IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 12, Issue 10, October 2025

DOI: 10.17148/IARJSET.2025.121022

Deep Learning: Hybrid CNN–LSTM for Multivariate Weather Prediction

Divyashree M S[1], Sparshakala V S[2], Shridevi Sali[3], Bhavya B V[4]

Department of CSE, Assistant Professor, The National Institute of Engineering, Mysuru, Karnataka, India[1]

Department of CSE, Assistant Professor, Don Bosco Institute of Technology, Bengaluru, Karnataka, India[2]

Department of AIML, Assistant Professor, SJB Institute of Technology, Bengaluru, Karnataka, India[3]

Department of ISE, Assistant Professor, Don Bosco Institute of Technology, Bengaluru, Karnataka, India[4]

Abstract: Weather forecast is essential for agriculture, transportation, disaster management, and environmental planning. Traditional numerical and statistical models are helpful, but they do not capture the complex, nonlinear, and dynamic relationships among numerous atmospheric variables. To address this problem, the study combines and evaluates several approaches for multivariate weather forecast using Artificial Intelligence (AI) and Deep Learning (DL). By applying meteorological datasets with different parameters, including temperature, humidity, wind speed, and precipitation levels, the study evaluates more sophisticated architectures for deep learning (e.g., Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit based (GRU), and a hybrid Convolutional Neural Networks-Recurrent Neural Networks (CNN-RNN) model), as well as machine learning regressors (e.g., Random Forest, Gradient Boosted Regression). The contribution of the hybrid CNN-RNN model shows that it better captured the underlying spatial-temporal dependencies in the dataset, yielding the best forecasting accuracy and precision compared to all other models. In general, results showed a greater decrease in prediction error (RMSE, MAE) and improved consistency across various climatic conditions. Overall, work serves as a unified framework showing the potential of AI-based forecasting systems to enhance the accuracy, reliability, and representation of weather prediction systems.

Keywords: Weather forecasting, Artificial Intelligence, Deep Learning, Machine Learning, CNN, RNN, LSTM, GRU, Hybrid Models, Multivariate Prediction, Atmospheric Parameters, Time-series Analysis, Meteorology, Predictive Modeling.

I. INTRODUCTION

Weather prediction is essential to modern society and influences areas such as agriculture, transportation, energy, and disaster preparedness. Forecasting provides communities and sectors with dynamic decision-making capabilities, the ability to limit economic loss, and protect lives as a result of extreme climate events, including floods, droughts, and storms. While traditional statistical and numerical weather forecasting models have provided the necessary basis of weather prediction, they face challenges processing extremely large and complex datasets, and capturing nonlinear interactions between atmospheric state variables. Traditional numerical weather models also rely heavily upon physical assumptions and equations which may not fully encapsulate the chaotic and dynamic nature of the Earth's climate system.

Artificial intelligence (AI) and deep learning (DL) have recently transformed data-driven weather prediction. Machine learning algorithms such as Random Forest, Decision Tree, and Gradient Boosting have been successfully deployed to predict the short- and medium-term. Unfortunately, these models are constrained regarding their ability to model long-term temporal dependencies and spatial correlations in meteorological datasets. Deep learning techniques, such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks, and Gated Recurrent Unit (GRU) networks, effectively overcome both of these constraints by learning sequential and temporal patterns from multivariate time-series datasets. These architectures properly represent the evolving functional relationships

Additionally, hybrid deep learning models—comprised of the pairing of Convolutional Neural Networks (CNN) and RNNs—have demonstrated effectiveness through the hybridization between spatial feature extraction and temporal sequence model. Convolutional neural network (CNN) layers are effective for capturing local spatial variations, and recurrent layers are suitable for examining temporal trends, which can both lead to an increase in accuracy and robustness in forecasting. Studies have shown that hybrid structures give superior performance measures (mean square error [MSE],

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 12, Issue 10, October 2025

DOI: 10.17148/IARJSET.2025.121022

root mean square error [RMSE], and mean absolute error [MAE]) than both classical regression and regular deep learning models.

This has been further supported by available, high spatial-resolution meteorological datasets from satellites, sensors, and global networks of observations, which has stimulated the use of AI-oriented models for climate forecasting. These environments provide large amounts of data to train deep architectures that can examine complex and hidden patterns among atmospheric systems. Moreover, the interaction of AI and deep learning, with time-dependence and distance, advances weather prediction by increasing forecast accuracy and reliability, while at the same time reducing the computational time as compared to traditionalized models that require complicated physical modeling.

The objective of this collective research is to investigate and synthesize a diverse multi-method mix of AI and deep learning options for multivariate weather forecasting and to assess their performance across various climate parameters. The investigation will compare traditional machine learning models with newer models such as deep learning and hybrid architectures. This research will show that artificial intelligence-supported modeling frameworks have the potential to transform existing forecasting into adaptive, fast-moving, scalable, and accurate modeling systems of the future for meteorological forecasting and applications.

II. LITERATURE SURVEY

Paul and Dhanalakshmi [1] proposed a hybrid framework titled *"Deep Learning Techniques for Weather Prediction"*, focusing on the development of a CNN-RNN-based model for enhanced weather forecasting accuracy. The study used the Jena climate dataset, comprising 14 meteorological parameters, to evaluate model performance. The proposed hybrid architecture combined the feature extraction power of Convolutional Neural Networks (CNN) with the sequential learning capability of Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM). Comparative analyses with conventional algorithms—such as Autoregressive Integrated Moving Average (ARIMA), Random Forest, Multilayer Perceptron (MLP), and Support Vector Machine (SVM)—revealed that the CNN-RNN model achieved superior results across various performance metrics, including RMSE and MAE. The authors concluded that deep hybrid architectures effectively address the limitations of both traditional statistical and standalone machine learning models, offering a scalable and data-driven approach to modern weather prediction.

Ramana et al. [2] presented a study titled *"Advanced Deep Learning Techniques for Multivariate Weather Prediction Using RNN and LSTM Models"*, which investigated both traditional machine learning and modern deep learning methods for weather forecasting. The authors utilized a multivariate dataset containing parameters such as temperature, humidity, wind speed, and precipitation to analyze model performance across different climatic variables. Initially, regression-based models like Random Forest, Gradient Boosted Regression, and Multiple Linear Regression were implemented as baselines. Subsequently, deep learning architectures such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRU) were applied to capture temporal dependencies within the data. The study demonstrated that LSTM and GRU significantly outperformed traditional models in terms of Mean Squared Error (MSE) and R-squared values. However, the authors noted that further integration of spatial data and real-time inputs could enhance prediction reliability and adaptability in diverse meteorological conditions.

Kadel et al. [3] in their paper *"Advancing Weather Prediction and Forecasting: A Comparative Study of AI and Deep Learning Techniques"* provided an extensive comparative analysis of artificial intelligence algorithms for predicting complex weather phenomena, including rainfall, floods, and cyclones. The research explored various AI models—such as Logistic Regression, Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN)—and compared them with advanced deep learning models like Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). By analyzing datasets sourced from meteorological stations and satellite imagery, the study highlighted that deep learning models, particularly LSTM networks, provided higher predictive accuracy and robustness in handling non-linear, multivariate weather data. The authors emphasized the potential of hybrid models that combine machine learning and physics-based approaches for improving long-term forecasting. Nonetheless, the research acknowledged the computational demands and data integration challenges that persist in large-scale weather modeling.

Abdalla et al. [4] in their work titled *"Deep Learning Weather Forecasting Techniques: Literature Survey"* conducted an extensive review of deep learning architectures developed for weather prediction. The authors analyzed several neural network models, including Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Autoencoders, and hybrid frameworks, emphasizing their ability to capture the nonlinear and dynamic characteristics of atmospheric data. The study categorized models based on spatial and temporal prediction scales, benchmark datasets, and their computational efficiency. Their survey highlighted that deep learning models—particularly LSTM and CNN

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 10, October 2025

DOI: 10.17148/IARJSET.2025.121022

architectures—outperform traditional statistical and numerical weather prediction methods by learning intricate spatiotemporal dependencies in climate variables such as temperature, humidity, and wind speed. However, the paper also noted that challenges like model interpretability, data imbalance, and high computational demands remain key barriers to achieving a fully generalized AI-driven weather prediction system. The study serves as a strong theoretical foundation for future hybrid deep learning approaches that integrate domain knowledge with data-driven modeling.

Yang et al. [5] presented a paper titled *“Extreme Weather Prediction for Highways Based on LSTM-CNN”*, focusing on the application of hybrid deep learning models for real-time extreme weather forecasting along highway networks. The authors proposed a Long Short-Term Memory–Convolutional Neural Network (LSTM-CNN) architecture capable of capturing both temporal and spatial correlations in meteorological and road-related datasets. The model incorporated inputs such as precipitation, visibility, temperature, humidity, and road material properties to predict short-term weather conditions, including fog, snow, and heavy rainfall. Experimental evaluations using two years of historical data demonstrated that the LSTM-CNN framework achieved superior accuracy, recall, and F1 scores compared to standalone LSTM, CNN, and traditional machine learning methods like SVM and KNN. The findings revealed that the model not only improves short-term forecast accuracy but also provides practical insights for highway design and maintenance under varying climatic conditions. This research underscores the potential of deep hybrid architectures to enhance predictive performance in localized, high-risk environments such as transportation systems.

III. METHODOLOGY

This methodology combines artificial intelligence (AI) and deep learning methods to create a model for weather forecasting that is accurate and efficient. The methodology is based on a structured data-driven pipeline that supports data collection, data cleaning, feature engineering, model training, model evaluation, and proactive system deployment. Each stage seeks to maximize the performance of the model while maintaining its ability to adapt to various weather systems.

3.1 Data Acquisition Layer

The basis of precise weather forecasting is related to both the quality and diversity of the data inputted. For this study, historical weather data is collected from open-source sites including the Indian Meteorological Department (IMD), NOAA, and Kaggle. The dataset consists of essential climate parameters such as temperature, humidity, wind speed, air pressure, and precipitation, at both hourly and daily measurements.

Preprocessing guarantees reliability and consistency of the data prior to input to the deep learning model. Preprocessing includes the following steps:

Treating missing values: Missing values are treated through interpolation or mean imputation.

Identifying outlier data: Outlier data is identified, and then smoothed, using statistical methods and z-score normalization.

Applying feature scaling: Feature scaling is accomplished through min-max normalization so that each parameter impacts the overall training and learning equally.

Structuring temporally: Data will be structured into a sequence of time-windows, to capture short- and long-term weather dependencies.

Once preprocessing is applied, the dataset is structured for structural and temporal analysis, and allows for reduced bias in prediction and improved model learning efficiency.

3.2 Preprocessing Layer

Feature engineering improves the model's comprehension of atmospheric patterns by creating several additional informative features. Correlation analysis is performed to look for relationships between features, such as temperature and humidity, wind speed and rainfall, etc. To enhance predictive accuracy, new composite features—such as heat index, dew point, and pressure tendency—are calculated. Principal Component Analysis (PCA) is then performed in order to reduce dimensionality but retain significant information. This step improves both computation efficiency and lessens overfitting, allowing the model to learn meaningful climatic trends.

3.3 Processing and Classification Layer

The system that has been proposed incorporates a hybrid architecture that features the spatial learning capability of Convolutional Neural Networks (CNNs) and the learning capabilities of temporal sequence data by Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) units.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 10, October 2025

DOI: 10.17148/IARJSET.2025.121022

CNN Layers: Implement spatial feature learning on meteorological grids and extract high-level features across associated weather parameters.
LSTM layers: Learn and capture long-term temporal dependencies that include daily, seasonal, and inter-annual variability.
Dense Layers: Transform extracted features into numerical weather forecasts using dense, interconnected layers.
Dropout Regularization: Regularization is introduced to prevent overfitting and to create a generalized model.

The CNN-LSTM hybrid framework produces a model that effectively captures both the immediate variation of the weather (e.g. temperature fluctuations during a day) and long-term dependencies (e.g. seasonal weather patterns).

3.4 Evaluation and Decision Layer
The training phase uses the preprocessed dataset to fit the hybrid model. The model is trained using the Adam optimizer with an adaptive learning rate and Mean Squared Error (MSE) as the primary loss function.

To enhance model robustness:

Data augmentation techniques simulate varied weather conditions.
Early stopping prevents overtraining when validation loss plateaus.
Batch normalization stabilizes learning and accelerates convergence.

Training is performed using TensorFlow/Keras frameworks on GPU-enabled systems to expedite computation and handle large-scale datasets efficiently.

3.5 Deployment Layer
Once trained, the model is evaluated on unseen test data to assess its accuracy and generalization capability. Multiple performance metrics are employed, including:

Mean Absolute Error (MAE): Measures average magnitude of prediction errors.
Root Mean Squared Error (RMSE): Evaluates model precision in predicting continuous values.
R^2 Score: Indicates how well the model explains variability in observed data.

The results are compared with benchmark models such as Linear Regression, Random Forest, and standalone LSTM to validate the superiority of the proposed hybrid approach. Visual analyses—such as time-series plots and error distribution graphs—further confirm prediction reliability.

3.6 Deployment Layer
In practice, the model is operationalized as an interactive web-based forecasting system. This allows users to specify the location and time of interest and obtain predicted weather parameters, and visualize future trends through navigable dashboards.
The back-end services are implemented in Flask, which integrates the trained model with real-time weather APIs, ensuring regular updates to the data. The front-end interface displays predictions through graphics, allowing meteorologists, researchers, and the general public to easily interpret forecast information. The deployment enables cloud-based scalability and edge-level adaptability, ensuring access across different devices and locations.

IV. EXPERIMENTAL SETUP AND EVALUATION

The experimental protocol was meant to assess the efficiency, accuracy, and robustness of the proposed CNN-LSTM based hybrid deep learning model for multivariate weather forecasting. The objective of this experiment is to assess the predictive capability of the system in forecasting important atmospheric parameters such as temperature, humidity, wind speed, and precipitation using sequential historical values. The experiment aims to evaluate three critical areas — forecast accuracy, prediction stability in time, and computational efficiency — to promote confidence in the model's suitability for real-world weather predictions.

4.1 Software Environment and Tools
The experiments were conducted with Python utilizing libraries such as The model was implemented using a suite of AI and data analytics tools integrated into a Python-based deep learning framework. The system leverages both cloud and local GPU computation to accelerate training and testing.

IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

Impact Factor 8.311 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 12, Issue 10, October 2025

DOI: 10.17148/IARJSET.2025.121022

Tool / Framework	Purpose
Python 3.10	Core programming language for model development
TensorFlow / Keras	Implementation and training of CNN–LSTM architecture
NumPy, Pandas	Data manipulation, preprocessing, and analysis
Matplotlib / Seaborn	Visualization of training trends and prediction outputs
Scikit-learn	Evaluation metrics computation and baseline ML comparisons
OpenCV	Data normalization and spatio-temporal feature visualization
Flask/ Streamlit	Deployment and interactive interface for prediction display
Google Colab /GPU Runtime	Accelerated training environment for deep learning models

4.2 Model Behavior and Observation

The dataset used in this study comprises multivariate meteorological records obtained from publicly available repositories such as the Indian Meteorological Department (IMD), NOAA Climate Data Center, and Kaggle Global Weather Dataset. The dataset contains daily and hourly readings for atmospheric parameters across multiple regions and seasons.

Dataset Characteristics:

Data Type: Time-series meteorological data

Attributes: Temperature, humidity, rainfall, wind speed, air pressure, and dew point

Time Frame: 10 years of historical data

Resolution: Hourly and daily intervals

Data Size: ~100,000 samples after preprocessing

Before training, the dataset undergoes:

Data cleaning to remove duplicates and missing entries,

Normalization using Min–Max scaling,

Temporal slicing to generate fixed-length sequences for LSTM input, and

Train–Test split (80:20) to ensure fair model validation.

4.3 Experimental Procedures

Data Preprocessing:

All features are normalized to the [0,1] range to stabilize learning and accelerate convergence. The time-series data is reshaped into 3-D tensors. Correlated variables are combined into composite indices such as *heat index* and *humidity-pressure interaction factor* to strengthen predictive relationships.

Model Architecture:

The hybrid deep learning model integrates:

CNN Layers: Extract spatial correlations among atmospheric variables.

LSTM Layers: Capture long-term temporal dependencies in sequential weather data.

Dense Output Layer: Produces continuous predictions for each weather parameter. Dropout regularization and early stopping mechanisms prevent overfitting, while the **Adam optimizer** fine-tunes weights efficiently.

Training Configuration:

Epochs: 100

Batch Size: 64

Optimizer: Adam (learning rate = 0.001)

Loss Function: Mean Squared Error (MSE)

Hardware: NVIDIA GPU (Tesla T4, 16 GB VRAM)

Prediction Horizon: The model is tested for short-term (24–48 hours) and mid-term (3–7 days) forecasts to evaluate generalization and stability.

DOI: 10.17148/IARJSET.2025.121022

4.4 Evaluation Matrics

To assess the model's prediction quality, multiple quantitative and comparative metrics are employed. These metrics provide a holistic evaluation of both **accuracy** and **consistency** in weather forecasting.

1.Mean Absolute Error (MAE):

Measures the average magnitude of prediction errors, regardless of direction.

$$MAE = (1 / n) \times \Sigma \mid y_i - \hat{y}_i \mid$$

2. Root Mean Squared Error (RMSE):

Emphasizes larger deviations and reflects how well the model handles extreme fluctuations.

$$RMSE = \sqrt{((1 / n) \times \Sigma (y_i - \hat{y}_i)^2)}$$

3. Mean Squared Error (MSE):

Evaluates the squared difference between observed and predicted values to assess model bias

$$MSE = (1 / n) \times \Sigma (y_i - \hat{y}_i)^2$$

4. Coefficient of Determination (R^2 Score):

Indicates how well the predicted outcomes explain the variance in actual observations.

$$R^2 = 1 - [\Sigma (y_i - \hat{y}_i)^2 / \Sigma (y_i - \bar{y})^2]$$

5. Mean Absolute Percentage Error (MAPE):

Provides a percentage-based error measure for easier interpretability.

$$MAPE = (100 / n) \times \Sigma \mid (y_i - \hat{y}_i) / y_i \mid$$

6. Execution Time and Model Latency:

Measures total time taken per forecast cycle, evaluating computational efficiency and real-time applicability.

4.5 Experimental Results and Observations

The proposed hybrid CNN–LSTM model achieved strong predictive accuracy across all climatic parameters. Compared to baseline models such as Linear Regression and Random Forest, the hybrid model reduced RMSE by approximately 18–25%.

Sample performance metrics on the test dataset are summarized as follows:

Metric	Observed Value
MAE	1.82 °C
RMSE	2.41 °C
R^2 Score	0.97
MAPE	3.8 %
Average Inference Time	1.7 s per prediction cycle

These results demonstrate that the proposed approach effectively captures both short-term fluctuations and long-term dependencies, providing accurate and stable weather forecasts suitable for practical deployment.

V. CONCLUSION

The research effectively showcases how Artificial Intelligence (AI) and Deep Learning (DL) techniques can help improve the accuracy, flexibility, and efficiency of contemporary weather forecasting systems. The model presented in this research utilizes a hybrid CNN–LSTM architecture, combining the advantages of spatial learning and temporal

DOI: 10.17148/IARJSET.2025.121022

learning to accurately forecast several multivariate weather variables, including temperature, humidity, wind speed, and rainfall. This model mitigates the limitations of traditional numerical based models that heavily depend on static assumptions and simplify physical equations, for flexibility toward the complex, non-linear, and non-static character of weather prediction. In comparison, the deep learning method described in this research directly learns from massive amounts of data, revealing hidden patterns and relationships, which otherwise would remain undetectable.

The outcome of experimentation indicates the CNN–LSTM model provides improved estimation outcomes relative to classical machine learning regression methods Linear Regression, Random Forest and Gradient Boosting addressing accuracy, stability and compute cost. The CNN-LSTM model produced a low RMSE and MAE while securing a large R2 score indicative of its ability to generalize across climatic conditions. With the combination of data pre-processing steps, including normalization, feature selection and time-window sequencing, the CNN-LSTM model successfully managed and processed large-scale and large-time series datasets while filtering the intermitted noise of the datasets.

A key aspect of this investigation is its focus on usable research. The trained model was applied into an interactive, web-based platform with scalability and accessibility in mind. The open access deployment facilitates end-users, meteorologists and researchers the ability to visualize forecast in real time, perform trend analysis through graphical dashboards, and request localized predictions. The lightweight model implementation interacting with cloud technology will open the option for integration into IoT based weather monitoring systems in real time for the benefit of agriculture, transportation, disaster management, urban planning, and others.

These findings provide an important contribution to climate informatics and measurable implications of AI. In addition to increasing prediction accuracy, deep learning models decrease the computing load and time taken to result in reliable forecast. This mode of analysis, as incoming data is processed for each prediction, allows continuous refinement of convective allowance forest. As more meteorological information is available, the model will result in greater precision. The learning framework represents deep learning, and therefore AI-based forecasting, as a significant contribution to global issues such as climate change, preparedness for extreme weather events, and efficiency of resource use.

This research recognizes, notwithstanding its success, certain limitations. The model's performance relies on the quality and quantity of historical data, and any inconsistencies in data collection and sensor calibration will yield some minor biases in the predictions. Moreover, incorporating external environmental parameters—such as ocean indices, satellite images, and atmospheric pressure patterns—could improve accuracy even further, even though our CNN-LSTM architecture is effective at spatial-temporal relationships. Future expansions of this work may want to analyze the use of Transformer architectures or hybrid attention models for better interpretability and long-term forecasting. Additionally, supporting explainable AI of the type is helpful, as it will help meteorologists understand model decisions better, ultimately leading to better trust and confidence in AI based climate analytics.

In summary, this research presents a robust and scalable AI-led framework that effectively applies the benefits of deep learning to achieving accurate, real-time weather forecasting. The research serves as a large advancement toward building data-driven intelligence with meteorological science by establishing a directed platform for further leaps in predictive climatology and sustainable weather technology. The proposed system adds forecasting skill and contributes to global resiliency to climatic uncertainties, which provides an asset to both scientific advancement and societal wellbeing.

REFERENCES

[1]. D. Paul and R. Dhanalakshmi, *"Deep Learning Techniques for Weather Prediction," International Journal of Engineering Research and Technology (IJERT)*, vol. 12, no. 2, pp. 134–140, 2023.

[2]. S. Ramana, A. Rajasekar, and P. Kumar, *"Advanced Deep Learning Techniques for Multivariate Weather Prediction Using RNN and LSTM Models," International Journal of Innovative Research in Computer Science and Engineering*, vol. 11, no. 3, pp. 45–52, 2023.

[3]. R. Kadel and M. Thapa, *"Advancing Weather Prediction and Forecasting: A Comparative Study of AI and Deep Learning Techniques," Proceedings of the International Conference on Artificial Intelligence and Data Science (ICAIDS)*, pp. 221–228, 2023.

[4]. A. Abdalla, M. Elhassan, and L. Al-Shehri, *"Deep Learning Weather Forecasting Techniques: Literature Survey," Journal of Applied Artificial Intelligence*, vol. 9, no. 4, pp. 88–97, 2024.

[5]. X. Yang, Q. Zhang, and L. Wang, *"Extreme Weather Prediction for Highways Based on LSTM–CNN," IEEE Access*, vol. 12, pp. 113254–113263, 2024.

DOI: 10.17148/IARJSET.2025.121022

[6]. S. A. Hussain and H. Chen, *"A Comparative Study of Machine Learning and Deep Learning Techniques for Climate Prediction," Environmental Data Science Journal*, vol. 5, no. 2, pp. 76–85, 2023.

[7]. N. Patel, P. Verma, and A. Gupta, *"Hybrid CNN–LSTM Architecture for Rainfall Forecasting," International Conference on Computational Intelligence and Smart Systems (CISS)*, pp. 312–318, 2023.

[8]. J. Lee and K. Park, *"Long-Term Temperature Forecasting Using Recurrent Neural Networks and Attention Mechanisms," IEEE Transactions on Geoscience and Remote Sensing*, vol. 62, no. 4, pp. 2198–2209, 2024.

[9]. F. Rahman and L. Zhao, *"Deep Learning-Based Spatiotemporal Model for Rainfall and Humidity Prediction," Journal of Atmospheric and Climate Sciences*, vol. 14, no. 1, pp. 112–124, 2023.

[10]. T. Sharma, B. Singh, and R. Patel, *"AI-Driven Weather Forecasting Using GRU and CNN Hybrid Models," International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 14, no. 6, pp. 58–66, 2024.

[11]. L. Nguyen, P. Tran, and M. Hoang, *"A Deep Neural Network Framework for Short-Term Wind Speed Prediction," Renewable Energy and AI Journal*, vol. 8, no. 3, pp. 41–49, 2023.

[12]. E. Johnson and S. Raj, *"Real-Time Flood Forecasting Using LSTM Networks: An AI Perspective," Hydrological Modelling and Data Analytics*, vol. 11, no. 2, pp. 90–100, 2024.

[13]. R. Al-Mutairi, F. Khan, and A. Alam, *"Integrating Satellite Imagery and Deep Learning for Extreme Weather Event Detection," IEEE Transactions on Big Data*, vol. 10, no. 1, pp. 230–239, 2024.

[14]. P. Deshmukh and V. Rao, *"Comparative Analysis of AI Models for Temperature and Rainfall Prediction," International Journal of Artificial Intelligence and Climate Research*, vol. 6, no. 1, pp. 15–25, 2023.

[15]. K. Wu, H. Zhang, and J. Lin, *"Enhanced Meteorological Forecasting through Hybrid Deep Learning and Data Fusion Approaches," IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 5, pp. 4259–4270, 2024.