Rainfall Forecasting in Sub-Sahara Africa-Ghana using LSTM Deep Learning Approach

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Abstract—**Prediction of rainfall is a critical activity, and rainfall is a vital event for Human activities. Rainfall prediction is challenging and even more complicated due to the weather's dynamic nature. In this report, we make hourly rainfall predictions about Axim in the western region of Ghana. Rainfall data were obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF). We study the predictive capacity of deep learning and builtt an Artificial Neural Networks (ANN) model by using the Long Short-Term Memory (LSTM) algorithm and the Spearman coefficient based on selected parameters (seven) reported by the weather station. A correlation analysis was performed on the chosen parameters to get the best combination, which significantly influenced rainfall. Validations were carried out first on each parameter, Precipitation, Relative Humidity, MSLP, and Temperature; Secondly, on Precipitation (R) against Relative Humidity (H), Pressure (M), and temperature; Thirdly on (R) against (T) /(M), (R) against (T)/(H), (R) against (M)/(H). Finally, the testing on the (R) against (T) /(M)/(H) produced the best MSE result of 0.002 with a MAE result of 0.021.**

Keywords—Artificial Neural Networks (ANN); Rainfall Prediction; Meteorological Data; Long Short-Term Memory (LSTM

I. INTRODUCTION

Rainfall is a complex atmospheric process that is quite difficult to predict due to the complex weather system [1]. Several human activities, including farming practices, electricity production, and construction activities, are affected by rainfall [2]. It is one significant factor directly linked with adverse natural events [3], such as flooding, drought, landslide, and avalanches. These events are widely common worldwide, causing natural disasters that destroy properties and lives [4], [5],[6] [7]. Rainfall forecast is closely connected to the agriculture market, contributing to nations' economies worldwide, especially developing countries. Thus, makes rainfall prediction a vital issue. An appropriate rainfall prediction approach promotes preventive and mitigation measures for related natural phenomena.

Despite many advances in recent decades, accurate rainfall forecasts are among the most significant operational hydrology challenges owing to rainfall's non-linear nature. And with forecasts, precision techniques (traditional) still below the acceptable standard. Thus, leading to the application of the Artificial neural network (ANN) algorithm, which is an appealing inductive approach to precipitation prediction due to its extremely non-linearity, consistency, and data-driven learning in building models with no previous knowledge of catchment activity and flow processes [8] -[9].

Artificial neural networks (ANN) are programs of computing structures composed of entangled processors called weight-linked neurons. It is a computer framework inspired by a biological nervous system. It comprised of processors called neurons that are very basic and strongly interconnected. They are used to process vast collections of data in several different areas offering helpful insights that allow new data to be predicted and recognised. The process consists of data collection, analysis and processing, the configuration of the network structure, number of hidden layers, number of hidden units, setup, network preparation, network emulation, modification of weights/bias, and network checking. They compute structural data through a process of learning and training. In real-world applications, they are applied in weather, medical, business, finance, etc. In applications like speech recognition, imaging, control, estimation, optimisation, and a host of other things.

Rainfall prediction using the ANN model has mainly been performed by several researchers across the world for situations like rainfall-runoff modelling [10], flood warning systems[10], catchment management [11], and reservoir operation and flooding prevention. As rainfall prediction remains a serious concern, it has drawn attention from the scientific community to governments, industries, and risk management entities, among others. A rainfall prediction model can play a crucial role in providing relevant information on possible natural disasters like flooding, landslide, and avalanche. It can help plan the various sector's day-to-day activities (such as construction, farming, power station, etc.) in many areas. Damages can be reduced, and management can be efficiently planned by developing such a model in many places by decreasing the economic and environmental impacts of rainfall or efficiently managing water resources and planning agricultural activities [12].

Several machine learning methods and models have been used to make reliable and timely predictions to overcome this ambiguity. Some researchers have used Recurrent Neural Networks (RNNs) for sequence prediction of rainfall. Although several RNNs exist for sequence prediction, the authors of this research seek to explore Long Short-Term Memory (LSTM) method. LSTMs are effective in solving many time series tasks which other feedforward networks could not solve. Our study aims to provide an end-to-end machine learning life cycle via a deep-learning approach, starting from data preprocessing to model implementation and evaluation to develop an efficient and accurate rainfall prediction model using the LSTM algorithm.

The objectives of this paper are stated as follows:

- Develop a deep learning model and predict rainfall using the model and collected weather data on Axim (Ghana).
- Determine the performance and efficiency of the prediction model.

II. RELATED WORK

This section presents a review of some of the recent works in rainfall prediction relevant to our work. ANNs have been widely used and accepted by researchers for precipitation prediction [13]. ANN techniques such as Back Propaganda Network, General Regression, Pearson Coefficient Technique are available to researchers [14]. The ANN techniques like Back Propagation (BP) besides Learning Vector Quantization (LVQ) technique was proposed and used for rainfall prediction [15]. In their study, they concluded that LVQ takes less time in training as compared to Back Propagation. However, the authors claimed that fewer resources were gathered due to the lead time. They argued that their techniques performed better in terms of accuracy. Still, on the BPN, Immune Evolutionary Algorithm was suggested and implemented by Du et al. (2012)[16] in their studies whereby a higher accuracy and better stability was achieved by their designed model [17]. The authors claimed that their model had superior predicting capability besides enhanced generalisation capacity after comparing their result with the traditional linear statistical forecast method. The author also insists that their paradigm is appropriate for the solution of complex optimisation problems.

Several previous studies have also used ANN models for short-term as well as long-term rainfall forecasting. A study was done in Western Sydney (Australia) for 16 locations within an urban catchment area predicted rainfall with 15 minutes lead time. These scholarly authors [18] proved the supremacy of modular artificial neural networks over linear regression, K-nearest neighbour, and ANN models. It is established through a comparative analysis of different time-series rainfall data and additional data pre-processing techniques.

The researchers used an ensemble empirical mode decomposition (EEMD) and Genetic algorithm based on Backpropagation Neural Network to propose novel wind speed forecasting [19]. Wind speed data collected every ten minutes were taken for five days, providing 721 test results. EEMD decomposed the wind speed data for the first time in eight separate IMF and residues. Later, the GA-BPNN was used to estimate the IMF. The IMF's results were then merged, and the predicted outcome for wind speed was obtained. Thus, the approach proved to be more effective in predicting wind speed than the conventional GA-BP and hybrid EMD and GA-BP. Here, however, the prediction was made considering only the wind speed, which was not sufficient to predict rainfall. A monthly rainfall prediction by researchers implemented an ensemble method based on ANFIS and ARIMA [20]. Decision Tree Method using SLIQ generated classification rule for rainfall prediction with 72.3% accuracy[21]. In their study, Adhikari and Agrawal used Feed-forward NN-based NAR model for forecasting time series, which also gives an essential outcome for forecasting [22].

Hung et al. used the Artificial Neural Network model to forecast precipitation in Bangkok, Thailand, with lead times of 1 to 6 hours [23]. Their research was followed through with a real-world case scenario set up in Bangkok which led to the development of an ANN model employing four years of hourly data from 75 rain gage stations in the region. They used the built ANN model for real-time rainfall forecasting and flood control. Another ANN-based rainfall prediction has been reported where four years of hourly data have been used to predict rainfall one to three hours ahead in Bangkok, Thailand [23]. The prediction model was based on meteorological parameters such as wet bulb temperature, air pressure, relative humidity, and cloudiness. The authors found that the deciding factor in rainfall prediction could be wet-bulb temperature.

Researchers [24] used Artificial Neural Network in the study for rainfall prediction in Thailand. They used the Back Propagation Neural Network for prediction, which reported an acceptable accuracy. And for future direction, and it was indicated that few extra functionalities will be included in rainfall forecast input data such as Sea Surface Temperature for locations around Andhra Pradesh and the South part of India. Applying Back Propagation, Radial Base Mechanism, and Neural Network, these authors [21]predicted annual rainfall. For prediction, the dataset was collected from the Coonoor region in the Nilgiri district (Tamil Nadu). The performance was evaluated in terms of the Mean Square Error. Higher accuracy was recorded from the Radial Base Function Neural Network results with a smaller Mean Square Error. Besides, these methods have also been used by researchers to forecast future precipitation. Solanki and Panchal presented a Hybrid Intelligent System by integrating Artificial Neural Network and Genetic Algorithm [25]. In ANN, MLP serves as a Data Mining engine to make accurate predictions.

On the other hand, the Genetic Algorithm was also used for inputs, the link design between the input, the output layers, and the Neural Network training. The authors[26] carried out a comparative study of the Support Vector Machine (SVM), the Artificial Neural Networks (ANN), and the Adaptive Neuro-Fuzzy Inference System (ANFIS) for precipitation prediction cases. The authors compared the prediction models in four terms: (i) by using different lags as modelling inputs; (ii) by using training data of heavy rainfall events only; (iii) performance of forecasting for 1 hour to 6 hours and; (iv) performance analysis in peak values and all values. According to their results, ANN performed better when trained with a dataset of heavy rainfall. A study by Rolnick et al. in 2019 did a comparative analysis of various data mining techniques for rainfall prediction in Malaysia such as Random Forest, Support Vector Machine, Naive Bayes, Neural Network, and Decision Tree[27]. For this experiment, the dataset was obtained from various weather stations in Selangor, Malaysia. Before the classification process, Pre-processing tasks were applied to deal with the noise and missing values in the dataset. The results showed Significant performance of Random Forest as it correctly classified the large number of

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instances with a small amount of training data. [28] performed a survey on various Neural Network architectures used for rainfall prediction in the last 25 years. The authors highlighted that most of the researchers got significant results in rainfall prediction by using the Propagation Network. Moreover, the forecasting techniques which used SVM, MLP, BPN, RBFN, and SOM are more suitable than other statistical and numerical methods.

Furthermore, the research proposed an ANN-based algorithm for temperature prediction. The BPN is used because it can reasonably approximate a large class of functions. The authors proposed a model that takes a real-time dataset with fifteen parameters as input, which was then normalised using min-max normalisation to scale data between zeros to one. It was then learned and tested using the Back Neural Propagation Network. The results are then compared with the meteorological department to verify the model's minimum error and reliability.The model was found to have the ability to predict the temperature. The paper failed to predict the complete precipitation condition like rainfall, clouds, and others.

[29] deployed ANN and LSTM network models to simulate the rainfall-runoff process based on flood events from 1971 to 2013 in the Fen River basin, which was tracked by 14 rainfall stations and one water station in the catchment area. Experimental data were taken from 98 precipitation-runoff events during this time. Around 86 rainfall-runoff cases were observed and used as a training set, forming most of the remaining cases as a test set. The results show that both networks are appropriate for rainfall-runoff models and better than conceptual and physical models. LSTM models exceed ANN models with R2 and NSE values above 0.9, respectively. The work concluded that the ANN model is much more prone to many irregular variations, whereas the LSTM model is far more intelligent than the ANN model. In this analysis, the runoff is modified in time-series that the data are time-related. The ANN model is built by fitting the various characteristics of the proposed state and making predictions. In contrast, the LSTM model does not just take full advantage of the system data characteristics; it also uses its gate structure to determine the previous features.

[30] proposed a Long short-term memory (LSTM) recurrent neural network (RNN) for discharge level prediction and forecast in the Cimandiri river, Indonesia. Regular discharge data were analysed at two river gauge stations. These stations are Leuwilisung (17-year data) and Tegaldatar (13 years of data). And the result indicates that relative errors are below 10%, which is appropriate. The proposed method predicted and forecasted the release of five days ahead to help the decision-maker monitor the irrigation process.

In relation to the studies highlighted above, this present study is the first comprehensive study to employ a artificial intelligence/deep learning approach in rainfall prediction based on the dataset from the study area.

III. METHOD

A. Study Area

Our study is carried out at Axim(Ghana), situated on the southern end of the area between latitude 4.866 -90 to +90 degrees and longitude -2.235 -180 to +180 degrees [31]. In terms of climatic conditions, rainfall is experienced throughout the year, with temperatures between 25oC and 30oC. According to the Ghana Meteorological Service (Nzema East Office), the average rainfall in the municipality is around 29.40 mm, with average annual rainfall between 1800 mm [32]. The area has double maxima cycles that are at the peaks of May-July and September-November. The site has the highest rainfall in the country, with an annual average of about 2000mm of rain. Annual mean rainfall estimates range from 26.8mm to 46.6mm. The community reports high relative humidity figures ranging from 26.6 per cent to 27.6 per cent between May and June and 27.3 per cent to 27.9 per cent for the remainder of the year. Fig. 1 shows the Map of Axim.

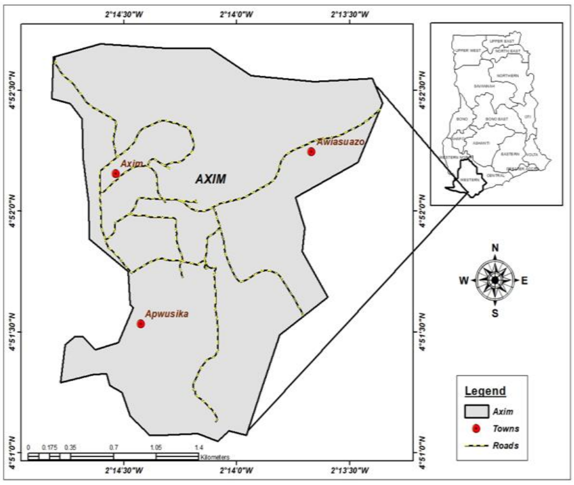

Fig. 1. The geographical map of Axim

B. Dataset

This study's historical dataset is collected from the European Centre for Medium-Range Weather Forecasting (ECMWF) [33]from their Ghana website. The obtained meteorological data for the research from ECMWF includes the temperature, wind (both Zonal and south), total precipitation, mean sea level pressure, relative humidity, and precipitation hours between August 31, 2000, to August 2020.

C. Data Preparation

Ideally, hourly observed datasets from the Ghana Meteorological Agency (GMA) would have been used to train the model. However, the study could not acquire the dataset due to bureaucratic reasons. This study's historical dataset is collected from the European Centre for Medium-Range Weather Forecasting (ECMWF) [49] from their Ghana website. The obtained meteorological data for the research from ECMWF includes the Sea Surface Temperature (SST), Wind (both Zonal and South), Total Precipitation, Mean Sea Level Pressure, Relative Humidity, and precipitation hours between August 31, 2000, to August 2020. The dataset contains a total of forty-nine (49) defining features, including temperature, relative humidity, mean sea level pressure, Wind and Dew, and other derivatives of the critical variables. To grasp the data set, the authors categorised the data set, as shown in Table 1. Data was further normalised and divided into training, testing, and validation for the forecast

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parameters. using a min-max scaler to obtain a new scaled value. The normalisation was done using the equation::

$$r = \frac{c - \min(c)}{\max(c) - \min(c)} \tag{1}$$

Where c is the value to be normalised; min(c) and max(c) represents the minimum and maximum values, respectively, and r is the output.

Furthermore, we performed correlation coefficient analysis on the data to find which factor (s) has the best correlation with rainfall using Spearman's correlation and (humidity, temperature and MSLP) were selected, as shown in Table 2.

Table 1. Input dataset for LSTM model

Parameters	Input	Description	Observation
Rainfall	1-5	Rainfall in the last 5 hours ago	Measurement unit: mm
	6	Rainfall average 7hours ago	
	7	Difference between the rainfall at 5:00 to the current time	
Temperature	8-12	The temperature in the last 5 hours ago	Measurement unit: C
	13	Temperature average 7hours ago	
	14	Difference between the temperature at 5:00 to current time	
Relative Humidity	15-19	Relative humidity in the last 5 hours ago	Measurement unit: %
	20	Relative humidity average 7hours ago	
	21	Difference between the Relative Humidity at 5:00 to the current time	
Zonal Wind (mwind)	22-26	Zonal Wind in the last 5 hours ago	Measurement unit: m/s
	27	Zonal Wind average 7hours ago	
	28	Difference between the Zonal Wind at 5:00 to current time	
Meridional Wind (rwind)	29-33	Meridional Wind in the last 5 hours ago	Measurement unit: m/s
	34	Meridional Wind average 7hours ago	
	35	Difference between the Meridional Wind at 5:00 to current time	
Mean Sea level pressure (MSLP)	36-40	MSLP in the last 5 hours ago	Measurement unit: hPa
	41	MSLP average 7hours ago	
	42	Difference between the MSLP at 5:00 to current time	
Dew	43-47	Dew in the last 5 hours ago	Measurement unit: k
	48	Dew average 7hours ago	
	49	Difference between the Dew at 5:00 to the current time	

Table 2. Spearman's correlation coefficient table

Parameters	Correlation
Precipitation and Precipitation	1.0
Precipitation and Humidity	0.23161180630179107
Precipitation and Temperature	0.14732279759517072
Precipitation and MSLP	0.10467821541115839
Precipitation and mWind	0.06713736671737774
Precipitation and Dew	0.03647588031409096
Precipitation and rWind	0.03077391347713960

D. Long Short-Term Memory (LSTM)

An artificial recurrent neural network (RNN) architecture [34] used in the field of deep learning is Long Short-Term Memory (LSTM). LSTM has feedback links, unlike regular feedforward neural networks. It processes single data points (such as pictures) and entire data sequences (such as speech or video). For example, LSTM refers to tasks such as unsegmented recognition of related handwriting [35], speech recognition, and identification of anomalies in network traffic or intrusion detection systems [36]. The LSTM unit comprises a cell, an input gate, an output gate, and a forget gate. The cell remembers values over arbitrary time intervals, and the three gates regulate the flow of information into and out of the cell. The equations for an LSTM unit is given in the form:

$$x_1 = f(W_1 Y + c_1) \tag{2}$$

$$X_2 = f(W_2 X_1 + c_2) \tag{3}$$

$$X_3 = f(W_3 X_2 + c_3) \tag{4}$$

$$R = f(W_4 X_3 + c_4) \tag{5}$$

Where the variables:

X is input vector (temperature, humidity, and pressure) consisting of observed hourly data from ECMWF to the LSTM unit

$X_{1,}\ X_2, X_3$ are the outputs of sample three hidden layers

$W_{1,}\ W_{2,}\ W_3 \ldots W_{n,}$ are the weight vector at the input and the hidden layers, respectively.

$C_1, C_2, C_3 \ldots C_n$ are the bias terms associated with the input and the hidden layer

R is the output of the predicted rainfall

Fig.2 shows the process flow for the LSTM model used in the study.

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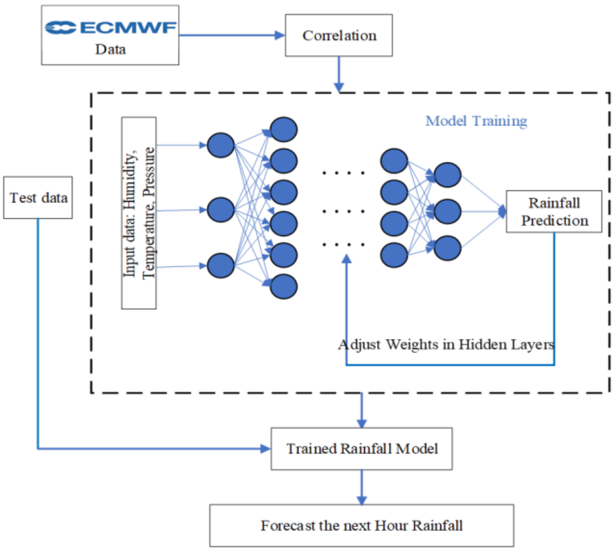


Fig. 2. The process flow for the LSTM model

IV. VALIDATION, RESULTS AND DISCUSSIONS

A. Validation

We performed validation analysis on the parameters selected to get the best combination at this phase, significantly influencing rainfall using the Mean squared error (MSE) We use MSE to calculate the average square difference between the predicted values and the actual values. Mathematically,

$$MSE = \frac{1}{n}\sum (y - y)^2 \qquad (5)$$

where is the actual value, and is the predicted value and to measure errors between our predicted and observed values of labels.

B. Results

Based on the analysis carried out separately on each parameter, Precipitation, Relative Humidity, MSLP, and Temperature as shown in Fig. 3(a) and (b) shows scattergram of rainfall and MSE results of 0.002 respectively. In Fig. 4 (b), (d), and (f), our model was trained on Precipitation (R) against Relative Humidity (H), Pressure (M), and temperature (T), which predicted MSE results of 0.008, 0.222, and 0.015 respectively. The respective Scattergrams shown in Fig 4 (a), (c), (e), and (g). In Fig. 5 (b), (d), and (f), our model was trained on (R) against (T) /(M), (R) against (T)/(H), (R) against (M)/(H) the LSTM predicted MSE results of 0.004, 0.002, and 0.004 respectively. Finally, In Fig. 6 (b), (d), and (f), the model was trained on the (R) against (T) /(M)/(H), which produced an MSE result of 0.002.

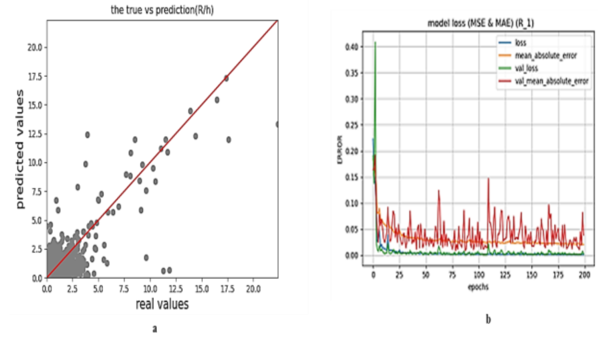


Fig. 3. **(a)** Scattergram of rainfall; **(b)** Model loss for rainfall

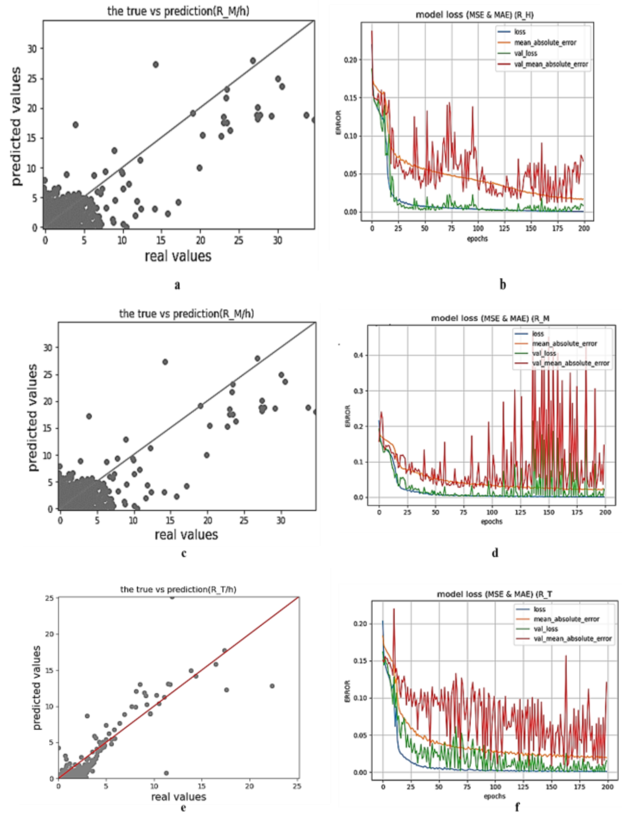
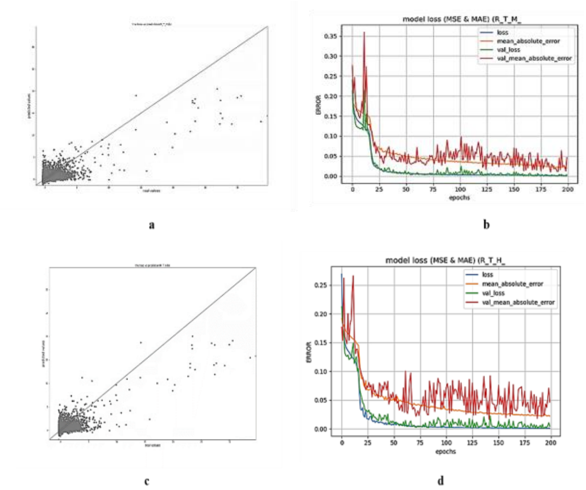


Fig. 4. **(a)** Scattergram for (R_H); **(b)** Model loss for (R_H); **(c)** Scattergram for (R_M); **(d)** Model loss for (R_M); **(e)** Scattergram for (R_T); **(f)** Model loss for (R_T)



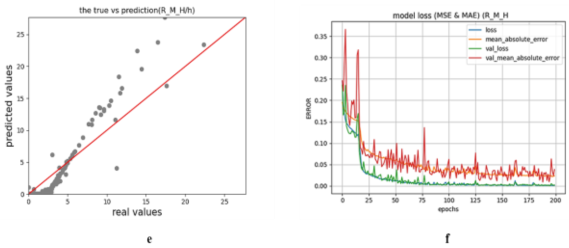


Fig.5.**(a)** Scattergram for (R_T_M); **(b)** Model loss for (R_T_M); **(c)** Scattergram for (R_T_H); **(d)** Model loss for (R_T_H); **(e)** Scattergram for (R_M_H); **(f)** Model loss for (R_M_H).

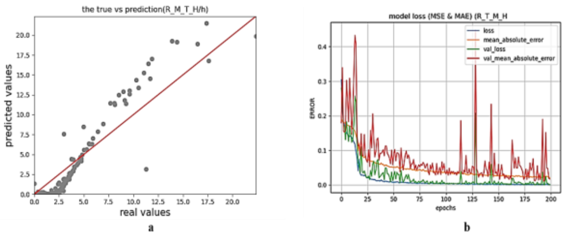


Fig. 6. **(a)** Scattergram for (R_T_M_H); **(b)** Model loss for (R_T_M_H).

C. Discussions

We use the Mean Square Error (MSE) to verify the loss and average squared difference between the predicted values and the true value; Mean Absolute Error (MAE) was also used to test the regression problem's accuracy with Adam Optimiser function. The data for the feature set is (181178,7) of the whole dataset table. We used 200 epochs for each experiment which took more than four hours to finish depending on the dataset at the learning rate set at 0.001. Table 4 shows the analysis results separately on each parameter, Precipitation, Relative Humidity, MSLP, and temperature with MSE results of 0.002, 0.322, 0.361 and 0.291 respectively. Testing on Precipitation (R) against Relative Humidity (H), Pressure (M), and temperature (T) predicted MSE results of 0.008, 0.222, 0.015 with MAE of 0.067, 0.147 and 0.121, respectively. Further testing on (R) against (T) /(M), (R) against (T)/(H), (R) against (M)/(H) predicted MSE results of 0.004, 0.002, 0.004 with MAE of 0.046, 0.038, and 0.047 respectively. Finally, testing on the (R) against (T) /(M)/(H), which produced an MSE result of 0.002. However, the top factors that influence rainfall were precipitation with other parameters, such as temperature, pressure, and humidity. The ranking for MSE values based on parameters and combination of parameters is shown in Table 3.

Table 3 Ranking of all Parameter using MSE.

Parameters	Ranking
R & T & M & H	0.001174
R & M & H	0.001822
PRECIPITATION(R)	0.001972
R & T & M	0.003829
R & T & H	0.004069
R & H	0.007898
R & T	0.015216
R & M	0.022048
TEMPRETURE(T)	0.291133
HUMIDITY(H)	0.322180
PRESSURE(M)	0.361079

Table 4.Performance result using MSE

Parameters	**MSE**	**Val MSE**	**TRAINING TIME(S)**	**Total computing time(s)**
R & T & M & H	0.0012	0.1540	31916.8	32034.9
R & M & H	0.0018	0.2177	24186.8	24290.4
PRECIPITATION(R)	0.001972	0.1656	6075.5	6096.1
R & T & M	0.003829	0.1777	23338.3	23435.2
R & T & H	0.004069	0.1624	24528.8	24663.7
R & H	0.007898	0.1876	12885.5	12926.8
R & T	0.015216	0.1661	12675.7	12714.1
R & M	0.022048	0.1652	13052.9	13091.1
TEMPRETURE(T)	0.291133	0.4206	6041.6	6077.1
HUMIDITY(H)	0.322180	0.3297	5886.6	5930.0
PRESSURE(M)	0.361079	0.3502	5838.7	5860.9

V. CONCLUSION AND FUTURE WORKS

The ability to predict future events is the most crucial element which ANN promises to show better performance. Monitoring and forecasting of precipitation is a primary concern in weather conditions. The strength of LSTMs with advantages for long sequences is that the method can understand how to make a one-shot forecast that is useful for forecasting time series. The forecasting accuracy trend (extremely good or worse) varies with the size of the data. We analyse each input parameter's impact by selecting 5 hours ago data, the average of 7 hours and the time difference of 5 hours to current time in each input parameter, alternatively based on the LSTM model. It showed that precipitation (rainfall) with these three parameters, temperature, pressure and humidity, are the most important variables affecting the rainfall forecast efficiency of the LSTM model. Moreover, meridian wind as part of our parameters is moving air from the southern part of Ghana and the study area closed to the sea bartered by it. The wind carries the water vapour in the air from the sea to the land affecting humidity level. The findings indicate that our proposed design outperforms other methods in terms of having a lower MSE and RMSE value. In future works, we are working to improve our architecture with more epochs, since the more the epoch of training, the better or, the lesser the error or, the lesser the loss. But the disadvantage is that it takes a lot of time during the experimental time; we will use more datasets to forecast daily rainfall. We will also consider training our model in more than 200 epochs because the more time of training, the more the model learns and the results get better.

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