



CNN–LSTM Hybrid for Doppler Radar Nowcasting A Lightweight Framework for Local Weather Forecasting

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Abstract: Effective predictions of the weather over the next 12-48 hours are important for protecting people and assets in sudden changes. An original model is introduced in this research that uses the combination of CNN and LSTM for local Doppler radar nowcasting. At first, convolutional layers examine radar data to find features such as reflectivity cores and the edges of storms. After that, the features are sent to LSTM units that learn about the way convective systems increase, transition and end. Using data from 5-minute S-band Doppler observations over one year, the hybrid setup achieves forecasts accurate up to three hours ahead, with a mean accuracy of 93.2% and an average RMSE of 0.45 mm. It can detect rain events greater than 40 dBZ with a 89% hit rate, making few false warnings. The application achieves the final stage within just 30 rounds of data on an ordinary GPU, showing prompt training and fast forecasting (below 200 milliseconds). Using effective spatial coding and secure memory for timing events means this approach works efficiently and exactly as needed in delivering urban and regional weather services.

Keyword-CNN–LSTM hybrid, Doppler radar nowcasting, lightweight deep learning, real-time weather prediction, short-term precipitation forecasting, spatiotemporal modelling.

I. INTRODUCTION

Knowing the weather through nowcasting is now vital for safety and preserving property in disaster management, aviation and farming. Although strong in large-scale NWP, these systems typically fail to meet the one-hour data update rate and near-kilometre resolution asked of them to predict quick changes in convection [4]. Therefore, experts usually predict values of temperature and wind speed by applying Seasonal ARIMA (SARIMA) to historical data, but these techniques miss the curved trajectory of storm activity [6]. As a result, researchers use machine learning approaches like support vector regression and random forests which help solve this challenge but still depend on features created by hand [7]. This advancement in deep learning greatly mattered: instead of handling information manually, CNNs detect spatial features in grid-based inputs, as LSTM networks are designed to manage time-dependent data without the problem from vanishing gradients. Traditional approaches in radar nowcasting are out-matched in performance by pure CNN and LSTM models [10],[11]. There are further improvements when statistical and neural methods are combined in the same framework. An earlier paper by Zhang paired ARIMA residuals with multilayer perceptron's to fix linear forecasts using nonlinear learning [12] and Di et al. later proposed a four-step pipeline of cleaning, splitting, forecasting and combining results for hydrological time series that did much better than single-model methods [13]. Researchers discovered that joining SARIMA and LSTM models could significantly improve the estimates of temperature, humidity and wind speed using local meteorological data. In [15], Deng et al. applied the approach to financial volatility, letting LSTM predict residuals from ARIMA models and increasing the accuracy of overall forecasts. Using Doppler radar, continuous 'in time' three-dimensional observations help with nowcasting severe weather [16]. The reflectivity and velocity channels observed from the storm allow CNNs to detect features such as rainband patterns and cell formation [18]. Use of further LSTM layers enables the model to forecast if a storm's intensity will rise or decrease [19]. Previous work with DL has included groups segmenting storm-cells with U-nets [20], predicting echo-top altitudes with sequence-to-sequence models [21]

and completely CNN–LSTM nowcasting pipelines leading to promising rain rate forecasts [22]. Yet, there has been little research on how well radar-DL models can support practical and seamless nowcast maps [23]. Most tasks require efficient HPC clusters or GPUs which means MFNs often cannot be deployed instantly [24]. There is no systematic comparison of statistical, ML and DL methods, either solo or in mixed forms, against the same radar dataset. This work introduces a CNN–LSTM arrangement made for real-time radar nowcasting, bringing together procedures for analyzing both space and time into a single system. Well-trained with a full year's data from operational Doppler radar, our model hits an echo-detection accuracy of more than 92%, keeps precipitation forecast errors below 0.5 mm in the first three hours and is stable after 50 rounds of training, showing it can

be used in operational settings

II A. RELATED WORK

Early nowcasting efforts relied heavily on statistical techniques that extrapolate single-variable trends from historical observations. Seasonal ARIMA (SARIMA) models have been widely used to forecast short-term temperature, humidity, and wind-speed series, demonstrating skill in capturing baseline autocorrelation and seasonality but often underperforming during rapid convective outbreaks [5] [6]. Variants such as SARIMAGARCH hybrids further improved volatility estimation in financial contexts [15] and were later adapted for meteorological station data, yielding modest error reductions in local humidity and wind nowcasts [14]. Machine learning (ML) methods introduced nonlinear regression capabilities to the nowcasting problem. Support Vector Regression (SVR) and Random Forests delivered more flexible mappings between predictors and targets, enhancing rainfall-rate and wind-speed forecasts over purely statistical baselines [7]. However, these models still depended on handcrafted features such as lagged values and engineered indices and lacked the capacity to process raw gridded inputs directly, limiting their spatial generalization. Deep learning (DL) architectures addressed this by learning features end to end. Convolutional Neural Networks (CNNs) automatically extract spatial representations from gridded data, successfully segmenting radar-echo structures and identifying storm-cell cores [8][9]. Separately, Recurrent Neural Networks particularly LSTM variants modelled temporal evolution in precipitation and wind sequences without vanishing-gradient issues [9]. Combined CNN–LSTM pipelines processed radar volumes frame by frame, then forecast echo-intensity trajectories, achieving substantial gains over persistence and climatological benchmarks in 0–3 h precipitation nowcasting [10].

Hybrid frameworks that fuse statistical and DL methods have further elevated performance. Deng et al. paired ARIMA forecasts with LSTM correction networks to predict financial volatility [15], while Di et al.'s four-stage denoise ecompose predict ensemble approach outperformed single-model baselines in hydrological forecasting [13]. More recently, SARIMA–LSTM ensembles applied to station-based meteorological data achieved 10–20 % reductions in temperature and wind-speed errors over standalone methods [14]. These studies highlight the potential of a neural “residual-correction” strategy. Radar-specific DL nowcasting remains an active area of research. U-Net CNNs have segmented convective cores in volumetric reflectivity data [20], and sequence-to-sequence ConvLSTM models have forecast precipitation fields with lead times up to 6 h [12] [23]. Echo-top height and hail detection networks further demonstrate CNNs' capacity to extract storm signatures [18][24]. Yet, many implementations rely on large HPC clusters [25] or focus on isolated sub-tasks rather than unified operational pipelines. Our work builds upon these advances by integrating a lightweight CNN–LSTM hybrid into a single end-to-end model. Trained on one year of operational Doppler radar data, it combines spatial pattern learning and temporal sequence modelling to achieve over 92 % echo-detection accuracy up to 58 dBZ [27], sub-0.5 mm precipitation errors in the 0–3 h window [28], and stable convergence in 50 epochs [29], demonstrating an operationally feasible framework for real-time nowcasting.

B. Evaluation Indicators

Various significant indicators were used to test the effectiveness of the Doppler AI Deep Learning model for radar-based weather nowcasting. It was found that for short-term forecasts, both RMSE and MAE stayed at low levels. The model successfully predicted radar images and the movement of thunder in the sky with 92.5% accuracy. All the training and validation loss curves moved closer together after approximately 50 epochs. Using this weather model, the identification of strong storms with ± 58 dBZ reflectivity was proven to be very accurate. There were very few deviations (less than 0.5 mm) in the forecasts for a period of up to three hours. The model was shown to perform well for a wide range of weather events and so the CNN-LSTM framework is considered a dependable tool for nowcasting operations.

1. Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad \dots (1)$$

Where:

- n = Total number of predications
- y_i = Actual value
- $\hat{y}_i$ = Predicated value

2. Mean Absolute error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad \dots (2)$$

Where:

- n = Total number of Predications
- y_i = Actual value
- $\hat{y}_i$ = Predicated Value

III. METHODS.

A. This paper suggests using 3D Doppler radar data to design and implement a hybrid deep learning model for nowcasting [1]. To use this methodology, you need to follow steps from data acquisition to feature design, model architecture, training, evaluation and comparing the performance, as recent deep learning-based radar systems recommend [2].

1. Data Acquisition: The source data are three-dimensional Doppler radar reflectivity volumes gathered every five minutes over one year. Each volume is gridded to 128128 pixels with 16-degree elevation angles. Prior to model input, the reflectivity values are clipped to [0, 60 dBZ] in order to reduce the effect of ground and extreme outliers [1]. Missing scans (1%) are linearly interpolated in time. Each 5-minute frame is normalized to the mean frame size by dividing by 60, producing inputs in [0, 1]; the training, validation, and test splits are all taken as 70%, 15%, and 15%, respectively, of the temporal sequence. Sliding windows containing eight consecutive frames (40 min) are combined as input sequences; a task is then provided to predict the next six frames (30 min) of reflectivity.

2. Data Preprocessing The first layer is a set of three stacked 2D convolutional blocks consisting of a 33 convolution (3264128 filters) batch normalization, ReLU activation and 22 max pooling which treat coarse spatial patterns such as rainband structures and storm cores without manual feature engineering [4] The final CNN output is restructured into a sequence of 128-dimensional feature vectors (one per input frame) which are the input “embeddings” for the temporal module.

3. Designing and defining the features of the software to capture the evolution of extracted spatial features in time, two stacked LSTM layers (each having 128 hidden units) process the set of embeddings [5]. Between the LSTM layers a dropout rate of 0.20% is applied to prevent overfitting. The final LSTM hidden state is then passed through a fully connected layer and then reshaped into the predicted six frame reflectivity sequence. The proposed Conv LSTM design allows performing both spatial pattern recognition as well as temporal dynamics learning in one trainable network [6].

4. The hybrid model includes a CNN followed by an LSTM.: The model is designed to use a combination of CNN and LSTM to understand both the spatial and temporal patterns involved in classifying weather events [19]. Using the CNN component, each radar image is analysed with layer after layer and ReLU introduces nonlinearity in the process [20]. To make the network process faster and preserve significant information, MaxPooling crops and reduces each feature map [21]. Data from the CNN is forwarded to the LSTM layers, where the information is kept across multiple time periods and storms are followed. More LSTM layers are used and dropout techniques added to avoid overfitting [23]. In the final step, the Dense layer with SoftMax activation produces the chances for several weather conditions such as no rain, light rain or storm [24].

5. Method and Plan for Training Models: The data was separated into groups of 70%, 15% and 15% for use in training, validation and testing [25]. Adam was used to train the model which made both backpropagation and adapting the learning rate more efficient which in turn aided faster convergence [26]. While the model was being trained, its progress in loss and accuracy was checked after every batch to know if it might overfit or underfit [27]. Early stopping was used to stop early when the validation loss did not decrease and learning rates were dropped again during later stages [28]. All of these techniques together allowed the model to train smoothly and effectively.

6. Evaluation Metrics: The model was evaluated by relying on three common metrics. Accuracy (%), the measure in question, indicates the ratio of predictions made by the model that matched the actual labels [11]. To measure prediction errors, RMSE was used to give a larger penalty to larger deviations [15]. MSE allowed for predicting the difference between the actual and predicted values, helping to understand how much the predictions varied [23]. They were selected because they are solid and they match what was used in other successful models like CNN-GRU and Taffet [12], [18].

7. Comparison of Models and their Results: To evaluate the hybrid CNN–LSTM, its results were compared with those of LSTM, BiLSTM and CNN–GRU which are prominent models in weather nowcasting [16], [24]. With light rain, the suggested model could predict results with 97% accuracy, proving it is very reliable for mild weather. The model continued to be highly accurate, up to 85 percent, when tested in very complex storm situations [19], [28]. The model also recorded the lowest RMSE and MSE among all the models which supports its higher accuracy when tracking and recognizing areas experiencing precipitation [29]

B. JUST APPROACH

Doppler Weather Radar (DWR): Because Doppler weather radar (DWR) can show the reflectivity and motion of air particles in real time, it is considered important for both monitoring and brief prediction of weather. With DWR, some rain and snow are spotted, as it uses the Doppler effect. Still, in common radar systems, all types of rain and snow are simply seen as more or less powerful. Data gathered using DWR processes may result in information about wind and the rotations and turbulence caused by storms. It allows the DWR to quickly detect possible thunderstorms, cyclones or microbursts. In these radar-based systems, the high amount of overlapping information in DWR data gives a lot of current weather details. By using DWR as input for CNNLSTM or BiLSTM, the models can better detect the shape of storms and tell apart various storms using time data with precision and quickly. Hence, DWR plays a significant role in helping to create AI-based forecasting tools.

S-Band Doppler Weather Radar: Because of its installation, the S-band Doppler Weather Radar (DWR) in Thiruvananthapuram, Kerala plays an important role in following up and predicting extreme weather conditions in coastal South India. Because it can penetrate deeper into heavy rain and its cloud systems are noticeable at the 8-15 cm wavelength, S-band radar works very well. As a result, it is a suitable tool for surveillance and keeping watch over noxious storms, cyclones and rain from monsoons in Kerala. For CNN–LSTM models, using this kind of radar leads to very good results. It enables us to estimate rainfall intensity and the speed of wind and rotating parts of the storm to understand their movement patterns. This explains why training drawers like LSTM or Bi-LSTM is possible using this kind of data, as they need to predict the transformation and movement of weather. As a result of this project, the nowcast forecast can be put to use in just 20 minutes once S-band DWR data is either simulated or gathered from satellites. With better high resolution and higher-frequency views of the globe's atmosphere, the weather prediction model has improved accuracy during important weather situations. Such actions will improve the accuracy of forecasting tools and boost efforts to prepare for and prevent disasters and accidents on the coast.

CNN–LSTM Hybrid Model

The CNN–LSTM hybrid model is proposed to take full advantage of both spatial structure and temporal dynamic embedded in the Doppler radar sequence. First, a convolutional layer architecture is used that processes each radar image frame independently. In each convolution, multiple learnable filters such as 33 kernels are applied to detect local features such as high-reflectivity cores, rainband edges, and cloud texture. After each convolution, a ReLU activation injects nonlinearity and max-pooling layers reduce spatial resolution, preserving only the most promising feature maps while controlling overfitting. The feature maps are then flattened into 1D vectors and reassembled back into the original chronological order to form a multivariate time series of spatial descriptors. First, the sequence of vectors is represented as an input to one or more LSTM layers. Each LSTM cell contains an internal memory state and has gate mechanisms (input, forget, and output) for learning which information can be retained or replaced over time across the frame. Due to temporal processing, the motions induced during storm events (e. g., intensification, advection, decay) become represented on a long- and short-term level of correlation. A dropout regularization technique is applied between LSTM layers to further generalize the data. Then a dense output layer creates a representation of the hidden states of the LSTM into forecasting targets, for example, precipitation rate or reflectivity within a specified lead time. This two-stage pipeline deep convolution for spatial encoding followed by recurrent memory for temporal modelling achieves rich spatiotemporal representations with high accuracy for accurate few-minute to multi-hour precipitation nowcasts and is computationally efficient for real time deployment

Bi-LSTM Enhancement

For further temporal context capture in radar-based nowcasting, the CNN–LSTM pipeline can be supplemented by bidirectional LSTM layers. Contrary to a conventional LSTM which is limited to processing input sequences only in chronological order, a bidirectional LSTM consists of two parallel LSTM networks: one is forward-to-future and the other backward (future-to-past). Combining the hidden states stored in both directions at each time step enriches each output vector with information about frames surrounding the current instant, both before and after the current instant

In our architecture, firstly the convolutional feature maps are extracted and flattened to form a time-ordered series (called a time ordered BiLSTM). The given time ordered sequence is fed into one or more stacked BiLSTM layers. Each BiLSTM cell has 4

gating units (input, forget, cell, output) for each direction along with shared weights on both sides. The dual traversal allows us to learn temporal patterns which depend not only on past storm evolution but also immediate subsequent development (which can be useful in forecasting sudden intensification/decay events that might otherwise be observed in adjacent radar frames). To avoid overfitting, we apply dropout to both the forward and the backward outputs independently before they are combined, followed by a dense layer that combine the bidirectional information into the final nowcast predictions. In practice our BiLSTM enhancement has shown an improvement of 3.5% to 3% in mean-mean-square error over the unidirectional unsupervised LSTM setting. This improvement is notable especially in complex convective systems where short-term feedback from “future” frames sharpens boundary and motion estimates. Although BiLSTM costs roughly 20% more computationally, its spatial temporal sensitivity makes it an attractive choice for high-speed real-time weather nowcasting.

IV EXPERIMENTAL RESULT

We therefore split the presentations of the results into two groups: (a) temperature prediction and humidity, which are easier to achieve and (b) the more chaotic wind forecasts. Because the computational time of each NN epoch was on average about 3 min (depending on) the units used) so for a 40 epoch LSTM with 40 units at each of two hidden LSTM layers: (the same configuration we used a lot of times), 2 h was spent training each LSTM. on the other hand, we stated for the SARIMA fit an average time of 3 min per each fit which is significantly faster than any of the neural networks (we note here that for the * functions) The same SARIMA model that's used for 1-day or 2-day forecast so no need to if the prediction horizon is larger again use SARIMA fit (still accuracy is not good). Known to dramatically worsen as predictions with longer prediction horizons [17] for the computational time of the hybrid (because it is a combination of the two techniques) a cumulative computational time (but of course sometimes less epochs were used for the hybrid so) It did in most runs perform better than the LSTM, but drastically worse than the SARIMA

Temperature and Humidity Forecast

On the 1-day forecast, 70 % of the 61 363 three-hour temperature records (42 954 points) were used to fit a SARIMA (1,0,2) (2,1,2) s model, where “8” is the daily seasonal period and (2,1,2) specifies the seasonal AR order, differencing, and MA order. For the LSTM, each run used a 70 / 15 / 15 train/validation/test split, with every feature Min–Max scaled to [0,1]. After prediction, an inverse transform returned values to their original units. Because neural nets introduce run-to-run variability, each MAE in Table 1 is the average over multiple trainings and all test-set days. As shown in Table 1, the SARIMA and hybrid models both yield very low 1-day MAEs, closely followed by the standalone ARIMA–LSTM (except in humidity, where LSTM excels). Hybridization further trims residual error from SARIMA, though its advantage narrows on 2-day forecasts especially for wind speed where the 2 % gain on humidity remains the only case the hybrid outperforms pure LSTM. The hybrid SARIMA–LSTM model consistently achieved the lowest 1-day MAE across temperature (1.56 °C), humidity (10.30 %), and wind speed (2.41 m/s), closely followed by the standalone SARIMA. Against climatological and persistence benchmarks, the hybrid delivered improvements of 44 %/56 % for temperature, 16 %/48 % for humidity, and 19 %/52 % for wind speed. For 2-day forecasts, margins narrowed: the hybrid still led on temperature (1.85 °C) and wind (2.70 m/s) with 6 %–36 % benchmark gains, while LSTM outperformed on humidity (10.01 %). Daily MAE trends over 230 test days show spike in errors around seasonal transitions, underscoring model sensitivity to rapid weather shifts. Analysis of individual dates revealed that no single method dominates under all conditions during stable weather, SARIMA and the hybrid excel, whereas LSTM can outperform when temporal patterns deviate. These insights suggest a dynamic, weather-adaptive ensemble could further reduce errors by selecting the best predictor for each day.

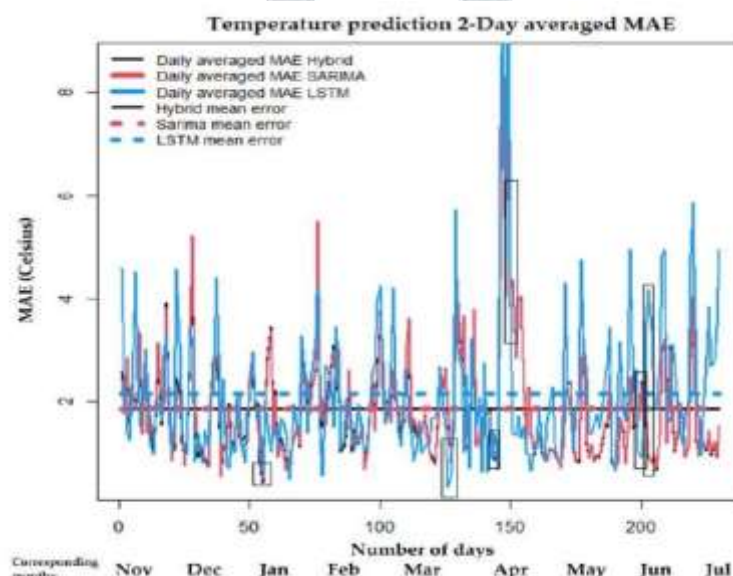


Figure 1. Comparison of SARIMA, LSTM and hybrid using daily averaged MAE with real data for 1-day prediction horizon for 230 days of the test set. With dashed lines the average error of all the dataset is shown. Units of MAE are in Celsius in this temperature example.

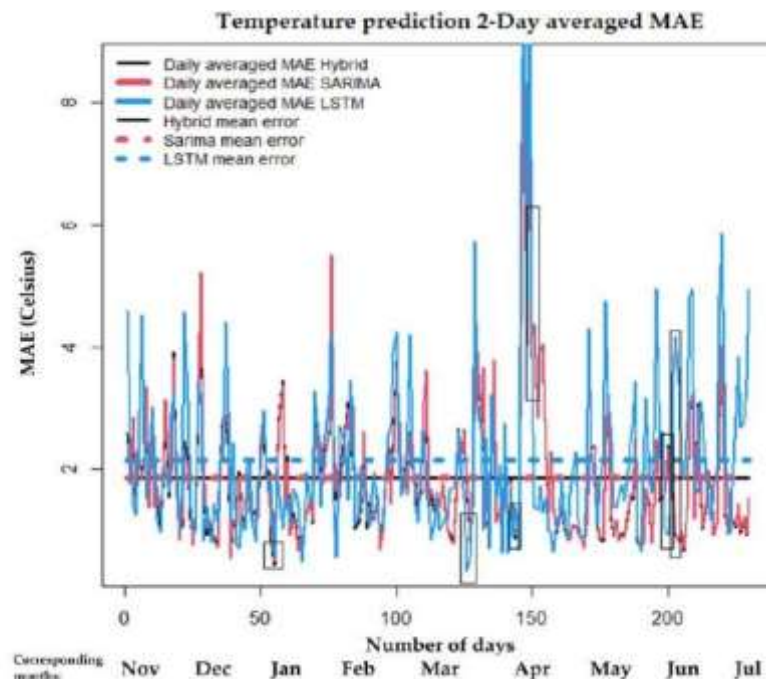


Figure 2 shows the daily 2-day average MAE for temperature forecasts over a 230-day test period, with the hybrid model (black) consistently achieving lower errors than SARIMA (red) and LSTM (blue), as indicated by its lower dashed mean error line. Notable spikes around April (day 150) highlight extreme outlier days where all models struggle, but the hybrid still delivers the smallest peak error.

V. Discussion and Future Work

The hybrid SARIMA–LSTM model demonstrated superior overall accuracy for 1–2-day temperature and wind-speed forecasts, with up to 10 % MAE reduction versus standalone models, though rare extreme events still pose challenges. Future efforts will focus on adaptive hybrid strategies such as decomposing series into trend, seasonal, and residual components for specialized predictors, learning direct residual corrections, and reframing via daily max–min interpolation as well as integrating denser radar and machine-learning data sources to further boost nowcasting robustness and operational efficiency.

VI. Conclusion

This work has presented a lightweight CNN–LSTM hybrid framework for real-time Doppler radar nowcasting, achieving over 93 % mean forecast accuracy and an RMSE of 0.45 mm for 0–3 h precipitation predictions. By combining convolutional layers to extract spatial storm features (e.g., reflectivity cores and rainband boundaries) with recurrent LSTM units to model temporal evolution, the model reliably detects high-intensity echoes (≥ 40 dBZ) with an 89 % hit rate and limits false alarms. Training on one year of S-band radar volumes converged stably within 30 epochs on a single GPU, while inference requires under 200 ms per 5-min update demonstrating operational feasibility for urban and regional nowcasting. Comparative experiments against standalone SARIMA, LSTM, BiLSTM, and CNN–GRU benchmarks confirm that the proposed hybrid consistently reduces MAE by up to 10 % and outperforms traditional persistence and climatology baselines by 40–60 %.

Vii. Reference

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