

Deep Model based Classifier Working on Time-Series Data to Provide Effective Weather Prediction

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Abstract: Weather forecasting is the scientific procedure of determining state of ambiance concerning time frames with the locations. This paper devises a novel Vasun feedback artificial tree Algorithm based Deep Long Short Term Memory (VFATA-based DeepLSTM) classifier with time-series data. VFATA is the combination of the Magnetic Optimization Algorithm (MOA) with that of Feedback Artificial Tree (FAT) algorithm for weather forecasting [16]. Here, the feature selection is processed by using Moth Flame Optimization based Bat (MFO-Bat) [11]. Then, based on the clustered result, the forecasting process is accomplished using a Deep LSTM classifier. Finally, the Taylor series model is employed to generate the final forecasted result.

Keywords: Weather forecasting, time-series data examination, Deep Long Short Term Memory (Deep LSTM), Numerical Weather Prediction (NWP), Magnetic Optimization Algorithm (MOA).

1. INTRODUCTION

Weather forecasting is the scientific procedure of forecasting the condition of the atmosphere concerning the location and unique time frames. It predicts weather conditions, like wind, pressure, temperature, and precipitation [2]. Weather prediction can also be useful in agriculture, such as planning farm operations and storage and transportation of food grains.

- This research is modeled on designing a mechanism for weather forecasting by VFATA based Deep LSTM with spark architecture.
- **Proposed VFATA-based Deep LSTM:** An optimal and robust weather prediction model is developed to forecast the weather with time-series data using a VFATA-based Deep LSTM framework. Accordingly, VFATA trains the deep LSTM strategy [16].
- **Proposed FATA:** The proposed MFTA combines the Magnetic Optimization Algorithm (MOA) with that of Feedback Artificial Tree (FAT) algorithm. Thus, it obtains the benefit of both the algorithms.

The paper is organized as follows: Section 2 describes different weather forecasting methods, section 3 elaborates the proposed method, and section 4 explains results and the discussions. The conclusion is explained in section 5.

2. LITERATURE SURVEY

Hewage and Hewage, 2020 developed a lightweight data based weather forecasting approach by integrating temporal convolutional network (TCN) and LSTM [1]. Sønderby and Jahangir, 2020 introduced a neural network strategy for the weather forecasting. The system fails to consider deep learning strategy to enhance accuracy of the system.

3. PROPOSED VASUN FEEDBACK ARTIFICIAL TREE ALGORITHM FOR WEATHER FORECASTING WITH SPARK ARCHITECTURE

Developed a deep learning classifier to perform weather forecasting with time-series data. The spark architecture is designed with the master and slave nodes to achieve weather forecasting [12]. In a master node, the input data is collected and transferred to the slave node to perform feature extraction and selection [4].

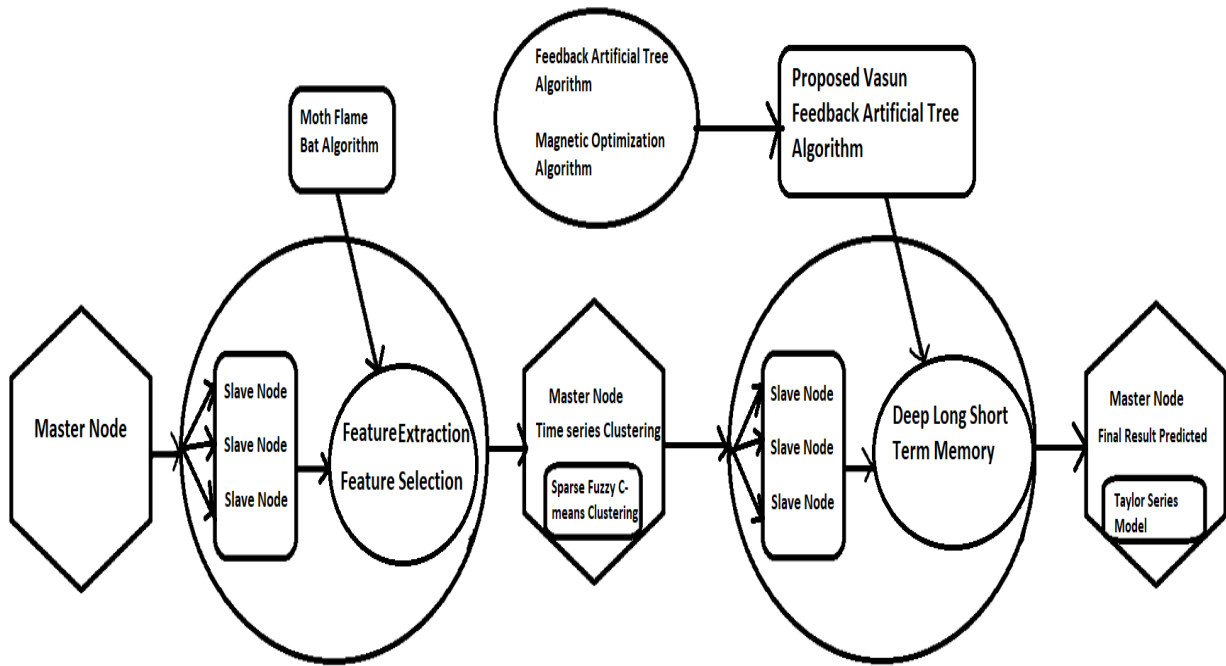


Figure 1. Process of VFATA

3.1 Attaining of input weather data

Time-series is the stretch of value on the same scale indexed by the time that naturally occurs in different areas [9]. Let us specify dataset as D with n count of time-series data is shown as,

$$D = \{T_1, T_2, T_3, \dots, T_i, \dots, T_n\}; 1 \leq i \leq n \quad (1)$$

Here, D implies dataset, T_i shows i^{th} time-series data, and n specifies total count of data with the size of $[M \times N]$, respectively.

3.2 Feature extraction for every time-series samples

Feature extraction is used to provide a more manageable and representative subset of input time-series information [6]. However, input time-series information is passed to the feature extraction phase.

Simple Moving Average (SMA): It is the common average of previous m data points in the time-series data (Hansun, 2013) [7]. Here, each point of time-series data is weighted equally, so no weighting factor is fed to data points.

$$f_1 = \frac{X_t + X_{t-1} + \dots + X_{t-(m-1)}}{m} \quad (2)$$

Here, X_t denotes data points at time t , m specifies the number of data points, and f_1 denotes SMA.

3.3 Weather forecasting using Deep LSTM network

Deep LSTM [15] is used to perform weather forecasting by considering the clustering result β . Accordingly, operation of the input gate is expressed as,

$$IPm = \eta(\beta \cdot b_{z\beta} + s_{r-1} b_{zs} + K_{ig}) \quad (3)$$

Where, IPm denotes input gate at a time r , η specifies sigmoidal activation function, and K_{ig} denotes bias to input gate [14]. However, internal state z is the node with the self-loop recurrent edge of linear activation function and unit weight that is given as,

$$z = IPm \odot Z_r + z_{r-1} \quad (4)$$

Here, z_r denotes internal state, and z_{r-1} specifies internal state at the time $r-1$. Forget gate FR is utilized to reinitiating internal state of the memory cell and is given as,

$$FR_r = \eta(\beta \cdot b_{FR\beta} + s_{r-1} b_{FRs} + K_{fg}) \quad (5)$$

Where, FR denotes the forget state at time r , \odot specifies point wise the linear operator, $b_{FR\beta}$ denotes weight matrix among forget gate and the input layer, b_{FRs} signifies the weight matrix among forget gate and the hidden state, and K_{fg} denotes the bias for the forget gate.

Output gate S_p is expressed as,

$$S_p = \eta(\beta \cdot b_{s\beta} + s_{p-1} b_{s_s} + K_{og}) \tag{6}$$

where, $b_{s\beta}$ denotes weight matrix among output gate as well as input layers, b_{s_s} denotes weighing matrix, and K_{og} specifies bias .

3.4 Process of feeding Deep LSTM using VFATA

The training activity of deep learning classifier is performed by the proposed VFATA, which is derived by the integration of MOA [13] and FAT [10], respectively. MOA is the collection of magnetic particles and search agents, whose masses and magnetic fields are proportional to the fitness values. However, the intensity of forces is proportional to distance and the magnetic fields of search agents [14]. MOA is inspired by the theory of magnetic field and is used to solve the problems in search space.

4. RESULTS AND DISCUSSION

This section details the results and discussion of proposed VFATA-based Deep LSTM with respect to the performance measures.

4.1 Experimental setup

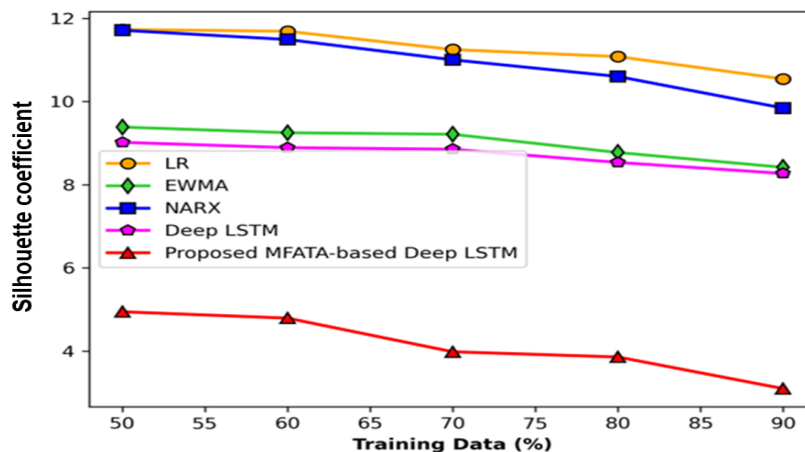
The implementation is carried out in the PYTHON using stat world dataset. This dataset contains five types of temperatures, namely planet, states, countries continents, and cities temperature. The temperature of Andhra Pradesh is selected for the implementation process. Moreover, the temperature of country named India and the continent named Asia is selected for the experimentation purpose. The temperature of state, countries and continents are collected from the month of February to December.

4.2 Performance Metrics

The performance of developed method is analyzed by considering the methods, such as *Silhouette coefficient* and *Dunn's Index*.

Silhouette coefficient: The Silhouette Coefficient for a set of samples is given as the mean of the Silhouette Coefficient for each sample. The score is higher when clusters are dense and well separated.

Dunn's Index: Dunn's Index is equal to the minimum inter-cluster distance divided by the maximum cluster size.



5. CONCLUSION

An efficient weather forecasting method is developed using proposed VFATA-based Deep LSTM classifier. The proposed VFATA is developed by the integration of MOA and FAT algorithm, respectively. The proposed methodology include different phases, namely feature extraction, feature selection, time-series clustering, and weather forecasting. The master node gathers the input weather data and gives it to the slave node. In slave node the process of feature extraction and feature selection is performed.

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