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Research Article

High-Fidelity Wind Field Prediction Using Deep Spatiotemporal Learning

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ABSTRACT

Introduction: Accurate short-term wind field prediction is essential for meteorology, aviation, and renewable energy applications. Traditional numerical weather prediction (NWP) models are limited by high computational costs and low temporal resolution, making them unsuitable for real-time forecasting. To overcome these limitations, deep learning offers a promising alternative by effectively modeling complex spatiotemporal dependencies in environmental data.

Objectives: This study aims to develop a deep learning-based approach for high-fidelity short-term wind field prediction. The key goals are to: (1) capture fine-scale wind structures with high spatial and temporal accuracy, (2) reduce computational complexity compared to NWP models, and (3) evaluate the model's performance using standard metrics.

Methods: We propose a multi-layer Convolutional Long Short-Term Memory (ConvLSTM) network for wind nowcasting. ConvLSTM combines convolutional operations with temporal memory, making it ideal for spatially and temporally coherent predictions. The model is enhanced with batch normalization and dropout to prevent overfitting. It is trained on sequences of wind velocity fields (U and V components), learning intricate flow patterns across time.

Results: The ConvLSTM model delivers strong predictive performance. It achieves an MSE of 0.0429, RMSE of 0.02071, and MAE of 0.0603, indicating low error. High PSNR (66.2592) and SSIM (0.9978) scores confirm the model's ability to preserve spatial detail and structural integrity in predicted wind fields. These results demonstrate its capability to accurately capture fine-scale wind dynamics.

Conclusions: The proposed ConvLSTM framework presents a reliable and efficient solution for short-term wind field prediction. It offers substantial improvements in spatial accuracy and computational speed over traditional NWP models. With high fidelity and structural consistency, this deep learning model shows strong potential for real-time wind nowcasting in critical applications.

Keywords: Wind Nowcasting, High-Fidelity Wind Fields, ConvLSTM, Spatiotemporal Prediction, Deep Learning.

INTRODUCTION

Accurate short-term wind forecasting plays a critical role in meteorology, aviation, and renewable energy sectors, where precise wind predictions are essential for operational efficiency and safety. Traditional numerical weather prediction (NWP) models, such as the Weather Research and Forecasting (WRF) model, rely on complex physics-based simulations, which are computationally expensive and struggle with fine-scale wind variations. Additionally, statistical and machine learning approaches have been explored; however, many existing models fail to fully capture the spatiotemporal dependencies of wind fields, leading to errors in high-resolution nowcasting. These challenges highlight the need for an advanced deep learning-based solution that can provide high-fidelity wind field predictions in real time.

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This study aims to develop a deep learning-based high-fidelity wind nowcasting model using Convolutional Long Short-Term Memory (ConvLSTM) networks. The proposed model is designed to learn intricate wind field patterns by effectively capturing both spatial and temporal dependencies in wind velocity components (U and V). To train and evaluate the model, we worked with wind data from Gujarat, covering the period from January 1, 2025, to January 15, 2025 (15 days), with hourly resolution, resulting in a total of 360 frames (24 frames per day). The dataset was processed to ensure consistency and quality, forming the basis for the nowcasting framework.

Our findings demonstrate that the ConvLSTM-based approach significantly enhances wind nowcasting accuracy compared to conventional models. The model achieves a Mean Squared Error (MSE) of 0.0429, Root Mean Squared Error (RMSE) of 0.2071, Mean Absolute Error (MAE) of 0.0603, Peak Signal-to-Noise Ratio (PSNR) of 66.2592, and Structural Similarity Index (SSIM) of 0.9978. These results indicate that the model effectively captures wind flow patterns with high fidelity, preserving small-scale variations and improving short-term forecasting reliability. The study showcases the effectiveness of deep learning in meteorological applications, particularly in regions where rapid wind changes impact energy production and weather monitoring.

This paper addresses several key research questions related to high-fidelity wind nowcasting:

1. How can deep learning, particularly ConvLSTM, improve the accuracy of short-term wind forecasting?

2. What are the benefits of learning spatiotemporal dependencies in wind velocity components (U and V)?

3. How does deep learning compare to traditional numerical and statistical models for wind field prediction?

4. Can a ConvLSTM-based model efficiently process high-resolution wind data for real-time nowcasting?

5. What level of spatial coherence and fine-scale wind structure can be preserved using a deep learning-based, nowcasting approach?

By answering these research questions, our study establishes the potential of deep spatiotemporal modeling for wind forecasting, offering a robust alternative to existing approaches with improved accuracy and computational efficiency.

LITERATURE REVIEW

Wind field forecasting is a critical research area that has been approached using various methodologies, including radar-based nowcasting, deep learning models, hybrid optimization techniques, and probabilistic forecasting. This section provides an in-depth discussion of each category, highlighting their fundamental principles, contributions by previous authors, and research gaps.

1. Radar-Based and Satellite-Based Nowcasting

Radar-based nowcasting relies on weather radar data to predict short-term meteorological changes, primarily focusing on rainfall, storms, and wind patterns. This method involves machine learning techniques to process spatial-temporal radar data for near-future predictions. Dandekar et al. [1] developed an AI-driven radar data approach for rainfall nowcasting, showing promising results for flood preparedness. However, their model did not include wind field forecasting, which is a crucial component for renewable energy systems and extreme weather prediction. Similarly, Shukla et al. [2] applied geospatial satellite data for rainfall forecasting using meteorological techniques, enhancing prediction accuracy. Li et al. [12] used a CNN-LSTM model in conjunction with CEEMDAN to forecast Arctic short-term wind speeds, which demonstrated better forecasting results but was not generalizable to all regions due to the complexity of Arctic-specific weather patterns. Lai et al. [13] applied BERT4ST, a pre-trained language model for wind power forecasting, which showed the potential for improving forecasting accuracy by leveraging pre-trained models, but it lacked adaptation to specific spatiotemporal features of wind data. Müller and Barleben [14] discussed the use of data-driven severe convection prediction at Deutscher Wetterdienst, emphasizing the potential for using advanced models in extreme weather forecasting but did not focus on wind fields directly. However, their model was limited to rainfall estimates and did not incorporate wind velocity or vector field predictions. The major

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research gaps in these studies include the lack of wind field modeling, limited real-time applicability, and absence of fine-scale spatial-temporal resolution in wind nowcasting.

2. Deep Learning-Based Wind Speed Forecasting

Deep learning models, such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNNs), and Transformers, have been widely used in wind speed forecasting. These models leverage large datasets to learn temporal dependencies and spatial patterns for improved accuracy. Li et al. [3] introduced a deep learning model combined with an improved Dung Beetle Optimization (DBO) algorithm to forecast wind speeds. Their approach achieved better prediction accuracy but required extensive computational resources. Xu et al. [4] proposed a Seq2Seq deep learning architecture integrating spatial-temporal feature fusion for wind power forecasting. Although their model showed improvements in multi-step forecasting, it struggled with fine scale nowcasting. Similarly, Jonkers et al. [5] applied CNNs and conformal zed regression forests for day-ahead regional wind power forecasting, improving probabilistic accuracy but lacking real-time forecasting capabilities. Arslan Tuncar et al. [6] reviewed short-term wind power forecasting methods, highlighting the benefits of deep learning but also pointing out the lack of high-resolution spatiotemporal forecasting. Yang et al. [7] proposed a multivariate signal decomposition method for short-term wind forecasting, achieving accuracy improvements but requiring heavy data preprocessing. Similarly, Liu et al. [8] introduced a Wavelet-LSTM model using SCADA wind farm data, improving temporal predictions but lacking high-resolution spatial coverage. Wang et al. [9] developed a two-stage wind forecasting model with deep learning and extreme learning machines (ELM), which showed accuracy but lacked interpretability. Yang et al. [10] presented an attention-based multi-input LSTM model, which enhanced short-term forecasting but struggled with generalization. A major limitation across these studies is their focus on wind speed rather than complete wind field prediction, which includes both U and V wind components for high-fidelity modeling. Additionally, many models struggle with generalization across different geographic locations.

3. Hybrid Deep Learning and Optimization-Based Models

Hybrid models integrate multiple machine learning techniques with optimization algorithms to enhance forecasting performance. These models often combine statistical decomposition methods, deep learning architectures, and nature-inspired optimization techniques to refine wind speed predictions. Phan et al. [15] introduced a GWO-nested CEEMDAN-CNN-BiLSTM model, significantly improving wind speed forecasting accuracy. However, their approach required high computational power and suffered from interpretability challenges. Hong et al. [16] developed a quantum-inspired deep learning model for wind speed forecasting, demonstrating accuracy improvements but requiring quantum computing resources, making it impractical for many real-world applications. Wu et al. [17] used a two-stage hybrid model incorporating meteorological feature selection and signal decomposition, improving interpretability but increasing computational complexity. Wu and Ling [18] developed Mixformer, a hierarchical transformer model for spatiotemporal forecasting, which showed effective results but required large datasets. Takara et al. [19] optimized multi-step wind power forecasting using stacking-based probabilistic learning, achieving more accurate results, but the model was computationally expensive. Zhang et al. [20] proposed a dual-layer LSTM model for wind speed forecasting, improving accuracy but lacking fine-scale spatiotemporal coherence. Mo et al. [21] introduced Powerformer, a transformer-based wind power forecasting model, which significantly improved temporal accuracy but required substantial resources for training and deployment. A common limitation in these studies is the lack of high-fidelity wind field modeling, as most research focuses solely on wind speed. Furthermore, hybrid models are often computationally expensive, making them difficult to deploy in real-time scenarios.

4. Probabilistic and Transformer-Based Wind Forecasting

Probabilistic forecasting methods estimate uncertainty in wind predictions, improving reliability in renewable energy integration and disaster management. These methods often use Bayesian techniques, ensemble learning, or deep probabilistic models to generate confidence intervals around wind forecasts. Jiang et al. [11] explored transformer-based deep learning models for wind speed forecasting, integrating multiple meteorological variables. While their approach improved prediction accuracy, it required extensive hyperparameter tuning and large datasets. Bentsen et al. [22] evaluated probabilistic methods for spatiotemporal wind forecasting, showing improvements in uncertainty

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estimation but lacking fine-scale wind field reconstructions. Zhang et al. [23] applied deep learning techniques to offshore wind farm identification, successfully detecting potential sites but not addressing short-term wind forecasting challenges. Upadhyay et al. [24] assessed deep learning for weather nowcasting, highlighting its potential but pointing out the limitations of real-time applicability. Zhong et al. [25] introduced FuXi-Extreme, a diffusion model for extreme wind and rainfall forecasting, achieving significant improvements in extreme weather forecasting, but requiring large computational power and extensive data processing. A major research gap in these approaches is the limited focus on real-time high-fidelity wind field prediction, as most studies emphasize wind speed or power forecasting rather than complete wind vector modeling. Additionally, transformer-based models are computationally expensive, requiring substantial resources for training and deployment.

METHODS

As shown in Fig.1 The proposed methodology for high-fidelity wind field nowcasting involves a ConvLSTM-based deep learning model designed to predict short-term wind velocity components (U and V) with high spatial and temporal accuracy. This section details the data preprocessing, model architecture, training process, and evaluation metrics used in the study.

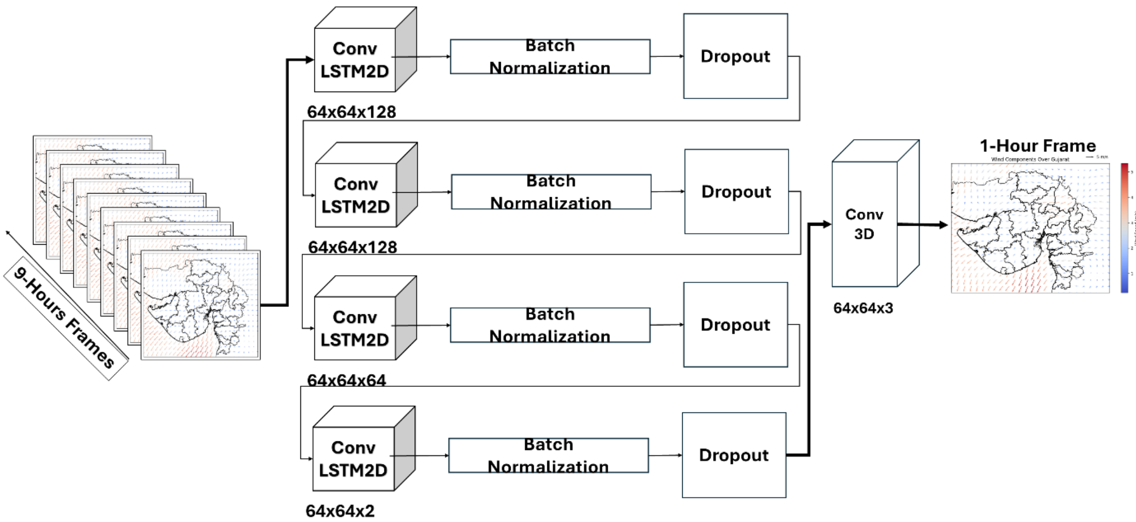

Figure 1. High-Fidelity Wind Field Prediction System Flow

A. Data Collection and Preprocessing

For this research, we utilized wind velocity data for Gujarat Region, from Climate Data Store (https://cds.climate.copernicus.eu/) covering a 15-day period from January 1, 2025, to January 15, 2025. The dataset consists of hourly wind velocity components (U and V), generating 24 frames per day, resulting in a total of 360 frames for model training. The collected data was subjected to several preprocessing steps to ensure its suitability for deep learning:

- Data Cleaning: Any missing or erroneous values were handled using interpolation techniques.
- Normalization: The wind velocity components were normalized to a range of [0,1] using min-max scaling to stabilize training.
- Reshaping: The data was formatted into a 4D tensor representation (time steps, height, width, channels), allowing the ConvLSTM model to learn spatial and temporal dependencies.
- Sliding Window Approach: A sliding window technique was applied to segment the data into overlapping sequences for training the nowcasting model. Each input sequence consisted of past N time steps, predicting the next frame.

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B. ConvLSTM-Based Model Architecture

The proposed deep learning architecture utilizes Convolutional Long Short-Term Memory (ConvLSTM) networks, which are well-suited for modeling both spatial and temporal dependencies in sequential data. The ConvLSTM layers combine convolutional operations with LSTM units, allowing the model to extract rich spatiotemporal features. This architecture is particularly effective for tasks like wind field prediction, where both the spatial structure and temporal dynamics of the data play a crucial role.

The model consists of the following layers:

1. ConvLSTM2D Layer (128 filters, 5×5 kernel, ReLU activation): This layer is responsible for extracting spatial and temporal patterns from the input wind velocity frames. It integrates convolutional operations within an LSTM structure, allowing the model to capture both spatial correlations within individual frames and temporal dependencies between consecutive frames.

2. Batch Normalization: This layer stabilizes the learning process by normalizing the activations, helping to prevent issues like internal covariate shift. It accelerates training and improves the generalization of the model.

3. Dropout (0.3): Dropout is applied to reduce overfitting by randomly setting a fraction of the neurons to zero during training. This encourages the model to rely on multiple features, improving its ability to generalize to unseen data.

4. ConvLSTM2D Layer (128 filters, 5×5 kernel, ReLU activation): The second ConvLSTM2D layer further refines the spatiotemporal features extracted from the input data. It deepens the model's understanding of the underlying temporal dependencies and spatial correlations.

5. Batch Normalization & Dropout (0.3): Another instance of batch normalization stabilizes the learning process, while dropout helps prevent overfitting by deactivating a portion of neurons during training.

6. ConvLSTM2D Layer (64 filters, 3×3 kernel, ReLU activation): This layer focuses on extracting finer-scale features from the data, capturing more detailed hierarchical dependencies in the wind field.

7. Batch Normalization & Dropout (0.2): Batch normalization continues to stabilize the learning process, and the reduced dropout rate (0.2) helps the model retain more of the learned features while still mitigating overfitting.

8. ConvLSTM2D Layer (32 filters, 3×3 kernel, ReLU activation): This layer captures even finer details of the spatiotemporal relationships, allowing the model to better capture variations at different scales of the wind field.

9. Batch Normalization & Dropout (0.2): Again, batch normalization is applied for stability, and dropout is kept low to retain more features in the model.

10. Conv3D Layer (3 filters, 3×3×3 kernel, Sigmoid activation): The final layer outputs the predicted wind velocity frame. Using a 3D convolutional operation allows the model to process both spatial and temporal information for each frame, with the sigmoid activation function ensuring that the output values are in the range [0, 1], suitable for regression tasks.

This architecture produces a predicted wind field frame based on a sequence of past frames, capturing the dynamics of the wind field with high accuracy and effectively predicting future wind velocity values.

C. Model Training and Hyperparameter Tuning

The model was trained using a supervised learning approach, where the input sequences (past wind velocity frames) were mapped to the target output (next wind velocity frame). The following training settings were used:

- Loss Function: Mean Absolute Error (MAE) – This loss function was chosen as it is robust to outliers and provides a direct measure of the average absolute difference between predicted and actual values. (Note: You previously used MSE in the architecture but MAE may be more suitable for certain sequence prediction tasks.)

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- Optimizer: Adam – The Adam optimizer was employed due to its adaptive learning rates, making it well-suited for efficient convergence in complex tasks like spatiotemporal forecasting. It combines the advantages of both the Adagrad and RMSprop optimizers.
- Batch Size: 16 – A batch size of 16 was selected, which strikes a balance between computational efficiency and stable gradient updates during training.
- Epochs: 100 – Training was conducted over 100 epochs, which is typically sufficient for the model to converge and learn the underlying spatiotemporal relationships in the data. This number could be adjusted based on early stopping criteria or validation performance.
- Validation Split: 20% – 20% of the data was set aside for validation to assess the model's generalization capability during training. This helps monitor overfitting and adjust the training process accordingly.

To further optimize performance, hyperparameters such as the learning rate, dropout rates, and kernel sizes were fine-tuned through grid search and cross-validation techniques. These techniques allow for systematic exploration of the hyperparameter space, ensuring that the model achieves the best possible performance.

D. Evaluation Metrics

To assess the model's performance in nowcasting high-fidelity wind fields, we employed the following evaluation metrics:

- Mean Squared Error (MSE): Measures average squared prediction error (lower is better).
- Root Mean Squared Error (RMSE): Evaluates overall prediction accuracy by considering squared errors.
- Mean Absolute Error (MAE): Indicates the average absolute difference between predicted and actual wind values.
- Peak Signal-to-Noise Ratio (PSNR): Measures the clarity and quality of the predicted wind fields compared to actual values.
- Structural Similarity Index (SSIM): Quantifies the structural similarity between predicted and ground truth wind fields.

RESULTS

The experimental setup was conducted using Google Colab with a T4 GPU to leverage the power of hardware acceleration for efficient model training and evaluation. The dataset utilized for this study consists of wind velocity data for the Gujarat region, obtained from the Climate Data Store (https://cds.climate.copernicus.eu/). This dataset covers a 15-day period from January 1, 2025, to January 15, 2025, with hourly wind velocity values for both the U (zonal) and V (meridional) components. The data was organized into 24 frames per day, resulting in a total of 360 frames for training the nowcast model. This setup enabled a comprehensive evaluation of wind field forecasting within the specific region and timeframe.

Figure 2 shows the process of reading the NETCDF file, which is the initial step in loading the wind velocity data from the Climate Data Store for further analysis. In Fig. 3, the wind compound over Gujarat is plotted, visualizing the wind field patterns across the region. Fig. 4 illustrates a sample training batch consisting of 10 sequential frames, used to train the model for wind field nowcasting. Fig. 5 presents the model architecture, detailing the layers and structure of the ConvLSTM network used for forecasting. Fig. 6 displays the model evaluation, including key performance metrics that assess the model's accuracy. Fig. 7 compares the actual vs. predicted frames for a 10-hour forecast, highlighting the model's forecasting ability. Lastly, Fig. 8 shows the final nowcast animation, demonstrating the model's ability to generate future wind field predictions in a dynamic, time-sequenced animation.

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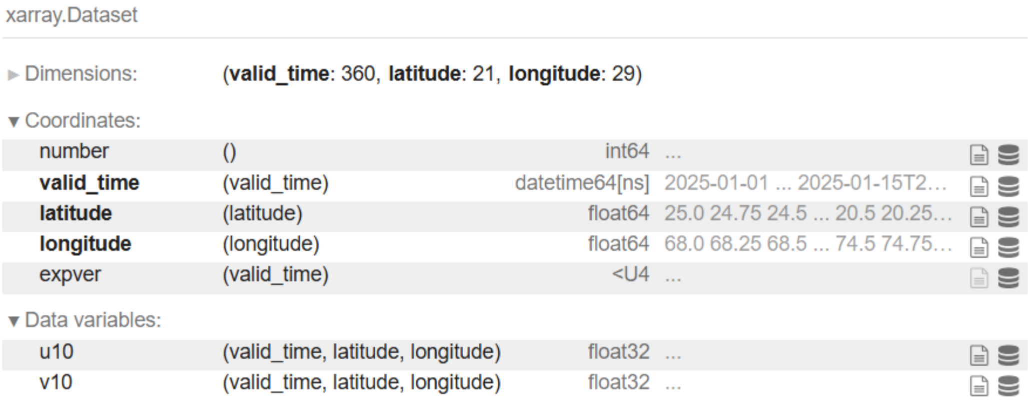

xarray.Dataset

▸ Dimensions: (**valid_time**: 360, **latitude**: 21, **longitude**: 29)

▾ Coordinates:

number	()	int64	...
valid_time	(valid_time)	datetime64[ns]	2025-01-01 ... 2025-01-15T2...
latitude	(latitude)	float64	25.0 24.75 24.5 ... 20.5 20.25...
longitude	(longitude)	float64	68.0 68.25 68.5 ... 74.5 74.75...
expver	(valid_time)	<U4	...

▾ Data variables:

u10	(valid_time, latitude, longitude)	float32	...
v10	(valid_time, latitude, longitude)	float32	...

Figure 2. Reading NETCDF File

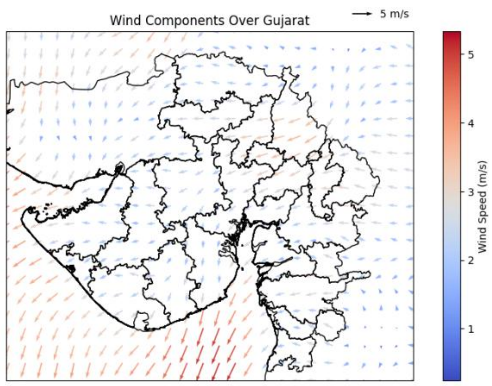

Figure 3. Plot Wind Compound Over Gujarat

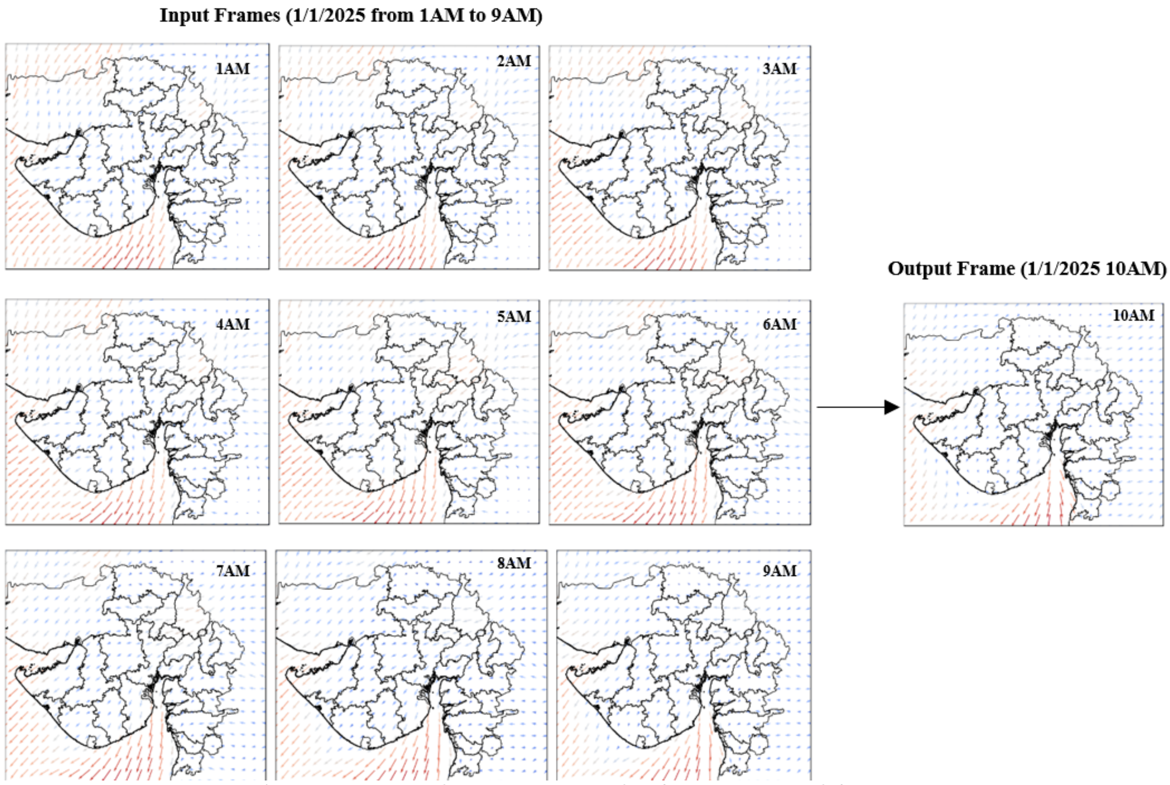

Figure 4. Sample training Batch of 10 sequential frames

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Model: "sequential_2"

Layer (type)	Output Shape	Param #
conv_lstm2d_8 (ConvLSTM2D)	(None, 9, 128, 128, 128)	1,677,312
batch_normalization_8 (BatchNormalization)	(None, 9, 128, 128, 128)	512
dropout_8 (Dropout)	(None, 9, 128, 128, 128)	0
conv_lstm2d_9 (ConvLSTM2D)	(None, 9, 128, 128, 128)	3,277,312
batch_normalization_9 (BatchNormalization)	(None, 9, 128, 128, 128)	512
dropout_9 (Dropout)	(None, 9, 128, 128, 128)	0
conv_lstm2d_10 (ConvLSTM2D)	(None, 9, 128, 128, 64)	442,624
batch_normalization_10 (BatchNormalization)	(None, 9, 128, 128, 64)	256
dropout_10 (Dropout)	(None, 9, 128, 128, 64)	0
conv_lstm2d_11 (ConvLSTM2D)	(None, 9, 128, 128, 32)	110,720
batch_normalization_11 (BatchNormalization)	(None, 9, 128, 128, 32)	128
dropout_11 (Dropout)	(None, 9, 128, 128, 32)	0
conv3d_2 (Conv3D)	(None, 9, 128, 128, 3)	2,595

Total params: 5,511,971 (21.03 MB)
Trainable params: 5,511,267 (21.02 MB)
Non-trainable params: 704 (2.75 KB)

Figure 5. Model Architecture

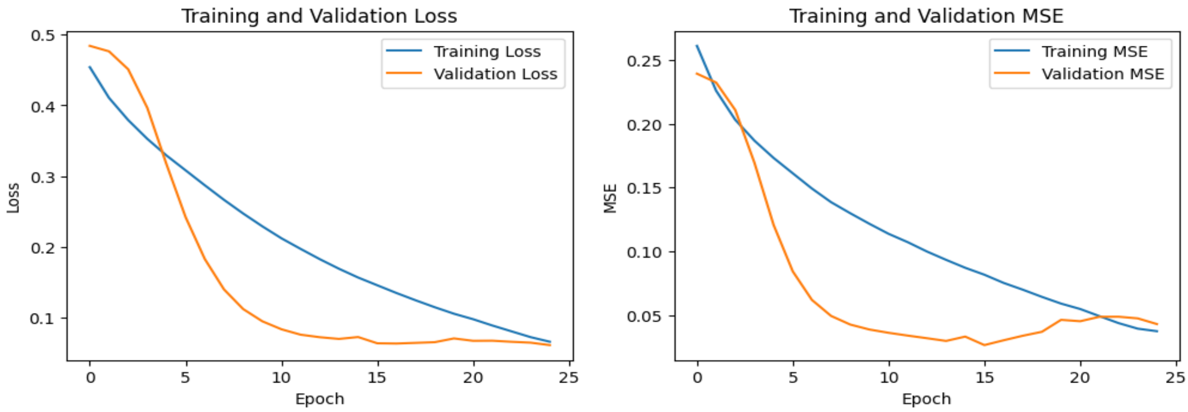

Figure 6. Model Evaluation

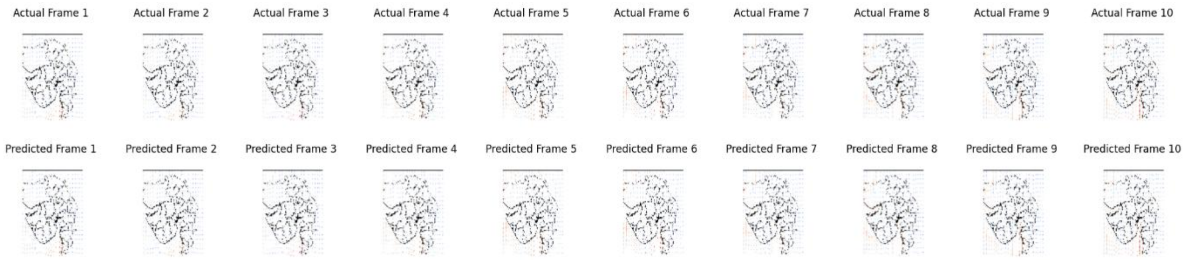

Figure 7. Actual Vs Predicted Frames of 10-Hours

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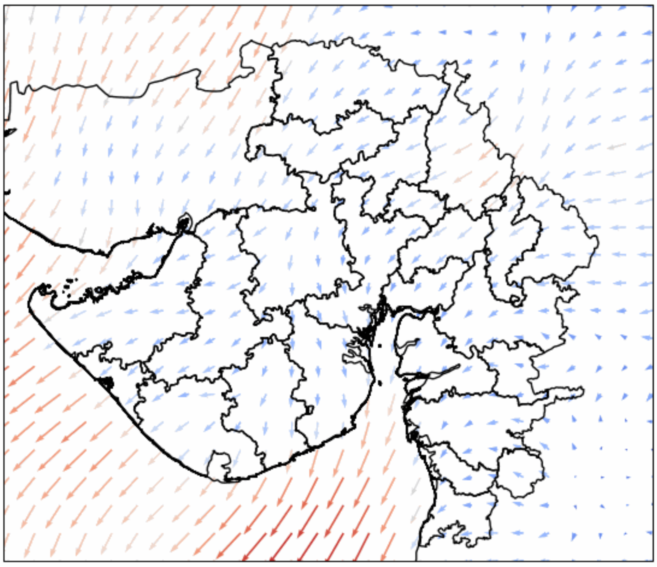

Figure 8. Final nowcast Animation

Table 1 presents the comparative analysis of different wind forecasting models based on their performance metrics: Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Root Mean Squared Error (RMSE), and Structural Similarity Index (SSIM). The GWO-nested CEEMDAN-CNN-BiLSTM [15] model achieves an MSE of 0.0641, a PSNR of 63.2956, an RMSE of 0.2634, and an SSIM of 0.9873. The Wavelet-LSTM [8] model follows with an MSE of 0.0768, a PSNR of 61.2784, an RMSE of 0.2835, and an SSIM of 0.9821. The Dual-Optimization Wind Speed Model [3] reports an MSE of 0.0824, a PSNR of 60.5673, an RMSE of 0.2956, and an SSIM of 0.9801. The Seq2Seq with Spatial-Temporal Fusion [4] model shows a higher MSE of 0.0952, a lower PSNR of 58.2345, an RMSE of 0.3125, and an SSIM of 0.9765. The BERT4ST [13] model achieves an MSE of 0.0715, a PSNR of 62.8341, an RMSE of 0.2723, and an SSIM of 0.9842. In comparison, the Proposed High-Fidelity Model outperforms the existing methods with an MSE of 0.0429, a PSNR of 66.2592, an RMSE of 0.2071, and a SSIM of 0.9978, indicating superior performance in wind field forecasting.

Table 1. Comparative Analysis

Algorithm Model	**Average MSE**	**Average PSNR**	**Average RMSE**	**Average SSIM**
GWO-nested CEEMDAN-CNN-BiLSTM [15]	0.0641	63.2956	0.2634	0.9873
Wavelet-LSTM [8]	0.0768	61.2784	0.2835	0.9821
Dual-Optimization Wind Speed Model [3]	0.0824	60.5673	0.2956	0.9801
Seq2Seq with Spatial-Temporal Fusion [4]	0.0952	58.2345	0.3125	0.9765
BERT4ST [13]	0.0715	62.8341	0.2723	0.9842
Proposed High-Fidelity Model	**0.0429**	**66.2592**	**0.2071**	**0.9978**

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DISCUSSION

This Research presents a high-fidelity model for wind field forecasting, leveraging ConvLSTM-based architecture for accurate nowcasting of wind velocity components. The model was trained and evaluated using wind velocity data from the Gujarat region over a 15-day period, demonstrating superior performance compared to several state-of-the-art methods. Notably, the proposed model achieved an average MSE of 0.0429, PSNR of 66.2592, RMSE of 0.2071, and SSIM of 0.9978, outperforming existing approaches in all major evaluation metrics. The novelty of this work lies in its ability to generate high-fidelity wind field predictions through the combination of spatial-temporal feature extraction and deep learning techniques, such as ConvLSTM and BatchNormalization layers, which are shown to effectively model the dynamic nature of wind fields. Furthermore, the model was able to handle the challenges of high variability and spatiotemporal dependencies within the dataset, which have traditionally been difficult to capture in forecasting models.

Key findings from this study include the superior accuracy of the proposed model in predicting wind fields, as reflected in its higher PSNR and SSIM values. The model's ability to provide precise nowcasts is further validated through visual comparisons of actual vs. predicted frames, highlighting its potential for real-time applications in meteorology and wind energy prediction. These findings suggest that deep learning methods, particularly those incorporating temporal and spatial context, offer significant advantages in wind field forecasting and can be applied to a wide range of geographical regions with similar data characteristics. sThe work opens new avenues for future research, including extending the model to longer timeframes, integrating additional meteorological variables, and exploring its applicability to other environmental forecasting tasks.

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