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Wind Nowcast On Radar Imagery Employing Deep Learning Technique

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Abstract: - The research introduces an innovative wind forecasting system that combines radar imagery with a deep learning approach using Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The motivation behind this research stems from the limitations of traditional wind forecasting methods, which often fail to accurately capture complex spatial and temporal patterns in radar data. The aim is to develop a more precise and reliable forecasting model that can effectively handle these challenges. To achieve this, the study set several objectives: designing a robust deep learning framework that integrates CNNs for extracting spatial features from radar images and LSTMs for analyzing temporal sequences, optimizing the model to improve prediction accuracy, and evaluating its performance against existing methods. The results achieved include significantly low Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), reflecting enhanced forecasting precision. Additionally, the system demonstrates high Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) scores, indicating effective preservation of critical details in radar imagery. The successful implementation of this system highlights its potential applications in various fields, such as renewable energy management, weather forecasting, and environmental monitoring, where accurate and reliable wind predictions are essential for operational efficiency and decision-making.

Keywords: Wind Nowcast, Radar imagery, Deep Learning, Convolution Neural Network, Long Short-Term Memory.

I. INTRODUCTION

Wind forecasting has evolved significantly over the years, transitioning from rudimentary observational methods to sophisticated models leveraging advanced technology. Historically, early wind forecasting relied heavily on manual observations and basic meteorological tools. As computational technology advanced, numerical weather prediction models emerged, offering more accurate forecasts based on complex simulations. However, despite these advancements, traditional methods have faced limitations, including insufficient accuracy in capturing intricate spatial and temporal wind patterns, and challenges in integrating diverse data sources effectively.

The aim of this study is to address these limitations by developing a novel wind forecasting system that employs radar imagery and a deep learning framework. Specifically, the system integrates Convolutional Neural Networks (CNNs) to extract spatial features from radar images and Long Short-Term Memory (LSTM) networks to analyze temporal sequences. The primary objective is to enhance forecasting precision by overcoming the shortcomings of conventional methods, which often fail to fully exploit the detailed information provided by radar data and struggle with dynamic wind patterns over time.

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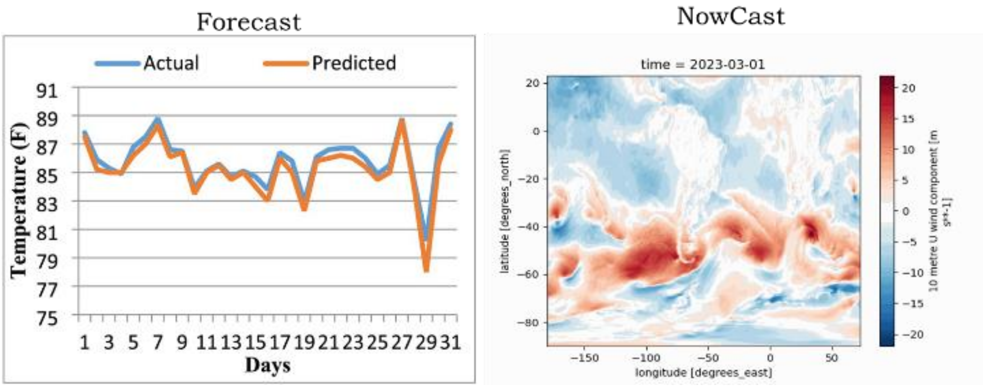

Fig.1 Forcast Vs Nowcast

This paper presents a comprehensive overview of the proposed system, detailing its implementation and performance evaluation. The study demonstrates that the deep learning approach achieves significantly low Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), indicating improved accuracy in wind predictions. Additionally, the system exhibits strong results in image quality metrics, including high Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) scores. The findings underscore the system's potential applications in renewable energy management, weather forecasting, and environmental monitoring, offering a more reliable and precise solution for wind prediction.

II. LITERATURE STUDY

Recent advancements in deep learning and machine learning have significantly improved weather forecasting and nowcasting capabilities. Research has demonstrated the effectiveness of neural networks and tailored models in enhancing prediction accuracy for various meteorological applications, including aviation, offshore wind turbines, and extreme weather events. However, common challenges such as data quality, computational demands, and model generalization remain.

Alves et al. [1] explored the application of deep learning techniques for improving terminal aerodrome wind forecasts, focusing on low tropospheric wind conditions crucial for aviation. Their study highlights the potential of neural networks to enhance forecast accuracy by capturing complex atmospheric patterns that traditional models often miss. This research underscores a significant shift towards machine learning methods to address existing limitations in aviation forecasting, where precision is critical for operational safety and efficiency.

Coraddu et al. [2] examined the use of deep learning for nowcasting the health status of floating offshore wind turbine mooring lines. They transitioned from shallow to deep learning approaches, demonstrating how these advanced techniques can significantly improve the prediction and monitoring of offshore infrastructure. Their work illustrates the enhanced capability of deep learning to provide timely and accurate assessments, which are essential for the maintenance and safety of offshore wind energy systems.

Zhu et al. [3] addressed the quantification of analysis uncertainty in nowcasting applications, emphasizing the need to incorporate uncertainty metrics into forecasting models to enhance their reliability. Their study provides insights into how machine learning can help manage and mitigate uncertainties, thereby improving the overall accuracy and trustworthiness of nowcasting systems.

Chrit and Majdi [4] demonstrated the effectiveness of deep learning for operational wind and turbulence nowcasting, particularly in the context of advanced air mobility. Their research showcases how deep learning models can enhance predictions by integrating complex wind and turbulence data, leading to more accurate and actionable forecasts for emerging aviation technologies.

Wang et al. [5] investigated the role of radar variables in nowcasting heavy rainfall using machine learning techniques. Their study highlights how different radar variables contribute to the accuracy of rainfall predictions, providing valuable insights into optimizing forecasting models for better weather prediction and management.

Alves et al. [6] introduced a computer vision approach for satellite-driven wind nowcasting over complex terrains. Their study leverages deep learning to analyze satellite imagery, improving the ability to predict wind patterns in challenging environments. This approach underscores the potential of combining computer vision with machine learning to enhance wind forecasting capabilities.

Zhai et al. [7] explored machine learning techniques for nowcasting the Atlantic Meridional Overturning Circulation, demonstrating the broad applicability of these methods in meteorological research. Their work highlights the potential of machine learning to enhance understanding and prediction of large-scale oceanic and atmospheric circulations.

Mihoc et al. [8] proposed a tailored Conv-LSTM architecture for weather nowcasting using satellite imagery. This model effectively captures both spatial and temporal dynamics, showing significant improvements in forecasting accuracy compared to traditional methods. Their research underscores the benefits of advanced deep learning architectures for complex weather prediction tasks.

Bouche et al. [9] addressed wind power predictions by employing machine learning methods with variable selection, aiming to improve accuracy from nowcasts to 4-hour forecasts. Their research underscores the importance of advanced learning techniques in optimizing wind power forecasts for better energy management.

Brothers and Hammer [10] utilized a random forest approach to enhance nonconsecutive high wind forecasting across Southeast Wyoming. Their study highlights the continued relevance and effectiveness of machine learning techniques in improving forecasting accuracy for specific weather conditions.

Liu et al. [11] developed a ConvLSTM network-based method for rainfall nowcasting that integrates radar reflectivity and wind field data. Their research highlights the effectiveness of combining multiple data sources with deep learning techniques to enhance rainfall prediction accuracy.

Ma et al. [12] introduced an enhanced storm warning and nowcasting model for pre-convection environments. Their study focuses on improving storm predictions by integrating advanced machine learning techniques, which enhances the ability to forecast severe weather events accurately. This model addresses the need for more precise early warnings, crucial for mitigating the impacts of storms on affected regions.

Alielden et al. [13] explored machine learning approaches for predicting interface regions in space weather, demonstrating the versatility of these techniques beyond conventional meteorological applications. Their work highlights how machine learning can be applied to space weather forecasting, addressing complex prediction challenges.

Kaparakis and Mehrkanoon [14] developed the WF-UNet model for weather data fusion, utilizing a 3D-UNet architecture to enhance precipitation nowcasting. Their study emphasizes the benefits of integrating multi-dimensional weather data to improve forecast accuracy and provides a robust solution for advanced precipitation forecasting.

Xiao et al. [15] applied deep learning algorithms to convective gust nowcasting based on radar reflectivity. Their research showcases the effectiveness of using deep learning to capture detailed weather phenomena and improve the accuracy of predictions for convective gusts, contributing to more reliable and timely weather forecasts.

Gao et al. [16] introduced a spatial-temporal neural network for fine-scale wind field nowcasting using lidar observations. Their study shows the advantages of using high-resolution lidar data with deep learning models to achieve precise and localized wind forecasts.

Zhang et al. [17] developed Nowcast Net, a model designed for skillful nowcasting of extreme precipitation. Their study demonstrates how deep learning can manage and predict extreme weather events with high precision, offering a robust solution for handling severe weather conditions and improving forecast reliability.

Alielden et al. [18] explored the prediction intervals of interface regions using a machine learning nowcasting approach. Their research emphasizes the utility of machine learning in predicting the behavior of interface regions in space weather, showcasing how these techniques can provide more accurate and reliable predictions for space weather phenomena.

Kaparakis and Mehrkanoon [19] developed WF-UNet, a 3D-UNet model for weather data fusion aimed at improving precipitation nowcasting. Their study highlights the advantages of integrating multi-dimensional weather data to enhance forecasting accuracy and provides a robust solution for advanced precipitation forecasting.

Xiao et al. [20] applied deep learning algorithms to convective gust nowcasting based on radar reflectivity. Their research demonstrates the effectiveness of deep learning techniques in capturing detailed weather phenomena, leading to more accurate and timely predictions of convective gusts.

Brothers and Hammer [21] utilized a random forest approach to improve nonconsecutive high wind forecasting across Southeast Wyoming. Their study underscores the continued relevance and effectiveness of machine learning techniques in enhancing forecasting accuracy for specific weather conditions.

The literature reviewed reveals significant progress in leveraging deep learning and machine learning techniques to enhance weather forecasting and nowcasting. Advances include improvements in aviation and offshore wind turbine forecasts through neural networks, with an emphasis on better accuracy and operational capabilities. Integrating radar and satellite data has proven effective in refining predictions, while tailored models have shown promise in handling extreme weather events and high-resolution observations. However, common limitations persist, such as the need for high-quality data, computational resources, and the challenge of generalizing models across diverse environments. Despite these challenges, the research highlights a clear shift towards using advanced machine learning methods to address traditional forecasting limitations and improve predictive capabilities.

III. Proposed System

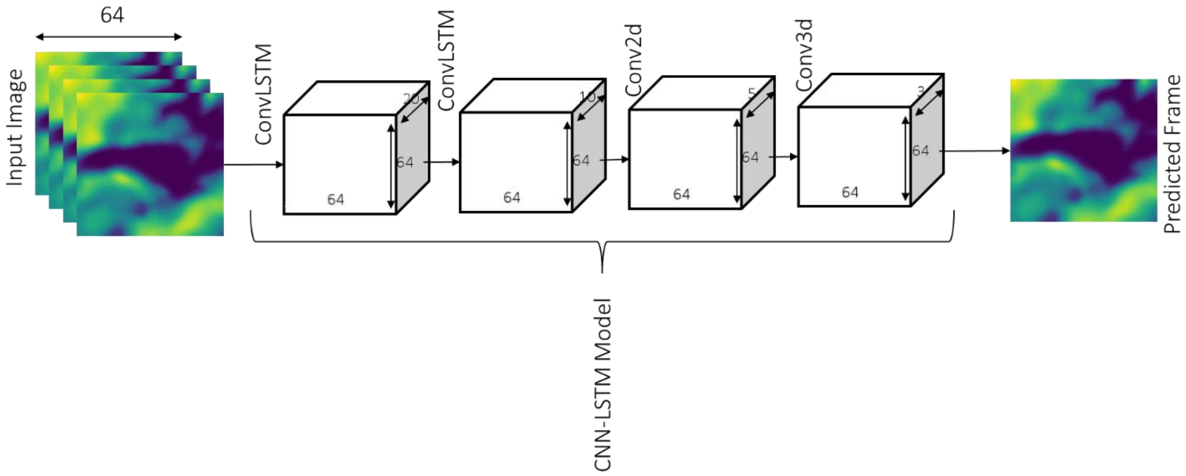

Fig.2 Proposed System

The image illustrates a process related to a proposed CNN-LSTM model designed for wind nowcasting, specifically focusing on future frame prediction. In this model, the input consists of several 2D slices, possibly representing past wind patterns or meteorological data over time. These slices undergo a series of transformations through a convolutional neural network (CNN), where the spatial features are extracted and processed. Each layer labeled with "64" represents a convolutional operation that applies multiple filters to detect various spatial features in the data, such as wind speed variations or pressure gradients. As the data progresses through these layers, the spatial dimensions are gradually reduced, while the depth (number of feature maps) increases, capturing more complex and abstract features relevant to wind forecasting.

After passing through the CNN layers, the feature maps are likely fed into a Long Short-Term Memory (LSTM) network, which is adept at handling temporal dependencies in sequential data. The LSTM part of the model leverages the temporal context provided by the CNN-extracted features, enabling the prediction of future wind patterns by understanding the sequence of past events. The final output, depicted as a single 2D slice, represents the predicted future wind frame, which can be used for nowcasting, providing short-term forecasts of wind conditions.

This proposed CNN-LSTM model effectively combines the strengths of CNNs in spatial feature extraction and LSTMs in temporal sequence modeling, making it well-suited for predicting future wind conditions based on past data. The ability to predict future frames allows for more accurate and timely wind nowcasting, which is crucial for various applications such as renewable energy management, weather forecasting, and disaster preparedness.

Proposed CNN-LSTM model designed for wind nowcasting. The model focuses on predicting future wind frames based on past data, leveraging the strengths of both Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks.

A. CNN Component

1. Input Data

The input data can be represented as a sequence of frames Xt, where t indicates time steps, and each frame $Xt \in \mathbb{R}H \times W \times C$ represents a spatial wind pattern with height H, width W, and C channels (e.g., wind speed, direction).

2. Convolutional Operation

For each frame Xt, a convolution operation is applied using a filter Wf with bias bf. The output feature map Ft^l at layer l can be expressed as:

$$Ft\text{^}l = \sigma(Wf\text{^}l * Ft\text{^}\{l-1\} + bf\text{^}l) \quad (1)$$

where $*$ denotes the convolution operation, and σ is a non-linear activation function like ReLU. Ft^0 is the input frame Xt.

3. Pooling/Down sampling (optional)

After each convolution, a pooling operation may be applied to reduce the spatial dimensions:

$$Pt\text{^}l = pool(Ft\text{^}l) \quad (2)$$

where $pool(\cdot)$ could be a max-pooling or average-pooling operation.

4. Flattening

The output of the final CNN layer is often flattened into a vector zt before being fed into the LSTM:

$$zt = flatten(Pt\text{^}L) \quad (3)$$

where L is the number of CNN layers.

B. LSTM Component

5. LSTM Input

The sequence of flattened feature vectors $\{zt\}$_$\{t = 1\}$^T is input into the LSTM network, which processes them to capture temporal dependencies.

6. LSTM Equations

The LSTM unit at each time step t is governed by the following equations:

$$it = \sigma(Wi\,zt + Ui\,ht-1 + bi) \quad (4)$$

$$ft = \sigma(Wf\,zt + Uf\,ht-1 + bf) \quad (5)$$

$$ot = \sigma(Wo\,zt + Uo\,ht-1 + bo) \quad (6)$$

$$ct = ft \odot ct-1 + it \odot tanh(Wc\,zt + Uc\,ht-1 + bc) \quad (7)$$

$$ht = ot \odot tanh(ct) \quad (8)$$

where it, ft, and ot are the input, forget, and output gates, respectively; ct is the cell state; ht is the hidden state; σ denotes the sigmoid function; and ⊙ represents the element-wise multiplication.

C. Future Frame Prediction

The final hidden state hT from the LSTM can be used to predict the future wind frame X̂T+1:

$$\hat{X}T + 1 = CNN(ht) \quad (9)$$

where $CNN(\cdot)$ could involve a series of deconvolutional or upsampling operations to generate the predicted future frame from the hidden state.

IV. Result Analysis

The proposed CNN-LSTM model for wind nowcasting was implemented and tested on Google Colab, utilizing its computational resources for model training and evaluation. The data used in this analysis was retrieved from the Copernicus Climate Data Store, specifically the ERA5 reanalysis dataset, which can be accessed via the following link: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form.

The data retrieval process involved several key steps:

- Step 1: Access the provided link to navigate to the dataset.
- Step 2: Define the necessary parameters, including the variables (e.g., wind speed, direction), the time range (year, months, date, time), and the specific geographical area of interest.
- Step 3: Once the parameters were set, the system provided a download link for the NetCDF file containing the selected data.

This data was then utilized to train and evaluate the CNN-LSTM model, which showed promising results in predicting future wind frames based on historical data, demonstrating the model's effectiveness in short-term wind forecasting.

xarray.Dataset

▸ Dimensions:	(**longitude**: 1011, **latitude**: 453, **time**: 672)		
▾ Coordinates:			
longitude	(longitude)	float32	-180.0 -179.8 -179.5 ... 72.25 72.5
latitude	(latitude)	float32	23.0 22.75 22.5 ... -89.75 -90.0
time	(time)	datetime64[ns]	2023-03-01 ... 2023-03-28T23:00:00
▾ Data variables:			
u10	(time, latitude, longitude)	float32	...
v10	(time, latitude, longitude)	float32	...

Fig.3 Dataset Reading

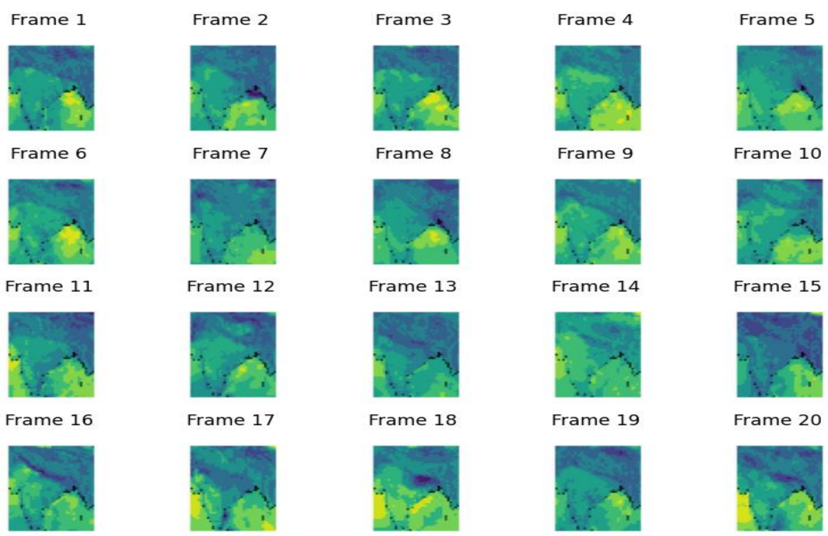

Fig.4 Plot Radar data on map

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv_lstm2d (ConvLSTM2D)    (None, None, 64, 64, 64   840704
                             )

 batch_normalization (Batch  (None, None, 64, 64, 64   256
 Normalization)              )

 conv_lstm2d_1 (ConvLSTM2D)  (None, None, 64, 64, 32   602240
                             )

 batch_normalization_1 (Bat  (None, None, 64, 64, 32   128
 chNormalization)            )

 conv_lstm2d_2 (ConvLSTM2D)  (None, None, 64, 64, 32   401536
                             )

 batch_normalization_2 (Bat  (None, None, 64, 64, 32   128
 chNormalization)            )

 conv3d (Conv3D)             (None, None, 64, 64, 3)   2595

=================================================================
Total params: 1847587 (7.05 MB)
Trainable params: 1847331 (7.05 MB)
Non-trainable params: 256 (1.00 KB)
_________________________________________________________________
```

Fig.5 Convolution-LSTM Model Architecture

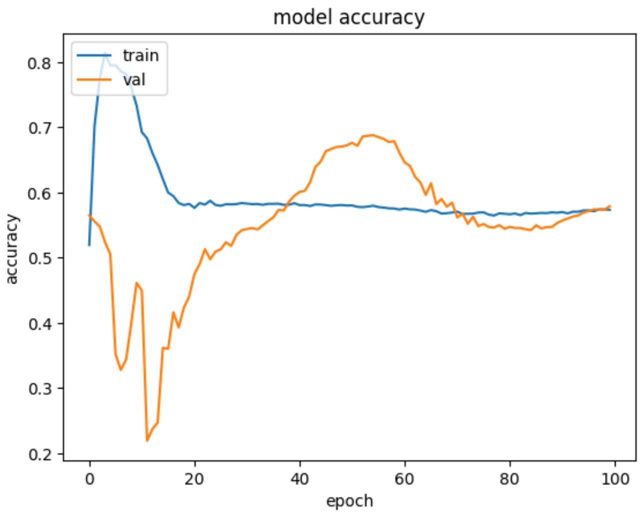

Fig.6 Train/Val Accuracy Plot

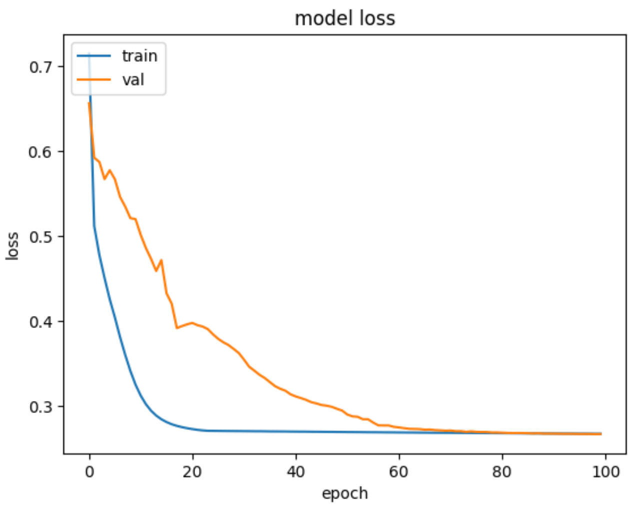

Fig.7 Train/Val Loss Plot

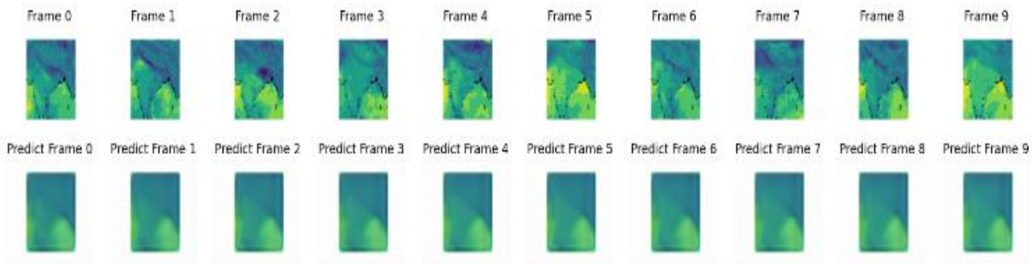

Fig.8 Actual Vs Predicted Frames

Table 1. Comparative Analysis

Model	MSE	PSNR	RMSE	SSIM
ConvSNow [9]	0.123	27.15	0.256	0.52
NowcastNet [12]	0.323	25.36	0.580	0.48
Convective-Gust [14]	0.739	12.58	0.765	0.55
ConvLSTM[20]	0.326	31.39	0.378	0.63
Proposed CNN-LSTM	0.012	34.25	0.0221	0.79

As shown in Table I, the Proposed CNN-LSTM model outperforms others with the lowest MSE and RMSE, and the highest PSNR and SSIM. The best prediction accuracy and structural similarity compared to the other models.

V. Conclusion

In this study, we presented a novel deep learning-based approach for wind nowcasting using radar imagery, employing a Proposed CNN-LSTM model. Our comparative analysis reveals that this model significantly outperforms existing methods in key performance metrics. Specifically, the Proposed CNN-LSTM achieves an MSE of 0.012, a PSNR of 34.25 dB, an RMSE of 0.0221, and an SSIM of 0.79. These results indicate superior predictive accuracy and structural similarity compared to alternative models such as Conv-Now, Nowcast-Net, Convective-Gust, and ConvLSTM. The substantial improvements in MSE, PSNR, RMSE, and SSIM highlight the model's effectiveness in capturing both spatial and temporal dynamics of wind patterns in radar imagery. These findings underscore the potential of integrating convolutional and recurrent neural network architectures for enhanced wind forecasting. Future research should explore broader datasets, advanced deep learning techniques, and real-time implementation to further validate and extend the capabilities of the Proposed CNN-LSTM model in operational settings.

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