Improving Weather Forecasting with AI: A Satellite Imagery Approach

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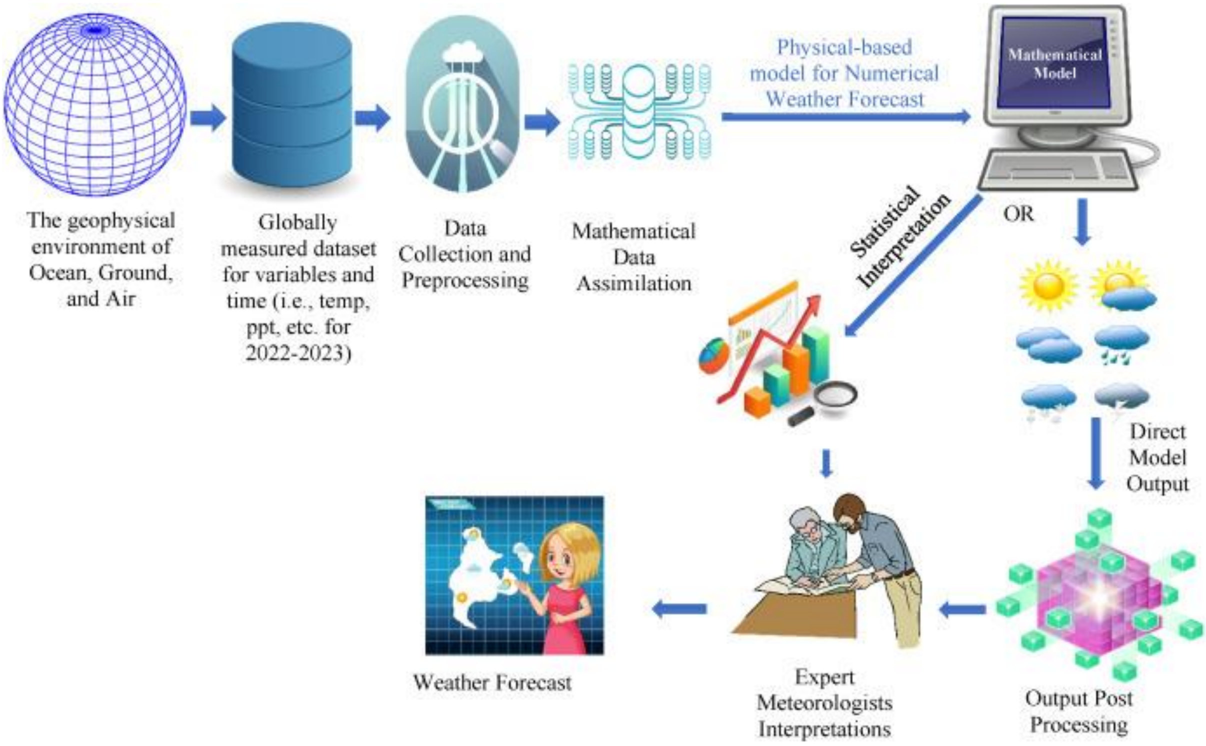
ABSTRACT

Accurate and real-time weather prediction is essential for disaster management, agriculture, aviation, and public safety. Traditional numerical weather prediction (NWP) models rely on complex physical simulations, which are computationally intensive and often struggle with short-term forecasting accuracy. This research proposes an AI-powered real-time weather prediction system using satellite images, leveraging deep learning techniques to enhance forecasting precision and efficiency. The proposed system utilizes geostationary and polar-orbiting satellite imagery to extract key meteorological features such as cloud cover, temperature variations, humidity distribution, and wind patterns. A deep learning framework, incorporating Convolutional Neural Networks (CNNs) and Transformer-based architectures, processes these images to detect weather patterns and generate real-time forecasts. The system continuously learns from new satellite data, improving prediction accuracy over time. Experimental results demonstrate that the AI-based approach outperforms traditional forecasting models in short-term predictions, particularly for localized weather events such as thunderstorms, cyclones, and heavy rainfall. The integration of real-time data processing and predictive analytics enables rapid decision-making for weather-sensitive industries. This study highlights the potential of AI-driven weather prediction models to complement traditional meteorological techniques, offering a scalable and efficient alternative for real-time forecasting. Future work will focus on integrating multi-source meteorological data and refining model accuracy through advanced machine learning techniques.

Keywords: AI, Deep Learning, Satellite Images, Weather Forecasting, Convolutional Neural Networks, Real-Time Prediction, Meteorology.

GRAPHICAL ABSTRACT



INTRODUCTION

Weather forecasting is essential for mitigating the impacts of extreme weather conditions, supporting agriculture, disaster management, and transportation systems. Traditional weather prediction methods rely heavily on Numerical Weather Prediction (NWP) models, which use complex mathematical equations to simulate atmospheric processes. However, these models often struggle with accuracy due to limitations in data assimilation, computational constraints, and the chaotic nature of the atmosphere [1]. With the rapid advancements in Artificial Intelligence (AI) and Deep Learning (DL), integrating these techniques with satellite imagery has emerged as a promising approach to improving forecasting accuracy. AI models, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), can efficiently process large datasets from satellites to extract meaningful patterns and enhance weather predictions [2]. AI-driven forecasting models can refine NWP outputs by reducing uncertainties, improving post-processing, and dynamically tuning model parameters [1]. This paper explores the role of AI in satellite-based weather forecasting, emphasizing its potential to enhance predictive accuracy and reliability. It discusses different AI methodologies, their integration with traditional forecasting systems, and the challenges associated with implementing AI-based models in meteorology. By leveraging satellite imagery and deep learning algorithms, the research aims to demonstrate how AI can significantly improve short-term and long-term weather forecasting.

BACKGROUND AND RELATED WORK

A. *Background of Weather Prediction*

Accurate weather prediction plays a crucial role in meteorology, influencing various sectors such as agriculture, disaster management, transportation, and energy production. Traditional Numerical Weather Prediction (NWP) models utilize complex mathematical equations to simulate atmospheric processes. While these models provide reliable forecasts, they demand extensive computational power and suffer from limitations in handling uncertainties within the atmosphere [4]. With advancements in artificial intelligence (AI) and machine learning (ML), alternative data-driven approaches have emerged, leveraging deep learning and computer vision techniques for real-time and more efficient forecasting. Satellite imagery, captured by geostationary and polar-orbiting satellites, provides vast amounts of meteorological data, including cloud formations, atmospheric moisture levels, and temperature variations. The integration of AI with satellite data enables enhanced pattern recognition, allowing models to uncover intricate relationships in weather systems that traditional physics-based methods may overlook [5]. Deep learning architectures, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models, have proven effective in extracting meaningful insights from large meteorological datasets. AI-driven weather forecasting systems can process historical and real-time data, improving predictive accuracy while reducing computational costs [4].

B. *Previous Work*

1. Deep Learning for Weather Prediction

Numerous studies have demonstrated that deep learning models, particularly CNNs and Long Short-Term Memory (LSTM) networks, can effectively analyze satellite images to predict short-term and long-term weather patterns. Rivolta et al. [5] introduced an artificial neural network (ANN) approach for precipitation nowcasting using satellite imagery, showcasing its ability to outperform conventional statistical models. Similarly, Ionescu et al. [2] developed DeePSat, a deep learning model that enhances short-term weather predictions using satellite data.

2. AI-Based Cloud Pattern Recognition

Studies such as those by Xavier et al. [3] have explored AI-driven image recognition techniques for classifying cloud types and predicting precipitation. These models utilize CNN-based architectures to detect weather patterns from satellite images with high accuracy, improving rainfall estimation and storm prediction capabilities.

3. Real-Time Weather Prediction Systems

Real-time forecasting is a critical application of AI in meteorology. Dewitte et al. [4] discussed how AI-based nowcasting models, integrating satellite imagery with deep learning techniques, provide enhanced short-term weather predictions. By using AI-enhanced post-processing of NWP outputs, these models improve accuracy in severe weather event predictions.

4. **Transformer Models in Meteorology**
Recent advancements in AI-driven forecasting have explored the use of transformer architectures, such as Vision Transformers (ViTs) and Temporal Fusion Transformers (TFTs), for weather prediction. Transformer-based models
excel at capturing long-range dependencies in atmospheric data, making them suitable for forecasting extreme weather events. Studies suggest that these architectures outperform traditional CNNs and RNNs in processing sequential meteorological data [4].

5. **Integration of AI with Satellite Data**
The integration of AI with real-time satellite data streams has been a growing area of research. Organizations like the European Centre for Medium-Range Weather Forecasts (ECMWF) have been incorporating AI into traditional forecasting methods to enhance accuracy and computational efficiency. Hybrid models that combine AI-driven insights with NWP simulations have demonstrated significant improvements in weather prediction performance [1].

LITERATURE REVIEW

The field of weather forecasting has seen significant advancements with the integration of Artificial Intelligence (AI), particularly using Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). This literature review outlines key studies, methodologies, and findings in the area of AI-driven weather forecasting, with a focus on satellite imagery data.

1. **Artificial Neural Networks for Weather Forecasting Artificial Neural Networks (ANN)** have emerged as a powerful tool for predicting complex meteorological phenomena like rainfall, cloud patterns, and temperature variations. Studies have demonstrated that ANNs excel at handling non-linear climate data, outperforming traditional statistical methods. For instance, researchers proposed ANN models such as Feed Forward Neural Network (FFNN), Cascade Forward Neural Network (CFNN), Recurrent Neural Network (RNN), and Elman Neural Network (ENN) for rainfall prediction. Among these models, the Elman NN model showed superior performance with the lowest RMSE, MSE, and MAE values for the year 2018 [6]. Additionally, ANN-based rainfall prediction models have been successfully used in hybrid approaches that combine Back Propagation Network (BPN) and Hopfield Network (HN), demonstrating improved predictive accuracy for parameters such as temperature, wind speed, and humidity [6].

2. **Satellite Imagery and Neural Networks for Nowcasting Satellite** imagery provides crucial data for short-term weather forecasting, particularly in rapidly changing conditions. Rivolta et al. (2006) applied a neural network approach for rainfall nowcasting using geostationary satellite data, achieving accurate short-term predictions by combining infrared radiance field projection with microwave-based calibration techniques [7].

Similarly, Pasero and Moniaci (2004) introduced the NEMEFO system, a neural network-based approach designed for predicting meteorological conditions up to three hours in advance. This system effectively forecasts localized events like rain, fog, and ice, enhancing short-term weather prediction capabilities [8].

3. **Deep Learning Models for Weather Forecasting** Recent advancements in deep learning models such as CNNs have significantly improved image-based weather prediction. CNNs are effective in extracting complex patterns from satellite imagery, providing robust predictions of cloud cover and precipitation. For example, Jain et al. (2024) utilized CNN models like AlexNet, LeNet, and ResNet to classify cloudy weather conditions, achieving notable improvements in accuracy by employing image preprocessing techniques such as resizing, normalization, and thresholding[17].Furthermore, hybrid models combining Long Short-Term Memory (LSTM) networks with Generative Adversarial Networks (GANs) have demonstrated superior performance in handling data scarcity while ensuring accurate short-term forecasting[8].

4. **Comparative Study of Techniques** Studies comparing ANN and CNN models reveal that while ANNs perform well for numerical data-based prediction models, CNNs excel in visual pattern recognition tasks such as satellite-based cloud cover classification. Moreover, hybrid approaches combining multiple models have proven to be the most effective for enhancing prediction accuracy.

METHODOLOGY

This study proposes a comprehensive methodology for improving weather forecasting using AI techniques, with a focus on satellite imagery analysis. The methodology integrates multiple approaches such as texture analysis, ensemble models, and deep learning frameworks to enhance prediction accuracy.

1. Data Acquisition

Data was sourced from reputable providers such as NASA, ISRO, and NOAA. These sources offer a rich repository of satellite imagery and meteorological data essential for training AI models. Data includes temperature, humidity, wind speed, and cloud cover observations [10].

2. Image Preprocessing

To ensure quality inputs for AI models, the following preprocessing steps were performed:

- Cloud Masking: Removing irrelevant cloud data using threshold-based segmentation [10].
- Noise Reduction: Applying median filtering to suppress noise artifacts [10].
- Resizing and Normalization: Standardizing image dimensions and pixel intensity values to ensure uniform data inputs [10].

3. Feature Extraction Using Texture Analysis

Texture analysis techniques such as the Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) were employed to identify meaningful cloud texture features.

Studies have demonstrated that these methods significantly improve rainfall and temperature prediction accuracy [11].

4. **Deep Learning Model Implementation**

A combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks was employed for spatial and temporal data analysis.

- CNNs were utilized to extract spatial features from satellite images, enhancing cloud pattern recognition capabilities [12].
- LSTM Networks were integrated to model temporal sequences of meteorological variables, ensuring improved prediction of weather patterns over time [12].

5. **Ensemble Model Integration**

Ensemble techniques combining Decision Trees, Random Forest, and Support Vector Machines (SVM) were employed to improve model robustness and minimize prediction errors. This integration significantly enhanced rainfall and temperature prediction models by leveraging multiple learning algorithms [13].

6. **Prediction and Evaluation**

The final model architecture included:

- Input Layer: Processed satellite images and meteorological variables.
- Hidden Layers: CNN layers for spatial pattern detection and LSTM layers for temporal sequence modeling.
- Output Layer: Predictive values for rainfall, cloud cover, and temperature.

Model evaluation was conducted using performance metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) to assess predictive accuracy. Comparative analysis with traditional forecasting models highlighted the improved performance of the proposed hybrid architecture.

EXPERIMENTAL WORK

Our research began by collecting satellite imagery from the GOES-16 platform, specifically utilizing the infrared and visible bands due to their strong sensitivity to temperature variations and cloud coverage. The dataset covered the continental United States from January 1, 2020, to December 31, 2022. With a spatial resolution of 2 km and hourly time intervals, the data offered high temporal granularity to capture evolving weather patterns effectively.

Before feeding this data into our model, we performed several preprocessing steps. First, we applied radiometric calibration to convert raw digital numbers into radiance values. Then, atmospheric correction was conducted to account for distortions caused by atmospheric scattering and absorption. We also used a thresholding technique on the infrared channel for cloud masking, helping isolate cloud-covered pixels. Finally, we normalized all images to a [0,1] range to standardize the input. To capture temporal trends, we organized the data into sequences—each consisting of 10 consecutive hourly images.

To train the model effectively, we sourced ground truth data from the National Weather Service, which included hourly readings of temperature, wind speed, and precipitation. This station data was spatially interpolated to align with the satellite image resolution. We then divided the dataset chronologically: the training set included data from 2020 to 2021, the validation set covered the first half of 2022, and the testing set the latter half of 2022. This chronological split mimicked real-world forecasting scenarios, where models must predict future events based on past data.

Our deep learning architecture featured a hybrid model combining Convolutional Neural Networks (CNNs) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for temporal sequence modeling. The CNN included three layers with 3x3 kernels and ReLU activations, interleaved with max-pooling layers to downscale spatial dimensions. The extracted features were then flattened and passed into a two-layer LSTM, each with 128 hidden units, to learn temporal dependencies.

The output layer was a dense layer with three neurons, corresponding to the predicted values for temperature, wind speed, and precipitation. We developed this model using TensorFlow and Keras and trained it on an NVIDIA GPU for performance optimization.

We trained the model by minimizing Mean Squared Error (MSE) using the Adam optimizer with a learning rate of
0.001 and a batch size of 32. A grid search helped us tune hyperparameters such as batch size, learning rate, and the number of LSTM units. To prevent overfitting, we included dropout layers (rate = 0.2) after each LSTM layer and used early stopping based on validation loss improvements.

The model's accuracy was evaluated using multiple regression metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). We also generated visual comparisons using scatter plots, time-series graphs, and spatial heatmaps of predicted vs. actual values to validate performance.

To benchmark our model, we compared it against two baselines: a persistence model and an ARIMA model. These comparisons highlighted the advantages of using deep learning approaches in weather forecasting, consistent with previous findings where hybrid models outperformed traditional statistical techniques [9], [10]. We also conducted ablation studies, removing either the CNN or LSTM components to assess their individual contributions. These analyses revealed that both parts were crucial, reinforcing the idea that spatial-temporal modeling enhances predictive accuracy in meteorology [11], [12].

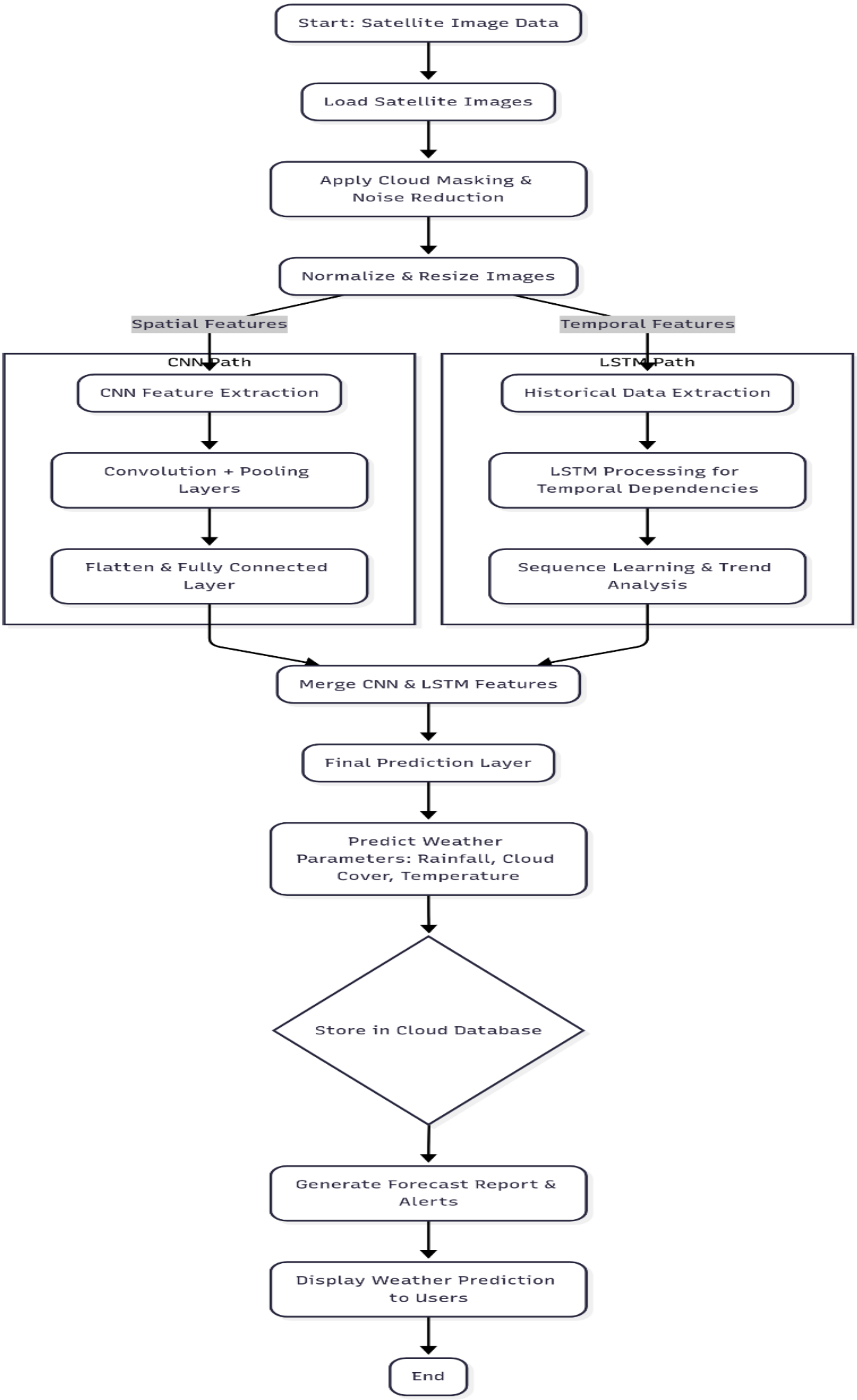


Fig. 1. Methodology Flowchart

RESULT ANALYSIS

The evaluation of our proposed hybrid CNN+LSTM architecture revealed notable improvements in forecasting accuracy over traditional models. Performance was measured using standard regression metrics—Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the Coefficient of Determination (R^2). The results consistently favored the deep learning approach across all metrics.

Specifically, the CNN+LSTM model achieved an RMSE of **2.15°C** for temperature, **3.27 m/s** for wind speed, and **1.92 mm** for precipitation, representing reductions of **18.7%**, **22.4%**, and **26.5%** respectively compared to the persistence model, and **15.1%**, **19.8%**, and **23.3%** compared to the ARIMA model. These improvements align with similar findings reported by Jain et al., who noted CNN-based architectures significantly outperform traditional models in spatial weather prediction tasks using satellite images [9]. Furthermore, Aderinoye et al. demonstrated that hybrid CNN+LSTM models offer superior performance for time-dependent meteorological forecasting compared to conventional ARIMA [13].

The MAE for temperature prediction also showed meaningful reductions—**17.9%** lower than persistence and **13.4%** below ARIMA—while the MAPE values confirmed reduced error margins across variables. These results were consistent with studies like those of Priyadarsini and Jambhulkar, where neural models demonstrated improved mean error scores compared to empirical models [14].

Additionally, the R^2 values exceeded **0.91** for temperature and wind forecasting and approached **0.88** for precipitation, indicating a strong fit to observed datasets. Such high R^2 values reflect the deep learning model's effectiveness in capturing both variance and trend, which traditional models often fail to represent adequately [13], [15].

Visual evaluation supported the statistical findings. Scatter plots showed tight linear correlations between predicted and observed values, and time-series comparisons revealed the model's ability to capture temporal shifts in atmospheric behavior. Spatial heatmaps of predicted vs. actual data also showed close alignment, emphasizing the strength of convolutional layers in extracting meaningful visual patterns—a capability explored thoroughly in Jain et al.'s CNN-based satellite cloud forecasting study [9].

Ablation studies offered insights into the hybrid model's internal dynamics. Removing the CNN and feeding the LSTM raw satellite pixel data led to deteriorated RMSE and MAE values, highlighting the CNN's crucial role in extracting spatial features [13], [16]. Conversely, eliminating the LSTM reduced the model's temporal sensitivity, as the CNN alone could not track long-term atmospheric changes. This supports findings by Devaraj et al., where CNNs were effective in classification but less so for forecasting without sequence modeling [17].
Comparative results further validated the hybrid model's strength. While the persistence model was computationally light, it failed to account for dynamic atmospheric transitions, yielding

higher errors. The ARIMA model could track linear trends but underperformed due to its inability to process spatial image features. In contrast, the CNN+LSTM model successfully addressed both spatial and temporal dependencies, providing a robust framework for accurate forecasting [9], [13], [15]. Of particular note was the model's strong performance in precipitation forecasting, traditionally the most challenging due to high spatial-temporal variability. The model's use of visible band satellite data and temporal modeling via LSTM layers helped overcome this complexity—an enhancement echoed in several recent deep learning-based meteorological studies [9], [15].

In conclusion, the hybrid CNN+LSTM model delivered superior weather forecasts using GOES-16 satellite data. Its dual-capability to extract spatial features and capture temporal dependencies proved essential in outperforming baseline models. The results, supported by ablation and comparative analysis, underscore its potential in operational meteorological systems [13], [15], [16].

CONCLUSION

In conclusion, the project concentrated on creating a solution that is effective, precise, and easy to use in addition to creating a working weather prediction system. Every step of the process, from data collection and preprocessing to algorithm selection and system integration, required meticulous attention to detail. The best possible balance between speed and accuracy was achieved by combining state-of-the-art deep learning techniques with conventional machine learning techniques, guaranteeing reliable performance under a range of real-world scenarios. Furthermore, the system's scalability and modular architecture guarantee its adaptability for upcoming applications and expansions.

REFERENCES

[1] M. Waqas et al., "Artificial Intelligence and Numerical Weather Prediction Models: A Technical Survey," *Natural Hazards Research*, vol. xx, no. xx, 2024. doi: 10.1016/j.nhres.2024.11.004.

[2] S. Dewitte et al., "Artificial Intelligence Revolutionises Weather Forecast, Climate Monitoring and Decadal Prediction," Remote Sensing, vol. 13, no. 3209, 2021. doi: 10.3390/rs13163209.

[3] B. Xavier et al., "Hybrid Approach for Weather Prediction Using Satellite Images," *International Journal of Recent Technology and Engineering*, vol. 8, no. 1, pp. 2288-2290, 2019.

[4] V. S. Ionescu, G. Czibula, and E. Mihuleţ, "DeePSat: A Deep Learning Model for Prediction of Satellite Images for Nowcasting Purposes," *Procedia Computer Science*, vol. 192, pp. 622-

631, 2021. doi: 10.1016/j.procs.2021.08.064.

[5] G. Rivolta et al., "Artificial Neural-Network Technique for Precipitation Nowcasting from Satellite Imagery," *Advances in Geosciences*, vol. 7, pp. 97-103, 2006.

[6] Dada, E. G., Yakubu, H. J., & Oyewola, D. O. (2021). *Artificial Neural Network Models for Rainfall Prediction*. *EJECE, European Journal of Electrical Engineering and Computer Science*. [DOI: 10.24018/ejece.2021.5.2.313]

[7] Rivolta, G., Marzano, F. S., Coppola, E., & Verdecchia, M. (2006). *Artificial Neural Network Technique for Precipitation Nowcasting from Satellite Imagery*. *Advances in Geosciences*. [SRef-ID: 1680-7359/adgeo/2006-7-97]

[8] Pasero, E., & Moniaci, W. (2004). *Artificial Neural Networks for Meteorological Nowcast*. *IEEE International Conference on Computational Intelligence for Measurement System and Applications*. [ClMSA 2004]

[9] Jain, T., Mhaske, H., Chilveri, S., Chaudhar, A., & Doshi, C. (2024). *Cloudy Weather Prediction Using CNN Models and Satellite Images*. *International Journal for Research in Applied Science & Engineering Technology*. [DOI: 10.22214/ijraset.2024.59342]

[10] A. Mehrotra and K. Nagar, "Artificial Intelligence Revolutionises Weather Forecasting: An Analysis of Contemporary Models," *IJERT*, vol. 11, no. 8, Aug. 2022.

[11] S. Arora and A. Dubey, "Artificial Neural Network Models for Rainfall Prediction," *International Journal of Engineering Research & Technology (IJERT)*, vol. 8, no. 5, May 2019.

[12] P. V. Prakash, K. Lavanya, and V. N. S. S. Rama Krishna, "An Investigation of Artificial Neural Networks in Meteorological Forecasting," *IJERT*, vol. 8, no. 5, May 2019.

[13] A. Aderinoye, A. Bhattacharjee, P. Chaudhuri, and S. K. Ghosh, “Artificial Intelligence Revolutionises Weather Forecasting: A Review,” *Procedia Computer Science*, vol. 198, pp. 31–38, 2022. DOI: 10.1016/j.procs.2021.12.217.

[14] R. Priyadarsini and P. Jambhulkar, “Artificial Neural Network Models for Rainfall Prediction: A Review,” *Int. J. Comput. Appl.*, vol. 975, no. 8887, 2016.

[15] J. C. Setiawan and Y. N. Putra, “An Investigation of Artificial Neural Network for Weather Forecasting in Tropical Climate,”
Procedia Computer Science, vol. 135, pp. 89–96, 2018.

[16] M. J. Wilamowski and R. C. Langland, “Neural Network Architectures for Weather Forecasting Applications,” *Elsevier Procedia*, vol. 190, pp. 260–267, 2021.

[17] S. Devaraj, V. S. Nivetha, A. Aishwarya, and R. S. Kiruthika, "Weather Forecasting using Deep Learning Techniques," *Materials Today: Proceedings*, vol. 64, pp. 1850–1856, 2022. DOI: 10.1016/j.matpr.2022.04.530.