IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

An Artificial Intelligence Based Rainfall Prediction Using LSTM and Neural Networks

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Abstract: The hardest thing a meteorologist has to do is forecast rainfall. In this work, we presented a rainfall prediction model that can be readily calibrated through the use of LSTM and artificial intelligence algorithms. This is a sophisticated way to determine the amount of rainfall. When it comes to the correctness of this kind of technique implementation, the deep learning approach is the most beneficial. When measuring memory sequence data, a long short-term memory method is used to quickly calculate historical data and produce the best forecast. This forecast technique is vital since the majority of the population in this nation depends on agriculture. Assessing rainfall in a timely manner will boost crop yields and save agricultural expenses. We have developed our model, which will assist us in estimating the quantity of rainfall, taking all these aspects into account.To achieve this, we have gathered data from six different regions. Six factors—temperature, dew point, humidity, wind pressure, wind speed, and wind direction have been used in our prediction. Our approach yielded an accuracy rate of 86% when all of our data was analysed. For the best outcome, we also concentrate on a large dataset on long-term weather.

Keywords: Long short-term memory; predictive analytics; rainfall prediction; recurrent neural network.

I.INTRODUCTION

One of the main extreme phenomena in the climate system is rainfall. It directly affects agriculture, management, water, ecosystems, and resources. For many who depend on water for their whole existence, rainfall is their primary supply. Arunachal Pradesh, Kerala, Karnataka, Goa, Orissa, West Bengal, Sikkim, and Uttarakhand are among the few states in India with substantial rainfall roughly 3000 to 1500 mm annually which enables farmers to develop their crops without worrying about a lack of water resources. However, extremely little rainfall less than 600 mm annually occurs in a few other states, including Gujarat, Rajasthan, and Uttar Pradesh, which is a key contributor to dryness in those regions. In certain places, like Kerala and Orissa, excessive rainfall may also cause floods, which negatively impacts people by seriously destroying their property. As a result, these states' economies decline for a while, and it takes a long time for the populace to resume their previous way of life and line of work. In 2018, floods in different parts of India claimed the lives of around 1400 individuals, so there was also a loss of human life.

However, a nation's main economic activity is reliant on its ability to produce enough food to feed its whole people. If this is achieved, the nation will be less dependent on importing food items from other nations. In India, the monsoon season gets 70% of the country's rainfall for irrigation purposes. However, because of rising temperatures and evapotranspiration, there isn't enough water for farmers to utilise all year round. As a result, anticipating future rainfall becomes crucial to rainfall data analysis and prediction, which may aid in the discovery of solutions during periods of excess or deficiency in rainfall.

Rainfall prediction is still a serious problem that has caught the interest of businesses, governments, risk management organisations, and the scientific community. Rainfall is one of the primary complicated meteorological phenomena. Rainfall is an unpredictable phenomenon with a complicated source. When it comes to weather forecasts, one of the climatic elements is that, even in situations with identical weather, it might rain right now but not tomorrow. Prediction therefore becomes essential to understanding the state of the atmosphere.

Conventional weather forecasting involves meteorologists sitting with weather charts spread in front of them and making forecasts based on their experience. This experience is based on prior information on weather theory and years of observations [2]. Predicting the amount of rainfall is crucial since it is the variable most closely correlated with unfavourable natural phenomena including avalanches, flooding, landslides, and mass movements. For years, society has been impacted by these tragedies. This seems to be the primary driving force for the development of machine learning techniques and numerical weather prediction.

Artificial Neural Networks (ANN) are a key component of prediction, and the type of data being analysed determines which neural network model is best. Neural networks may be classified into a variety of ways, each with a distinct prediction method, such as feed forward neural networks, neural networks with back-propagation, recurrent neural networks, etc. Recurrent neural networks are a superior choice for handling rainfall data since they can handle time series data effectively. Multilayer perceptrons, sometimes known as "guerrilla rainstorms" in Japan, are capable of predicting even unexpectedly high rainfall [4]. Back-propagation plays a significant role in prediction because neurons use their memory of the weights that apply to each input range to make predictions. Such a scenario carries out the least error monthly rainfall forecast for the Indonesian Kalimantan area using a Back-propagating Neural Network (BPNN) [5].

II.RELATED WORKS

One of nature's most amazing, important, and necessary elements which is crucial for the urban economy is rainfall.

The destruction of roads and crops caused by floods resulting from rainfall significantly lowers the standard of living. Numerous methods have been put out to precisely ascertain the prognosis that would transform an urban region into a thriving economic centre [1]. In many Indian states, the agricultural industry depends on rainfall, while in other states, the lack of rainfall has caused the area to become a desert. Many states have excessive rainfall that causes floods and landslides, which worsen the situation and lower the level of living in these areas while also having a negative impact on the economy. It is quite difficult to decide the ideal time for rainfall because it does not stick to any one schedule. Rainfall analysis is a unique method of keeping time-series that is used to forecast a variety of artificial neural network categories [2]. Among the natural resources is water. Data about precipitation is crucial for a region. Predicting rainfall can advance significantly if mathematical climate models are developed. Relationships between local observations and large-scale meteorological data may be established to develop rainfall models for various locations [3]. One of the causes of human fatalities and economic losses, which endangers our social lives and interferes with our everyday lives, is flooding. To eliminate this, we don't have to lose anything if we anticipate the river's flood and accurately depict it mathematically, but this is a very difficult procedure since it depends on a number of factors, including location, rainfall, soil type, climate, and river flow direction. The hydrology behind this procedure makes it more simpler. However, the typical model still has an inaccuracy [4]. Since tourism flow is not linearly altered, it is a process that is challenging to diagnose. Several techniques, including LSTM NN, ARTMA, and BPNN, have been employed at different phases to ascertain the accurate tourism flow [10].

A large number of scholars have worked on rainfall prediction analysis. This section discusses a few studies. The statistical technique and the machine learning approach are the two methods for forecasting rainfall. Statistical techniques were used in traditional rainfall forecast models. A technique like this is the Holt-Winters algorithm. Numerous studies have advocated Holt-Winters algorithm variants. A better prediction technique utilising additive Holt-Winters was covered in [10], and it is around 6% more accurate than the multiplicative Holt-Winters approach. This prediction method uses a large data technique, computing the average measure of the sequence in the past. Nonetheless, a restricted variety of datasets have been collected.

In [11], the Holt–Winters method which was applied for the Junagadh region using an Excel spreadsheet—was used to estimate the maximum and lowest temperature time series of the area. Three metrics are used to quantify the effectiveness of the methodology: MSE, MAPE, and MAD. The triple exponential smoothing approach is used. Because it is difficult to process large datasets in an Excel spreadsheet, this strategy works best with smaller datasets. In [12], the rainfall series of river catchment regions were analysed using the additive Holt–Winters technique. The model forecasts the amount of rainfall; the actual and forecasted data are then fed into the undesired model to assess the model's performance.

While reference [14] presented the Box Jenkins time series seasonal ARIMA model for forecasting rainfall on a seasonal basis, reference [13] concentrated on the production and prediction of time series values of solely rain attenuation. ARIMA models are typically employed in the modelling of hydrologic and geophysical time series data. The identification of the model order is a primary concern in these modelling procedures, which is why [15] concentrated on model identification of hydrological time series data. But because this ARIMA model relies on the assumption that the data are stable, it has very little capacity to handle non-stationary data. As a result, only linear applications may use statistical approaches. This is regarded as one of the primary disadvantages of using statistical techniques in non-stationary and non-linear situations.

Rainfall was predicted in [16] using data mining methods as Classification and Regression Tree models (CART), Random Forest (RF), and Logistic Model Tree (LMT).

After a comparison analysis, it was determined that Random Forest outperforms the other techniques and has a 0.83 success rate. However, because the associated components are dynamic, these models need ongoing information review. In [17], rainfall modelling and prediction utilising a data mining method were done. Temperature and radar reflectivity data are taken into consideration in this work. There were five different data mining techniques used: random forest, neural network, support vector machine, regression tree, k-nearest neighbour, and classification.
It was discovered that the Multi-Layer Perceptron (MLP) neural network outperformed the other methods. The disadvantage of MLP, however, is that it takes a while to converge depending on the starting values and reduction technique used.

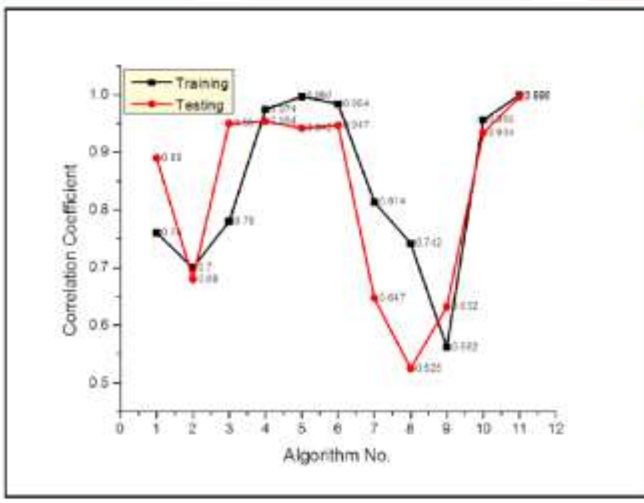
III. METHODLOGY

Research on rainfall and weather forecasting is being conducted globally. Additionally, it is noted that none of the models are universally effective or reliable. This is a result of how delicate the weather parameters are. Over time, they continue to evolve. Therefore, it's crucial to conduct a thorough analysis to track these models' performance. A thorough analysis of rainfall forecasting over a 25-year period utilising a variety of neural network methods and designs was conducted. Due to its relatively high rainfall prediction results when compared to other neural network forecasting approaches, the majority of academics appeared to be working on backpropagation neural networks with the Levenberg-Marquardt algorithm.

.	Algorithm	Author (s)	Training(%)	Testing(%)
1	Error BPN	Basu and Andharia	76.00	89.00
2	Regression Equation	Shukla and Mooley	70.00	68.00
3	Hybrid Algorithm	Sahai et al.	78.00	95.00
4	Backpropagation ANN (5:10:01)	Srikalra and Tanprasert	97.42	95.44
5	Backpropagation ANN (3:7:1)	Vamsidhar et al.	99.79	94.28
6	WNN Model:-	Venkata Ramana et al.	98.48	94.78
7	ANN Model:-	Venkata Ramana et al.	81.49	64.73
8	WANN Model:-	Solgi et al.	74.20	52.50
9	ANFIS Model:-	Solgi et al.	56.20	63.20
10	Backpropagation-9 Hidden nodes	Hashim et al.	95.67	93.47
11	Levenberg Marquardt - 3 Hidden nodes	Hashim et al.	99.90	99.60

Table 1. Training and Testing accuracy reported by various authors.

Rainfall prediction methods have been found to be effective when utilising a variety of algorithms, including MLP (Multi-Layer Perceptron), BPN (Backpropagation Network), ARIMA (Auto Regressive integrated moving average), MT (Model Tree), ANFIS (Artificial Neural Fuzzy Inference System), WNN (Wavelet Neural network), and SVR (Support Vector Regression). When comparing the stated RMSE values and errors for neural network predictions to those for a few statistical and numerical approaches, the results were noticeably lower.



S.No.	Algorithm Used
1	Error BPN
2	Regression Equation
3	Hybrid Algorithm
4	Back propagation ANN
5	Back propagation ANN
6	Wavelet Neural Network
7	Back propagation ANN
8	Hybrid Wavelet-Artificial Neural Network
9	Adaptive Neurofuzzy Inference System
10	Back Propogation-9 Hidden nodes
11	Levenberg Marquardt- 3 Hidden nodes

Figure 1. Comparison of various ANN algorithms used

IV. LONG SHORT TERM MEMORY

The LSTM architecture is a particular type of RNN that was created with temporal sequence modelling in mind. Compared to traditional RNNs, LSTM is more accurate because to its long-range reliance.

The error backflow problem in RNN architecture is caused by the back-propagation algorithm. The composite function chain rule is the underlying principle of the backpropagation algorithm. An effective method for locating the loss function's local minimum is stochastic gradient descent, or SGD. After obtaining the gradients of the computational graph's internally existent nodes, we may calculate the gradient of a beginning point and search in the direction of a negative gradient to obtain the gradients of the nodes. This is the method by which we find a local minimum the quickest.

An explicit memory cell for remembering and propagating unit outputs in various time steps is the fundamental building block of a long short-term memory (LSTM). The LSTM memory cell uses cell states to retain the knowledge about temporal contexts. In order to manage the information flow between several time steps, it also features an input gate, an output gate, and a forget gate. This study used time-series meteorological data to forecast background radiation using neural networks based on long short-term memory. The problem of vanishing gradient refers to the mathematical difficulty in determining the long-term relationships in the structure of recurrent neural networks. It is more difficult to capture the effect of the earlier phases as the input sequence lengthens. Gradients to the first few input points disappear and reach zero. Because the LSTM is recurrent, its activation function is regarded as the identity function with a derivative of 1.0; as a result, the backpropagated gradient neither disappears nor explodes, but stays constant.

A node's activation function defines the output of that particular node as discussed in Section 3.2.
Activation functions that are commonly used in LSTM network are sigmoid and hyperbolic tangent (tanh). The actual architecture of LSTM proposed is implemented with the sigmoid function for forget gate and input gate and with the tanh function for candidate vector that updates the cell state vector. These activation functions of LSTM are calculated for Input gate It, Output gate Ot, Forget gate Ft, Candidate vector C0 t, Cell state Ct, and Hidden state ht, using the following formulae,

$$I_t = sigmoid(W_i[X(t), h_{t-1}] + b_i)$$

$$F_t = sigmoid\big(W_f[h_{t-1}, X(t)\big] + b_f)$$

$$O_t = sigmoid((W_o[h_{t-1}, X(t)] + b_o)$$

$$C'_t = tanh(W_c[h_{t-1}, X(t)] + b_c)$$

$$C_t = F_t * C_{t-1} + I_t * C'_t$$

$$h_t = O_t * \tanh(C_t)$$

where X(t) is the input vector, ht-1 is the previous state hidden vector, W is the weight and b is the bias for each gate. The basic structural representation of LSTM network is shown in Figure 1.

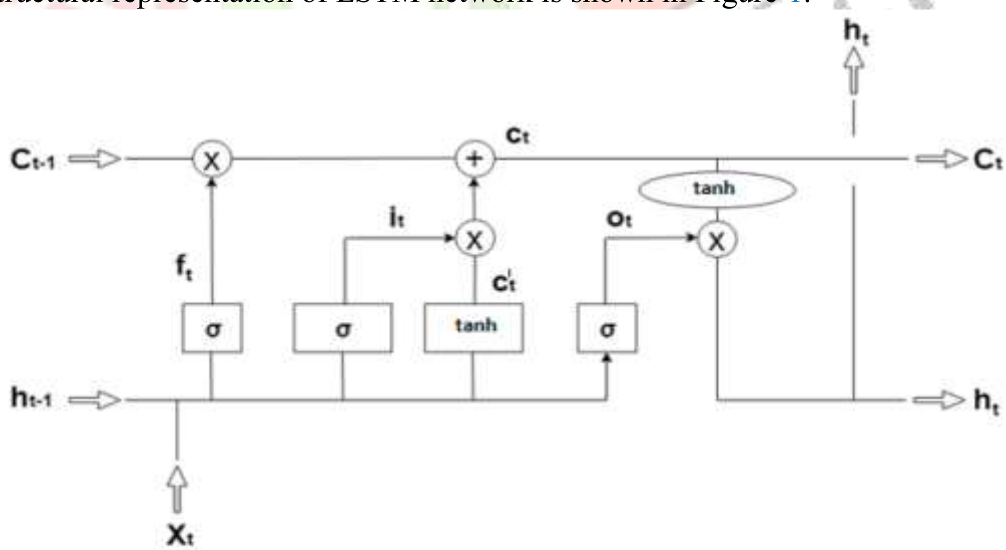


Figure 2. Schematic representation of LSTM.

V. RESULTS AND DISCUSSION

A Python library named "keras" was used to train the LSTM model on top of the Tensorflow backend. Prior to learning, hyperparameter hunting is a crucial procedure. For each hyper parameter, such as the number of hidden layers, learning rate, number of hidden nodes in each layer, dropout rate, and so on, a set of values is allocated. The machine is then allowed to choose a value at random from the set for each hyper parameter. Typically, we are able to identify the "best" model and matching "best" hyperparameters after looking through more than 300 models with various combinations of hyperparameter values.

The rainfall data used in the forecast procedure is from the Hyderabad area between 1980 and 2014. There is a training dataset and a testing dataset in this dataset. The dataset used to train the suggested Intensified LSTM based RNN model spans 34 years, from 1980 to 2013. Next, the 2014 dataset is used to test the trained model. The outcome variable is rainfall, while the experimental variables are wind speed, sunshine, evapotranspiration, maximum temperature, minimum temperature, maximum relative humidity, and minimum relative humidity. During the training phase, the network is fed all the experimental factors together with the related result variable so that it can learn and output the predicted outcome variable, Rainfall. The simulation results were acquired using Pycharm from Jetbrains. Six more prediction models, including Holt–Winters, ARIMA, ELM, RNN with Relu, RNN with Silu, and LSTM with sigmoid and hyperbolic tangent as activation function, were also compared. To demonstrate the superiority of the suggested Intensified LSTM based RNN prediction model, scores for RMSE, losses, accuracy, and learning rates were calculated for each model.

A total of two hidden layers, each including fifty neurons, are employed in the model's implementation, aside from the input and output layers. With a batch size of 2500 and 5 iterations, the initial learning rate is preset at 0.1 and no momentum is specified by default. The dataset has 12,410 rows altogether, each with 8 characteristics. Over the training time, a decline in the learning rate is anticipated. The optimizer Adam is used, the BPTT is fixed at 4, and the loss function we use in this case is the mean squared error. The suggested model improves the findings in a number of ways by utilising sigmoid and tanh, which are the endemic activation functions of neural networks, and the unique method covered.

All of the simulation results, comparisons, and validation of the suggested prediction model are covered in this part. The standard deviation of the prediction errors, or residuals, is known as the RMSE. RMSE is computed as a performance evaluation for the suggested methodology's decreased prediction error. Figure 3 displays the computed RMSE for the Intensified LSTM model plotted against the number of epochs. Although the RMSE decreases to at least 0.25 in the thirty epochs, the network underwent more training to get high accuracy, learning rate, and loss reduction. We find that the RMSE is 0.33 for the 40th epoch, and it varies at roughly the same value for subsequent epochs.

The error value is the difference between the properties of the actual and forecasted rainfall. The reduction of error values by back-propagation results in a minimised difference between the projected and actual output, which is referred to as loss. Stability results in a progressive reduction of errors, and the gradient is maintained throughout the suggested model, resulting in less losses. Figure 4 displays these losses plotted against the number of epochs. It is evident that in the early epochs, losses are significantly decreased, and in the later epochs, they remain within lower boundaries. The stability of the suggested model is demonstrated by the global minimum, which is determined to be 0.0054 at about 27 epochs and stays within 0.0055 until the 40th epoch. The learning rate, or weight adjustment based on the loss gradient, is the hyperparameter that controls the degree to which recently acquired data supersedes previously obtained data. The graph shouldn't have any sharp changes or big peaks in order to have a decent learning rate. As a result, it is anticipated that the learning rate would gradually decrease in relation to the proper weight variation.

At the 40th epoch, the suggested Intensified LSTM achieves this attribute with a value of 0.025, while the learning rate of the proposed model does not significantly change for subsequent epochs. The learning rate for the suggested model is computed for each epoch, and the numbers are shown as a graph, as Figure 5 illustrates. The suggested model self-stabilizes for the suitable input vector during training, as demonstrated by the learning rate's convergence at the 40th epoch and lack of plateauing.

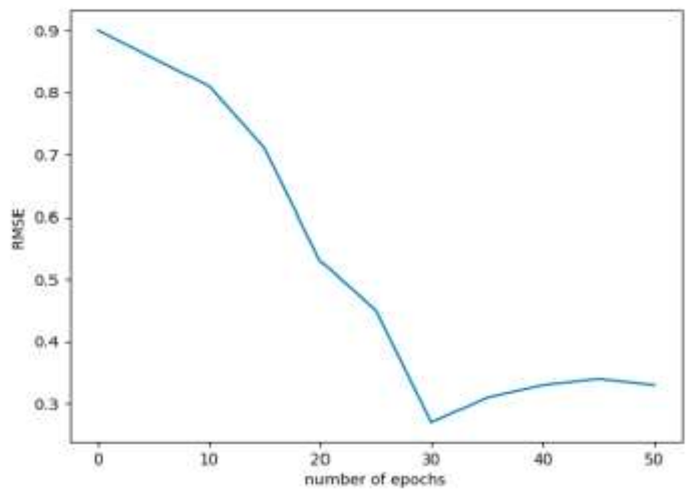


Figure 3. Decrease in RMSE for Intensified LSTM.

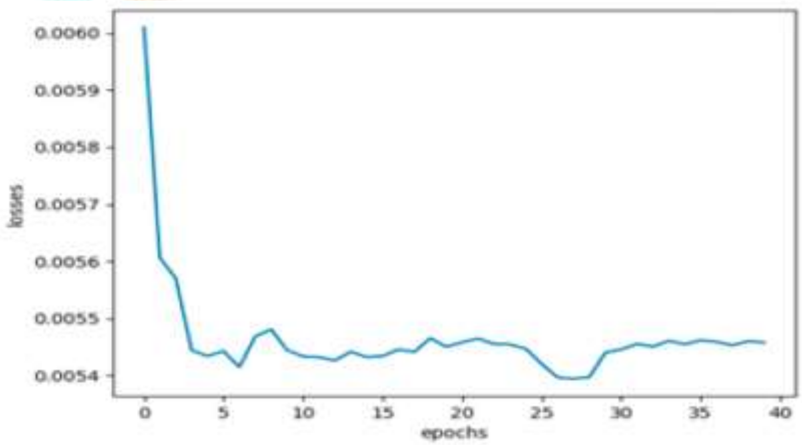


Figure 4. Reduction of losses for Intensified LSTM.

Figure 5. Gradual decrease in Learning rate for Intensified LSTM.

Six more models—Holt–Winters, ARIMA, ELM, RNN with Relu activation, and RNN with Silu activation function—are used to validate the results. Holt-Winters and ARIMA are statistical forecasting techniques, hence metrics like epochs and losses are not compared in this comparison. Since back-propagation is not a part of ELM, learning rate and loss measurements were not used. For the purpose of comparing and validating the suggested model, Table 1 presents performance assessment metrics for each of the seven models, including accuracy, RMSE, losses, and learning rate values.

Method	Epochs	Accuracy (%)	RMSE	Losses	Learning Rate
Holt–Winters	-	77.55	3.08	-	-
ARIMA	-	81.15	2.84	-	-
ELM	-	63.51	5.68	-	-
RNN with Relu	40	86.44	0.76	0.5824	0.9
RNN with Silu	40	86.91	0.76	0.5769	0.75
LSTM	40	87.01	0.35	0.1274	0.5
Intensified LSTM	40	88	0.33	0.0054	0.025

Table 2. Performance comparison table.

RMSE of our proposed system is compared with the aforementioned models, and the comparison is shown in Figure 8. The RMSE values obtained for the methods Holt–Winters, ARIMA, ELM, RNN with Relu, RNN with Silu and LSTM are 3.08, 2.84, 5.68, 0.7631, 0.7595, 0.35 respectively,
whereas the RMSE of Intensified LSTM is 0.33. The graph infers that RMSE of LSTM based RNN models shows better results than RNN without LSTM units in the hidden layer.

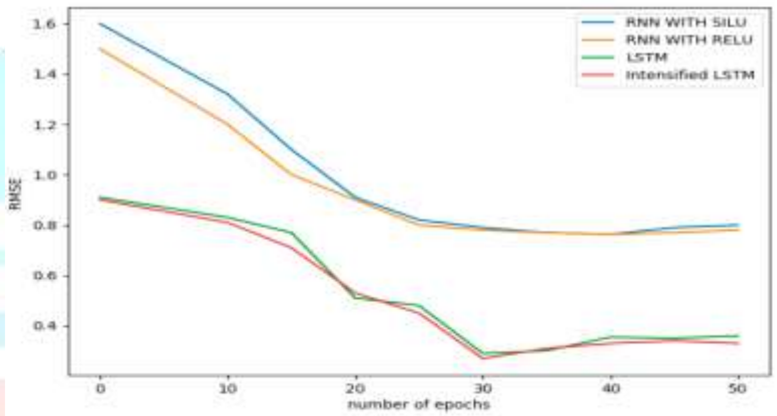


Figure 6. Comparison of RMSE for Neural Network-based prediction models.

Our suggested system is further validated in terms of accuracy. When the accuracy of the Intensified LSTM was compared to that of the Holt–Winters, ARIMA, RNN, ELM, and LSTM models, it was discovered that the Intensified LSTM model had superior accuracy. The suggested prediction model outperforms the other prediction models, as seen in Figure 9. The rainfall prediction model based on Intensified Long Short-Term Memory (LSTM) achieves 87.99% accuracy.

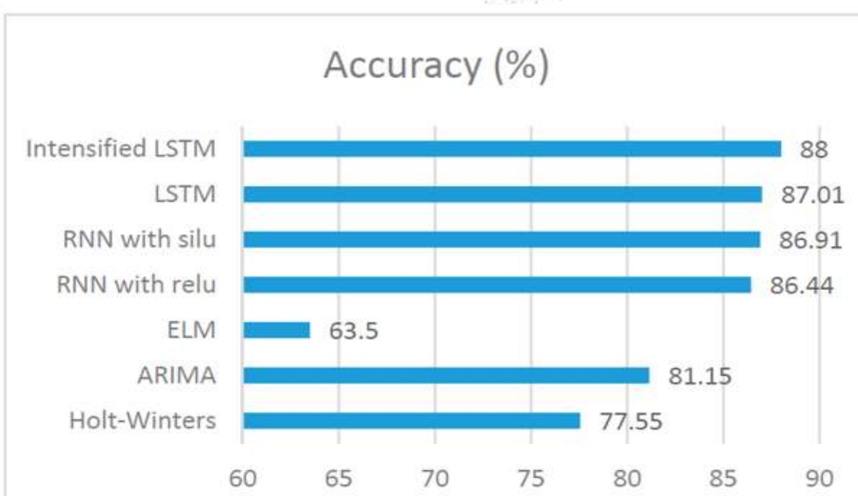


Figure 7. Accuracies of various techniques.

Figure 10 presents a bar chart comparing the accuracies and RMSE of the prediction models, taking into account the statistical techniques. This illustrates how the suggested Intensified LSTM based RNN model predicts rainfall efficiently. It makes sense that RNN models perform better for time series data than statistical models, which are less able to handle non-linear data than neural networks. Neural networks are less reliable when using quicker computation methods, such as Extreme Learning Machine, since there is no recurrence to feed the network with historical state information for prediction. Our suggested approach is an effective rainfall forecast model that may support the country's agriculture industry and make a major economic contribution.

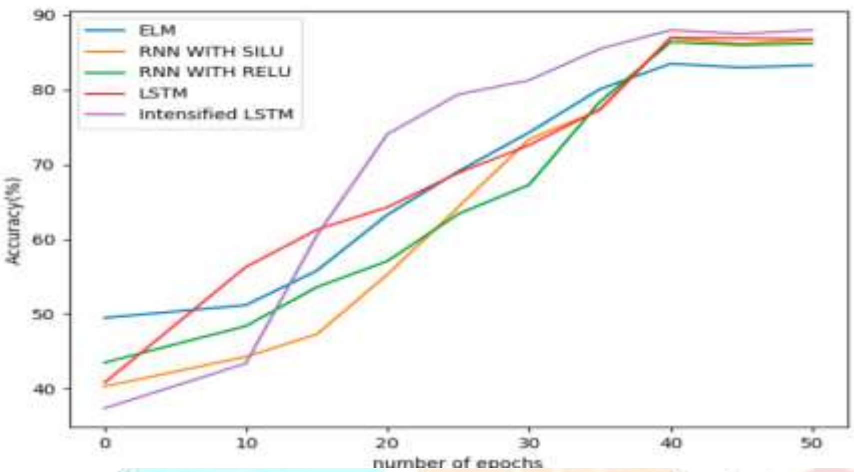


Figure 8. Comparison of accuracy for Neural Network based prediction model

The Holt–Winters method uses smoothing parameters like level, trend, and seasonal components to control the data pattern, and ARIMA transforms the non-stationary data into stationary data before prediction, so when the RMSE of all the methods is compared, the statistical methods compete with the LSTM based model. Because there is no weight adjusting for ELM, the RMSE is quite high.

While RNNs with Relu and Silu activation functions operate almost identically, RNNs with LSTM units have significantly lower error than RNNs without LSTM. Figure 11 displays the RMSE comparison of all the research methodologies employed in this study.

Figure 8, plots the actual rainfall against the projected rainfall. Plotting of the expected rainfall values in millimetres is done over a period of 97 days, from July to September 2014, using 34 years of historical data as training inputs. It is only feasible to store such a large dataset thanks to the RNN network's utilisation of the LSTM unit. To evaluate how well the model tracks the real graph, this plot is contrasted with the plot of the year's actual rainfall data. With the exception of the peaks, it is evident that the projected values nearly exactly match the actual values. The cause is that a small number of the dataset's data points may be regarded as outliers, which cause a large variance in the values that follow. During the training phase, the prediction techniques analyse if such a pattern currently exists and attempt to either map these locations or delete them.

Figure 9. Comparing the RMSE of different prediction models.

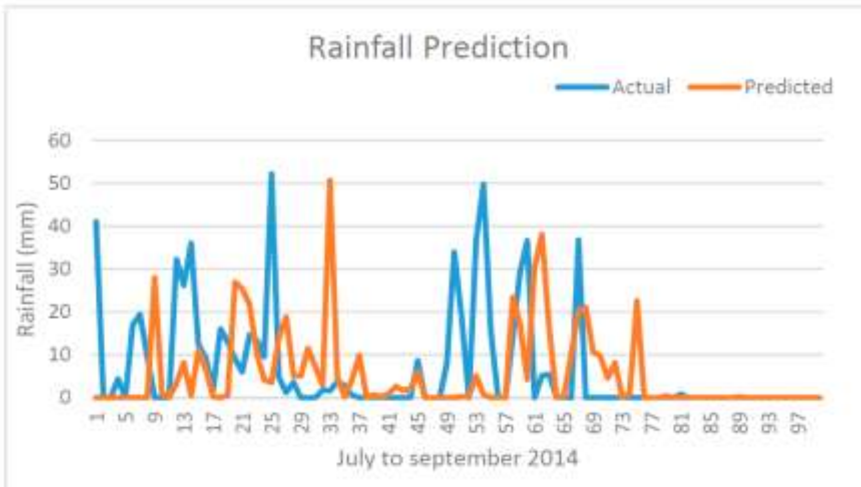


Figure 10. Comparison of actual and predicted rainfall.

VI.CONCLUSION

People are constantly curious about what will happen in the future. These days, there is an abundance of data, but there is less analysis and inference of the hidden realities from the data. Therefore, regardless of the application, data analytics and advancements in the prediction model might offer insights for improved decision making. This research study uses a deep learning technique to forecast rainfall.To forecast rainfall, a recurrent neural network based on intensified long short-term memory is built. To illustrate how the suggested strategy improves rainfall prediction, it is compared to various techniques such as Holt–Winter, ARIMA, ELM, RNN, and LSTM. In order to achieve high accuracy, historical datasets must be taken into account. The suggested Intensified LSTM network seems to exhibit greater prediction accuracy as it can store huge amounts of data in memory and prevent vanishing gradients. While the suggested Intensified LSTM prediction model shows lower loss, RMSE, and learning rate, it maintains accuracy for future epochs despite a little gain in accuracy over the current LSTM model based RNN. Any neural network that achieves a sufficient learning rate with loss depletion in a shorter number of epochs is considered to be able to maintain itself for any test data that may be used in the future with minimal fluctuations in performance metrics like error, accuracy, etc. Reducing running time through better outcomes in fewer epochs facilitates the processing and analysis of large data sets with high data volumes. The performance described above is achieved using the suggested model.

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