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Improving Rainfall Prediction Accuracy Using an LSTM-Driven Model Enhanced by M-PSO Optimization

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Abstract: - Precipitation, particularly rainfall, plays a crucial role in the economic productivity of the agricultural sector. In regions characterized by unpredictable rainfall patterns, accurately predicting future precipitation is vital for designing effective rainwater harvesting systems and formulating strategies to address potential challenges. The contemporary meteorological community faces a significant dilemma when it comes to forecasting heavy rainfall, as it has far-reaching implications for economic stability and human survival. Moreover, heavy rainfall often serves as a primary trigger for recurring natural disasters like floods and droughts, which impact regions worldwide on an annual basis. The constantly changing nature of our climate presents a formidable barrier to achieving highly precise forecasts of precipitation using traditional statistical methods. Current models used for forecasting rainfall demonstrate less than optimal performance when dealing with complex and non-linear datasets. This study presents a novel method that evaluates the effectiveness of combining Long Short-Term Memory (LSTM) with Modified Particle Swarm Optimization (M-PSO) compared to established rainfall forecasting systems. Experiments conducted using this proposed LSTM-M-PSO model have yielded significant improvements in Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) when predicting monthly rainfall. Consequently, the proposed LSTM-M-PSO method showcases its suitability for applications in global climate projection, particularly when working with extensive datasets. Its improved accuracy in forecasting rainfall holds promise for addressing the critical challenges posed by unpredictable precipitation patterns and their significant impacts on agriculture and society.

Keywords: LSTM networks, Rainfall Forecasting, Meteorological Models, Time Series Analysis, Data Preprocessing, Precipitation Patterns, Rainfall Variability, Weather Patterns, Early Warning Systems.

I. INTRODUCTION

Rainfall serves as the primary source of freshwater for sustaining life, encompassing humans, flora, and fauna. It nourishes our rivers, lakes, and water bodies, fostering the diverse ecosystem they support. In the realm of agriculture, particularly in countries like India where it constitutes a substantial economic pillar, rainfall assumes paramount significance. However, an excess of rainfall can transform into a perilous deluge, leading to catastrophic floods that inflict harm upon property and vital crops [1]. Therefore, the ability to predict rainfall in advance stands as a pivotal linchpin for advancing economic development. Precise forecasting not only supports flood risk mitigation, safeguarding both lives and valuable resources but also aids in managing the adverse consequences of insufficient rainfall, which can manifest as debilitating droughts and crop failures [2]. Moreover, the impact of rainfall extends far beyond these immediate concerns, reaching up into the atmosphere itself, where it plays a pivotal role in driving atmospheric circulation, and by extension, our climate systems. Yet, predicting rainfall has emerged as one of the most formidable challenges in the realm of scientific and technological inquiry in recent decades. Numerous techniques, such as regression analysis, clustering, Support Vector Machines (SVM), K-Nearest Neighbours (KNN), Artificial Neural Networks (ANN), and Recurrent Neural Networks (RNN), have been employed in rainfall forecasting [3][4]. However, these methods encounter difficulties when dealing with short-term dependencies. Using multiple neural network algorithms for rainfall prediction has yielded less than

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state-of-the-art results. Over the years, as rainfall data has become available, applying neural network models to such time series data has discovered nonlinearity and significant computational complexity. Among the challenges encountered, the "Vanishing Gradient" problem has led to reduced accuracy in estimating regional rainfall, making the training of neural network layers challenging. When applied to time series data, RNNs, like the standard ANN, suffer from low memory retention, leading to information loss when handling extensive datasets. To combat these hurdles, a modified version of RNN known as Long Short-Term Memory (LSTM) has emerged as a solution to enhance rainfall forecasting accuracy. LSTM introduces minimal data alterations through simple operations such as multiplications and additions. Data traverses through the cell states of LSTM, affording the network the ability to selectively remember or forget information. This mechanism relies on three critical components within each cell state: the previous cell state, the preceding hidden state, and the input accrued at the present time step. This architecture empowers LSTMs to make informed decisions about retaining or discarding information, effectively addressing issues like the "vanishing gradients" and "exploding gradients" associated with the training complexities of conventional neural networks. Given the multifaceted role of precipitation in both societal and environmental realms, the development and implementation of a comprehensive rainfall forecasting system are imperative. Such a system, with its capacity to offer invaluable insights and proactive knowledge regarding future precipitation patterns, stands as an indispensable tool in our quest for a sustainable and resilient future [5][6]. The importance of establishing a dependable rainfall forecasting system is a multifaceted endeavour with implications spanning across numerous sectors, ultimately impacting livelihoods, safety, sustainability, development, and its importance is described below.

Agriculture and Food Security: Agriculture's vitality hinges significantly on receiving adequate rainfall at the right times to ensure optimal crop growth and yields. The provision of accurate weather forecasts empowers farmers to make well-informed decisions regarding planting, irrigation, and harvesting [7].

Natural Disaster Management (NDM): The management of natural disasters, often triggered by excessive precipitation, encompasses cataclysmic events like floods, landslides, and mudslides. Accurate forecasting systems provide authorities with the capability to issue early recommendations areas, and allocate resources for disaster preparedness. This not only saves live but also safeguards property and mitigates the socio-economic impacts of such calamities [8].

Water Resource Management (WRM): A dependable forecasting system proves invaluable for water resource management by facilitating the judicious distribution and allocation of water for various purposes, such as drinking, industrial, agricultural, and hydroelectric power generation. Additionally, it helps alleviate water scarcity and ensures the sustainability of water management practices.

Infrastructure Development: The development of infrastructure, like highways, bridges, and drainage structures, requires the incorporation of rainfall trends to withstand the risk of flooding and erosion. Precise weather forecasts play a critical role in urban planning and design, thereby diminishing the vulnerability of cities and communities to weather-induced harm and strengthening their capacity to adapt [10]. Timely anticipation of intense rainfall empowers authorities to implement different strategies effectively integrate reducing health hazards linked to waterborne diseases and contaminants stemming from flooding [11].

Economic and Financial Impact: Variations in rainfall can have a substantial influence on the economy and diverse sectors, including energy production, transportation, and the tourism industry [11] [12]. A reliable prediction system enables organizations to make well-informed choices, improve operational effectiveness, and efficiently handle supply chains, consequently diminishing the risk of disruptions and economic setbacks[13].

Scientific Investigation and Climate Research: Rainfall trends serve as crucial data elements for climate studies, scientific investigations, and environmental assessments [14]. These forecasts contribute to climate change research by providing insights into long-term patterns and fluctuations, aiding the collection of precise historic dataset [15].

Program Development and Policymaking: Government entities, policymakers, and local administrations depend on accurate rainfall predictions to create successful policies related to disaster preparedness, water distribution, environmental conservation, and sustainable progress [16]. Decision-making founded on accurate information contributes to the overall well-being and progress of society [17]. In this context, the imperative for a dependable rainfall forecasting method transcends a multitude of sectors and directly impacts the welfare of individuals, safety measures, sustainability initiatives, and overall development [18]. A system with the capability to deliver precise and timely forecasts plays a pivotal role in enhancing resilience, mitigating risks, and enabling informed decision-making in the face of unpredictable weather conditions.

II. LITERATURE SURVEY

This review of the literature investigates various methodologies for rainfall prediction, with an emphasis on the adaptability of machine learning in environmental sciences. Long Short-Term Memory networks (LSTMs) are highlighted for their effectiveness in simulating runoff, as well as an innovative sliding window approach for superior rainfall forecasting and pioneering seq2seq learning for improved Earth science time series predictions. Novel solutions are proposed to address the challenges of short-term and long-term rainfall forecasting. The significance of accurate rainfall forecasting for water resource management is emphasized, highlighting LSTM's superiority in multi-month forecasts with implications for agricultural planning and flood forecasting. Despite advancement, challenges such as data intensity and limited generalizability persist, motivating the ongoing pursuit of precision in rainfall prediction methodologies.

F. Kratzert et al. [19] investigated the potential use of Long Short-Term Memory networks (LSTMs) in simulating runoff from meteorological data. LSTMs, a type of recurrent neural network, displayed comparable performance to the SAC-SMA + Snow-17 model in predicting runoff. The study found that LSTMs can accurately predict runoff, with a suggested minimum data requirement of 15 years. Additionally, the transfer of pre-trained models between catchments showed promise. Challenges include data intensity and the inherent complexity of LSTMs, but improving their interpretability could expand their applications in environmental sciences.

Sam C. and co-researchers [20] proposed a novel sliding window method for rainfall forecast. Contrasting conventional day-to-day forecasts, this technique concentrates on predicting total rainfall measures. Rainfall prediction is notoriously intricate, involving intricate datasets featuring extreme values, rainfall volatility, hitherto unseen patterns, and discontinuities. To confront these challenges, they have ingeniously combined well-established machine learning algorithms with conventional rainfall prediction techniques, yielding superior forecasts equally pre- and post-rainfall accumulation.

Z. Xiang et al. [21] presented a study introduced seq2seq learning, initially designed for language translation, to improve accuracy in Earth science time series predictions. The proposed LSTM-based seq2seq model for rainfall-runoff predictions, with one-layer LSTM, outperformed various machine learning models on five stations in two watersheds. Its success stems from nonlinear algorithms and treating input and output as two-time-series sequences. While it excels in many scenarios, it may be less effective during snow or spring flooding. A limitation is that this model relies on available data, potentially restricting its application in data-scarce environments.

Moulana M. et al [22] have been at the forefront of developing a rainfall prediction system aimed at mitigating the far-reaching effects of severe rain events. The accuracy of these forecasts plays a crucial role in allowing individuals to take precautionary actions. Differentiating between short-term and long-term rainfall predictions presents a distinct challenge, with short-term forecasts typically offering greater precision. The creation of models for long-term rainfall forecasting stays a persistent challenge. Given the diverse impacts of heavy rainfall on various aspects of human-life and the economy, the importance of precise rainfall forecasts cannot be overstated. Traditional statistical methods often fall short due to the dynamic nature of the environment.

K. Manideep et al. [23] have explored the domain of rainfall forecasting. Their selection of a prediction method was influenced by data quality, level, and trends. From the array of available forecasting techniques, the exponential smoothing method stood out for its simplicity, speed, efficiency, and cost-effectiveness. In their research, they implemented the Holt-Winters algorithm, using historical data for rainfall estimates. Their goal was not only to match the commonly used multiplicative Holt-Winters method in terms of accuracy and efficiency but also to surpass it. To achieve this, they introduced the concept of the Enhanced Additive Holt-Winters technique, which remarkably outperformed the multiplicative approach by 6% in forecast accuracy. This alternative method represents a significant advancement in rainfall data prediction, offering increased clarity and precision in forecasting future rainfall patterns.

Salaeh N. et al. [24] presented a study on accurate rainfall prediction that is vital for water resource management in the Thale Sap Songkhla basin, Thailand. This study assesses various machine learning algorithms, emphasizing the importance of large-scale climate and meteorological variables. LSTM emerges as the top-performing model for multi-month rainfall prediction, offering valuable insights for agricultural planning and water resource management. The proposed approach holds promise for enhancing long-term flood forecasting and irrigation strategies across the region. However, it is important to note that this study relies on a relatively small dataset, which may limit the generalizability of the findings

III. PROPOSED METHODOLOGY

The proposed system exhibits a notable efficacy in its ability to forecast rainfall. This system is comprised of five integral steps, each contributing to the overall functionality of this advanced forecasting framework. This algorithm covers a multi-step process for accurate rainfall forecasting using time series data. It commences with the acquisition of a comprehensive dataset from India's open government data repository, spanning over a century. This dataset undergoes thorough data preprocessing, including the correction of missing or erroneous values using techniques such as spline interpolation. For addressing missing data, linear interpolation is employed to maintain data integrity. Further techniques, such as smoothing, are used to reduce noise in the data. The algorithm introduces data augmentation using Generative Adversarial Networks for Time Series (GAN-TS), enabling the generation of synthetic data points that closely resemble the original data [25]. Additionally, it incorporates a Long Short-Term Memory (LSTM) model for rainfall forecasting, renowned for its ability to capture complex temporal dependencies in sequential data. Integrated optimization techniques like Q-learning ensure optimal hyperparameters for the LSTM model. This comprehensive approach not only effectively prepares data but also lays the foundation for precise and reliable rainfall forecasts, addressing the intricacies of long-term time series data. Figure 1 visually represents the key components of this system.

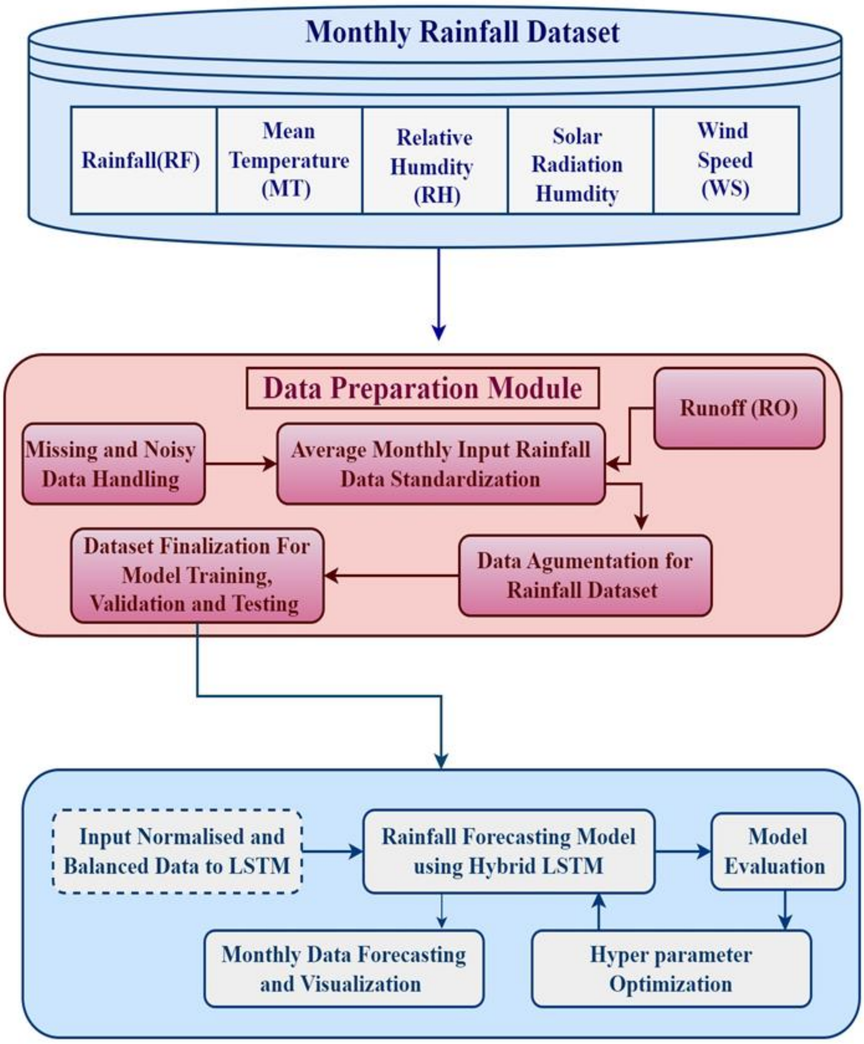

Fig. 1. The Proposed Methodology for Rainfall-Forecasting

The required data is first imported by the system, which then converts the month's columns from a string data type to a Date time data type format. Next, the primary index for data modification is allocated to the modified date time column. The data is then divided into distinct training and testing datasets, which is an essential stage in the creation of a model.

Following the processing of these training datasets, the subsequent stage involves multi-modal forecasting training of individual Long Short-Term Memory (LSTM) prediction models. Because these LSTM models can identify temporal relationships in the data, they are especially useful for forecasting precipitation.

Following the training phase, the Modified Particle Swarm Optimization (M-PSO) technique is applied to optimize each model. By fine-tuning the models, this optimization technique seeks to increase accuracy and predictive power. Testing each model's forecasting capacity and comparing the outcomes to a Random Population reference constitute the crucial next step. By calculating each model's fitness value, its performance is evaluated. The system keeps doing this iterative procedure until it reaches the nth iteration, at which time it finds the global minimum and chooses the model that performs the best.

3.1 ACQUISITION AND PREPARATION OF DATA

First, time series data are obtained from a public government data repository in India, which can be accessed through the Data.gov.in website. This comprehensive dataset encompasses monthly rainfall records meticulously collected over 118 years, commencing in 1901. Mathematically, this dataset can be represented in equation 1 as follows:

$$Rt = \{ R_1, R_2, R_3......., R_n\} \qquad (1)$$

Various orders of auto-regressive algorithms and spline interpolation are two methods used during the data pre-processing stage to guarantee that missing or inaccurate values are corrected.

3.2 PREPARATION OF DATA

The mathematical modelling approach for handling missing and noisy data in a time series dataset for rainfall forecasting using Linear Interpolation is described below.

Step 1: Identify Missing Data

Given a time series dataset, identify the locations of missing data points, which are represented as (T_MISSING, Y_MISSING), where T_MISSING is the time step and Y_MISSING is the missing value.

Step 2: Locate Nearest Observed Data Points

Locate the two nearest observed data points, (T1, Y1) and (T2, Y2), such that T1 < T_MISSING < T2. These observed data points should be on either side of the missing point (T_MISSING, Y_MISSING).

Step 3: Linear Interpolation

Utilize linear interpolation to estimate the missing value Y_MISSING: The linear interpolation formula is represented in equation 2 as follows:

$$Y_{MISSING} = Y1 + (Y2-Y1)*((T_{MISSING} - T1) / (T2 - T1)) \qquad (2)$$

Where:

- $Y_{\_MISSING}$ represents the estimated missing value.
- Y1 and Y2 are the values of the observed data points at times T1 and T2.
- $T_{\_MISSING}$ is the time step where the value is missing.
- T1 and T2 are the times of the observed data points.

Step 4: Update The Dataset

Substitute the missing value at time T_MISSING with the estimated value Y_MISSING in the time series dataset.

Step 5: Noise Reduction

After imputing missing data, additional noise reduction measures can be applied. Consider employing time series smoothing techniques, such as moving averages, exponential smoothing, or Savitzky-Golay filtering, to eliminate high-frequency noise while preserving the underlying trends.

Step 6: Utilize The Cleaned Data For Forecasting

Now, the pre-processed and cleaned time series data, including the imputed values, can be employed for your rainfall forecasting model. Utilize a variety of forecasting techniques like ARIMA, Exponential Smoothing, or machine learning models, as necessary for your specific forecasting requirements.

3.3 DATA AUGMENTATION FOR RAINFALL DATASET

This mathematical model provides a representation of the GAN-TS data augmentation process, making it effective for complex datasets involving rainfall and meteorological variables. The mathematical Model for GAN-TS Time Series Data Augmentation

Data Representation: Let RF, MT, RH, SR, and WS represent the original time series data for parameters Rainfall, Mean Temperature, Relative Humidity, Solar Radiation, and Wind Speed, respectively. Each time series is represented as a sequence of data points over time as represented mathematically using equation 3 to 7.

$$RF=\{RF_1,RF_2,RF_3,\ldots,RF_n\} \tag{3}$$

$$MT=\{MT_1,MT_2,MT_3,\ldots,MT_n\} \tag{4}$$

$$RH=\{RH_1,RH_2,RH_3,\ldots,RH_n\} \tag{5}$$

$$SR=\{SR_1,SR_2,SR_3,\ldots,SR_n\} \tag{6}$$

$$WS=\{WS_1,WS_2,WS_3,\ldots,WS_n\} \tag{7}$$

Where, n is the length of the original time series.

1. **GAN Architecture**: GANs consist of a Generator network (G) and a Discriminator network (D). The generator aims to create synthetic data points resembling the original data, while the discriminator distinguishes between real and generated data.

2. **Generator Network (G)**: The generator takes random noise (Z) as input to produce synthetic data points for each parameter and are represented using equation 8 to 12:

$$RF_{\text{gen}} = G(Z) \tag{8}$$

$$MT_{\text{gen}} = G(Z) \tag{9}$$

$$RH_{\text{gen}} = G(Z) \tag{10}$$

$$SR_{\text{gen}} = G(Z) \tag{11}$$

$$WS_{\text{gen}} = G(Z) \tag{12}$$

Utilize recurrent neural networks (RNNs), such as LSTM or GRU, in the generator to capture temporal dependencies, preserving the original time series' characteristics for each parameter.

Discriminator Network (D): The discriminator assesses the authenticity of data points. It evaluates real data (X) and generated data (Xgen) for each parameter and provides a probability score for each parameter and mathematically represented using equation 13 to 22.

$$D(RF) \text{ for real data} \in [0,1] \tag{13}$$

$D(MT)$ for real data $\in [0,1]$ (14)

$D(RH)$ for real data $\in [0,1]$ (15)

$D(SR)$ for real data $\in [0,1]$ (16)

$D(WS)$ for real data $\in [0,1]$ (17)

$D(RF_{\text{gen}})$ for generated data $\in [0,1]$ (18)

$D(MT_{\text{gen}})$ for generated data $\in [0,1]$ (19)

$D(RH_{\text{gen}})$ for generated data $\in [0,1]$ (20)

$D(SR_{\text{gen}})$ for generated data $\in [0,1]$ (21)

$D(WS_{\text{gen}})$ for generated data $\in [0,1]$ (22)

RNNs are employed in the discriminator to assess temporal coherence for each parameter.

Training Process: During training, the generator and discriminator networks engage in a competitive process. The generator strives to minimize the difference between generated and real data, while the discriminator aims to accurately differentiate between real and generated data. The adversarial training process can be represented by the minimax game for each parameter and mathematically is describe with the help of equation 23.

$$\min_G \max_D V(D,G) = \mathrm{E}_{X\sim p\text{data}(X)} [\log D(X)] + \mathrm{E}_{Z\sim pz(Z)} [\log(1-D(G(Z)))] \quad (23)$$

Where $p_{\text{data}}(X)$ represents the distribution of real data, and pz(Z) is the distribution of random noise.

3. **Data Augmentation**: Once the GAN is trained, use the generator to create augmented data points for each parameter by providing random noise (Z) as input represented using equation 24 to 28:

$RF_{\text{aug}} = G(Z)$ (24)

$MT_{\text{aug}} = G(Z)$ (25)

$RH_{\text{aug}} = G(Z)$ 26)

$SR_{\text{aug}} = G(Z)$ (27)

$WS_{\text{aug}} = G(Z)$ (28)

These augmented data points are synthetic and closely resemble the original time series data for each parameter.

4. **Augmented Dataset**: Combine the original time series data and the augmented data for each parameter to create augmented datasets (X_{aRF}, X_{aMT}, X_{aRH},X_{aSR}, X_{aWS}).

It is very significant to prepare the time series-based dataset for better generalization capability of the model. The algorithm for Data Preparation for Forecasting is described below. Every single data point in a time-series dataset contains important information, and time series analysis is the complex process of deciphering its complexities. However, before beginning model training, the data must be sufficiently pre-processed and organized in order to fully realized this potential. To prepare the dataset for time series analysis, a number of steps are involved, such as feature engineering and data preparation. An essential part of preparing time series data for accurate rainfall forecasting is the provided algorithm. It commences by initializing two critical data containers, 'x' and 'y,' responsible for storing the input sequences and corresponding target values, respectively. Additionally, it allows for customization by specifying the number of time steps in the input sequence ('t') and the number of steps to forecast ('day'). Subsequently, the algorithm meticulously extracts input sequences of 't' time steps, appends them to 'x,' and accurately calculates the target values 'day' steps into the future, ensuring their inclusion in 'y.' This systematic data preparation process lays the foundation for robust and precise rainfall predictions, making it an invaluable tool for machine learning model training and forecasting applications.

Algorithm: Data Preparation for Forecasting

Input:

data: Time series data for forecasting

t: Number of time steps in the input sequence

day: Number of time steps to forecast

Output:

x: Input data for forecasting

y: Corresponding target data for forecasting

Step 1: Initialize empty lists x and y.

Step 2: Set timesteps as t.

Step 3: Set forecast_hour as day.

Step 4: Prepare Training Data:

Loop through the data from timesteps to (length(data) – forecast_hour).

Step 5: Extract the Input Sequence: Extract the input sequence of t time steps as described mathematically using equation 29 as follows,

$$Xt = [\ Dt-1, Dt-2\ldots, Dt-t] \tag{29}$$

where Di represents the data at time step i.

Step 6: Append the Input Sequence 6. Append the input sequence Xt to the list x.

Step 7: Determine the Target Value 7. Determine the target value as shown in equation 30.

$$Yt = Dt + day \tag{30}$$

where Yt is the target value at time step t.

Step 8: Add the Target Value 8. Add the target value Yt to the list y.

End loop.

Step 9: Provide the Prepared Input and Target Data for Forecasting 10. Return x as the input data, and y as the target data.

The algorithm prepares time series data for rainfall forecasting by defining input sequences and target values. It initializes empty lists for input data (x) and target data (y) and specifies the number of time steps in the input sequence (t) and the number of time steps to forecast (day). The algorithm loops through the data, extracts input sequences of t time steps, and calculates target values t + day steps into the future. These input and target data are appended to lists x and y. The algorithm includes equations for the input sequence and target value, providing a mathematical foundation for data preparation, crucial for accurate rainfall forecasting.

3.4 MODEL OPTIMIZATION

Forecasting in this context entails two distinct modes: one-step forecasting and multi-step forecasting. In one-step forecasting, the method uses the input data utilized in training the model during the prediction phase to anticipate the next data point in the series. On the other hand, multi-step forecasting involves making forecasts for a given time frame, like a week (7 days), using relevant meteorological information, such rainfall. The main objective of the suggested approach is to anticipate a variety of rainfall estimations, such as the minimum, maximum, average that greatly improves the forecasts' accuracy and dependability.

LSTM Model for Rainfall Forecasting:

Long Short-Term Memory (LSTM) is highly effective for rainfall forecasting due to its unique capabilities in modelling complex temporal dependencies in sequential data. Rainfall data, which exhibits patterns evolving over time, benefits from LSTM's ability to remember and utilize information from past time steps. LSTMs accommodate variable-length sequences, making them adaptable to irregular time intervals and missing data points commonly encountered in meteorological data. LSTMs also excel at automatic feature extraction, reducing the need for manual feature engineering. This is particularly valuable for capturing intricate relationships between rainfall and meteorological factors like temperature, humidity, and wind patterns. Rainfall patterns are inherently nonlinear, and LSTMs are well equipped to model these intricate nonlinear dependencies.

Moreover, LSTMs can provide real-time adaptation to changing weather dynamics, making them suitable for immediate responses to weather shifts and short-term rainfall predictions. Their long-term memory aids in recognizing seasonality and trends in historical data. LSTMs support multi-step forecasting and seamlessly integrate with complementary data sources, such as radar and satellite data. By continually adapting and optimizing forecasting parameters through integration with reinforcement learning and other frameworks, LSTMs offer highly accurate and effective rainfall forecasts. This has wide-ranging applications, including flood prediction, agriculture, and water resource management, where precise rainfall predictions are crucial for decision-making and resource allocation.

Input Gate (i_t): For rainfall forecasting, the input gate (i_t) plays a vital role in deciding how incoming data (X_t) and historical rainfall patterns (H_{t-1}) contribute to the current cell state and is described using equation 31. This process is critical for capturing and interpreting the complex relationships in rainfall data.

$$i_t = \sigma(W_I * [H_{t-1}, X_t] + B_I) \qquad (31)$$

Forget Gate (f_t): The forget gate (f_t) helps the model determine which information from the past cell state should be retained. In the context of rainfall forecasting, it allows the LSTM model to forget outdated rainfall patterns while retaining essential historical data and is represented using equation 32.

$$f_t = \sigma(W_F * [H_{t-1}, X_t] + B_F) \qquad (32)$$

Candidate State (g_t): The candidate state (g_t) shown in equation 33 represents a potential update to the cell state. In the case of rainfall forecasting, this component captures new insights and patterns from the current data (X_t) and past rainfall behavior (H_{t-1}) using the hyperbolic tangent function (tanh).

$$g_t = \tanh(W_C * [H_{t-1}, X_t] + B_C) \qquad (33)$$

Output Gate (o_t): The output gate (o_t) represented in equation 34 determines which portion of the cell state is revealed as the hidden state. In the context of rainfall forecasting, it regulates which aspects of historical rainfall behavior (H_{t-1}) and current data (X_t) influence the model's prediction.

$$o_t = \sigma(W_O * [H_{t-1}, X_t] + B_O) \qquad (34)$$

Cell State (c_t): The hidden state (h_t) as described in equation 35 is derived from the cell state and helps in making rainfall predictions. It is controlled by the output gate (o_t) and the hyperbolic tangent function (tanh), ensuring that the model captures the most significant rainfall features.

$$c_t = f_t * C_{t-1} + i_t * g_t \qquad (35)$$

1. **Hidden State (h_t)**:

$$h_t = o_t * \tanh(c_t) \qquad (36)$$

2. **Prediction (y_t)**: The prediction (y_t) represented in equation 37 is the forecasted rainfall value at a given time step. It relies on the hidden state (h_t), which is adjusted by weights (W_Y) and biases (B_Y). Accurate predictions are crucial for effective rainfall forecasting.

$$y_t = W_Y * h_t + B_Y \qquad (37)$$

Integrated Optimization for Rainfall Forecasting:

i. **State (S_t)**: In the context of rainfall forecasting, the state (S_t) shown in equation 38 represents the current configuration of LSTM hyperparameters (weights and biases) and their associated performance metric (Metric_t). This state enables us to monitor and optimize the model's performance.

$$S_t = [W_I, W_F, W_C, W_O, W_Y, B_I, B_F, B_C, B_O, B_Y, Metric_t] \quad (38)$$

ii. **Action (A_t)**: Actions (A_t) in equation 39 signify changes to the LSTM hyperparameters. Adjusting these parameters, particularly when guided by the optimization process, aims to enhance the model's accuracy and its ability to capture rainfall patterns effectively.

$$A_t= [\Delta W_I, \Delta W_F, \Delta W_C, \Delta W_O, \Delta W_Y, \Delta B_I, \Delta B_F, \Delta B_C, \Delta B_O, \Delta B_Y] \quad (39)$$

iii. **Q-learning (Q)**: Q-learning helps optimize the LSTM model by determining the value of taking specific actions (adjusting hyperparameters) in different states (configurations). For rainfall forecasting, this guides the model in making informed decisions to improve prediction accuracy Q-Value Update is describe using equation 40

$$Q(S_t, A_t) = Q(S_t, A_t) + \alpha * [R_t + \gamma * max_a Q(S_{t+1}, a) - Q(S_t, A_t)] \quad (40)$$

iv. **Reward (R_t)**: The reward function as shown in equation 11 assesses the quality of rainfall predictions. In the context of rainfall forecasting, the reward combines the accuracy of predictions (Accuracy_t) and the complexity of the model (Complexity_t). The trade-off parameter λ ensures that the model strikes a balance between accuracy and simplicity. R_t represents reward equation (41)

$$R_t = Accuracy_t - \lambda * Complexity_t \quad (41)$$

Particle Swarm Optimization (PSO) for Rainfall Forecasting:

i. **Particle Position (θ_i)**: In PSO for rainfall forecasting, each particle's position represents a specific set of LSTM hyperparameters along with their associated performance metric. This approach allows particles to explore and optimize hyperparameter configurations that result in improved rainfall predictions. The particle position equation is represented using the equation 42.

$$\theta_i = [W_I, W_F, W_C, W_O, W_Y, B_I, B_F, B_C, B_O, B_Y, Metric_i] \quad (42)$$

ii. **Particle Velocity (v_i)**: Particle velocity is updated in the standard PSO manner to guide particles toward optimal LSTM configurations. While specific equations for particle velocity updates are not provided here, they facilitate the exploration of hyperparameter space for improved rainfall forecasting.

iii. **Global Best Position (θ_global_best)**: The global best position (θ_global_best) represents the most promising LSTM configuration and its corresponding performance metric known to the PSO algorithm. Particles within the PSO swarm are attracted to this optimal configuration, aiming to achieve the best rainfall forecasting results by finding the ideal hyperparameters.

IV. RESULT ANALYSIS

In this section, we examine the experimental results of the proposed System. The proposed system is implemented using the Python platform. From the dataset, 70% of the data is used for training, 15% for validation, and the remaining 15% for testing A comparative analysis of the prognostic performance of different rainfall forecasting systems is performed in the results section through the evaluation of their respective Root Mean Square Error (RMSE). The root mean square error (RMSE) values for the MLP and Auto encoder architectures are between 6.33 and 11.52 [3]. Conversely, the RMSE values for the ConvNet and LSTM Architectures range between 2.44 and 2.55 [3]. The Intensified LSTM Architecture is particularly noteworthy for its substantially diminished RMSE range of 0.33 to 5.68. By utilizing precipitation data spanning the years 2000 to 2017, Figure 2 visually depicts the training procedure of the model.

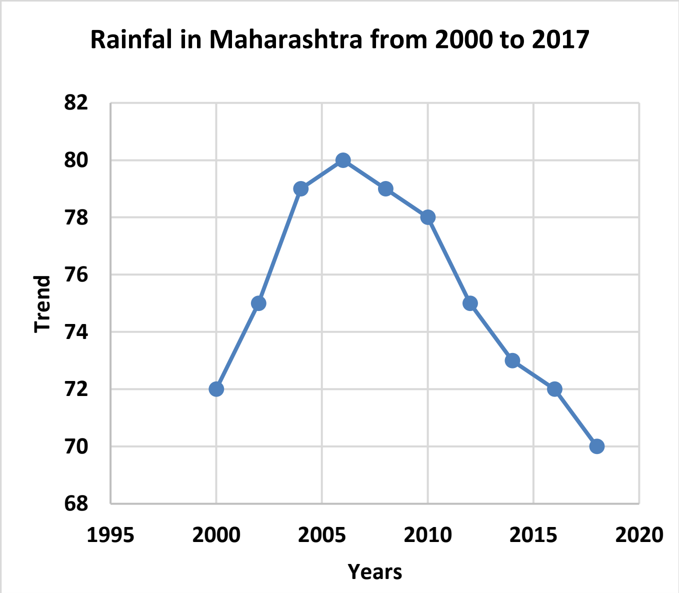

Fig. 2. Dataset of Rainfall in Maharashtra from 2000 to 2017

The data provided from 2000 to 2017 illustrates the annual precipitation in Maharashtra. There is evident variability in the annual precipitation levels during this time period, as determined by an examination of the data.

An overall positive trajectory can be observed in the annual precipitation from 2000 to 2006, as the values increase from 72 to 80. It would appear that this era is comparatively wetter, which would indicate favorable climatic conditions. Nevertheless, the following years' experience a marginal reduction in precipitation. The recorded precipitation is 79 millimetres in 2008, 75 in 2010, and 78 in 2011. This downward trend appears to suggest a transition towards arid conditions throughout this time frame.

This trend is sustained in 2014, when the number falls to 73. Nevertheless, it is critical to acknowledge that although there is an inclination towards reduced precipitation in these years, the values continue to lie within a moderate spectrum. The precipitation levels stabilize in 2016 and 2017, reaching 72 and 70 percent, respectively, indicating a degree of consistency in the arid conditions.

In general, Maharashtra experienced a fluctuating pattern of precipitation from 2000 to 2017. From the early 2000s onwards, there was a discernible trend of increased precipitation, which was subsequently succeeded by a reduction in subsequent years. Comprehending these variations is of the utmost importance in order to evaluate the ramifications on agriculture, water resources, and the region's environmental conditions as a whole. Furthermore, it emphasizes the criticality of monitoring and adjusting to shifting precipitation patterns in order to promote resource management and sustainable development.

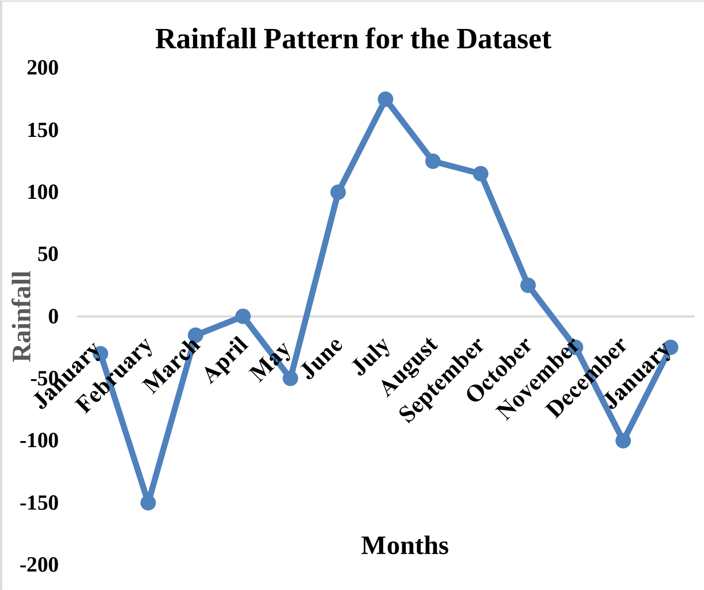

Fig. 3. Annual Pattern of the Rainfall Dataset

The data presented illustrates the monthly discrepancies in precipitation relative to the reference point for each respective month. Positive values denote above-average precipitation, whereas negative values signify below-average precipitation. The examination of the provided data yields valuable insights regarding the annual precipitation pattern.

January suffers from an initial precipitation deficit of -30 percent, which is subsequently intensified to -150 percent in February. After a marginal recovery in March (-15 deficit), the precipitation returns to the baseline in April (zero deviation), which represents the average precipitation for that month. Subsequently, may experiences a decline denoted by a negative deviation of -50, which signifies an arid state.

As the season shifts towards summer, June experiences a significant surge in precipitation, as indicated by a positive deviation of 100, which is indicative of above-average levels of precipitation. This trend continues in July and August, when deviations of 175 and 125 are recorded, respectively. The observed positive values signify an interval of increased precipitation throughout the summer season, aligning with customary monsoon patterns in specific geographical areas. September sustains an equanimous precipitation trend with a deviation of 115, whereas October undergoes a more moderate escalation characterized by a positive deviation of 25. As autumn approaches its late stages, November experiences a resurgence of below-average precipitation, as indicated by a deviation of -25. December, on the other hand, witnesses a more pronounced decline, with a deviation of -100. The aforementioned trend is replicated in January of the subsequent year, with the deviation remaining negative at -25, indicating that arid conditions persist. In general, the data provided suggests that the rainfall pattern exhibits a clear seasonal pattern, characterized by a substantial rainy season in the summer and a period of reduced precipitation in the winter. Comprehending these fluctuations is of the utmost importance in order to evaluate and regulate water resources, agricultural methodologies, and other facets that are impacted by regional precipitation patterns.

Figure 4 presents the ultimate rainfall forecast derived from both training and testing data, while Table 1 provides an overview of the error scores.

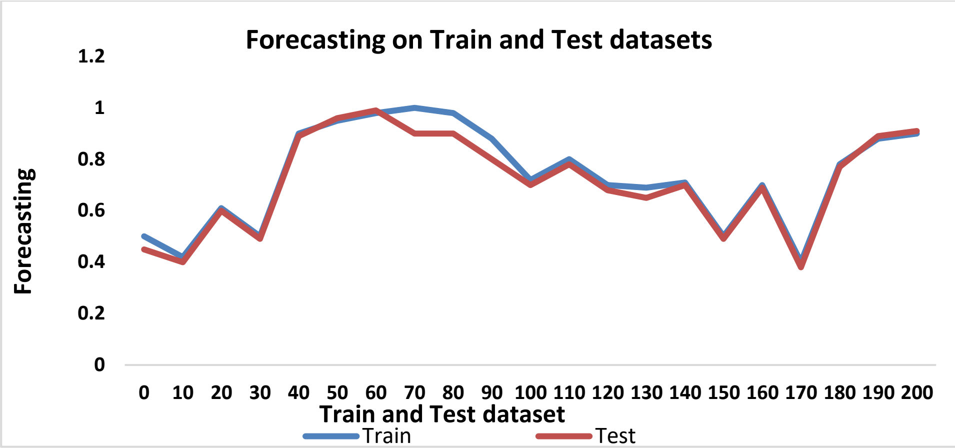

Fig. 4. Forecasting on Training and Testing Datasets

The results of a model's performance on training and test datasets during various iterations or epochs are presented in the table provided. By comparing the training and test values at each epoch, one can gain valuable insights regarding the generalization capability of the model. Throughout the initial epochs, the model demonstrates a training accuracy of 50%, which signifies a well-balanced initial state. The accuracy on the training dataset exhibits variability throughout the process, culminating in a maximal value of 98% at epoch 60. Nevertheless, a significant incongruity emerges when the model is assessed on the test dataset; at epoch 70, the accuracy declines to 90%. This indicates that the model may be susceptible to overfitting, as it seems to have excessively internalized the training data and struggles to extrapolate effectively to novel, unobserved data. Nevertheless, this decline in test accuracy, the model's performance remains consistent in succeeding epochs, averaging around 90% accuracy on the test dataset while the training accuracy fluctuates around 98%. This convergence indicates that the model successfully generalizes to the test data while also fitting the training data well. It is crucial to acknowledge that the proposed model exhibits a superior overall performance in comparison to conventional models that may overfit the training data, as indicated by the initial decline in test accuracy. The model's capacity to converge over time and sustain a high level of accuracy on the test dataset signifies an improved equilibrium between fitting the training data and extrapolating to novel, unobserved data. This attribute is of the utmost importance in guaranteeing the dependability and efficacy of the model in generating precise predictions on instances that have not been observed before. In summary, the outcomes presented indicate that the suggested model demonstrates a resilient ability to extrapolate to novel data, ultimately surpassing models that might encounter difficulties with overfitting throughout the training phase.

Table 1. Comparative Evaluation of Proposed System and Previous Models [19] in Terms of RMSE and MSE

Method	RMSE	MSE
Auto-encoder and MLP	6.34	40.12
MLP	6.5	42.35
Naïve 1	11.53	132.82
Naïve 2	9.4	88.46
The LSTM with M-PSO on the training dataset (The Proposed System)	**2.016**	**8.01**
The LSTM with M-PSO on the Test dataset (The Proposed System)	**2.009**	**8.145**

The table 1 above underscore the efficacy of different models, as assessed by Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The RMSE and MSE for the Auto-encoder and MLP combination were 6.34 and 40.12, respectively, among the standard models. In contrast, the standalone MLP model produced marginally higher values of 6.5 and 42.35. The Naïve 1 and Naïve 2 models exhibited relatively greater error rates, as evidenced by their respective RMSE values of 11.53 and 9.4, and MES values of 132.82 and 88.46. The outcomes produced by the proposed system, which combined LSTM and M-PSO, were considerably more impressive. The proposed model demonstrated remarkable results on the training dataset, attaining an RMSE of 2.016 and MES of 8.01. Moreover, the proposed system continued to outperform when evaluated on the validation dataset, with RMSE values of 2.009 and MES values of 8.145.

The significant decrease in both root mean square error (RMSE) and mean error standard deviation (MES) for the proposed model indicates that it is effective at generating more precise predictions in comparison to the standard models. The observed enhancement can be ascribed to the integration of LSTM and M-PSO, which seems to more efficiently capture the latent patterns and interdependencies within the dataset. Combined with the optimization capabilities of M-PSO, the ability of LSTM to retain information for extended periods of time contributes to the improved predictive accuracy observed in the proposed system.

In summary, the findings indicate that the LSTM with M-PSO model, which was proposed, represents a significant progression in comparison to conventional models, delivering exceptional predictive capabilities. The substantial decrease observed in both RMSE and MES highlights the potential of this methodology to improve the precision and dependability of forecasts within the specified framework.

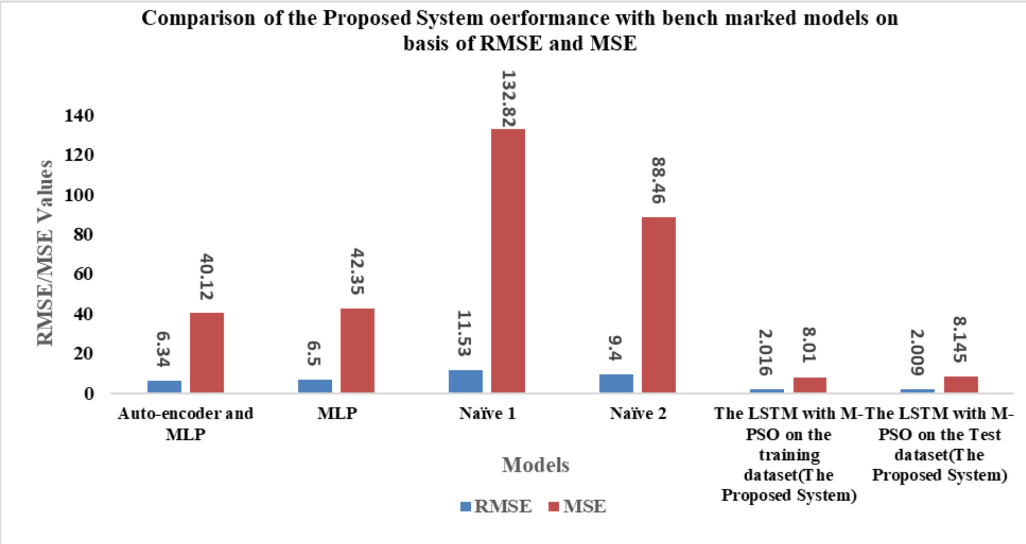

Fig. 5 Comparison of the proposed Mosel with the bench marked models using RMSE and MSE performance parameters

Table 2. Performance parameter for the Model

	Month	rf	Yhat_lower	Yhat_upper	Yhat
208	01-05-2022	17.9	16	21	18.5
209	01-06-2022	190.5	185.1	195.1	190.1
210	01-07-2022	282	278	288.1	283.05
211	01-08-2022	193.2	187	197.3	192.15
212	01-09-2022	192	186.1	193.9	190.01
213	01-10-2022	112	112.9	118	115.45
214	01-11-2022	6.1	5.1	12.1	8.6
215	01-12-2022	6.2	2.2	8.7	5.45

The table indicates outcomes of the proposed model applied to various months. It includes both actual values ('rf') and predicted values ('Yhat'), with prediction intervals denoted as 'Yhat_lower' and 'Yhat_upper', respectively. By comparing the predicted values to the actual observations, the performance of the model can be evaluated.

The model exhibited a satisfactory performance in January 2022, as it accurately predicted a value of 18.5 as opposed to the precise value of 17.9. As the months progress, the model consistently exhibits its effectiveness.

For example, in June 2022, the projected value of 190.1 exhibits an exceptionally high degree of proximity to the observed value of 190.5; this pattern persists throughout the subsequent months. The anticipated values for the months of July, August, and September (283.05, 192.15, and 190.01, respectively) exhibit a high degree of concordance with the measured values of 282, 193.2, and 192.

The predictive accuracy exhibits resilience even during months with lower values, as exemplified by October, where the model predicts 115.45 with an accuracy of 112. In a similar vein, the model exhibits its continued efficacy in November and December by generating predictions (8.6 and 5.45, respectively) that exhibit a high degree of correspondence with the empirical data (6.1 and 6.2).

The model's predictive accuracy is further underscored by the narrow prediction intervals ('Yhat_lower' and 'Yhat_upper'), which indicate a substantial degree of confidence in its estimations. The observed congruence between predicted and actual values over multiple months serves to emphasize the model's dependability.

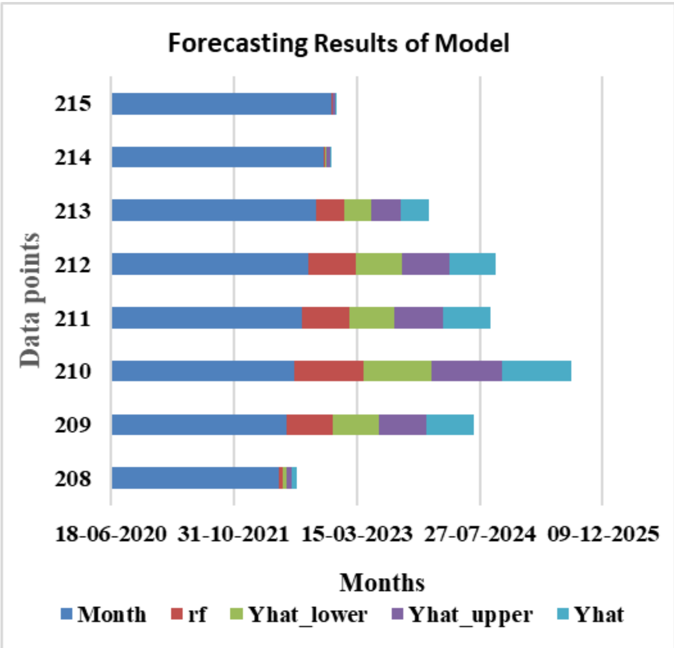

Fig. 6. Forecasting Results of Model

In summary, the findings suggest that the model under consideration exhibits commendable predictive capability for the target variable across various months, as predictions remain consistently in proximity to empirical observations. As indicated by the negligible discrepancy between predicted and observed values, the model effectively captures the fundamental patterns and trends within the data. The combination of this accuracy and the short prediction intervals demonstrates that the proposed model is superior at generating dependable and precise forecasts for the provided dataset.

V. CONCLUSION

The study highlights the utmost significance of precise rainfall prediction, especially in regions characterized by erratic precipitation patterns. The innovative combination of Long Short-Term Memory (LSTM) and Modified Particle Swarm Optimization (M-PSO) has demonstrated substantial enhancements in the accuracy of monthly rainfall forecasts, as evidenced by considerable reductions in both Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). The potential of this LSTM-M-PSO methodology extends to broad applications in global climate forecasting, particularly when dealing with extensive datasets. Its improved precision in rainfall prediction equips meteorologists, climate scientists, and policymakers with a valuable tool for addressing the multifaceted challenges posed by unpredictable precipitation patterns. These challenges, which have profound implications for agriculture, economic stability, and overall human well-being, require innovative and adaptable approaches in the face of a continuously evolving climate. This study not only underscores the promise of enhanced forecasting but also highlights the resilient and dynamic nature of meteorological science as it confronts the extensive and far-reaching impacts of heavy rainfall.

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