MULTIDIMENSIONAL TIME SERIES WEATHER PREDICTION USING LONG SHORT TERM MEMORY NEURAL NETWORK

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Abstract— Weather conditions around the world change rapidly and continuously. Correct forecasts are essential in the daily living of people due to over-dependency on weather forecasts heavily; from agriculture to industry, from traveling to daily commuting. A number of approaches such as ensemble weather prediction systems are highly time-ineffective such as Numerical Weather Prediction, and Trend Forecasting. This study proposed Long Short-Term Memory (LSTM) neural network model for forecasting weather parameters as improvement over existing approaches. This study used weather variables (such as dew point, pressure, relative humidity, temperature, wind speed and rainfall) collected from the Nigeria Meteorological Agency (NiMet), Abuja from first of January, 2015 to thirtieth of December, 2019 for four cities of Nigeria, including: Bauchi, Minna, Calabar and Ikeja. The performance of the model was validated for the daily and weekly time-steps on the basis of the selected multivariate weather variables. The outcomes reveal that the proposed model performed best for short-range forecasts (values by 20.10% to 79.90%) than medium-range forecasts (values by 26.94% to 73.06%) for Mean Square Error (MSE). Again, the proposed model performed best for Bauchi, Calabar and Ikeja city, and worst for Minna City for daily forecasts because of the relative stability in weather variables measured of the former. In the case for weekly forecasts performed with the model in which Ikeja city had the worst outcomes, while Bauchi city had the best outcomes due to the relative instability in the weather variables of the former. The study found that relative stability in the weather variable spread across the period influences on the learning capability of the proposed model. These outcomes can be attributed to memory capacity and feedback loop of computation of Recurrent Neural Network (RNN-LSTM) model.

Keywords— Weather, Forecast, Deep Learning, Trend Forecast, Accuracy, Errors, performance of models, Numerical Weather Prediction, Long-Short Term Memory

I. INTRODUCTION

Weather prediction is a task of forecasting the state of the atmosphere at a place and period by means of temperature, sunshine, wind speed, rain, pressure and other atmospheric conditions. The role of weather condition forecasting is important in all of human endeavors because precipitation information are used by hydro-power generating companies, agricultural sector, renewable energy, water resources, and flood occurrences [1].

Traditionally, weather prediction can be performed by means of dynamic and empirical approaches. The basic duty of meteorologists/forecaster is to determine Weather situations of places usually with principle of fluid known as analytical technique. The second approach is called empirical technique by means of mathematical and statistical inferences. In both cases, the research efforts are continuing due to deficiencies and potentials [2].

At present, efforts are directed towards automated processing and storage of weather station data by means of cloud services. This involves the use of sensor or Internet of things (IoT) devices for acquisition of atmospheric parameters and transmitted across wireless networks in more reliable manner [3].

There is profundity of Long Short-Term Memory (LSTM) classification technique offered by Recurrent Neural Networks (RNN) and Convolution Neural Networks (CNN). In particular, RNNs and LSTMs are most desirable for performing time series data including weather prediction, and pedestrian trajectory [4]; [5].

Weather conditions around the world change rapidly and continuously, correct forecasts are essential in today's daily life. From agriculture to industries, from traveling to daily commuting, from aviation to road construction we are dependent on weather forecasts heavily. As the entire world is suffering from the continuous climate change and its side effects, it is very important to predict the weather without any error to ensure easy and seamless mobility, as well as safe day to day operations. The weather forecasts are divided into the following categories:

Now Casting in which the details about the current weather and forecasts up to a few hours ahead are given. Short range forecasts (1 to 3 days), Medium range forecasts (4 to 10 days), and Long range /Extended Range forecasts (more than 10 days to a season).

To make an accurate prediction is one of the major challenges facing meteorologist all over the world. Numerical Weather Prediction (NWP) are common weather forecasting tools commonly used today by meteorologist for forecasting. It uses mathematical models of atmospheric weather data to predict the weather based on current weather conditions using the power of computers to make weather forecast. Complex computer programs (forecast models) run on supercomputers and provide predictions on many atmospheric variables such as temperature, pressure, wind, and rainfall.

The Numerical Weather Prediction method is flawed in that the equations used by the models to simulate the atmosphere are not precise, this leads to some error in the predictions. In addition, there are many gaps in the initial data since we do not receive many weather observations from areas in the mountains or over the ocean. If the initial state is not completely known, the computer's prediction of how that initial state will evolve will not be entirely accurate. Therefore, this work Multidimensional time series weather prediction using long short term memory neural network is developed to provide a model capable of forecasting more accurate, timely weather.

This paper provides enhanced weather forecasting model for atmospheric state prediction with deep learning techniques rather the traditional physics principles powered by statistical and empirical approaches. The obtainable approaches for determining subsequent weather behaviours of places are less accurate and time-effective as these approaches relies on complex computer and mathematical models to arrive at high accuracy within relatively shorter time.

This paper utilizes LSTM Neural Network deep learning algorithm to perform weather prediction using several weather conditions such as Temperature (in Degree Celsius), Atmospheric Pressure (in HectoPascal), Relative Humidity, Wind Speed (in Kilometre), Dew Point (in Degree Celsius), and Rainfall (in Millimetre). The reason being that, memory capacity and feedback loop of computation are provided by both RNN (LSTM) model. The models can be run on much less capital and resource intensive environments with less time, more accurate weather prediction. The datasets utilized in this paper are entirely in numerical format. The model of weather prediction is based on numerical classification and sentiment analysis of secondary data obtained.

The remaining section of the paper is sectioned as follows: related work is the second section. The proposed weather forecasting model is the third section. Results and discussion are in the fourth section. Conclusion is in the fifth section.

II. RELATED WORKS

In a survey conducted by [6], the challenges and techniques of time-series based forecasting in data center telemetry were presented. It identified the optimal prediction approaches, performance issues and recommendations for improvements. In a separate study by [7], it understudied the comparative models, methods and future research of wind power forecasting. The various deterministic and probabilistic approaches were comparatively analyzed and discussed.

The review paper by [8], underscores the challenges of space weather forecasting and nowcasting by means of machine learning. It offered expositions on machine and future open issues and prospecting works. The work in [9], carried out a Systematic Literature Review on data mining based techniques for the prediction of rainfall, which is an element of weather forecasting. It underscored the benefits of data mining in future works as related to weather forecasting. The issues of extreme weather events in field of agriculture were reviewed to identify the challenges in crop production. The consequence of uncertain adverse weather can cause low productivity and other chain-reactions.

A hybrid machine learning model composed of Particle Swarm Optimization and Multi-Layer Perceptron-Feed Forward Neural Network was proposed for forecasting rainfall by [10], the performance of the network increased as well as accuracy of rainfall forecasts against existing approaches using Root Mean Square Error (RMSE). The use of machine and deep learning methods for weather prediction was explored by [11], A model was formulated based on Convolutional LSTM and Convolutional Neural Network units' encoder-decoder architecture. The outcomes showed improved performance for spatio-temporal weather datasets with minimal errors.

A NowDeepN model based on a supervised learning-regression method was proposed by [12],. It makes use an ensemble of deep artificial neural networks for predicting the values for radar products at specific intervals. The values predicted by NowDeepN are highly accurate with Normalized Root Mean Square Error of 4%. This is useful to meteorologists in assessing the future development of potential severe phenomena; thereby replacing the time-consuming process of extrapolating the radar echoes.

An integrated modeling framework for predicting the performance of weather-induced delays of different transportation systems such as HSR and aviation was proposed by [13]. This applied machine-learning methods to real-world transportation performance data in order to examine the robustness of the method, variations of data characteristics and the different applications of the predictive modeling system. These provide important implications for the enhancing transportation system resilience to diverse severe weather-related disruptions through the understanding of the impact and its predictability of the system performance [13],. A method for design of cloud-based systems for storing and processing of sensor data from weather stations using IoT devices to capture data of local atmospheric parameters was proposed by [3]. The LSTM model was trained with the 17 parameters for the purpose of automatic processing, visualization and cloud storage. This enable correct features selections for local weather forecasts such as disasters.

III. *PROPOSED WEATHER FORECASTING MODEL*

In this paper, the proposed weather forecasting model uses the Long Short-Term Memory (LSTM) Neural Network algorithm essentially to train the developed model. Weather data such as Dew Point (in Degree Celsius), Pressure (in HectoPascal), Relative Humidity (in Percent), Temperature (in Degree Celsius), Wind Speed (in metre per second), and Rainfall in millimetre) in order to be able to classify/predict accurately with LSTM.

The weather dataset is received as input to the LSTM and trained with the neuron in the hidden layers of the LSTM network architecture. Weather forecasting is done by collecting information related to the present-day weather in regards to the previous and the present condition of the weather and utilizing this information to train LSTM model as indicated in Fig. 1.

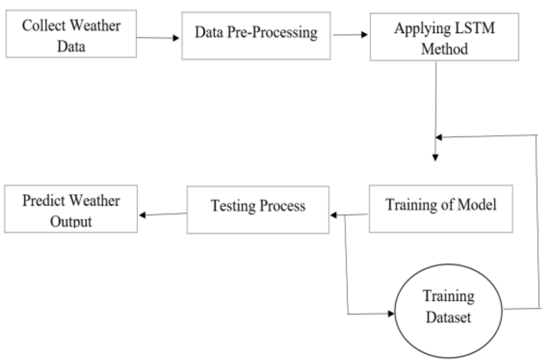


Fig. 1(a): Data Flow Diagram for the proposed Model

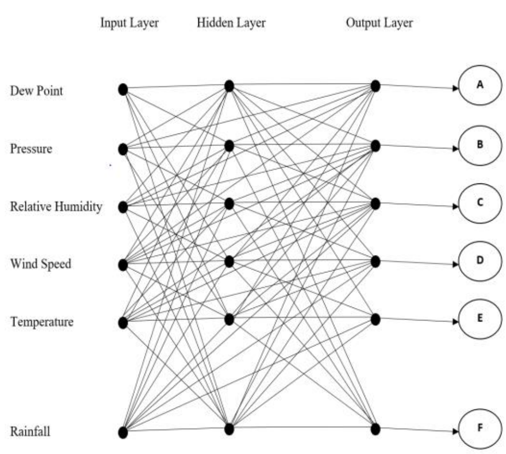


Fig. 1(b): Architecture for proposed LSTM (RNN) model

A. Performance evaluation parameter

The evaluation parameters used for measuring the proposed weather prediction model's errors and accuracy are given by Equations (1) (2), [13]:

$$Root\ Mean\ Square\ Errors\ (RMSE) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \hat{X}_i\right)^2} \quad (1)$$

$$Mean\ Square\ Errors = MSE\ (X_j) = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \hat{X}_i\right)^2 \quad (2)$$

where,

X_i is the target of actual value of sample output

$\hat{X}_i$ is the adjusted or predicted value of sample output

i is the term index from 1 to n of test data sample

n is total number of the test data sample

The outcomes obtained from the proposed model (RNN-LSTM) experimentation are to be compared the existing machine learning architecture.

IV. *RESULTS AND VALIDATION*

A. Data Training and Validation

This subsection provides the graphical representation of various weather datasets for the different cities selected for this study.

(a) Bauchi City Weather Data

In the case of the Bauchi city, the distributions of data elements for the dew point, pressure, relative humidity, temperature, wind speed, and rainfall are presented in Fig. 2.

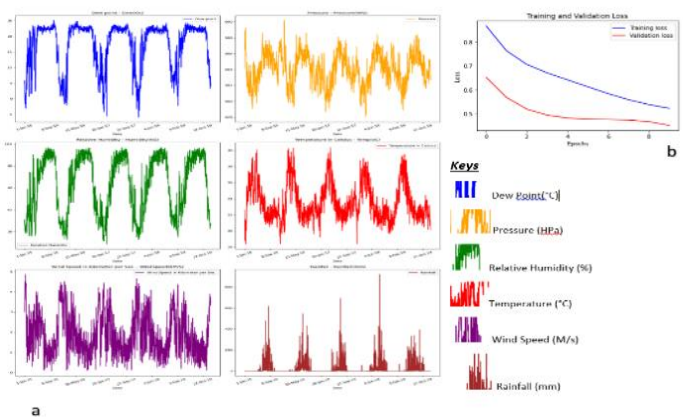


Fig. 2: The distribution of data elements and model performance for Bauchi city daily weather forecasts.

From Fig. 2, the data representation plot reveals similar trends in the distribution for dew point and relative humidity. The same trend is observed for pressure and temperature. But, there is no correlations in the data elements of the rainfall and wind speed.

The training and validation of the proposed weather forecasting model using the multivariate datasets of the selected weather variables are presented in Figure 2, it shows that, the validation curve was relatively lower than the training curve for the epoch 1 to 8, which indicates low errors or deviations of the proposed model for Bauchi city daily weather forecasts.

(b) Minna City Weather Data

The distribution of the data elements for the city of Minna in terms of the weather variables selected including: dew point, pressure, relative humidity, temperature, wind speed, and rainfall are presented in Fig. 3.

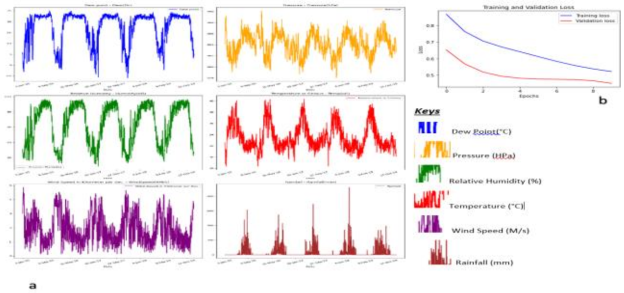


Fig. 3: The distribution of data elements in weather variable and Model performance for Minna city daily weather forecasts.

From Fig. 3, the data representation plot shows similar trends in the distribution for dew point and relative humidity. The comparable trends are observed for pressure and temperature. But, there is no correlations in the data elements of the rainfall and wind speed.

The validation curve was relatively larger than the training curve for the epoch 1 to 6, which indicates huge errors or deviations. But, the training and validation performance improved after epoch 6 to 10, which indicates increased outcomes of the proposed model for Minna city daily weather forecasts.

(c) Ikeja City Weather Data

In the case of the Ikeja city, the distributions of data elements for the dew point, pressure, relative humidity, temperature, wind speed, and rainfall are presented in Fig. 4

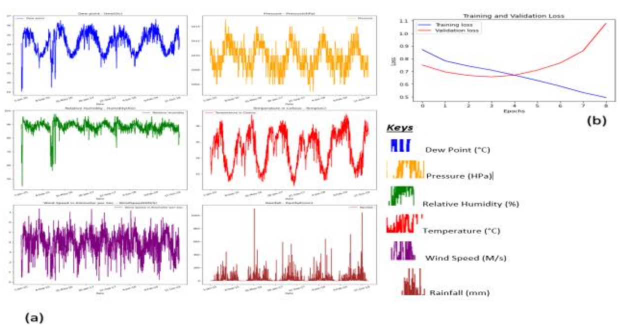


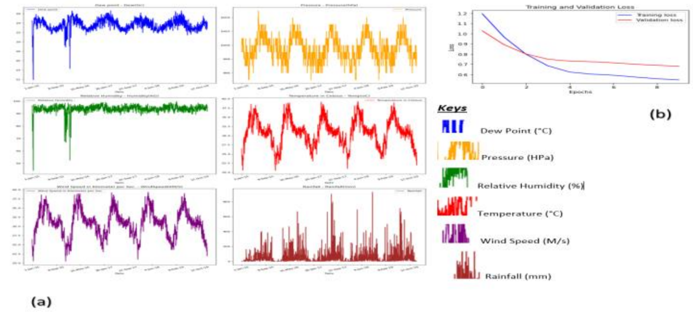
Fig. 4: The distribution of data elements in weather variables and Model performance for Ikeja city daily weather forecasts.

In Fig. 4, the data representation plot reveals similar trends in the distribution for dew point and temperature, pressure and wind speed. The reverse trend is observed for relative humidity and rainfall.

The validation curve was relatively lower than the training curve to converge at after epoch 4. The relative curves for both the training and validation started to diverge continuously after epoch4, which indicates high errors or deviations of the proposed model for Ikeja city daily weather forecasts.

(d) Calabar City Weather Data

In the case of the Calabar city, the distributions of data elements for the dew point, pressure, relative humidity, temperature, wind speed, and rainfall are presented in Figure 5.



Fig, 5: The distribution of data elements in weather variables and model performance for Calabar city daily weather forecasts.

From Fig. 5, the data representation plot reveals similar trends in the distribution for the dew point and relative humidity. The comparable trends were observed for pressure, wind and temperature. But, there is no correlations in the data elements of the rainfall.

The validation curve was relatively closer to the training curve for the epoch 0 to 2. This trend changed after epoch 2 and diverged continuous until epoch 10 which indicates low errors or deviations of the proposed model until epoch 2, while errors increased for Calabar city daily weather forecasts.

B. Prediction Outcome

The performance of the weather forecasting model for daily and weekly forecast for the multivariate weather parameters are presented in this subsection.

(a) Bauchi City

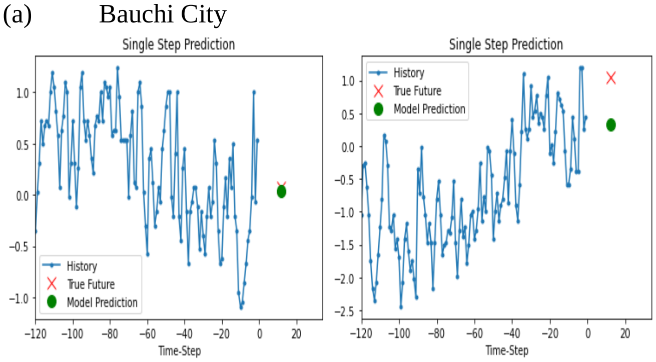


Fig. 6: The daily and weekly weather forecasts performance with proposed model.

The proposed model performance for daily forecasts of weather parameters were relatively accurate at 1 time-step as shown in Fig. 6.

Again, the model performance for weekly weather forecasts or a 7-day time-step shows the model lagging behind due to unstable pattern of the weather variables collected at Bauchi city.

(b) Minna City

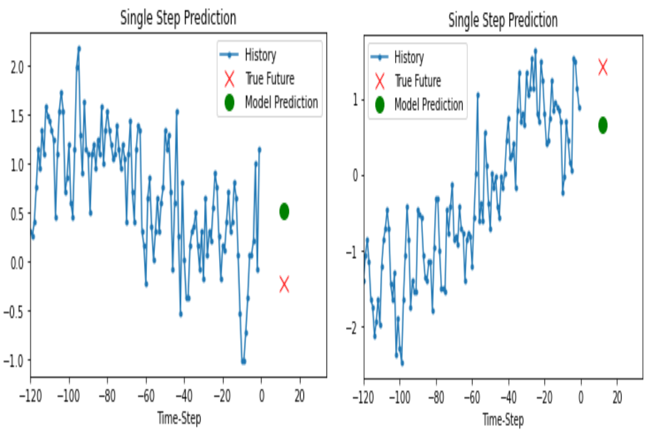


Fig. 7: The daily and weekly weather forecasts using multivariate dataset for Minna City.

The proposed weather model performance on daily forecasts of weather parameters large disparity between the model prediction and the actual values. The values of forecasts by the proposed model are more than the actual values as shown in Fig. 7.

In the same vein, the weekly performance of the proposed model or a 7-day time-step reveals the model lagging behind the expected weather data for Minna city caused by unstable patterns of the weather variables data collected as depicted in Fig. 7 above.

(c) Ikeja City

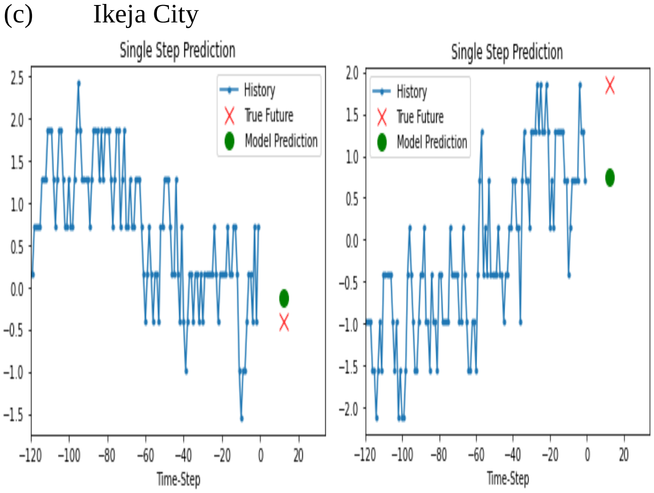


Fig. 8: The daily and Weekly weather forecasts performance with the proposed model.

The performance of the propose model for the daily forecasts of weather parameters were closely related with model values more than the actual values for a 1-day time-step as shown in Fig. 8

Similarly, the model performance for weekly forecasts or a 7-day time-step shows the model lagging behind due to unstable nature of the weather variables collected at Ikeja city.

(d) Calabar City

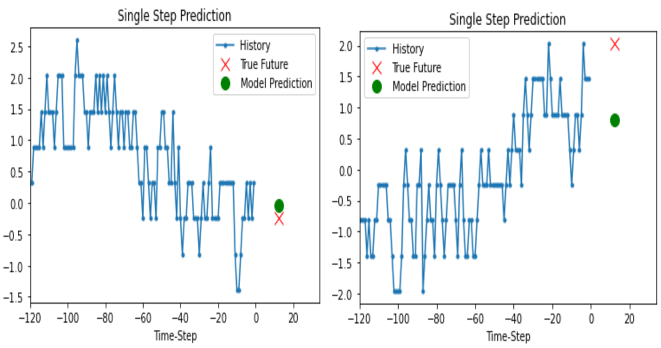


Fig.9: The daily and Weekly weather forecasts performance with proposed model.

The proposed model performance for daily forecasts of weather parameters were relatively accurate at 1 time-step as shown in Fig. 9.

Again, the model performance for weekly weather forecasts or a 7-day time-step shows the model lagging behind due to unstable pattern of the weather variables collected at Calabar city.

C. Performace Evaluation

The performance of the LSTM neural network for the daily and weekly weather conditions forecasts of the selected cities in the four regions of Nigeria are presented in Table I.

TABLE I. TABLE 1: THE PROPOSED WEATHER MODEL FORECASTING OUTCOMES USING MSE.

Table Head	The proposed weather model forecasting outcomes using MSE	
Bauchi	0.0252	0.3977
Minna	0.0167	0.4505
Ikeja	0.0042	1.0784
Calabar	0.0069	0.6804

From Table 1, the proposed weather model performed best for Bauchi city based on weekly forecasts due to the relative defined patterns of multivariate datasets used during training. Whereas, the proposed model performed worst for Ikeja city because of unsteady patterns of the multivariate datasets used during training.

V. *CONCLUSION*

People are always interested in knowing about future occurrences, Data is abundant nowadays but analyzing the data and inferring the hidden facts is done to a lesser degree. Thus, data analytics and improvements in the prediction model can provide insights for better decision making regardless of applications. In this study, deep learning approach is carried out for weather prediction in selected weather stations in Nigeria. The Long Short-Term Memory (LSTM) neural network is used to develop the model for predicting weather parameters.

This approach is compared with other methods, namely, Numerical Weather Prediction, Trend Forecasting in order to demonstrate the improvement of weather forecasting in the proposed approach.

This study validated the proposed model using weather variables for four cities across Nigeria (Bauchi, Minna, Calabar and Lagos). The model was evaluated for the daily and weekly time step on the basis of multivariate weather variables of dew point, pressure, relative humidity, temperature, wind speed and rainfall. The outcomes reveal that the proposed model performed best for short-range forecasts (values by 20.10% to 79.90%) than medium-range forecasts (values by 26.94% to 73.06%) for Mean Square Error (MSE).

Again, the proposed model performed best for Bauchi, Calabar and Ikeja city, and worst for Minna City for daily forecasts because of the relative stability in weather variables measured of the former. In the case for weekly forecasts performed with the model in which Ikeja city had the worst outcomes, while Bauchi city had the best outcomes due to the relative instability in the weather variables of the former.

Future works in the direction of weather forecasting models can explore more optimization algorithms and data mining algorithms to improve the performance of the model. Again, there is need to adopt this model in other scenarios such stock price forecasting, energy forecasting, and retail pump price forecasting.

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