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PROPOSING A BIG DATA ANALYTICAL TRAINED LSTM BASED MODEL FOR WEATHER FORECASTING EXPERT SYSTEM

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Abstract
The average person who evaluates the changes occurring in the status of the atmosphere nowadays views weather forecasting as an essential and vital procedure in daily life. Accurate prediction of environmental factors leading to the final weather forecast, or "big data analytics," in this case can be an effective solution, as it has been proven to be the best way to uncover hidden patterns and useful information that produce more beneficial outcomes, like the weather forecast in our case. Our solution to this is the development of an expert system based on artificial intelligence and big data analytics. The proposed solution is based on creating a lightweight, fine-grained LSTM-based weather forecasting model from scratch and integrating it with ARIMA. The solution has shown proven results in terms of various evaluation matrices such as means square errors and mean absolute errors, etc. In future work, the present small expert system can be integrated with the existing climate model suggested to produce a more precise and long-term weather forecast for regional level applications.
Keywords: Big data analytics,LSTM model,Weather forecast,ARIMA

1. Introduction

Before the development of weather forecasting tools like the hygrometer and anemometer, sky observation was the primary method of forecasting [1]. Since the launch of special meteorological satellites [2] and radars, observational methods and prediction tools have advanced to the state-of-the-art, allowing us to closely and precisely monitor the weather. With the use of meteorological satellites, nations communicate weather observations and modifications quickly in today's fast telecommunication network to generate remarkably precise forecasts [3]. In addition to numerous government agencies and weather observatory stations, several private firms have developed to provide weather predictions. The fact that this information is disseminated via the newest smart gadgets is a positive sign reflecting the rise of the private sector. However, the practice of predicting the atmosphere's condition for a specific location using several meteorological characteristics to accurately forecast the weather is still a challenging task.

Hence, research into accurate weather forecasting with a suitable solution is still a challenging task.

Previously, various solutions to weather forecasting have been proposed, known as "dynamical numerical weather prediction" (NWP) models. All such models have used statistical formulas to make weather predictions based on atmosphere and ocean data. The NWP models failed in the situation where weather features and/or processes took place inside a single model grid. Other than this, such models are computer programmes that meteorologists use to create forecasts. Future weather predictions made by these forecasting models rely on estimations and assumptions because they cannot collect data for that time period.

In addition to this, the solution given by the NWP model was also not reliable as the atmosphere is constantly changing. Hence, machine learning models have been proposed to tackle the issues associated with NWP models. However, the solutions provided by the machine learning models have been effective to some extent, and the reason is the continuous development of climate observation systems like satellite meteorological observation as well as the rapid rise in the amount of weather data.

Weather forecasting has now entered the era of big data, and the conventional computational intelligence algorithms (machine learning and NWP models) felt inappropriate when has to making accurate weather predictions.

Moreover, accurate weather and climate prediction becomes possible and successful thanks to the development of deep learning techniques and suitable data visualization approaches. The deep learning techniques are more effective than the machine learning techniques in handling large datasets since they can learn from the past and predict the future more accurately. The architecture of neural networks consists of numerous layers, which have been utilized for the deep learning of important patterns in large datasets. As a result, a deep-architecture neural network can precisely extract high-level abstract features from big data.

Previously various types of machine learning and deep learning weather forecasting modles has been developed for example, Author of [4], has proposed machine learning approach to weather forecasting. The author has suggested a technique that uses artificial convolutional neural networks. The suggested CNN model has been trained on previous weather predictions and is based on deep learning. Although the proposed approach performs less well than ensemble weather forecast models in terms of forecast uncertainty prediction, it is computationally very economical and outperforms a number of competing approaches that do not entail making numerical forecasts.Similarly based on machine learning, a weather forecasting approach has been suggested in [5]. Author has found that Machine learning has often been used by the National Center for Atmospheric Research (NCAR) to solve problems with weather prediction. One of the initial automated weather forecasting systems was the Dynamically Integrated Forecasting (DICast®) System. It currently has a wide range of uses and is used by numerous businesses. Renewable energy, public transportation, and wildfire forecasting are some of the applications NCAR is working on with DICast and other artificial intelligence tools. Hence this approach has been found to be effective for weather furcating too.

It is well known, according to the author of [6], that mechanistic models require a lot of computing. Therefore, the author emphasized the importance of creating models that are more accurate than traditional meteorology models at predicting weather conditions. In addition to that, the science world has shown a great deal of interest in machine learning too. Hence, the author found it to be interesting to investigate if an artificial neural network could work well for weather forecasting when combined with big data sets due to its use in a wide range of industries. The benefit of using big data sets is the availability of weather data, which from various web sources is available. Author of the perused his work using Python API to read meteorological data and has been created to streamline data retrieval. ANN models were created using TensorFlow machine learning in Python for weather forecasts based on freely available weather data.

Similarly, a study on several weather prediction models using decision trees, support vector machines, and ANN was conducted by [7]. In their study of machine learning-based weather forecasts and related issues, [8] covered a range of weather prediction application areas. Using MapReduce and machine learning algorithms, [9] investigated various big data weather forecasting models. The authors also discussed the drawbacks and problems of big data weather prediction, particularly predicting rainfall.

An enhanced rainfall forecast model using wavelet transform and seasonal ANN was suggested by [10]. The authors also looked into other approaches for forecasting monthly precipitation.

In a comparison of market forecasting models utilizing ANN,[11] found that neural networks gave results that were more reliable than those from other techniques. Author [12]investigated the effects of using neural networks to ensemble weather forecasts for post-processing in order to calculate the temperatures in Germany.

Further various deep learning model to weather forecasting has been proposed for example author in [13] offer a data-driven architecture that uses an innovative deep learning pattern recognition method. The author has suggested using capsule neural networks, or CapsNets in this work to weather forecast.

Author [14] found the recent excitement surrounding artificial intelligence but also found little evidence to suggest that by integrating big data mining and neural networks into the weather forecasting workflow, prediction. In this work, author has proposed a review on DL techniques for weather forecasting that can fully replace the existing numerical weather models and data assimilation systems. Author in [15] without explicating the information from the physical phenomena, has proposed a simple weather prediction models based on the deep convolutional neural networks (CNNs). The proposed CNN model had trained on historical data of weather. The proposed system has anticipate one or two basic meteorological fields on a Northern Hemisphere grid. Author in [16] has described an ensemble weather predictive model that iteratively forecasts six important meteorological variables with a six-hour temporal resolution using the Deep Learning Weather Prediction (DLWP) models. Furthermore, deep neural networks have emerged as a crucial research tool as the use of numerical weather predictions (NWP) to predict the probable outcomes of wind power is a topic of widespread interest in the field of wind power prediction as per [17]. Motivated from the same, the research has develops the EALSTM-QR neural network forecasting models, which take input from the NWP and deep learning into account when predicting wind power.

Deep learning has been successfully applied in many fields, which has spurred its usage in weather forecasting and is a significant advance for the weather sector. Recurrent neural networks and long short-term memory networks are examples of deep learning architectures.

Motivated by the same, the present research work also approaches the development of a deep learning model (LSTM) for big data analysis of weather for accurate forecasting. The major contribution of the research paper are given below.

1. An LSTM model has been developed from scratch for weather forecasting.

2. The proposed LSTM model is integrated with NWP model named as ARIMA for long term weather forecasting.
3.The performance assessment of the proposed expert system based on LSTM network integrated with ARIMA model has been conducted with mean square error rate.

2. Material and methodology

The deatile discription of the research methodology implemented in this work has been shown in figure 1.

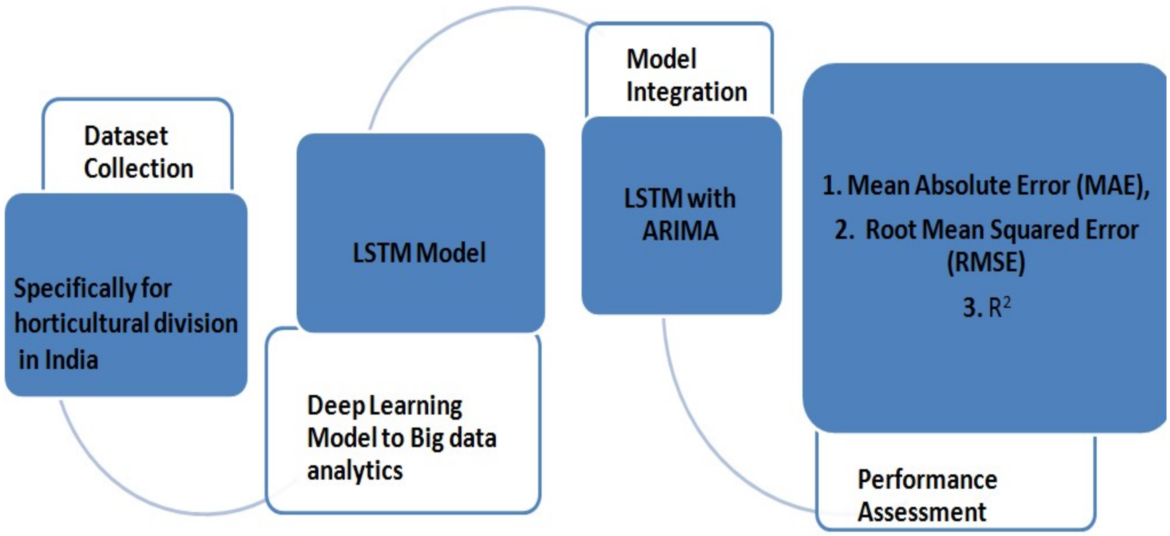

Figure 1: Proposed research methodology

The deatiled discription of material and methodology used for the present research has given below.

2.1 Dataset

The dataset has been taken for Delhi region in India for its weather forecasting.Since 2013 to 2017 the dataset has contained environment factors deatils. The dataset has contained the five different attributes to forecast the weather. The attributes of the dataset has been enlisted below.

1.Date
2.Meantemp
3.Humidity
4.Wind_speed
5.Mean pressure

Here in this section dataset for weather forecasting has been visualized using various aspects of the dataset to provide a thorough understanding of the dataset's characteristics and the quantity of various factors in detail.

2.1.1 Mean temperature visualization

The graphical representation for mean temperature visualization in the dataset is shown in Figure 2. Figure 2. shows the variation in mean temperature from 2013 to 2017 in Delhi. It has been observed from Figure 2. that the temperature has a minimum value in the first month of each year and a maximum temperature in the July month of those years.

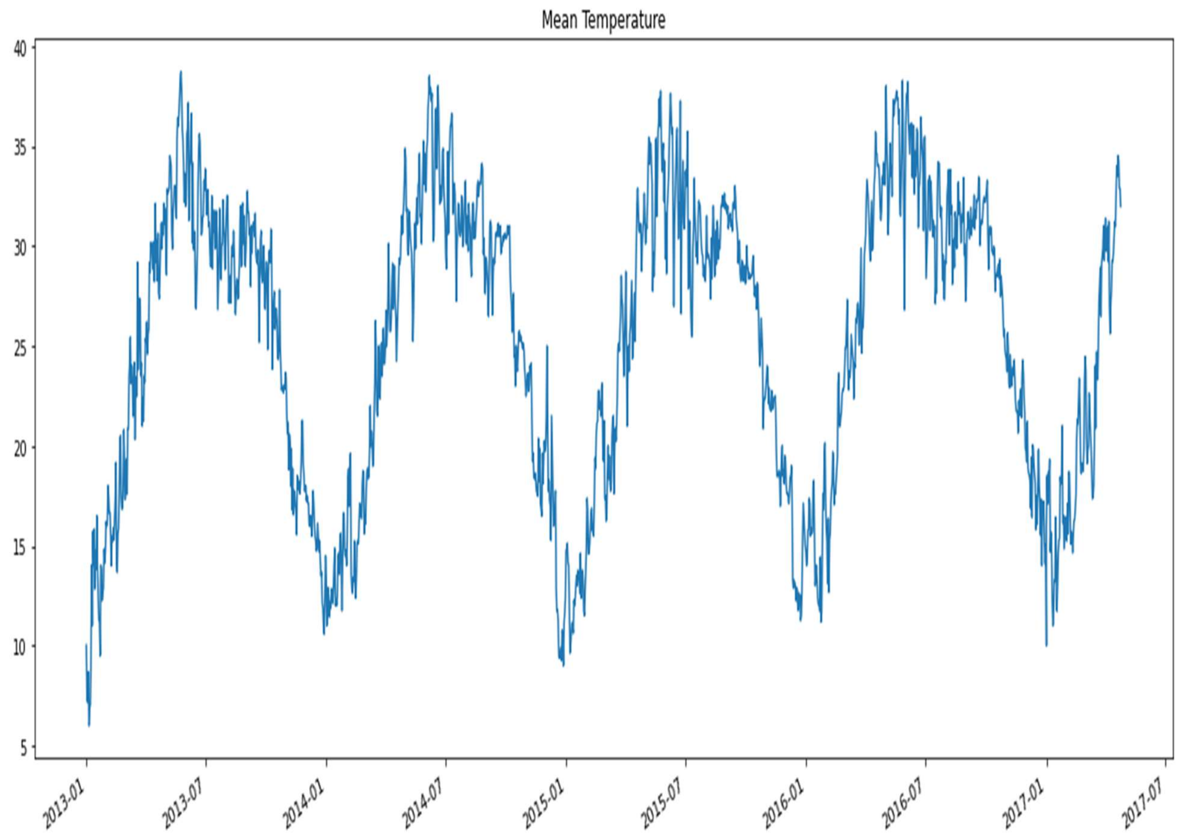

Figure 2.: Mean temperature visualization

2.1.2 Humidity visualization

The graphical representation for Humidity visualization in the dataset is shown in Figure 3.. Figure 3 shows the variation in Humidity from 2013 to 2017 in Delhi.

It has been observed from Figure 3 that the Humidity has a maximum value in the first month of each year and a minimum Humidity in the July month of those years.

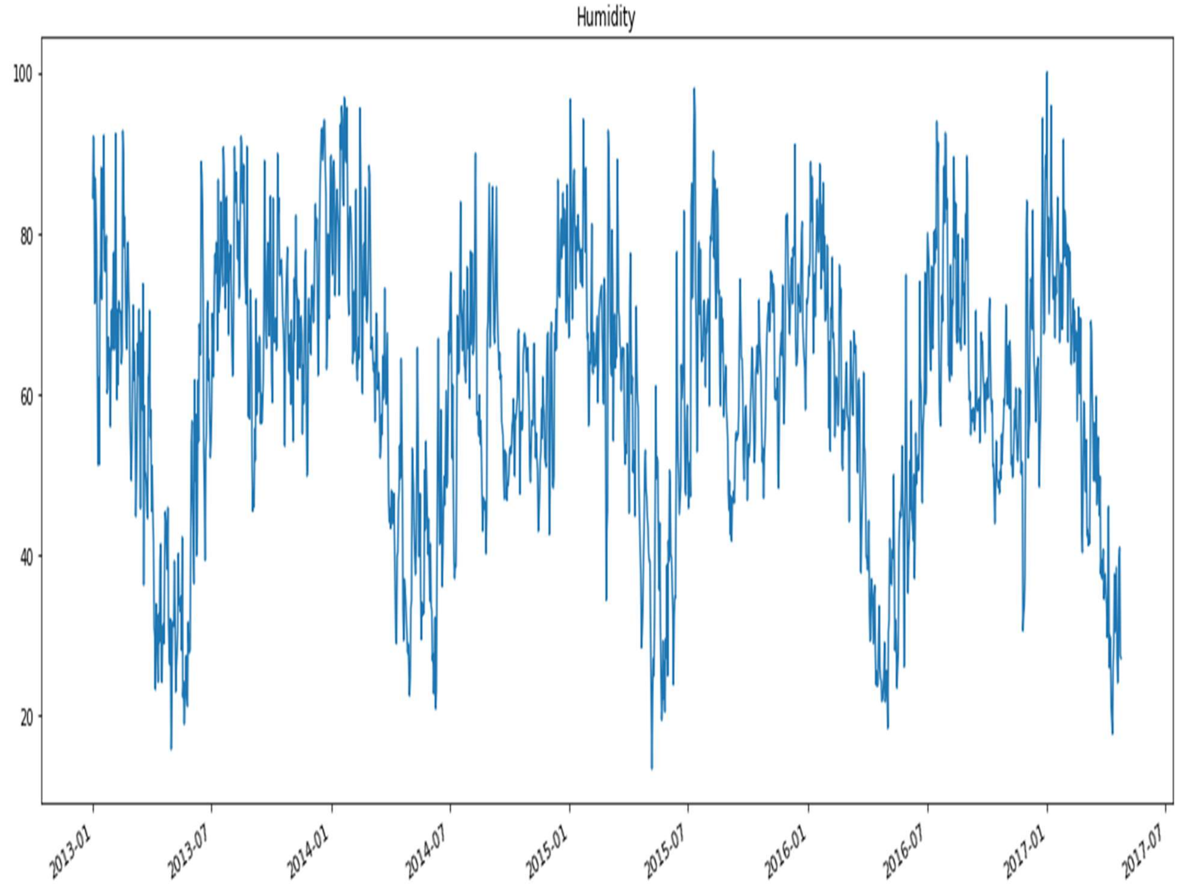

Figure 3.: Humidity visualization

2.1.3 Wind speed visualization

The graphical representation for Wind speed visualization in the dataset is shown in Figure 4.. Figure 4. shows the variation in Wind speed from 2013 to 2017 in Delhi.

It has been observed from Figure 4. that the Wind speed has a minimum value in the first month of each year and a Wind speed in the August or September month of those years.

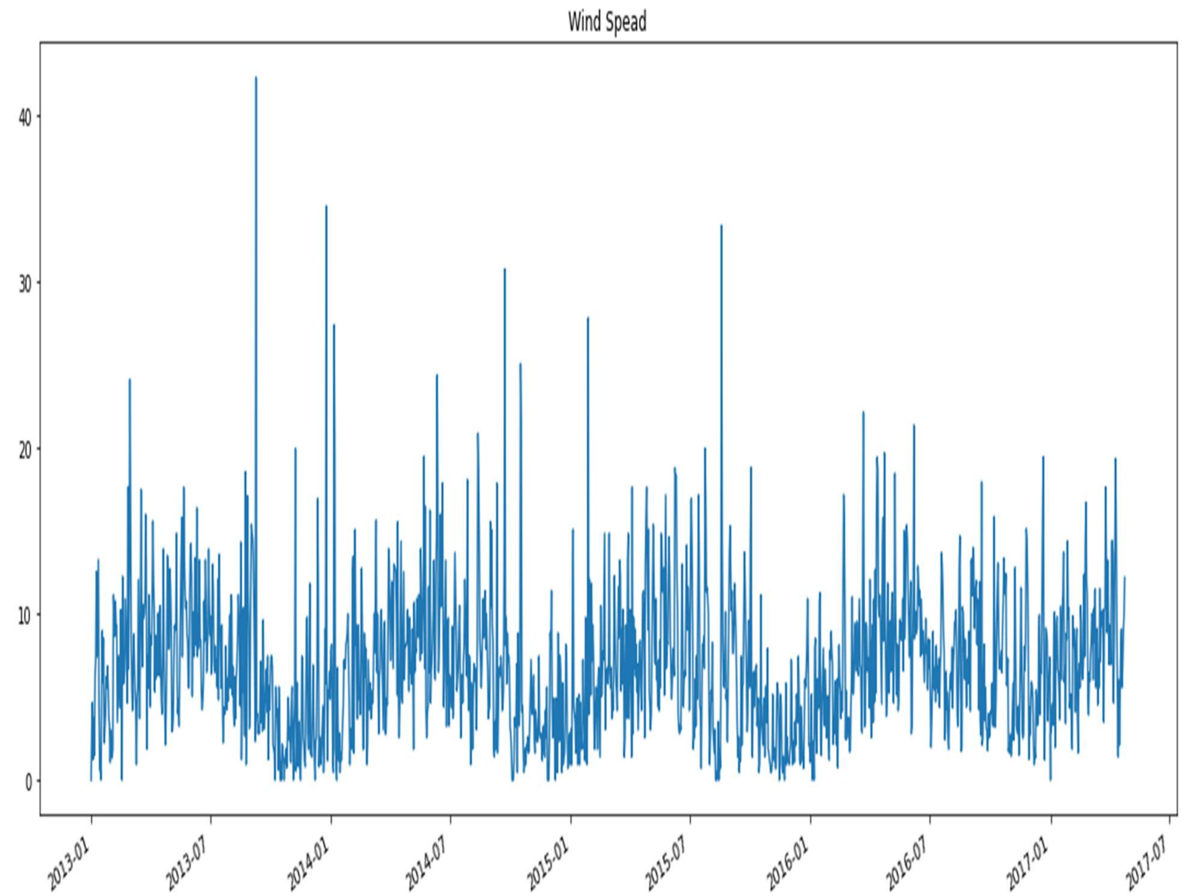

Figure 4.Wind speed visualization

2.2.4 Mean pressure visualization

The graphical representation for Mean pressure visualization in the dataset is shown in Figure 5. Figure 5 shows the variation in Mean pressure from 2013 to 2017 in Delhi.

It has been observed from Figure 5 that the Mean pressure has a minimum value in the first month of 2017 and eight or ninth month of 2016 and a Mean pressure in the April to May month of 2016 has its maximum value.

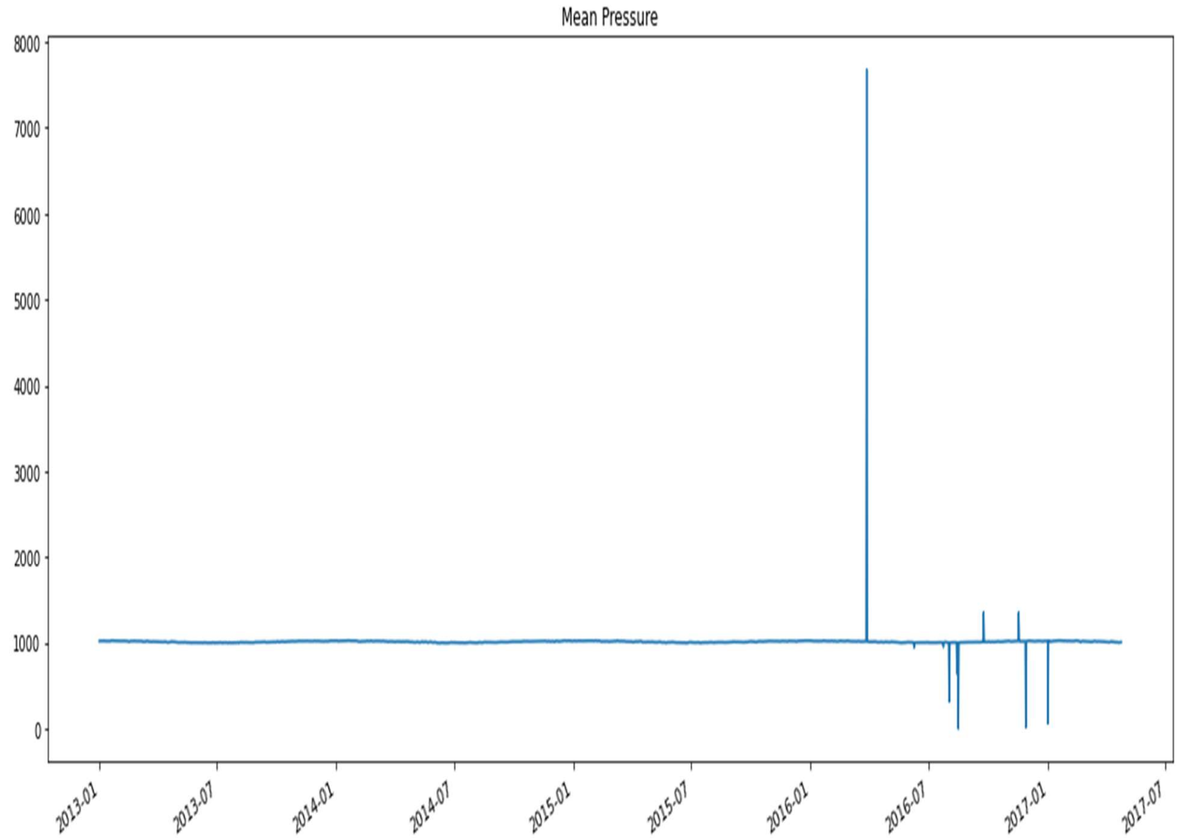

Figure 5. Mean pressure visualization

2.2 Dataset splitting

In data science, data splitting is essential, especially when creating models from data.

The dataset has been divided into training and testing sets using a 1:3 ratio for the sake of the current research project.

That means 75% of total data entries have been employed in the training set for improving the learning of the model, and the remaining 25% of data entries have been employed in the testing set for evaluating the learning of the model.

As a result of this, total of 1182 rows in the dataset has been used for training and 394 for testing set.

2.3 Proposed Model

The proposed LSTM model has been designed with two hidden layers and three dense layers. The model's layers parameters and description has been shown in figure 6

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 60, 50)            10400

 lstm_3 (LSTM)               (None, 64)                29440

 dense_3 (Dense)             (None, 32)                2080

 dense_4 (Dense)             (None, 16)                528

 dense_5 (Dense)             (None, 1)                 17

=================================================================
Total params: 42,465
Trainable params: 42,465
Non-trainable params: 0
```

Figure 6: Layers description of LSTM

2.4 Training parameters

The learning or training parameters of the model have played a significant role in the model's performance.

Hence, after a rigorous process, the following training parameters have been chosen for the proposed model as represented by table 1..

Table 1: Training Parameters of the Model

Table 3.1: Training Parameters of the Model

Parameters	Value
Input Shape	5,1
Model	Sequential
Layers	50
First Dense Layers	32
Second Dense Layers	16
Third Dense Layers	1
Activation Function for First Dense Layer	Relu
Activation Function for Second Dense Layer	Softmax
Loss Function	Sparse categorical crossentropy
Optimizer	Adam
Metrics	MSE
Epochs	100

2.5 ARIMA model

The ARIMA demonstration was developed by Box and Jenkins; hence, this model is also known as a Box-Jenkins model. Basically, time arrangement estimation, parameter estimation, and determination are all done using the ARIMA model. There are several different strategies for estimating time arrangements, including auto regression (AR), moving average (MA), auto regression integrated moving average (ARIMA), etc.

The aforementioned tactics could be based on a request for AR, MA, or an integrated degree known as P, Q, or D. The model is known as an auto-regressive (AR) model if both q and d are zero. The above model is known as a moving average (MA) model if both p and d are zeros. The auto-regressive moving average (ARMA) model is used when p and q attributes are present.

The proposed LSTM has been integrated with the ARMA model in our research work to provide effective weather forecasting results in the Delhi region. The results of both have been compared to get the most effec**tive prediction based on the root mean square value.**

3.Results and analysis

In this section, the details of the results and analysis of the proposed work have been presented. The proposed LSTM model has been simulated using various training parameters on the dataset of environmental conditions in Delhi (India). The results of various perforation and evaluation parameters have been discussed in this chapter.

The results section in this chapter has been divided into categories. The first category of results is based on weather forecasting using LSTM, and the second category of results is based on the ARIMA model.

The detailed description of all such results has been discussed in detailed in the following sub sections.

3.1Results of Correlation Matrix

A Correlation Matrix can be used to more effectively describe the performance of the categorization models. The effectiveness of a classification on a set of train or test data is described by a confusion matrix. Figure 7 provides a description of the proposed weather categorization model's Correlation Matrix.

As discussed the proposed model has been trained using 1182 entries (row) for 384different parameters from the dataset, while the testing using consists of the remaining384 entries (row). After running the model for 100 epochs the results of training and testing accuracy has been presented below in figure 7.

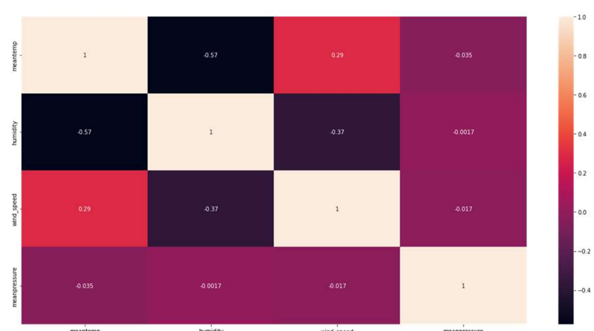

Figure 7. Correlation matrix

3.2 Loss Curve

The loss curve for the proposed LSTM model has been shown in figure19. The proposed LSTM model's loss curve has shows its performance in term of mean square error.

Two curve named as mean square error and mean absolute error has been shown in figure 8.

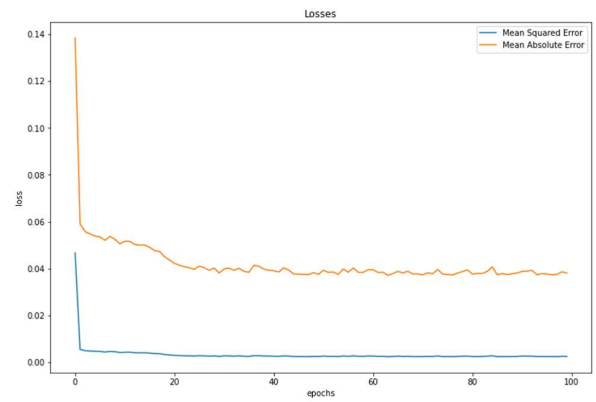

Figure 8: MSE results of proposed LSTM model

As per the graph, the proposed LSTM's training and testing losses have been reduced as each epoch has been increased.

As per the observation, at epoch 1, the loss was 0.0467 and MSE is 0.1384, the loss has been reduced to 0.0025 and MSE to 0.0381 at the 100th epoch.

Hence the proposed model has been successfully trained useing the proposed dataset.

3.2 ARIMA results

The results of ARIMA for forecasting the weather based on the training on the proposed dataset has been presented in figure 9 (a) and 9(b)

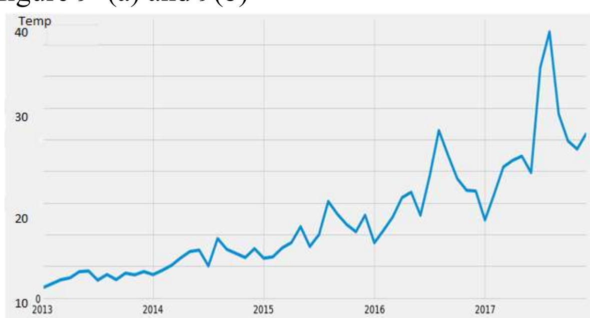

Figure 9(a): Weather forecasting using ARIMS

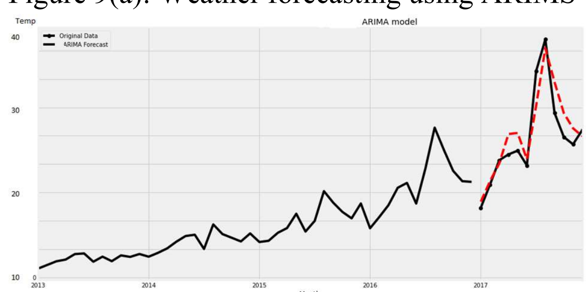

Figure 9(b): MSE for ARIMS predic**tion**

4. Conclusion

An expert system for weather forecasting has been proposed in this study. The expert system has been developed based on the deep learning model and big data analytics. The LSTM model has be built from scratch. The proposed deep learning model (LSTM model) has been simulating on big data of weather parameters collected for horticultural division.

In order to prepare the present model for long-term forecasting of weather, the results obtained using the ARIMA model has been integrated with the LSTM model.

The work also includes a detailed analysis of the classification of weather prediction models and publicly accessible open data sets.

The research's future studies will combine the data from various local weather stations to produce a regional forecast and also will combine the results of current weather forecasting models with those of the existing forecasting model and combine local to produce an accurate and fine-grained regional weather forecasting model.

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