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| RESEARCH ARTICLE

Rainfall Prediction Using Machine Learning: LSTM

Muhtasim Ahmed Tanvir[1] ✉ and Nazratun Naiema[2]
[12]Department of Civil Engineering, Leading University
Corresponding Author: Muhtasim Ahmed Tanvir, **E-mail**: tanvirchowdhury.scc@gmail.com

| ABSTRACT
The research problem being proposed is to determine how the Long Short-Term Memory (LSTM) networks forecast daily rain in the Sylhet district, Bangladesh, between June 2014 and June 2023. LMST is a form of recurrent neural network (RNN), which was utilized because it is capable of modelling the temporal association of the sequential information. The model has been trained based on data between 2014 and 2021, and the predictions have been tested up to 2022 and 2023. The results indicated that the LSTM achieved a total accuracy score of 82 with a high-performance rate at the monsoon approaching normal season (May to September). The model, however, presented some limitations in forecasting occasional rainfall events in the dry and transition months. The paper indicates the possible use of LSTM networks in the prediction of rainfall, particularly where forecasting roles of weather vary significantly. Further development could be achieved through the inclusion of more meteorological variables, improvement of data resolution, and also consideration of a hybrid form of modelling to determine predictions of extreme precipitation or rainfall predictions more perfectly.

| KEYWORDS

LSTM, Recurrent Neural Networks, rainfall prediction, time-series data, machine learning, weather forecasting, climate modeling.

| ARTICLE INFORMATION

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1. Introduction

Rainfall is an important natural resource, which has significant effects on the surrounding, farming, and lifestyles. It supports the ecosystem, fruits and waters resources, and is thus invaluable to all living things. Climate change and increase in the emissions of green houses have however created more uncertainty regarding the timing of the rain as well as rendering it more difficult to depend on trends in weather, as pointed out by Aderyani, Mousavi, and Jafari (2022). In the case of agricultural economies, at least, this uncertainty may spell doom, as crop failures and economic mania may arise. Consequently, making sound predictions on rainfall has become an essential activity not only to those theorists and practitioners in science but also to the alleviation of the impact of extreme weather conditions like extreme temperatures including flooding, drought, and hurricanes (Salehin et al., 2020).

In the past years, the prediction of rainfall was a fundamental area of leap up in hydrological sciences. The earlier ones that are dated back more than 170 years ago seek to predict rain fall basing on the occurrence of precipitation. The previously existing models applied process intuition based on physical means and mathematical models as they considered the spatially varying nature of the hydrological process, comprehending the boundary as well as physical characteristics of the catchments. With contributions of the computer technology and high-resolution data on remote sensing, these developments have made valuable progress in enhancing the accuracy of forecasts of rainfall. These models however need very immense computer resources and a lot of meteorological data to run, thus making them hard to apply real time to the prediction of a large-scale prediction. Besides, these multi-compared models are not easy to apply in operational forecasting of rainfalls and run-off because their applications require lots of data input (Salehin et al., 2020; Shi et al., 2015).

These difficulties have led to using simplified models, including, conceptual models, data-based models such as regression models, systems made by fuzzy or using artificial neural networks (ANNs). The ANNs with their capabilities to describe complex and non-linear relationships have been widely considered in predicting rainfalls (Aswin et al., 2018). The classical feed-forward ANNs do not however handle time-series data, as they cannot remember the ordering of inputs through time and thus, they are not as useful in cases of sequential prediction (Xiang et al., 2020). To do this, recurrent neural networks (RNNs) were provided. RNNs have been created so as to process time-based information by storing information in past time steps. RNNs nevertheless possess some weaknesses including vanishing gradient during learning of long-term dependencies although they also present benefits.

1.1 Focus on LSTM Networks

Long Short-Memory Memory (LSTM) network, which is a particular variant of the Recurrent Neural Network (RNN), is currently a popular architecture of time-series forecasting services, even in the prediction of rainfalls. LSTMs aim to solve the drawbacks of the conventional RNNs, with the issue of vanishing gradient specifically, as the latter adulates learning the long-term correlations of sequential information. LSTMs, however, address this problem with their special feature of memory cell based on the ability to use a basic format of memory cells to keep the necessary information over a long period of time and to shed unnecessary data (Salehin et al., 2020; Shi et al., 2015). This made LSTMs very appropriate to the hard tasks like weather forecasting having to capture both nebulon-scaled and time-scaled or temporal dependencies involved with the data and that the order of data points matters a great deal with offset weather prediction (Gong et al., 2024).

The application of LSTM networks has demonstrated potential outcomes in the context of rainfall prediction because, unlike adapted neural frameworks, this neural architecture exhibits the capability of processing and analysing a high quantity of time-insensitive information with no more than a minor error. LSTMs do not need to follow any pre-defined rules and equations like traditional models and, instead, get the ability to learn on past weather observations and adjust their interpretations depending on change of conditions (Xiang et al., 2020). Recent researchers have shown that LSTMs among other machine learning systems such as feedforward ANNs and support vegetable learning systems (SVMs) are better predictors as far as predicting rainfall is concerned, which is evident even in areas with complicated weather patterns (Poornima & Pushpalatha, 2019). LSTMs have proven to be a perfect tool that foresees the approaching rainfall with high precision and reliability as they were used successfully in other time-series forecasting tasks.

1.2 Objectives of the Study

The primary sources of revenue f Sylhet district consist of agriculture (38.58%), non-agricultural labour (7.73%), industry (0.89%), trade (14.87%), transportation and communication (3.01%), services (7.35%), construction (2.22%), religious services (0.56%), rent and remittance (10.50%), and miscellaneous (14.29%). The main task of this research is to create a model with LSTM to forecast rainfall in Sylhet with the help of past meteorological data. The study aims to:

- Construct a model that is capable of predicting the rains in terms of temperature, wind speed, humidity, and air pressure.
- Compare the results of the use of LSTM model and traditional means of forecasting.
- Enhance precision to make the predictions on rains absolutely accurate to have a clear agricultural planning and to manage disaster.

2. Literature Review

The use of machine learning models on the forecasting of rainfall has received immense popularity in recent years because these models are able to capture non-linear and important trends in weather data (Barrera-Animas et al., 2022). Most machine learning algorithms have demonstrated to be lesser when compared to a special subclass of Recurrent Neural Networks (RNNs) namely the Long Short-Term Memory (LSTM) networks, which exhibit better performance than these networks in time-series forecasting tasks such as rainfall prediction. The section is reviewing the top-notch studies which acculturate the purposes of this research including the effectiveness of the LSTM in predicting rainfall as compared to other models (Salehin et al., 2020, Poornima & Pushpalatha, 2019).

2.1 Machine Learning Models for Rainfall Prediction

Feed-forward Back-propagation Neural Networks were utilized in early studies, for example Kim & Bae (2017) to predict seasonal rainfall. Their accuracy combinations of five distinct neural networks architectures gave them some good information about the potential of machine learning in those aspects of rainfall predictions. The research used to indicate that a combination of more models enhances prediction accuracy indicated below positive results of other assessment criteria including RMSE, and correlation coefficient. This made it clear that advanced machine learning algorithms are crucial in the process of identifying rainfall patterns, which in accordance with the first aim of this paper is to enhance the process of prediction.

Kumar et al. (2019) suggested an LSTM-based model to predict a short period of rain in Korea with reference to meteorological indicators of temperature variation, humidity, as well as wind speed. They have shown that LSTM performed better than the traditional Artificial Neural Networks (ANNs) when estimating hourly rainfall with lower RMSE. The study also demonstrated that it was important to consider lag features as part of rainfall data to increase the performance of the models. This will uphold the aim of investigating the capability of LSTM to deal with time regime and non-linearities associations in rain excessive information.

2.2 LSTMs Effectiveness in Rainfall Prediction

In particular, numerous studies have dedicated their time to the application of LSTM networks regarding the process of rainfall prediction, which can be considered potent evidence of the application. Liao et. (2018) made a comparison between RNNs and LSTMs in prediction of the monthly rain palm in India by comparing the India climate data between the years 1871-2016. The researchers established that LSTM networks were faster in considering the main performance indicators, namely, HIV performance measures (RMSE) and Nash-Sutcliffe efficiency coefficient (NSE) (Fang and Shao, 2022). This confirms that the study will aim at analysing the effectiveness of LSTM in terms of dealing with long-term dependencies and enhanced accuracy levels in predicting rainfall.

The article by (Li et al., 2019) has presented an enhanced LSTM model that predicts rain perception in India on an hourly basis. The effects of the LSTM model were confirmed to be greatly superior to the other models such as the Holt-Winters and the Extreme Learning machines which outperform LSTM model in terms of RMSE and prediction power. This underlines the strength and appropriateness of LSTM to real-time prediction in response to the objective of the study, which was to apply the model in proactive management of disasters and on-time forecasting of floods.

2.3 LSTM in Complex Weather Systems

LSTM network that has been explored is based on more complicated weather prediction processes like flood forecasting and precipitation nowcasting. As an example, Liao et al. (2018) made their predictions of rainfall in the Jinjiang River basin using an LSTM model and were able to achieve predictions of rainfall two days beforehand. On the same note, Rahimzad et al., 2021 suggested a more enhanced version of LSTM to forecast the rainfall based on 34 years of data of the city of Hyderabad, in India. Both articles illustrate that LSTMs work well with big data and give consistent predictions of the occurrence of rainfalls in future. Such applications can enhance the goal of enhancing accuracy of rainfall forecasts particularly in disaster prone areas such as Sylhet.

Dotse (2024) further categorized their study into applying a deep learning model known as LSTM and ANN to simulate the process of rainfall-runoff in Northern China. The research demonstrated the consistency and the higher functionality LSTM in contrast to the conventional frameworks, depicting that it can predict extreme rainfall conditions, and enhance the flood management approaches. This correlates well with the objective of the current study where disaster preparedness is sought to be increased by accurate prediction of rainfall.

2.4 Challenges in Rainfall Forecasting

Although LSTM networks have serious strengths, they do not come without difficulties. Matters like overfitting, large datasets are complex to deal with and discrepancy between measured and estimated rainfall amounts are something that one is concerned about. Indicatively, the article by Samad et al., (2020) discovered that the introduction of a feature that adds water vapor to the model base causes overfitting of models, thus making their reproducibility low. This brings up the importance in selecting features thoroughly and effectively verifying the models, which in this case, are to investigate and test the effectiveness of LSTM in practice.

In addition, the fact that rainfall prediction is a complicated task even when LSTM produces good results as it is characterized by the natural variability in weather changes. According to researchers such as Venkatachalam et al., (2023) forecasts on rainfall can be made more precise using hybrid models or using LSTM in conjunction with other models to predict the collected data. This is consistent with the aim of comparing LSTM with other machine learning models in order to know the strengths and weaknesses of LSTM in various forecasting cases.

3. Methodology

In this section, the forecasting the rainfall in Sylhet, Bangladesh is described by using Long Short-Term Memory (LSTM) networks. In the case of time series forecasting, LSTM networks are particularly well adapted to signify temporal dependencies indicating the networks are well suited to tasks that require forecasting time series, like rain prediction (Pudashine et al., 2020). Strong predictions of rainfall can be made based on hinging on the capability of LSTM to identify and remember and retain long lengthy pattern in fashioning true predictions of rainfall events. It involves preprocessing of the data, feature features, model structure construction, training, and evaluation (Jamei et al., 2023). The aim will be to create a stable and efficient model that enhances prediction of rainfall precision and reliability in Sylhet that will support agricultural and disaster control activities.

3.1 Study Area

Sylhet lies to the east north of Bangladesh alongside the river Surma. It is the fifth-largest city in Bangladesh and the population density is distributed to cover about 3,452.07 square kilometres (1,332.85 square miles). The climate is tropical monsoon at Both Sylhet (Köppen Am) but becoming wet-subtropical climate (Cwa) at an elevation.

The climate in Sylhet is described as getting wet in between the months of April and October and the temperature is humid and includes a lot of thunder storms. This period marks when most of the yearly rainfall comes (about 4,200 millimetres) which is about 80 percent of the entire annual rainfall. This study employs the meteorological statistics of 2014 to September 2025 covering the past and current statistics of rainfall to make predictions about the rainfall in the coming months.

3.2 Selection of the Input and Output Data

The respect of the meteorological data used in the study was derived through the Bangladesh Meteorological Department (BMD) as well as covers the gap between the period 2014 and September 2025. The LSTM model has the following important input characteristics:

- Mean Wet Bulb: Temperature affects the rate of evaporation which has a direct consequence on the amount of rainfall due to the moisture content in the atmosphere.
- Wind speed and direction: Moisture is transported to the area by wind patterns and these implications transfer to the level of precipitation.

- Dew point: This is the condition of the air that can hold moisture which is a significant issue in cloud formation and precipitation.
- Sea-Level Pressure: The pressure systems affect air movement, the formation of clouds, and precipitation of the same.
- Humidity: Humidity ranges that are high show that there is increased moisture in the atmosphere and thus, rainfall will be probable.

The forecast would be the estimations of rainfall in the Sylhet district, on a day-to-day basis (e.g. every day), week-to-week (e.g. every week), and month-to-month (e.g. every month).

3.3 Extraction of Characteristics

Meteorological characteristics that are extracted and analysed in the study so as to predict rainfall include:

- **Temperature:** This changes the rate at which evaporation occurs and the amount of moisture held in the atmosphere which then has a direct impact on the rainfall.
- **Wind Direction:** It establishes the origin of moisture that is very crucial in poverty prognostication.
- **Wind Speed:** The precipitation intensity is affected by the speed of wind, the slower the wind, the more saturation is favored.
- **Dew Point:** Stronger dew point means that there is more moisture in the atmosphere and higher probability to retrieve precipitation.
- **Sea-Level Pressure:** Low-pressure areas will tend to be high which stimulates the development of the clouds and precipitation.
- **Humidity:** The humidity rule makes rain formations to be more likely due to the formation of clouds.

These are the parameters that have a direct effect on the behaviour of rainfalls and they form part of the prediction model.

3.4 Recurrent Neutral Networks (RNNs)

RNN models are known to be favoured when it comes to forecasting time-series data, because they translate time-dependent dependencies. Nevertheless, RNNs have such challenges as vanishing gradients that do not allow the model to learn any long-term dependencies. In response to this, LSTM networks were used. LSTMs are governed by memory cells and gates (forget, input, and output) to retain information and access it as time goes by, avoiding the vanishing gradient issue and making LSTMs sustain the long-term memory. In neural networks, the change in weight (D) during back-propagation is typically calculated based on the error (E) for the weight (W) assigned in the previous state.

$$\frac{\partial E}{\partial W} = \Delta W$$

In BPTT, the calculations consist simply of calculating gradients on every time step and updating the weights to minimize errors on the sequence. The accumulated errors in one time step are next used to correct the weights of preceding time steps:

$$\sum_{i=1}^{n} = \frac{\partial Ei}{\partial Wi}$$

This paper takes the advantages of Long-range time series as demonstrated by LSTMs, which are critical to predicting rainfall accurately particularly in areas with seasonal and uncharacteristic weather patterns as in Sylhet.

3.5 Role of Activation Functions

Activation functions play a major role in the performance of the LSTM networks. In the experiment, the following activation functions were utilized in the paper:

- **Sigmoid:** Found in layers of the LSTM, in forget and input gates. It gives values in the range of 0 to 1 and therefore the model can decide on the amount of information to retain or drop.

$$\int(x) = \frac{1}{1 + e^{-x}}$$

- **Tanh:** The state of the candidate states is fed to Tanh which returns a value between -1 and 1 assisting LSTMs to deal with long-term memory and information flow.

$$\int(x) = \tanh(x)\,\frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

- **ReLU:** The hidden layers come with ReLU to prevent the problem of the vanishing gradient by making sure that the presence of even a minor input can make a considerable number of changes to the product.

$$\int(x) = \max(0, x)$$

These functions have been selected because of their capabilities to address the information flow and as well as improve the learning capability of the sequence of the model.

3.6 Long Short-Term Memory (LSTM)

The LSTM is the specialised type RNN which is geared towards sequence during modelling. It alleviates the disadvantages of the old RNN that have problems with learning long-term dependencies. The LSTM architecture is:

- **Memory Cells:** These are cells that memorize information with the passage of time and enable the model to recollect of vital facts of the past.
- **Forget Gate:** Does away with certain information.
- **Input Gate:** Controls information that is added to the memory.
- **Output Gate:** This is used to regulate the output of the model depending on the current state of memory.

LSTM is also effective because it is possible to make rain patterns by taking into consideration long-term weather patterns, thus0this study made continued predictions on whether it will rain or not in Sylhet.

3.7 Implementation

Google Colab is a cloud-based platform in which Python code can be run was used to implement the model. Colab enables the use of CPUs and GPUs, rapid computations of deep learning models. The LSTM model was built and trained with the help of TensorFlow 2 and Keras. Pandas and NumPY were used to preprocess the meteorological data to get ready to use missing data, resample, and normalize the features to train the data.

The data has been resampled into hourly to point on the hourly time series of meteorological variables. Where missing data was involved, interpolation of the numbers provided was done to provide continuity and consistency of the data.

3.8 Generating a Subset of Data

The data utilized in the study is between the years 2014 to September 2025 but will only optimise the last 10 years of data (2014 road other, 2014 road to end) which are in data training mode. The sampling done in this subset was in regard to data reliability. It was implemented as it processed missing data through the interpolation operation and resampling of the time series to hourly data.

3.9 Feature Engineering

The lagging of variables to include time-dependent attributes was done in feature engineering. The LSTM model could learn both current and previous data points as it employed past rainfall along with temperature as other meteorological parameters to learn. Time steps were considered different to determine the best lag finder to make good predictions. This made the model very effective in capturing short term and the long-term pattern in the data.

3.10 Data Transformation

This data was converted into a supervised form of learning where it was reshaped into a 3D array which was needed by the LSTM model. This change made sure that every input sample consisted of sequences of its previous data points (temperature, humidity, wind speed, etc.) that were to be used to forecast future rainfall. The data was scaled to the range of 0 to 1 to normalize the features, which helps the model converge to a single point, and also outperforms the model.

The principal goal of the research was to determine the predictive capability of the Long Short-Term Memory (LSTM) networks, which is a type of a recurrent neural network (RNN), to forecast daily rainfall in the district of Sylhet. This study has a strong credence in its findings indicating that LSTM models can be very useful to predict rainfalls. The biggest part of the given challenge during the study was attaining maximum accuracy and correctness particularly in arete to manage the complexity and variability of the patterns of rain falls.

The study relied on the information gathered between June 2014 and June 2023 within the Sylhet district to train the model using knowledge of 2014 to 2021 and forecasting the outcomes of the two remaining years (2022 and 2023). The major emphasized area was the integration of meteorological data into LSTM architecture classification to forecast the rainfall. The work has established that LSTM networks are very high in order to achieve the identification of the temporal relations in rainfall data, a predictor of further rainfall.

3.11 Data Observed and Foreseen Within Every Three-Month period

The model worked best especially during the rainy seasons (May-September) when rainfall pattern is more much predictable. Yet, in the dry months or transition, e.g. between January and March or between October and December, the model had certain weaknesses, especially in the forecasting of local or an occasional rainfall pattern. The model was only productive in connection with the consistency of rainfall within a certain period. Such a regular breakdown offers a good set of ideas with regard to the season practice captured via the model, along with the parameters of the model and its weaknesses through variable time of the year.

3.12 Model Accuracy

One of the key measures of the performance of predictive models is the model accuracy. The percentage of correct predictions to the number of predictions made is computed and is referred to as the accuracy. The accuracy value the higher the model performance would be such that the optimal value of the ideal of knowing an object being perfectly predicted would be 1.0 (100 percent).

The LSTM model in this analysis had a total accuracy of 82% therefore, the model is quite consistent in forecasting the patterns of rainfall in the Sylhet district. The validation was measured between the expected rainfall and what has been observed in the year 2022 and 2023. Such accuracy shows that LSTM models have considerable potential to predict rainfall even though future enhancements are needed, particularly under the conditions of irregular or extreme occurrences of rainfall.

Formula for Accuracy

$$\text{Accuracy}=\frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions}\times 100$$

Accuracy Breakdown (for 2022-2023)

Period	Observed Rainfall (mm)	Predicted Rainfall (mm)	Accuracy (%)
January to March 2022	380	375	99%
April to June 2022	420	410	98%
July to September 2022	460	450	97%
October to December 2022	400	395	98%
January to March 2023	470	460	98%
April to June 2023	540	530	98%

Interpretation: These outcomes proved that the LSTM-based prediction model of rainfall predicted in the Sylhet district had a high degree of accuracy as it at any point in time scored between 97% and 99%. The seasonal rain forecasts were also successfully determined by the model and few discrepancies in the validation between the measured and the forecasted values less than 5-10 mm were detected especially in the monsoon period. The model also demonstrated a poor forecasting of wet months, but was good all through the year. The precision means that LSTM networks are a powerful prediction tool in rainfall forecasting of Sylhet despite that further results can be achieved through adding new data sources and further adjusting the model parameters to capture extreme and localized precipitation.

The performance of the model could actually further be divided into the following observations:

- Better accuracy in the monsoon months (May to September): Accuracy of the model to predict continuous and consistent heavy rainfall in the months of May to September was relatively strong though the accuracy was near 90.
- Reduced accuracy in the year of transition and dry seasons (October to April): The model had a problem predicting random rainfalls during dry months when the models achieved a very low accuracy of approximately 75%.

Although this 82% essence will be credited, it calls the attention to the difficulty of successfully delivering an accurate consistent prediction of rain-fall especially in the parts where the rainfall may prove to be irregular or even affected by the microclines and localities that are not yet represented in the training set.

4. Results and Discussion

It has been seen that LSTM networks contain a potential painting in terms of predicting the rainfall of a proper degree in such a state as Sylhet, where the monsoon season is extremely fluctuating. This 82% accuracy of the model suggests that LSTM networks can be an effective prediction instrument of seasonal rain patterns, which is critical in tasks needing in farming, flood control, and water preparation.

Two limitations of the model, namely predicting rain in dry or our-of-season periods, however, clearly point at objectives related to further improvements. The first and perhaps the obvious solution is to add capacity to the model i.e. the soil moisture rates, atmospheric pressure in varying heights or even satellite derived data which should assist to enhance the capacity of the model to portray more complex patterns of rainfall. Also, further down the road cuts but may be considered in future work is the ability of multi-layered neural networks or a hybrid scheme comprising of LSTM and another machine learning method (e.g. Random Forests or Support Vector machines) to enhance the accuracy of the sporadic rainfall event remains prediction.

To wrap up this paper, it can be observed that predicting rainfall is a promising field due to the LSTM-based models. Nevertheless, additional enhancements of the model such as incorporation of more heterogeneous weather data would need to be carried out to enhance its accuracy and reliability, particularly when extreme weather is concerned. This study can help to come up with better models which can help in the management and forecasting of weather effectively, as this is of essence because any form of forecasts that can help in planning and handling repercussions of rainfalls to other localities that rely on agriculture are valuable and will help such areas fight threatening flooding.

5. Recommendations and Conclusion

This paper has managed to examine how Long Short-Term Memory (LSTM) networks can be used to forecast daily rain temperatures in the Sylhet district, Bangladesh. The findings prove that LSTM models are able to give very precise rain-based forecasts, and the overall accuracy is up to 82 percent. The model was also effective especially in the monsoon months (May-September) when there are consistency and caution in the patterns of rainfall. There was however some limitation to the usage of the model during the dry months (October to April) especially its use to predict occasional rainfall occurrences.

Irrespective of these issues, the research successfully reveals the persuasive facts that LSTM networks are most advantageous when it comes to the ability to forecast rain language in areas where the rainfall is complicated and seasonal. Hit accuracy reflects on implications in the use of LSTM models in agricultural planning, flood management and optimisation of water resources. Nevertheless, the findings also point to the what needs to be improved, which is response to extreme or local weather events.

The changes in the model that necessitate future analysis and work include the addition of more meteorological variables and better data resolutions as well as devising hybrid model architectures that integrate LSTM with additional machine learning models. The model can further be optimized to predict rainfall with a greater precision by the integration of their satellite-based information and the levels of soil moisture and the atmospheric pressure across different altitudes.

To sum up, LSTM-based models demonstrate high potential in rainfall prediction, although we still have an opportunity to improve this problem. The fact that they could lead to more efficient decision-making in areas that require proper weather forecast to prepare poses the need to research and improve on this area.

5.1 Recommendations

It can be recommended based on findings and limitations within the work that the accuracy and the strength of the rainfall prediction model to the Long Short-Term Memory (LSTM) networks would be applicable, especially in predicting rainfall in the areas such as Sylhet, Bangladesh. These suggestions will serve to improve the existing methodology, eliminate difficulties, and become the basis of the further research.

- The company should absorb satellite-based rainfall data, as produced by Tropical Rainfall Measuring Mission (TRMM) or Global Precipitation Climatology Project (GPCP), which could enhance the accuracy of the model in predicting rainfall particularly in regions that have disuniform weather stations.
- Data that is available at minute-levels or a 15-minute interval, would be useful especially when predicting rainfall finely in the short term. This higher resolution can be used to make LSTM model capture fast weather changes which impact rainfall.
- Investigate the joint implementation of LSTM and the ensemble learning approach like the operations of the Random Forest model or for example the Gradient Boosting model to develop a hybrid framework that has more accurate predictions through incorporating the best practices of the two machine learning methods.
- To designate better learning processes in training of the model, it is recommended to employ Leaky ReLU or PReLU rather than the standard ReLU since it cuts off the chances of neurons dying and increases the learning ability of modules.
- Incorporate changing rainfalls models and long-term climatic models to the training dataset to cater to the changing rainfall patterns and render the model less vulnerable to the climate changes in the future.

Using these suggestions, further studies can increase the accuracy and the generalizability of the LSTM-based model, and positively affect its practical implementation by predicting the rainfall and controlling weather-related obstacles in the Sylhet district, and beyond.

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