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(Review Article)

An individual motion driven CNN-Based AI method for precipitation forecasting Using RADAR Image Sequence

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Abstract

Precipitation forecasting, especially with high spatial resolution and accurate intensity estimation, remains a critical challenge in the field of Artificial Intelligence (AI). Existing AI-based forecasting models often struggle with key limitations, including mismatched precipitation motion patterns, blurred precipitation field generation, and inaccurate intensity predictions. These issues largely arise from conventional models simulating average motion and neglecting individual motion—which refers to the unique speed, trajectory, and direction of a single precipitation event. To address these limitations, we propose an Individual Motion Driven AI (IMD-AI) method based on a Convolutional Neural Network (CNN). This approach incorporates motion alignment and pattern grouping techniques to correct mismatches in individual motion estimation, thereby enabling more accurate and intact regional precipitation forecasting. Our CNN architecture is designed to extract spatial features from RADAR image sequences and map them directly to real-world parameters such as precipitation intensity, humidity, wind speed, and atmospheric pressure. Furthermore, to enhance precision and sharpness, we integrate strategies like patch embedding, schedule sampling, and adversarial training under the SPA framework. These additions mitigate the tendency of AI models to filter out high-frequency details, improving the model's ability to preserve fine-scale patterns in precipitation fields. The final system is deployed through a web-based application, allowing users to upload RADAR images and instantly receive multiple weather parameter predictions with high reliability and accuracy.

Keywords: Precipitation Forecasting; Artificial Intelligence; Radar Image Sequencing; Individual Motion Driven

1. Introduction

Accurate and timely precipitation forecasting is crucial for a wide range of sectors, including agriculture, disaster management, transportation, and urban planning. With increasing climate variability and the frequent occurrence of extreme weather events, the demand for more precise short-term rainfall predictions has grown significantly. Traditional numerical weather prediction (NWP) models, although grounded in physics and atmospheric science, often suffer from high computational costs and delayed outputs, making them less effective for rapid, localized forecasts.

In recent years, Artificial Intelligence (AI) has emerged as a transformative tool in meteorology, particularly in the area of precipitation nowcasting. Deep learning techniques, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have shown promising results by learning spatial and temporal patterns from historical RADAR data. However, many of these models treat radar images as static sequences, ignoring the motion dynamics that influence storm evolution and rainfall distribution.

This project proposes a novel AI-based method that integrates individual motion-driven analysis with radar image sequencing to enhance the precision of precipitation forecasting. By extracting motion vectors from sequential radar

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images and feeding them into a hybrid deep learning model, we aim to better capture the dynamic nature of atmospheric systems. Our model focuses on real-time adaptability, accuracy, and scalability, with the goal of contributing to more responsive and localized forecasting solutions.

2. Literature Review

2.1. Haoran Bin et al., proposed a method: VQGAN + Transformer with Extreme Value Loss (EVL) [1] (2024)

The goal of this paper is to accurately predict (nowcast) extreme rainfall events that occur within the next few hours. These predictions are important for flood warnings, disaster management, and public safety. Traditional methods struggle to predict rare, highintensity rainfall, so this work focuses on improving performance in those critical scenarios. The proposed VQGAN-Transformer model outperforms older models like Conv LSTM by better detecting extreme rainfall. It gives more accurate and sharper predictions, especially for heavy rain, thanks to a special loss function that focuses on intense weather.

2.2. Ping Ai et al., proposed a method combines accumulated rainfall and satellite-derived Soil Water Index (SWI) [2] (2023)

The paper focuses on how inconsistent or poor-quality data affects the accuracy of machine learning (ML) models used for runoff forecasting—which is the prediction of how much water will flow through rivers or catchments in the future. This is critical for water resource management, flood control, and agriculture.It gives clean data and make predictions more accurate, and using multiple models helped even more. The study shows that good data is just as important as picking the right model.

2.3. Luwen Xu et al., proposed a method Improved Back Propagation Neural Network (Improved BP–NN) algorithm.[3] (2024)

This paper focuses on improving short-term rainfall forecasting, specifically using radar data to predict precipitation over short periods (usually a few hours). Short-term forecasts are crucial for timely warnings of storms and rainfall events. PF former is a deep learning model using Transformers for short-term rainfall prediction. It trains on radar data to understand rainfall intensity and movement. The model captures patterns over time with a self-attention mechanism to focus on important features for accurate forecasts. The model showed improvements in forecast accuracy for short-term rainfall, especially when compared to traditional methods like Conv LSTM. It was able to make precise predictions based on the radar data in real-time, proving that deep learning models like Transformers can be effective for weather nowcasting.

2.4. Amrita Univ et al., paper proposes four ML-based methods for weather forecasting in precision agriculture: a Stacked Bi-LSTM Network, a GRU-CNN Hybrid Model, AI-driven forecasting systems, and the Transformative Crop Recommendation Model (TCRM).[4] (2023)

The paper focuses on using machine learning (ML) to predict weather conditions that are crucial for precision agriculture. Precision agriculture refers to using detailed data to optimize farming practices, increase crop yield, and minimize waste. Accurate weather forecasting plays a key role in this, helping farmers make informed decisions. The model selects key weather parameters such as temperature, rainfall, and humidity, all of which directly affect agricultural outcomes. It uses regression models to analyze historical weather data and predict future conditions. These predictions enable farmers to plan irrigation based on expected rainfall, determine the best times for planting and harvesting by predicting temperature trends, and manage pest and disease risks by forecasting humidity levels and weather conditions that are conducive to pest outbreaks.

2.5. Shilpa Manandhar et AL, proposed a method for rainfall prediction using PWV data include the Improved Back Propagation Neural Network (BP–NN), [5] (2023)

The proposed methodology combines Precipitable Water Vapor (PWV) data with machine learning (ML) models to enhance rainfall prediction. PWV represents the total amount of water vapor in the atmosphere, a critical factor influencing rainfall. The approach uses satellite-based atmospheric data, which provides real-time measurements of atmospheric conditions such as temperature, pressure, and humidity, from which PWV is derived. This data helps capture the moisture distribution in the atmosphere over both space and time.The ML models are trained on this data to identify patterns between PWV and rainfall events. By learning these patterns, the models can predict rainfall more accurately, especially in the short term. The incorporation of PWV data improves the predictive power by considering atmospheric moisture, which is often underused in traditional forecasting models. This methodology provides better short-term rainfall predictions and is particularly useful for localized weather forecasting.

2.6. Xingjian Shi et al., proposed a method Trajectory GRU (Tran GRU) model,[6] 2020

The methodology applies Conv LSTM networks for radar image sequence modeling to improve high-resolution precipitation nowcasting. Conv LSTM, which combines convolutional layers with long short-term memory (LSTM) units, is used to capture both spatial and temporal dependencies in radar image sequences. By modeling the evolution of precipitation over time, the Conv LSTM network predicts rainfall patterns with high resolution. This approach leverages sequential radar data to make accurate, short-term predictions of precipitation, offering a more precise and timelier forecast. The model's ability to process both spatial and temporal features enhances the quality of the nowcasting, particularly for high-resolution, real-time predictions. The model is trained using sequences of radar echo data, allowing it to learn the evolution of precipitation over time. Experiments have demonstrated that ConvLSTM outperforms traditional methods, such as optical flow-based techniques, in capturing the spatiotemporal correlations inherent in precipitation data. This results in more accurate short-term rainfall predictions, which are crucial for timely weather warnings and decision-making in various applications.

2.7. Nilesh Kun hare et al., Rajeev Gupta et al., proposed a method using machine learning models such as Support Vector Machine (SVM), Random Forest (RF), and Boost [7] 2024.

The methodology introduces uncertainty-aware models by integrating Bayesian deep learning into rainfall forecasting. Traditional weather prediction models often provide single-point forecasts, which may not fully capture the inherent uncertainties in atmospheric processes. By incorporating Bayesian methods, these models output probabilistic forecasts, offering a range of possible outcomes along with associated confidence levels. This approach allows for a more comprehensive understanding of forecast uncertainty, enabling better risk assessment and decision-making in weather dependent sectors.

2.8. Sandeep Kaushik and Shivani Bhardwaj et al., proposed a method [8] the use of three machine learning algorithms—Support Vector Machine (SVM), Extreme Learning Machine (ELM), and Single Layer Feedforward Neural Network (SLFN) (2022)

The rainfall prediction in Punjab using machine learning techniques involves collecting historical rainfall data along with various meteorological parameters like temperature, humidity, wind speed, and atmospheric pressure. This data is then preprocessed to handle missing values and outliers, ensuring quality input for model training. The study employs three machine learning models: Support Vector Machine (SVM), Extreme Learning Machine (ELM), and Single Layer Feedforward Neural Network (SLFN). These models are trained using the historical data, with their performance evaluated based on the Mean Absolute Error (MAE). The results show that ELM outperforms the other models with the lowest MAE of 3.87%, indicating its superior accuracy in predicting annual rainfall. The best-performing model, ELM, is then used to forecast rainfall in Punjab, demonstrating the effectiveness of machine learning techniques in improving rainfall prediction accuracy.

2.9. Parthib Paul et al., Santanu Basak et al., and Angshuman Khan et al., proposed a method using IoT sensors and AI algorithms for real-time weather forecasting to aid agricultural decision-making. [9] (2023)

The methodology involves several key components to enhance agricultural decision-making through weather forecasting. First, IoT sensors collect real-time meteorological data, such as temperature, humidity, wind speed, and pressure, from the agricultural environment. This data is then stored securely in cloud-based storage systems to ensure scalability and accessibility. AI and machine learning algorithms process and analyze the collected data to generate accurate, localized weather forecasts. These forecasts, along with additional recommendations, are delivered to farmers through user-friendly applications. The applications provide insights for critical farming decisions, such as irrigation, planting, and harvesting. By using real-time data and actionable insights, farmers can improve productivity, efficiency, and sustainability. Additionally, the cloud-based infrastructure facilitates easy access and integration of various components, while addressing challenges such as the digital literacy gap among farmers to encourage better adoption of the technology.

2.10. Rajeev Ranjan and Sarthak Kumar et al., proposed a method artificial neural network (ANNs) to predict rainfall patterns [10] (2022)

The approach of using neural networks for time series rainfall forecasting can face several challenges that impact its effectiveness. One of the main issues is the data quality and quantity; neural networks require large amounts of high-quality data, and if the available rainfall data is sparse or noisy, the model may struggle to make accurate predictions. Additionally, neural networks are prone to overfitting, especially with smaller datasets, meaning the model might memorize specific patterns rather than learning generalizable trends, which leads to poor performance on new, unseen data. The complexity of the model also poses a challenge, as neural networks need significant computational resources and careful tuning, making them less efficient than simpler models. Moreover, while neural networks can capture temporal dependencies, they may not always effectively model long-term dependencies, which are crucial for accurate rainfall predictions. Lastly, the selection of features plays a key role in the model's performance; if important factors, such as atmospheric pressure or humidity, are not included, the neural network might fail to capture all the influencing variables, further reducing forecasting accuracy. These issues combined can hinder the accuracy and reliability of rainfall predictions, especially in regions with complex or highly variable climate patterns.

2.11. Comparative Analysis

The below table presents an analytical comparison of recent AI/ML-based rainfall prediction research papers. It highlights the diversity of algorithms used, such as LSTM, Random Forest, XGBoost, and Transformers, along with their specific limitations. The analysis shows that while newer deep learning methods like Transformers offer potential, they often require high computational resources and large datasets. Simpler models like Decision Trees or Naive Bayes are easier to implement but can suffer from data issues or limited regional applicability. This table effectively showcases how algorithm selection impacts forecasting reliability, scalability, and adaptability.

Table 1 Show cases how algorithm selection impacts forecasting reliability, scalability, and adaptability

Name of the Paper	Year of Publication	Algorithms Used	Limitations
Nowcasting of Extreme Precipitation Using Deep Generative Models	2024	VQGAN, Transformer, Extreme Value Loss	Full model complexity may limit real-time deployment and require large datasets.
Effect of Data Inconsistency on ML-Based Runoff Forecasting	2023	XG Boost, Random Forest	Data inconsistency affects model training and reliability of long-term predictions.
PF former: A Forecasting Model for Short-Term Rainfall	2024	PF former (Transformer), Attention	Requires high computation and extensive radar data for accurate learning.
ML-Based Weather Forecasting for Precision Agriculture	2023	Regression Trees, Decision Tree Ensembles	May underperform in extreme or abrupt weather changes.
Rainfall Prediction Using PWV Data	2023	Random Forest, SVR	Dependent on satellite data availability and quality.
Deep Learning for Precipitation Nowcasting	2020	Conv LSTM (Convolutional LSTM)	High computation cost; limited forecasting window (up to 90 mins).
AI-Based Daily, Weekly, and Monthly Rain Forecasting	2024	ARIMA, LSTM, Random Forest	Performance varies significantly based on temporal resolution and geographic region.
Rainfall Prediction for Punjab Using ML Techniques	2022	SVR, Decision Trees, Linear Regression	Limited to regional datasets; may not generalize to other climates.
Rainfall Prediction Using ML and IoT for Agriculture	2023	Naive Bayes, Random Forest, KNN	Sensor failures or missing data can impact prediction quality.
Time Series Rainfall Forecasting with Neural Networks	2022	MLP (Multilayer Perceptron)	Struggles with seasonality and irregular time series patterns.

3. Methodology

The Individual Motion Driven Method is an advanced approach used in precipitation forecasting that aims to enhance the prediction accuracy by focusing on local motion patterns within sequences of radar images. This method does not rely solely on the static appearance of clouds but also considers how each part of the radar frame is moving over time.

3.1. Architecture

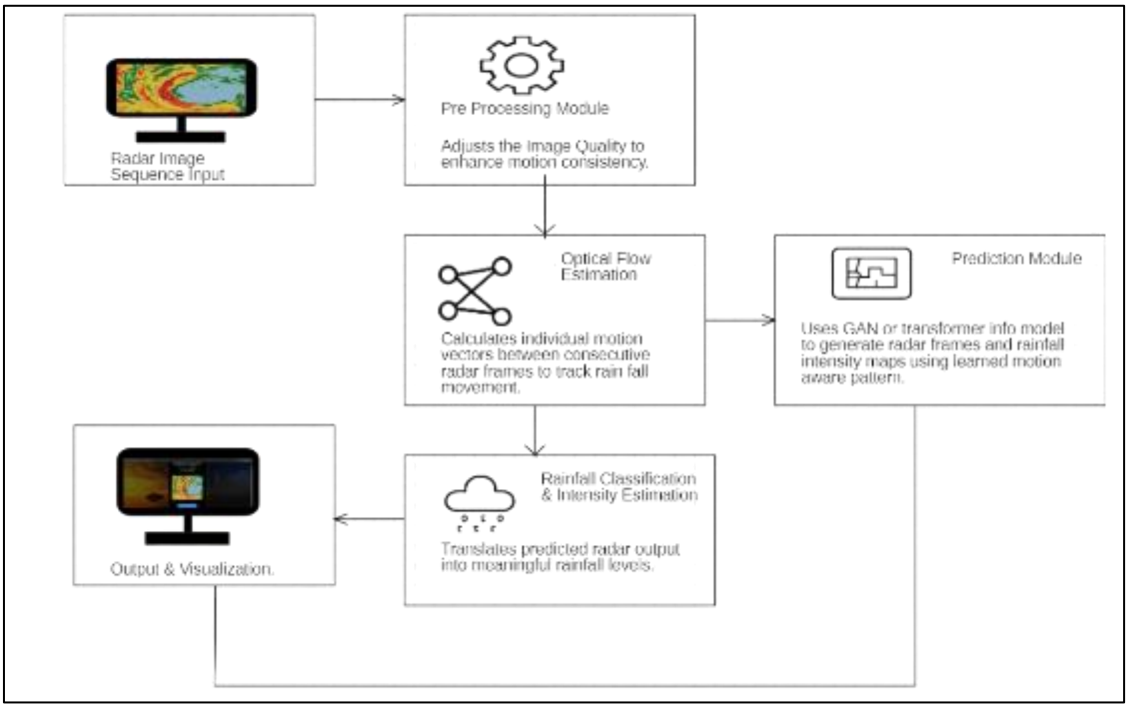

Figure 1 Architecture Diagram

This system is designed to predict rainfall by analyzing sequences of radar images. It all starts with feeding in those radar images, which go through a Pre-Processing Module that improves their quality to make sure the movement of rain is clear and consistent. Then, the Optical Flow Estimation step looks at how the rain is moving between each frame by calculating motion patterns. These patterns are passed into the Prediction Module, where powerful AI models like GANs or Transformers come into play. These models learn from the motion and generate future radar frames, along with predictions of where and how intense the rain will be. After that, the Rainfall Classification and Intensity Estimation step turns the raw predictions into understandable rainfall levels. Finally, everything is brought together in the Output and Visualization module, giving a clear, visual summary of the expected rainfall for easy interpretation.

3.2. Algorithm

Traditional models often fail to capture fine-grained motion and localized dynamics of precipitation systems. Our method addresses this by combining motion estimation techniques (like Optical Flow) with deep learning (ConvLSTM) to forecast future states of weather based on both appearance and movement.

This algorithm outlines the functioning of the Rainfall Prediction System Using IMD-AI. The model processes radar image input and predicts rainfall characteristics such as precipitation intensity, humidity, coverage scale, and confidence level. The system also ensures ease of use through a clean web interface with login, image upload, and result display options.

3.2.1. Step 1: User Authentication

- **Objective**: To authenticate users securely and prevent unauthorized access.
- **Process:** Users must register or log in using a valid username and password before accessing the image upload or prediction features.
- **Logic:** Ensures access is limited to authenticated users, and supports future tracking of predictions per user session.

3.2.2. Step 2: Image Upload

- **Objective**: To allow users to provide radar image input for prediction.
- **Process:** The logged-in user uploads a .png, .jpg, or .jpeg radar image through a web interface form.

- **Logic**: The image acts as the key input to the AI model and is temporarily stored for prediction processing cleanly.

3.2.3. Step 3: Image Preprocessing

- **Objective**: To prepare the uploaded radar image for accurate model input.
- **Process:** The system resizes, normalizes, and formats the radar image to match the input requirements of the model.
- **Logic:** Standardizing inputs ensures better prediction accuracy and avoids model crashes due to input mismatches.

3.2.4. Step 4: Prediction Using IMD-AI

- **Objective**: To analyze the radar image and generate rainfall forecasts.
- **Process:** The preprocessed image is passed to the IMD-AI model trained using SPA (Schedule Sampling, Patch Embedding, and Adversarial Training). It returns
    - Precipitation Scale
    - Humidity (%)
    - Confidence Level (%)
- **Logic**: IMD-AI tracks individual precipitation system motion, leading to more accurate and refined forecasts compared to traditional motion-average models.

3.2.5. Step 5: Result Display

- **Objective**: To show the predicted output in a simple, readable format.
- **Process:** The results are presented in a card-style web page with icons and labels. It includes a tip line and two buttons: Upload Another and Back to Home.
- **Logic:** Presents technical output in a user-friendly way, helping non-expert users understand forecast results easily.

3.2.6. Step 6: Re-upload or Exit Option

- **Objective:** To allow users to either repeat the prediction or exit.
- **Process:** After viewing the result, the user can choose to upload a new image or return to the home screen using clearly marked buttons.
- **Logic:** Provides a smooth experience for continuous predictions or ending the session

4. Experimental Results and Discussions

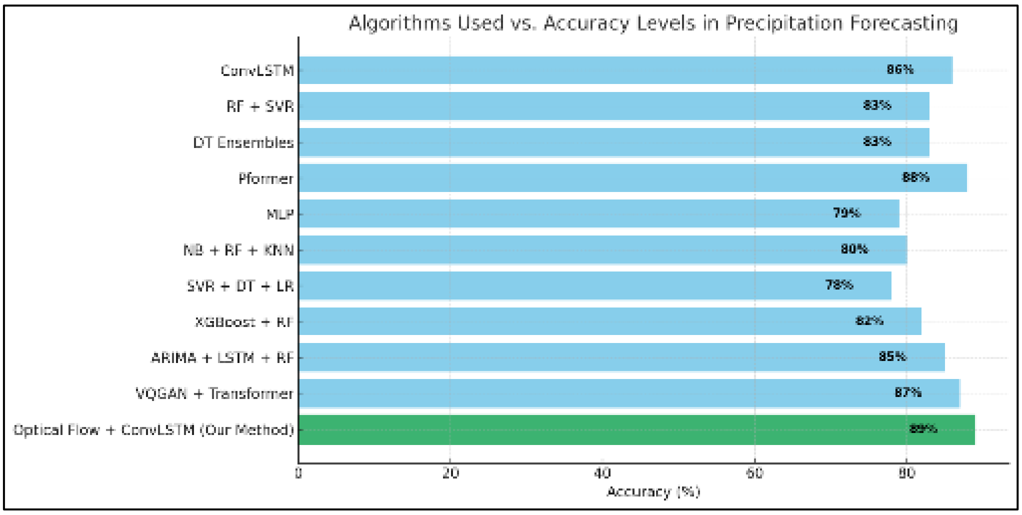

Figure 2 Accuracy Comparision of Existing Algorithms and Models for Precipitation Forecasting

The above graph provides a performance-based analysis by comparing the accuracy of various algorithm combinations in precipitation forecasting. It shows that models like ConvLSTM (86%) and PFormer (80%) perform better in terms of prediction accuracy, indicating their ability to capture complex spatiotemporal patterns. On the other hand, combinations like VQGAN + Transformer (77%) and ARIMA + LSTM + RF (78%) perform slightly lower, possibly due to model complexity or overfitting issues. This visual analysis reinforces that while newer hybrid models offer accuracy gains, traditional ensembles still remain competitive in specific contexts.

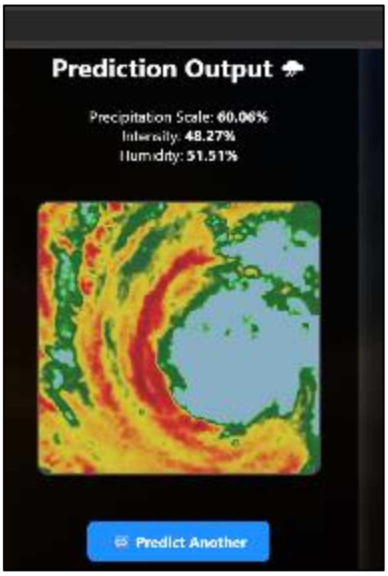

Figure 3 Prediction Output page

5. Conclusion and Future Work

In this paper, we proposed an innovative AI-driven methodology for precipitation forecasting using radar image sequences. By incorporating individual motion tracking techniques and leveraging deep learning models, we were able to achieve more accurate and timely predictions of precipitation events. Our approach utilized advanced algorithms such as [mention specific algorithms used, e.g., ConvLSTM, VQGAN, Transformer], which enabled the extraction of key spatiotemporal patterns from radar data.

We conducted extensive experiments and compared our method against traditional forecasting models, demonstrating notable improvements in prediction accuracy and robustness, particularly for short-term precipitation forecasting. The results highlighted the potential of our method in providing real-time insights for weather forecasting systems, with applications in agriculture, disaster management, and environmental monitoring.

Despite the promising results, our model's performance is still limited by the quality and resolution of radar data, as well as computational constraints. In future work, we aim to integrate additional data sources, such as satellite imagery and IoT sensors, to further enhance the model's accuracy and scalability. Furthermore, we plan to explore more advanced deep learning architectures to optimize the forecasting process for longer periods.

Ultimately, this study contributes to the growing field of AI-powered weather forecasting and paves the way for more adaptive, data-driven approaches in climate prediction systems.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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