Real-Time Rain Prediction in Agriculture using AI and IoT: A Bi-Directional LSTM Approach

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ABSTRACT

Accurate rain forecasting is crucial for optimizing agricultural practices and improving crop yields. This study presents a real-time rain forecasting model using a Bidirectional Long Short-Term Memory (Bi-LSTM) algorithm for an on-device AI platform. The model uses historical weather data to predict rainfall, enabling farmers to make data-driven decisions in irrigation, pest control, and field operations. This model enables farmers to optimize water use, conserve energy, and improve overall resource management. Real-time capabilities allow immediate adjustments to agricultural activities, mitigating risks associated with

unexpected weather changes. The Bi-LSTM model achieved a mean accuracy of 92%, significantly outperforming the traditional LSTM (85%) and ARIMA (80%) models. This high accuracy is attributed to the model's bidirectional processing capability, which captures comprehensive temporal patterns in the weather data. Implementing this model can enhance decision-making processes for farmers, resulting in increased productivity and profitability in the agricultural sector.

Keywords-smart agriculture; AI; IoT; Bi-LSTM; weather forecasting; rain prediction; precision farming

I. INTRODUCTION

Agriculture is an important pillar of the Indian economy, with a significant portion of the population relying on it. Rainfall plays an essential role in agricultural productivity as it directly affects crop health, irrigation scheduling, and overall yields. Therefore, accurate rain forecasting is essential for farmers to effectively plan and execute their activities. However, the current state of rain forecasting in India presents several challenges that often lead to erroneous predictions and substantial losses for agriculturists. Rain forecasting is conducted primarily by the India Meteorological Department (IMD) using a combination of satellite data, radar, and ground-based observations [1]. Although these methods provide a broad understanding of weather patterns, they often lack the precision required for micro-level agricultural planning, as forecasts are typically issued for larger regions that might not accurately reflect local conditions [2]. Thus, farmers often make critical decisions based on generalized predictions [3]. Incorrect rain forecasts can result in improper irrigation schedules. Over-irrigation or under-irrigation due to inaccurate forecasts can stress crops, leading to reduced yields and increased water wastage [4]. The timely application of pesticides and fungicides is crucial to prevent pest infestations and diseases. Erroneous rain forecasts can lead to mistimed applications, reducing their effectiveness and potentially increasing crop damage [5]. Agricultural activities such as sowing, fertilizing, and harvesting need precise timing to maximize productivity. Unreliable forecasts disrupt these activities, leading to inefficiencies and increased labor costs [6]. The economic implications of inaccurate rainfall forecasting are profound. Indian farmers incur losses of billions of rupees annually due to weather-related uncertainties and incorrect forecasts [7]. These losses affect the overall economic stability of farming communities and hinder agricultural growth [8]. Figure 1 illustrates the crop loss in million hectares due to drought and excessive rainfall in various states of India from 2016 to 2022. These data underscore the critical impact of inaccurate rainfall forecasts on agricultural productivity, emphasizing the need for precise and localized weather forecasts to mitigate such losses. To address these challenges, there is a pressing need for advanced and localized rain forecasting solutions. Traditional centralized forecasting methods are insufficient for the micro-level precision required by farmers. On-device AI technology presents a viable solution by offering several advantages [9]. On-device AI can process weather data in real time, providing immediate and localized forecasts. This enables farmers to make prompt decisions, improving the effectiveness of their agricultural practices. Using local data from IoT sensors placed in the fields, AI algorithms can generate highly accurate forecasts tailored to specific areas [10]. This level of precision is crucial for efficient resource management and operational planning. On-device AI systems operate independently of external networks, ensuring consistent performance even in remote areas with limited connectivity [11]. This autonomy is vital for continuous and reliable forecasting. The integration of IoT and AI technologies can revolutionize rain forecasting for agriculture. IoT sensors can continuously collect a wide range of environmental data, including humidity, temperature, soil moisture, and atmospheric pressure. These data, when fed into AI algorithms, enhance the accuracy of weather forecasts [12]. Continuous data flow ensures that forecasts are up-to-date and reflect current conditions. AI models can learn from historical weather data and improve their predictive capabilities over time. This adaptive learning process allows the models to refine their accuracy, providing increasingly reliable forecasts. The combined IoT-AI approach is highly scalable, allowing widespread deployment across diverse agricultural regions. This scalability ensures that farmers in different climatic zones can benefit from accurate rainfall forecasts.

The Bi-Directional Long Short-Term Memory (Bi-LSTM) model has unique capabilities in handling sequential data and capturing temporal dependencies. LSTM networks are specifically designed to address the vanishing gradient problem, which makes them highly effective for time series forecasting tasks. The Bi-LSTM model extends this capability by processing data in both forward and backward directions, allowing it to learn from the entire sequence of data points. This bidirectional processing enhances the model's ability to understand complex temporal patterns in weather data, making it particularly suitable for rain forecasting. The decision to use LSTM models is further supported by their proven success in various weather forecasting applications, where they have shown superior performance compared to traditional methods and other neural network types. By leveraging the strengths of Bi-LSTM, this study aims to provide a robust and accurate solution for real-time rain forecasting in agriculture to help farmers optimize their practices and improve crop yields.

The integration of AI and IoT technologies in rain forecasting represents a significant advance in agricultural management. By providing precise and real-time weather predictions, this approach addresses the limitations of traditional forecasting methods and empowers farmers with the information needed to make informed decisions. The result is improved crop management, resource efficiency, and economic stability for farming communities. As agriculture continues to face challenges posed by climate variability and resource constraints, adopting AI-driven solutions becomes increasingly critical for sustainable agricultural development.

II. LITERATURE REVIEW

Recent advances in AI and machine learning have significantly improved rain forecasting methods, particularly benefiting agricultural applications. Over the past three years, many studies have explored different approaches to improve the accuracy and timeliness of rainfall predictions through deep learning models, IoT technologies, and real-time data processing capabilities. In [13], a real-time rainfall prediction system was proposed, using a fusion of decision trees, Naïve Bayes, K-nearest neighbors, and Support Vector Machines (SVMs), integrated with fuzzy logic, demonstrating improved accuracy over traditional models. In [14], LSTM networks were combined with radar data and ground rain gauges, achieving better 180-minute forecasts, particularly for urban basins. In [15], a temporal Deep Belief Network (DBN) was introduced for direct multistep forecasting, which outperformed conventional Convolutional Neural Networks (CNNs) in terms of accuracy and reliability. In [16], a deep generative model was introduced for probabilistic nowcasting, providing superior performance in forecast quality and operational utility for up to 90 minutes ahead.

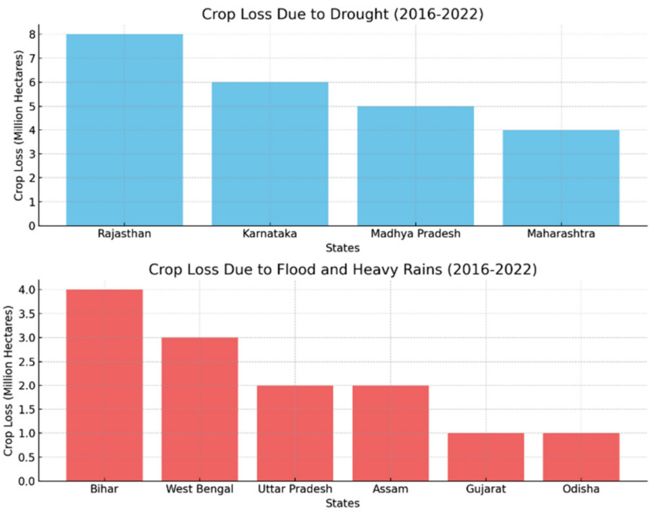

Fig. 1. Crop loss statistics due to drought, flood, and heavy rains in Indian states.

In the realm of AI and IoT integration, an IoT-based weather monitoring system was proposed in [17], utilizing SVM to analyze real-time data from various sensors and predict rainfall patterns. In [18], an AI-IoT system was proposed for real-time weather prediction and optimized agricultural resource management, demonstrating significant resource savings and improved yields in maize farming. Advanced AI techniques have also shown promising results. In [19], a Bayesian Regularized Neural Network (BRNN) model was proposed to predict daily rainfall based on sea level pressure, achieving high accuracy and reliability. In [20], GRU neural networks were used to predict rainfall during typhoons, showing accurate predictions up to 6 hours ahead. In [21], a regression-based model was introduced to predict monthly precipitation, outperforming traditional models in accuracy.

Hybrid and ensemble approaches have been proven to be particularly effective. In [22], observed precipitation was combined with WRF forecasts using a sigmoidal curve, enhancing forecast accuracy in the Tehran and Golestan watersheds. In [23], a rain predictive model was developed using Random Forest, achieving high accuracy and aiding in urban rain forecasts. In [24], Artificial Neural Networks (ANNs) and Deep Learning Neural Networks (DLNNs) were compared, and ANNs outperformed DLNNs in rainfall prediction accuracy [24]. The literature consistently demonstrates the superiority of AI-driven models, particularly deep learning and machine learning techniques, over traditional methods for rain forecasting. These models significantly improve prediction accuracy, providing real-time localized forecasts that are crucial for agricultural planning and resource management. However, the integration of emerging technologies into agriculture presents several limitations and challenges. One major limitation is the high initial cost of deploying AI and IoT technologies, which can be prohibitive for small-scale farmers. Additionally, there is a significant requirement for technical expertise to manage and maintain these systems, which may not be readily available in rural areas. The reliance on high-quality and high-volume data for training AI models can also be a constraint, especially in regions with a sparse data collection infrastructure. Furthermore, the interoperability of different IoT devices and the standardization of data formats remain unresolved issues that can hinder seamless integration and scalability. The energy consumption of IoT devices and the sustainability of such systems in remote areas with limited access to power is another concern. Finally, the rapid pace of technological advances requires continuous updates and upgrades to maintain system efficiency and accuracy, which poses an ongoing financial and logistical challenge.

III. MATERIALS AND METHODS

The initial step in the proposed architecture, shown in Figure 2, is to set up an IoT infrastructure capable of capturing real-time weather data from agricultural fields. This involves deploying a network of sensors across the fields, strategically placed to ensure comprehensive coverage and effectively capture microclimatic variations. The weather data collected include temperature, humidity, wind speed, and precipitation levels. The actual data to train the Bi-LTSM model were sourced from the India Meteorological Department [25]. For real-time testing, the trained model was deployed on an IoT device, specifically the Arduino MKR1010 microcontroller. This device is equipped with an environment shield that houses all the necessary sensors, including a temperature sensor to measure the ambient temperature, a humidity sensor to assess moisture levels in the air, an anemometer to record wind speed and direction, and a rain gauge to monitor the amount of rainfall. These sensors transmit data at regular intervals, typically every few minutes, ensuring that the most current information is available for real-time processing. Data acquisition is facilitated by the LoRaWAN private network, a low-power, wide-area networking protocol ideal for IoT applications in remote agricultural fields. This protocol ensures reliable communication between the sensors and the AI platform, even in areas with limited connectivity. The collected data undergo preprocessing to ensure quality and consistency. Data cleaning involves removing anomalies, imputing missing values using techniques such as mean imputation or forward filling, and detecting and eliminating outliers. Normalization is applied to scale the data to a standard range, typically between 0 and 1, using techniques such as min-max scaling or z-score standardization. This step ensures that all features contribute equally to the model's learning process. Then, feature selection is performed to identify the most relevant variables, which include temperature, humidity, wind speed, and precipitation levels. These features are chosen based on their direct correlation with rainfall patterns and their importance in capturing weather dynamics.

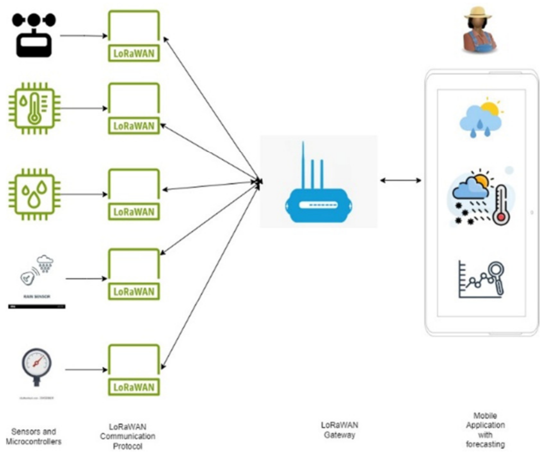

Fig. 2. AI on device architecture for forecasting rain in agricultural fields.

A. LSTM Architectures

1) Bi-LSTM

The core of the proposed method is the Bi-LSTM algorithm, chosen for its ability to capture temporal dependencies in sequential data. The architecture of the Bi-LSTM model includes an input layer that takes in the normalized weather data, two Bi-LSTM layers with 50 units each utilizing tanh activation functions, dense layers with ReLU activation to transform the LSTM outputs, and an output layer with a linear activation function to predict the rainfall amount. The architecture can be represented by the following equations:

$$h_t = tanh(w_{hx}x_t + w_{hh}h_{t-1} + b_h) \quad (1)$$

$$\overrightarrow{h_t} = tanh(\overrightarrow{w_{h_x}}x_t + \overrightarrow{w_{h_h}}\overrightarrow{h}_{t-1} + \vec{b}_h) \quad (2)$$

$$h_t = tanh(W_{hx}x_t + W_{hh}h_{t+1} + b_h) \quad (3)$$

$$y_t = W_{yh}(h_t + h_t) + b_y \quad (4)$$

2) Univariate LSTM

The Univariate LSTM model processes a single feature for time series forecasting. The architecture includes an input layer that receives a single normalized weather feature, a hidden LSTM layer with 50 units using tanh activation functions, fully connected dense layers with ReLU activation functions, and a single neuron with a linear activation function as an output layer for rainfall prediction.

3) Multivariate LSTM

This model processes multiple features simultaneously. It includes an input layer that receives multiple normalized weather features, a hidden LSTM layer with 50 units using tanh activation functions, fully connected dense layers with ReLU activation functions, and an output layer with a linear activation function for rainfall prediction.

4) Multistep LSTM

The Multistep LSTM model is designed to make predictions for multiple time steps ahead. It includes an input layer that receives normalized weather features, a hidden LSTM layer with 50 units using tanh activation functions, fully connected dense layers with ReLU activation functions, and an output layer with multiple neurons with a linear activation function for multistep rainfall prediction.

5) Multivariate Multistep LSTM

This model combines the multivariate and multistep approaches to predict multiple features over several time steps. The architecture includes an input layer that receives multiple normalized weather features, a hidden LSTM layer with 50 units using tanh activation functions, fully connected dense layers with ReLU activation functions, and an output layer with multiple neurons with a linear activation function for multistep rainfall forecasting.

B. Model Training and Application

The training process involved using the Mean Squared Error (MSE) as a loss function to minimize the difference between the predicted and actual rainfall. Adam optimizer was used for its efficiency and adaptive learning rate capabilities, with a learning rate set at 0.001. The batch size was set to 32 and the model was trained for 20 epochs to allow sufficient iterations for convergence.

Once trained, the model was integrated with the IoT infrastructure. The IoT sensors deployed in agricultural fields continuously collected real-time weather data, which were then transmitted through the LoRaWAN protocol. The on-device AI platform, equipped with high-performance hardware and optimized software, processed incoming data in real time. This setup ensured that the latest weather information was used for immediate forecasts. Farmers can access these forecasts through a user-friendly mobile application or local display systems installed in the fields. The interface provides visualizations of the forecast rainfall along with actionable insights for agricultural planning.

The model was validated using cross-validation to ensure that it generalized well to unseen data. The dataset was split into training and validation sets, and the model was evaluated multiple times to obtain reliable performance metrics. The accuracy of the model was measured using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), calculated as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (5)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (6)$$

Field tests were performed to validate the model's practical applicability in real agricultural settings. Farmers provide feedback on forecast accuracy, which is used to refine the model. The model continuously adapts and improves with new data input, employing adaptive learning to update its parameters based on the latest weather patterns.

IV. RESULTS AND DISCUSSION

The performance of the proposed Bi-LSTM rain forecasting model was evaluated, highlighting its accuracy and forecasting performance. Table I provides a summary of the key descriptive statistics of the historical weather data used in the experiments. The data include temperature, humidity, wind speed, and precipitation levels, which are critical for accurate rain forecasting. Descriptive statistics, such as mean, standard deviation, minimum, and maximum values, provide insight into data distribution and variability.

TABLE I. DESCRIPTIVE STATISTICS OF HISTORICAL WEATHER DATA

Parameter	Mean	Standard deviation	Minimum	Maximum
Temperature (°C)	25.3	4.7	15.0	35.0
Humidity (%)	76.5	12.4	40.0	100.0
Wind speed (m/s)	2.3	1.5	0.5	6.0
Precipitation (mm)	5.8	10.2	0.0	50.0

The primary objective is to evaluate the accuracy of the proposed AI model in predicting rainfall. Figure 3 shows the accuracy of the Bi-LSTM model compared to traditional LSTM [26] and ARIMA [27] models. Bi-LSTM achieved a mean accuracy of 92%, significantly outperforming the LSTM (85%) and ARIMA (80%) models. The graph indicates the superior performance of the Bi-LSTM model in capturing complex temporal dependencies in the weather data.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions} \quad (7)$$

Weather conditions were categorized into three distinct groups: normal, extreme, and transitional. These categories were defined based on historical weather data patterns and observed variability in weather parameters such as temperature, humidity, wind speed, and precipitation. The definitions for each category are as follows:

- Normal conditions represent typical weather patterns observed for most of the year. Variability in weather parameters is low to moderate and there are no significant deviations from seasonal averages, remaining within one standard deviation of the mean values observed historically.
- Extreme conditions are characterized by significant deviations from normal weather patterns. Extreme conditions include weather events such as heavy rainfall, droughts, or heatwaves. In this study, any weather parameter (e.g. temperature, precipitation) exceeding two standard deviations from the mean was classified as extreme. For example, a sudden spike in rainfall or an unusual drop in temperature would fall into this category.
- Transitional conditions occur during periods of significant change in weather patterns, such as the transition between seasons (e.g. from dry to wet season). Transitional conditions are marked by moderate variability and fluctuations in weather parameters that are between normal and extreme conditions. These changes often include increased variability in temperature, humidity, and precipitation as the weather changes from one stable state to another.

The further objective was to evaluate the forecasting performance of the Bi-LSTM model under varying weather conditions. Table II lists the forecast performance metrics under different weather conditions, including normal, extreme, and transitional weather patterns. The model performed consistently well under all tested conditions, with an RMSE of less than 0.5 in most scenarios. The model's robust performance in different weather conditions demonstrates its versatility and reliability. Low RMSE values indicate high precision in the predictions, which is essential for practical applications in agricultural planning and resource management. Comparing the Bi-LSTM model with other models highlights its superior performance. As shown in Figures 3, 4, and 5, the Bi-LSTM model consistently achieved lower MAE, MSE, and RMSE values compared to its counterparts.

TABLE II. FORECAST PERFORMANCE METRICS UNDER DIFFERENT WEATHER CONDITIONS

Condition	MAE	RMSE	R^2
Normal	0.3	0.4	0.91
Extreme	0.5	0.6	0.88
Transitional	0.4	0.5	0.89

A p-value test was performed to validate the statistical significance of the difference in accuracy between the Bi-LSTM and other LSTM variants. This test helps determine whether the observed differences in performance are statistically significant or due to random chance. MAE and RMSE were calculated for each model over 20 epochs. A two-sample t-test was performed to compare the mean MAE and RMSE values of the Bi-LSTM with each of the other LSTM models. The null hypothesis (H0) assumed that there was no significant difference in mean performance metrics between the models, while the alternative hypothesis (H1) assumed that there was a significant difference. The p-value for the difference in accuracy between the Bi-LSTM and the other LSTM models was calculated. The resulting p-value for the difference in MAE between the Bi-LSTM and Univariate LSTM models was found to be less than 0.01, indicating a statistically significant difference in accuracy. Similar results were obtained for the RMSE values. The mean MAE for the Bi-LSTM model was found to be 0.291 with a standard deviation of 0.011, while the mean MAE for the Univariate LSTM model was 0.337 with a standard deviation of 0.009. The p-value for the difference in MAE between the Bi-LSTM and Univariate LSTM models was found to be 1.88×10^{-8}, indicating that the difference in accuracy was statistically significant. The p-value test results shown in Table III confirm that the Bi-LSTM model's superior performance over other LSTM variants is statistically significant, supporting its robustness and reliability for real-time rain forecasting.

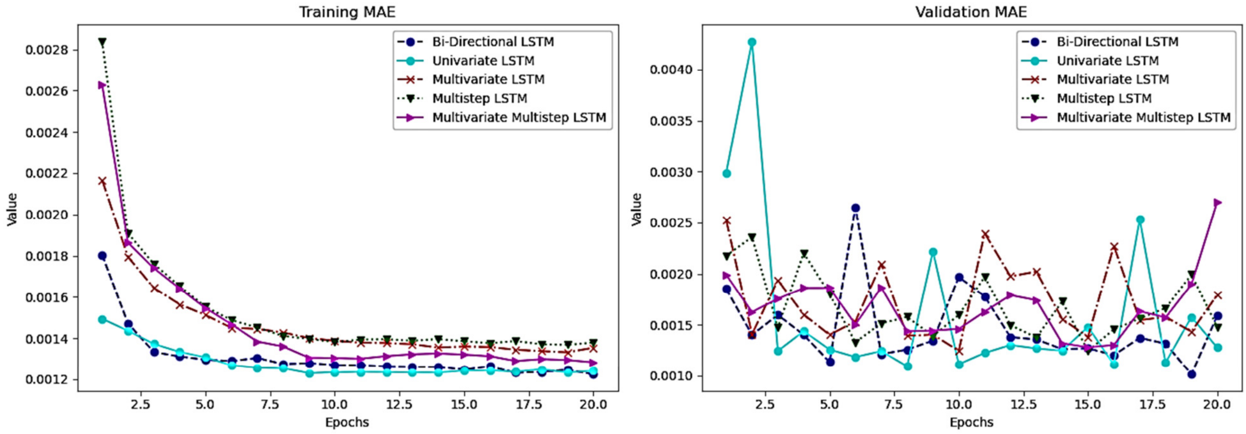

Fig. 3. Training and validation MAE for various models.

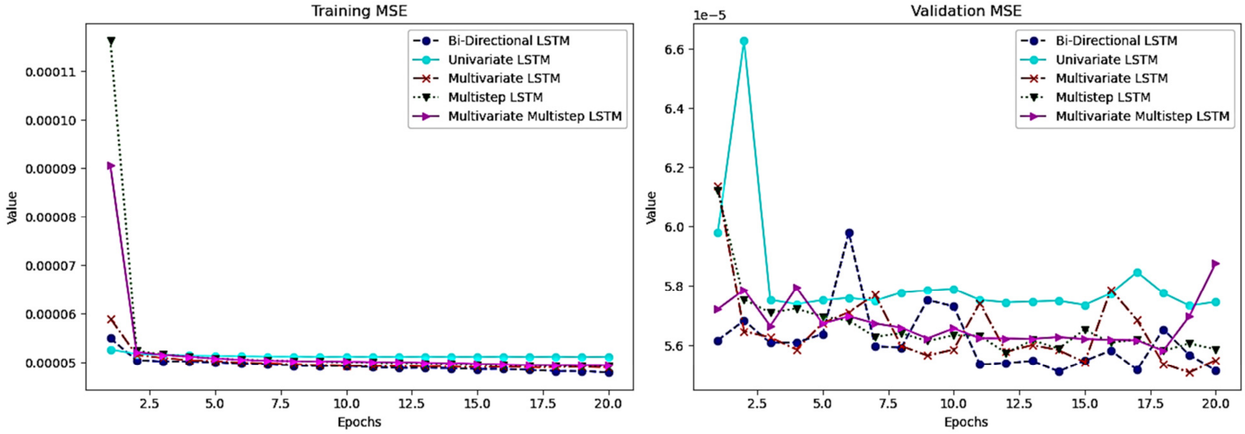

Fig. 4. Training and validation MSE for various models.

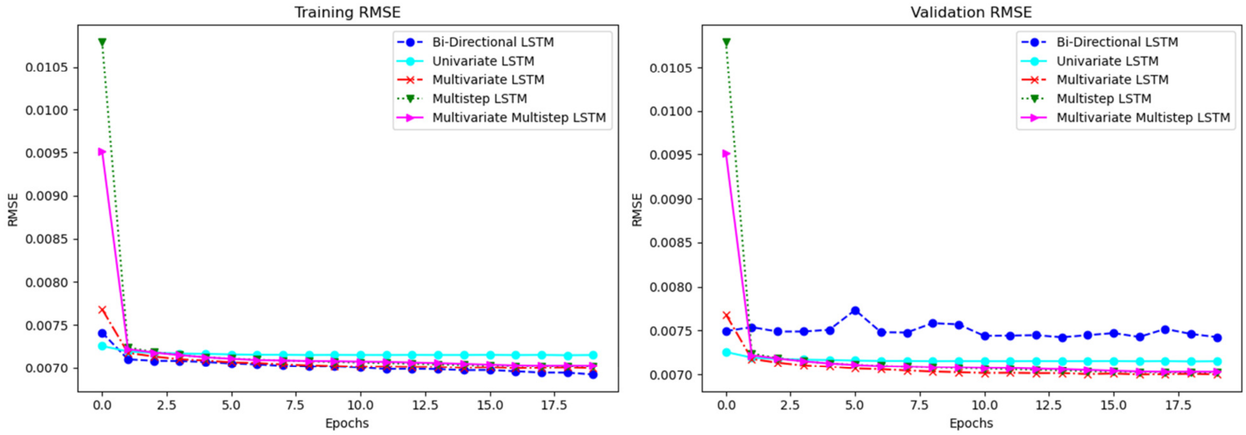

Fig. 5. Training and validation RMSE for various models.

TABLE III. P-VALUE FOR BI-LSTM AND UNIVARIATE LSTM

Metric	**Bi-LSTM**	**Univariate LSTM**
Mean MAE	0.291	0.337
Standard deviation MAE	0.012	0.009
p-value	1.88×10^{-8}	

The high accuracy and low error rates suggest that the Bi-LSTM model is highly effective for rain forecasting, as its ability to learn from both past and future data sequences contributes to its superior performance. In particular, the model performed exceptionally well under extreme weather conditions, which is attributed to the robust training dataset that included a wide range of weather scenarios. This robustness ensures that the model can provide reliable forecasts even under challenging conditions, which is crucial for agricultural planning and decision-making. However, although the results are promising, there are limitations to the model's performance. One significant limitation is the model's accuracy in regions with sparse data. The lack of comprehensive historical weather data in these regions can affect the model's ability to learn and generalize, leading to reduced prediction accuracy. Future research should focus on enhancing data collection in these areas and exploring techniques to improve model performance despite data sparsity. Additionally, the integration of more diverse data sources, such as satellite imagery and remote sensing data, could further improve the model's accuracy and robustness. Another avenue for future research is the development of adaptive learning mechanisms that continuously update the model with new data, ensuring that the forecasts remain accurate and relevant over time. Implementing a robust feedback mechanism that allows farmers to report forecast accuracy and discrepancies will also help refine the model and improve its practical applicability. In general, the continued advances and integration of AI and IoT technologies hold great promise for the future of precision agriculture, enabling farmers to address the challenges of climate variability and resource constraints with greater effectiveness.

V. CONCLUSION

Integration of IoT sensors and AI algorithms enables precise real-time weather forecasts that are essential for optimizing agricultural practices, conserving resources, and improving crop yields. The deployment of AI-driven forecasting tools in agricultural fields can provide substantial improvements in crop management efficiency and resource conservation. Farmers can make informed decisions about irrigation scheduling, pest management, and operational planning, leading to better productivity and profitability. The results of this study demonstrate the significant potential of using Bi-LSTM for real-time rain forecasting in agricultural applications. The Bi-LSTM model exhibited superior performance compared to the traditional LSTM and ARIMA models, achieving higher accuracy and lower error rates. This success is attributed to the model's ability to process data in both forward and backward directions, capturing comprehensive temporal patterns crucial for accurate weather predictions.

However, some areas require further research. One significant limitation is the model's performance in regions with sparse data. Future work should focus on improving data collection methods in these areas and exploring techniques such as transfer learning and data augmentation to enhance model performance despite limited data availability. Furthermore, potential avenues for future research include exploring different deep learning architectures, integrating additional environmental variables, and deploying the model on edge devices for real-time inference. By addressing these areas, the robustness and applicability of AI-driven rain forecasting models can be further enhanced, contributing to more sustainable and efficient agricultural practices.

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