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

BY

AGADA, Michael Ugbede

(M.Tech/SICT/2018/8621)

DEPARTMENT OF COMPUTER SCIENCE

FEDERAL UNIVERSITY OF TECHNOLOGY MINNA

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A THESIS SUBMITTED TO THE POSTGRADUATE SCHOOL FEDERAL UNIVERSITY OF TECHNOLOGY, MINNA, NIGERIA IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF MASTER OF TECHNOLOGY (M.Tech) IN COMPUTER SCIENCE.

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ABSTRACT

Since weather forecasts are extensively relied upon in every aspect of human life—from agriculture to business, from travel to daily commuting—weather conditions around the world change quickly and frequently. Accurate forecasts are therefore crucial. In order to anticipate the weather, a variety of techniques are used, including trend forecasting and numerical weather prediction. However, these techniques are capital intensive, time-consuming, and have low accuracy. As an enhancement over current methods, this study presented a Long Short-Term Memory (LSTM) neural network model for forecasting meteorological parameters. This study used weather data (including dew point, pressure, relative humidity, temperature, wind speed, and rainfall) gathered by the Nigerian Meteorological Agency (NiMet), Abuja, for weather stations/four cities in Nigeria: Bauchi, Minna, Calabar, and Ikeja from 1 January 2015 to 30 December 2019. On the basis of the chosen multivariate weather variables, the model's performance was validated for the daily and weekly time-steps. The results show that for Mean Square Error, the proposed model performs better for short-range forecasts (values by 20.10% to 79.90%) than for medium-range forecasts (values by 26.94% to 73.06%). (MSE). Again, due to the relative consistency in meteorological variables measured at the station, the suggested model performs best for daily forecasts in Bauchi, Calabar, and Ikeja, and poorest in Minna City. Due to the relative volatility in the meteorological variables at the station, Ikeja city had the lowest results for the weekly forecasts made using the model, whereas Bauchi city had the best results. The study discovered that the proposed model's capacity for learning is influenced by the relative stability of the weather variable spread across the period. These results can be attributed to the LSTM model's memory capacity and feedback computation loop.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIX

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background to the Study

Weather refers to the state of the atmosphere on earth at a certain location as regards cloudiness, dryness, sunshine, wind, rain, soon, etc. it is disorderly, continuous, dynamic, and data-intensive (Sokolov *et al*., 2020). Weather forecasting is the process of estimating the state of the atmosphere for a specific location using physics principles and a variety of empirical and statistical approaches (Ahmed *et al.*, 2020). Weather prediction has been a fascinating area to people from the beginning of time, and it is one of the most scientifically and technologically hard issues in the world today (Balsamo *et al*., 2012). One of the greatest issues facing meteorologists and forecasters around the world today is making an accurate and timely prediction. Weather forecasting is typically accomplished through a collection of quantitative data related to the current state of the atmosphere, which is then used to portray future changes in the atmosphere based on scientific understanding of atmospheric processes (Pooja & Balan, 2019). Present conditions of weather across a location are realized by employing observation from the ground, aircraft, ships, radio sounds, and satellites.

This data is forwarded to meteorological centres, which collect, analyze, and present the data in a variety of charts, maps, and graphs. Thousands of observations are transferred onto surface and upper-air maps using modern high-speed computers. The meteorological centres receive this transmitted information from the point of the data, which are subsequently examined for prediction (Pooja & Balan, 2019).

Weather forecasting employs a variety of methodologies, ranging from simple sky observation to highly complicated computerized mathematical models. Weather forecasts can be made for one day, one week, or several months (Tuv *et al.*, 2009). Weather forecasts, on the other hand, lose a lot of accuracy after a week (Tuv *et al.,* 2009).

Weather forecasting, as conducted by professionally educated meteorologists, is now a highly developed skill based on scientific principles and methods and utilizing advanced technical tools (Aremu, 2001). Since 1950, technology advancements, basic and applied research, and the application of new knowledge and procedures by weather forecasters have resulted in a significant increase in forecast accuracy. High-speed computers, meteorological satellites, and weather radars are just a few of the tools that have helped improve weather forecasts (Cross *et al*., 1995). The study of weather patterns has resulted in a variety of rainfall forecasting approaches over the years, these entails a mix of computer models, interpretation, and familiarity with weather trends (Hayati & Mohebi 2007).

i. Use of barometer

Since the late 1800s, barometric pressure and pressure tendency measurements have been employed in forecasting. The greater the shift in pressure, the greater the likelihood of a change in weather. If the pressure drops, a low pressure system is approaching, which means rain is more likely to occur (Lynch, 2006).

ii. Looking at the sky

The condition of the sky together with pressure tendency is one of the most essential characteristics used to forecast weather in mountainous terrain (Lynch, 2006). The invasion of a higher cloud deck or the thickening of cloud cover are both signs of impending rain (Oliver, 1997). At night, high thin clouds can cause halos around the moon, indicating the approach of a warm front and the rain that comes with it. Rainy conditions are preceded by wind or clouds, which inhibit fog development while morning fog foreshadows fair conditions (Oliver, 1997).

iii. Nowcasting and Analog technique

Nowcasting is a term use to describe weather predictions of the next six hours. Smaller features like as individual showers and thunderstorms, as well as other variables too small to be resolved by a computer model, can be forecasted with fair accuracy in this time range. Given the most recent radar, satellite, and observational data, it is possible to better analyze the small scale features present and hence create a more accurate forecast for the next several hours (Pidwirny, 2008).

The analog technique is also referred to as trend forecasting (Ahmed *et al*., (2020), it involves analyzing weather features such as pressure, temperatures, etc. on use of weather chats and using those features to forecast the weather. It is a difficult method to forecast weather since it requires the forecaster to recall a former weather occurrence that is expected to be repeated by a future event. It's still a good way to observe rain in locations like oceans, as well as projecting precipitation levels and dispersion in the future. Teleconnections, a related strategy used in medium-range forecasting, uses systems in other regions to assist pin down the location of another system within the surrounding regime (Refallack, 1987).

iv. Numerical Weather Prediction model

The science of predicting the weather using atmospheric models and computing tools is known as numerical weather prediction (NWP). To predict weather, current meteorological conditions are fed into mathematical models of the atmosphere (Seinfeld *et al.*, 2006). This model typically offers surrounding points with a spatial resolution of a few kilometers around the wind farm. To generate a forecast, NWP relies on the computing capability of computers. A forecaster looks at how the computer's projected features will combine to create the weather for the day. The NWP technique is problematic because the models' equations for simulating the environment are not precise (Seinfeld *et al.*, 2006).

Weather forecasting has traditionally relied on huge, complicated models that take into account a variety of atmospheric factors over a lengthy period. Because of weather system perturbations, these conditions are frequently unstable, causing models to make erroneous forecasts. These models typically make use of hundreds of nodes in a huge High-Performance Computing (HPC) environment, which uses a lot of energy (Ganai *et al*., 2021). The issue of model reliability in weather prediction is a complicated one, as it is dependent on several variables and the technical infrastructure that supports them. Further-more, the reliability of the observations is essential for the numerical reasoning and the quality of the simulation, since there are various sources of problems such as uncertainties, error measurements, and load forecasts (Coulibaly *et al*., 2020).

Recently, there is a shift from the use of numerical simulations for weather forecasts because of inherent uncertainties. These uncertainties arise from imprecise knowledge of initial and boundary conditions for atmospheric models, which are often imperfect. In fact, there are several errors of forecasts due to chaotic nature of the atmosphere and non-linear dynamics. Several approaches such as ensemble weather prediction systems are highly time-ineffective and available on high-performance supercomputers (Astakhova *et al*., 2021).

In truth, weather forecasting is a tricky subject in meteorology, a serious area of study for decades. Several works in this direction have been done giving rise to numerous methods not without their strengths and weaknesses. There are two main approaches for weather forecasting namely; dynamic methods and empirical methods. Short-range weather forecasting has relied on the dynamic methods which are analytical and are based on the principles of fluid dynamics. The long-range weather forecasting utilises empirical methods which are mathematical and statistical approaches. In either approaches, there are significant and distinct flaws and benefits (Prasetya & Ridwan, 2019).

Weather conditions around the world change rapidly and continuously, correct forecasts are essential in today's daily life (Sharma & Datta, 2007). 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. In particular, the changes in climate and weather continue to threaten the humanity and environment directly, which influence the quests to enhance numerical methods of predictions (Coulibaly *et al*., 2020).

The weather forecasts are divided into the following categories (Bazionis & Georgilakis, 2021): Nowcasting: in which the details about the current weather and forecasts up to a few hours ahead are given. Short range forecasts for the next one to three days that include the weather (mostly rainfall) for each succeeding day (Schulz et al., 2021). Up to three days of intervals can be predicted. Medium range forecasts (4 to 10 days): Medium range forecasts average weather conditions and the weather on each day may be prescribed with progressively lesser details and more accuracy than that for short range forecasts. Long range /Extended Range forecasts (more than 10 days to a season): There is no rigid definition for Long Range Forecasting, which may range from a monthly to a seasonal forecast.

In this thesis, a multidimensional time series weather prediction technique that employs a deep learning algorithm called the Long Short-Term Memory (LSTM) Neural Network is presented. The rationale for this is that the long short term memory recurrent neural network (LSTM-RNN) paradigm provides memory capacity and a computation feedback loop. The created model allows for far less expensive and resource-intensive operation, resulting in quicker and more precise weather forecasting. The datasets that were used to create this thesis are only available in numerical form. The numerical categorization and sentiment analysis of gathered secondary data form the basis of the weather forecast model.

1.2 Statement of the Research Problem

The major challenge facing meteorologist all over the world is the subject of obtaining accurate weather conditions of places at specific intervals. Also, the reliability of many forecasting models cannot be measured accurately (Ganai *et al*., 2021). Numerical Weather Prediction (NWP) are weather forecasting tools commonly used today by meteorologist for short-term forecasting (Dhib *et al*., 2021). 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 (Dhib *et al*., 2021).

The mastery of hazardous phenomena (floods, air pollution, and natural disasters) depends on the reliability of the numerical model for predicting weather and climate. But, there is a need for advanced works oriented for a better understanding of the weather forecasting models and the analysis of the main associated parameters. Again, it is important to look for ways to improve the reliability of these numerical prediction models of weather and climate (Coulibaly *et al*., 2020).

The NWP method is flawed in that the equations used by the models to simulate the atmosphere are not precise and associated with spatial scales (less than numerical scales), these lead to errors in the predictions. In case of artificial intelligence models, if the initial state is not completely known, the computer's prediction of how that initial state will evolve will not be entirely accurate. Though, several present-day emulation models rely heavily on neural networks and deep neural networks approaches due to their great promise in theoretical and memory performances (Chantry *et al*., 2021). In addition, the weather forecasting is concerned with determining how present state of atmosphere changes over time. It is a complex task due to the chaotic and unpredictable nature in diverse domain of applications such as advisories for aviation, maritime, and severe weather notifications. In fact, majority of uncertainty abound in spatial locations utilized by visualization scientists and meteorologists for determining weather conditions (Pooja & Balan, 2019).

The synoptic method of forecasting consists of the simultaneous collection of weather observations, and the plotting and analysis of these data on geographical maps. An experienced analyst, having studied several of these maps in chronological succession, can follow the movement and intensification of weather systems and forecast their positions. This forecasting technique requires the regular and frequent use of large networks of data. The synoptic forecasts are limited because they are almost exclusively based upon surface observations. The stratosphere, a layer of air generally located above levels from 9 to 13 km and characterized by temperatures remaining constant or increasing with elevation, acts as a cap on much of the world's weather (Brenner & Laurie, 2021).

Though numerical forecasts continue to improve, statistical forecast techniques, once used exclusively with observational data available at the time of the forecast, are now used in conjunction with numerical output to predict the weather.

Statistical methods, based upon a historical comparison of actual weather conditions with large samples of output from the same numerical model, routinely play a role in the prediction of surface temperatures and precipitation probabilities (Brenner & Laurie, 2021).

Trends method of forecasting involves determining the speed and direction of movement for fronts-, high- and low-pressure centres, vortexes, isotherms, wind speed and directions, areas of clouds and precipitation from weather charts, Weather chats consist of curved lines drawn on a geographical map in a way that indicates weather parameters and features. Using this information, the forecaster can predict where he or she expects those features to be at some future time. This method is flawed in that it is never accurate, time consuming, historical data may not give a true picture of an underlying trend, capital consuming in training and retraining forecasters in the ever changing weather systems.

Because the equations used by the models to represent the atmosphere are imprecise and linked to spatial scales rather than numerical scales, the developed LSTM model is more accurate than the NWP model. Labor-intensive forecasting methods include trend forecasting, which is problematic because it is never precise, time-consuming, historical data may not accurately depict an underlying trend, and capital-consuming because forecasters must be continually retrained in the ever-changing weather systems. Additionally, because of the limitations imposed by the data available, surface observations are the primary source of information used by synoptic forecasts.

1.3 Aim and Objectives of the Study

The aim of this study is to develop a Multidimensional Time Series Weather Prediction using Long Short-Term Memory (LSTM) Neural Network.

The specific objectives are to:

i. Design an improve weather forecasting model based on Long Short-Term Memory (LSTM) Neural Network.

ii. Implement the design model in (i)

iii. Evaluate weather forecasting model in (iii) for daily and weekly range weather forecast using Mean Square Error (MSE)

iv. Compare the results of the model to other artificial neural network.

1.4 Justification for the Study

Transportation systems, built sector, construction, government and regulatory agencies, agriculture, educational sector and markets can take advantage of this thesis due to possibility of generating accurate and timely weather predictions about certain places in order to forestall delays and adjust policies for the overall growth and development of a nation.

Based on data about the system's past and present status, the proposed model makes it possible to predict how the weather will behave in specific locations in the future. This is helpful in overcoming a number of real-world issues, including bad weather, network traffic, road construction, agriculture, and disruptions in the petroleum (or oil) industry, transportation, and other systems.

1.5 Scope of the Study

This thesis performs weather prediction utilizing a number of weather factors, including temperature (in degrees Celsius), atmospheric pressure (in hectopascals), relative humidity, wind speed (in kilometers per hour), dew point (in degrees Celsius), and rainfall (in Millimetre). The Nigerian Meteorological Agency (NiMet) provided the datasets for this thesis, all of which were in numerical format. The numerical categorization and sentiment analysis of gathered secondary data form the basis of the weather forecast model.

1.6 Thesis Organization

This thesis titled Multidimensional Time Series Weather Prediction using Long Short Memory Neural Network is divided into five chapters. Chapter One considers the introductory aspect comprising the background to the study, statement of the problem, aim/objectives of the study, significance of the study and scope of the study. Chapter two entails a review of related literature on weather forecasting, deep learning approaches, trends in weather forecasting and weather forecasting techniques. Chapter three consist of research process and design, model description, experimental requirements, and performance evaluation parameters. Chapter four covers results and discussion, data training and validation, prediction outcome performance evaluation and benchmarking of performances. Chapter five provides the thesis's conclusion and recommendations.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 The Concept of Weather Forecasting

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, and pressure. The role of weather condition forecasting are important in all of human endeavours because precipitation information are used by hydro-power generating companies, agricultural sector, renewable energy, water resources, and flood occurrences (Gad & Hosahalli, 2020).

In the construction industry, the concept of climate change is often taken seriously by architects and engineers in determining energy efficiency of building, roads, rain ways, airports and infrastructure. The meteorological year weather has been used to simulate weather data generated but incapable presenting future energy consumption of buildings (Hosseini *et al.*, 2020). A number of modelling approaches have been critiqued, objectively compared and categorized into physical, statistical, artificial intelligence, ensemble and hybrid techniques (Ahmed *et al.*, 2020).

The quality of images or videos can be affected by bad weather conditions or videos which can be corrected through appropriate weather information during the image/video processing algorithms for better performance. Selection Based on Accuracy Intuition and Diversity (SAID) is a typical ensemble method (Oluwafemi & Zenghui, 2019).

One of the most widespread forecasting techniques is the Artificial Neural Network (ANN) despite its simplicity of implementation, there are drawbacks particularly the intricate architecture, a huge training dataset, and selection of the optimal number of hidden layers and input nodes, poor accuracy of outcomes (Kwon *et al.*, 2019).

In terms of capability to extract knowledge from large data sample, K-Nearest Neighbor (K-NN) has great potentials with higher accuracy with balanced data distribution over comparable techniques such as SVM (Wang *et al.*, 2018).

Traditionally, weather prediction can be performed by means of dynamic and empirical approaches. The basic duty of meteorologists 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 (Prasetya & Ridwan, 2019).

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 (Sokolov *et al*, 2020).

There is a profundity of Long Short-Term Memory (LSTM) classification technique offered by Recurrent Neural Networks (RNNs) and Convolution Neural Networks (CNNs). In particular, RNNs and LSTMs are most desirable for performing time series data operations including weather prediction, and pedestrian trajectory (Nguyen *et al*, 2020; Zhang *et al*, 2020).

2.2 Deep Learning Neural Network

Deep learning, also known as deep neural networks (DNNs), is a type of artificial intelligence that is inspired by how the brain functions (Sarvepalli *et al*., 2015; Sze *et al*., 2017). The ability of deep learning architectures to grasp the meaning of data in vast quantities and to automatically adapt the derived meaning with fresh data without the requirement for domain expert knowledge is their main strength. Deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are commonly used in real-world applications.

CNN architectures are typically used for spatial data, while RNN architectures are typically utilized for temporal data (Bermant *et al.*, 2019). For spatial and temporal data processing, a mix of CNN and Long Short-Term Memory (LSTM) is used (Bermant *et al*., 2019; Khan *et al*., 2020).

2.2.1 Recurrent Neural Network (RNN)

A recurrent neural system (RNS) is a type of Artificial Neural Network (ANN) in which the connections between the units form a sequential chart. This allows it to demonstrate dynamic temporal behavior for a certain time period (Graves, 2012; Murugan, 2018). It is doubtful that a feed forward neural network or a recurrent neural network can process sequences of inputs using memory from internal storage.

RNNs can remember important details about the information they received, allowing them to predict what will happen next. This is why, when compared to other techniques, they generate a more understanding of sequence and its context, which is why they are the preferred methodology for sequential data such as time series, speech, text, financial data, audio, video, weather, and much more. The data in a recurrent neural network loops back on itself. When it makes a choice, it considers the current input as well as what it has learned from previous information (Graves, 2012; Zinov'ev & Sole, 2004).

2.2.2 Long Short-Term Memory Neural Network

Long short-term memory (LSTM) is a deep learning artificial recurrent neural network (RNN) architecture. Since it has feedback connections, it differs from other standard feed-forward neural networks in that it can analyse not just single input points but also complete sequences such as audio, video, pictures, and numerals. The RNN's vanishing gradient weakness is addressed by the Long Short-Term Memory (LSTM) (Staudemeyer & Morris, 2019; Zinov'ev & Sole, 2004).

2.2.3 Long Short-Term Memory Architecture

Long Short–Term Memory (LSTM) networks are a type of recurrent neural network that extends the memory of the original. In this way, critical encounters with long circumstances lapses in the middle are acceptable to profit from. The units of Long-Short Term Memory networks are the supporting units to the surface of a recurrent neural network, which is often known as an LSTM network. Recurrent neural networks can recall their given information for a long time using Long Short–Term Memory (Mikami, 2016). The reason for this is that recurrent neural networks store their data in memory that is quite similar to the memory of a computer, given that the LSTM may read, write, and erase data from its memory (Staudemeyer & Morris, 2019).

The memory cell is the basic structure of an LSTM, and it is used to remember and propagate unit outputs explicitly at different time steps. The memory cell of the LSTM uses cell states to remember information from temporal contexts (Murugan, 2018; Poornima, 2019). To manage information flow between different time steps, it also features a forget gate, an input gate, and an output gate. In this thesis, LSTM-based neural networks are used to forecast background radiation from time-series weather data. The problem of vanishing gradient refers to the mathematical difficulty of learning long-term dependencies in the structure of recurrent neural networks. It gets more difficult to capture the influence of the earlier phases as the input sequence lengthens. The gradients between the first few input points disappear and become zero. The activation function of the LSTM is viewed as the identity function with a derivative of 1.0 due to its recurrent nature. As a result, the back-propagated gradient does not disappear or explode, but rather remains constant (Poornima, 2019).

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(Apaydin *et al*., 2020; Song *et al*., 2020).

These activation functions of LSTM are calculated for Input gate I_t, Output gate O_t, Forget gate F_t, Candidate vector $C`_t$, Cell state C_t, and Hidden state h_t, using the following formulae,

$$I_t = \text{sigmoid}(W_i[X(t), h_{t-1}] + b_i \tag{2.1}$$

$$F_t = \text{sigmoid}(W_f[h_{t-1}, X(t)+b_f) \tag{2.2}$$

$$O_t = \text{sigmoid}((W_o[h_{t-1}, X(t)] + b_o) \tag{2.3}$$

$$C`_t = \tanh(W_c[h_{t-1}, X(t)] + b_c) \tag{2.4}$$

$$C_t = F_t{*}C_{t-1} + I_t * C`_t \tag{2.5}$$

$$h_t = O_t * \tanh(C_t) \tag{2.6}$$

where X(t) is the input vector, h_{t-1} is the previous state hidden vector, W is the weight, b is the bias for each gate, Input gate I_t, Output gate O_t, Forget gate Ft, Candidate vector $C`_t$, Cell state C_t, and Hidden state h_t,. The basic structural representation of LSTM network is shown in Figure 2.1 below.

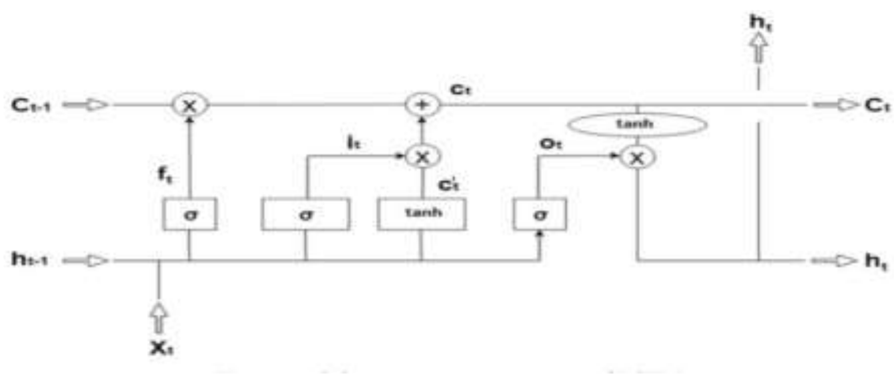

Figure 2. 1 Schematic representation of LSTM (Song *et al*., 2020).

2.2.4 Intensified Long Short-Term Memory

The real LSTM architecture includes sigmoid and tanh functions, as stated in the preceding section, however the activation functions utilized by LSTM raise a number of questions. To prevent the vanishing gradient problem, the gradient must be maintained at specified levels of back-propagation, allowing learning to continue with active neurons throughout the training period (Apaydin *et al*., 2020). Back-propagation gradient problems are addressed with sigmoid weighted linear units which multiply the input value to the sigmoid activation function. The memory space, also known as the cell state, is a region designed expressly for the storage of previous data. It functions similarly to how the human brain does while making choices. To update the prior cell state, the operation is performed. At this point, we remove the previous data and replace it with the new data (Apaydin et al., 2020; Szandaa, 2021).

Actual LSTM employs three sigmoid functions (forget gate, input gate, output gate) and two tanh functions (candidate vector and output gate) but multiplying the input value with the forget gate and output gate is ineffective because the forget gate decides whether to keep the current input or not, and the output gate yields the predicted value, which has already been processed using cell state information. As a result, the input gate and the candidate vector are clearly important in updating the cell state vector, from which the LSTM learns new information and analyses to forecast the output value based on the current input (Song *et al*, 2020; Poornima, 2019).

The input value is then multiplied by the sigmoid function in the input gate and the tanh function in the candidate vector (Apaydin *et al*., 2020; Murugan, 2018; Tomasi, 2012). It is evident that the intensified LSTM has a more complicated spatial structure. It works in the same way that the human brain does while making decisions. The operation is carried out in order to update the previous cell state (Brogärd & Song, 2020).

At this moment, we replace the outdated information with the freshest. However, multiplying the input value with the forget gate and output gate is ineffective because the forget gate decides whether to keep the current input or not, and the output gate yields the predicted value, which has already been processed using cell state information (Brogärd & Song, 2020). The actual LSTM uses three sigmoid functions (forget gate, input gate, and output gate) and two tanh functions (candidate vector and output gate).

To update the cell state vector, from which the LSTM learns new information and conducts analyses to predict the output value based on the current input, the input gate and candidate vector are therefore obviously crucial. The input value is multiplied with the sigmoid function in the input gate and the tanh function in the candidate vector based on this. Figure 2.2 shows the structural representation of the proposed Intensified LSTM. To capture the cyclical relationship between the input and hidden layer, LSTM has a more complicated structure. The same as with a conventional RNN, the output ht can be retrieved. The components of the Intensified LSTM are as follows:

• Input Gate "I_t" (with sigmoid activation function multiplied by the input);

• Forget Gate "F_t" (with sigmoid activation function);

• Candidate vector "C_t'" (with tanh activation function multiplied by the input);

• Output Gate "O_t" (with Softmax activation function);

• Hidden state "h_t" (hidden state vector);

• Memory state "C_t" (memory state vector).

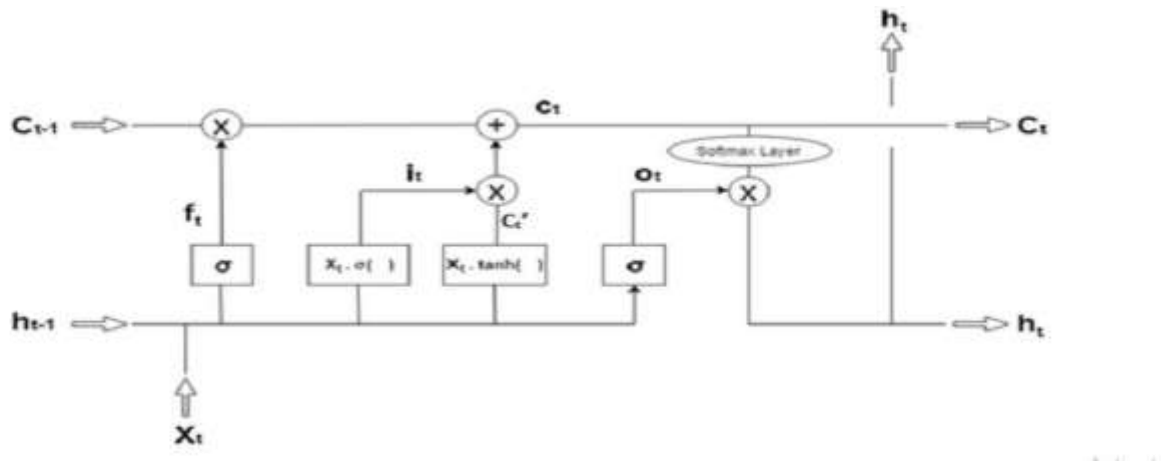

Figure 2. 2 Schematic representation of Intensified LSTM (Brogärd & Song, 2020).

All the gate inputs and layers inputs are initialized. X(t) (current input) is the input sent into the memory cell of LSTM, h_t (previous hidden state) and C_t (previous memory state). The layers are single-layered neural networks with the sigmoid function multiplied by input serving as the activation function in the input gate, the tanh function multiplied by input serving as the activation function for the candidate layer, the sigmoid function serving as the activation function for the forget gate, and the Softmax regression function serving as the activation function for computing the hidden state vector. With the help of the forget gate, the influence of current input over the previous state is analysed and decides whether the current input needs to be stored in cell state or not (data is stored through input and candidate vector). If not needed, then the sigmoid function produces 0, which deactivates the forget gate; if needed, it then produces 1 to activate the gate (Brogärd & Song, 2020; Poornima, 2019). Based on this decision, all the other gates in LSTM are activated or deactivated for certain input.

$$F_t = \{ \begin{matrix} 1 \; store\ the\ data \\ 0 \; discard\ the\ data \end{matrix} \quad (2.7)$$

When I_t is selected to keep the current input, the network compares I_t to the prior state to learn the new information carried over by the current input. The knowledge about all prior inputs and the accompanying change in output for various input vectors is stored in the previous state vector h_{t-1}. The input gate's sigmoid function is first processed resulting in a value between 0 and 1 that represents the range of new information accessible in the current input, and the obtained value is multiplied by the input value as follows: Now the range of value produced is [0, ∞] at the input gate, which in turn avoids the vanishing gradient for the same range of values in the input vector thereby empowering the network to learn from every input as shown in equation (2.8) (Cross *et al*., 1995).

$$I_t = X(t) \text{ x } \mathrm{sigmoid}(W_i[X(t), h_{t-1}] + b_i) \quad (2.8)$$

With respect to the candidate gate $C`_t$, tanh function is activated using the current input and previous hidden state, which produces a value between -1 and +1 that illustrates the contemporary data to be updated in the cell state vector. In order to improve learning to update the new information in the cell state vector for an even smaller change in time series, this obtained value is multiplied by the current input, producing a candidate vector falling between [-, +]. (Cross *et al*., 1995; Jurafsky & James, 2020).

$$C`_t = X(t) * \tanh(W_c[h_{t-1}, X(t) + b_c) \quad (2.9)$$

The aforementioned method has the benefit of self-stabilization, which lowers the rate of propagation, and the global minimum, where the derivative is zero, functions as a soft floor on the weights, which in turn acts as a regularizer indirectly limiting weight learning for large magnitudes. As a result, a gradient network that learns new information while minimizing data loss and network error is constantly present (Cross *et al*., 1995; Jurafsky & James, 2020).

Softmax regression computes the probability distribution of one event over n different events. The computed probability distribution can be used later for finding the target output for the inputs given. Outputs from the memory cell of LSTM are h_t (current hidden state) and C_t (current memory state). The mathematical formulae for the output gate and hidden state are given.

$$O_t = \text{softmax}(W_o[h_{t-1}, X(t)]+b_o) \tag{2.10}$$

$$h_t = O_t * \text{softmax}(C_t) \tag{2.11}$$

The output layers compute all the processed outputs and the iteration continues until the error value of the hidden value results to zero.

2.3 Related Works

In a survey conducted by Jadon *et al*., (2021), the challenges and techniques of time-series based forecasting in data centre telemetry were presented. It identified optimal prediction approaches, performance issues and recommendations for improvements while further work on hybrid models for telemetry data forecasting is advised. In a separate study by Bazionis & Georgilakis, (2021), it understudied the comparative models, methods and future research of wind power forecasting were understudied. The various deterministic and probabilistic approaches were comparatively analyzed and discussed. The review paper by Camporeale, (2019) 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 Aftab *et al*., (2018) carried out a systematic literature review on data mining based techniques for predicting rainfall, which is a component 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 Abdul-Kader *et al.,* (2020). There is need to explore computer-related approaches for predicting infectious illnesses using weather data.

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 learning and deep learning methods for weather forecasting was investigated by Tekin *et al*., (2021). A model was formulated based on Convolutional LSTM and Convolutional Neural Network unit encoder-decoder architecture. The outcomes showed improved performance for spatio-temporal weather datasets with minimal errors. There is need to urgently make efforts at improving classification models performances.

A NowDeepN model based on a supervised learning-regression method was proposed by Czibula *et al*., (2021). 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. There is need to increase speed and accuracy of forecasts by means of featuring and preprocessing generations.

An integrated modeling framework for predicting the performance of weather-induced delays of different transportation systems such as HSR and aviation was proposed by Chen *et al*., (2021). The authors 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 enhancing transportation system resilience to diverse severe weather-related disruptions through the understanding of the impact and its predictability of the system performance. There is a need to urgently make efforts at improving classification model performances Chen *et al*., (2021).

Gad & Hosahalli, (2020) proposed K-Nearest Neighours model and Support Vector Machine in the study of National Climate Data Centre (NCDC) weather classification accuracy with the study limited to identifying forecasting ineffectiveness and suggesting future work in multiplicity of weather data to improve weather forecasting accuracy. There is need for the adoption of weather forecasting components into the renewable energy forecasting applications or systems.

The study by Bazionis & Georgilakis, (2021) used deterministic forecasting models, probabilistic forecasting models and statistical models with Artificial Intelligence in the field of wind power forecasting and some limitations of the study include uncertainty in behaviours, instability of energy operations, inaccuracy of forecasting models, instability of energy systems performance large errors of forecasting models while the suggestion future work to evolve accurate forecasting models for energy industry. There is need to urgently make efforts at improving classification models performances.

In Hosseini *et al*., (2020) a random forest regression and K-nearest-neighbour models were used in predicting the effect of climate change on building energy efficiency. The study found negative impact of climate change on the environment and extreme weather conditions on building energy efficiency while suggesting future works to generate future weather data for different scenarios of climate change on yearly basis. There is need to emulate parameterization technique with neural networks.

In the study carried out by Ahmed *et al*., (2020), convolutional neural networks and an online sequential extreme learning machine were used to predict solar energy efficiency with climate change some limitations of the study include inclusion of photovoltaics in power grids are inefficient due to solar energy, climate change conditions impact on the photovoltaic outputs and insufficient utilities planning. There is need to urgently make efforts at improving classification models performances.

Coulibaly *et al*., (2020) used K-nearest-neighbour, Auto-Regression Integrated Moving Average (ARIMA) in weather data forecasts. The limitations of the study shows threats from climate change, inappropriate forecasts, inappropriate rule-based machine learning knowledge discoveries and advices more research to incorporate uncertainty management and improve minimal simulation errors.

Back-propagation neural network in temperature weather forecasting in Baboo & Shereef (2010) Massive computations, imprecise numerical models, and data links are some of the study's flaws and restrictions. The incorporation of weather forecasting elements into applications or systems for forecasting renewable energy.

Sokolov *et al*., (2020) carried out a study using LSTM neural network architecture in cloud-based weather data processing and storage. The study lack of precise method of data gathering, lack of visualization of processed data, low automation of processes, storage difficulty and inaccurate forecasts. They is need to extend subsequent LSTM models for soil parameter acquisition and to utilize open-source dataset for training of models.

In a survey by Nkambule *et al.*, (2020) the challenges and techniques of PV System performance with varied weather conditions were presented. It identified the Weighted K-nearest neighbour (WK-NN) and linear discriminant with difficulties as low performances of models while future work was recommended to reduce the training errors of models especially in WK-NN.

In a separate study by Salvador, *et al.* (2020) it understudied synoptic meteorological patterns in air quality synoptic classification. The limitations of the study includes instability of atmospheric processes and heterogeneous classification models are implausible. There is need for further work to explore other forms of analysis of atmospheric sciences such as particle formation or air quality.

Nguyen *et al*., (2020) used LSTM neural networks in classification of metamodels (or environmental modelling) with the model susceptible to errors and tedious classification procedures. There is need for further study to explore transfer learning for pre-trained weight for performance improvement and also to empower capability of classification algorithms with larger datasets.

Zhang *et al*., (2020) used deep learning models in the study of Structural health monitoring due to harsh environmental conditions. The challenge encountered by the study include difficulty to identify biased patterns against intact condition, harsh environment factors, large vibrations and dependence of time series datasets. They suggest further research on time series classification with deep learning models (LSTM-FCN) for real-time warning systems. There is need to increase speed and accuracy of forecasts by means of featuring and preprocessing generations.

In another study by Abdul-Kader, *et al.,* (2020) using Particle Swarm Optimization (PSO) and Feed-Forward Neural Networks in Rainfall forecasting models. The limitations of the study are inaccurate prediction models, slow training procedure, uncertain weights parameters, large errors and uncertainty and inter-dependence of weather events. There is need for future work to optimize the weights of training networks for ANN.

In addition, Leiva *et al.,* (2020) carried a study on time series modelling for mortality using Birnbaum-Saunders Autoregressive Moving Average (BARMA) Model and Auto-Regressive Moving Average (ARMA) Time Series Model. Some limitations of the study included non-negative and asymmetric data modelling, parameters estimation, Real-world data analysis and accuracy of forecasting models while suggesting further works to understudy the adequacy of generalized Cox-Snell residual in complex models.

In a survey carried out by Prasad *et al*., (2014), they used Medium rage weather forecasting model in global data assimilation forecasting system weather forecasting. While the study lacked of real-time supports, accuracy, over reliance on Numerical Weather Prediction (NWP) centres while suggesting future work to develop real-time assimilation of satellite data for weather forecasting. The concept of smart weather reporting systems can be investigated.

Similarly, Balsamo *et al*., (2012) carried out a study on lake surface temperature using global weather forecasting model. The study had no considerations of lakes data for weather forecasting and the use of NWP schemes encountering various inaccuracy. There is need to empower capability of classification algorithms with larger datasets.

Sharma & Datta, (2007) used images and adaptive forecasting model for weather forecasting. The constraints of the study include poor accuracy, numerous weather parameters, information extraction is complex while suggesting future research to consider more weather parameters for improved forecasting. There is need to empower capability of classification algorithms with larger datasets.

In a research by Lee & Liu, (2004) using intelligent java agent development environment in weather forecasting, some shortfall of the research include unbiased dataset is unsuitable, low accuracy. They suggested subsequent research to introduce monograph of the agent-based technology for weather prediction. The concept of smart weather reporting systems can be investigated.

Uno *et al*., (2003) carried out a study in Chemical Weather Forecast System using Surface observations and multitracers. The study was inflexible, no interpretation, lack of accuracy.

Qian, *et al.,* (2020) used ensemble models, full-field version models and Numerical Weather Prediction Model in weather forecasting and analysis. Limitations and shortfall of the study are diversity of weather events, uncertainty, integration of subsystems, accuracy of outcomes while there is need to utilize in real-world full meteorological understanding and interpretation.

Ordinary linear regression and bayesian belief networks was used in a study by Panidhapu, *et al.,* (2019) in water quality through water pathogen monitoring best on weather prediction. Some of the challenges in the sturdy include delays and time lags, interactions of various variables and poor modelling approaches. There is need for further work to include site-specific models and land use into predicting models of weather-based water quality.

Similarly, a Non-linear regression methods and support vector regression was employed in weather forecasting techniques with lesser prediction accuracy, longer period of time, unpredictive and chaotic nature, large computations (Pooja & Balan, 2019). The weather classification models of K-Means, Adaptive Boosting and Random Forest can be investigated.

Oluwafemi & Zenghui, (2019) proposed SAID model, Native Bayes, Random Forest in Image based weather classification. The limitations of the work are high cost of approach, bad weather, low performances, data extraction difficulty, weak classification, low accuracy. Future work was recommended to improve forecasts performance using tuning models and also explore computer vision in weather forecasts. The concept of smart weather reporting systems can be investigated.

Also, in a related work by Findawati *et al.,* (2019) a Naïve Bayes was used in the work titled weather forecasts methods. Shortcoming of the work are classification accuracy and reliance on meteorological information with interdependency of other fields and low performance effectiveness. To improve the accuracy of forecasts provided by classification algorithms was suggested by the authors. There is need to urgently make efforts at improving classification models performances.

The study by Kwon *et al.*, (2019) in Solar Irradiance forecast with weather variables uses ARIMA, Native Bayes as its method. The study had uncertain weather conditions with large forecasts errors, low accuracy and low forecast speed which are time inefficient. It recommended to improve the time for training and input value learning.

In the work on weather data analytics, a Classification Tree, Naïve Bayes and KNN model was used. The work had deficient methods, lacked performance accuracy and inability to ascertain association within data attributes. Future work was encouraged to increase the dataset dimensions and ranges and also to improve the accuracy of models Prasetya & Ridwan, (2019).

Wang *et al.*, (2018), similarly engaged K-nearest neighbor, support vector machine in power forecasting with weather classification. Limitations of the research are classification accuracy, large dataset, uncertainty of weather, negative impact on renewable energy supply, high dimensional data training difficulty and low performance. There is need to for further work in weather classification models of K-means, Adaptive Boosting, and Random Forest and also to evaluate other machine learning classification models.

The work in Keswani *et al.*, (2018) made use of Fuzzy logic system, micro controller and neural networks in weather conditions for smart irrigation with low accuracy, difficulties in data collection, high cost implications and low classification performance. The work suggested further work to extend model to include other machine algorithms for weather forecasting applications.

Mukherjee *et al.,* (2018) worked on Weather-induced power outages using Random Forest model and support vector machine. The limitations and shortcomings of the study are not limited to economic disruptions due adverse weather, infrastructural damages, and lack of reliable forecasting models. Future work on the field was recommended to further assess the level of weather-related power outages and also to provide decision support models for building resilience systems.

In Cheng, *et al.*, (2017) a Data assimilation/weather forecasting system model was used in the research work tittle wind turbine anemometer measurement assimilation. The problems identified in the work are short-term wind forecast, no initial conditions, inaccurate wind prediction, and no reliance on NWP approaches. It was suggested future investigation be carried out to increase the accuracy of short-term wind forecasts.

A method for design of cloud-based systems for storing and processing of sensor data from weather stations using internet of things (IoT) devices to capture data of local atmospheric parameters was proposed by (Sokolov *et al*., 2020). 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. There is need for flexibility and effectiveness of operational forecasting performance using reliable and empirical relations.

2.3.1 Trends in Weather Forecasting

This subsection analyses the distribution of studies reviewed in this thesis in terms of year of publication, domain of study, challenges, forecasting techniques, limitations and shortcomings of the studies is presented in Table 2.1.

Table 2. 1: The distribution of included studies for the Systematic Literature Review (SLR)

S/N	Author(s)	Year of publication	Techniques used	Domain of study	Problems identified	Research gaps
1.	Hochman *et al*.,	2021	-Stepwise Multiple regression models. -Weather regime approach. -Correlation coefficient models.	Weather related seasonal diseases.	-Climate change impacts on diseases spread. -Low accuracy of prediction models. -Traditional data gathering is effective.	-To explore computer-based approaches for forecasting infectious disease using weather data.
2.	Gupta *et al*.,	2021	-Natural Processing Language. -Machine learning classification. -K-means. -SVM.	Weather and COVID-19 pandemic reduction.	-Influenza seasonality. -Uncertainty in weather dynamics. -Impact on disease spread. -Inaccuracy of claims and methods of estimation.	-To improve on the accuracy effect classifier to recognize more nuances languages such as tones and sarcasm.
3.	Chen, *et al*.,	2021	-Bayesian network. -SVM. -Ensemble. -Decision Tree. -Linear Regression.	Weather-induced delays in transportation sector.	-Lack of reliability in schedules. -Uncertainty in weather information. -Low system performance. -Low accuracy and robustness of predictive models. -Severe weather conditions.	-To enhance the applicability and predictability of model real-world environment.
4.	Czibula, *et al*.,	2021	-Deep Neural Networks. -CNN model. -SVM. -MAR-CNN.	Weather and Radar products' values forecasting.	-Slow process. -Inaccuracy of forecasting models. -Low performance of models/systems. -Poor preparation of disasters.	-To examine CNN models and supervised classifiers-based on relational association rule mining.
5.	Dutta *et al* .,	2021	-Fuzzy logic identification. -Wind Turbine Clutter (WTC). -General Likelihood Ratio Test (GLRT).	Weather information systems.	-Clutter suppression. -Signal subspace estimation. -Low performance. -Low accuracy of models.	-To improve detection of weather accuracy.
6.	Ali *et al*.,	2021	-BERT. -ANN. -Decision Tree. -Naïve Bayes Multinominal. -K-Nearest Neighour.	Deep learning classification of multi-events.	-Classification accuracy. -Non-existent processing resources. -Unavailability of datasets/resources. -Conversion of text to numeric values. -Knowledge extraction from sentences.	-To ascertain event classification performance on balance datasets. -To improve accuracy of performance in classification models.

7.	Mazzarella *et al*.,	2021	-3D/4D Var- variational assimilation methods. -Weather Research and Forecasting Model. -Time series for precipitation.	Weather Radar Reflectivity with 3D/4D.	-Precipitation predication difficulty. -Severe weather events. -Inaccurate numerical weather prediction. -Huge cost of computation. -Low performance. -Uncertain sources of datasets. -Radar errors.	-To improve reliability of the precipitation prediction.
8.	Chen,	2021	-CNN. -Joint Damage Scale. -Residue neural network (ResNet). -Deep neural networks.	Building damage classification.	-Lack of infrastructure damage models. -Inaccurate prediction models. -Computational complexity. -Training difficulty.	-To extend work to helping increasing humanitarian crisis and climate change phenomenon. -To experiment gradient class activation maps for the models in prior and post disaster images.
9.	Chinchawade & Lamba	2021	-Automation with Internet of Everything. -Smart monitoring system.	Secure weather reporting system.	-Insecurity. -Data collection difficulty. -Weather conditions and parameters monitoring remotely. -Interpretation and broadcasts.	-To explore the concept of smart weather reporting systems.
10.	Astakhova *et al*.,	2021	-Ensemble prediction system. -Numerical weather prediction.	Weather forecasting effectiveness with ensemble.	-Chaotic nature of atmosphere. -Poor forecasts outcomes. -Large uncertainty. -Time ineffective models. -Large errors related to instabilities. -Unreliability.	-To expand the scope of spatial verification of mesoscale ensemble prediction system for weather.
11.	Ganai *et al*.,	2021	-T382164 model. -Integrated Forecast System. -Numerical weather prediction.	Operational weather prediction.	-Low performance. -Longer time constraint. -Uncertainty. -Inaccurate spatial-temporal simulation results. -Extreme weather conditions.	-To increase the accuracy of heavy rainfalls with additional conversion parameters models.

12.	Javanshiri, *et al.*,	2021	-Numerical weather prediction models. -Ensemble model output statistics (EMOS). -Bayesian model averaging (BMA). -Weather and Research Forecasting (WRF) model.	Precipitation forecasting effectiveness.	-Lagging accuracy of numeral approaches. -Large mathematical procedures. -Less accurate data collection devices. -Performance of forecasting models are still poor. -Classification of events and non-events.	-To examine modern post-processing techniques such as machine learning, neural networks for better flexibility and effectiveness.
13.	Dhib *et al.*,	2021	-Statistical coefficient. -Weather and Research Forecasting model.	Weather-based downscaling events.	-Uncertainty determination. -Inaccuracy of models. -Existing models rely on startup datasets. -Output reliability and verification. -Performance depreciations.	-To adopt ensemble approaches for improved outcomes for WRF model. -To ascertain the sensitivity of parameters in WRF modeling.
14.	Nugroho *et al.*,	2021	-Seasonal Autoregressive Integrated Moving Average (SARIMA). -Statistical models.	Weather forecasting for precision agriculture management.	-Daily environment parameters determination. -Extreme weather patterns. -Large uncertainties in agricultural applications and systems. -Remote monitoring of parameters. -Less accuracy of forecasting models.	-To minimize errors and increase acceptable accuracy of novel hourly forecasting models.
15.	Narechania, *et al.*,	2021	-Numerical solution approaches. -MHD model.	Space weather forecasting.	-Adverse impact of weather on well-being of humans. -Lack of sufficient warning systems. -Lack of information concerning environmental conditions. -Low accuracy. -Data collection complexities.	-To improve the operational forecasting performance with reliable data and empirical relations.

16.	Jadon, *et al.*,	2021	-State Space Models (SSM): ARIMA. -Deep learning approaches: LSTM, RNN. -Exponential Weighted Moving Average. -Generalized Autoregressive Conditonal Heteroskedastic Model. -Seasonal Trend Decomposition Predictor. -Probabilistic Models: Hidden Markov Models.	Weather data forecasting.	-Accuracy of telemetry data forecasting. -Low performance. -Interpretation and analysis of data. -High efforts required during interpretation. -Large datasets. -Numerous data dimensions.	-To experiment hybrid models for telemetry data forecasting. -To adopt deep neural networks for computationally capable systems.
17.	Schulz *et al*.,	2021	-Statistical methods. -Numerical Weather Prediction. -Ensemble forecasting models. -Probabilistic prediction models.	Weather prediction based on numerical data.	-Systematic biases of outcomes. -Uncertainty. -Diverse conditions considerations. -Inaccuracies are large. -Inconsistencies. -Extended training periods of models.	-To build weather forecasting component into renewable energy forecasting applications or systems.

From Table 2.1, the rate of publication on the weather forecasting for the selected studies revealed upward spike in research works over the period of 2018-2021 as shown in Figure 2.1. The reason for this can be strongly associated with relevance of weather to diverse area of endeavours such as power supply, agriculture, irrigation, disease controls, building and critical infrastructures.

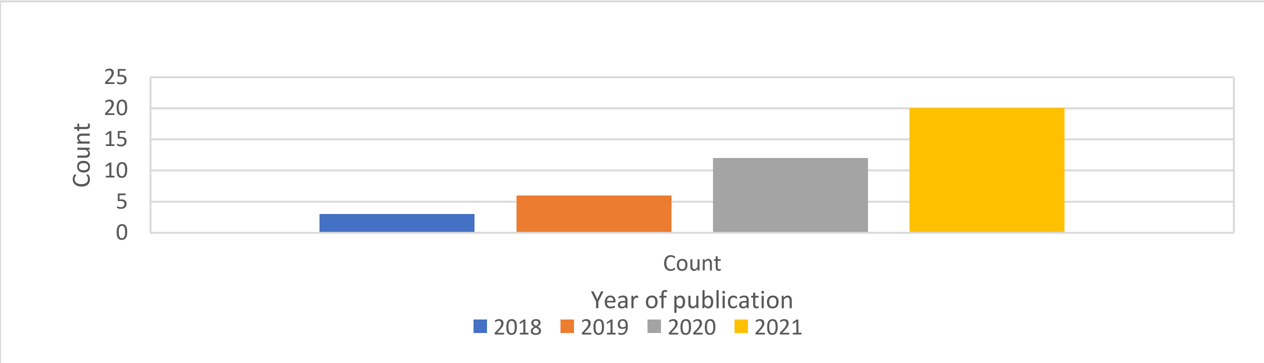

Figure 2. 3: The rate of research works in weather forecasting

Similarly, the research interests of authors for the selected studies are presented in Figure 2.1. This shows that majority of studies focus on ways weather forecasting support decisions making processes or systems, followed by weather and climate information system with the least interest being transportation. In particular, weather forecasting researches are greatly beneficial for precipitation estimation, agriculture, transportation, structural resilience, power generation systems, weather and climate information systems, decision support systems, and diseases controls.

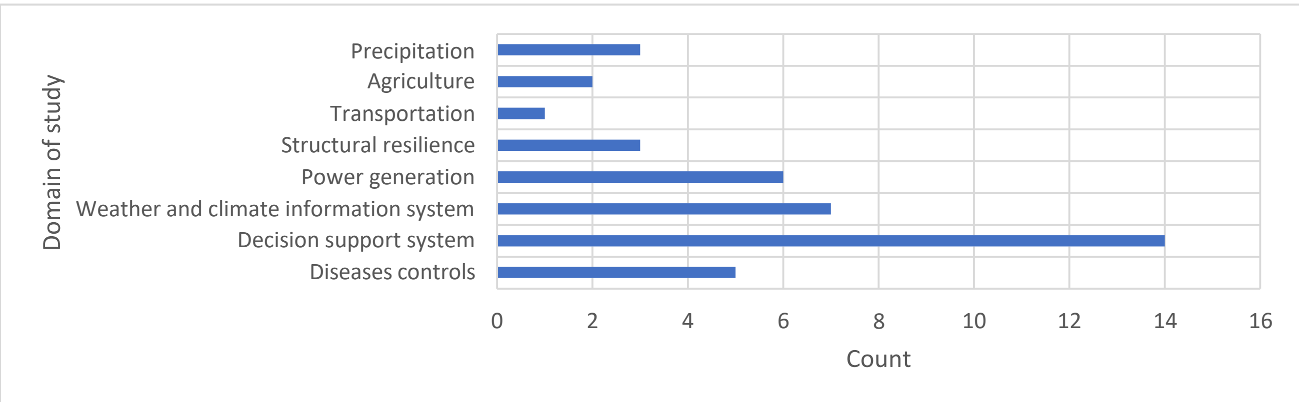

Figure 2. 4: Distribution of research interests of selected studies

2.4 Weather Forecasting Techniques

The processes of weather forecasting have employed diverse techniques, models and methods as identified by selected studies. These techniques, methods and models of weather forecasting can be classified into two including traditional and contemporary approaches.

i. Traditional approaches

From Table 2.1, weather forecasting approaches are summarized into Statistical methods such as: Linear Regression models, Correlation coefficient models, Stepwise multiple regression models, Time Series for Precipitation, Numerical weather prediction, Bayesian Model Averaging, Seasonal Autoregressive Integrated Moving Average, Multivariate Linear Regression, Ordinary linear regression, Non-linear regression, Linear discriminant analysis.

ii. Contemporary approaches:

From Table 2.1, weather forecasting approaches are summarized into Machine learning methods, examples are: Convolutional Neural Network (CNN), Support Vector Machine (SVM), Decision Tree, Ensemble, Bayesian network, K-Means, K-Nearest Neighbor (K-NN) K-NN, Random Forest, Recurrent Neural Network (RNN), Deep Learning Neural Network DNN, Baie Bayes Multinominal, Fuzzy Logic Identification, Convolutional Long Short-Term Memory (LSTM), U-Net, Artificial Neural Network (ANN), particle Swarm optimization (PSO), Weighted K-Nearest Neighbour, Natural processing language, Smart monitoring system and Internet of Things (IoT).

CHAPTER THREE

3.0 RESEARCH METHODOLOGY

3.1 Research Design

The research methodology consists of three phases: Preparing time series data, optimizing the predictive model, and applying the predictive model (Zain *et al.*, 2021). The first phase "Preparing time series data" consists of normalizing time series data, and splitting the time series data into training and testing datasets. The second phase "Optimizing the predictive models" consists of three steps: Optimize the model, train the model, and evaluate the model. The model were optimized to get the best hyperparameters. The total time series data set is 1826 columns and 2 rows, of which starts on 1st January 2015 to 30th December, 2019 for a period of 5 years for each of the weather parameter. The models were then trained using the best hyperparameters on the training dataset. The trained models were then evaluated on the test dataset, the forecasting was estimated and compared with the real values. The third stage "Applying the predictive models" entails applying the model to historical multivariate weather data (Pidwirny, 2008). Figure 3.1 shows the research methodology embarked upon in this thesis.

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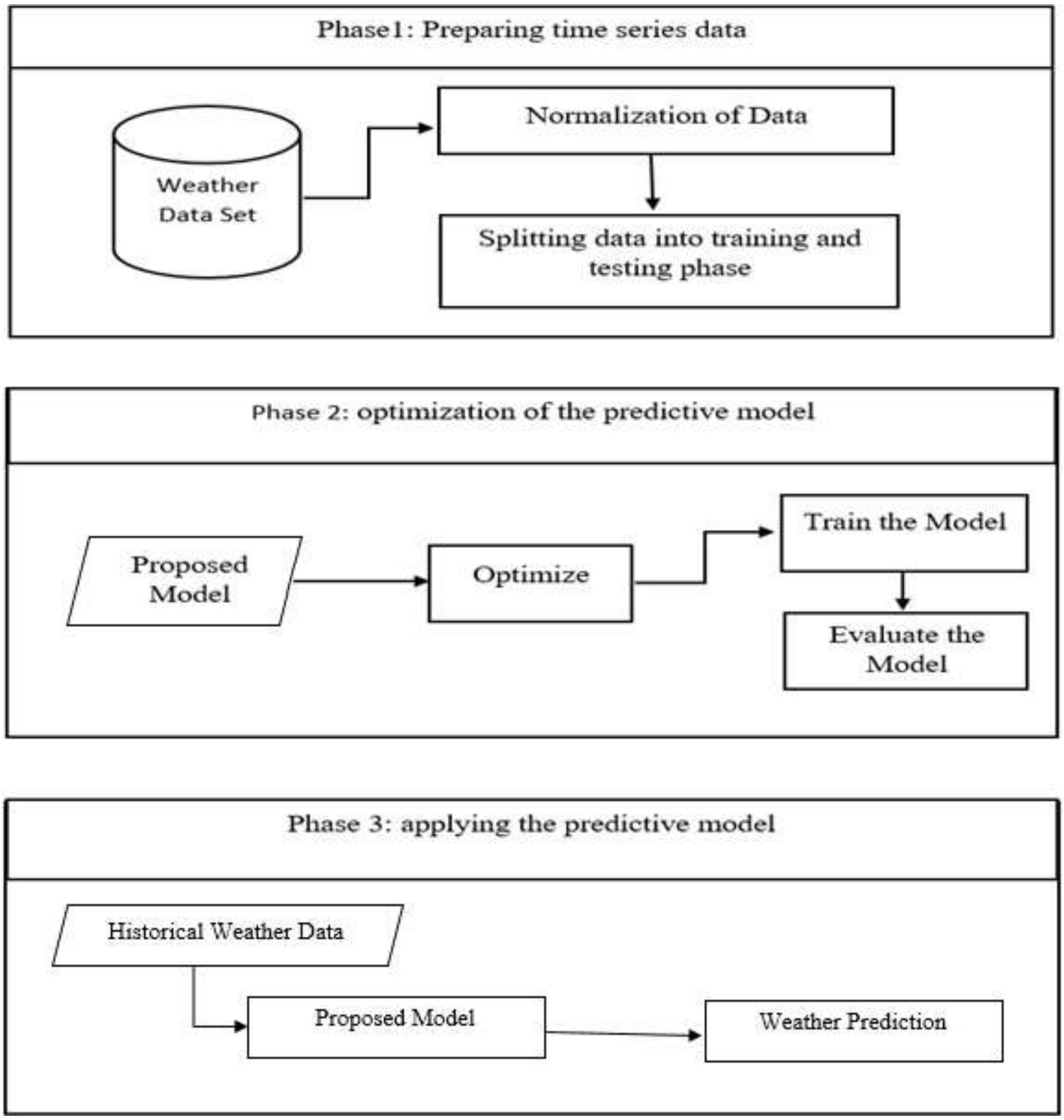

Figure 3. 1: Illustration of the Research Methodology.

From Figure 3.1, the different phrases in the research method and their relationship are shown. From the collection and preparation of the daily multivariate time series weather data consisting of each of temperature, pressure, relative humidity, wind speed, Dew Point, and Rainfall to optimization of the predictive model and them the application of the model.

Figure 3.2 shows the flowchart for the research process.

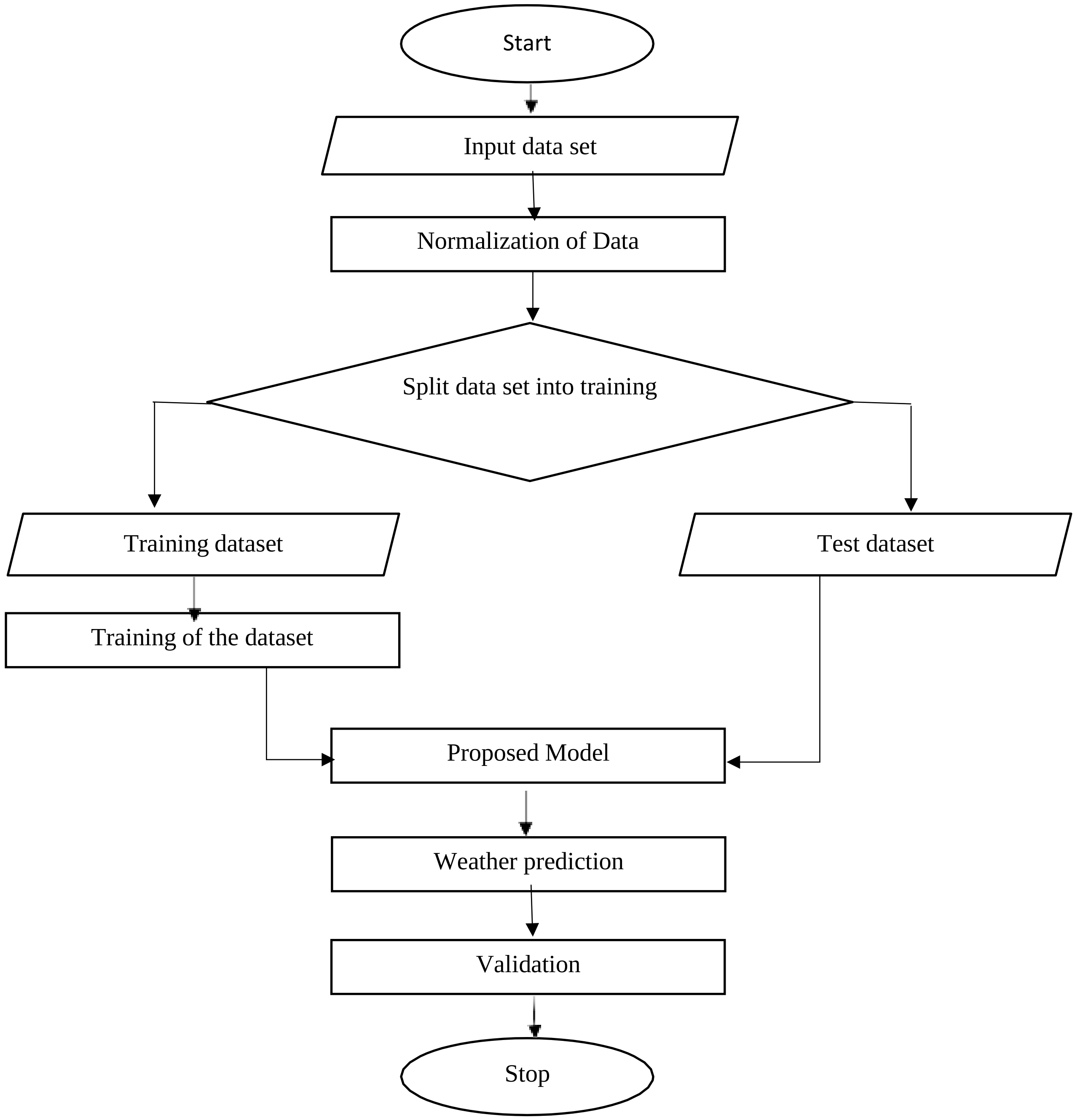

Figure 3. 2: Flowchart for the LSTM Model

From the Figure 3.2, the study procedure begins with data collection, which is then pre-processed by partitioning multivariate meteorological data into training and validation/testing sets, and then used as input to the Long Short-Term Memory Neural Network (LSTM). With the development of prediction output, the model is trained and validated.

3.2 LSTM Weather Forecasting Algorithm

The series of steps to be undertaken by this thesis in developing proposed weather model include the following algorithm:

Input: Historical daily weather data

Output: Weather prediction data

Step 0: Start

Step 1: Data Preparation

Weather Dataset are collected on daily basis for a specific weather stations, regions/states across Nigeria in which weather conditions vary depending upon the regions. The parameters collected are Temperature, Pressure, Relative Humidity, Wind Speed, Dew point and Rainfall in form of Microsoft Excel file format.

The algorithm for preparation of the multivariate weather data set is shown below

Step 1.1: Start

Step 1.2: Convert dataset into time series.

Step 1.3: Normalize time series data: The time-series data from the selected weather stations (Bauchi, Minna, Calabar and Ikeja) were normalized using min–max normalization within the range [0, 1].

Step 1.4: Split time series data sequentially, to prepare the time series for model development, 1826 columns and 2 rows of the normalized time series data were divided into 70 % training and 30% testing

Step 1.5: End.

Step 2: Create the Architecture for our LSTM model

Step 3: Train the Model

Now that we have defined our model, we can finally move on with training it on our sequence data. We can subdivide the training process into smaller steps, namely:

Step 3.0: Start

Step 3.1 : Check the loss on training data

Step 3.1.1 : Forward Pass

Step 3.1.2 : Calculate Error

Step 3.2 : Check the loss on validation data

Step 3.2.1 : Forward Pass

Step 3.2.2 : Calculate Error

Step 3.3 : Start actual training

Step 3.3.1 : Forward Pass

Step 3.3.2 : Backpropagate Error

Step 3.3.3 : Update weights

Step 3.4: Stop

We need to repeat these steps until convergence. If the model starts to overfit, stop! Or simply pre-define the number of epochs.

Step 3.1: Check the loss on training data

To determine the loss value, we will do a forward pass over our LSTM model and calculate the squared error for all predictions.

Step 3.2: Check the loss on validation data

The loss on validation data will be calculated in the same way.

Step 3.3: Start actual training

We'll now get down to business with the network's actual training. We'll execute a forward pass to calculate the errors and then a backward pass to calculate and update the gradients.

Step 3.3.1: Forward Pass

We start by multiplying the input by the weights shared by the input and hidden layers. Combine this with the weight multiplication in the LSTM - RNN layer. This is because we want to keep track of the preceding timestep information. Use a sigmoid activation function to activate it. This is multiplied by the weights of the hidden and output layers. We have a linear activation of the values at the output layer, thus we don't need to transmit the value via an activation layer directly. In a dictionary, save the current layer's state as well as the state from the previous timestep (Faizan, 2019).

Step 3.3.2: Backpropagate Error

After the forward propagation step, we calculate the gradients at each layer, and backpropagate the errors. We will use truncated back propagation through time (TBPTT), instead of vanilla backprop. It may sound complex but it is actually pretty straight forward. The core difference in BPTT versus backprop is that the backpropagation step is done for all the time steps in the RNN layer (Faizan, 2019).

Step 3.3.3: Update weights

Lastly, we update the weights with the gradients of weights calculated. One thing we have to keep in mind that the gradients tend to explode if you don’t keep them in check.

This is a fundamental issue in training neural networks, called the exploding gradient problem. So we have to clamp them in a range so that they don't explode (Faizan, 2019).

Step 4: Use the output of the last layer as prediction of the next time step.

Step 5: Repeat steps 4 and 5 until optimal convergence is reached.

Step 6: Obtain predictions by providing test data as input to the model.

Step 7: Evaluate accuracy by comparing predictions made with actual data.

Step 8: End

3.3 The Long Short-Term Memory Weather Forecasting Model

In this thesis, the developed weather forecasting model is trained primarily using the Long Short-Term Memory (LSTM) Neural Network. To effectively categorize or predict using LSTM, weather data like 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 millimeter) are required. 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.

The forecasting model used in this study was fine-tuned based on the selected hyperparameters under various prediction criteria using the Adam framework to optimize the hyperparameters for the model, because selecting the best and most accurate forecasting model for weather forecasting is a very complicated process.

Hyperparameter optimization is the study of tweaking or selecting the best collection of hyperparameters for a learning system. The output of any deep-learning algorithm is greatly impacted by a set of ideal hyperparameters. It is one of the most time-consuming, but also one of the most critical, processes in the deep-learning training pipeline.

3.3.1 Training and Forecasting

A series of input/output training pairs is required to tune the weights of a neural network. The inputs are fed into the network, and a loss function is used to quantify the difference between the expected and received outputs (Higham & Higham, 2019). The error is then backpropagated through the model, with the weights being updated using a gradient descent algorithm.

LSTM was proposed for language models where the length l and the dimension d of the sequence of inputs and outputs is pre-determined (for example, when training on subsequences of l = 5 consecutive characters of English text with d = 26 letters). By contrast, for time series forecasting, the training set is constructed from a single time series $T = [t_1, t_2, \ldots, t_N]$ and there are no canonical lengths of the input and output sequences (Makridakis, 2019).

3.3.2 Feeding data to the LSTM

We want to train a recurrent model on input sequences of length l, say input = $(x^{(1)}, x^{(2)}, \ldots, x^{(l)})$. For simplicity of presentation, suppose that l = 3, and we want an output sequence of length one. The model is recurrent and so the function S is applied three times (Schmidhuber *et al.,* 2005). We can think of this procedure as a model M such that

$$(H^{(3)}, C^{(3)}) = M(H^{(0)}, C^{(0)}, \text{input}) \tag{3.1}$$

$$= S(S(S(H^{(0)}, C^{(0)}, x^{(1)}), x^{(2)}), x^{(3)}). \tag{3.2}$$

Figure 3.3 illustrates how the states and input sequence are fed into the function *M* with respect to the function *S*. Note that the weights inside *S* remain fixed when evaluating *M*.

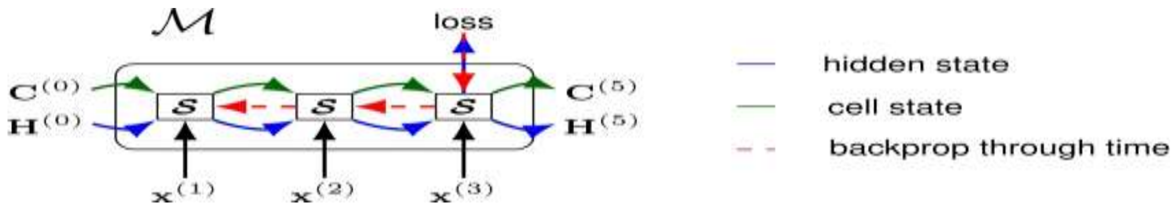

Figure 3. 3: illustration of the training procedure for LSTM network (Schmidhuber *et al*., 2005)

From figure 3.3 the training procedure for an LSTM network with sequences of length $l = 3$. The function *M* takes in the initial states and the input = ($x^{(1)}$, $x^{(2)}$, $x^{(3)}$). The first two outputs of the stacked LSTM are ignored. The blue lines show the path of the hidden state and the green lines show the path of the cell state. The red dashed lines show the route taken during the back-propagation to update the weights inside *S*. The weights inside *S* receive three additive updates (Schmidhuber *et al.*, 2005).

During backpropagation, each weight in the hidden layer S of the model receives *l* additive updates, one corresponding to each time element in the input sequence. The length of the input sequence *l*, often referred to as the lag parameter, plays a critical role in defining the function *M*. In time series forecasting, we want the model to have access to as many historical observations as possible. Any memory about the time series prior to the input, $input_i = (t_i, t_i+1, t_i+2, t_i+3, t_i+4)$, must come from the cell state and the hidden state (Hyndman & Billah, 2003).

3.3.3 Producing Forecast

After the recurrent model, say *F*, has been trained, we would like to produce out-of-sample multi-step time series forecasts. In other words, given the time series T = [$t_1, t_2, . . . , t_N$], we would like to forecast *k* time points into the future to obtain $\hat{t}_{N+1}, \hat{t}_{N+2}, . . . , \hat{t}_{N+k}$. to produce the *k*-step forecasts is given as (Makridakis, 2019; Atiya, *et al*., 1999).

Train k 'many-to-one' functions $F_1, \ldots, F_k$ such that

$$t_{i+l} \approx F_1(t_i, \ldots, t_{i+l-1}) \tag{3.3}$$

$$t_{i+l+1} \approx F_2(t_i, \ldots, t_{i+l-1}) \tag{3.4}$$

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$$t_{i+l+k-1} \approx F_k(t_i, \ldots, t_{i+l-1}) \tag{3.5}$$

for $i = 1, 2, \ldots, N - l - k + 1$. This also requires a priori choice of the value k. A k-step forecast can be made by evaluating $F_1, \ldots, F_k$ at $(t_{N-l+1}, \ldots, t_{N-1}, t_N)$ (Atiya *et al*., 1999).

The architecture for the forecasting model using the Long Short-Term Memory (LSTM) based on recurrent neural network-based LSTM is shown in Figure 3.4

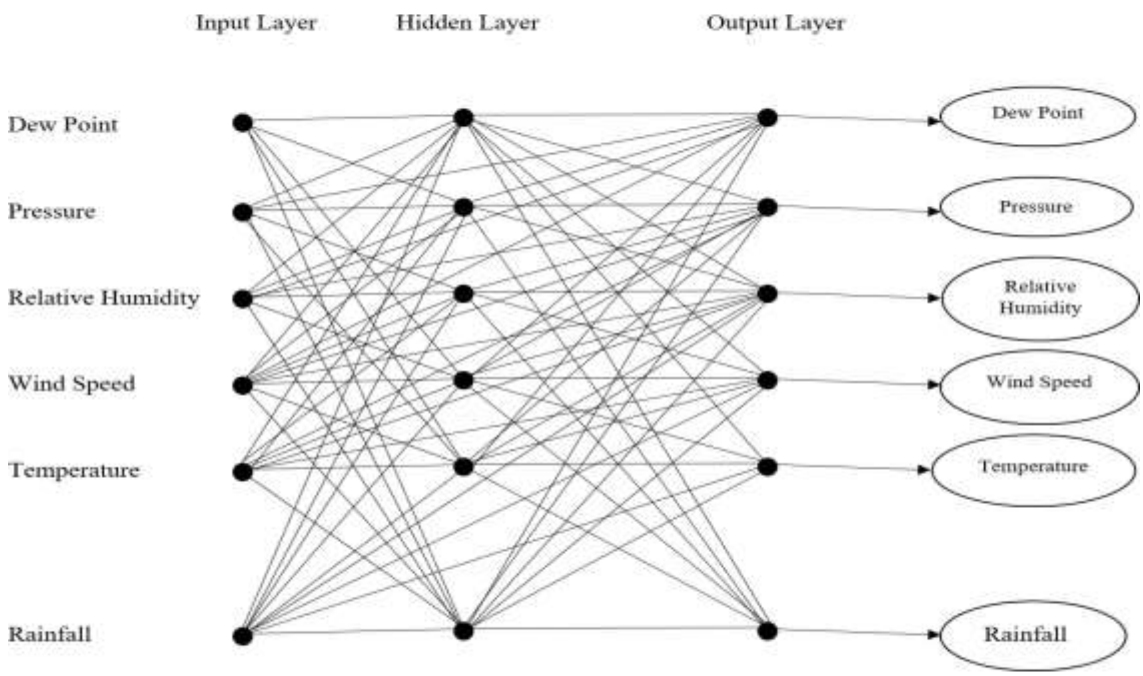

Figure 3. 4: Neural Network Architecture for LSTM model

3.4 Description of Dataset

This thesis primarily relied on secondary data obtained from Nigeria Meteorological Agency (NiMet), Abuja and Era Interim. These include: Air Temperature, Pressure (In Hectopascal, HPa = 100 Pa), Rainfall (In Millimetres), Wind Speed, Relative Humidity, and Dew point. The data comprises of daily weather reports recorded from 1st January, 2015 to 30th December, 2019 for the selected parameters. The entire dataset 1826 columns and 2 rows for each of the temperature, pressure, dew point, relative humidity, wind speed, and rainfall. Thereafter, the data divided into training and testing datasets on the ratio of 70% to 30%, that is, 1278 colums and 2 rows to 548 columns and 2 rows respectively. These attributes are the given information to the recurrent neural network and trained using LSTM algorithm. The Table 3.1 shows a section of the dataset from the original source data presented in Appendix.

Table 3.1: Sample data.

Date	**Dew (Oc)**	**Pressure (hPa)**	**Humidity (%)**	**Temp (oC)**	**WindSpeed (M/S)**	**Rainfall (mm)**
1-Feb-15	24.97	1010	92.36	34.66	4.839	4
2-Feb-15	25.48	1008	92.09	34.97	4.608	0
3-Feb-15	25.27	1008	92.01	34.96	5.576	2
4-Feb-15	25.36	1009	92.4	34.92	4.813	2
5-Feb-15	25.31	1008	91.65	35.01	5.077	1
6-Feb-15	25.42	1008	91.3	35.09	5.124	1
7-Feb-15	25.11	1008	90.41	35.07	4.696	4
8-Feb-15	25.18	1008	89.74	35.14	5.422	1

3.5 LSTM Model Setup

Google Colaboratory, sometimes known as "Google Colab" or just "Colab," is a Google Research tool that allows developers to write and run Python code directly in their browser. For deep learning tasks, Google Colab is a good tool Ganai *et al*., (2021).

In only a few lines of code, Colab allows you to import an image dataset, train an image classifier on it, and assess the model, as well as use the full power of popular Python packages to analyze and visualize data.

Colab notebooks executes code on Google's cloud servers, allowing you to tap into the power of Google hardware, such as Graphical Processing Unit (GPUs) and Tensor Processing Units (TPUs), regardless of your machine's capabilities. All you need is a browser to get started. Colab notebooks let you blend executable code and rich text, as well as graphics, HTML, LaTeX, and more, in a single document. Your Colab notebooks are saved in your Google Drive account when you create them (Orhan, 2020).

Colab is used extensively in the machine learning community with applications including: Getting started with TensorFlow, Developing and training neural networks, experimenting with TPUs, disseminating AI research Schulz *et al*., (2021).

The minimal hardware and software requirements for the experimenting concept of weather prediction system-based LSTM model are presented in Table 3.2.

Table 3.2: Minimal experimental parameters.

System Requirements	Attributes
Hardware	Samsung Computer System
Solid State Drive	140 GB
RAM	12.0 GB
Processor	GPU
Speed	HD Graphics 2.40 GHz
System Type	X64-based processor
Operating system	Windows 10
Operating system	64-bit
IDE	Google Chrome
Feature Extractor	RNN, LSTM
Data types	Numerical
Simulator	Google Colaboratory

Similarly, hyperparameters training for the LSTM involves choosing hyperparameters as the key aspect of the deep learning techniques. This is achieved through a manual or automatic tuning whose objective is to reduce the cost and memory of execution. The training algorithm makes use of the hyperparameter settings for purpose of training datasets on the LSTM mode as shown in Table 3.3.

Table 3.3: Minimal parameters for RNN.

Hyperparameter	Value
Network model	LSTM
Number of layers	5
Embedding dimension	100
Number of hidden units	180
Max number of Epochs	5
Gradient Threshold	1
Initial leaning rate	0.01
Optimizer	Adam
Input type	Numerical

3.6 Performance Evaluation Parameters

The evaluation parameters used for measuring the proposed weather prediction model's errors and accuracy are given by Equations 3.1, and 3.2 (Z. Chen et al., 2021):

$$\text{Root Mean Square Errors (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - \hat{X}_i)^2} \tag{3.1}$$

$$\text{Mean Square Errors} = \text{MSE}(X_j) = \frac{1}{n}\sum_{i=1}^{n}(X_i - \hat{X}_i)^2 \tag{3.2}$$

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

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 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 Figure 4.1.

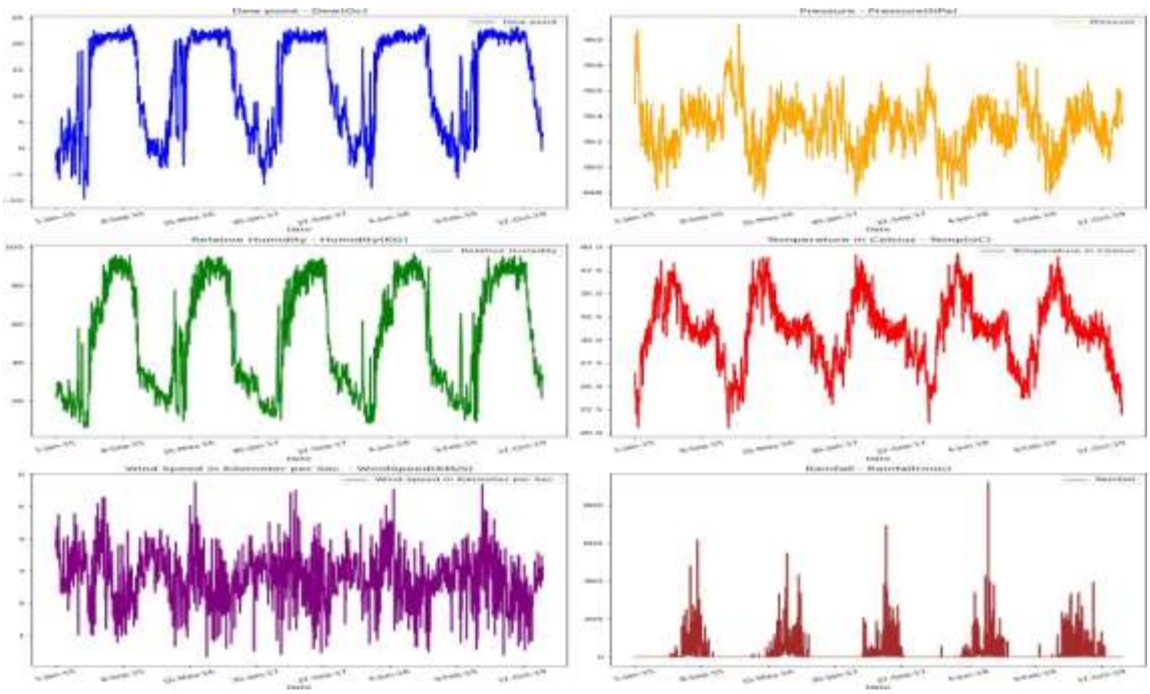

Figure 4.1: The distribution of data elements in weather variables of Bauchi city

From Figure 4.1, 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 features in the datasets for the distinct weather variables for the Bauchi City are presented in Figure 4.2.

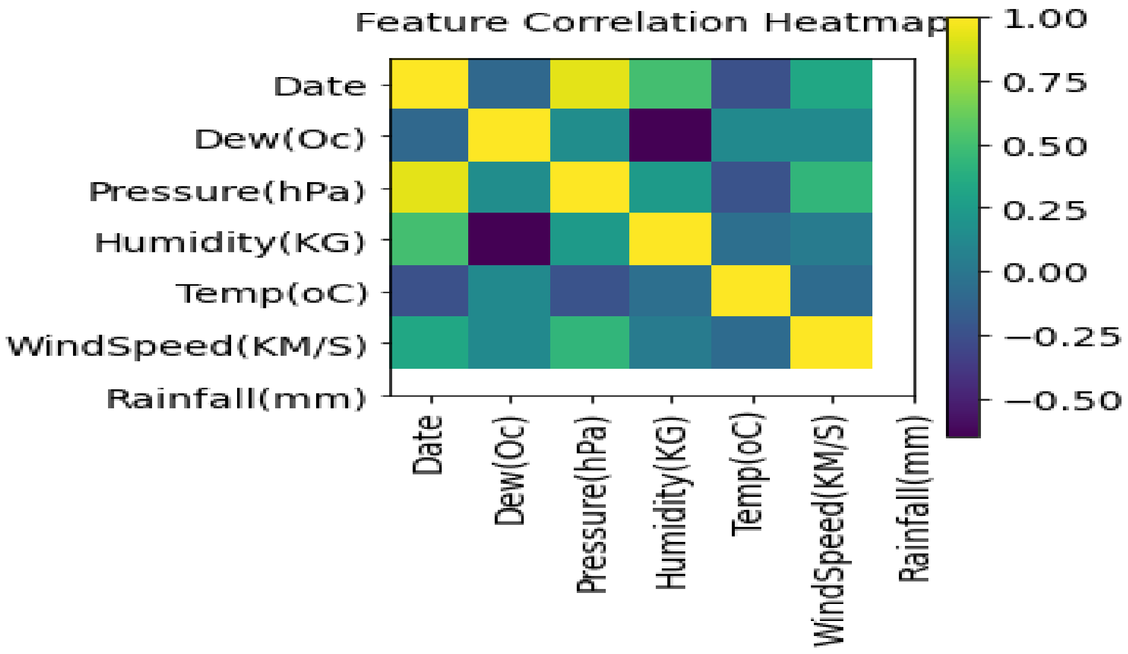

Figure 4.2: The feature correlation heatmap for Bauchi city weather dataset.

From Figure 4.2, there are large correlations between wind speed and pressure, humidity and wind speed, and pressure and dew point. However, there no correlation between rainfall and other weather variables investigated for Bauchi City.

The training and validation of the proposed weather forecasting model using the multivariate datasets of the selected weather variables are presented in Figure 4.3.

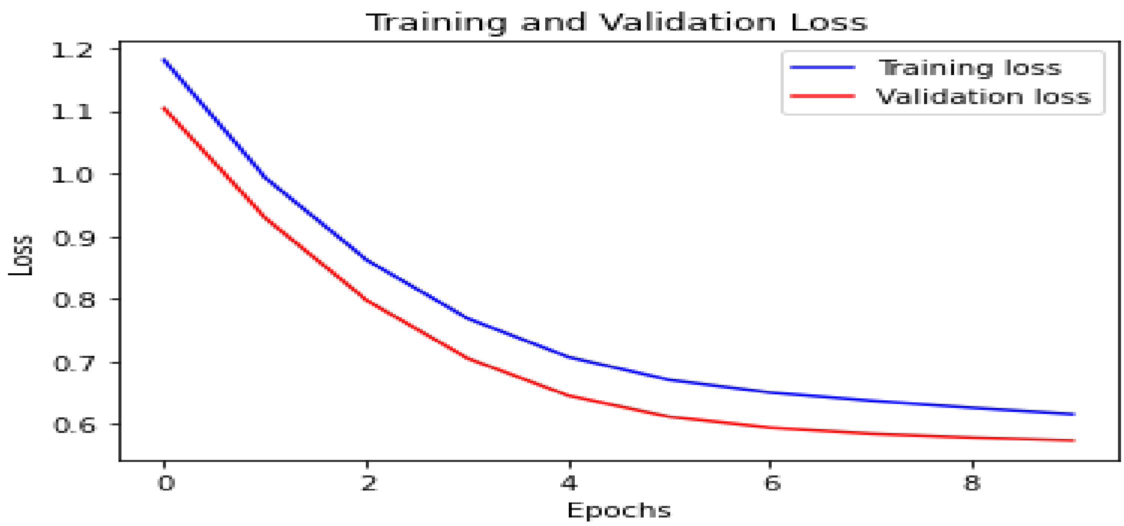

Figure 4.3: Model performance for Bauchi city daily weather forecasts.

The Figure 4.3 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 Figure 4.4.

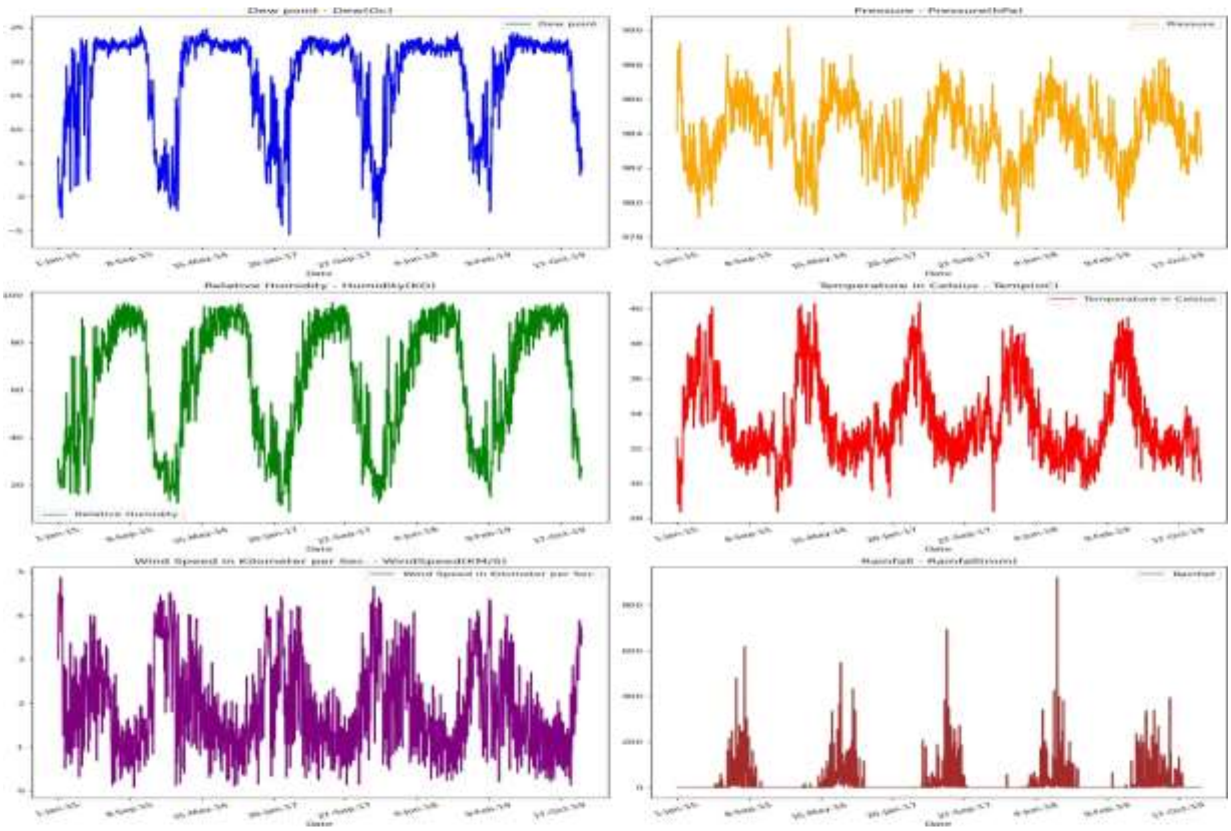

Figure 4.4: The distribution of data elements in weather variable of Minna City.

From Figure 4.4, 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 features in the datasets for the distinct weather variables for the Bauchi City are presented in Figure 4.4.

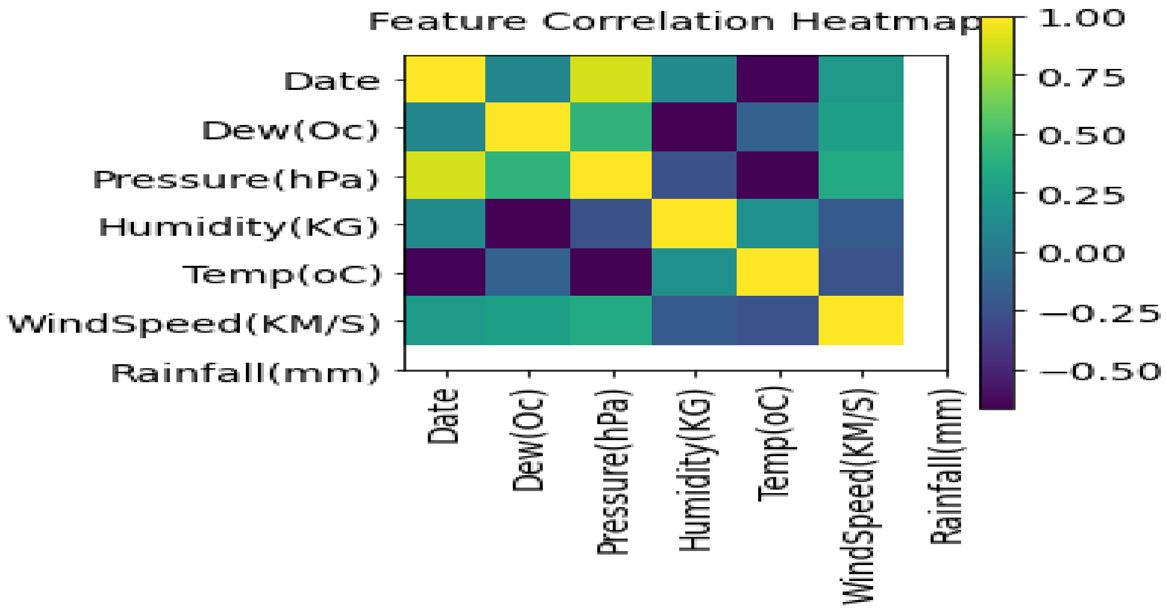

Figure 4.5: The feature correlation heatmap for Minna City weather dataset.

From Figure 4.5, large correlations between wind speed and pressure, humidity and wind speed, and pressure and dew point, dew point and wind speed were observed. However, there no correlation between rainfall and other weather variables selected for Minna City. The training and validation of the proposed weather forecasting model using the multivariate datasets of the selected weather variables are presented in Figure 4.6.

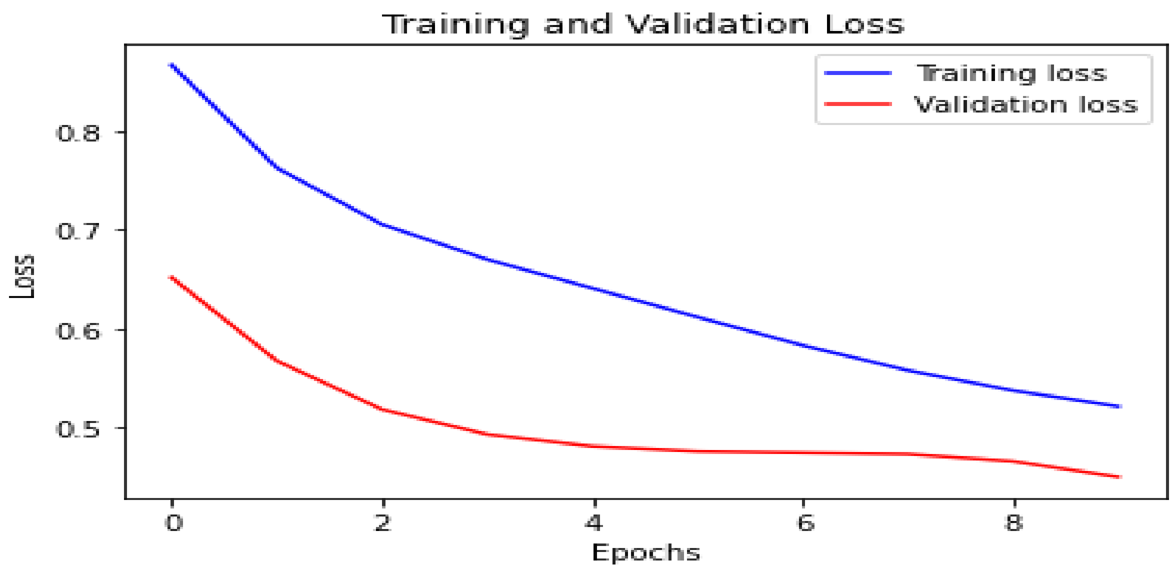

Figure 4.6: Model performance for Minna city daily weather forecasts.

The Figure 4.6 shows that, the validation curve was relatively large 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 Figure 4.7.

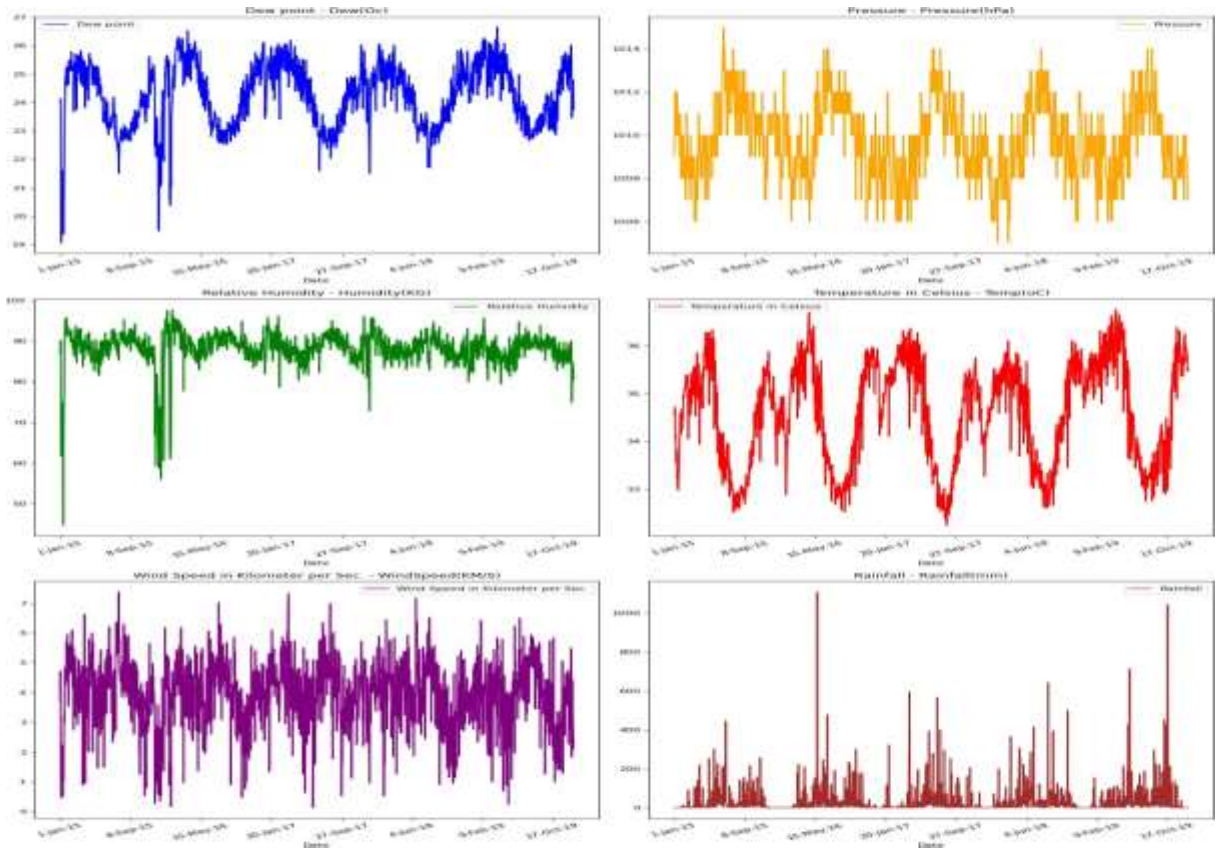

Figure 4.7: The distribution of data elements in weather variables of Ikeja City.

In Figure 4.7, 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 features in the datasets for the distinct weather variables for the Ikeja City are presented in Figure 4.8.

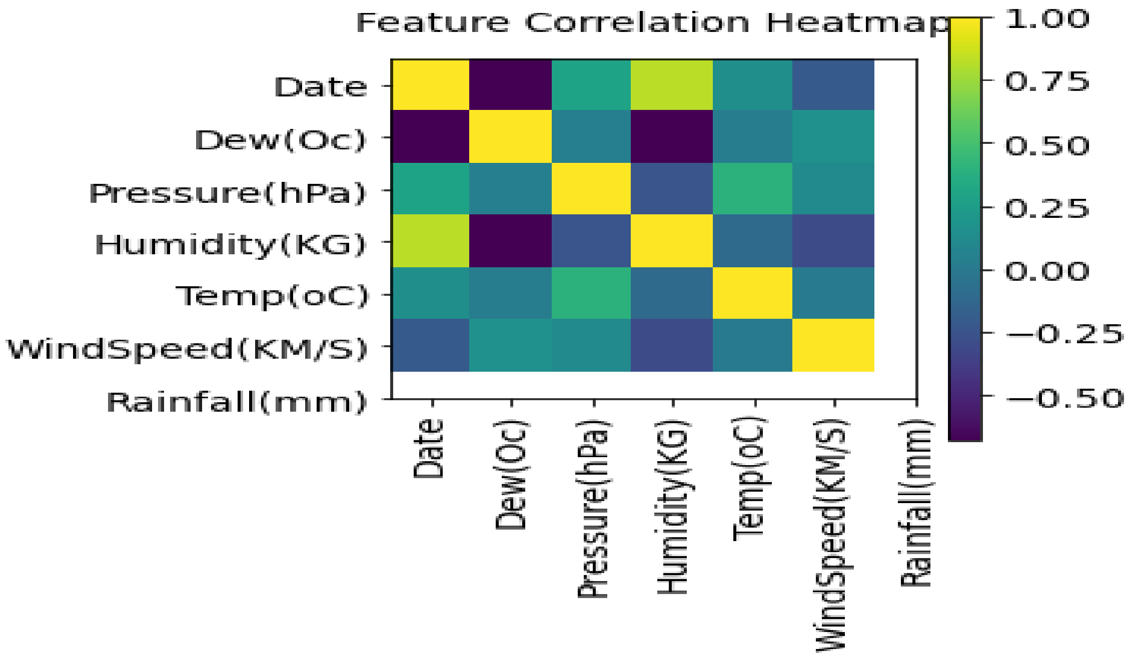

Figure 4.8: The feature correlation heatmap for Bauchi city weather dataset.

From Figure 4.8, there are large correlations between dew point and wind speed, and pressure and temperature and wind speed, and pressure and dew point. However, there no correlation between rainfall and other weather variables investigated for Ikeja City.

The training and validation of the proposed weather forecasting model using the multivariate datasets of the selected weather variables are presented in Figure 4.9.

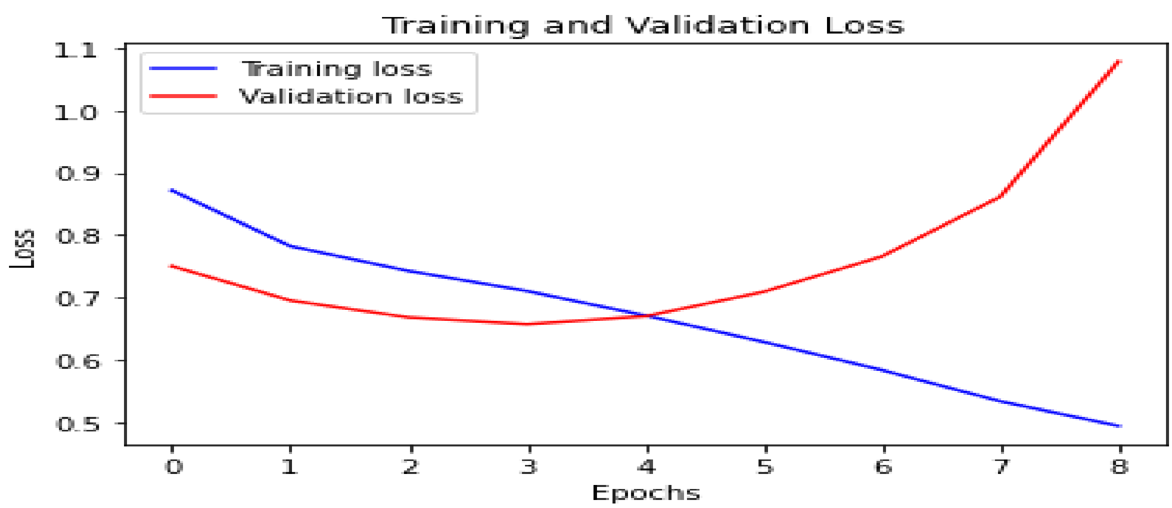

Figure 4.9: Model performance for Ikeja city daily weather forecasts.

The Figure 4.9 shows that, 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 Bauchi city, the distributions of data elements for the dew point, pressure, relative humidity, temperature, wind speed, and rainfall are presented in Figure 4.10.

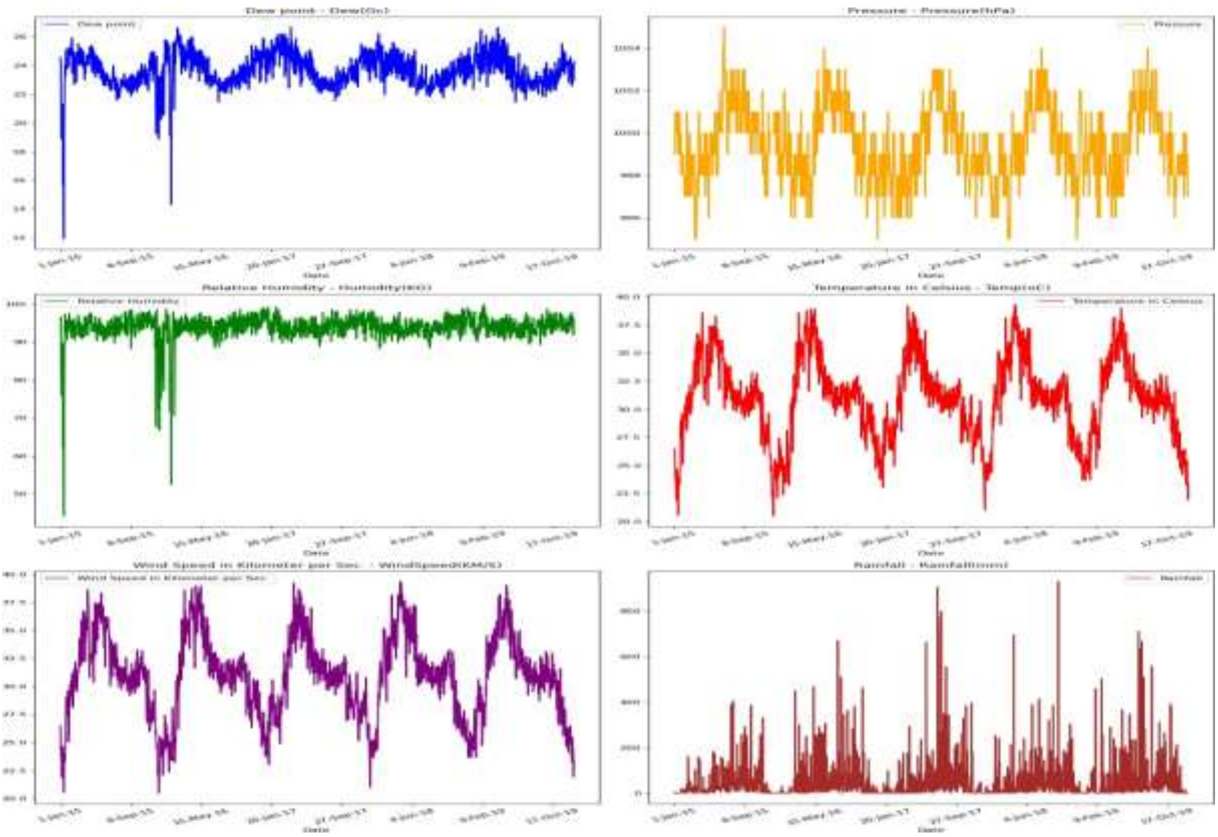

Figure 4.10 : The distribution of data elements in weather variables for Calabar City.

From Figure 4.10, 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 features in the datasets for the distinct weather variables for the Calabar City are presented in Figure 4.11.

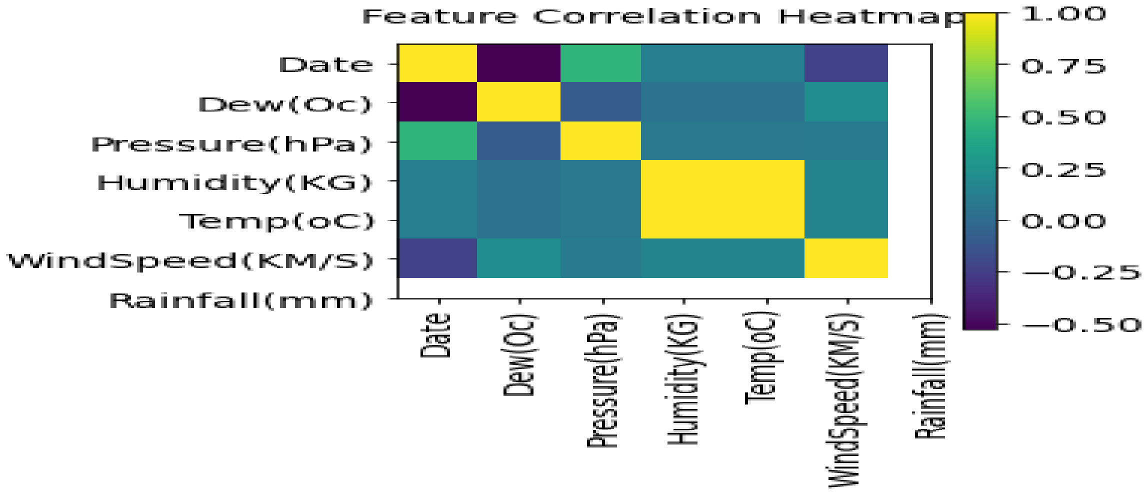

Figure 4.11: The feature correlation heatmap for Bauchi city weather dataset.

From Figure 4.11, there are high correlations between relative humidity and temperature, humidity with pressure and temperature. However, there no correlation between rainfall and other weather variables investigated for Calabar City.

The training and validation of the proposed weather forecasting model using the multivariate datasets of the selected weather variables are presented in Figure 4.12.

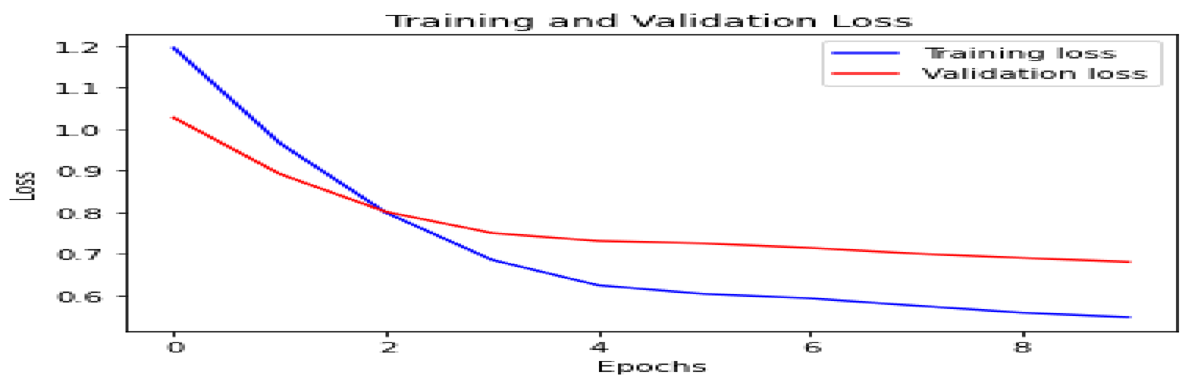

Figure 4. 12: Model performance for Calabar city daily weather forecasts.

The Figure 4.12 shows that, 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.

4.2 Prediction Outcomes

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

The proposed model performance for daily forecasts of weather parameters were relatively accurate at 1 time-step as shown in Figure 4.13.

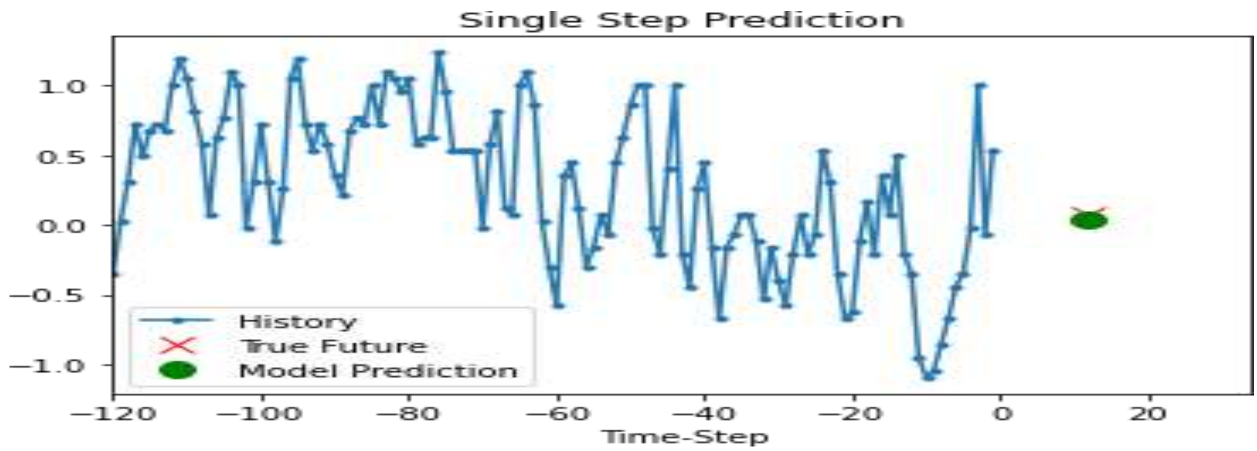

Figure 4. 13: The daily weather forecasts using multivariate dataset for Bauchi city.

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 as illustrated in Figure 4.14.

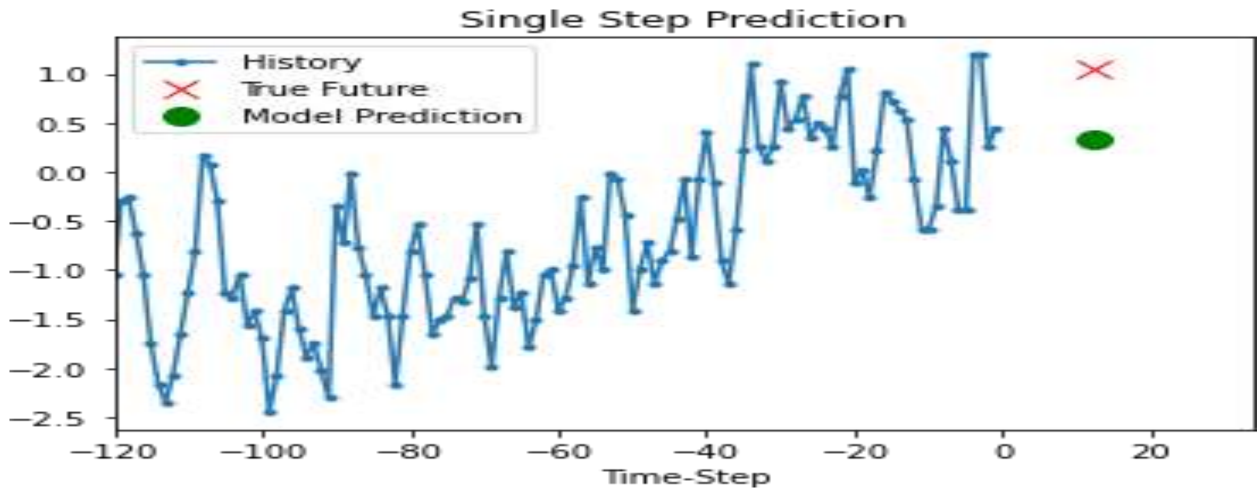

Figure 4.14: Weekly weather forecasts performance with proposed model.

(b) 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 Figure 4.15.

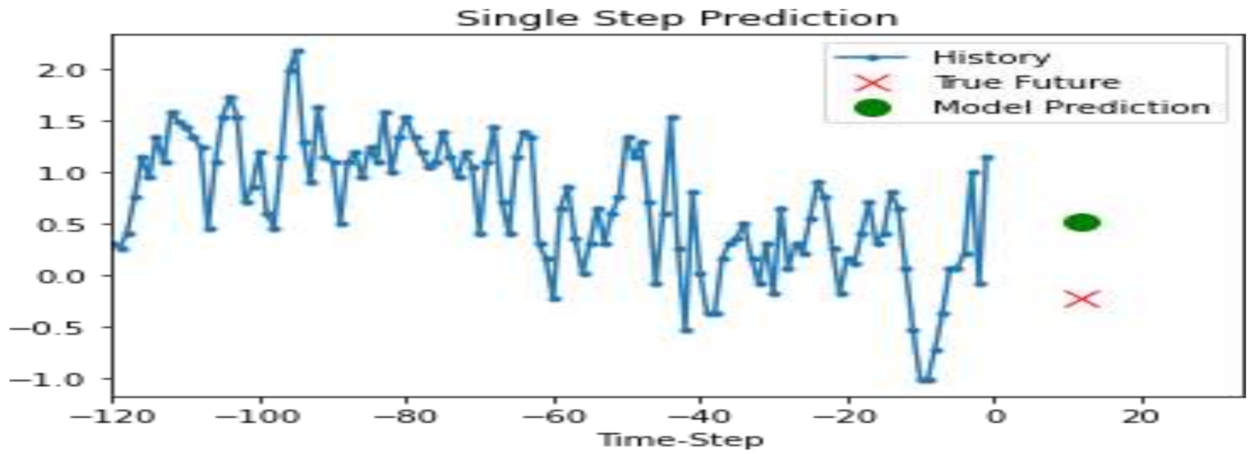

Figure 4.15: The daily weather forecasts using multivariate dataset for Minna City.

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 Figure 4.16.

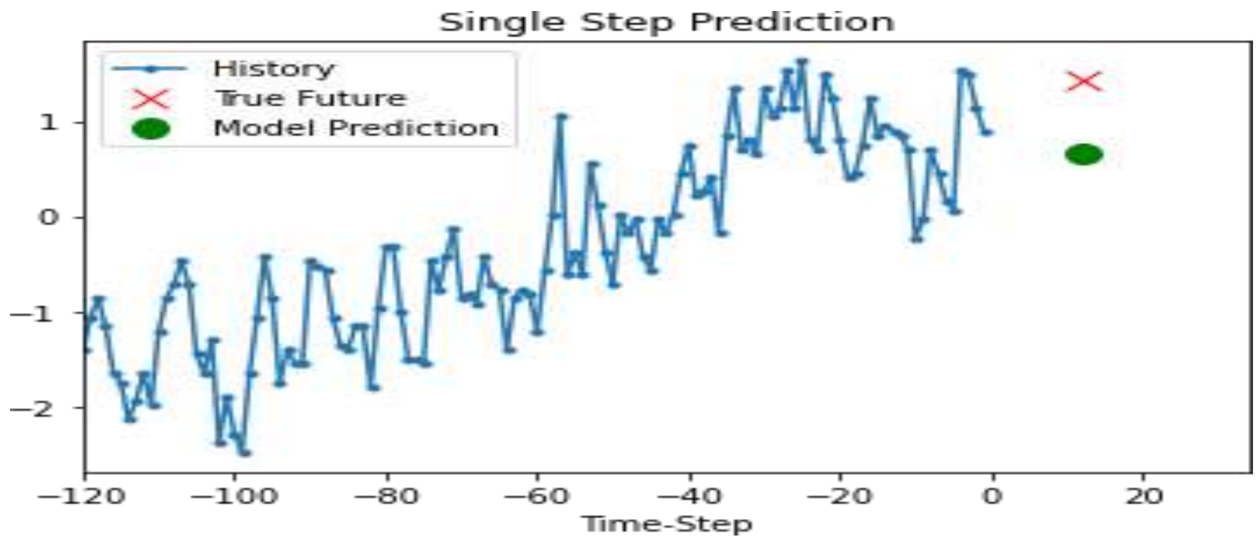

Figure 4.16: Weekly weather forecasts performance with proposal model.

(c) Ikeja City

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 Figure 4.17.

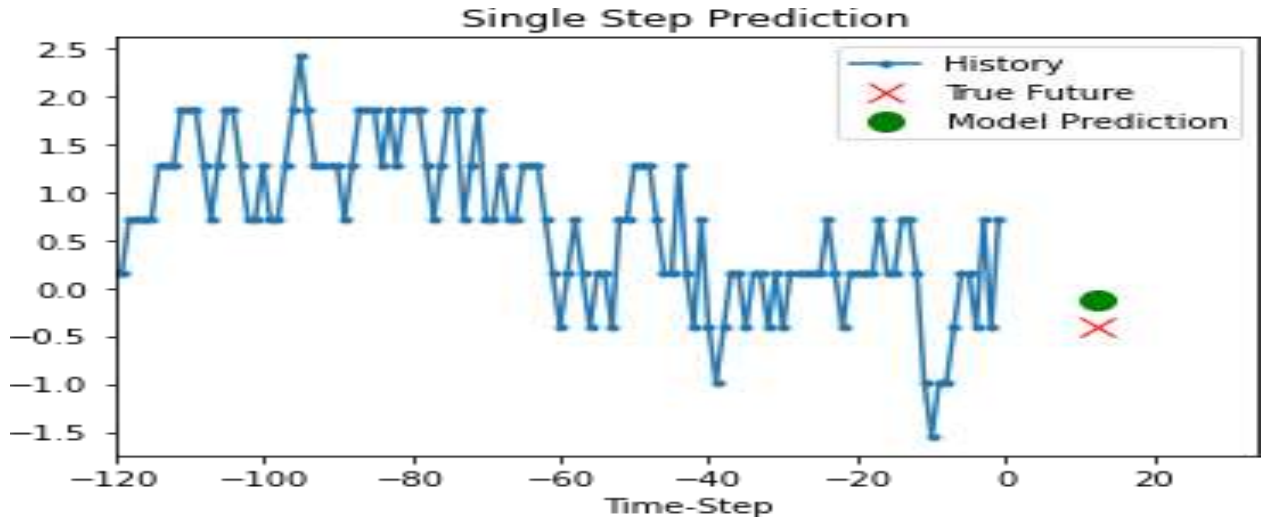

Figure 4.17: The daily weather forecasts using multivariate dataset for Ikeja city.

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 as illustrated in Figure 4.18.

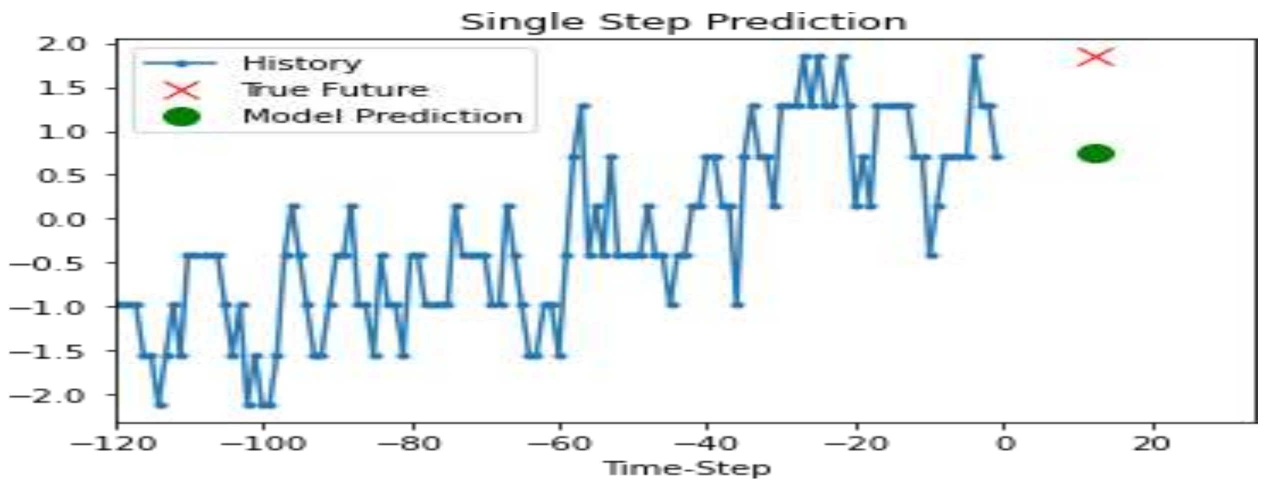

Figure 4.18: Weekly weather forecasts performance with the proposed model.

(d) Calabar City

The proposed model performance for daily forecasts of weather parameters were relatively accurate at 1 time-step as shown in Figure 4.19.

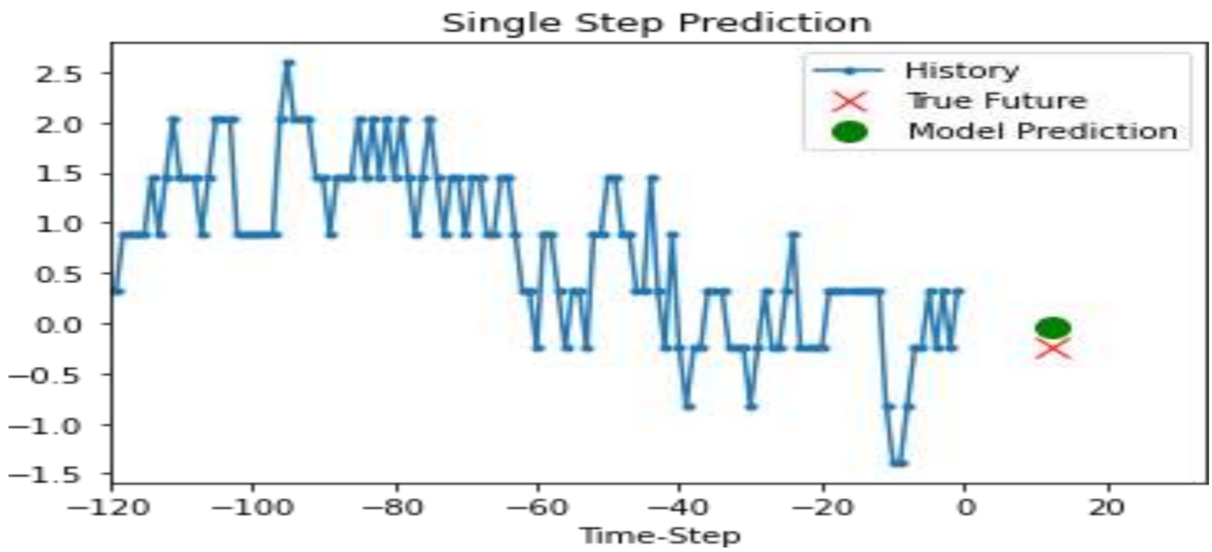

Figure 4. 19: The daily weather forecasts using multivariate dataset for Calabar city.

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 as illustrated in Figure 4.20.

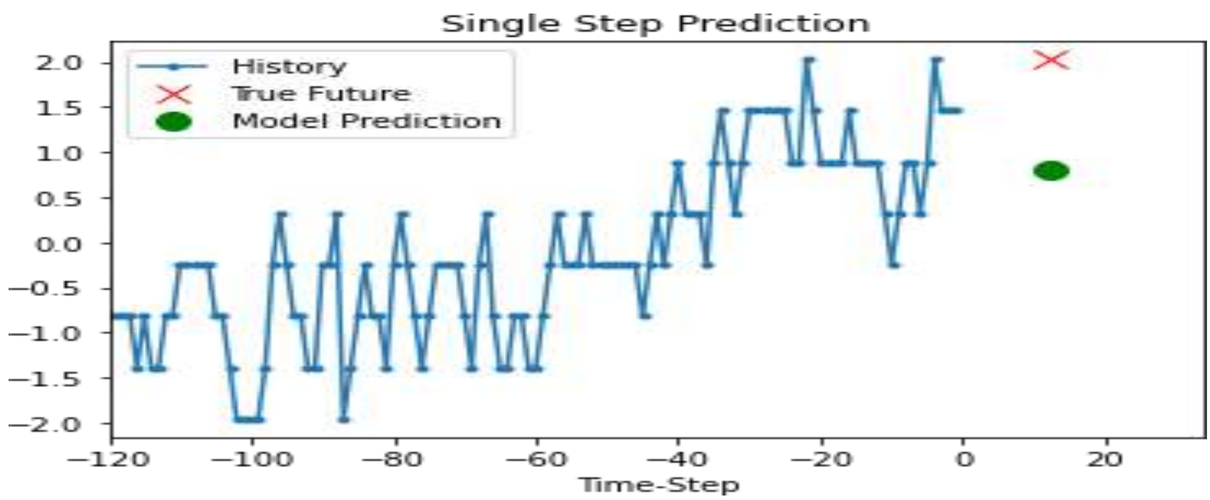

Figure 4.20: Weekly weather forecasts performance with proposed model.

4.3 Performance 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 4.1.

Table 4.1 The proposed weather model forecasting outcomes using MSE.

City	**Daily**	**Weekly**
Bauchi	0.0252	0.3977
Minna	0.0167	0.4505
Ikeja	0.0042	1.0784
Calabar	0.0069	0.6804

From Table 4.1, the 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.

Similarly, the proposed weather model performed best for Ikeja city based on the daily forecasts due to the relatively stable trends of the multivariate datasets used during training. While, the proposed model performed worst for Bauchi city due to the large uncertainty and instability of the weather data elements.

4.3.1 Performance Benchmarking

The relative performance of the proposed model and comparable weather forecasting models are presented in Table 4.2.

Table 4. 2: Performance benchmarking.

Evaluation Metric	**Proposed model**	**ANN**
MSE	0.0252	0.4792
RMSE	0.0167	0.6922

From Table 4.2, the performance of the proposed weather forecasting model based on LSTM outclassed the traditional ANN due to increased memory for historical events and feedback characteristics of the later (Czibula *et al*., 2021; Erivaldo *et al*, 2019), that is, 0.0252 and 0.4792. The similar trends are observed for the RMSE, which is 0.0167 and 0.6922 for the LSTM model and ANN respectively. These outcomes can be depicted in Figure 4.21.

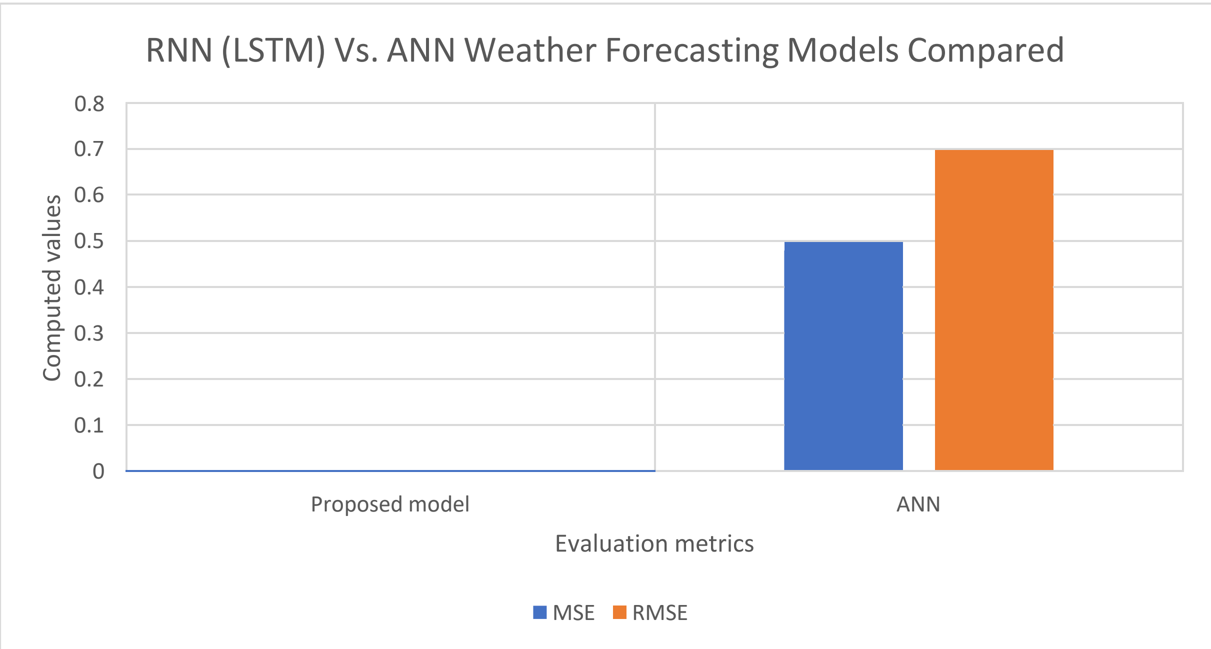

Figure 4. 21: The comparisons of performance of the proposed model against ANN

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

People around the world 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, traditional Artificial Neural Network, Trend Forecasting in order to demonstrate the improvement of weather forecasting in the proposed approach.

This study validated the model using weather variables for four meteorological stations/cities across of Nigeria namely Minna, Bauchi, Lagos and Calabar due to their distant climatic attributes. 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 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.

5.2 Recommendations

It is recommended that this model be used in the development of better weather forecasting systems. Other than the ones included in this study, there is a need to incorporate more weather variables. The model must be expanded to handle non-numerical values as input data, such as texts, audio, weather chats and video. This model should be used to forecast weather conditions in Nigerian cities and throughout Africa.

5.3 Suggestions for Further Research

Future research in the field of weather forecasting models could look into more optimization and data mining algorithms to increase the model's performance. This approach should be used in other contexts as well, including stock price forecasting, energy forecasting, and retail pump price forecasting.

5.4 Contribution to Knowledge

The contributions reached at the end of this work could be summarized as:

i. Design and implementation of an improve weather forecasting model based on Long Short-Term Memory (LSTM) Neural Network.

ii. The LSTM model has been successfully applied to produce for daily and weekly forecast.

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Appendix A

Source Code 1

Timeseries forecasting for weather prediction

Description: This notebook demonstrates how to do timeseries forecasting using a LSTM model.

Setup

This example requires TensorFlow 2.3 or higher.

[ ]

```
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
from tensorflow import keras
from pandas import read_csv
```

Climate Data Time-Series

We will be using daily weather data recorded by Nigerian Meteorological Agency (NiMet). The dataset consists of 5 features such as temperature, pressure, humidity etc,
Location: Nigeria
Time-frame Considered: Jan 01, 2015 - December 31, 2019
The table below shows the column names, their value formats, and their description.

Index	Features	Format	Description
1	Date Time	01.012009 0010:00	Date-time reference
2	p (mbar)	996.52	The pascal SI derived unit of pressure used to quantify internal pressure. Meteorological reports typically state atmospheric pressure in millibars.

Index	Features	Format	Description
3	T (degC)	-8.02	Temperature in Celsius
4	Tpot (K)	265.4	Temperature in Kelvin
5	Tdew (degC)	-8.9	Temperature in Celsius relative to humidity. Dew Point is a measure of the absolute amount of water in the air, the DP is the temperature at which the air cannot hold all the moisture in it and water condenses.
6	rh (%)	93.3	Relative Humidity is a measure of how saturated the air is with water vapor, the %RH determines the amount of water contained within collection objects.
7	VPmax (mbar)	3.33	Saturation vapor pressure
8	VPact (mbar)	3.11	Vapor pressure
9	wv (m/s)	1.03	Wind speed
10	max. wv (m/s)	1.75	Maximum wind speed
11	wd (deg)	152.3	Wind direction in degrees

[ ]

```
from google.colab import drive
drive.mount('/content/gdrive')
```

[ ]

```
#from google.colab import files
#uploaded = files.upload()
```

[ ]

```
# csv_path = "/content/gdrive/MyDrive/weather bauchi csv.csv"
#  csv_path  =  "/content/gdrive/MyDrive/weather minna csv.csv"
#  csv_path  =  "/content/gdrive/MyDrive/weather ikeja csv.csv"
# csv_path = "/content/gdrive/MyDrive/weather calabar csv.csv"
df = pd.read csv(csv path)
```

[ ]

```
#from google.colab import drive
drive.mount('/content/drive')
```

Raw Data Visualization

To give us a sense of the data we are working with, each feature has been plotted below. This shows the distinct pattern of each feature over the time period from January 2015 to December 2019. It also shows where anomalies are present, which will be addressed during normalization.

[ ]

```
titles = [
    "Dew point",
    "Pressure",
    "Relative Humidity",
    "Temperature in Celsius",
    "Wind Speed in Kilometer per Sec.",
    "Rainfall",
    ]
feature_keys = [
    "Dew(Oc)",
    "Pressure(hPa)",
    "Humidity(KG)",
    "Temp(oC)",
    "WindSpeed(KM/S)",
    "Rainfall(mm)",
    ]
colors = [
    "blue",
    "orange",
    "green",
    "red",
    "purple",
    "brown",
    ]
date_time_key = "Date"
def show_raw_visualization(data):
    time_data = data[date_time_key]
    fig, axes = plt.subplots(
        nrows=3, ncols=2, figsize=(15, 20), dpi=80, facecolor="w", edgeco
lor="k"
    )
    for i in range(len(feature_keys)):
        key = feature_keys[i]
        c = colors[i % (len(colors))]
        t_data = data[key]
        t_data.index = time_data
        t_data.head()
        ax  =  t_data.plot(
            ax=axes[i // 2, i % 2],
            color=c,
            title="{} - {}".format(titles[i], key),
            rot=25,
```

```
        )
        ax.legend([titles[i]])
    plt.tight_layout()
show_raw_visualization(df)
```

This heat map shows the correlation between different features.

[]

```
def show_heatmap(data):
    plt.matshow(data.corr())
    plt.xticks(range(data.shape[1]), data.columns, fontsize=14, rotation=
90)
    plt.gca().xaxis.tick_bottom()
    plt.yticks(range(data.shape[1]), data.columns, fontsize=14)
    cb = plt.colorbar()
    cb.ax.tick_params(labelsize=14)
    plt.title("Feature Correlation Heatmap", fontsize=14)
    plt.show()
show_heatmap(df)
```

Data Preprocessing

This thesis primarily relied on secondary data obtained from Nigeria Meteorological Agency (NiMet), Abuja and Era Interim. These include: Air Temperature, Pressure (In Hectopascal, HPa = 100 Pa), Rainfall (In Millimetres), Wind Speed, Relative Humidity, and Dew point. The data comprises of daily weather reports recorded from 1st st January, 2015 30th December, 2019 for the selected parameters.
The entire dataset 1826 columns and 2 rows for each of the temperature, pressure, dew point, relative humidity, wind speed, and rainfall. Thereafter, the data divided into training and testing datasets on the ratio of 70% to 30%, that is, 1278 columns and 2 rows to 548 columns and 2 rowss respectively. These attributes are the given information to the recurrent neural network and trained using LSTM algorithm.
We are tracking data from past 720 timestamps (720/6=120 hours). This data will be used to predict the temperature after 72 timestamps (72/6=12 hours).
Since every feature has values with varying ranges, we do normalization to confine feature values to a range of [0, 1] before training a neural network. We do this by subtracting the mean and dividing by the standard deviation of each feature.
The model is shown data for first 5 days i.e. 720 observations, that are sampled every hour. The temperature after 72 (12 hours * 6 observation per hour) observation will be used as a label.

Total dataset = 1826 Colums, divided *1278* columns for training, per daily

observation... bold text

[]

```
split_fraction = 0.70
train_split = int(split_fraction * int(df.shape[0]))
step = 1
past = 120
future = 24
learning_rate = 0.001
batch_size = 256
epochs = 10
def normalize(data, train_split):
    data_mean = data[:train_split].mean(axis=0)
    data_std = data[:train_split].std(axis=0)
    return (data - data_mean) / data_std
```

We can see from the correlation heatmap, few parameters like Relative Humidity and Specific Humidity are redundant. Hence we will be using select features, not all.

[ ]

```
print(
    "The selected parameters are:",
    ", ".join([titles[i] for i in [0, 1, 2, 3, 4, 5]]),
)
selected_features = [feature_keys[i] for i in [0, 1, 2, 3, 4, 5]]
features = df[selected_features]
features.index = df[date_time_key]
features.head()
features = normalize(features.values, train_split)
features = pd.DataFrame(features)
features.head()
train_data = features.loc[0 : train_split - 1]
val_data = features.loc[train_split:]
```

Training dataset

The training dataset labels starts from the 792nd observation (720 + 72).

[ ]

```
start = past + future
end = start + train_split
x_train = train_data[[i for i in range(5)]].values
y_train = features.iloc[start:end][[1]]
sequence_length = int(past / step)
```

The `timeseries_dataset_from_array` function takes in a sequence of data-points gathered at equal intervals, along with time series parameters such as length of the sequences/windows, spacing between two sequence/windows, etc., to produce batches of sub-timeseries inputs and targets sampled from the main timeseries.

[ ]

```
dataset_train = keras.preprocessing.timeseries_dataset_from_array(
    x_train,
    y_train,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,)
```

Validation dataset

The validation dataset must not contain the last 792 rows as we won't have label data for those records, hence 792 must be subtracted from the end of the data.
The validation label dataset must start from 792 after train_split, hence we must add past + future (792) to label_start.

[ ]

```
x_end = len(val_data) - past - future
label_start = train_split + past + future
x_val = val_data.iloc[:x_end][[i for i in range(5)]].values
y_val = features.iloc[label_start:][[1]]
dataset_val = keras.preprocessing.timeseries_dataset_from_array(
    x_val,
    y_val,
    sequence_length=sequence_length,
    sampling_rate=step,
    batch_size=batch_size,
)
for batch in dataset_train.take(1):
    inputs, targets = batch
print("Input shape:", inputs.numpy().shape)
print("Target shape:", targets.numpy().shape)
```

Training

[ ]

```
inputs = keras.layers.Input(shape=(inputs.shape[1], inputs.shape[2]))
lstm_out = keras.layers.LSTM(32)(inputs)
outputs = keras.layers.Dense(1)(lstm_out)
model = keras.Model(inputs=inputs, outputs=outputs)
```

```
model.compile(optimizer=keras.optimizers.Adam(learning_rate=learning_rate
), loss="mse")
model.summary()
```
[]

We'll use the `ModelCheckpoint` callback to regularly save checkpoints, and the `EarlyStopping` callback to interrupt training when the validation loss is not longer improving.

[]

```
path_checkpoint = "model_checkpoint.h5"
es_callback = keras.callbacks.EarlyStopping(monitor="val_loss", min_delta
=0, patience=5)
modelckpt_callback = keras.callbacks.ModelCheckpoint(
    monitor="val_loss",
    filepath=path_checkpoint,
    verbose=1,
    save_weights_only=True,
    save_best_only=True,
)
history = model.fit(
    dataset_train,
    epochs=epochs,
    validation_data=dataset_val,
    callbacks=[es_callback, modelckpt_callback],
)
```

We can visualize the loss with the function below. After one point, the loss stops decreasing.

[]

```
def visualize_loss(history, title):
    loss = history.history["loss"]
    val_loss = history.history["val_loss"]
    epochs = range(len(loss))
    plt.figure()
    plt.plot(epochs, loss, "b", label="Training loss")
    plt.plot(epochs, val_loss, "r", label="Validation loss")
    plt.title(title)
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()
visualize_loss(history, "Training and Validation Loss")
```

Prediction

The trained model above is now able to make predictions for 5 sets of values from validation set.

[ ]

```
def show_plot(plot_data, delta, title):
    labels = ["History", "True Future", "Model Prediction"]
    marker = [".-", "rx", "go"]
    time_steps = list(range(-(plot_data[0].shape[0]), 0))
    if delta:
        future = delta
    else:
        future = 0
    plt.title(title)
    for i, val in enumerate(plot_data):
        if i:
            plt.plot(future, plot_data[i], marker[i], markersize=10, labe
l=labels[i])
        else:
            plt.plot(time_steps, plot_data[i].flatten(), marker[i], label
=labels[i])
    plt.legend()
    plt.xlim([time_steps[0], (future + 1) * 5])
    plt.xlabel("Time-Step")
    plt.show()
    return
for x, y in dataset_val.take(5):
    show_plot(
        [x[0][:, 1].numpy(), y[0].numpy(), model.predict(x)[0]],
        12,
        "Single Step Prediction",)
```

II. Source Dataset 1

(a) Source Dataset: Calabar dataset:

Date	Dew(Oc)	Pressure(hPa)	Humidity(KG)	Temp(oC)	WindSpeed(KM/S)	Rainfall(mm)
1-Jan-15	24.58	999	95.42	26.51	26.51	0.8
2-Jan-15	24.28	1000	96.63	25.19	25.19	1.9
3-Jan-15	24.02	1001	96.33	24.2	24.2	5.5
4-Jan-15	21.31	1001	81.57	23.7	23.7	0
5-Jan-15	18.89	1000	75.91	23.77	23.77	0
6-Jan-15	19.71	1000	78.39	22.32	22.32	0
7-Jan-15	20.97	1000	84.87	21.89	21.89	0
8-Jan-15	20.66	1000	82.36	23.25	23.25	0
9-Jan-15	21.3	1001	89.82	24.67	24.67	0
10-Jan-15	15.68	1001	62.22	23.99	23.99	0

11-Jan-15	19.25	1001	81.29	22.41	22.41	1.8
12-Jan-15	13.89	1000	52.67	22.17	22.17	0
13-Jan-15	11.93	999	44.18	20.55	20.55	0
14-Jan-15	18.17	1000	72.31	21.17	21.17	0
15-Jan-15	21.06	1000	81.01	23.85	23.85	0
16-Jan-15	22.77	1000	94.51	23.95	23.95	0
17-Jan-15	23.73	999	92.42	23.59	23.59	0
18-Jan-15	24.01	1001	97.44	23.3	23.3	0
19-Jan-15	23.3	1000	92.61	24.48	24.48	0
20-Jan-15	24.5	999	93.96	25.1	25.1	0
21-Jan-15	24.96	999	94.46	27.85	27.85	0.1
22-Jan-15	24.88	1000	95.03	29.03	29.03	0.6
23-Jan-15	25.15	999	96.01	28.9	28.9	4
24-Jan-15	24.56	998	91.55	28.62	28.62	15
25-Jan-15	24.03	998	90.59	28.65	28.65	22.6
26-Jan-15	23.78	999	91.47	27.4	27.4	21.5
27-Jan-15	24.21	999	93.47	29.64	29.64	12.7
28-Jan-15	24.33	999	95.22	29.52	29.52	8.3
29-Jan-15	24.49	999	94.05	28.26	28.26	3.8
30-Jan-15	23.93	999	93.92	25.07	25.07	5.2
31-Jan-15	24.86	999	95.29	25.89	25.89	0.2
1-Feb-15	25.05	999	96.82	27.4	27.4	0.8
2-Feb-15	25.28	998	97.61	29.26	29.26	2.6
3-Feb-15	24.73	998	93.82	28.24	28.24	17.8
4-Feb-15	24.72	998	92.8	29.27	29.27	1.3
5-Feb-15	25.02	997	95.71	29.59	29.59	0.8
6-Feb-15	24.83	998	94.18	30.23	30.23	0.7
7-Feb-15	24.65	997	93.57	29.55	29.55	2
8-Feb-15	24.78	998	93.39	30.47	30.47	18.2
9-Feb-15	25.16	997	94.44	30.06	30.06	3.2
10-Feb-15	25.48	998	91.2	29.42	29.42	6
11-Feb-15	25.93	997	95.94	29.09	29.09	0.1
12-Feb-15	25.65	998	93.89	31.15	31.15	2.6
13-Feb-15	23.47	1000	95.5	29.01	29.01	39
14-Feb-15	24.36	1001	91.99	28.1	28.1	11.1
15-Feb-15	24.72	1000	93.99	28.56	28.56	0
16-Feb-15	25.03	1000	91.33	28.76	28.76	6.1
17-Feb-15	24.92	999	92.4	29.94	29.94	8
18-Feb-15	24.05	997	92.95	31.45	31.45	161.1
19-Feb-15	22.67	998	96.22	31.53	31.53	85.7
20-Feb-15	23.79	997	90.45	30.48	30.48	9.8
21-Feb-15	24.54	997	90.74	29.9	29.9	60.2
22-Feb-15	24.4	997	91.34	31.41	31.41	28
23-Feb-15	24.05	999	94.65	32.03	32.03	6.8
24-Feb-15	23.66	1000	93.52	32.19	32.19	51.3
25-Feb-15	24.92	998	94.53	31.58	31.58	8.7
26-Feb-15	24.88	998	93.63	29.52	29.52	46.4
27-Feb-15	22.83	998	93.2	31.27	31.27	10

28-Feb-15	23.9	999	91.73	29.85	29.85	11.8
1-Mar-15	24.79	998	93.53	29.6	29.6	21
2-Mar-15	24.74	997	95.14	30.1	30.1	6.7
3-Mar-15	24.68	998	94.47	30.21	30.21	7.5
4-Mar-15	24.79	999	95.69	31.12	31.12	8.9
5-Mar-15	24.68	999	97.12	31.5	31.5	0.2
6-Mar-15	25.52	998	96.21	31.3	31.3	0.5
7-Mar-15	25.28	998	96.86	31.41	31.41	2.4
8-Mar-15	24.04	998	95.08	32.53	32.53	32.2
9-Mar-15	24.57	998	91.43	32.66	32.66	19.2
10-Mar-15	24.22	998	95.23	34.01	34.01	0
11-Mar-15	24.21	999	95.54	34.28	34.28	2.7
12-Mar-15	24.86	998	94.77	34.31	34.31	0
13-Mar-15	25.05	996	92.51	32.07	32.07	9.9
14-Mar-15	24.08	995	95.11	31.8	31.8	0.2
15-Mar-15	25.16	995	94.99	32.15	32.15	1.4
16-Mar-15	24.25	997	90.94	35.47	35.47	103.2
17-Mar-15	25.22	997	93.56	35.2	35.2	4
18-Mar-15	24.19	997	93.74	35.93	35.93	1.3
19-Mar-15	24.76	995	93.12	34.21	34.21	23.2
20-Mar-15	23.93	996	92.63	32.13	32.13	31.1
21-Mar-15	25.05	996	94.36	35.25	35.25	7.2
22-Mar-15	24.02	998	94.27	34.62	34.62	13.9
23-Mar-15	24.91	997	92.56	36.76	36.76	0.9
24-Mar-15	24.96	998	93.42	33.95	33.95	9
25-Mar-15	24.38	997	91.11	35.48	35.48	27.4
26-Mar-15	23.84	999	94.2	36.26	36.26	12
27-Mar-15	23.73	1000	95.32	36.63	36.63	159.1
28-Mar-15	22.99	1001	96.84	36.07	36.07	83.4
29-Mar-15	23.84	1000	92.54	32.25	32.25	90.6
30-Mar-15	24.19	999	91.87	32.22	32.22	68.2
31-Mar-15	23.38	1000	93.55	34.58	34.58	148.2
1-Apr-15	23.57	998	94.63	34.38	34.38	94.3
2-Apr-15	24.06	1000	94.27	34.52	34.52	36.6
3-Apr-15	24.26	998	96.47	35.23	35.23	1.8
4-Apr-15	24.49	998	95.18	36.15	36.15	0.9
5-Apr-15	24.73	998	95.82	35.16	35.16	15.6
6-Apr-15	24.11	998	93.53	35.25	35.25	0.3
7-Apr-15	24.06	998	93.51	35.08	35.08	1.6
8-Apr-15	24.09	999	95.41	37.83	37.83	1.8
9-Apr-15	24.76	999	91.69	38.61	38.61	6.8
10-Apr-15	24.57	998	92.73	37.61	37.61	1.5
11-Apr-15	24.02	999	93.16	36.9	36.9	17.1
12-Apr-15	24.01	999	96.09	34.09	34.09	3.6
13-Apr-15	24.14	999	97.42	32.71	32.71	71.1
14-Apr-15	24.48	999	96.9	32.26	32.26	0
15-Apr-15	25.27	998	96.15	31.26	31.26	2.6
16-Apr-15	24.51	999	96.08	30.78	30.78	19.1

17-Apr-15	25.29	1000	97.12	32.85	32.85	0.3
18-Apr-15	25.15	999	97.75	32.05	32.05	0.3
19-Apr-15	25.26	999	95.17	32.34	32.34	2.4
20-Apr-15	24.95	998	95.08	32.89	32.89	5.2
21-Apr-15	24.98	997	94.63	32.43	32.43	0.3
22-Apr-15	25.42	998	97.2	32.42	32.42	1.2
23-Apr-15	23.81	998	95.83	32.64	32.64	0.5
24-Apr-15	23.65	999	92.7	33.38	33.38	10.2
25-Apr-15	24.22	1000	93.57	35.82	35.82	14.5
26-Apr-15	24.95	1000	94.67	34.36	34.36	6
27-Apr-15	23.45	999	93.31	34.06	34.06	0.2
28-Apr-15	25.2	999	94.43	33.01	33.01	0.4
29-Apr-15	24.06	998	94.97	30.34	30.34	1
30-Apr-15	24.35	999	94.36	33.42	33.42	20.9
1-May-15	24.85	997	92.77	33.62	33.62	5.2
2-May-15	24.86	996	93.72	33.47	33.47	0.3
3-May-15	23.66	998	93.82	35.2	35.2	4.8
4-May-15	24.37	998	93.95	36.28	36.28	24.2
5-May-15	24.51	999	92.85	37.46	37.46	82.6
6-May-15	23.17	999	96.66	35.12	35.12	13.9
7-May-15	24.51	999	93.87	32.84	32.84	10.5
8-May-15	24.22	1000	93.78	36.37	36.37	8
9-May-15	24.72	1000	91.53	37.34	37.34	9.7
10-May-15	24.64	999	90.34	36.36	36.36	8.2
11-May-15	23.73	999	91.38	36.49	36.49	13.6
12-May-15	24.43	1000	92.57	35.55	35.55	29.6
13-May-15	23.47	999	93.67	36.35	36.35	20.4
14-May-15	24.56	998	94.72	34.1	34.1	106.6
15-May-15	23.92	999	93.29	36.74	36.74	52.9
16-May-15	23.86	999	93.57	36.49	36.49	0.4
17-May-15	24.41	1000	92.31	37.41	37.41	19.4
18-May-15	24.17	1000	95.89	36.17	36.17	183
19-May-15	23.5	999	93.48	36.82	36.82	24.7
20-May-15	23.81	1000	94.88	36.7	36.7	10.3
21-May-15	24.29	1000	92.97	36.95	36.95	15.2
22-May-15	24.15	1000	96.39	37.49	37.49	2.7
23-May-15	24.39	1000	91.55	37.2	37.2	82.7
24-May-15	23.1	1000	94.94	36.03	36.03	172.5
25-May-15	23.94	1001	94.97	36.5	36.5	17.7
26-May-15	24.21	999	93.9	35.65	35.65	22.4
27-May-15	24.13	999	91.88	38.32	38.32	71.3
28-May-15	24.17	1000	92.85	36.28	36.28	74.8
29-May-15	23.01	998	93.78	36.29	36.29	52.1
30-May-15	23.35	999	91.66	37.2	37.2	18
31-May-15	22.94	1000	93.66	35.91	35.91	123.7
1-Jun-15	23.78	1000	91.67	37.1	37.1	11.8
2-Jun-15	22.64	998	94.52	37.13	37.13	122.2
3-Jun-15	23.74	1000	90.21	34.95	34.95	41.7

4-Jun-15	22.99	1001	90.86	34.85	34.85	53.5
5-Jun-15	23.23	1000	93.83	34.49	34.49	118.1
6-Jun-15	22.94	1001	93.61	36.21	36.21	16.3
7-Jun-15	22.98	1001	93.15	33.42	33.42	34.1
8-Jun-15	22.63	1000	93.95	34.72	34.72	32.2
9-Jun-15	22.91	1000	92.52	31.72	31.72	16.7
10-Jun-15	22.73	1000	91.59	34.26	34.26	12.7
11-Jun-15	23.44	1002	90.56	36.16	36.16	32.3
12-Jun-15	23.52	1001	91.98	35.94	35.94	26.3
13-Jun-15	22.55	1001	92.09	35.27	35.27	17.5
14-Jun-15	22.77	1001	90.7	34.98	34.98	27.6
15-Jun-15	22.96	1000	93.34	35.97	35.97	3.3
16-Jun-15	23.07	1001	94.24	35.88	35.88	158.6
17-Jun-15	23.38	1001	94.69	36.04	36.04	76.7
18-Jun-15	23	1000	93.17	35.7	35.7	45.4
19-Jun-15	23.12	1001	91.53	36.17	36.17	83.1
20-Jun-15	23.28	1001	95.38	35.32	35.32	29.6
21-Jun-15	22.92	1003	94.77	35.56	35.56	149.3
22-Jun-15	22.97	1004	95.77	34.83	34.83	20.3
23-Jun-15	22.77	1004	94.65	34.33	34.33	77.2
24-Jun-15	22.57	1004	94.52	34.58	34.58	44.4
25-Jun-15	22.54	1005	93.08	33.26	33.26	63
26-Jun-15	22.43	1005	91.95	31.75	31.75	49.2
27-Jun-15	22.26	1003	94.09	30.03	30.03	116.1
28-Jun-15	23.03	1003	92.14	32.69	32.69	10.3
29-Jun-15	22.65	1003	91.35	33.63	33.63	24.7
30-Jun-15	22.49	1002	92.53	32.54	32.54	19.9
1-Jul-15	22.34	1002	94.52	34.16	34.16	64.8
2-Jul-15	22.28	1002	96.13	31.17	31.17	88.7
3-Jul-15	22.89	1003	95.23	32.5	32.5	5.8
4-Jul-15	22.92	1003	94.95	32.07	32.07	28.9
5-Jul-15	22.9	1002	94.96	30.84	30.84	110.6
6-Jul-15	23.3	1000	94.12	32.74	32.74	3.5
7-Jul-15	23.65	1000	93.29	32.67	32.67	40.6
8-Jul-15	23.98	999	91.75	33.75	33.75	19.4
9-Jul-15	23.66	1000	94.74	33.78	33.78	10.5
10-Jul-15	23.57	1001	93.71	32.03	32.03	139.5
11-Jul-15	22.99	1002	95.01	32.85	32.85	102.2
12-Jul-15	22.36	1002	97.08	33.48	33.48	63
13-Jul-15	22.32	1001	89.75	31.8	31.8	110.2
14-Jul-15	22.94	1001	96.41	33.48	33.48	0.6
15-Jul-15	22.87	1000	92.42	32.1	32.1	22.3
16-Jul-15	22.26	1001	91.22	31.61	31.61	31.1
17-Jul-15	22.93	1002	92.56	32.25	32.25	8.5
18-Jul-15	23.18	1001	92.49	33.88	33.88	9.3
19-Jul-15	22.74	1001	94.87	32.13	32.13	38.8
20-Jul-15	22.79	1001	95.82	30.88	30.88	389.4
21-Jul-15	21.57	1002	92.07	31.79	31.79	134.8

22-Jul-15	22.69	1003	96.69	31.55	31.55	72.5
23-Jul-15	22.75	1002	91.89	32.51	32.51	63.2
24-Jul-15	22.33	1002	95.21	31.3	31.3	213.7
25-Jul-15	22.28	1002	93.84	30.61	30.61	30.6
26-Jul-15	22.45	1002	93.39	31.87	31.87	41
27-Jul-15	22.18	1001	96.2	29.95	29.95	404.7
28-Jul-15	21.96	1002	92.7	31.2	31.2	39.3
29-Jul-15	21.75	1003	91.56	31.33	31.33	44.2
30-Jul-15	22.07	1003	94.27	30.44	30.44	18.9
31-Jul-15	21.82	1003	92.93	30.9	30.9	42.6
1-Aug-15	22.3	1002	93.72	31.02	31.02	7
2-Aug-15	22.24	1002	92.4	31.3	31.3	96
3-Aug-15	22.58	1001	97.28	31.76	31.76	42.3
4-Aug-15	23.08	1002	93.33	30.68	30.68	25
5-Aug-15	22.55	1002	93.62	31.38	31.38	53.8
6-Aug-15	22.8	1001	93.99	30.85	30.85	13.6
7-Aug-15	22.61	1000	93.4	29.75	29.75	38.7
8-Aug-15	22.51	1000	94.95	30.89	30.89	48.7
9-Aug-15	22.74	1001	93.85	30.2	30.2	8.4
10-Aug-15	22.78	1000	93.83	30.95	30.95	19.2
11-Aug-15	22.98	1001	94.65	31.57	31.57	131.2
12-Aug-15	22.75	1002	94.56	30.96	30.96	216.9
13-Aug-15	22.61	1003	94.27	31.73	31.73	32.9
14-Aug-15	22.99	1001	94.52	30.2	30.2	9.4
15-Aug-15	22.69	1002	94.02	30.93	30.93	25.3
16-Aug-15	23.44	1003	93.18	31.54	31.54	8.3
17-Aug-15	22.6	1002	96.8	30.4	30.4	51.1
18-Aug-15	22.78	1001	98.11	31.19	31.19	46.9
19-Aug-15	22.42	1001	92.12	30.41	30.41	38.6
20-Aug-15	22.76	1000	94.87	31.24	31.24	66.2
21-Aug-15	22.85	1000	98.05	30.42	30.42	119.8
22-Aug-15	22.41	1000	92.31	31.6	31.6	44.7
23-Aug-15	22.97	1000	97.01	32.57	32.57	40.2
24-Aug-15	22.97	1000	96.85	31.53	31.53	67.9
25-Aug-15	22.61	1001	95.93	30.52	30.52	27.8
26-Aug-15	22.96	1002	91.55	30.94	30.94	10
27-Aug-15	23.1	1001	94.32	29.56	29.56	22.8
28-Aug-15	22.17	1000	94.41	30.72	30.72	258.5
29-Aug-15	22.54	1002	92.26	30.14	30.14	90.1
30-Aug-15	22.37	1003	92.84	30.74	30.74	27.5
31-Aug-15	22.51	1003	94	30.5	30.5	52.5
1-Sep-15	22.2	1003	95.03	29.99	29.99	221.2
2-Sep-15	22.2	1002	97.12	30.04	30.04	54.1
3-Sep-15	22.64	1003	96.78	30.53	30.53	86.3
4-Sep-15	23.09	1002	98.16	30.84	30.84	68.3
5-Sep-15	22.73	1001	96.63	29.16	29.16	24
6-Sep-15	23.29	1002	97.96	31.09	31.09	97.2
7-Sep-15	22.31	1003	98.49	31.02	31.02	91.9

8-Sep-15	21.97	1001	97.14	29.41	29.41	291.7
9-Sep-15	22.15	1000	88.29	29.71	29.71	24.6
10-Sep-15	21.87	1000	94.84	31.22	31.22	11.9
11-Sep-15	22.39	1000	95.68	31.26	31.26	47.6
12-Sep-15	22.89	1000	98.49	30.62	30.62	3.6
13-Sep-15	23.14	1000	91.86	32.05	32.05	50.4
14-Sep-15	23.43	1002	95.64	30.26	30.26	251.7
15-Sep-15	22.85	1002	95.85	30.79	30.79	215.9
16-Sep-15	22.52	1001	94.7	30.35	30.35	144.2
17-Sep-15	22.12	1001	94.99	30.17	30.17	82.7
18-Sep-15	23.07	1000	96.34	29.73	29.73	21.8
19-Sep-15	23.16	1001	93.94	31.35	31.35	5.4
20-Sep-15	23.25	1002	95.01	31.48	31.48	16.7
21-Sep-15	22.31	1002	94.47	30.22	30.22	8.4
22-Sep-15	22.49	1000	92.03	29.36	29.36	22.7
23-Sep-15	22.52	1001	91.19	30.96	30.96	17.3
24-Sep-15	22.87	1000	92.57	31.08	31.08	47.6
25-Sep-15	22.39	1001	94.59	30.59	30.59	107.2
26-Sep-15	22.97	1001	94.26	31.58	31.58	12.6
27-Sep-15	22.59	999	94.43	31.08	31.08	19.8
28-Sep-15	23.16	999	94.59	32.34	32.34	45.9
29-Sep-15	22.78	999	97.46	29.8	29.8	99
30-Sep-15	22.85	1000	96.63	31.72	31.72	385.7
1-Oct-15	22.14	1000	94.4	32.39	32.39	31
2-Oct-15	23.42	999	93.96	33.26	33.26	25.9
3-Oct-15	22.97	999	94.66	32.31	32.31	23.6
4-Oct-15	23.38	1000	95.53	30.86	30.86	4.6
5-Oct-15	23.22	1001	93.67	30.03	30.03	65.1
6-Oct-15	23.65	1001	92.38	31.28	31.28	52.1
7-Oct-15	23.36	1000	95.47	32.03	32.03	49.3
8-Oct-15	22.51	1000	95.77	30.37	30.37	24.2
9-Oct-15	22.66	1001	95.43	29.99	29.99	52.9
10-Oct-15	22.53	1000	96.87	30.51	30.51	11.8
11-Oct-15	23.57	1001	93.51	31.76	31.76	44.3
12-Oct-15	23.32	1000	98.04	31.13	31.13	5.8
13-Oct-15	23.45	1001	93.52	31.8	31.8	22.3
14-Oct-15	23.52	1000	94.89	32.7	32.7	78.1
15-Oct-15	23.12	1000	94.88	31.74	31.74	123
16-Oct-15	24.1	999	96.7	31.89	31.89	11.6
17-Oct-15	23.05	1000	93.13	31.76	31.76	32.7
18-Oct-15	22.68	1001	94.99	31.51	31.51	19.9
19-Oct-15	23.66	1000	94.23	33.21	33.21	35.9
20-Oct-15	22.77	1000	93.25	32.27	32.27	32.3
21-Oct-15	23.28	1000	97.53	32.2	32.2	52.8
22-Oct-15	23.22	1000	95.69	30.62	30.62	107.7
23-Oct-15	23.33	1001	97.9	31.28	31.28	52.3
24-Oct-15	23.73	1000	94.71	30.99	30.99	63.9
25-Oct-15	23.12	1000	95.61	31.06	31.06	1.9

26-Oct-15	23.51	1000	95.96	31.09	31.09	45
27-Oct-15	23.3	1000	93.57	31.63	31.63	64.2
28-Oct-15	24.08	1000	95.88	31.5	31.5	113.5
29-Oct-15	23.29	1000	95.68	31.84	31.84	150.4
30-Oct-15	22.72	999	97.29	30.25	30.25	125.3
31-Oct-15	23.09	999	95.12	30.32	30.32	39.6
1-Nov-15	23.03	999	96.22	31.48	31.48	176.8
2-Nov-15	22.58	1000	95.92	30.4	30.4	257.2
3-Nov-15	22.87	1000	97.9	28.34	28.34	38.6
4-Nov-15	23.77	1000	95.31	27	27	2.7
5-Nov-15	22.91	999	96.08	26.84	26.84	208.8
6-Nov-15	22.97	1000	97.29	26.75	26.75	17.9
7-Nov-15	23.43	999	94.87	28.29	28.29	14.1
8-Nov-15	23.12	1000	93.72	27.72	27.72	104.8
9-Nov-15	22.23	1002	96.33	31.5	31.5	70.6
10-Nov-15	23.14	1001	94.72	30.7	30.7	331.7
11-Nov-15	22.68	1000	97.86	29.37	29.37	13.3
12-Nov-15	23.33	998	97.34	29.15	29.15	0
13-Nov-15	24	998	97.07	28.87	28.87	0.3
14-Nov-15	24.45	999	98.28	26.89	26.89	4.1
15-Nov-15	24.22	1000	94.76	25.97	25.97	40.5
16-Nov-15	23.64	1000	97.66	27.19	27.19	4.3
17-Nov-15	23.79	998	96.19	26.51	26.51	18.3
18-Nov-15	24.04	997	96.52	27.92	27.92	1.3
19-Nov-15	24.91	997	96.08	28.05	28.05	1.2
20-Nov-15	24.26	998	95.99	27.74	27.74	2.1
21-Nov-15	23.93	998	93.41	27.6	27.6	0.5
22-Nov-15	24.31	997	94.93	26.83	26.83	3
23-Nov-15	24.47	997	94.33	28.71	28.71	10.8
24-Nov-15	24.09	999	94.9	27.74	27.74	45.6
25-Nov-15	22.87	999	96.28	28.53	28.53	0
26-Nov-15	24.96	998	96.18	27.24	27.24	2.9
27-Nov-15	24.32	997	94.94	26.92	26.92	7.5
28-Nov-15	23.36	999	93.7	27.47	27.47	0.1
29-Nov-15	24.66	1000	95.59	26.96	26.96	10.9
30-Nov-15	24.98	1001	96.02	26.93	26.93	0.1
1-Dec-15	24.35	1000	97.02	29.68	29.68	17.3
2-Dec-15	24.46	1000	95.59	28.69	28.69	4.8
3-Dec-15	23.84	1000	96.77	27.81	27.81	0
4-Dec-15	23.52	999	88.57	26.85	26.85	0
5-Dec-15	23.97	1000	91.32	26.29	26.29	0
6-Dec-15	24.02	1000	97.61	25.63	25.63	6
7-Dec-15	20.98	1000	71.85	25.96	25.96	0
8-Dec-15	19.23	1000	67.64	25.27	25.27	0
9-Dec-15	24.58	1000	97.53	24.43	24.43	0
10-Dec-15	24.67	1000	98.59	24.98	24.98	5.3
11-Dec-15	23.49	1000	90.34	24.81	24.81	0
12-Dec-15	22.06	1000	85.85	23.61	23.61	0

13-Dec-15	20.91	1000	88.62	22.21	22.21	0
14-Dec-15	23.24	1000	93.79	22.73	22.73	0
15-Dec-15	21.67	1000	84.5	22.08	22.08	0
16-Dec-15	18.86	1000	72.2	21.6	21.6	0
17-Dec-15	20.29	1000	78.57	20.49	20.49	0
18-Dec-15	21.09	1000	80.53	21.59	21.59	0
19-Dec-15	20.18	1000	66.72	21.97	21.97	0
20-Dec-15	21.96	1001	82.54	23.79	23.79	0.2
21-Dec-15	23.25	1001	94.18	25.57	25.57	0.5
22-Dec-15	22.29	1000	87.02	25.31	25.31	1.2
23-Dec-15	20.21	1000	75	24.53	24.53	0
24-Dec-15	22.25	1000	90.23	23.77	23.77	0
25-Dec-15	21.71	1001	83.28	24.43	24.43	0.1
26-Dec-15	20.77	1000	79.79	24.87	24.87	0
27-Dec-15	22.36	999	89.6	25.34	25.34	0
28-Dec-15	21.67	999	82.23	24.44	24.44	0
29-Dec-15	23.63	1000	90.98	24.13	24.13	0
30-Dec-15	22.71	1001	86.15	23.5	23.5	0.1
31-Dec-15	24.1	1000	95.28	22.97	22.97	0
.	.	.	.	.	.	.
.	.	.	.	.	.	.
30-Dec-19	22.91	997	94.9	21.92	21.92	0.2
31-Dec-19	24.3	997	96.04	23.29	23.29	0

(b) Source Dataset: Ikeja dataset

Date	Dew(Oc)	Pressure(hPa)	Humidity(KG)	Temp(oC)	WindSpeed(KM/S)	Rainfall(mm)
1-Jan-15	24.09	1009	87.03	34.61	3.72	0
2-Jan-15	24.07	1010	87.99	34.57	4.037	0
3-Jan-15	24.13	1012	88.11	34.72	4.726	0
4-Jan-15	24.12	1012	90.19	34.59	1.564	0
5-Jan-15	21.28	1012	73.14	34.09	0.463	0
6-Jan-15	19.06	1010	61.72	34.13	1.734	0
7-Jan-15	19.84	1010	65.31	33.78	2.245	0
8-Jan-15	21.06	1011	71.62	33.55	1.975	0
9-Jan-15	21.62	1012	74.87	33.82	1.34	0
10-Jan-15	21.39	1012	62.28	33.48	1.764	0
11-Jan-15	19.6	1012	64.7	33.24	0.51	0
12-Jan-15	19.48	1011	44.72	33.29	1.845	0
13-Jan-15	20.64	1010	57.48	33.05	2.027	0
14-Jan-15	19.37	1010	64.64	33.24	1.063	0
15-Jan-15	20.8	1010	74.56	32.98	3.21	0
16-Jan-15	22.25	1011	82.21	33.26	2.964	0
17-Jan-15	22.98	1010	85.27	33.35	3.316	0
18-Jan-15	23.86	1011	91.37	33.57	4.435	0
19-Jan-15	23.92	1011	93.52	33.74	4.865	0
20-Jan-15	24.88	1009	95.53	33.99	4.28	0
21-Jan-15	24.89	1009	94.37	34.2	4.412	0
22-Jan-15	24.95	1011	92.56	34.41	4.761	0

23-Jan-15	25.22	1010	94.27	34.6	4.392	0
24-Jan-15	25.26	1008	94.06	34.47	5.712	0
25-Jan-15	25.05	1008	95.78	34.17	5.14	2
26-Jan-15	24.59	1009	91.11	34.28	5.556	2
27-Jan-15	25.09	1010	93.88	34.49	4.812	3
28-Jan-15	25.23	1009	92.26	34.68	5.956	2
29-Jan-15	24.77	1009	93.19	34.25	4.635	3
30-Jan-15	24.9	1009	92.64	34.52	3.7	4
31-Jan-15	24.65	1010	91.79	34.47	3.539	13
1-Feb-15	24.97	1010	92.36	34.66	4.839	4
2-Feb-15	25.48	1008	92.09	34.97	4.608	0
3-Feb-15	25.27	1008	92.01	34.96	5.576	2
4-Feb-15	25.36	1009	92.4	34.92	4.813	2
5-Feb-15	25.31	1008	91.65	35.01	5.077	1
6-Feb-15	25.42	1008	91.3	35.09	5.124	1
7-Feb-15	25.11	1008	90.41	35.07	4.696	4
8-Feb-15	25.18	1008	89.74	35.14	5.422	1
9-Feb-15	25.5	1008	91.47	35.11	5.637	3
10-Feb-15	25.47	1008	90.57	35.21	4.925	0
11-Feb-15	25.79	1007	92.83	35.39	4.706	0
12-Feb-15	25.55	1009	90.59	35.34	5.753	4
13-Feb-15	25.33	1010	89.88	35.21	6.097	2
14-Feb-15	25.13	1011	88.86	35.39	5.637	1
15-Feb-15	25.18	1010	90.61	35.28	4.161	1
16-Feb-15	25.18	1010	88.09	35.23	4.941	0
17-Feb-15	25.31	1009	90.32	35.37	4.832	0
18-Feb-15	25.26	1008	88.15	35.01	5.497	37
19-Feb-15	23.67	1008	88.99	34.05	2.745	91
20-Feb-15	24.1	1008	86.3	34.61	4.811	14
21-Feb-15	24.81	1008	87.63	34.97	3.599	3
22-Feb-15	25.14	1008	88.63	34.87	5.203	36
23-Feb-15	25.4	1009	91.17	35.1	4.093	2
24-Feb-15	24.75	1009	91.02	34.82	3.178	0
25-Feb-15	25.7	1008	93.76	35.01	4.845	0
26-Feb-15	25.71	1007	93.11	35.05	5.203	1
27-Feb-15	25.11	1007	89.04	34.92	4.289	3
28-Feb-15	23.74	1010	85.01	34.55	3.549	3
1-Mar-15	24.74	1009	84.68	35.44	3.672	1
2-Mar-15	25.3	1008	90.45	35.08	4.402	0
3-Mar-15	25.44	1008	91.57	35.06	4.443	0
4-Mar-15	25.2	1009	92.66	34.79	3.553	5
5-Mar-15	25.05	1009	88.75	35.08	2.911	5
6-Mar-15	25.67	1008	91.58	35.3	3.96	0
7-Mar-15	25.63	1008	91.72	35.2	4.629	0
8-Mar-15	25.36	1008	90.93	34.98	4.944	0
9-Mar-15	25.37	1008	92.96	34.98	4.023	2
10-Mar-15	25.52	1008	92.68	35.11	5.097	1
11-Mar-15	25.57	1009	90.31	35.55	4.018	3

12-Mar-15	25.69	1008	90.43	35.51	3.308	1
13-Mar-15	25.08	1007	88.05	34.95	4.371	105
14-Mar-15	24.75	1006	86.92	35.12	4.011	4
15-Mar-15	25.72	1006	88.87	35.58	3.895	0
16-Mar-15	25.83	1007	90.29	35.52	4.605	1
17-Mar-15	25.82	1008	93.17	35.11	3.42	3
18-Mar-15	24.66	1008	90.11	34.53	3.612	26
19-Mar-15	25.58	1006	90.35	35.13	3.979	0
20-Mar-15	25.61	1007	89.69	35.45	4.262	1
21-Mar-15	25.5	1007	87.82	35.33	4.893	60
22-Mar-15	24.57	1009	88.88	34.88	0.89	105
23-Mar-15	25.04	1007	83.7	35.86	3.402	2
24-Mar-15	25.5	1008	89.95	35.55	4.774	0
25-Mar-15	25.01	1007	88.77	34.95	4.651	140
26-Mar-15	24.91	1009	89.24	35.18	2.575	79
27-Mar-15	25.03	1010	85.9	35.3	3.594	39
28-Mar-15	25.17	1011	85.45	35.63	5.444	33
29-Mar-15	25.47	1010	89.58	35.36	6.627	1
30-Mar-15	25.01	1009	88.05	35.38	4.438	10
31-Mar-15	23.95	1010	90.43	34.02	2.223	219
1-Apr-15	23.82	1010	88.86	33.94	0.949	143
2-Apr-15	24.59	1010	87.77	34.94	3.108	0
3-Apr-15	25.04	1009	89.65	35.17	3.987	0
4-Apr-15	25.25	1008	91.64	35.13	3.936	0
5-Apr-15	25.13	1008	91.67	34.76	4.877	8
6-Apr-15	24.45	1009	88.1	34.72	3.137	20
7-Apr-15	24.79	1008	88.92	35.09	3.582	2
8-Apr-15	24.6	1008	88.75	35.18	3.774	4
9-Apr-15	25.29	1009	88.34	35.38	4.463	6
10-Apr-15	25.16	1008	88.44	35.34	4.211	3
11-Apr-15	24.57	1009	86.52	35.45	2.309	1
12-Apr-15	24.08	1010	89.15	34.69	2.008	103
13-Apr-15	24.6	1010	88.73	35.24	3.086	2
14-Apr-15	25.29	1009	91.37	35.54	3.418	0
15-Apr-15	25.64	1009	92.21	35.35	5.799	1
16-Apr-15	25.73	1009	91.56	35.47	5.609	1
17-Apr-15	25.38	1010	88.87	35.86	4.182	0
18-Apr-15	25.38	1010	87.67	35.79	4.585	1
19-Apr-15	25.55	1009	88.65	35.84	5.028	1
20-Apr-15	25.49	1008	85.74	36	5.327	4
21-Apr-15	25.35	1007	86.14	35.81	5.275	4
22-Apr-15	25.44	1008	84.76	36.29	4.994	0
23-Apr-15	25.35	1009	85.6	36.05	4.871	2
24-Apr-15	25.19	1009	86.91	35.79	4.554	6
25-Apr-15	24.82	1010	87.94	35.5	6.005	9
26-Apr-15	25.33	1010	90.09	35.77	4.496	3
27-Apr-15	24.61	1009	86.92	35.51	1.992	0
28-Apr-15	25.03	1009	86.02	35.86	4.35	0

29-Apr-15	25.27	1009	86.17	35.58	5.682	37
30-Apr-15	25.02	1008	84.13	36.26	4.171	0
1-May-15	25.05	1007	83.22	36.19	4.452	13
2-May-15	25.05	1007	82.61	36.1	2.854	8
3-May-15	25.29	1008	84.27	36.29	4.607	4
4-May-15	24.75	1008	85.12	35.6	2.821	34
5-May-15	24.78	1009	88.39	34.77	3.517	252
6-May-15	24.6	1009	86.6	35.27	3.985	1
7-May-15	25.13	1009	86.83	36.1	4.111	0
8-May-15	25.25	1010	90.41	35.5	4.755	41
9-May-15	25.22	1010	87.54	36.02	3.45	14
10-May-15	24.86	1009	84.77	35.91	4.23	31
11-May-15	24.65	1009	84.76	35.47	4.063	43
12-May-15	25.06	1009	84.73	36.16	2.825	27
13-May-15	25.3	1010	86.4	35.78	4.004	28
14-May-15	25.11	1008	87.8	36.03	3.212	51
15-May-15	24.21	1009	84.28	35.27	1.46	87
16-May-15	24.83	1010	82.26	36.34	2.378	4
17-May-15	25.09	1009	83.46	36.32	3.67	0
18-May-15	25.23	1010	87.72	35.78	4.492	25
19-May-15	24.8	1010	86	35.34	2.943	65
20-May-15	24.85	1010	86.6	35.84	2.982	2
21-May-15	24.74	1010	81.5	36.16	4.928	5
22-May-15	24.9	1010	87.44	35.67	3.528	15
23-May-15	24.29	1010	89.72	34.26	4.006	301
24-May-15	24.29	1012	88.16	34.31	2.567	133
25-May-15	24.3	1010	85.25	35.31	2.641	4
26-May-15	24.62	1010	84.02	35.71	5.432	8
27-May-15	24.4	1009	88.67	34.36	4.425	85
28-May-15	24.22	1010	90.17	34.37	3.333	137
29-May-15	24.08	1009	87.85	34.53	2.775	152
30-May-15	24.12	1009	85.01	35.18	4.001	3
31-May-15	24.08	1010	88.83	34.51	4.388	115
1-Jun-15	24.18	1010	86.43	35.03	3.237	17
2-Jun-15	24.2	1009	89.12	34.34	4.639	95
3-Jun-15	23.34	1010	86.07	34.38	4.468	44
4-Jun-15	23.31	1012	90.12	33.75	3.394	226
5-Jun-15	23.68	1010	87.8	34.32	4.501	57
6-Jun-15	23.29	1010	86.7	33.98	1.491	32
7-Jun-15	23.41	1011	90.22	34	3.402	63
8-Jun-15	23.48	1010	87.82	33.86	3.107	73
9-Jun-15	23.31	1010	88.64	34.03	3.838	66
10-Jun-15	23.34	1011	89.59	33.49	3.71	105
11-Jun-15	23.57	1012	88.3	34.1	5.073	11
12-Jun-15	24.16	1011	92.04	34.2	4.944	15
13-Jun-15	23.78	1011	89.81	34.15	3.31	24
14-Jun-15	23.38	1011	89.49	33.4	3.278	67
15-Jun-15	23.11	1011	87.34	33.8	3.343	22

16-Jun-15	23.4	1011	86.31	34.14	5.21	15
17-Jun-15	23.26	1011	87.51	33.96	4.326	64
18-Jun-15	24.01	1010	89.52	34.14	5.051	13
19-Jun-15	23.52	1010	89.76	33.74	5.267	57
20-Jun-15	23.62	1012	90.21	33.95	5.454	35
21-Jun-15	22.97	1013	89.04	33.21	4.338	206
22-Jun-15	22.87	1014	90.29	33.09	4.131	66
23-Jun-15	22.97	1014	85.53	34.03	5.08	22
24-Jun-15	23.08	1014	87.28	34.06	5.789	3
25-Jun-15	23.33	1015	86.93	34.19	6.204	12
26-Jun-15	23.1	1015	88.3	33.76	5.398	34
27-Jun-15	23.23	1013	86.67	33.84	5.278	32
28-Jun-15	23.25	1013	89.74	33.51	4.166	86
29-Jun-15	23.17	1014	89.5	33.22	4.542	220
30-Jun-15	23.27	1013	89.11	33.43	4.685	30
1-Jul-15	23.13	1013	88.09	33.49	5.258	28
2-Jul-15	23.52	1012	89	33.67	5.198	32
3-Jul-15	23.25	1012	92.67	33.2	3.87	445
4-Jul-15	23.1	1013	91.05	33.16	3.303	46
5-Jul-15	23.42	1012	91.15	33.43	4.176	7
6-Jul-15	23.36	1010	89.61	33.66	3.367	6
7-Jul-15	23.58	1010	90.57	33.85	2.727	3
8-Jul-15	23.6	1010	89.49	33.97	2.339	4
9-Jul-15	24.01	1010	90.94	33.9	3.822	2
10-Jul-15	24.2	1011	92.65	33.86	4.668	4
11-Jul-15	23.7	1013	93.12	33.65	2.546	3
12-Jul-15	24	1012	91.2	33.94	3.8	4
13-Jul-15	23.52	1011	91.47	33.45	4.781	8
14-Jul-15	23.62	1011	92.21	33.58	4.532	9
15-Jul-15	23.44	1011	90.93	33.41	4.485	27
16-Jul-15	22.9	1012	88.85	32.85	3.886	110
17-Jul-15	22.72	1013	89.77	33.23	2.72	17
18-Jul-15	23.6	1012	92	33.43	4.218	2
19-Jul-15	23.39	1011	91.3	33.37	6.252	21
20-Jul-15	22.94	1011	87.64	33.1	6.322	79
21-Jul-15	22.67	1012	90.43	32.96	6.16	18
22-Jul-15	22.61	1013	89.64	33.06	5.24	8
23-Jul-15	22.57	1013	89.84	33.1	5.291	0
24-Jul-15	22.58	1013	87.16	33.17	6.383	7
25-Jul-15	22.3	1012	86.29	33.1	5.339	15
26-Jul-15	22.45	1013	87.75	33.03	5.721	10
27-Jul-15	22.6	1012	89.03	32.99	5.855	1
28-Jul-15	22.1	1012	85.23	32.91	7.377	42
29-Jul-15	21.51	1014	85.55	32.52	5.636	5
30-Jul-15	22.11	1013	89.62	32.71	5.322	1
31-Jul-15	22.11	1013	89.05	32.7	5.847	13
1-Aug-15	22.66	1012	89.55	32.88	4.615	2
2-Aug-15	22.74	1012	91.44	32.76	5.218	3

3-Aug-15	22.81	1011	92.07	32.75	4.366	3
4-Aug-15	22.81	1013	92.3	32.56	4.377	8
5-Aug-15	22.68	1012	90.6	32.66	4.491	2
6-Aug-15	22.95	1011	90.83	32.74	4.626	1
7-Aug-15	23.08	1010	91.97	32.92	4.701	10
8-Aug-15	22.8	1011	92.31	32.64	3.95	13
9-Aug-15	22.84	1011	92.22	32.75	3.84	4
10-Aug-15	22.74	1010	91.79	32.76	4.868	24
11-Aug-15	22.62	1012	89.58	32.81	4.798	18
12-Aug-15	22.8	1013	91.23	32.78	5.052	5
13-Aug-15	22.82	1013	91.77	32.63	4.553	10
14-Aug-15	22.98	1012	90.45	32.95	4.544	6
15-Aug-15	22.96	1011	91.94	32.86	6.295	23
16-Aug-15	22.95	1013	90.35	32.81	4.022	7
17-Aug-15	23.22	1013	95.36	32.58	5.311	6
18-Aug-15	22.9	1011	90.17	32.78	5.322	28
19-Aug-15	22.97	1011	90.81	32.9	4.51	8
20-Aug-15	22.7	1010	89.05	32.83	4.28	39
21-Aug-15	22.76	1010	91.94	32.64	5.95	143
22-Aug-15	22.79	1011	91.74	32.79	4.765	23
23-Aug-15	22.8	1010	90.3	32.93	5.292	6
24-Aug-15	23.12	1011	90.78	33.04	3.835	20
25-Aug-15	22.96	1011	90.61	32.92	4.69	16
26-Aug-15	22.83	1012	90.3	33.04	4.201	28
27-Aug-15	23.01	1011	90.2	32.98	4.934	4
28-Aug-15	22.76	1010	88.5	33.09	5.822	30
29-Aug-15	22.84	1012	90.01	32.98	4.293	21
30-Aug-15	22.69	1013	89.23	32.94	3.991	17
31-Aug-15	22.84	1013	90.22	32.9	5.281	4
1-Sep-15	22.67	1012	91.45	32.9	5.931	128
2-Sep-15	22.78	1012	90.85	32.85	5.339	9
3-Sep-15	22.66	1013	89.47	32.8	4.845	5
4-Sep-15	22.96	1012	91.68	32.81	3.559	2
5-Sep-15	23.07	1011	92.75	33.01	4.112	7
6-Sep-15	23.02	1012	89.75	32.96	4.735	155
7-Sep-15	22.94	1013	91.07	32.91	4.728	14
8-Sep-15	22.85	1011	93.14	32.69	4.745	43
9-Sep-15	22.65	1011	87.53	33.04	4.965	71
10-Sep-15	22.95	1011	91.47	32.87	3.962	5
11-Sep-15	23.33	1010	92.85	32.87	4.576	0
12-Sep-15	23.13	1010	93.1	32.96	3.003	2
13-Sep-15	23.24	1011	89.99	33.28	4.256	27
14-Sep-15	23.19	1012	91.31	33.32	4.261	10
15-Sep-15	23.11	1012	90.07	33.27	4.286	95
16-Sep-15	22.99	1012	90.29	33.1	5.119	131
17-Sep-15	23.2	1010	92.26	33.22	4.498	14
18-Sep-15	23.49	1010	92.56	33.06	3.856	16
19-Sep-15	23.21	1011	89.55	33.12	4.47	15

20-Sep-15	23.19	1012	92.22	33.18	2.646	3
21-Sep-15	23.05	1012	91.55	33.09	2.607	7
22-Sep-15	22.88	1011	90.26	33.07	4.569	34
23-Sep-15	23.16	1011	89.62	33.36	3.701	8
24-Sep-15	23.74	1011	94.26	33.51	5.057	4
25-Sep-15	22.98	1011	91.03	33.33	3.573	80
26-Sep-15	23.47	1011	89.97	33.62	4.921	215
27-Sep-15	23.73	1009	89.8	33.59	4.411	8
28-Sep-15	23.63	1009	88.68	33.83	4.941	14
29-Sep-15	23.39	1010	90.6	33.64	3.645	56
30-Sep-15	23.31	1010	89.8	33.44	3.432	104
1-Oct-15	23.37	1010	90.02	33.61	4.287	17
2-Oct-15	23.44	1009	90.45	33.65	4.765	7
3-Oct-15	23.25	1009	89.52	33.61	3.992	37
4-Oct-15	23.09	1011	88.71	33.52	3.367	105
5-Oct-15	23.61	1012	88.33	33.97	3.316	26
6-Oct-15	23.68	1011	90.13	34.02	3.838	10
7-Oct-15	23.57	1011	89.34	33.81	3.188	139
8-Oct-15	23.5	1011	87.44	33.72	4.12	93
9-Oct-15	23.48	1012	89	33.7	2.979	45
10-Oct-15	23.6	1011	91.22	33.79	1.978	25
11-Oct-15	23.68	1012	89.25	34.12	3.651	26
12-Oct-15	23.97	1011	88.02	34.43	1.243	1
13-Oct-15	24.11	1011	89.34	34.62	3.645	2
14-Oct-15	24.12	1010	88.28	34.28	3.785	83
15-Oct-15	23.87	1010	86.76	34.4	2.52	16
16-Oct-15	24.44	1009	88.35	34.64	3.874	12
17-Oct-15	24.36	1010	88.61	34.51	4.314	56
18-Oct-15	24.01	1011	89.12	34.3	3.795	67
19-Oct-15	24.14	1011	88.36	34.78	4.051	7
20-Oct-15	24.09	1010	89.9	34.09	2.837	55
21-Oct-15	23.94	1010	89.08	34.08	2.538	156
22-Oct-15	23.83	1010	86.11	34.54	3.243	8
23-Oct-15	23.84	1011	87.41	34.6	3.361	12
24-Oct-15	24.3	1010	87.96	34.82	3.958	23
25-Oct-15	24.16	1010	88.07	34.75	4.001	14
26-Oct-15	24.33	1011	90.54	34.53	3.442	29
27-Oct-15	24.34	1011	87.31	35.1	3.828	15
28-Oct-15	24.34	1010	89.34	34.67	0.529	32
29-Oct-15	23.84	1010	87.15	34.56	3.012	11
30-Oct-15	23.53	1010	86.22	34.24	2.727	27
31-Oct-15	23.84	1009	85.76	34.63	1.488	20
1-Nov-15	23.29	1011	92.01	33.7	1.075	256
2-Nov-15	23.36	1010	90.2	33.58	2.362	239
3-Nov-15	23.36	1010	87.97	34.41	0.786	11
4-Nov-15	24.29	1010	85.65	35.18	3.548	1
5-Nov-15	24.21	1010	84.91	34.83	4.374	18
6-Nov-15	23.98	1010	88.28	34.38	2.703	32

7-Nov-15	23.9	1010	85.5	34.68	3.106	15
8-Nov-15	24.17	1010	87.22	34.72	2.792	10
9-Nov-15	23.87	1012	87.49	34.27	2.647	97
10-Nov-15	23.8	1012	83.82	34.91	3.218	13
11-Nov-15	23.86	1010	84.66	34.76	2.864	19
12-Nov-15	24.81	1009	86.13	35.54	3.655	0
13-Nov-15	25.11	1009	89	35.49	4.371	0
14-Nov-15	25.62	1010	91.23	35.49	4.456	0
15-Nov-15	25.12	1010	87.55	35.57	5.652	0
16-Nov-15	24.99	1009	88.67	35.47	3.586	0
17-Nov-15	24.34	1009	87.7	34.99	3.472	2
18-Nov-15	24.29	1008	85.92	34.94	3.241	56
19-Nov-15	24.84	1007	87.38	35.47	4.305	0
20-Nov-15	25	1008	88.36	35.39	4.223	0
21-Nov-15	24.9	1008	87.13	35.41	4.381	0
22-Nov-15	25.06	1007	86.93	35.52	4.557	0
23-Nov-15	25.12	1007	87.96	35.45	4.069	0
24-Nov-15	25.19	1009	88.76	35.49	4.077	1
25-Nov-15	24.71	1010	86.96	35.37	3.627	3
26-Nov-15	24.94	1008	85.7	35.55	4.975	0
27-Nov-15	24.77	1008	84.31	35.64	4.883	0
28-Nov-15	25	1009	85.51	35.68	4.492	2
29-Nov-15	25.34	1010	88.09	35.69	4.522	0
30-Nov-15	25.21	1011	88.57	35.64	3.369	0
1-Dec-15	25.15	1011	88.98	35.7	4.042	0
2-Dec-15	25.13	1011	87.13	35.89	3.732	1
3-Dec-15	24.55	1010	86.87	35.23	2.447	5
4-Dec-15	23.58	1010	78.7	35.44	0.276	0
5-Dec-15	22.47	1010	66.93	35.47	0.982	0
6-Dec-15	23.01	1011	70.66	35.02	2.751	0
7-Dec-15	23.38	1011	77.81	34.9	1.562	0
8-Dec-15	23.31	1011	59.29	35.01	0.992	0
9-Dec-15	22.1	1011	71.21	34.99	1.695	0
10-Dec-15	23.2	1011	77.27	34.89	2.585	0
11-Dec-15	23.45	1011	79.51	34.79	2.912	0
12-Dec-15	23.48	1011	81.98	34.66	2.665	0
13-Dec-15	23.11	1011	79.7	34.68	2.677	0
14-Dec-15	22.24	1010	74.38	34.72	3.603	0
15-Dec-15	22.47	1010	76.53	35.08	1.626	0
16-Dec-15	21.28	1011	67.84	34.66	0.576	0
17-Dec-15	19.49	1010	63.45	34.82	2.323	0
18-Dec-15	20.74	1011	65.04	34.77	2.551	0
19-Dec-15	20.06	1011	58.7	35.37	1.894	0
20-Dec-15	21.43	1011	64.22	35.13	2.833	0
21-Dec-15	21.31	1011	66.57	34.9	2.657	0
22-Dec-15	22.56	1011	73.75	34.76	1.78	0
23-Dec-15	21.5	1011	64.8	34.8	0.357	0
24-Dec-15	21.04	1011	68.71	34.66	1.607	0

25-Dec-15	21.11	1012	63.79	34.63	0.533	0
26-Dec-15	22.02	1011	56.02	34.11	0.681	0
27-Dec-15	21.17	1010	70.82	34.17	2.017	0
28-Dec-15	21.98	1009	73.88	34.12	2.697	0
29-Dec-15	23.59	1011	88.58	33.56	3.091	0
30-Dec-15	23.5	1011	90.4	33.5	2.537	0
31-Dec-15	24.39	1011	92.8	33.95	4.503	0
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30-Dec-19	24.41	1007	83.03	35.54	2.104	0
31-Dec-19	23.73	1007	80.52	35.48	2.47	0

(c) Source Dataset: Minna dataset

Date	Dew(Oc)	Pressure(hPa)	Humidity(KG)	Temp(oC)	WindSpeed(KM/S)	Rainfall(mm)
1-Jan-15	5.07	984.1	26.81	32.62	3.005	0
2-Jan-15	5.86	985.2	31.21	31.77	3.197	0
3-Jan-15	1.33	987.4	23.02	30.63	3.916	0
4-Jan-15	-0.84	988.9	20.31	30.4	4.52	0
5-Jan-15	-1.63	987.9	21.22	29.56	4.512	0
6-Jan-15	1.86	986.5	25.84	28.8	3.615	0
7-Jan-15	1.66	986.8	26.52	29.74	3.959	0
8-Jan-15	-0.76	986.8	22.04	31.04	4.034	0
9-Jan-15	0.94	988.3	22.68	31.45	4.121	0
10-Jan-15	-1.56	988.8	19.27	31.07	4.878	0
11-Jan-15	-2.77	989.3	18.49	29.48	4.591	0
12-Jan-15	-2.51	987.8	19.52	29.25	4.121	0
13-Jan-15	-2.56	987.1	19.45	28.35	4.336	0
14-Jan-15	-3.09	987	19.34	29.01	4.276	0
15-Jan-15	0.36	986.4	21.54	30.9	4.43	0
16-Jan-15	1.52	986.6	24.33	31.24	3.76	0
17-Jan-15	3.86	985.8	25.36	31.18	3.507	0
18-Jan-15	5.38	986.2	27.94	29.99	1.932	0
19-Jan-15	5.58	984.7	28.1	30.56	1.332	0
20-Jan-15	7.42	983	29.43	31.03	1.255	0
21-Jan-15	10.76	983.2	35.62	32.83	1.5	0
22-Jan-15	11.74	984.9	37.27	33.18	1.421	0
23-Jan-15	5.05	984.3	24.49	35.57	2.877	0
24-Jan-15	3.02	982.6	18.86	33.07	2.271	0
25-Jan-15	11.3	981.8	31.69	35.6	0.5	0
26-Jan-15	13.37	982.4	37.37	33.75	0.756	0
27-Jan-15	14.36	983.2	43.6	33.82	1.147	0
28-Jan-15	8.07	982.8	30.6	33.32	1.964	0
29-Jan-15	10.28	982.9	32.8	34.34	2.778	0
30-Jan-15	15.14	983.6	47.44	33.71	1.572	0

31-Jan-15	19.39	983.9	58.81	34.74	0.882	0
1-Feb-15	17.48	983.2	50.33	34.96	1.72	0
2-Feb-15	10.31	982.5	33.45	34.4	1.535	0
3-Feb-15	12.14	981.8	33.98	33.73	1.242	0
4-Feb-15	10.8	982.3	33.01	34.79	1.82	0
5-Feb-15	11.78	981.7	36.29	33.64	1.317	0
6-Feb-15	10.97	981.8	35.23	34.53	1.584	0
7-Feb-15	15.11	981.1	40.34	35.07	1.212	0
8-Feb-15	15.44	981	39.73	37.44	0.822	0
9-Feb-15	13.51	981	36.36	34.29	1.55	0
10-Feb-15	16.42	981.4	44.98	36.43	1.21	0
11-Feb-15	11.3	981.7	34.87	34.92	2.02	0
12-Feb-15	3.02	982.9	18.22	36.36	3.322	0
13-Feb-15	0.75	984.3	16.47	35.42	3.381	0
14-Feb-15	5.45	984.6	23.67	34.91	2.403	0
15-Feb-15	15.43	983.5	40.14	37.22	0.602	0
16-Feb-15	15.43	982.7	38.94	36.96	0.774	0
17-Feb-15	16.59	982.1	41.57	36.35	1.552	0
18-Feb-15	17.94	980.6	43.3	36.26	0.75	0
19-Feb-15	21.99	982.7	74.45	34.88	2.389	0
20-Feb-15	20.2	981.4	59.89	35.55	1.703	0
21-Feb-15	18.84	981	54.05	36.22	2.593	0
22-Feb-15	20.5	981.6	56.02	36.8	1.823	0
23-Feb-15	12.66	983	33.86	37.27	1.593	0
24-Feb-15	10.13	983.7	29.38	36.59	2.649	0
25-Feb-15	13.96	982.4	35.71	35.87	0.974	0
26-Feb-15	15.66	981.1	38.5	37.04	1.553	0
27-Feb-15	17.05	981.4	44.91	35.65	2.128	0
28-Feb-15	21.59	984.6	74.07	33.18	1.379	0
1-Mar-15	13.18	983.6	36.83	34.51	1.71	0
2-Mar-15	1.54	982.4	16.65	35.79	3.069	0
3-Mar-15	5.14	982.1	22.19	34.21	2.055	0
4-Mar-15	7.35	983.8	26.54	34.41	2.53	0
5-Mar-15	5.93	983.6	23.82	35.53	2.956	0
6-Mar-15	6.97	982.4	24.59	35.3	2.796	0
7-Mar-15	12.16	981.3	32.47	35	1.172	0
8-Mar-15	15.31	980.6	36.35	37.27	1.38	0
9-Mar-15	12.44	980.9	29.43	36.92	0.987	0
10-Mar-15	11.71	981.1	29.68	37.64	1.199	0
11-Mar-15	15.39	982.1	37.28	38.33	2.449	0
12-Mar-15	19.83	981.9	50.85	37.71	1.979	0
13-Mar-15	1.74	980.4	15.94	36.63	2.369	0
14-Mar-15	8	979.7	23.49	36.07	2.095	0
15-Mar-15	9.77	980	27.73	35.6	1.12	0
16-Mar-15	5.97	980.6	19.68	39	0.309	0
17-Mar-15	16.96	981.4	42.77	37.77	1.392	0
18-Mar-15	17.11	981.1	43.55	37	2.03	0
19-Mar-15	16.65	979.1	39.69	37.91	1.449	0

20-Mar-15	18.69	979.5	43.96	38.74	2.663	0
21-Mar-15	20.11	979.8	48.94	39.14	2.507	0
22-Mar-15	23.46	981.7	74.54	36.15	2.37	0
23-Mar-15	21.49	981	54.25	38.85	3.009	0
24-Mar-15	20.24	980.7	49.6	37.59	2.79	0
25-Mar-15	22.45	981.2	73.65	36.66	2.168	0
26-Mar-15	23.05	984.7	90.29	33.49	0.561	1
27-Mar-15	22.16	983.3	67.9	34.57	1.584	0
28-Mar-15	20.36	984.3	62.72	35.15	3.064	0
29-Mar-15	16.59	982.5	46.19	34.44	0.892	0
30-Mar-15	18.75	982	51.97	34.85	2.579	0
31-Mar-15	22.51	985	86.72	33.25	3.093	0
1-Apr-15	20.13	984	55.13	34.43	1.008	0
2-Apr-15	9.12	984.7	32.18	34.08	1.471	0
3-Apr-15	10.93	982.5	28.54	35.19	1.431	0
4-Apr-15	14.64	981.3	34.41	36.28	2.318	0
5-Apr-15	17.58	980.4	45.27	36.82	2.603	0
6-Apr-15	19.75	981.8	54.35	36.73	3.408	0
7-Apr-15	19.56	981.7	51.72	36.76	2.412	0
8-Apr-15	21.12	981.9	54.2	37.81	3.354	0
9-Apr-15	20.85	981.2	54.35	38.74	3.304	0
10-Apr-15	23.22	981.1	69.74	36.95	3.089	0
11-Apr-15	21.56	982.6	61.7	36.82	2.224	0
12-Apr-15	21.09	983.9	60.48	36.2	2.088	0
13-Apr-15	11.76	984.6	26.02	34.97	1.67	0
14-Apr-15	3.61	984.1	18.45	35.22	2.637	0
15-Apr-15	3.02	982.4	16.53	34.59	2.395	0
16-Apr-15	7.12	982.3	22.73	35.5	0.892	0
17-Apr-15	10.02	983.8	27.6	34.6	1.943	0
18-Apr-15	2.33	983.6	17.84	33.47	2.555	0
19-Apr-15	6.15	982.9	20.53	33.79	1.75	0
20-Apr-15	7.32	981.8	22.74	34.99	1.687	0
21-Apr-15	13.8	980.7	34.3	36.36	1.167	0
22-Apr-15	14.65	981.2	36.28	38.08	1.628	0
23-Apr-15	14.58	980.8	35.88	38.07	2.409	0
24-Apr-15	17.92	981.6	39.93	39.44	3.364	0
25-Apr-15	19.42	983	48.15	39.69	4.014	0
26-Apr-15	18.43	983.1	44.24	37.41	1.87	0
27-Apr-15	17.62	982.9	45.37	37.72	2.132	0
28-Apr-15	15.18	982.1	37.66	38.65	1.795	0
29-Apr-15	14.58	981.3	38.88	37.26	2.747	0
30-Apr-15	16.91	981.5	39.14	37.19	2.322	0
1-May-15	18.01	980.5	41.42	39.05	3.395	0
2-May-15	18.62	979.8	44.89	39.11	3.001	0
3-May-15	20.49	981	48.1	40.1	3.823	0
4-May-15	21.62	981.3	52.96	39.56	3.803	0
5-May-15	22.78	983.5	86.54	34.52	1.78	0.1
6-May-15	22.07	983.5	75.54	33.51	1.613	0

7-May-15	20.39	982.3	57.38	35.19	1.794	0
8-May-15	19.98	983	56.29	36.44	3.999	0
9-May-15	21.33	984.2	60.19	36.58	2.124	0
10-May-15	23.42	983.9	77.48	35.14	1.558	0
11-May-15	21.84	982.8	66.93	36.33	2.838	0
12-May-15	21.5	983.6	68.08	35.29	1.912	0.7
13-May-15	23.02	983	65.99	37.06	2.451	0
14-May-15	23.45	981.2	69.85	36.26	2.1	17.3
15-May-15	23.28	983.6	86.98	33.68	0.683	0.1
16-May-15	23.24	983.5	70.02	35.96	1.442	14.9
17-May-15	23.6	983.8	73.57	36.78	1.317	1.6
18-May-15	23.13	983.1	72.68	35.97	3.442	0
19-May-15	22.47	982.8	66.66	36.86	3.195	0
20-May-15	22.37	984.6	73.47	35.34	2.703	0
21-May-15	22.69	983.1	63.48	36.45	2.33	0
22-May-15	22.99	984.8	72.53	36.27	2.323	0
23-May-15	21.84	983	64.8	37.04	1.753	0
24-May-15	22.63	984.9	78.16	34.14	2.21	12.8
25-May-15	22.49	984.4	72.19	35.43	2.664	0.1
26-May-15	22.46	982.2	63.69	36.79	2.482	0
27-May-15	22.97	982.6	69.83	36.99	3.486	0
28-May-15	23.11	983.3	71.11	36.76	3.01	22.6
29-May-15	23.17	982.6	73.31	36.45	2.888	0
30-May-15	22.33	982.5	74.28	34.42	3.117	0
31-May-15	23.26	983.4	75.34	35.29	2.458	0
1-Jun-15	21.76	984	66.89	35.66	2.695	0
2-Jun-15	22.34	982.6	71.63	35.17	3.054	0
3-Jun-15	22.44	984.6	85.72	32.49	1.66	60.6
4-Jun-15	22.78	985.1	84.69	33.36	1.313	1.1
5-Jun-15	23	984.4	82.5	34.24	1.92	0
6-Jun-15	22.91	984.4	83.85	33.9	1.885	0
7-Jun-15	21.92	984.4	76.95	33.94	2.598	36.4
8-Jun-15	22.8	984.3	80.96	33.62	1.979	10.7
9-Jun-15	21.67	983.5	84.41	32.11	1.685	4.8
10-Jun-15	23.14	984.6	78.2	33.99	1.677	0
11-Jun-15	23.32	985	77.77	34.64	2.467	0
12-Jun-15	22.68	985.1	79.18	34.54	2.761	1.5
13-Jun-15	22.88	984.4	80.4	34.02	2.247	5.6
14-Jun-15	22.12	984.2	74.51	33.38	2.293	0.4
15-Jun-15	23.09	984.4	78.19	34.55	1.905	1.2
16-Jun-15	22.99	984.4	76.46	34.68	2.442	0
17-Jun-15	22.58	984.4	76.93	34.57	3.315	0
18-Jun-15	22.24	983.1	73.92	35.58	2.401	0
19-Jun-15	22.62	983.9	76.45	34.88	2.758	0
20-Jun-15	22.7	984.9	75.22	34.96	2.629	2.3
21-Jun-15	22.02	986.3	78.73	33.26	3.234	0
22-Jun-15	21.56	987.1	74.83	33.61	2.338	0.1
23-Jun-15	21.16	987.7	73.53	33.38	2.426	1.3

24-Jun-15	20.58	986.7	67.77	33.86	2.609	0.1
25-Jun-15	21.02	988.2	78.26	32.81	2.132	40.3
26-Jun-15	22.76	988.6	89.83	32.47	2.093	162.7
27-Jun-15	22.32	987.3	85.11	32.37	1.866	75.4
28-Jun-15	22.64	986.8	79.61	33.88	1.931	1.8
29-Jun-15	22.12	987.2	73.83	34.49	2.573	12.8
30-Jun-15	21.27	986	72.51	33.66	1.906	4.1
1-Jul-15	21.53	985.8	72.02	33.91	2.31	0
2-Jul-15	21.16	985.9	76.51	34.33	1.966	216.9
3-Jul-15	22.44	986.9	87.28	32.42	2.213	18.6
4-Jul-15	21.55	986.5	80.63	32.85	2.195	0
5-Jul-15	22.24	985.8	81.9	32.95	1.296	120.4
6-Jul-15	23.2	985	81.94	32.72	1.082	60
7-Jul-15	22.81	984.3	75.33	34.03	0.67	32.9
8-Jul-15	23.56	984	79.8	34.06	0.347	8.8
9-Jul-15	23.33	984.3	81.76	34.12	0.307	13.3
10-Jul-15	22.71	985.8	91.7	32.75	0.124	162.7
11-Jul-15	21.8	986.7	88.19	31.52	0.547	34
12-Jul-15	23.41	985.6	81.88	34.67	2.446	250
13-Jul-15	21.84	984.8	80.05	32.74	1.385	25.6
14-Jul-15	22.82	985.3	85.31	33.05	1.206	20.6
15-Jul-15	22.72	984.1	88.61	32.66	2.056	6.8
16-Jul-15	22.15	985.4	81.62	33.32	2	25
17-Jul-15	22.49	986.1	89.74	31.82	1.667	26.7
18-Jul-15	23.08	985.5	78.36	34.25	0.192	20.4
19-Jul-15	22.79	984.5	81.62	34.33	2.662	19.9
20-Jul-15	22.14	984.8	93.43	31.15	1.646	128.5
21-Jul-15	22.79	986.9	93.86	32.09	1.492	16.3
22-Jul-15	22.32	987.2	83.34	32.79	0.767	7.1
23-Jul-15	22.48	986.2	79.2	33.75	0.964	19.1
24-Jul-15	22.69	986.4	92.87	31.74	1.093	51.5
25-Jul-15	21.88	986.1	89.08	31.82	1.713	6
26-Jul-15	21.43	986.6	82.06	32.05	1.92	28.7
27-Jul-15	22.15	985.5	96.02	31.07	0.97	480
28-Jul-15	21.67	986.8	92.45	30.81	1.524	43.3
29-Jul-15	21.67	987.7	90.33	30.79	1.236	2.9
30-Jul-15	21.95	986.8	87.54	31.4	0.888	124.6
31-Jul-15	21.96	986.8	90	31.98	1.597	139.8
1-Aug-15	22.59	985.5	85.52	32.31	0.943	8.8
2-Aug-15	22.18	985.7	91.27	31.23	1.261	116.2
3-Aug-15	22.82	985.6	88.94	32.4	0.558	185.3
4-Aug-15	22.28	987	94.16	31.3	0.612	133.7
5-Aug-15	22.34	986.4	87.7	31.93	0.575	29.8
6-Aug-15	22.6	985.1	86.76	32.14	0.252	154.3
7-Aug-15	22.04	984.5	90.6	31.72	0.823	274.5
8-Aug-15	22.05	985.3	92.74	31.44	1.055	137.3
9-Aug-15	22.86	985.3	93.59	32.18	0.312	20.9
10-Aug-19	21.93	984.4	92.76	31.04	1.054	1.2

11-Aug-19	22.59	985.5	87.87	32.62	1.477	2.1
12-Aug-19	22.75	986.7	94.5	31.55	0.442	228.5
13-Aug-19	22.11	987.2	95.46	30.93	0.539	8.4
14-Aug-19	22.81	985.5	84.22	32.95	1.161	240.1
15-Aug-19	22.72	986	91.23	31.84	1.311	0.4
16-Aug-19	23.17	987.2	86.86	33.01	1.376	247.8
17-Aug-19	22.53	986.6	96.85	31.18	1.098	155.8
18-Aug-19	22.36	985.6	92.51	31.57	1.003	0.1
19-Aug-19	23.1	985.4	89.07	32.72	0.854	82.9
20-Aug-19	22.66	984.7	88.82	32.07	0.868	50.6
21-Aug-19	22.2	984.6	94.33	31.21	0.903	60.4
22-Aug-19	22.77	985.6	91.87	32.08	0.727	42.6
23-Aug-19	22.67	984.3	85.23	33.05	0.547	0.2
24-Aug-19	23.14	984.1	95.43	32.33	1.345	617.9
25-Aug-19	22.25	984.5	88.36	31.55	1.111	254.8
26-Aug-19	22.13	986.7	88.82	31.81	1.103	0
27-Aug-19	22.25	984.9	86.32	32.05	1.264	51.3
28-Aug-19	22.37	984.4	92.14	31.79	1.592	285.9
29-Aug-19	21.93	986.2	93.97	30.88	0.671	111
30-Aug-19	22.18	987.7	88.78	31.64	0.892	72
31-Aug-19	21.84	987.3	88.51	31.95	0.487	305.4
1-Sep-15	21.82	986.8	96.54	30.51	1.486	95
2-Sep-15	22.33	985.9	90.87	32.03	1.644	68.9
3-Sep-15	22.34	986.8	89.75	32.28	1.421	85.4
4-Sep-15	22.31	986.5	91.14	31.46	0.399	60.6
5-Sep-15	22.33	985.7	94.84	31.38	0.622	0.2
6-Sep-15	22.74	986.5	86.43	32.9	1.304	0
7-Sep-15	22.6	987.2	86.19	32.27	1.437	222
8-Sep-15	20.96	985	90.18	30.82	1.134	54.8
9-Sep-15	22.09	984.9	92.77	31.47	1.425	0
10-Sep-15	22.47	985.2	82.51	33.15	1.343	2.8
11-Sep-15	22.76	984.3	87.49	32.32	0.739	3.1
12-Sep-15	22.44	984.1	89	31.99	0.555	39.4
13-Sep-15	23.54	984.4	86.29	33.29	0.842	3.3
14-Sep-15	22.37	986.3	95.66	31.23	0.953	16.9
15-Sep-15	22.83	986.2	92.76	32	1.279	71.2
16-Sep-15	22.06	986.1	94.16	31.16	0.967	52.6
17-Sep-15	22.79	984.9	94.08	31.95	0.998	87.2
18-Sep-15	22.38	984.6	94.91	31.4	1.272	0
19-Sep-15	22.79	986.4	90.23	31.98	0.559	8.3
20-Sep-15	22.37	987	87.27	32.52	0.539	37.5
21-Sep-15	22.45	986.9	92.59	31.42	0.815	161.1
22-Sep-15	22.32	985.1	87.42	31.87	0.072	0
23-Sep-15	22.94	984.9	86.2	33.03	0.672	19.6
24-Sep-15	22.98	985.5	92.99	32.14	0.471	77.9
25-Sep-15	21.96	985.9	95.05	30.76	0.565	0
26-Sep-15	22.78	986	84.68	32.69	1.56	45.4
27-Sep-15	22.76	984	83.57	32.67	1.26	10.1

28-Sep-15	23.57	984.1	92.25	32.84	1.728	6.5
29-Sep-15	22.08	983.7	89.2	31.3	0.83	24.8
30-Sep-15	22.93	984.9	87.98	32.63	1.15	0
1-Oct-15	22.65	983.8	84.99	32.77	0.78	0
2-Oct-15	23.97	983.3	87.46	33.24	0.766	0
3-Oct-15	22.13	983.5	93.28	30.91	1.627	10.3
4-Oct-15	22.4	985.7	91.74	31.72	1.02	94.8
5-Oct-15	22.8	986.2	92.54	31.7	0.7	0.1
6-Oct-15	23.28	985.4	93.01	32.37	1.007	0
7-Oct-15	23.51	985.3	92.2	32.69	0.735	1.5
8-Oct-15	22.44	985.1	91.93	31.4	0.747	1.5
9-Oct-15	22.44	986.2	87.24	31.75	1.105	0
10-Oct-15	22.53	985.6	91.97	31.51	0.425	0
11-Oct-15	23	986.3	95.39	31.44	0.649	0
12-Oct-15	22.37	985.3	89.35	31.83	0.709	0
13-Oct-15	23.96	985.1	89.32	32.65	1.18	0
14-Oct-15	25.12	984.5	91.29	33.97	1.913	0
15-Oct-15	23.09	984	88.67	32.32	1.332	0
16-Oct-15	23.75	983.3	89.59	33.14	0.679	0
17-Oct-15	23.22	983.9	88.14	32.91	1.945	0
18-Oct-15	23.29	985.2	86.9	33	1.642	0
19-Oct-15	24.57	985.1	85.75	34.11	1.871	0
20-Oct-15	22.74	984.7	93.4	31.68	1.529	28
21-Oct-15	23.22	985.1	92.39	32.21	1.171	0
22-Oct-15	23.68	983.9	90.83	32.85	1.437	0
23-Oct-15	23.96	985.4	85.06	33.83	1.564	0
24-Oct-15	23.11	984.4	80.51	33.09	1.381	0
25-Oct-15	23.12	984.4	81.08	33.51	1.647	0
26-Oct-15	22.9	984.9	86.06	32.77	1.365	0
27-Oct-15	23.49	984.5	87.28	32.96	1.135	0
28-Oct-15	22.73	984.7	87.54	32.3	1.403	0.9
29-Oct-15	23.04	984	86.52	32.82	1.245	0
30-Oct-15	21.87	983.9	85.42	31.59	1.522	0
31-Oct-15	22.49	984	85.55	32.32	0.559	0
1-Nov-15	22.68	984	83.97	32.51	1.267	0
2-Nov-15	23.1	984.2	86.27	32.46	1.65	0
3-Nov-15	22.61	984.8	89.63	31.85	1.28	0
4-Nov-15	20.96	984.2	76.27	32.63	1.284	0
5-Nov-15	19.91	984.1	71.92	31.63	0.87	0
6-Nov-15	21.26	984.9	75.37	33.07	1.214	0
7-Nov-15	19.71	984.5	67.35	31.92	0.835	0
8-Nov-15	20.84	984.5	73.27	32.72	1.246	0
9-Nov-15	21.03	986.3	73.3	32.79	1.407	0
10-Nov-15	21.14	985.9	75.08	31.97	0.711	0
11-Nov-15	19.22	985.1	69.08	31.45	1.073	0
12-Nov-15	13.43	983.3	46.59	32.01	2.291	0
13-Nov-15	11.3	983.7	39.41	32.65	2.906	0
14-Nov-15	11.94	985	42.79	31.12	2.818	0

15-Nov-15	15.18	985	52.74	30.42	1.763	0
16-Nov-15	17.24	984.8	61.14	30.55	1.648	0
17-Nov-15	16.01	983.3	55.53	31.53	1.862	0
18-Nov-15	13.05	983.1	46.59	31.49	2.513	0
19-Nov-15	12.14	982.4	42.84	32.44	2.857	0
20-Nov-15	13.88	983.2	47.75	32.15	1.986	0
21-Nov-15	13.06	983	44.73	32	2.368	0
22-Nov-15	13.27	982.1	45.2	32.07	1.912	0
23-Nov-15	15.16	981.9	48.56	33.07	1.282	0
24-Nov-15	13.16	983.9	42.52	32.78	2.298	0
25-Nov-15	13.88	984.1	44.93	32.49	1.944	0
26-Nov-15	11.5	982.6	40.31	32.06	2.092	0
27-Nov-15	16.47	982.2	51.3	31.82	1.3	0
28-Nov-15	17.3	983.7	51.15	33.47	0.832	0
29-Nov-15	15.18	984.5	48.61	33.02	1.469	0
30-Nov-15	11.07	985.8	36.72	32.77	2.395	0
1-Dec-15	6.94	985.6	31.57	31.82	2.705	0
2-Dec-15	6.11	985.7	27.22	34.15	3.664	0
3-Dec-15	6.95	986.8	31.11	33.83	3.59	0
4-Dec-15	6.14	986.3	28.95	31.91	4.083	0
5-Dec-15	5.73	986.2	28.33	31.84	3.619	0
6-Dec-15	5.01	986.5	30.73	31.79	3.803	0
7-Dec-15	7.02	986.9	33.99	31.94	3.852	0
8-Dec-15	6.93	987.6	31.74	31.46	3.888	0
9-Dec-15	5.84	986.3	28.94	31.95	3.615	0
10-Dec-15	4.99	986.6	26.53	32.07	3.966	0
11-Dec-15	4.46	986.4	26.32	31.73	4.012	0
12-Dec-15	4.71	987.6	29.23	29.93	3.924	0
13-Dec-15	4.99	986.6	30.88	29.32	3.521	0
14-Dec-15	4.69	986.1	29.99	30.3	3.869	0
15-Dec-15	3.49	986.8	28.06	29.29	4.29	0
16-Dec-15	2.73	987	26.52	29.27	4.005	0
17-Dec-15	0.73	986.8	22.69	28.42	3.98	0
18-Dec-15	2.54	987.3	26.08	28.37	4.017	0
19-Dec-15	3.7	987.3	26.53	29.42	3.949	0
20-Dec-15	2.84	987.5	27.15	30.91	3.668	0
21-Dec-15	4.39	986.8	29.22	31.63	3.496	0
22-Dec-15	4.11	986.9	26.71	31.74	4.031	0
23-Dec-15	1.71	986.9	22.38	31.21	4.466	0
24-Dec-15	1.18	987	22.65	29.76	4.228	0
25-Dec-15	2.01	987.9	25.48	30.74	4.337	0
26-Dec-15	4.96	986.6	27.41	30.84	4.27	0
27-Dec-15	4.04	985.8	27.28	30.84	3.83	0
28-Dec-15	6.13	985	29.76	31.25	3.47	0
29-Dec-15	4.54	986.7	26.89	30.63	3.82	0
30-Dec-15	2.48	987.1	26.03	30.81	3.967	0
31-Dec-15	3.88	986.2	26.71	30.73	3.528	0
1-Jan-16	3.89	986.7	27.73	30.99	3.87	0

2-Jan-16	3.26	986.5	28.19	29.58	4.348	0
3-Jan-16	4.2	985.9	27.48	31.63	4.236	0
4-Jan-16	5.92	985.5	30.27	30.24	3.713	0
5-Jan-16	6.28	985.1	31.99	31.29	3.193	0
6-Jan-16	7.59	985.1	32.56	32.64	3.093	0
7-Jan-16	6.84	985.5	29.86	32.68	2.926	0
8-Jan-16	0.78	985.6	16.51	31.9	2.73	0
9-Jan-16	1.01	985.6	17.18	35.19	3.692	0
10-Jan-16	8.6	985.2	34.06	32.81	1.779	0
11-Jan-16	4.65	985.1	25.33	33.56	2.81	0
12-Jan-16	1.16	983.3	17.45	32.74	3.989	0
13-Jan-16	1.31	983.2	20.42	33.17	3.849	0
14-Jan-16	4.68	984	25.84	31.31	3.387	0
15-Jan-16	2.37	983.6	22.21	32.75	3.744	0
16-Jan-16	3.72	983.9	24.34	32.28	3.109	0
17-Jan-16	5.15	983.5	25.38	30.61	2.55	0
18-Jan-16	6.23	983.8	30.32	31.81	2.136	0
19-Jan-16	6.4	983.6	27.65	33.13	3.625	0
20-Jan-16	4.03	983.7	25.23	33.3	3.574	0
21-Jan-16	0.63	984.5	19.86	33.16	3.497	0
22-Jan-16	0.53	984.7	16.9	31.02	3.466	0
23-Jan-16	-0.64	985.6	16.72	32.7	3.879	0
24-Jan-16	-0.99	987.9	13.2	32.35	4.541	0
25-Jan-16	-0.9	990.2	17.41	29.79	4.499	0
26-Jan-16	0.1	988.8	20.19	31.07	4.091	0
27-Jan-16	-1.7	989.5	17.83	30.34	4.49	0
28-Jan-16	-1.55	987.5	18.75	31.27	4.332	0
29-Jan-16	0.03	986.9	19.9	31.29	4.49	0
30-Jan-16	-1.09	986.7	17.38	30.57	4.027	0
31-Jan-16	-0.52	985.8	21.94	31.33	3.759	0
1-Feb-16	3.76	985.2	26.14	29.94	2.818	0
2-Feb-16	6.67	984.3	30.41	30.46	1.801	0
3-Feb-16	7.53	983.7	30.64	33.07	2.386	0
4-Feb-16	7.13	984.1	29.03	33.56	2.356	0
5-Feb-16	3.91	984.3	20.84	34.86	3.678	0
6-Feb-16	0.49	985.6	19.43	34	3.647	0
7-Feb-16	2.9	985.8	18.87	33.88	4.057	0
8-Feb-16	1.57	986.4	19.74	33.97	3.825	0
9-Feb-16	2.91	987.1	20.79	33.48	4.343	0
########	-0.89	986.5	15.84	32.74	4.185	0
########	-1.35	985.1	15.53	32.02	4.174	0
########	0.23	983.7	18.23	32.68	3.609	0
########	2.69	984.1	20.25	32.41	3.305	0
########	4.22	984.6	20.91	32.3	2.305	0
########	7.6	982.4	28.12	32.83	0.837	0
########	14.63	982.6	37.68	35.71	0.121	0
########	13.92	983.6	35.39	35.68	1.282	0
########	2.34	982.6	17.11	34.77	2.773	0

########	13.24	981	31.5	36.83	0.634	0
########	-1.69	980.7	18.66	37.53	2.861	0
########	-2.05	982.1	12.39	35.91	3.87	0
########	1.98	982.3	18.7	36.29	3.009	0
########	-0.39	982.5	13.05	36.17	4.039	0
########	0.54	982	14.06	35.59	3.613	0
########	7.76	982.4	26.39	35.55	2.175	0
########	9.06	982.4	26.37	35.62	1.301	0
########	9.54	980.6	24.39	35.96	1.009	0
########	17.34	980.4	36.74	40.02	1.763	0
########	18.44	981.5	43.25	38.33	1.644	0
1-Mar-16	17.82	981.5	39	39.29	0.173	0
2-Mar-16	16.53	982.3	38.64	38.45	2.596	0
3-Mar-16	16.69	979.9	36.24	38.12	1.76	0
4-Mar-16	17.64	979.9	41.39	39.1	1.91	0
5-Mar-16	19.54	981.5	51.97	38.8	1.26	0
6-Mar-16	21.64	982.1	59.14	37.16	2.397	0
7-Mar-16	18.9	982.3	43.88	40.22	2.858	0
8-Mar-16	21.15	982.1	63.77	37.95	2.354	0
9-Mar-16	18.78	981.4	45.4	37.65	1.818	0
########	16.14	980.3	35.93	38.82	2.077	0
########	17.73	980.6	42.75	39.38	3.028	0
########	22.25	982.7	60.74	37.94	1.733	0
########	22.94	984.1	78.61	35.14	0.505	0
########	21.59	983.1	66.01	35.36	1.017	7.6
########	21.63	984.7	60.16	36.82	0.388	0
########	20.23	983.9	52.15	38.64	1.344	0
########	21.34	983.8	54.47	39.1	1.208	0.6
########	22.99	984	77	36.38	2.116	0.4
########	23.79	982.9	72.48	36.49	1.519	0
########	22.01	983.3	66.85	36.65	2.453	0
########	22.18	985.1	77.78	35.6	2.928	16.7
########	22.92	984	63.94	37.11	1.51	0
########	21.33	982.2	52.85	38.53	2.246	0
########	22.41	979.8	63.73	37.71	2.525	0
########	21.79	984.1	80.89	33.43	1.964	0
########	21.99	984.5	59.86	36.56	1.964	0
########	19.46	983.2	46.17	36.79	1.242	0
########	20.05	981.5	46.98	37.59	1.146	0
########	20.28	981.3	48.47	37.68	1.794	0
########	21.73	981.7	51.59	38.82	1.122	0
########	21.78	982.2	54.88	39.15	2.316	0
1-Apr-16	21.56	981.7	55.84	38.17	4.027	0
2-Apr-16	23.7	981.2	63.41	37.22	3.325	0
3-Apr-16	21.11	981.9	52.92	38.63	2.656	0
4-Apr-16	21.39	981	46.93	39.81	2.697	0
5-Apr-16	22.08	980.8	53.87	39.58	4.015	0
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30-Dec-19	3.89	982.7	25.93	30.27	3.548	0
31-Dec-19	5.22	983.3	25.53	30.11	3.477	0

(d) Source Dataset: Bauchi dataset

Date	Dew	Pressure	Humidity	Temp	WindSpeed	Rainfall
	(Oc)	(hPa)	(KG)	(oC)	(KM/S)	(mm)
1-Jan-15	-0.66	954.9	23.06	26.51	3.96	0
2-Jan-15	-2.21	956.4	22.69	25.19	3.706	0
3-Jan-15	-1.38	958.6	24.57	24.2	4.357	0
4-Jan-15	-4.31	960.3	21.41	23.7	3.989	0
5-Jan-15	-4.7	959	23.13	23.77	3.409	0
6-Jan-15	-1.05	957.5	30.22	22.32	3.395	0
7-Jan-15	-2.55	958.2	27.9	21.89	3.393	0
8-Jan-15	-3.73	958.1	23.62	23.25	3.938	0
9-Jan-15	0.06	959.6	29.58	24.67	4.505	0
10-Jan-15	-3.26	960.8	26.44	23.99	4.762	0
11-Jan-15	-4.15	960.3	23.96	22.41	4.13	0
12-Jan-15	-3.48	958.9	25.75	22.17	3.99	0
13-Jan-15	-5.96	958.7	24.26	20.55	3.622	0
14-Jan-15	-4.7	958.3	24.04	21.17	3.113	0
15-Jan-15	-2.31	957.9	26.06	23.85	3.577	0
16-Jan-15	0.23	957.8	30.05	23.95	3.444	0
17-Jan-15	-0.75	956.6	26.28	23.59	3.074	0
18-Jan-15	0.08	956.7	27.17	23.3	2.345	0

19-Jan-15	1.55	955.2	28.14	24.48	2.356	0
20-Jan-15	2.69	953.6	28.74	25.1	2.787	0
21-Jan-15	5.81	953.4	27.96	27.85	2.363	0
22-Jan-15	5.36	955.2	27.3	29.03	2.743	0
23-Jan-15	2.22	954.7	20.84	28.9	2.433	0
24-Jan-15	1.32	952.9	19.29	28.62	2.28	0
25-Jan-15	3.14	951.6	22.33	28.65	2.506	0
26-Jan-15	3.36	952.3	23.93	27.4	3.111	0
27-Jan-15	3.14	953.5	21.95	29.64	2.961	0
28-Jan-15	0.75	953.5	19.88	29.52	3.587	0
29-Jan-15	-1.66	954.3	15.24	28.26	4.003	0
30-Jan-15	-2.95	955	17.52	25.07	3.192	0
31-Jan-15	-0.67	955	22.47	25.89	2.664	0
1-Feb-15	1.15	954.4	21.66	27.4	2.311	0
2-Feb-15	0.56	953.2	19.38	29.26	2.297	0
3-Feb-15	-0.41	952.5	15.95	28.24	2.362	0
4-Feb-15	1.19	952.8	19.9	29.27	2.424	0
5-Feb-15	1.63	951.7	19.45	29.59	2.75	0
6-Feb-15	0.78	951.9	17.41	30.23	2.779	0
7-Feb-15	3.04	951.2	19.49	29.55	2.495	0
8-Feb-15	4.02	951	21.57	30.47	2.746	0
9-Feb-15	2.74	951.1	18.94	30.06	2.388	0
10-Feb-15	2.32	951.5	18.5	29.42	2.527	0

11-Feb-15	-2.42	952.8	14.17	29.09	2.807	0
12-Feb-15	0.06	954	18.24	31.15	4.087	0
13-Feb-15	-0.99	955.1	17.34	29.01	2.775	0
14-Feb-15	-0.97	955.3	16.1	28.1	2.38	0
15-Feb-15	1.05	953.5	18.45	28.56	1.773	0
16-Feb-15	3.87	952.3	20.72	28.76	1.997	0
17-Feb-15	7.71	951.4	31.31	29.94	2.467	0
18-Feb-15	4.77	950.8	22.77	31.45	3.556	0
19-Feb-15	7.15	951.8	27.13	31.53	2.987	0
20-Feb-15	1.38	950.9	19.6	30.48	2.999	0
21-Feb-15	3.1	950.6	23.17	29.9	2.775	0
22-Feb-15	5.74	950.4	24.67	31.41	2.278	0
23-Feb-15	2.07	952.3	17.42	32.03	3.721	0
24-Feb-15	2.76	953.7	22.17	32.19	3.011	0
25-Feb-15	-0.48	953	16.73	31.58	3.712	0
26-Feb-15	-0.3	951.6	17.03	29.52	2.683	0
27-Feb-15	-0.31	951.9	14.24	31.27	2.845	0
28-Feb-15	-5.68	954.4	11.49	29.85	3.737	0
1-Mar-15	-4.15	954.3	11.97	29.6	3.209	0
2-Mar-15	-4.62	953	12.37	30.1	3.052	0
3-Mar-15	-4.84	952.8	13.16	30.21	3.927	0
4-Mar-15	-1.6	955	19.36	31.12	3.712	0
5-Mar-15	3.71	954.2	24.98	31.5	3.89	0

6-Mar-15	1.69	953.4	20.41	31.3	2.982	0
7-Mar-15	2.25	951.7	18.88	31.41	2.508	0
8-Mar-15	3.94	950.5	20.15	32.53	2.523	0
9-Mar-15	3.88	950.5	18.84	32.66	3.153	0
10-Mar-15	4.72	950.7	19.24	34.01	3.184	0
11-Mar-15	2.3	951.9	16.72	34.28	3.566	0
12-Mar-15	-3.3	952.5	12.55	34.31	4.786	0
13-Mar-15	-5.15	951.5	11.62	32.07	3.431	0
14-Mar-15	-2.93	951	12.8	31.8	3.516	0
15-Mar-15	0.09	950	15.65	32.15	3.283	0
16-Mar-15	2.18	950.7	17.34	35.47	2.928	0
17-Mar-15	0.72	951.3	15.7	35.2	4.448	0
18-Mar-15	3.41	950.7	18.07	35.93	3.427	0
19-Mar-15	6.04	948.9	22.21	34.21	3.28	0
20-Mar-15	5.55	948.7	20.47	32.13	3.073	0
22-Mar-15	11.84	949.1	31	34.62	3.587	0
23-Mar-15	9.63	949.6	24.79	36.76	2.459	0
24-Mar-15	7.11	949.3	19.27	33.95	1.759	0
25-Mar-15	10.73	948.2	27.85	35.48	1.011	0
26-Mar-15	18.52	951.4	58.21	36.26	3.846	1
27-Mar-15	12.26	950.5	32.34	36.63	3.843	0
28-Mar-15	6.39	951.4	21.58	36.07	3.856	0
29-Mar-15	-6.73	951.7	9.67	32.25	3.365	0

30-Mar-15	-6.98	952.1	8.93	32.22	3.928	0
31-Mar-15	-0.06	953.2	16.42	34.58	3.291	0
1-Apr-15	-1.15	953.4	12.37	34.38	3.307	0
2-Apr-15	-2.49	953.8	14.15	34.52	3.138	0
3-Apr-15	-0.25	952.5	16.5	35.23	3.27	0
4-Apr-15	4.63	950.5	19.94	36.15	2.696	0
5-Apr-15	4.18	949.7	20.48	35.16	2.884	0
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30-Dec-19	2.21	953.4	33.6	21.92	2.713	0
31-Dec-19	2.98	953.9	32.78	23.29	3.143	0