Enhancing Rainfall Forecasting Efficiency with LSTM-based Model and M-PSO Optimization

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Abstract. Rainfall is regarded as the key source of a substantial amount of the agriculture sector's economic output. In areas where the amount of rain that falls might be unpredictable, estimating the amount of rain that will fall is vital for designing an effective rainwater collection system and planning for any challenges that may occur. Forecasting heavy rain in modern times is a major worry for the meteorological department due to the fact that it is intricately tied to the economy as well as the mere existence of humans and that it is the root cause of natural disasters such as floods and droughts that take place on a yearly basis all over the world. The ever-changing nature of the climate makes it difficult for statistical methodologies to produce accurate forecasts of precipitation with a high degree of precision. The performance of the currently available rainfall forecasting methods is subpar when applied to complex and non-linear datasets. The proposed system analyzes how well the proposed LSTM with M-PSO performs in comparison to other rainfall forecasting systems that are currently in use. The findings of the experiments conducted using the suggested LSTM with the M-PSO approach produce an improved MSE and RMSE in the month's rainfall forecasting. As a consequence of this, the method that has been suggested is suitable for global climate projections that need the processing of a significant number of data.

Keywords: LSTM networks, WRM, M-PSO, Rainfall, Rainfall Forecasting, NDM,

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INTRODUCTION

Rainfall is the primary source of freshwater for humans, plants, and animals. Rainwater nourishes rivers, lakes, and waterways, sustaining the existence of a variety of species. Rainfall is extremely important in agriculture, particularly in nations like India, where agriculture is a major source of income. Excessive rainfall can cause disastrous floods that harm property and crops, therefore forecasting rainfall in advance is critical for greater economic development. Accurate rainfall forecasting aids in the mitigation of flooding risks, protecting lives and resources. Insufficient rainfall, on the other hand, can cause droughts and crop failures. Furthermore, rainfall is the primary driver of atmospheric circulation [1].

Predicting rainfall has become one of the most difficult topics in science and modern technology in recent decades. Regression processing, clustering, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), and Recurrent Neural Networks (RNN) are among the approaches used to predict rainfall [2]. These strategies, however, perform badly when dealing with short-term dependencies. Rainfall forecasting utilizing multiple neural network algorithms has not produced cutting-edge results. For many years, rainfall data has been available, and applying neural network models to this type of time series data has revealed non-linearity and significant computational complexity. Due to the "Vanishing Gradient" problem, these factors contribute to lower accuracy in computing regional rainfall amounts, making neural network layer training difficult. For time series data, RNNs, for example, have low memory retention, leading in information loss when processing big datasets. To solve this issue, the Long Short-Term Memory (LSTM) network, a modified form of RNN, has been proposed to increase rainfall forecasting accuracy [3].

LSTM introduces little data alterations such as multiplications and additions. Data travels through the cell states of the LSTM, allowing the network to remember or forget information selectively [4]. The LSTM networks depend on three key elements within each cell state: the preceding cell state, the prior concealed state, and the input obtained at the present time step. This dependency mechanism allows LSTMs to choose keep or reject information, overcoming issues like as "vanishing gradients" and "exploding gradients," which are both associated with network training difficulties [5].

Because of the vital role that precipitation plays in a wide variety of facets of both society and the environment, it is essential to design and execute an all-encompassing rainfall forecasting system. Because it is able to provide crucial insights and proactive knowledge on future precipitation patterns, a system of this kind is absolutely necessary [6]. The following is an in-depth explanation of why it is necessary to construct a reliable rainfall forecasting system:

Agriculture and Food Security: Agriculture is highly dependent on sufficient rainfall that occurs at the appropriate times for optimal crop development and yield. Farmers are able to make more educated choices regarding planting, irrigation, and harvesting when they have access to a reliable weather forecasting system. Accurate forecasts allow for the optimization of resource allocation, the improvement of crop management, and the assurance of food security by avoiding production losses brought on by unforeseen weather events[7].
Natural Disaster Management(NDM): Management of Natural Disasters Excessive precipitation can result in disastrous catastrophes such as floods, landslides, and mudslides. The authorities are in a better position to provide early warnings, evacuate sensitive regions, and devote resources for disaster preparation and response when they have access to an accurate forecasting system [8]. This has the potential to save lives, safeguard property, and lessen the socioeconomic effect of disasters of this nature.

Water Resource Management(WRM): Rainfall is the most important source of freshwater replenishment for rivers, lakes, and reservoirs, according to the management of water resources. A reliable forecasting system is beneficial to the management of water resources because it makes it easier to determine the appropriate distribution and allocation of water for drinking, industrial, agricultural, and hydroelectric power generation uses. In addition to this, it helps to reduce water scarcity and guarantees that water management techniques are sustainable.

Planning and development of infrastructure: Infrastructure projects, such as roads, bridges, and drainage systems, need to take into account rainfall patterns in order to withstand the possibility of flooding and erosion. Planning and development of infrastructure[9]. Accurate weather forecasts help influence urban planning and design, which in turn lowers cities' and communities' susceptibilities to weather-related damage and increases their resilience. The timely prediction of heavy rainfall enables authorities to conduct public health and safety measures such as disease management in flood-affected areas, emergency medical services, and sanitation in a timely manner [10][11]. It helps decrease the health concerns connected with waterborne infections and pollutants caused by flooding.

Economic and Financial Impact: The impacts of fluctuations in rainfall can have a negative impact on the economy and the finances of a number of different industries, including the generation of energy, transportation, and tourism[12]. A dependable forecasting system enables organizations to make educated decisions, improve operational efficiency, and better manage supply chains, all of which help to reduce the likelihood of interruptions and financial losses [13].

Scientific Research and Climate Studies: Rainfall patterns are essential data points for climate study, scientific inquiries, and environmental examination[14]. Research on climate change is aided by the provision of insights into long-term patterns and fluctuations that may be gained through a forecasting system that has been well-established and which makes a contribution to the collecting of accurate historical data[15].

Policy Formulation and Decision-Making: In order to design efficient policies for disaster management, water allocation, environmental protection, and sustainable development, government agencies, policymakers, and local authorities rely on reliable rainfall forecasts [16][17]. Making decisions based on accurate information is beneficial to the health and advancement of society as a whole.

In essence, the need for a reliable rainfall forecasting system is multidimensional and extends across a wide range of industries, with implications for people's livelihoods as well as safety, sustainability, and development [18]. A system like this one, which is able to make precise and timely forecasts, contributes greatly to increasing resilience, reducing risks, and enabling informed decision-making in the face of erratic weather circumstances.

1 RELATED THEORY

Emilcy H. et al. [19] presented a system that uses deep learning to forecast next-day cumulative precipitation by combining auto-encoders and neural networks. The approach was used to anticipate daily rainfall accumulation in Manizales, Colombia's central region. When compared to alternative methodologies, their architectural design performed better in terms of MSE and RMSE. Light rain scenarios must be considered, as they can have a negative impact on architectural improvements.

Sam c. et al. [20] suggested a sliding window approach for rainfall prediction. Unlike daily forecasts, this method focuses on forecasting total rainfall amounts. The fundamental issue in rainfall prediction is dealing with complex datasets that contain severe values, rainfall volatility, previously unknown patterns, and discontinuities. To solve these challenges, a combination of well-established machine learning algorithms and commonly used rainfall prediction approaches is used, providing better predictions both before and after rainfall accumulation.

Aswin s. et al. [21] used LSTM and ConvNet architectures to create a system for predicting and forecasting global monthly average rainfall. The number of hidden layers is increased to reduce

RMSE and Mean Absolute Percentage Error (MAPE), resulting in excellent precision. This technique not only improves climatic accuracy but also produces reasonably accurate projections for future months. The approach can be modified to use time series datasets specific to certain countries, allowing for detailed prediction outcomes using comparable techniques.

Moulana Mohammed et al. [22] developed a rainfall forecast system to handle the serious impacts of severe rain events. Forecasting accuracy is critical for citizens to take precautionary steps. Short-term and long-term rainfall forecasting are unique difficulties, with short-term forecasts often giving more accurate outcomes. Building models for long-term rainfall prediction remains a significant challenge. Given the effects of heavy rain on various facets of human life and the economy, accurate rainfall forecasts are critical. Because of the dynamic nature of the environment, traditional statistical methods fall short of delivering appropriate precision.

K. Manideep [23] et al. presented their research on predicting rainfall in their paper. The qualities of the data, as well as its level and trend, had a role in the decision-making process on which method of forecasting would be the most effective. The exponential smoothing method stood out as a popular choice among the several methods of forecasting that were accessible owing to the fact that it was straightforward, quick, effective, and economical. In the course of our research, we utilized the Holt-Winters algorithm to generate estimates of rainfall data by using previous observations as input. Our objective was to develop a strategy that not only was comparable to the frequently applied multiplicative Holt-Winters method in terms of precision and productivity, but that also managed to outperform it. In order to do this, we came up with the idea of using the Improved Additive Holt-Winters technique, which surpassed the multiplicative approach by an astonishing 6% in terms of the accuracy of its forecasts. This alternate technique offers a substantial development in the process of forecasting rainfall data, offering improved clarity and precision in the prediction of future rainfall patterns.

Gundalia, M. J. [24] et al. proposed the Holt-Winters approach, which is also known as Triple Exponential Smoothing. This method is a commonly used and successful methodology for forecasting time series data that display both trend and seasonality. The research project utilized the method of triple exponential smoothing in order to make predictions for the highest and lowest temperature time series. This method was given in order to improve the accuracy of weather forecasts and produce more accurate temperature predictions.

The literature review on rainfall forecasting investigates a variety of methodologies and techniques, such as machine learning models such as SVM, KNN, ANN, RNN, and LSTM, as well as optimization approaches such as M-PSO. The dynamic and non-linear structure of rainfall data presents a number of issues that need to be addressed, and these approaches are used to anticipate patterns of precipitation and provide solutions. When compared to conventional methods, comparisons demonstrate that LSTM with M-PSO provides a higher level of accuracy. The ability to accurately anticipate rainfall is essential for many industries, including agriculture and emergency management. Researchers want to improve these forecasting systems so that society may make better decisions and reap the rewards of their work.

2 PROPOSED METHODOLOGY

The proposed system is effective in forecasting rainfall. The proposed system consists of five steps: data collecting, feature engineering, preparation of data, and a multimodal forecasting model based on M-PSO and Optimal LSTM and is represented using figure 1.

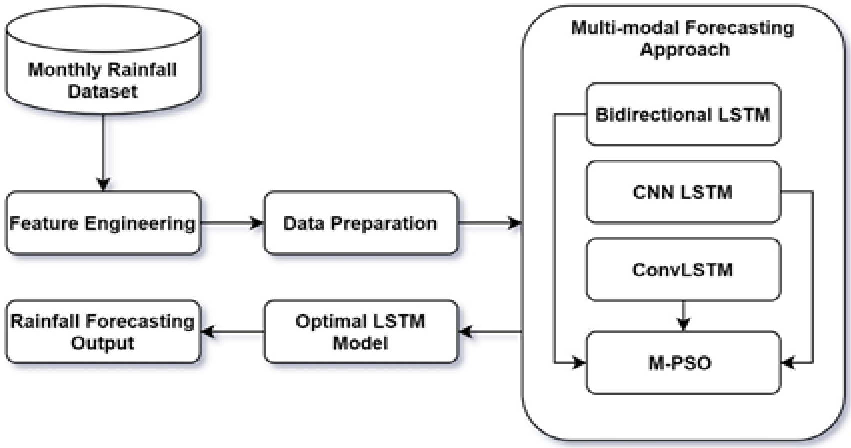

Fig. 1. Rainfall forecasting system

The system begins by importing data and then transforms the month's columns from string datatype to Datetime datatype(format). The modified datetime column is then designated as the main index. Following that, the data is divided into training and testing datasets. Individual LSTM predictive models are then trained using these training datasets in a multi-modal forecasting manner.

Following training, each model goes through M-PSO optimization. The next stage is to test each model's forecasting ability and compare the results to those of the Random Population. The fitness value of each model is then determined. This process is repeated until the nth iteration is reached, at which point the global minimum is identified and the best model is chosen.

Finally, the chosen model is used for one-step or multi-step forecasting. Forecasting includes predicting rainfall using the Minimum, Maximum, and Average Range, which improves the accuracy and dependability of the forecasts.

3.1 Acquisition and Preparation of Data

To begin, time series data is obtained from India's open government data repository, which is accessible via the Data.gov.in portal. Monthly rainfall records have been collected systematically for the past 118 years, beginning in 1901. Equation (1) denotes this data mathematically:

$$Rt = R1, R2, R3......., Rn \quad (1)$$

Missing or incorrect values are corrected using spline interpolation and various orders of autoregressive algorithms during the data preprocessing step.

3.2 Feature Engineering

Feature engineering is used to prepare the data in a suitable structure during this stage. This planning is essential for carrying out experiments, permitting good data analysis, and detecting changes in rainfall trends. During the feature engineering phase, the proposed solution leverages a binning algorithm. This approach works well with both numerical and categorical data. The suggested method employs this binning technique to create a resilient model, thereby limiting the risk of overfitting.

2.3 Preparation of Data and Multi-modal Prediction

This phase prepares data for the training and testing processes. The suggested approach divides the dataset into three independent parts: the training dataset, the validation dataset, and the test dataset. The system employs a multi-model forecasting strategy, which is supplemented by a modified Particle Swarm Optimization (M-PSO) technique. This method generates a random population and iteratively refines it to maximize results based on MSE and RMSE fitness functions over a the set number of iterations. Following that, the improved model is used to forecast rainfall, providing the lowest, highest, and mean values for both single-step and multi-steps forecasting.

Time-series dataset contains a vital information in each instance, and time series analysis is the process of unraveling its complexities. However, before entering the model training step, data must be properly prepared and formatted in order to fully realize this potential. Feature engineering and data preparation are many steps that transform a dataset into a usable time-series objects. The presented system does the following tasks: 1. Conversion of the Month's column from string data format to datetime format; 2. Employing the converted datetime columns as the designated index.; 3. Segmentation of the series into different input/output patterns known as samples. These measurements make it easier to derive valuable insights from raw data. Following that, the dataset is divided into training and testing subsets, which are then input into the multi-model forecasting technique.

The suggested approach employs three various types of Long Short-Term Memory (LSTM) models within the multi-model forecasting framework: Bidirectional LSTM, CNN LSTM, and ConvLSTM. These models are trained on the dataset concurrently, yielding a set of forecasted variables. These predictions are compared to the test dataset, and the proposed system uses the Modified Particle Swarm Optimization (M-PSO) technique to improve model performance, concentrating on both local best and globally optimum solutions.

2.4 Model Optimization

Particle-Swarm-Optimization (PSO) is a stochastic optimizing approach inspired by flocks of birds. This strategy has proven to be effective in a variety of research and application sectors. When compared to other methodologies such as Fuzzy Logic or Genetic Algorithms, Modified Particle Swarm Optimization (M-PSO) produces superior outcomes more quickly and at a lower cost. It is also amenable to parallelization and operates without regard for the gradient of the optimization problem, resulting in a small number of hyperparameters. M-PSO exhibits its skill by performing well across a wide range of tasks using the same set of hyperparameters, demonstrating its extraordinary versatility.

During the testing phase, a group of particles (representing probable solutions or instances from the test dataset) travels through a search space in pursuit of the global minimum. The fitness value of each particle corresponds to the fitness requirements of the optimization problem. Particles update their locations directed by velocities over subsequent iterations, moving towards both their personal level best positions and the best solutions of the ensemble, known as the global best.

$$P_i^{t+1} = P_i^t + V_i^{t+1} \tag{2}$$

$$V_i^{t+1} = wV_i^t + c_1 r_1 (P_{best(i)}^t - P_i^t) + c_2 r_2 (P_{bestglobal}^t - P_i^t) \tag{3}$$

When the starting velocity is zero, the particles are initialized utilizing equation 2 to attain global minima, which is due to the personal best positions and the globally best positions. M-PSO uses the personal optimum and globally best position to update the velocities as well as improvise equation 2 using equation 3. An 'inertia weight' is the solution to this problem. The equation 4 represents a 'inertia weight' () as a control parameter for the velocity (V).

$$\omega_{t+1} = (\omega_t - 0.4) \frac{(t_{max} - t)}{t_{max} + 0.4} \tag{4}$$

An inertia weight fluctuates with time for each repetition. A random selection of an inertia weight has a mean and standard deviation. Equation 5 represents the modified inertia weight numerically. Choosing an inertia weights at random yields a particular mean and standard deviation.

$$\omega_{t+1} = \omega_0 + (\omega_{t_{max}} - \omega_0) \frac{e^{m_i(t)} - 1}{e^{m_i(t)} + 1} \tag{5}$$

As demonstrated in equations 6 and 7, the model focuses on the global best solution, which entails effective optimization, MSE, along with RMSE as fitness function across iterations. The best model was selected and used to forecast rainfall.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{6}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}{n}} \tag{7}$$

For assessing the fitness function's value f_k^i in PSO, if the function value is lower than the preceding function value, the function's value becomes a local fitness function, as illustrated in equations 8 and 9 below.

$$if\ f_k^i \leq f_{best}^i\ then\ f_{best}^i = f_k^i\ , p_k^i = x_k^i \tag{8}$$

$$if\ f_k^i \leq f_{best}^g\ then\ f_{best}^g = f_k^i\ , p_k^g = x_k^i \tag{9}$$

To obtain the optimal dynamic model as well as the largest velocity reduction, minimize the problem's sensitive dependency on individual parameters, that is connected to prior formulations of inertia that is statistically described via equation 10.

$$v_{k+1}^i = w * v_k^i + c_1 * r_1 * (p_k^i - x_k^i) + c_2 * r_2 * (p_k^g - x_k^i) \tag{10}$$

2.5 The model forecasting Method

A one-phase forecast entails projecting the next data point in the series based on the input data used for model training during the prediction phase. A multi-step forecast, on the other hand, is a common method for generating predictions for a certain length, such as a one-week (7-day) view, utilizing weather information such as rainfall. The suggested approach focuses on forecasting the range of minimum, maximum, and average rainfall estimates in this context.

3 RESULT ANALYSIS

In the result section, we compare the predictive performance of various rainfall forecasting systems using the RMSE. The RMSE values for the Autoencoder and MLP Architectures range from 6.33 to 11.52 [3]. Meanwhile, the RMSE values for the ConvNet and LSTM Architecture range between 2.44 and 2.55 [3]. The Intensified LSTM Architecture, in particular, have a reduced RMSE range of 0.33 to 5.68.

Figure 2 depicts the model's training using rainfall data spanning the years 2000 to 2017. Figure 3 depicts the dataset in a standardized format, with values ranging from 0 to 1.0. The dataset is arranged monthly, and Figure 4 depicts the annual trend of the rainfall data.

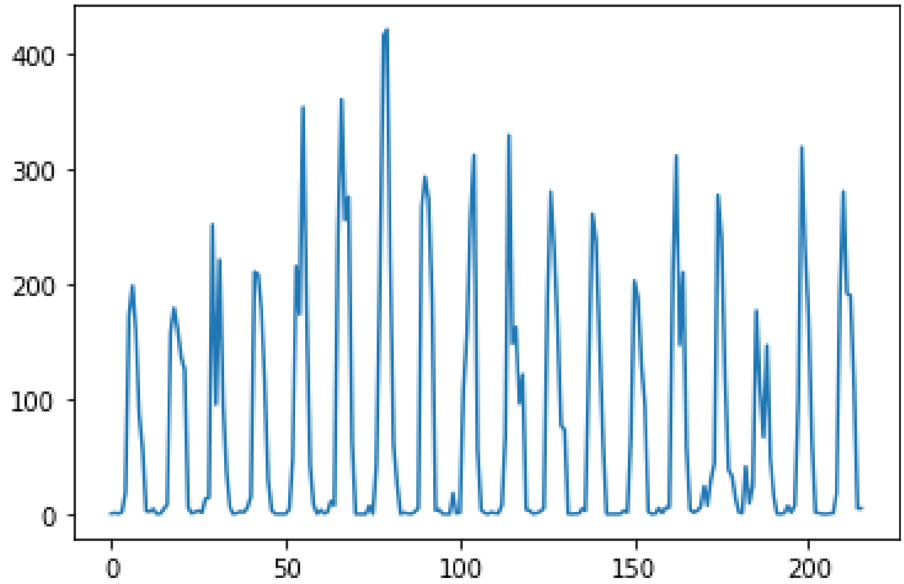

Fig. 2. Dataset of Rainfall in Maharashtra from 2000 to 2017

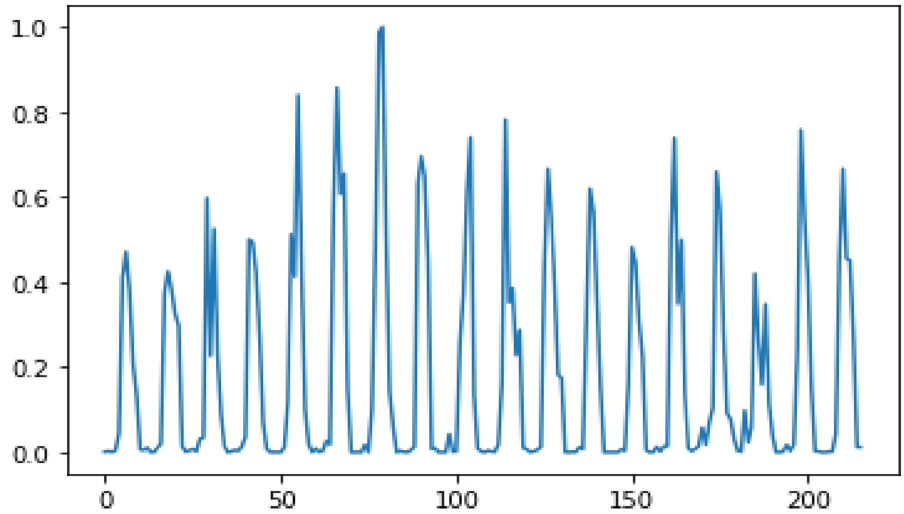

Fig. 3. Standardized dataset.

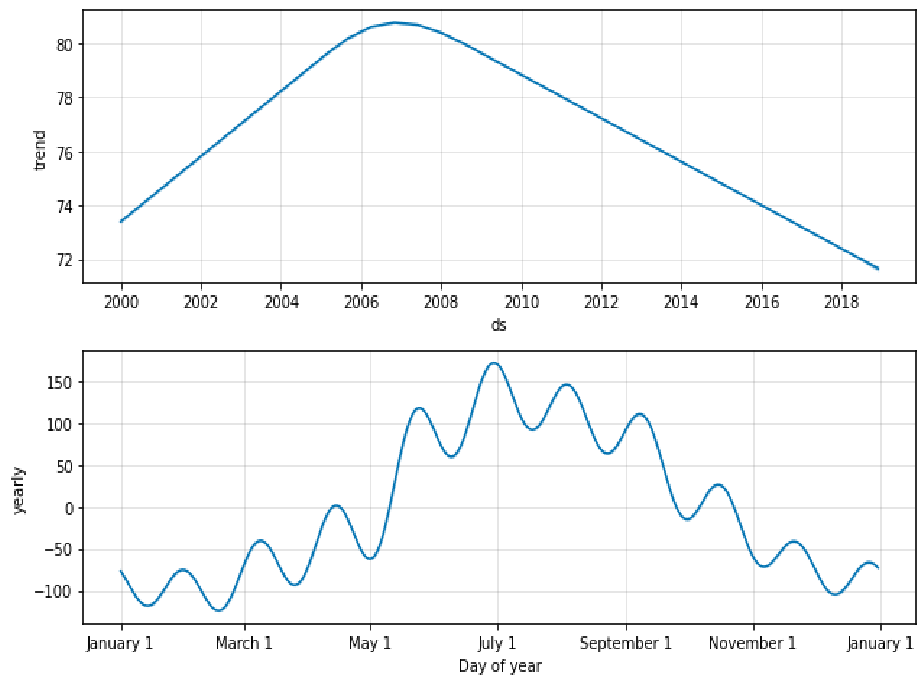

Fig. 4. Annual Pattern of the Rainfall Dataset

Figure 5 depicts the final rainfall forecast based on train and test data, while Table 1 shows the error score.

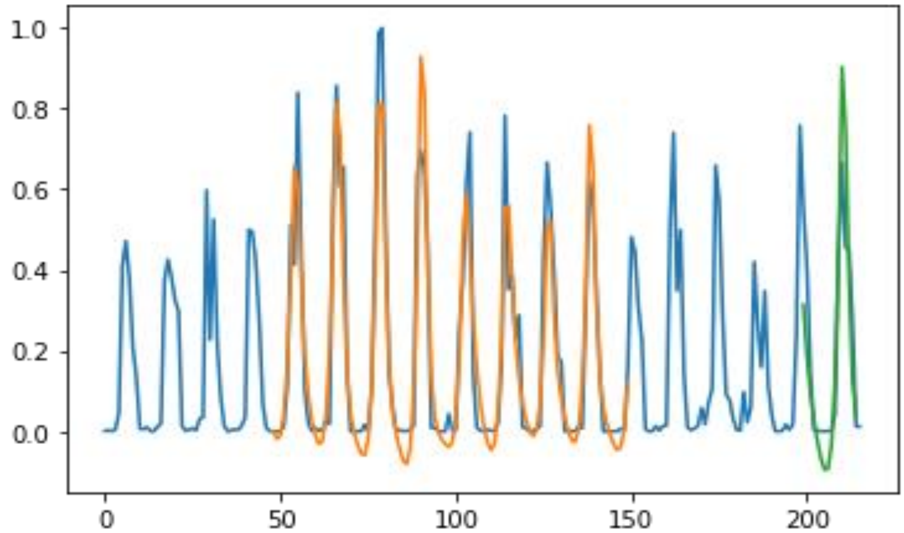

Fig. 5. Forecasting on Training and Testing Datasets

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

Method	RMSE	MES
Auto-encoder and MLP	6.33	40.11
MLP	6.51	42.34
Naive 1	11.52	132.82
Naive 2	9.4	88.43
The LSTM with M-PSO on the training dataset (The proposed System)	**2.124**	**8.98**
The LSTM with M-PSO on the Test dataset (The proposed System)	**2.065**	**8.345**

Table 1 compares the proposed system to previous approaches, evaluating their performance using measures such as MES and RMSE. The RMSE values for the auto-encoder and MLP techniques are 6.33 and 6.51, respectively, with MES values of 40.11 and 42.34. The RMSE values for the Nave 1 and Nave 2 techniques are 11.52 and 9.4, respectively, with MES values of 132.82 and 88.43. In comparison, the proposed LSTM with M-PSO obtains reduced RMSE values of 2.124 and 2.065 for training and test datasets, respectively, while displaying MES values of 8.98 and 8.345 for the same datasets. In terms of forecasting accuracy, the suggested system surpasses existing techniques such as auto encoder, MLP, Naive1, and Naive2. Figure 6 depicts the data from Table 1 in a graphical format.

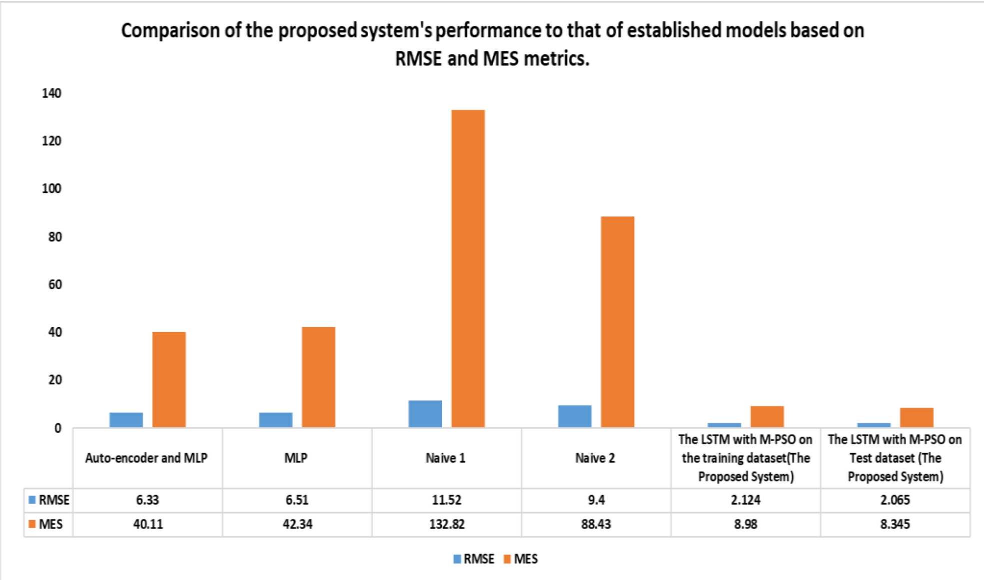

Fig. 6 Comparison of the proposed system's performance to that of established models based on RMSE and MES metrics.

The conclusive prediction outcome is visually depicted in Figure 7.

	Month	rf	yhat_lower	yhat_upper	yhat
208	2017-05-01	18.0	17.0	21.0	19.0
209	2017-06-01	189.2	186.2	192.2	189.2
210	2017-07-01	280.9	278.9	285.9	282.4
211	2017-08-01	192.0	190.0	196.0	193.0
212	2017-09-01	190.1	188.1	193.1	190.6
213	2017-10-01	112.8	110.8	115.8	113.3
214	2017-11-01	5.0	4.0	10.0	7.0
215	2017-12-01	5.1	1.1	7.1	4.1

Fig. 7. Forecasting results of model

4 Conclusion

The proposed system introduces an advanced approach to rainfall forecasting in the Maharashtra region, employing LSTM networks and multi-modal forecasting techniques. Enhanced accuracy is achieved by incorporating Modified Particle Swarm Optimization (M-PSO) for parameter refinement. This system outperforms existing models, ensuring more reliable and precise predictions. Future plans include expanding the model to cover additional regions, refining it using state-of-the-art optimization methods, and implementing real-time retraining in a production environment with edge devices for up-to-date and accurate forecasts. In essence, the proposed system offers a comprehensive solution to improve rainfall prediction accuracy and applicability.

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