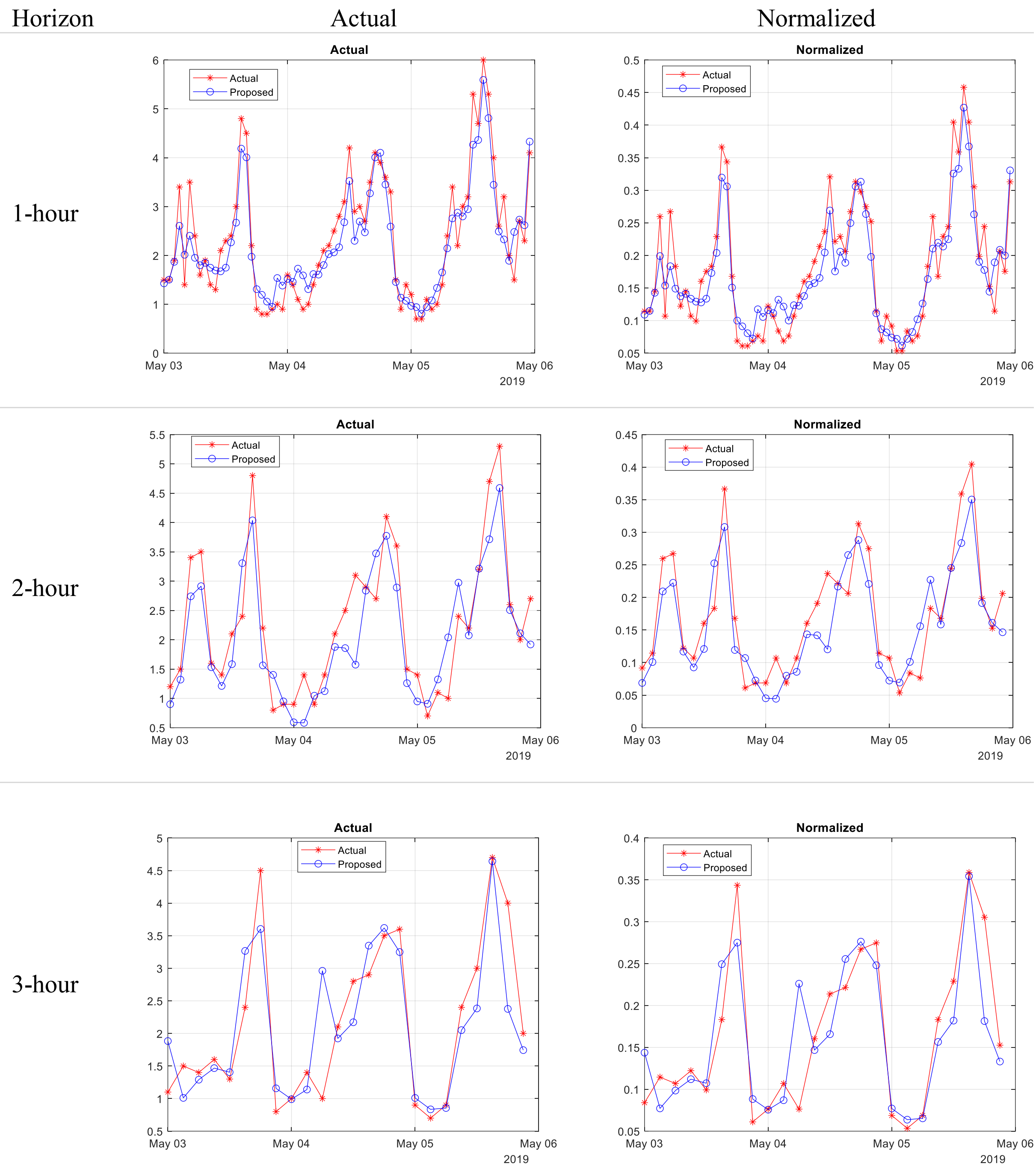

Figure 6. Wind speed forecasting results for 1-hour, 2-hour and 3-hour horizon

4. Conclusions

This study aims to develop a wind speed forecast model based on deep learning. This method involves first converting the wind speed data into scalogram images, which are then used to extract features from the AlexNet convolutional neural network model based on transfer learning to predict wind speed.

The results demonstrate that the proposed AlexNet model performs exceptionally well for shorter forecast periods. Specifically, the RMSE, MAE and R values for 3-hour horizon forecasts have performance values of 0.0505, 0.0346 and 0.8365, respectively. The 2-hour horizon forecasts show a slight increase in performance with RMSE, MAE and R values of 0.0443, 0.0357 and 0.8908, respectively. For the 1-hour horizon forecasts, the model reaches RMSE, MAE and R values of 0.0335, 0.0275 and 0.9517, respectively, and it is observed that its performance is further improved, and it has a high level of accuracy and reliability.

The experimental results show that the 1-hour horizon forecast is the most effective and reliable for wind speed forecasting. Similarly, the actual and normalized speed forecast plots also support this conclusion. For the 1-hour horizon forecast, the actual and normalized results closely match the observed data, reinforcing the effectiveness of the model in short-term wind speed forecasting.

In future studies, the researchers will investigate the effects on CNN models by converting time-dependent wind speed data into images with different approaches to further improve short-term wind speed prediction accuracy.

5. Acknowledgment

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6. Author Contribution Statement

Author 1: Provided a contribution to the literature review, conducted experimental studies, and prepared the article. Author 2: Contributed to experimental studies and evaluated the results obtained. Author 3: Contributed to the formation of the idea, the design of the study, and was responsible for spell check and content control of the manuscript.

7. Ethics Committee Approval and Conflict of Interest

Ethics committee permission is not required for this study. Additionally, there is no conflict of interest with any person or institution.

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