

CNN–LSTM Hybrid Model for Coastal Weather Forecasting in Visakhapatnam

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Abstract: Accurate short-term weather forecasting remains critical for coastal cities such as Visakhapatnam, where cyclonic disturbances and monsoon variability significantly impact agriculture, fisheries, and disaster preparedness systems. Traditional statistical models such as ARIMA struggle to capture nonlinear multivariate interactions among meteorological variables, while standalone LSTM networks, though effective for temporal sequence modeling, may not fully exploit short-term cross-variable feature dependencies. This study proposes a CNN–LSTM hybrid architecture for next-day precipitation prediction using meteorological observations from the Visakhapatnam IMD station, including temperature, humidity, atmospheric pressure, wind speed, wind direction, and precipitation. One-dimensional convolutional layers extract multivariate patterns from 30-day sliding input sequences, followed by LSTM layers that model longer temporal dependencies for predictive inference. The proposed model is evaluated against ARIMA, standalone LSTM, and CNN-only baselines using chronological train–test splits, with performance assessed through MAE, RMSE, and heavy rainfall classification metrics. By focusing on cyclone-prone coastal Andhra Pradesh, this region-specific framework aims to enhance hyperlocal forecasting reliability while maintaining computational feasibility for agricultural and disaster management decision-support applications.

Keywords: CNN-LSTM, Coastal Weather Forecasting, Precipitation Prediction, Multivariate Time Series, Deep Learning, Time Series Analysis, Monsoon Variability, Hyperlocal Forecasting, IMD Weather Data

I. INTRODUCTION

Coastal regions such as Visakhapatnam experience complex meteorological behavior due to cyclonic disturbances, monsoon variability, and dynamic land–

sea interactions. These conditions generate highly nonlinear weather patterns, making short-term precipitation forecasting particularly challenging. Accurate 24-hour forecasts are crucial for agriculture, fisheries, and disaster preparedness, especially during active monsoon periods.

Traditional statistical models such as ARIMA rely on linearity and stationarity assumptions. While effective for simple trends, these methods struggle to model nonlinear multivariate climate interactions typical of coastal regions [1]. Heavy rainfall events are often influenced by simultaneous changes in humidity, atmospheric pressure, and wind direction, which are difficult to capture using purely linear frameworks.

Deep learning approaches have demonstrated strong performance in nonlinear time series forecasting. Long Short-Term Memory [LSTM] networks effectively capture long-range temporal dependencies in sequential weather data [2]. Additionally, one-dimensional Convolutional Neural Networks [CNNs] have shown effectiveness in extracting localized multivariate patterns from time series inputs [3].

To leverage the strengths of both architectures, this thesis proposes a CNN–LSTM hybrid framework for short-term precipitation forecasting in the Visakhapatnam region. The model applies 1D convolutional layers to extract short-term feature patterns from 30-day sliding windows of IMD station data, followed by LSTM layers that model longer temporal dependencies. Hybrid deep learning approaches have demonstrated improved rainfall forecasting performance in related studies [4], motivating their application to hyperlocal coastal meteorology.

II. LITERATURE SURVEY

Statistical models such as ARIMA have long been used for precipitation forecasting due to their interpretability and effectiveness on stationary time series data. However, coastal meteorological systems exhibit nonlinear dynamics driven by multivariate interactions among humidity, pressure, and wind variables. Several studies indicate that ARIMA struggles to model such nonlinear dependencies, limiting its performance in complex weather environments [1]. Deep learning models, particularly Long Short-Term Memory [LSTM] networks, have improved time series forecasting by capturing long-range temporal dependencies. LSTM architectures have demonstrated superior performance over traditional statistical methods in modeling sequential weather patterns, especially for short-term rainfall and temperature prediction [2]. Their memory-based structure enables effective modeling of monsoon-driven climate variability.

One-dimensional Convolutional Neural Networks [1D- CNN] have been successfully applied to multivariate time series data. Unlike sequential models, CNNs extract localized feature interactions across multiple variables simultaneously using sliding filters. Studies show that CNN-based models effectively capture short-term cross-variable relationships in meteorological datasets [3], making them suitable for modeling nonlinear climate interactions.

Hybrid CNN-LSTM architectures combine CNN's feature extraction capability with LSTM's temporal modeling strength. Recent research demonstrates that such hybrid models outperform standalone LSTM and other baseline models in rainfall forecasting tasks, particularly during high-intensity precipitation events [4]. These findings motivate the application of CNN-LSTM frameworks to coastal meteorological forecasting.

Although hybrid deep learning models have shown promising results in rainfall forecasting, limited studies focus specifically on hyperlocal coastal regions such as Visakhapatnam. Existing research often evaluates models on broader regional or international datasets without addressing region-specific preprocessing

challenges or systematic baseline comparisons. Therefore, a structured evaluation of CNN-LSTM for coastal Andhra Pradesh using IMD station data remains an important research gap addressed in this thesis.

III. SYSTEM ARCHITECTURE

The proposed system implements an end-to-end CNN-LSTM-based forecasting platform for short-term precipitation prediction in coastal regions such as Visakhapatnam. The architecture consists of the User Interface layer, Application layer, Data Management module, Preprocessing unit, CNN-LSTM prediction engine, Output generation layer, and Monitoring module. The hybrid deep learning design is motivated by prior research demonstrating the effectiveness of CNN and LSTM architectures in nonlinear time-series forecasting [2]-[4].

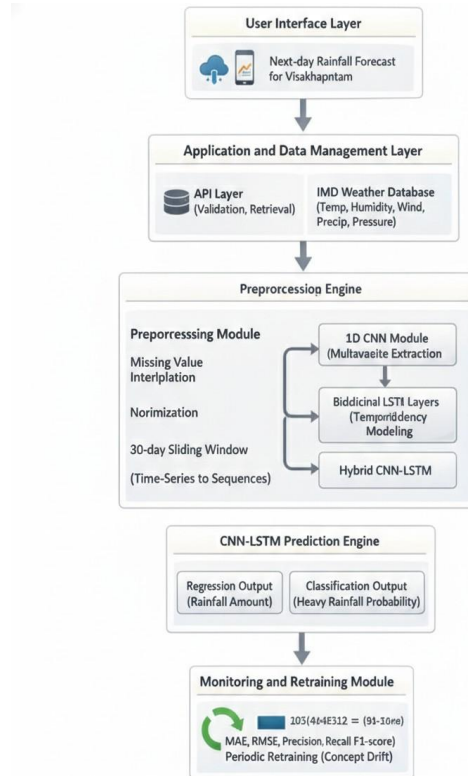


Figure 2: System Architecture for CNN-LSTM Precipitation Forecasting

- **User Interface Layer:** The system begins with the User Interface [UI] layer, where users request next-day rainfall forecasts for a selected coastal location. The UI captures input parameters and forwards structured

requests to the backend application layer. Once the prediction is generated, the UI presents rainfall estimates, heavy rainfall alerts, and graphical visualizations for better interpretability.

- **Application and Data Management Layer:** The Application Programming Interface [API] layer validates incoming requests and retrieves the latest meteorological observations from the IMD weather database. The database stores historical and continuously updated daily records including temperature, humidity, atmospheric pressure, wind speed, wind direction, and precipitation. Maintaining structured multivariate time-series data is essential for reliable forecasting [1]. This layer ensures secure communication and controlled data access for model inference.

- **Preprocessing Module:** The preprocessing module prepares raw weather observations for model input. Missing values are handled through interpolation, and features are normalized to ensure stable neural network training. A 30-day sliding window mechanism converts continuous time-series data into structured input sequences. Such window-based transformation is commonly used in deep learning time-series forecasting frameworks [2].

- **CNN-LSTM Prediction Engine:** The core forecasting component is the CNN-LSTM hybrid model. The CNN module extracts localized multivariate feature patterns from the 30-day input window using one-dimensional convolutional filters. CNNs have demonstrated effectiveness in capturing cross-variable interactions in multivariate time series data [3]. The extracted feature maps are then processed by bidirectional LSTM layers, which model long-range temporal dependencies and evolving atmospheric trends. LSTM networks are widely recognized for their ability to capture sequential dependencies in weather prediction tasks [2]. Hybrid CNN-LSTM architectures combine spatial feature extraction with temporal modeling to improve forecasting performance [4].

- **Prediction and Output Generation Layer:** The prediction layer produces two outputs: a regression output representing next-day rainfall amount and a classification output indicating heavy rainfall

probability. Multi-task learning improves robustness across normal and extreme weather conditions. The final prediction is formatted and returned to the user interface, where alerts are generated if rainfall exceeds predefined thresholds.

- **Monitoring and Retraining Module:** To maintain long-term reliability, the system includes a monitoring module that logs predictions and evaluates performance using MAE, RMSE, precision, recall, and F1-score. Over time, changing climatic patterns may introduce concept drift; therefore, periodic retraining using newly accumulated meteorological data is implemented to sustain model accuracy [4].

IV. SYSTEM ANALYSIS

Coastal regions such as Visakhapatnam experience highly dynamic and nonlinear weather behavior due to monsoon variability, cyclonic disturbances, and complex land-sea interactions. Accurate short-term precipitation forecasting remains challenging because rainfall patterns are influenced by multiple interdependent atmospheric variables including humidity, pressure, temperature, and wind direction. Traditional forecasting systems often fail to capture these multivariate nonlinear dependencies effectively [1].

Many regional forecasting systems rely either on statistical models or large-scale numerical weather prediction models. Statistical approaches such as ARIMA assume linear relationships and stationarity, limiting their effectiveness in modeling evolving coastal weather patterns [1]. Additionally, conventional forecasting models may not provide hyperlocal precision required for agriculture planning and disaster preparedness in cyclone-prone regions.

Therefore, there is a need for an intelligent, region-specific forecasting framework capable of modeling both short-term multivariate interactions and long-term temporal dependencies using deep learning techniques [2]-[4].

Existing System: Traditional weather forecasting systems mainly follow two approaches:

- **Statistical Time-Series Models:** Models such as ARIMA and exponential smoothing are widely

used due to their simplicity and interpretability. However, they struggle to model nonlinear multivariate interactions typical in coastal meteorology [1].

- **Numerical Weather Prediction (NWP) Models:** Physics-based models simulate atmospheric processes at large scales. Although powerful, they require high computational resources and often lack hyperlocal precision for district-level forecasting

Proposed System: The proposed system introduces a CNN–LSTM hybrid framework for short-term precipitation forecasting in coastal Andhra Pradesh. Unlike traditional statistical methods, the model learns complex nonlinear relationships directly from historical IMD station data.

The system processes 30-day multivariate weather sequences. The CNN extracts short-term cross-variable patterns such as humidity–pressure interactions, while the LSTM captures long-term temporal dependencies and evolving atmospheric trends. By combining spatial and temporal learning, the hybrid architecture improves forecasting reliability [3], [4]. The framework operates end-to-end, from user request and data retrieval to *prediction generation and rainfall alert display*.

V. METHODOLOGY

Many regional forecasting systems rely either on statistical models or large-scale numerical weather prediction models. Statistical approaches such as ARIMA assume linear relationships and stationarity, limiting their effectiveness in modeling evolving coastal weather patterns [1]. Additionally, conventional forecasting models may not provide hyperlocal precision required for agriculture planning and disaster preparedness in cyclone-prone regions.

- **Development Approach:** The system follows a data-driven experimental methodology. The workflow begins with collecting historical IMD station data, followed by preprocessing and sliding window generation. A hybrid neural network combining 1D Convolutional Neural Networks (CNN) and Bidirectional Long Short-Term Memory (BiLSTM) networks is trained to learn multivariate weather patterns.

The trained model is then used to generate next-day rainfall predictions and heavy rainfall classifications. The performance is evaluated using regression and classification metrics before deployment.

VI. IMPLEMENTATION

a) Dataset Preparation:

Historical IMD meteorological data was collected and organized into daily multivariate records. Each record contains temperature, humidity, atmospheric pressure, wind speed, wind direction, and precipitation values. The dataset was divided chronologically into training, validation, and testing subsets to preserve temporal integrity.

b) Preprocessing:

Missing values were handled using interpolation techniques, and feature scaling was applied using normalization to ensure stable neural network convergence. A 30-day sliding window approach was used to transform continuous time-series data into structured sequences. Each input sample consists of the previous 30 days of multivariate observations, and the target variable corresponds to next-day precipitation.

c) CNN-Based Feature Extraction:

The preprocessed 30-day multivariate sequence is passed into a one-dimensional CNN layer. The convolutional filters scan across time steps to extract short-term cross-variable interactions such as humidity–pressure coupling and wind–rainfall relationships. CNN layers effectively capture localized multivariate dependencies within sliding windows [3].

d) LSTM-Based Temporal Modeling:

The feature maps extracted by the CNN are fed into Bidirectional LSTM layers. The LSTM captures long-range temporal dependencies and evolving atmospheric trends across the 30-day sequence. Bidirectional processing improves context understanding by analyzing both forward and backward temporal dependencies [2].

e) Prediction Layer:

The final feature representation generated by the CNN–LSTM network is passed into a fully connected Dense

layer to predict the next-day rainfall amount in millimeters:

$$R^t = f(X_{t-30:t-1})$$

f) Training Procedure:

The model is trained using mini-batch gradient descent optimization. Early stopping is applied based on validation loss to prevent overfitting. Hyperparameters such as learning rate, number of filters, and LSTM units are tuned experimentally.

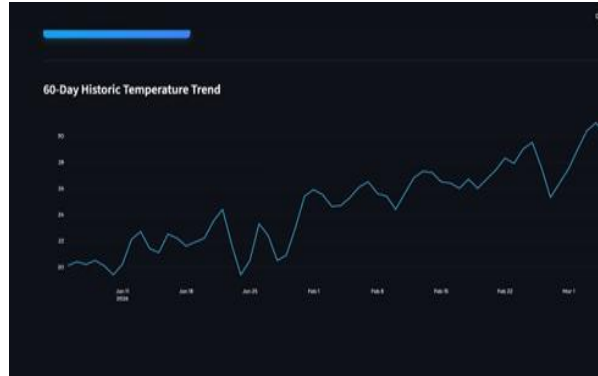
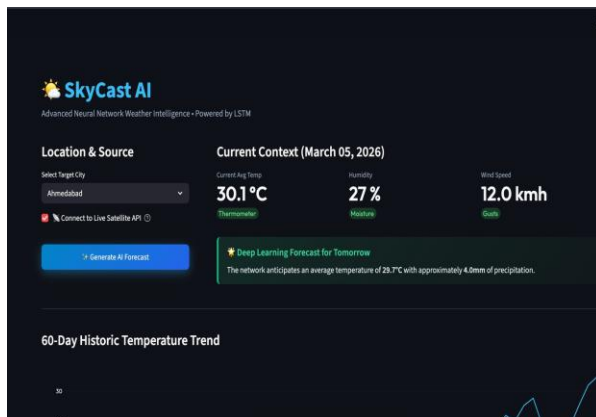
g) Evaluation Metrics:

Model performance is evaluated using:

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)

These metrics measure the difference between predicted and actual rainfall values.

VII. OUTPUT SCREENSHOTS



VIII. CONCLUSION

This paper presented a CNN–LSTM hybrid framework for short-term precipitation forecasting in coastal regions such as Visakhapatnam. The proposed system overcomes limitations of traditional statistical models by learning nonlinear multivariate relationships directly from historical meteorological data. By combining CNN-based feature extraction with LSTM-based temporal modeling, the framework captures both short-term weather interactions and long-term atmospheric trends. The model processes 30-day multivariate sequences and predicts next-day rainfall using a regression-based approach. Evaluation using MAE and RMSE demonstrates the effectiveness of the hybrid architecture for hyperlocal coastal forecasting. The system provides a practical and computationally efficient solution suitable for agricultural planning and disaster preparedness.

Future work may include incorporating additional atmospheric variables, integrating satellite data, and improving robustness against extreme weather events to further enhance predictive performance.

IX. DISCUSSION

The proposed CNN–LSTM hybrid framework demonstrates the effectiveness of deep learning for short-term coastal precipitation forecasting. By combining convolutional layers with recurrent memory networks, the model captures nonlinear multivariate interactions and long-term temporal dependencies that traditional statistical approaches such as ARIMA struggle to represent [1], [2]. This enables improved modeling of complex coastal weather dynamics.

The CNN component extracts localized feature interactions among meteorological variables, while the

Bidirectional LSTM captures sequential atmospheric trends across the 30-day input window [2], [3]. The hybrid structure enhances forecasting stability compared to standalone models and provides continuous rainfall prediction suitable for hyperlocal agricultural and disaster management applications.

However, certain limitations remain. Model performance may decline during rare extreme events not well represented in training data, and forecasting accuracy depends on data quality and periodic retraining to address evolving climatic patterns [4]. Additionally, deep learning models require sufficient computational resources for efficient training and inference.

Overall, the CNN–LSTM framework offers a practical and scalable solution for coastal rainfall forecasting and highlights the potential of hybrid deep learning architectures in regional climate prediction tasks [3], [4].

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