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Rainfall Forecasting: A Comparative Analysis of Deep Learning and Machine Learning Models with Application to Environmental Data

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Abstract: Accurate daily rainfall prediction is essential for enhancing agricultural productivity and ensuring the availability of food and water resources. This research explores the field of data mining and deep learning techniques, specifically focusing on the utilization of LSTM (long short-term memory) and ARIMA (auto-regressive integrated moving average) models utilizing environmental datasets from diverse regions. This study offers an exhaustive investigation of these two models to improve the precision of daily rainfall forecasting. The research outcomes underscore a comparative assessment of LSTM and ARIMA models in the field of precipitation prediction. LSTM demonstrates remarkable results with minimal RMSE during both the training and testing phases, achieving a high R2 score, which signifies its efficacy in capturing rainfall patterns. Conversely, the ARIMA model exhibits competitive performance, characterised by low MSE, MAE, and RMSE values, underscoring its dependability in predicting rainfall. The study draws attention to the unexplored Vidarbha region, which includes 11 districts, using Nagpur district as a representative instance. This study offers valuable insights into the realm of climate prediction, particularly concerning rainfall forecasting. These insights carry substantial implications for strategic decision-making in agriculture and water resource management, ultimately promoting food and water security and safeguarding the well-being of the populace.

Keywords: *Deep learning, linear regression, Arima model, LSTM, Rainfall prediction.*

1. Introduction

Deep learning methods utilised for the prediction of daily rainfall encompass both the LSTM and ARIMA models. These algorithms fall under the umbrella of ensemble learning, a technique that combines multiple models to enhance predictive accuracy [1]. Accurate rainfall forecasting plays a pivotal role in bolstering agricultural output, thereby ensuring a stable food supply and access to clean water resources for a country's population. The insufficiency of rainfall has adverse implications on aquatic ecosystems, water quality, and agricultural productivity. The sustenance of agriculture and water quality hinges on the daily and annual fluctuations in rainfall and water availability. Consequently, the precise prediction of daily rainfall presents a formidable challenge to effectively managing these critical aspects of agriculture and water supply.

The dataset spans from January 1, 2016, to December 31, 2022, encompassing temperature readings ranging from 14.38 degrees Celsius to 32.58 degrees Celsius and humidity levels spanning from 49.62% to 98.55%. This dataset serves as a valuable resource for scrutinising temperature and humidity patterns in Nagpur. Researchers have harnessed data mining techniques [2], conducted extensive big data analyses, and leveraged various deep learning algorithms to enhance the precision of rainfall predictions at daily, monthly, and annual scales.

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In a previous study, we employed machine learning techniques to investigate how various environmental factors impact both the occurrence and intensity of rainfall [4]. These factors included temperature, relative humidity, sunshine, pressure, and evaporation, all of which were assessed for their direct or indirect roles in shaping rainfall patterns. Building on this earlier work, the current study shifts its focus to the application of deep learning models, specifically LSTM and ARIMA, with the goal of identifying significant atmospheric features responsible for rainfall and making predictions about daily rainfall intensity [5]. To ensure data suitability for analysis, the dataset utilised in this experiment is the Nagpur xlsx, which underwent thorough pre-processing. This study exclusively delves into the utilisation of LSTM and ARIMA deep learning models for the precise prediction of rainfall.

2. Related Work

A comprehensive literature review was conducted, integrating recent research on rainfall prediction and its multidisciplinary implications. The convolutional 3D GRU (Conv3D-GRU) model, as introduced by Sun et al. [6], was examined. This model employs 3D convolution and GRU for the analysis of radar echo patterns over time, effectively extracting spatial information. It was observed that this approach, which combines both temporal and spatial data, is vital for enhancing the precision of short-term rainfall forecasts. The study by Srivastava and Nigam [7] on the influence of inclement weather, including rainfall, on intelligent transportation systems

(ITS) was reviewed. Deep learning models like CNN-LSTM and LSTM-LSTM were employed to predict traffic flow and speed. The integration of rainfall data into their models was found to improve prediction accuracy, showcasing the pertinence of rainfall prediction to diverse domains. In addition, the image-based Rainfall CNN (irCNN) model described by Yin et al. [8] was evaluated. This model harnesses rainfall images and associated intensity data from various sensors to predict urban rainfall with remarkable precision. Its spatiotemporal granularity renders it suitable for urban flood risk management, making it a cost-effective solution. The literature review also encompassed Nithyashri et al.'s [9] work on coastal rainfall prediction in India, employing deep reinforcement learning. Their model achieved an impressive accuracy rate of 89%, highlighting the potential for integrating advanced machine learning techniques into specialised geographical contexts. Lastly, the research by Flores et al. [10] applied functional data analysis and regression models to predict rainfall for maize fields in Ecuador. Their high-accuracy models were observed to have broader applicability to similar agricultural regions like North Peru.

Several studies have contributed valuable insights in these domains, offering opportunities for integration to advance our understanding. Khan and Maity [11] introduced a hybrid Conv1D-MLP model for rainfall prediction, excelling at capturing complex relationships but facing challenges with longer lead times. This limitation aligns with Essa et al.'s [13] study on thunderstorm severity prediction, emphasising the need to address declining model performance over extended lead times. Combining insights from these studies could improve long-range rainfall forecasts, which are vital for disaster preparedness. Hydrological modelling, as explored by Kim [15] using LSTM networks, underscores the importance of historical hydrological data. This perspective resonates with Khan and Maity's call for incorporating GCM simulations, offering an opportunity to fuse different data sources for more robust models. Climate change impacts and adaptation are central to understanding shifting precipitation patterns. Shigute et al.'s [14] research in Ethiopia's Genale River basin, revealing drier trends and rising temperatures, has implications for water resource management akin to Kim and Kim's work. Integrating these findings can inform adaptive strategies for regions facing similar challenges. As Essa et al. [12] emphasise, improving input data and model fusion requires data integration from several sources, such as climate data, meteorological stations, and lightning detection networks. Such fusion can enhance the accuracy of rainfall predictions and water resource management models.

Rainfall prediction plays a pivotal role in water resource management. Recent studies in this domain offer valuable insights and potential integration opportunities across various regions. Statistical models have been prominently used, with a study in northern Ghana by Paul Dankwa et al. [16] highlighting the straightforward seasonal exponential smoothing model as a strong predictor. However, to enhance accuracy and address missing data issues, researchers like Muhammed E. Akiner [17] in Duzce and Bolu, Turkey, suggest integrating machine learning, specifically artificial neural networks (ANNs). Handling missing data is a recurring challenge in rainfall prediction. Akiner's study demonstrates how the Levenberg-Marquardt method can be employed to train ANNs when historical data is incomplete, serving as a useful reference for researchers dealing with extended data gaps. Urban water management poses distinctive challenges, as showcased in a study for the Kolkata Municipal Corporation by Md. Juber Alam and Arijit Majumder [18], where Excel regression functions and Python ARIMA models proved effective. Collaboration with studies like the one in northern Ghana can help assess changing rainfall impacts on local hydrological systems, emphasising the significance of integrated water resource planning. Expanding spatial coverage by collaborating across regions can lead to more comprehensive rainfall pattern insights. Researchers in Sylhet, Bangladesh Bari et al. [19], and Nanchang, Jiangxi Province Zhao et al. [20], could share methodologies and findings, facilitating model cross-validation and transferability assessments. Additionally, the merging of conventional ARIMA models with neural networks, as in Nanchang's study [20], shows promise in enhancing forecasting accuracy, inspiring future research into model combinations for improved predictions. Integrating these insights can advance rainfall prediction and, subsequently, water resource management strategies, addressing the evolving challenges posed by changing rainfall patterns [21].

3. Methodology

3.1 Modelling Annual Temperature Dynamics: Identifying Trends as well as Variations

The yearly temperature fluctuations in Nagpur, Maharashtra, are graphically shown in Figure 1, This graphically depicts the temperature range from year to year, including both the minimum and highest values [22]. This graph efficiently depicts the trends of variations in temperature over time by using the horizontal axis to signify years and the vertical axis to represent temperature in degrees Celsius, providing greater knowledge of the local climate dynamics. By selectively focusing on Nagpur as a single, valuable instance, the research simplifies the presentation of substantial data from several districts.

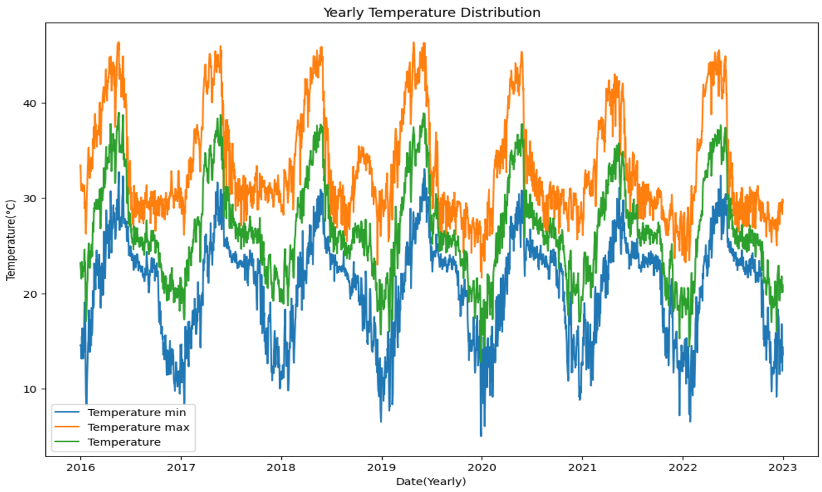

Fig 1. Annual Temperature Distribution Variations

The average daily reported precipitation in Nagpur, Maharashtra, emerges dynamically as a time series visual in Figure 2. The x-axis represents the date and spans the full dataset, while the y-axis represents the amount of precipitation in millimeters (mm). This visual representation illustrates daily rainfall variations, indicating certain patterns throughout the selected timeframe [23]. The depicted blue line adequately illustrates these variances, allowing for visual interpretation of precipitation level variations. This dataset provides useful insights into Nagpur's climatic patterns, allowing for an in-depth analysis of the area's precipitation pattern and facilitating directed weather-related variants.

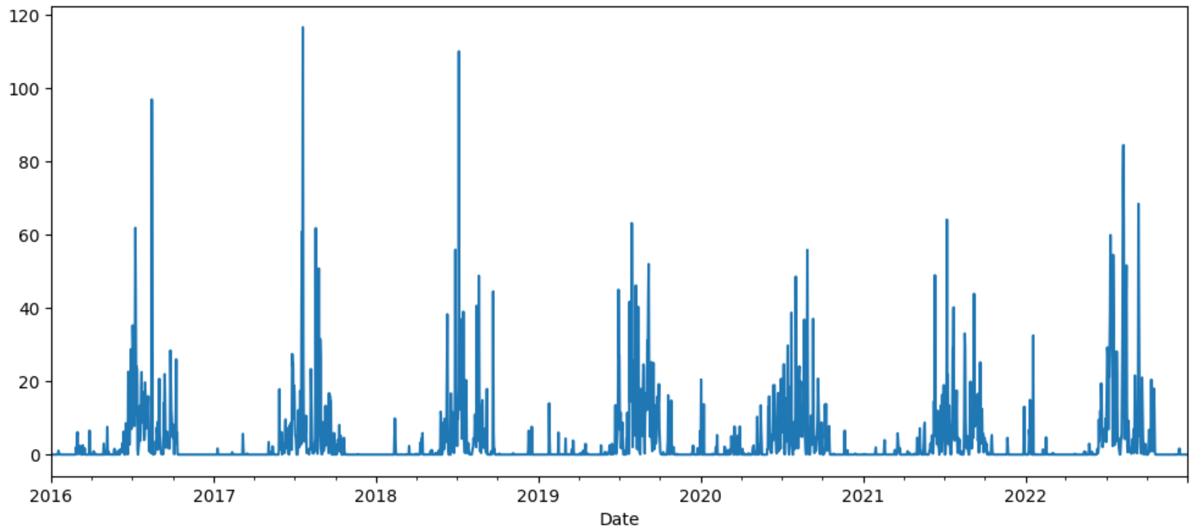

Fig 2. Daily Precipitation in Nagpur

The forecasting approach employing different ML algorithms is shown in the figure 3. It includes fundamental procedures, data pre-processing, data cleaning, missing value management, and scalability. Following that, the data is separated into training and test sets [25]. These sets are used to train and assess ML-learning algorithms such as ARIMA, LSTM, CNN, and Simple RNN. The accuracy of the models is evaluated and investigated, and the best-performing model is chosen for prediction. This method may be used for a variety of forecasting jobs, such as forecasting product sales [40]. Data gathering, pre-processing, splitting, training models, assessing performance, and finally picking the best model for future forecasts are all part of the process [26]. The flowchart provides an adaptable structure that may be applied to a variety of forecasting instances.

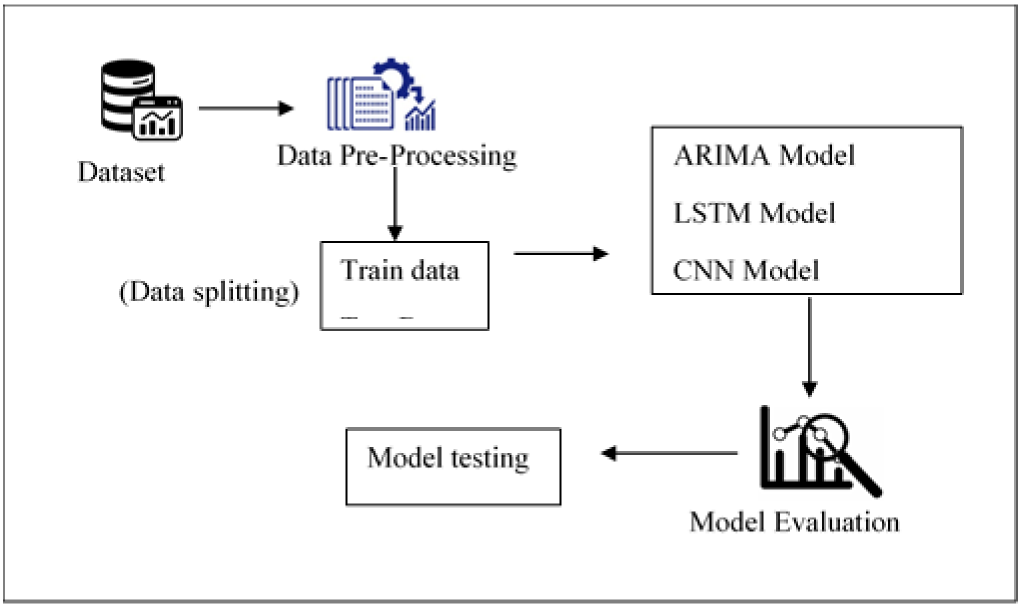

Fig 3. flowchart for forecasting

In this study, the rainfall was predicted using a deep learning technique. Deep learning algorithms such as the Arima, LSTM, CNN and Simple RNN Model were analysed, which took input variables having moderately and strongly related environmental variables with rainfall [34]. The better deep learning algorithm was identified and reported based on performance measures using MSE (Fig. 3).

3.2 Deep Learning Algorithms for Rainfall Prediction

An accurate evaluation of relevant research on rainfall prediction was undertaken in order to determine the best deep learning algorithms for forecasting daily rainfall quantities [27]. Two relevant algorithms, LSTM and ARIMA, were selected for the experimental study in order to estimate daily rainfall intensity using real-time environmental data. To identify the best method for daily rainfall quantity prediction, the study concentrated on the comparative assessment of LSTM and ARIMA models [28].

A. Arima Model

The ARIMA model is a popular analytical tool for estimating time series, incorporating daily rainfall quantities [29]. It is made up of three parts: auto-regressive (AR), integrated (I), and moving average (MA) [30].

AutoRegressive (AR) Component: This section of the model adjusts for the link between the time series current value and its prior values. It employs a linear regression of the current value on its lags. The AR element is represented by the letter 'p', which denotes the total number of lag values in the equation [31].

AR Equation (of order p):

$$X_t = c + \emptyset_1 * X_{t-1} + \emptyset_2 * X_{t-2} + \cdots X_{t-p} + \varepsilon_t$$

Integrated (I) Component: This component represents the number of differences needed to make the time series stationary (i.e., with a constant mean and variance). The letter 'd' denotes the order of differencing required to achieve stationarity [32].

I Equation (of order d):

$$Y_i = X_t - X_{t-d}$$

Moving Average (MA) Component: This part accounts for the relationship between the current value and past forecast errors. It uses a linear combination of past forecast errors. The MA component is denoted by the letter 'q,' which represents the number of past errors included in the model [33].

MA Equation (of order q):

$$X_t = c + \varepsilon_t + \emptyset_1 * \varepsilon_{t-1} + \emptyset_2 * \varepsilon_{t-2} \cdots \emptyset_q * \varepsilon_{t-q}$$

B. LSTM (Long Short-Term Memory)

Long Short-Term Memory (LSTM) is a sort of recurrent neural network (RNN) architecture that excels at modelling and forecasting data series with long-term dependencies [34]. It was developed to overcome the diminishing gradient issue that may arise in regular RNNs, resulting in it being more successful for applications such as time series forecasting, considering daily rainfall quantities [35].

Memory cells and filtering mechanisms in networks of LSTM allow them to capture and recall information over lengthy sequences [36]. They are made up of three main gates:

Input Gate (i_t): This gate controls what information from the current input should be stored in the cell state [37]. It uses the current input and the previous cell state to calculate this. The equation for the input gate is:

$$i_t = \sigma(W_i \cdot [l_t, x_t] + b_i$$

Forget Gate (f_t): The forget gate determines what information from the previous cell state should be forgotten or retained [38]. It considers the previous cell state and the current input to make this decision. The equation for the forget gate is:

$$f_t = \sigma(W_f \cdot [l_t, x_t] + b_f$$

Output Gate (o_t): The output gate determines which data from the current cell state will be utilized to generate the result [39]. It considers the current input, previous cell state, and the information the cell has gathered. The equation for the output gate is:

$$o_t = \sigma(W_o \cdot [l_t, x_t] + b_o$$

Here,

i_t, f_t and o_t are the input, forget, and output gate vectors, accordingly.

W_i , W_f and W_o are weight matrices for the gates.

l_t denotes the prior cell state (long-term memory).

x_t is the current input at time step t.

$\boldsymbol{\sigma}$ denotes the sigmoid activation function.

gates and the current candidate values $(\widetilde{c_t})$ as follows:

$$c_t = f_t \cdot c_t - 1 + i_t \cdot \widetilde{c_t}$$

Lastly, the outcome (h_t) for every single point is computed depending upon the modified cell state:

$$h_t = o_t \cdot \tanh c_t$$

4. Experimental Results and Data Analysis

4.1 Performance Evaluation of ARIMA Model

The variations between expected and observed amounts of precipitation are shown in Figure 4, which examines precipitation predictions for the months of May through January. Key metrics such as MSE, MAE and RMSE were produced to quantify the effectiveness of the model. The computed results are 90.85 for MSE, 4.91 for MAE, and 9.53 for RMSE, in that order. These metrics are used to assess the level of forecast accuracy as well as the variation among predictions and actual outcomes.

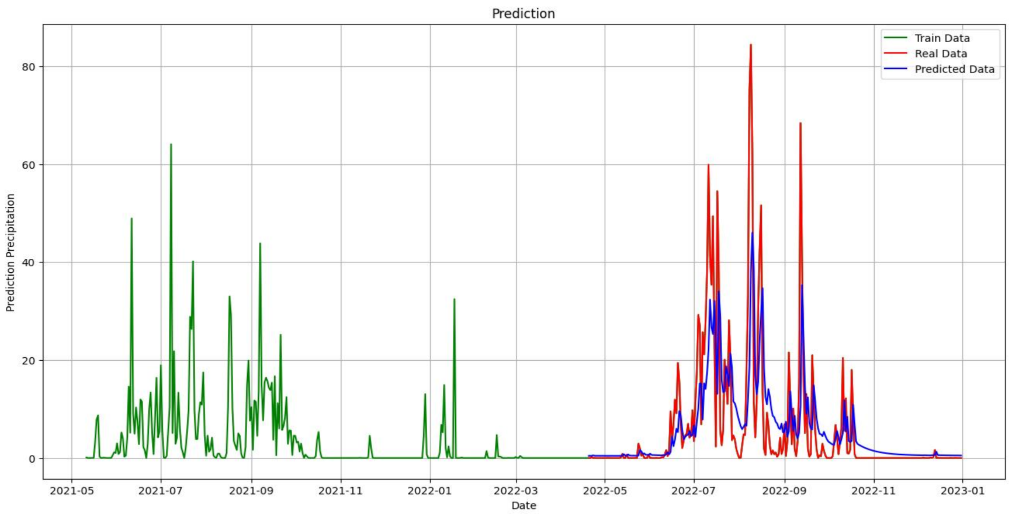

Fig 4. Predicted vs. Actual Precipitation (Arima)

4.2 Deep Learning Techniques for Predicting Daily Rainfall Amount Using LSTM

The importance of the LSTM model is precisely illustrated in Figure 5 in the study of time series estimation, with a special emphasis on daily rainfall, with an effective test RMSE of 7.643. Expanding training data to promote generalization and fine-tuning hyperparameters for best performance are recommended methods to improve prediction accuracy. A possible path is combining the LSTM model with complementary methodologies, possibly combining its trend recognition skills with the accuracy of another approach to assessing rainfall amounts. This collaborative approach has the ability to produce thorough projections.

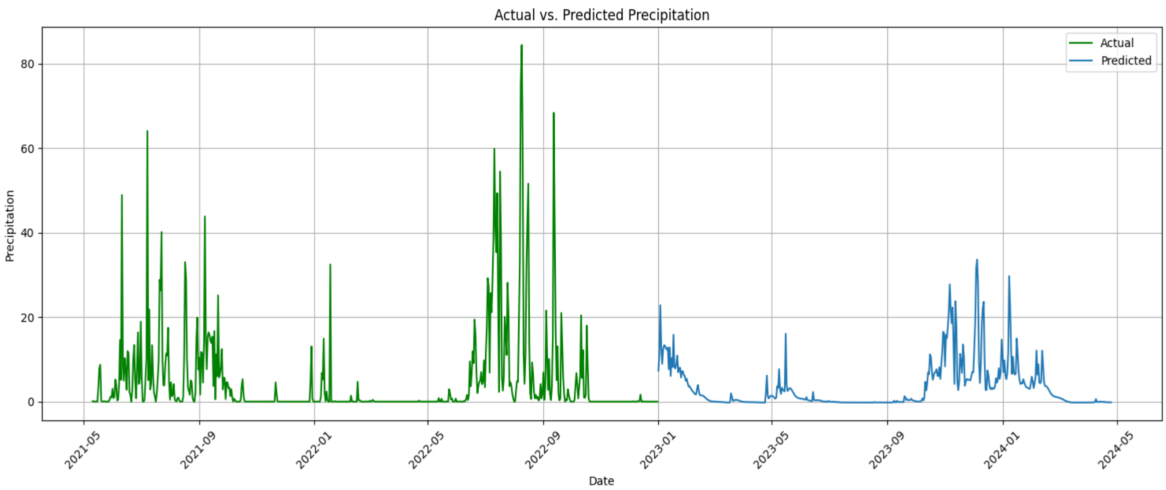

Fig 5. LSTM Model Performance on Test Data

4.3 Comparative Analysis of Precipitation Prediction Models and RMSE Evaluation

The ARIMA and LSTM models anticipated precipitation outputs are shown in Figure 6 (a). The blue line is the ARIMA model's estimate; the green line is the LSTM model's estimate; and the green line is the actual rainfall data. The visual depiction clearly depicts the LSTM model's superior capacity for collecting data trends as compared to the ARIMA model. The LSTM framework successfully predicts highs and lows, demonstrating its ability to recognize the data's complicated structures. This ability arises from the LSTM's ability to comprehend long-term dependencies, as opposed to ARIMA's emphasis on short-term interactions. The LSTM model's potential to overfit the data highlights its capacity to absorb noise alongside underlying patterns, restricting its flexibility to new data. The RMSE for both approaches is shown in Figure 6 (b). RMSE measures the difference between anticipated and actual values, with smaller values showing a better fit. The graph shows that the LSTM model has a lower RMSE than the ARIMA model, indicating greater forecasting accuracy.

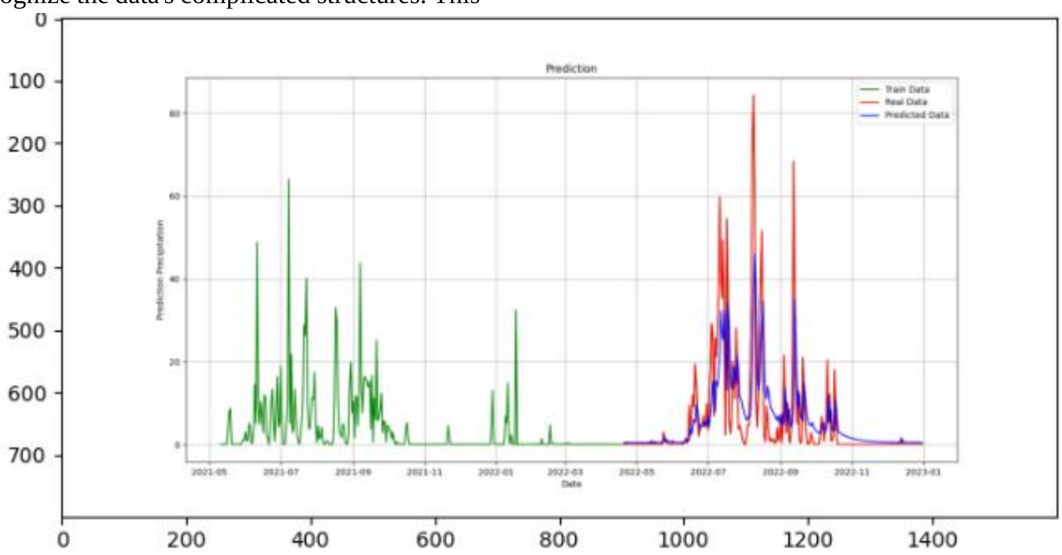

Fig 6 (a). Predicted vs. Actual Precipitation Comparison

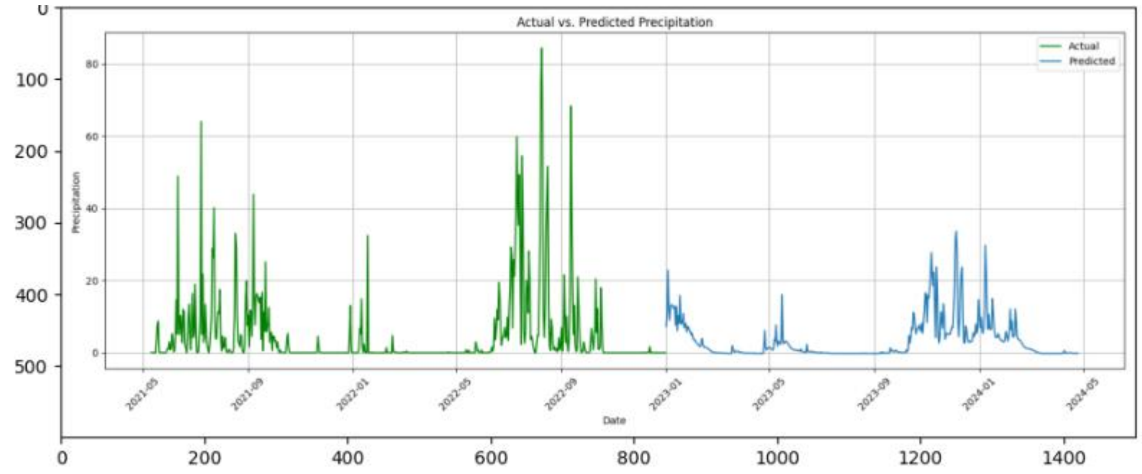

Fig 6 (b). RMSE Evaluation for Prediction Models

4.4 Analysis of Temperature Data Using Seasonal Decomposition

The trend component captures the data's long-term temporal evolution. The trend in this instance is positive, implying a steady temperature increase, as shown in figure 7. The seasonality factor represents repeating variations that occur at regular intervals. The seasonality component follows an angular structure with frequent fluctuations. These swings are greatest in the summer and lowest in the winter. The residual element is low, highlighting the trend and seasonality aspects' success in explaining a major percentage of the data variation. Using seasonal breakdown to improve temperature data offers potential for improving the precision of forecasting. Models that include the seasonality element make more exact forecasts and cover a larger range of variations in time.

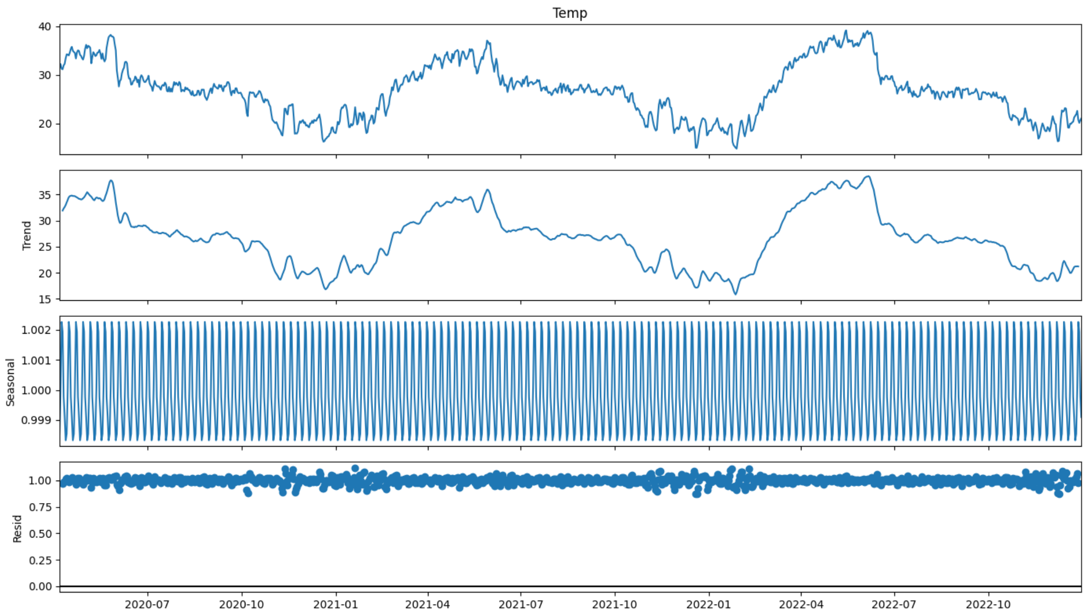

Fig 7. Trend, Seasonality, and Residual Components of Temperature Data

4.5 Enhancing Daily Rainfall Forecasts through Arima and LSTM Machine Learning Models: A Comparative Analysis on Temperature Prediction

Our study focuses on improving daily precipitation predictions using machine learning, especially the Arima and LSTM models. These models have the potential to improve forecast accuracy dramatically. The study performs a thorough comparison analysis with an emphasis on temperature forecasting. The study provides insight into the prediction capacities of both models by rigorously examining their performance. Figures 8(a) and 8(b) provide graphical representations of the Arima and LSTM models' predictions of temperature trends. These visualizations provide insights into how each model shows and forecasts temperature fluctuations over time, laying the groundwork for evaluating model success and finding ways to enhance it. This comparative study increases rainfall prediction approaches by emphasizing machine learning's critical role in deciphering complex environmental data for more precise forecasting. The research adds to the continuous effort of refining daily rainfall forecasts and increasing readiness and management techniques in the face of changing climatic circumstances.

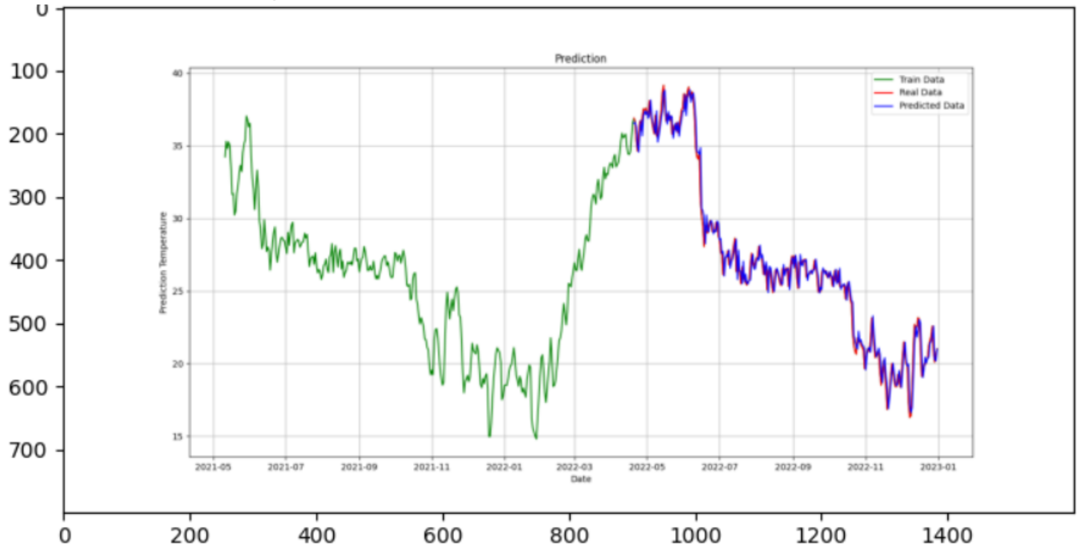

Fig 8 (a). Temperature Prediction by Arima Model

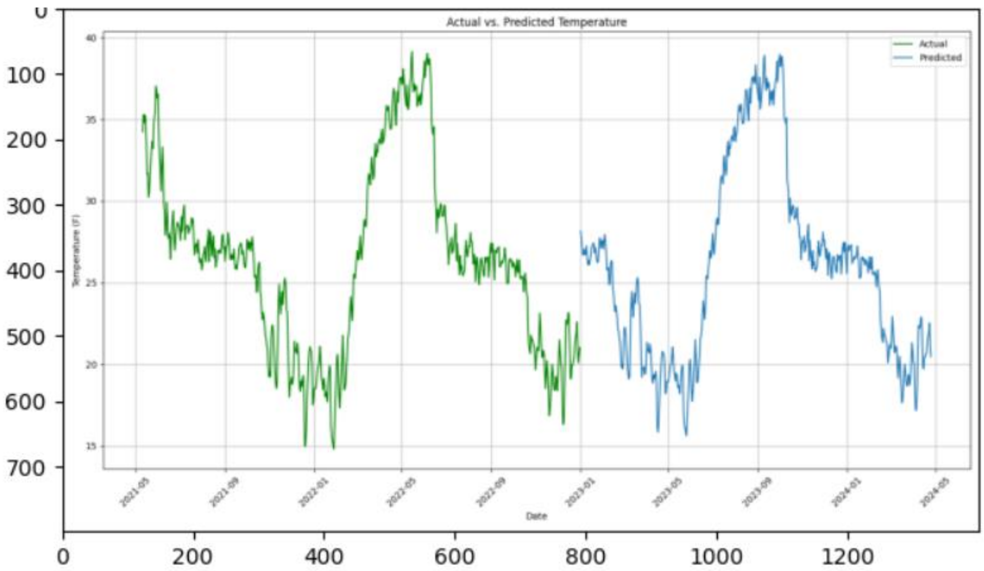

Fig 8 (b). Temperature Prediction by LSTM Model

4.6 Deep learning Model Evolution CNN and RNN

In the comparative analysis of projected and actual rainfall levels presented in Figure 9, the CNN and RNN algorithms take center stage. The CNN framework has great accuracy, with the majority of samples correlating projected and real temperatures. Some outliers, in which projected temperatures diverge greatly from real values, are linked to the CNN model's ability to extract geographical properties from data. The findings of the RNN model are shown in Figure 10, which likewise shows promise in temperature prediction; however, there are notable instances with significant disparities between predicted and actual temperatures. For this comparison evaluation, we used both RNN and CNN models in all 11 districts, especially Nagpur, although we chose Nagpur as an example for demonstrative purposes. These findings highlight the potential of both techniques in rainfall prediction, with CNN being outstanding at recognizing spatial trends and the RNN model showing promise but requiring extra fine-tuning for accurate and predictable forecasts.

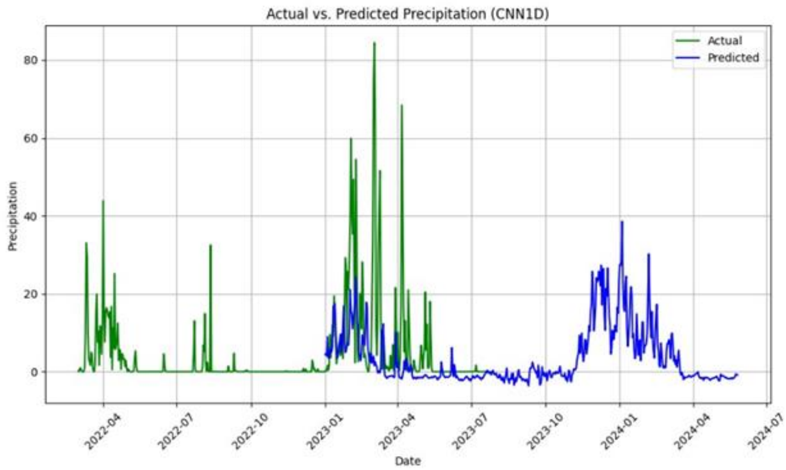

Fig 9. Actual vs. Predicted Precipitation (CNN1D)

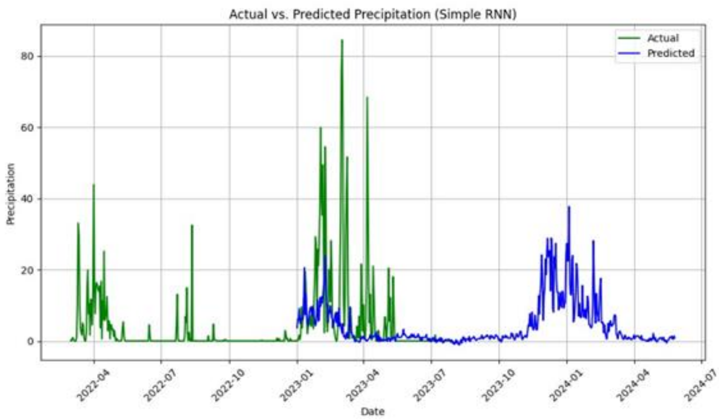

Fig 10. Actual vs. Predicted Precipitation (Simple RNN)

4.7 Evaluation Metrics for 1D CNN and Simple RNN Models

The efficiency of two deep learning algorithms, CNN and RNN, is meticulously examined across multiple districts in Table 1. The RNN model clearly outperforms CNN at its best in Bhandara (88.40%), although it is more precise in a few districts, including Buldhana (86.72%). Compared to the RNN, the CNN model frequently demonstrates lower error rates (MSE, RMSE, and MAE) in most districts, signifying that its forecasts are typically more exact. CNN accuracy varies slightly among districts, with figures varying from 50.59% to 88.40%. Figure 11 indicates that, in comparison to RNN, CNN achieves the highest efficiency in Bhandara and Nagpur.

Table 1: Comparison of CNN and RNN Model Performance Districts

District	RNN					CNN				
	MSE	RMSE	MAE	R2 Score	Accuracy	MSE	RMSE	MAE	R2 Score	Accuracy
Akola	42.647	6.53	2.623	0.415	84.77%	37.871	6.154	2.894	0.48	77.15%
Amravati	44.571	6.676	2.77	0.485	75.78%	45.131	6.718	3.365	0.479	50.59%
Bhandara	53.567	7.319	4.141	0.522	52.93%	51.914	7.205	3.645	0.537	88.48%

Buldhana	31.633	5.624	2.672	0.45	86.72%	28.02	5.293	2.898	0.513	75.00%
Chandrapur	90.872	9.533	3.928	0.436	60.74%	100.116	10.006	3.719	0.379	81.64%
Gadchiroli	89.754	9.474	3.854	0.464	68.75%	95.54	9.774	4.123	0.43	62.50%
Nagpur	71.819	8.475	3.47	0.359	87.11%	47.883	6.92	3.67	0.573	88.09%
Wardha	47.98	6.927	3.5	0.555	59.38	59.739	7.729	3.759	0.446	86.13%
Yavatmal	41.3	6.427	3.16	0.527	84.38%	46.642	6.83	3.053	0.466	75.20%
Washim	32.629	5.712	2.996	0.496	53.32%	30.033	5.48	3.066	0.536	69.53%
Gondia	34.664	5.888	2.877	0.633	62.50%	37.094	6.09	2.498	0.608	44.73%

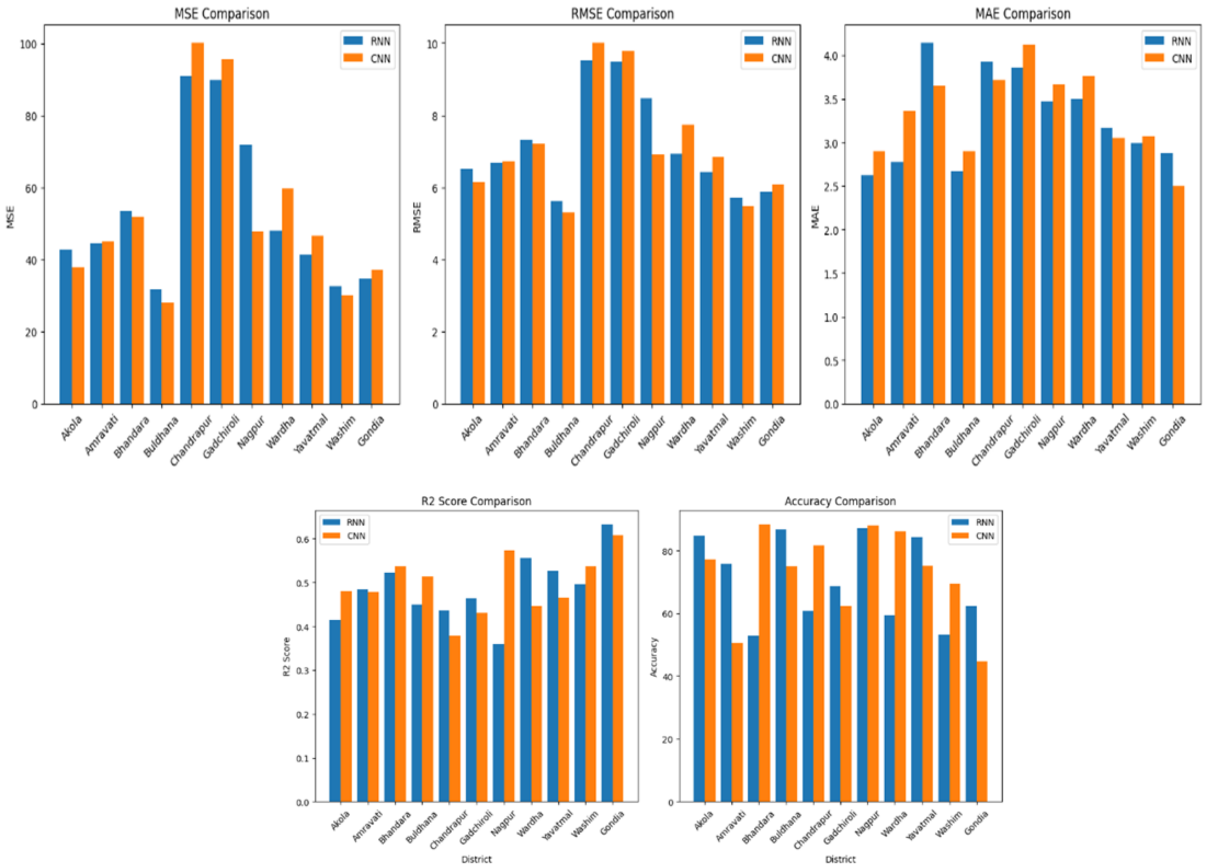

Fig 11. Comparison of Model Performance Metrics for Different Districts

4.8 Comparative Evaluation of Forecasting Systems for Regular Rainfall Forecasting: Evaluation Perspectives and Systems Choice

a visualization of the test RMSE values for the ARIMA and LSTM algorithms when applied to the daily rainfall forecast is shown in figure 12. The graphic clearly demonstrates the LSTM model's improved performance, with a lower test RMSE of 7.65 compared to the ARIMA model's test RMSE of 9.56. This visual illustration emphasizes the LSTM model's improved prediction accuracy, focusing on its utility as a reliable tool for predicting daily rainfall amounts.

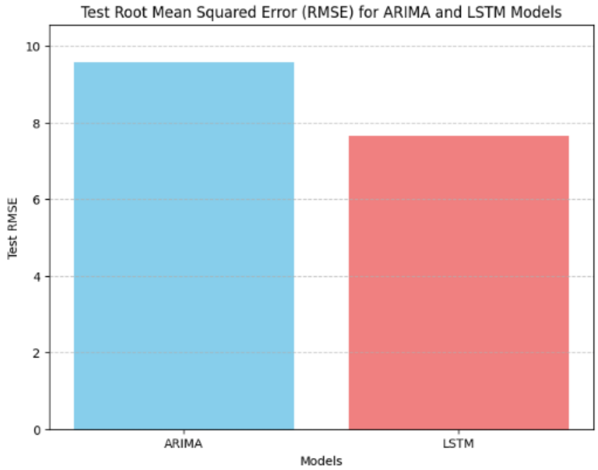

Fig 12. Comparative Analysis of Predictive Models for Daily Rainfall

In the thorough assessment of deep learning models for rainfall prediction shown in Table 2, in terms of accurate rainfall forecasting in districts such as Akola, Amravati, Bhandara, and Buldhana, In Akola, for example, the LSTM model operates the ARIMA model, with a much lower RMSE of 6.947 compared to the ARIMA model's RMSE of 8.3819. This enhanced accuracy is especially essential in areas where precise predictions of rainfall are essential for crop forecasting and effective water resource management. As seen in Table 2, variances in the model's effectiveness are less obvious in Chandrapur, Gadchiroli, and Nagpur, with the LSTM model typically exhibiting slightly lower RMSE values. This indicates that specific regional characteristics and data anomalies may impact the approach to selecting. As seen in Table 2, Wardha, Yavatmal, Washim, and Gondia all have efficiency that is equal for both models, giving decision-makers a chance to select the model that best meets their requirements. Weather experts and water resource managers may utilize our research, as shown in Table 2, to help them decide which rainfall forecast model is appropriate for their specific locations. These findings illustrate the capabilities of deep learning, namely the LSTM approach, in boosting rainfall forecasting precision within specific regions while recognizing the importance of geographical specifics in choosing models. Figure 13 depicts the differences in performance metrics- ARIMA MSE, RMSE, MAE and LSTM RMSE across districts.

Table 2: Comparative Performance of LSTM and ARIMA Models in Rainfall Prediction across Districts.

District	**Traditional ARIMA**			**LSTM**
	MSE	RMSE	MAE	RMSE
Akola	70.255	8.3819	4.0662	6.947
Amravati	86.23	4.27	9.28	7.568
Bhandara	91.46	4.903	9.56	7.708
Buldhana	48.99	3.68	6.99	5.948
Chandrapur	101.51	4.95	10.07	10.631
Gadchiroli	144.63	5.38	12.02	10.541
Nagpur	91.46	4.90	9.56	7.65
Wardha	80.73	4.45	8.98	7.79
yavatmal	84.03	4.16	9.16	7.408
Washim	49.97	3.65	7.06	6.324
Gondia	89.65	4.705	9.468	7.337

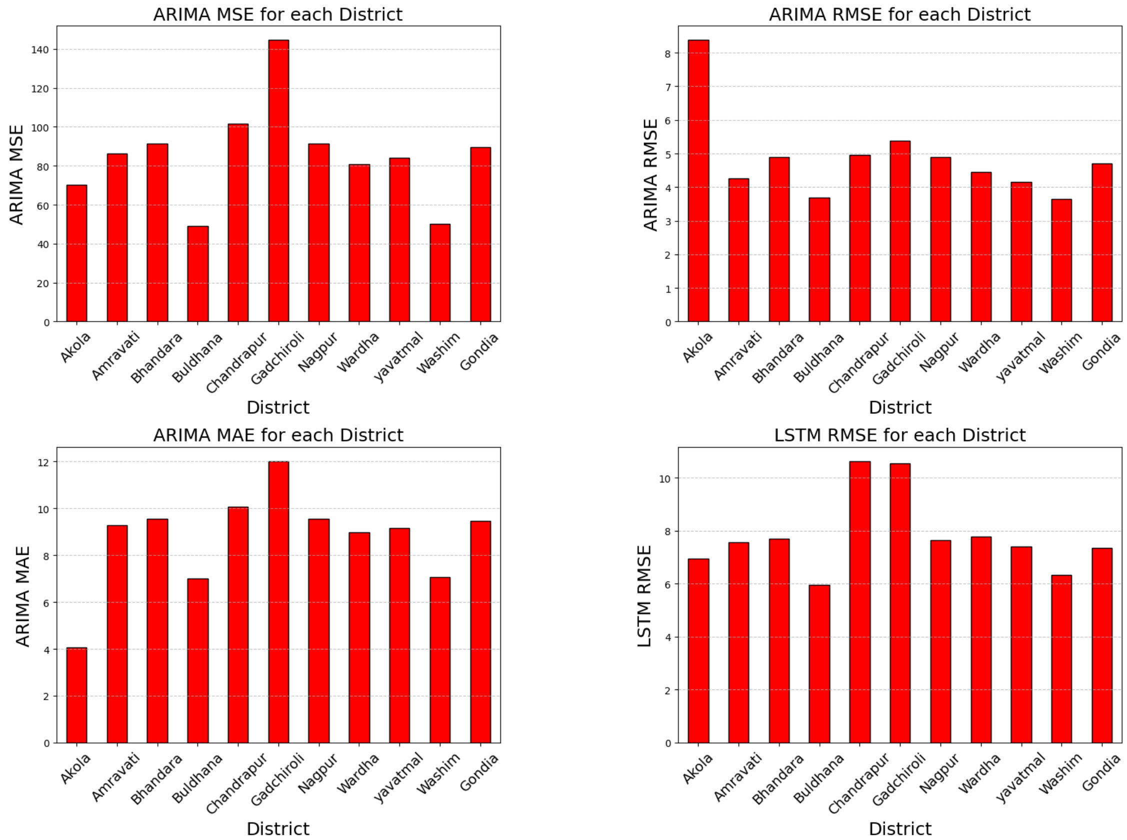

Fig 13. Comparative Performance of LSTM and ARIMA Models in Rainfall Prediction across Districts

5. Conclusion

This research emphasizes the critical importance of precise daily rainfall projections for agricultural, food, and water resource availability and public health. We conducted a thorough investigation of environmental datasets from several regions, applying DL and ML approaches, with a particular emphasis on LSTM, ARIMA, RNN, and CNN models. According to our research, LSTM excels at identifying complicated rainfall patterns, with excellent R2 scores and continuously low RMSE values. The ARIMA model is dependable, with low MSE, MAE, and RMSE values highlighting its superior performance. The expanded research further demonstrates the effective use of RNN and CNN models in various districts, with capabilities in precision and accuracy. The model should be chosen based on geographical details and unique features of the data. The research gives significant information for weather projections, especially rainfall forecasting, allowing for more accurate choices for optimal agricultural and water resource management. It shows how deep learning approaches may improve rainfall prediction accuracy in a variety of regions.

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