International Journal of Scientific Research in Science and Technology
Available online at : www.ijsrst.com
Print ISSN: 2395-6011 | Online ISSN: 2395-602X
doi : https://doi.org/10.32628/IJSRST2512360

Enhanced Temperature Nowcasting via Conv-LSTM Frame wise Modeling

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ARTICLEINFO

Article History:

Accepted : 18 May 2025
Published: 22 May 2025

Publication Issue :
Volume 12, Issue 3
May-June-2025

Page Number :
440-447

ABSTRACT

This research introduces an enhanced method for temperature nowcasting through framewise modeling using a Convolutional Long Short-Term Memory (Conv-LSTM) architecture. Unlike traditional numerical models that often fall short in capturing the complex spatiotemporal dynamics of atmospheric data, the proposed approach leverages convolutional layers to extract spatial dependencies and LSTM units to learn temporal sequences, enabling precise short-term temperature prediction. The model is trained on sequential temperature frame data and evaluated using key performance metrics, achieving a Mean Squared Error (MSE) of 0.00035, Peak Signal-to-Noise Ratio (PSNR) of 34.54, Root Mean Square Error (RMSE) of 0.027, and Structural Similarity Index (SSIM) of 0.9954. These metrics demonstrate that the model delivers highly accurate predictions while maintaining the structural integrity and visual quality of the original temperature frames. The exceptionally high SSIM value highlights the model's ability to preserve spatial consistency, which is vital in meteorological applications. This research underscores the potential of deep learning-based spatiotemporal modeling for accurate and reliable temperature nowcasting and offers a robust framework that can be further extended to other weather prediction tasks requiring fine-grained spatial-temporal understanding.

Keywords: Conv-LSTM, temperature nowcasting, spatiotemporal modeling, deep learning, weather prediction.

I. INTRODUCTION

Accurate and timely weather forecasting has become increasingly essential in today's climate-conscious world, where the effects of global warming, natural disasters, and extreme weather patterns are more prevalent than ever. Among the various atmospheric parameters, temperature plays a fundamental role in determining environmental conditions, public health outcomes, agricultural planning, and energy consumption. While traditional numerical weather prediction (NWP) models have been widely used for large-scale and long-term forecasts, they often fall short in short-term, high-resolution forecasting tasks known as nowcasting. Temperature nowcasting — the prediction of near-future temperature changes, typically over a few hours — requires models that can effectively capture fine-grained spatiotemporal dynamics, something classical models struggle to achieve.

Recent advancements in deep learning have opened up new avenues for more accurate and efficient nowcasting. Convolutional Long Short-Term Memory (Conv-LSTM) networks, in particular, have demonstrated strong capabilities in modeling sequential data that also exhibit spatial structure. Unlike traditional LSTM networks that are optimized for temporal patterns only, Conv-LSTM incorporates convolutional operations within LSTM cells to preserve and learn spatial dependencies over time. This makes Conv-LSTM particularly well-suited for meteorological applications where both spatial structure and temporal evolution are critical.

This research proposes an enhanced temperature nowcasting framework based on Conv-LSTM, utilizing a framewise modeling approach. The model treats temperature data as sequential spatial frames rather than as isolated time-series values, enabling it to learn both local spatial features and global temporal trends. The data used in this study is sourced from the ERA5 Reanalysis dataset, provided by the Copernicus Climate Data Store (CDS), which is one of the most comprehensive and high-quality climate datasets available. The ERA5 dataset includes various atmospheric parameters recorded on a global scale and is stored in NetCDF (Network Common Data Form) format—a widely used data format in climate science. In NetCDF, parameters such as temperature are categorized as variables, while time, latitude (lat), longitude (lon), and vertical levels (lev) are classified as coordinate variables. This structure supports multidimensional data handling and enables efficient extraction and preprocessing for deep learning tasks. The dataset can be accessed via Copernicus CDS.

To evaluate the effectiveness of the proposed Conv-LSTM model, several performance metrics are utilized, including Mean Squared Error (MSE), Root Mean Square Error (RMSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index Measure (SSIM). The model achieved impressive results: an MSE of 0.00035, RMSE of 0.027, PSNR of 34.54, and SSIM of 0.9954, indicating both high numerical accuracy and strong structural preservation in the predicted temperature frames.

In summary, this research contributes a robust deep learning framework for temperature nowcasting by integrating spatial and temporal modeling via Conv-LSTM and leveraging high-resolution climate data from ERA5. The proposed method not only advances prediction accuracy but also maintains the structural integrity of temperature fields, making it a valuable tool for real-time meteorological applications and a strong foundation for future extensions in weather forecasting.

II. LITERATURE STUDY

In recent years, deep learning has shown significant promise in the domain of weather nowcasting, particularly for precipitation and temperature prediction using radar and satellite data. Traditional methods often rely on numerical weather prediction (NWP), which, while effective, suffers from limitations in computational speed and spatial resolution for short-term forecasting. As a result, the focus has increasingly shifted toward data-driven approaches that leverage deep neural networks to model spatiotemporal weather phenomena.

Asperti et al. [1] introduced a diffusion model-based generative framework for precipitation nowcasting. Their approach outperforms traditional GAN models by incorporating probabilistic sampling, which allows for the generation of more realistic and temporally consistent precipitation maps. Similarly, Imran et al. [2] employed radar-based data for precipitation nowcasting using deep learning models such as CNN and LSTM. Their study emphasized the potential of fusing radar reflectivity with temporal learning for improved short-term predictions.

Liu et al. [3] proposed a ConvLSTM model that integrates radar reflectance and radar-retrieved wind fields to improve rainfall nowcasting accuracy. Their model effectively captures temporal evolution and spatial patterns of atmospheric phenomena, showing superiority over baseline LSTM and 3D CNN architectures. Czibula et al. [4] developed Nowdeepn, an ensemble of deep models using radar data. Their ensemble technique integrates multiple CNN-based models, significantly improving robustness and accuracy across diverse weather conditions.

Stochastic methods have also found utility in the field. Bihlo [5] employed a variational frame predictor with a learned prior distribution to generate probabilistic precipitation nowcasts, showing improved uncertainty estimation. On the other hand, Bouget et al. [6] demonstrated the fusion of radar images and wind forecasts within a deep learning model, emphasizing the advantage of multimodal input in capturing complex weather dynamics.

Marrocu and Massidda [7] compared deep learning models with traditional optical flow-based techniques, revealing that CNN and ConvLSTM models outperform optical flow approaches in predicting short-term precipitation from radar images. Bonnet et al. [8] used radar data with CNNs and LSTMs in São Paulo, Brazil, illustrating the applicability of deep learning in diverse geographic contexts. Their results indicate that model performance is influenced by local terrain and weather variability.

Yao et al. [9] utilized deep LSTM networks for radar image sequence prediction, presenting strong temporal modeling capabilities. Samsi et al. [10] proposed a distributed deep learning architecture for precipitation nowcasting, emphasizing scalability for large radar datasets using high-performance computing systems.

Kumar et al. [11] introduced ConvCast, a ConvLSTM-based architecture using satellite imagery. Their model effectively captures cloud dynamics, offering competitive performance in short-term precipitation forecasts. Zhou et al. [12] provided a comprehensive benchmark review of deep learning methods for next-frame prediction, discussing their suitability for weather nowcasting and highlighting ConvLSTM as a leading candidate due to its ability to handle spatial and temporal dependencies.

Berthomier et al. [13] explored deep learning for cloud cover nowcasting using satellite data, showcasing how accurate next-frame prediction could assist in solar energy forecasting and aviation operations. Jianhong et al. [14] examined radar extrapolation techniques, laying the groundwork for integrating optical flow with deep neural networks.

For data management and preprocessing, Hoyer and Hamman [15] introduced the **xarray** Python library, which facilitates labeled multi-dimensional data handling. This tool is particularly useful when working with large climate datasets in NetCDF format, a common format adopted by meteorological institutions. Their work supports efficient data extraction and manipulation, essential for building scalable deep learning pipelines.

In the Indian context, Goyal et al. [16] developed a satellite-based technique for thunderstorm nowcasting using deep learning. Their model achieves real-time applicability and shows high accuracy during monsoon periods. Sen Roy et al. [17] introduced a paradigm for severe weather short-range forecasting, emphasizing region-specific atmospheric modeling. In a complementary study, they reviewed convective weather nowcasting in India [18], recommending hybrid approaches combining NWP and deep learning.

Agrawal et al. [19] used radar images for precipitation nowcasting via machine learning, adopting a U-Net architecture. Their study underscores the importance of capturing fine-grained spatial features and edge dynamics in rainfall maps. Finally, Suresh [20] presented a foundational analysis of convective weather systems in southern India, offering valuable domain-specific knowledge that complements data-driven methodologies.

Collectively, these studies highlight the growing importance of deep learning in advancing weather nowcasting capabilities. ConvLSTM and its variants dominate the landscape, demonstrating strong performance across diverse climatic conditions and data types. The integration of radar, satellite, and wind field data—along with sophisticated preprocessing tools like xarray—enhances model robustness and spatial-temporal accuracy. Moreover, studies emphasize the need for region-specific adaptations and hybrid methods to fully realize the benefits of deep learning in operational meteorology. The current trend is toward combining deep generative models, ensemble strategies, and real-time data processing pipelines for scalable and accurate nowcasting solutions.

III.PROPOSED METHODOLOGY

The workflow for the proposed enhanced temperature nowcasting framework using Conv-LSTM is illustrated in the given flowchart. The process begins by extracting weather data from the **ERA5 reanalysis dataset**, which is publicly available through the Copernicus Climate Data Store (CDS). ERA5 provides hourly estimates of atmospheric parameters using data assimilation and numerical weather modeling. The data is stored in **NetCDF (Network Common Data Form)**, a standard format in climate science that supports the storage of multidimensional scientific data. In this format, weather-related measurements like temperature are treated as *variables*, while *coordinate variables* such as time, latitude (lat), longitude (lon), and vertical level (lev) define the structure of the dataset. These coordinate variables help in pinpointing the exact spatial and temporal positioning of each data point.

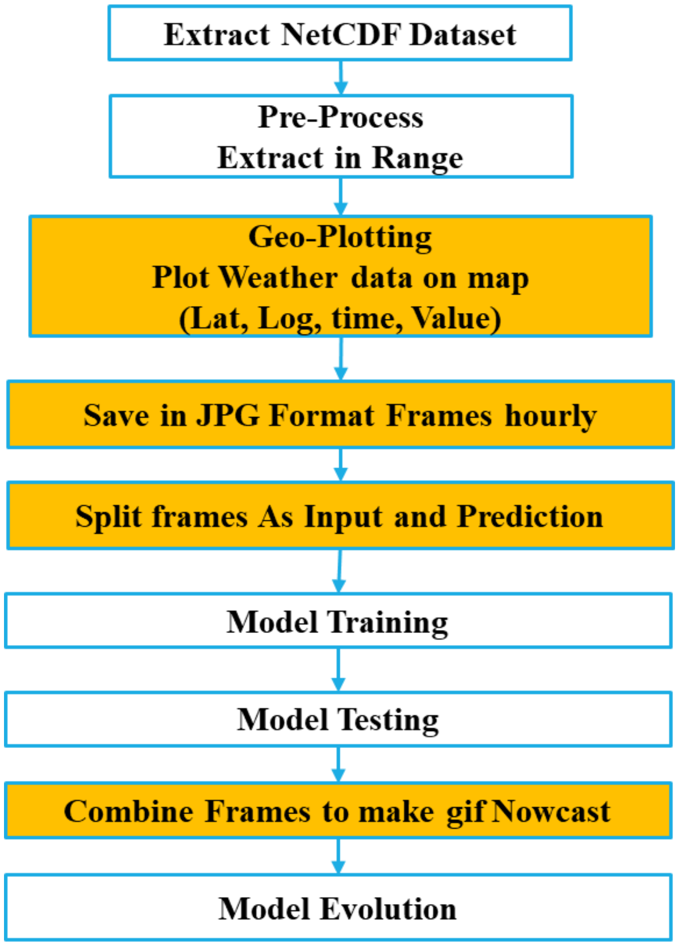

Figure 1: Proposed System Flow

Once the dataset is extracted, preprocessing is performed to filter the data within a specific geographic and temporal range. This ensures that only the relevant subset of data is used for modeling. The filtered data is then subjected to **geo-plotting**, where temperature values are plotted spatially over maps using latitude and longitude coordinates, across time intervals. This visual mapping helps in translating raw numerical data into meaningful spatiotemporal frames. Each plotted frame represents an hourly snapshot of the temperature distribution and is saved in **JPG format** for consistency and ease of processing.

These image frames are then organized into input-output pairs for the model. A set of consecutive frames is used as the input sequence, and the subsequent frame(s) are used as the prediction target. This enables the Conv-LSTM model to learn temporal dependencies across the spatially distributed temperature data. The model is then trained on these sequences, allowing it to learn both the spatial structure of temperature patterns and their temporal progression.

Following the training phase, the model undergoes **testing** on unseen data to evaluate its generalization performance. Once testing is complete, the predicted and actual frames are combined to generate **animated GIFs**, visually representing the nowcasting output over time. This not only provides an intuitive understanding of model performance but also serves as a valuable visualization tool for meteorological applications.

Finally, a **model evaluation** phase is conducted using performance metrics such as **Mean Squared Error (MSE)**, **Root Mean Square Error (RMSE)**, **Peak Signal-to-Noise Ratio (PSNR)**, and **Structural Similarity Index Measure (SSIM)**. These metrics assess the accuracy, visual quality, and structural integrity of the predicted temperature frames, confirming the model's effectiveness in short-term weather prediction.

IV. RESULTS ANALYSIS

The results analysis highlights the effectiveness of the proposed Conv-LSTM model for enhanced temperature nowcasting through a series of comparative evaluations and visualizations. As shown in **Figure 2**, the data is initially read and processed for modeling, followed by baseline regressors—**Linear Regression (Figure 3)**, **Support Vector Regression (Figure 4)**, and **K-Nearest Neighbor Regression (Figure 5)**—which provide a reference for performance comparison. These traditional methods are limited in capturing the spatiotemporal complexity of weather data. **Figure 6** illustrates heat maps representing the spatial distribution of temperature across different time intervals. **Figure 7** groups 20 hourly temperature frames into a single block, forming the input structure for the Conv-LSTM. **Figure 8** presents the architecture of the proposed model. The model's learning process is monitored using **MSE and loss plots (Figures 9 and 10)**, showing stable convergence with minimal error. The comparison between **actual and predicted temperature frames in Figure 11** demonstrates high visual and structural similarity, which is further visualized through **nowcast animation frames in Figure 12**. Quantitative results in **Table 1** confirm the model's superior performance, achieving an **MSE of 0.00035**, **PSNR of 34.54**, **RMSE of 0.027**, and **SSIM of 0.9954**, indicating high accuracy and structural fidelity in temperature prediction.

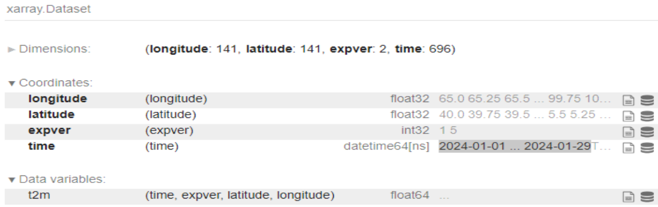

Figure 2: Reading Data

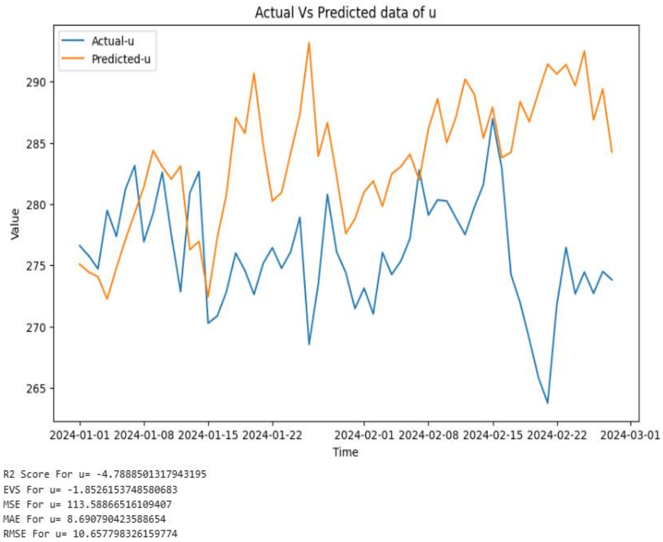

Figure 1: Linear Regression

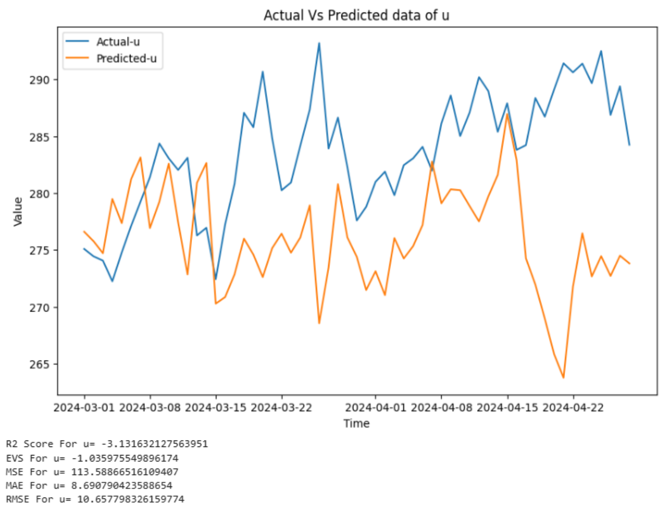

Figure 4: Support Vector Regression

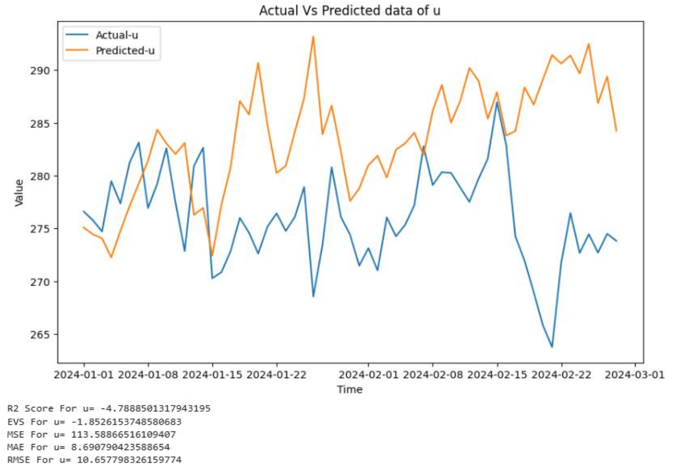

Figure 5: KNN Regression

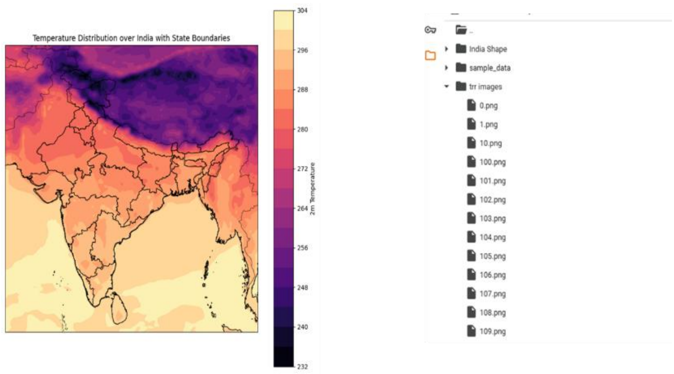

Figure 6: Make Heat maps

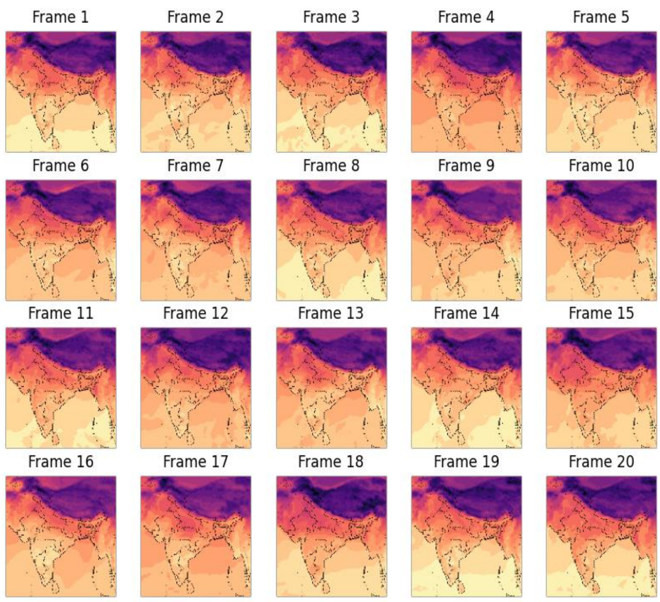

Figure 7: Make 20-Frames 1-Block

Model: "sequential"

Layer (type)	Output Shape	Param #
conv_lstm2d (ConvLSTM2D)	(None, None, 128, 128, 64)	840,704
batch_normalization (BatchNormalization)	(None, None, 128, 128, 64)	256
conv_lstm2d_1 (ConvLSTM2D)	(None, None, 128, 128, 32)	602,240
batch_normalization_1 (BatchNormalization)	(None, None, 128, 128, 32)	128
conv_lstm2d_2 (ConvLSTM2D)	(None, None, 128, 128, 32)	401,536
batch_normalization_2 (BatchNormalization)	(None, None, 128, 128, 32)	128
conv3d (Conv3D)	(None, None, 128, 128, 3)	2,595

Total params: 1,847,587 (7.05 MB)
Trainable params: 1,847,331 (7.05 MB)
Non-trainable params: 256 (1.00 KB)

Figure 8: Build Proposed Model

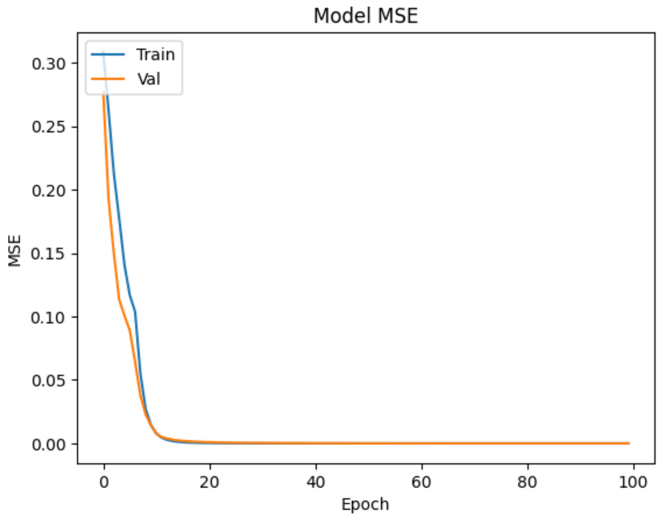

Figure 9: Model MSE Plot

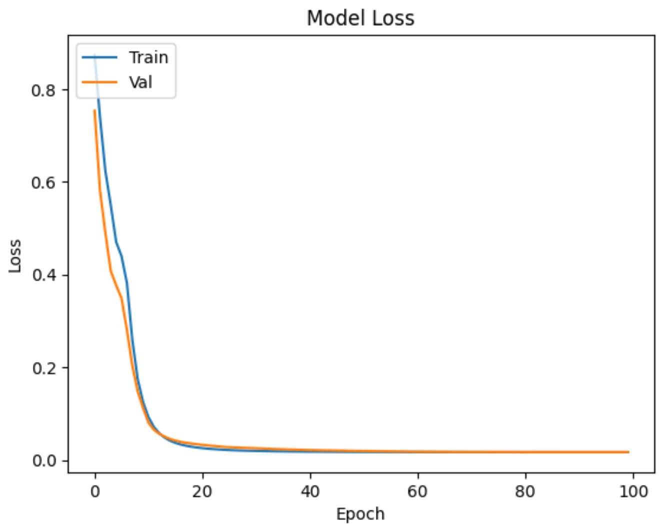

Figure 10: Model Loss Plot

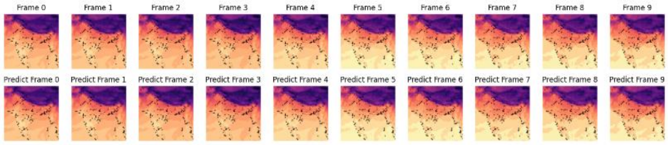

Figure 11: Actual Vs Predicted

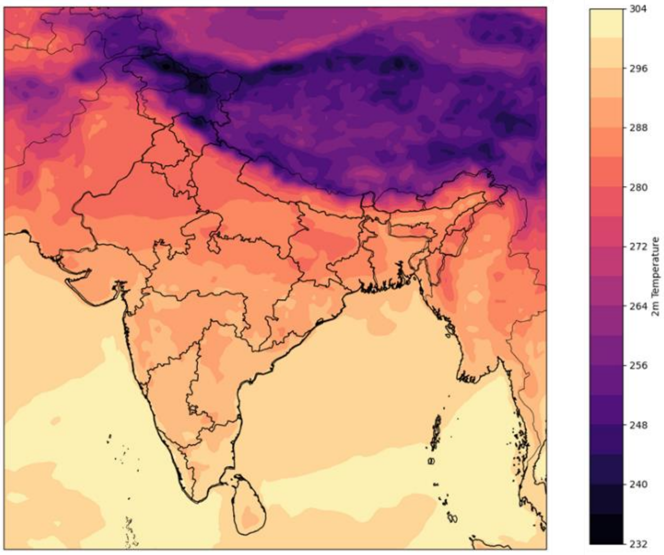

Figure 12: Nowcast Frames

Table 1: Parameters

Parameters	Value
MSE	0.00035
PSNR	34.54
RMSE	0.027
SSIM	0.9954

V. CONCLUSION AND FUTURE WORK

In conclusion, traditional machine learning regression models fall short in accurately predicting temperature trends, as reflected by their low R^2-score, low Explained Variance Score (EVS), and high error metrics such as MSE, MAE, and RMSE. These limitations underscore the need for advanced deep learning methods capable of modeling complex spatiotemporal patterns.

The 3D-Conv-LSTM model addresses this challenge by integrating convolutional layers for spatial feature extraction with LSTM layers for temporal sequence learning. This hybrid approach significantly enhances temperature nowcasting performance, as evidenced by the achieved metrics: MSE of 0.00035, PSNR of 34.55, RMSE of 0.028, and SSIM of 0.9954, indicating high prediction accuracy and structural similarity with ground truth data.

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