Recurrent Neural Network (RNN), Long short-term memory (LSTM) for Aerosol Optical Depth (AOD) using NASA's MERRA-2 Reanalysis

Mohammed Magooda[1], Mohamed Eltahan[2], and Karim Moharm[3]

[1]Cairo University
[2]Julich
[3]Alexandria University

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Abstract

Predication of temporal trends of aerosol optical depth (AOD) within the numerical climate models with enabled chemistry module is very challenging and computationally expensive. In this work, new predication model is introduced based on artificial neural networks (ANN) in order to estimate average AOD over Egypt. Long short-term memory (LSTM) algorithm which is artificial recurrent neural network (RNN) architecture, is selected to construct the predication model. Seven input datasets for LSTM algorithm are from NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) reanalysis within period (1980-2017). The seven variables are pressure (PR), temperature (T), wind speed (W), dust surface particulate matter (PM2.5), surface (SO2) and (SO4) concentrations and (CO) concentration. AOD is the output of the trained and validated model. Effects of changing the number of both hidden layers and number of neurons per layers were evaluated. The results of increasing the number of neurons per one hidden layer revealed that increasing the number of neurons leads to three main finding (a) leads to faster convergence of loss function. (b) Produces more realistic AOD estimation (c) RMSE is reduced by increasing number of neurons. It was also found that, the model with one hidden layer and 50 neurons is the best model setup with RMSE (0.06). However, our studies showed also that increasing the number of hidden layers has no dominant effect on model RNN performance. The proposed LSTM model showed a very high level of accuracy with percentage 99.94 %. Future work can include more variables that has direct effect on AOD calculations. Both ensemble algorithms and different datasets can have more positive impact on the current proposed model.

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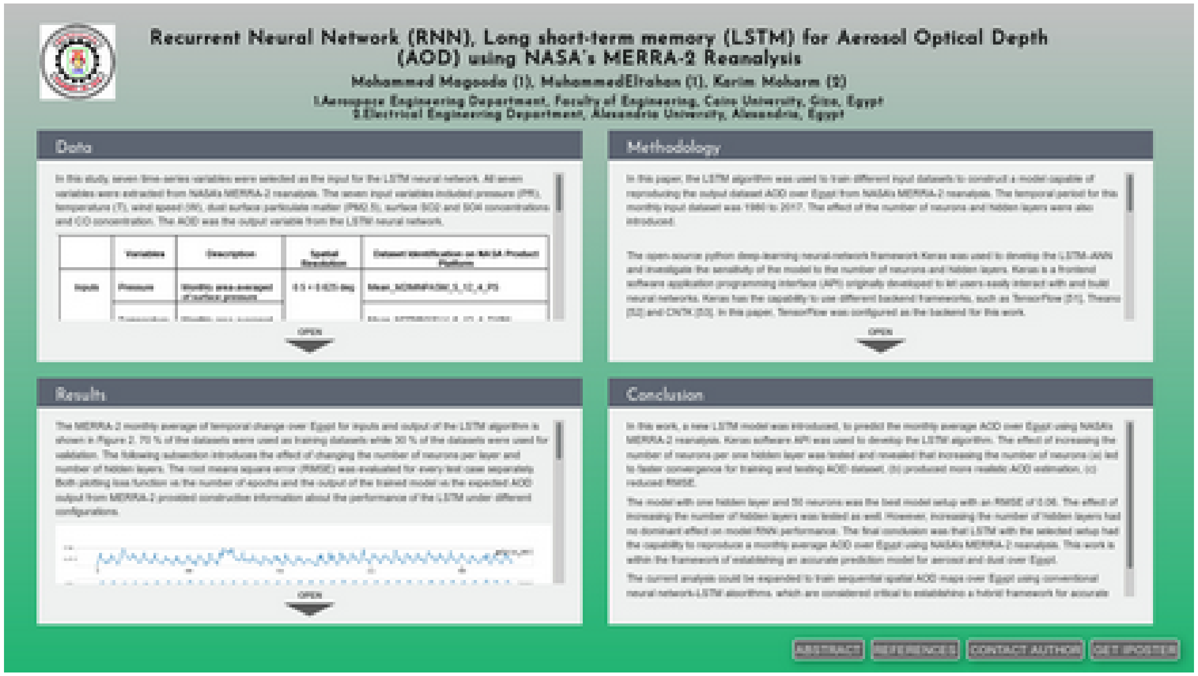

Mohammed Magooda (1), MuhammedEltahan (1), Karim Moharm (2)

1.Aerospace Engineering Department, Faculty of Engineering, Cairo University, Giza, Egypt
2.Electrical Engineering Department, Alexandria University, Alexandria, Egypt

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DATA

In this study, seven time-series variables were selected as the input for the LSTM neural network. All seven variables were extracted from NASA's MERRA-2 reanalysis. The seven input variables included pressure (PR), temperature (T), wind speed (W), dust surface particulate matter (PM2.5), surface SO2 and SO4 concentrations and CO concentration. The AOD was the output variable from the LSTM neural network.

	Variables	Description	Spatial Resolution	Dataset Identification on NASA Product Platform
Inputs	Pressure	Monthly area-averaged of surface pressure	0.5 × 0.625 deg	Mean_M2IMNPASM_5_12_4_PS
	Temperature	Monthly area-averaged of temperature at 10 m above the surface		Mean_M2TMNXSLV_5_12_4_T10M
	Wind speed	Monthly area-averaged of surface wind speed		Mean_M2TMNXFLX_5_12_4_SPEED
	Dust surface particle (PM2.5)	Monthly area-averaged of dust surface mass concentration - PM 2.5		Mean_M2TMNXAER_5_12_4_DUSMASS25
	Surface SO4	Monthly area-averaged of SO4 surface mass concentration (ENSEMBLE)		Mean_M2TMNXAER_5_12_4_SO4SMASS
	Surface SO2	Monthly area-averaged of SO2 surface mass concentration (ENSEMBLE)		Mean_M2TMNXAER_5_12_4_SO2SMASS
	Surface CO	Monthly area-average of CO surface concentration in ppbv (ENSEMBLE) monthly		Mean_M2TMNXCHM_5_12_4_COSC
Outputs	AOD	Monthly area-average of aerosol optical depth analysis		Mean_M2IMNXGAS_5_12_4_AODANA

Table 1. Input and Output Variables Definitions for the LSTM Neural Network

RESULTS

The MERRA-2 monthly average of temporal change over Egypt for inputs and output of the LSTM algorithm is shown in Figure 2. 70 % of the datasets were used as training datasets while 30 % of the datasets were used for validation. The following subsection introduces the effect of changing the number of neurons per layer and number of hidden layers. The root means square error (RMSE) was evaluated for every test case separately. Both plotting loss function vs the number of epochs and the output of the trained model vs the expected AOD output from MERRA-2 provided constructive information about the performance of the LSTM under different configurations.

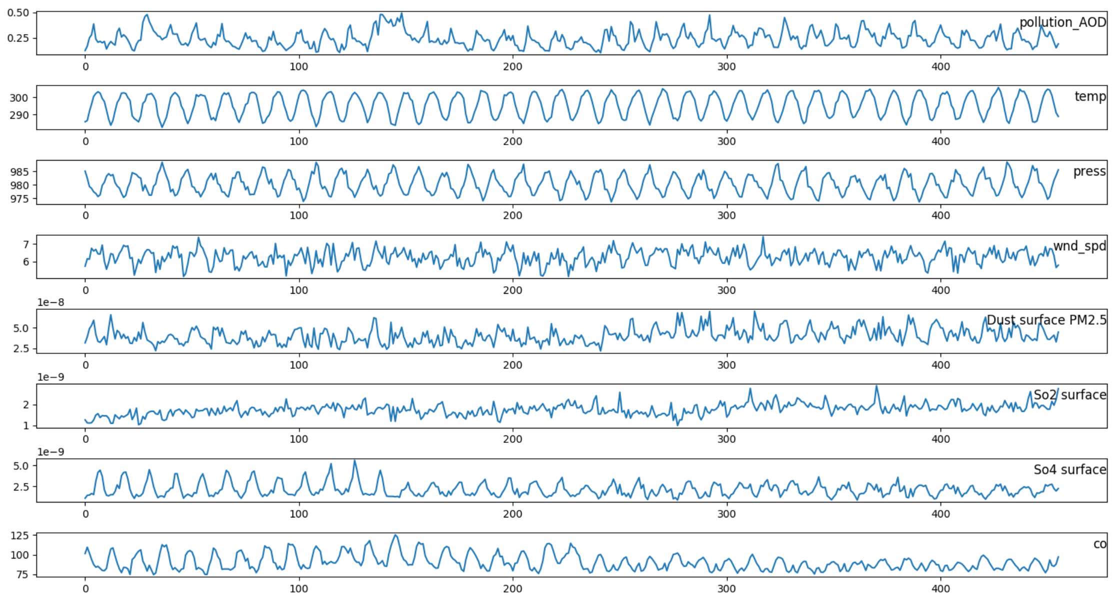


Figure 2. Monthly average over Egypt (1980–2017) of all input and output variables mentioned in section 2.

The effect of increasing neuron numbers

The effect of increasing the number of neurons per hidden layer on our predicative model was investigated. There were 80 epochs. The number of neurons ranged from five to 260 neurons per hidden layer. Increasing the number of neurons led to a number of positive effects on the ANN model:

(a) faster convergence for training and testing AOD dataset
(b) more realistic AOD estimation
(c) reduced RMSE

Moreover, increasing the number of neurons by more than 50 neurons per one hidden layer led to starting converge but at a higher loss error at the later epochs. By increasing the number of neurons, the convergence at a higher value of error for the testing dataset began to occur in earlier epochs. The effect of increasing the number of neurons per hidden layer on RMSE calculations is shown in Figure 3.

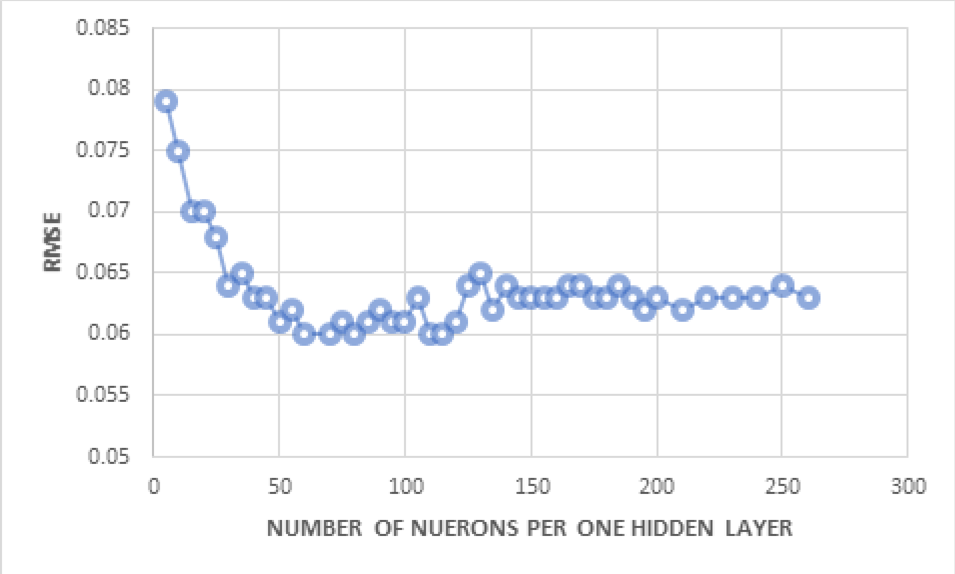
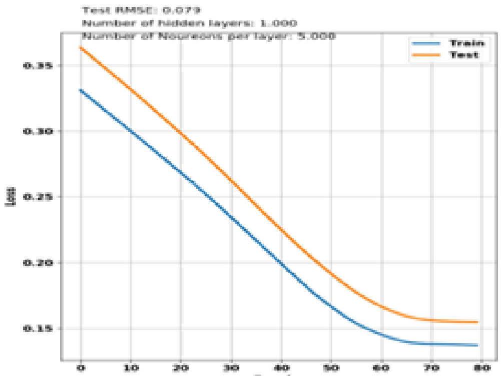
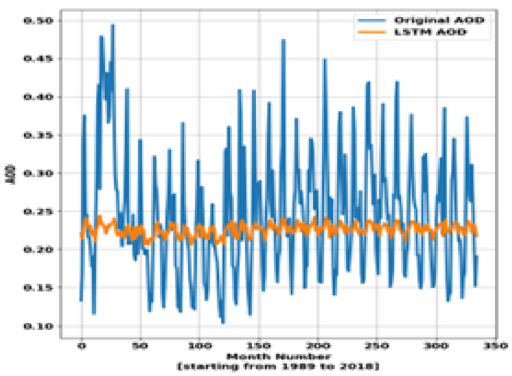


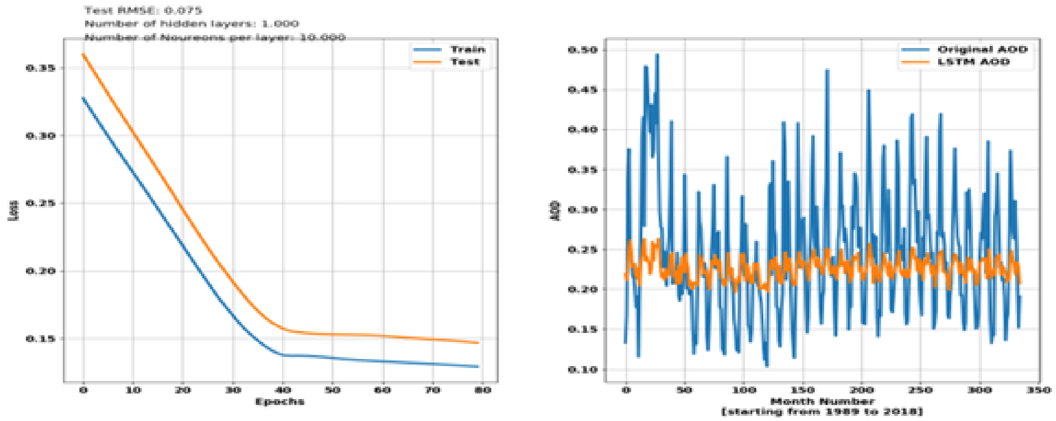
Figure 3. Effect of increasing the number of neurons per hidden layer on RMSE.

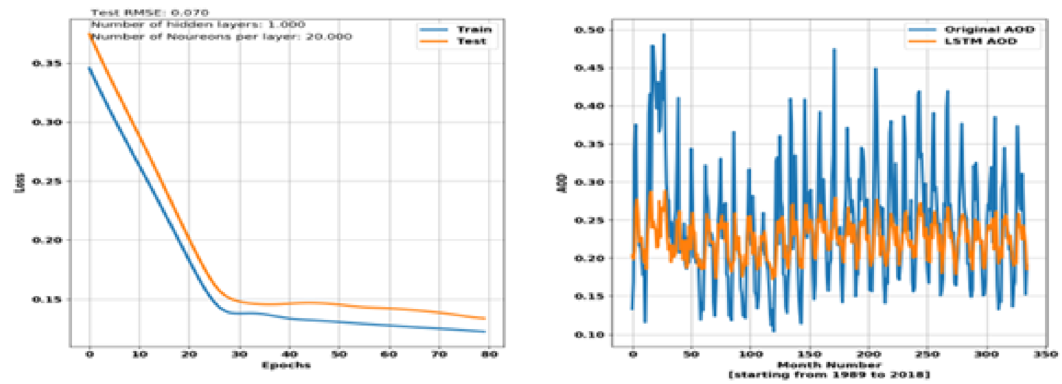
The effect of increasing the number of hidden layers

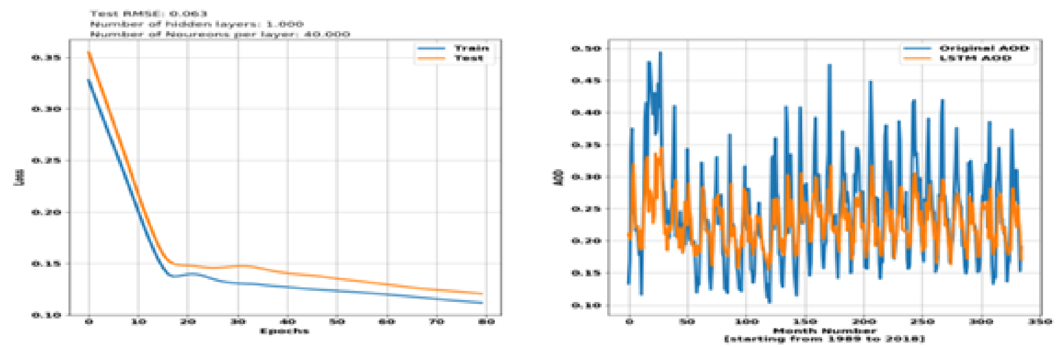
The effect of adding more hidden layers to the current RNN model setup is shown in Figure 8. Adding more hidden layers to the current setup using the existing MERRA-2 monthly dataset didn't improve the RMSE. After adding hidden layer number 9 to the model, the response of the model became unstable and had a higher RMSE (.084) with respect to the model with one hidden layer, which had an RMSE of.061.






Test RMSE: 0.075
Number of hidden layers: 1.000
Number of Noureons per layer: 10.000
Train
Test
Loss
Epochs
Original AOD
LSTM AOD
AOD
Month Number
[starting from 1989 to 2018]


Test RMSE: 0.070
Number of hidden layers: 1.000
Number of Noureons per layer: 20.000
Train
Test
Loss
Epochs
Original AOD
LSTM AOD
AOD
Month Number
[starting from 1989 to 2018]


Test RMSE: 0.063
Number of hidden layers: 1.000
Number of Noureons per layer: 40.000
Train
Test
Loss
Epochs
Original AOD
LSTM AOD
AOD
Month Number
[starting from 1989 to 2018]

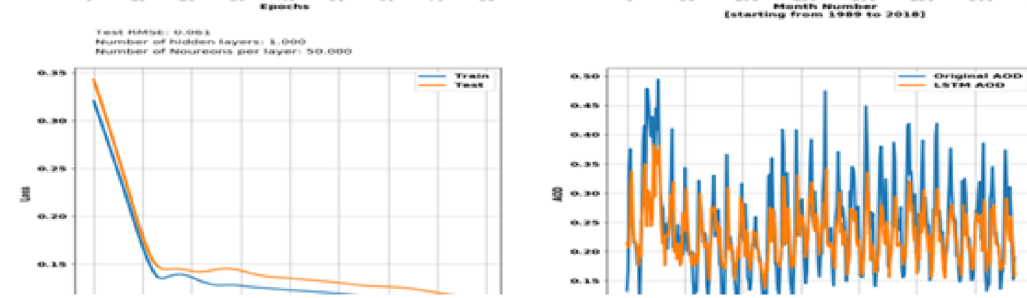

Test RMSE: 0.061
Number of hidden layers: 1.000
Number of Noureons per layer: 50.000
Train
Test
Loss
Original AOD
LSTM AOD
AOD

Figure 4. The left column shows loss function for both train and test model for a different number of hidden layers. The right column shows the predicated AOD vs original AOD dataset from MERRA-2 for a different number of hidden layers.

METHODOLOGY

In this paper, the LSTM algorithm was used to train different input datasets to construct a model capable of reproducing the output dataset AOD over Egypt from NASA's MERRA-2 reanalysis. The temporal period for this monthly input dataset was 1980 to 2017. The effect of the number of neurons and hidden layers were also introduced.

The open-source python deep-learning neural-network framework Keras was used to develop the LSTM–ANN and investigate the sensitivity of the model to the number of neurons and hidden layers. Keras is a frontend software application programming interface (API) originally developed to let users easily interact with and build neural networks. Keras has the capability to use different backend frameworks, such as TensorFlow [51], Theano [52] and CNTK [53]. In this paper, TensorFlow was configured as the backend for this work.

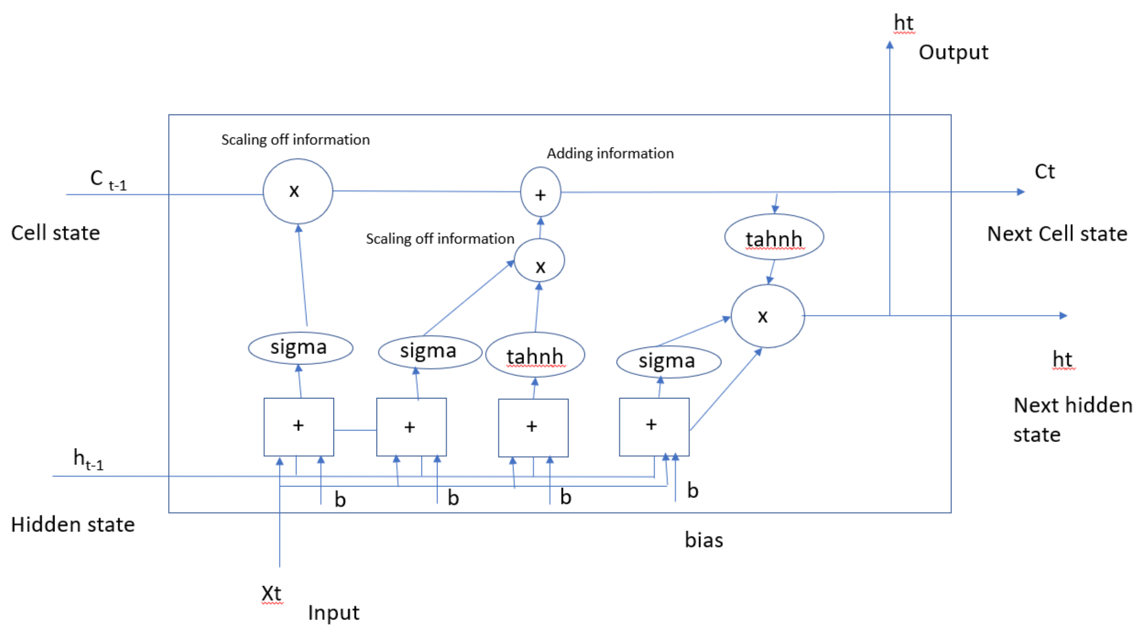


Figure 1 The structure of LSTM–ANN

CONCLUSION

In this work, a new LSTM model was introduced, to predict the monthly average AOD over Egypt using NASA's MERRA-2 reanalysis. Keras software API was used to develop the LSTM algorithm. The effect of increasing the number of neurons per one hidden layer was tested and revealed that increasing the number of neurons (a) led to faster convergence for training and testing AOD dataset, (b) produced more realistic AOD estimation, (c) reduced RMSE.

The model with one hidden layer and 50 neurons was the best model setup with an RMSE of 0.06. The effect of increasing the number of hidden layers was tested as well. However, increasing the number of hidden layers had no dominant effect on model RNN performance. The final conclusion was that LSTM with the selected setup had the capability to reproduce a monthly average AOD over Egypt using NASA's MERRA-2 reanalysis. This work is within the framework of establishing an accurate prediction model for aerosol and dust over Egypt.

The current analysis could be expanded to train sequential spatial AOD maps over Egypt using conventional neural network-LSTM algorithms, which are considered critical to establishing a hybrid framework for accurate predication of AOD over Egypt.

Sorry for the inconvenience!

DISCLOSURES

AUTHOR INFORMATION

ABSTRACT

Predication of temporal trends of aerosol optical depth (AOD) within the numerical climate models with enabled chemistry module is very challenging and computationally expensive. In this work, new predication model is introduced based on artificial neural networks (ANN) in order to estimate average AOD over Egypt. Long short-term memory (LSTM) algorithm which is artificial recurrent neural network (RNN) architecture, is selected to construct the predication model. Seven input datasets for LSTM algorithm are from NASA's Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) reanalysis within period (1980-2017). The seven variables are pressure (PR), temperature (T), wind speed (W), dust surface particulate matter (PM2.5), surface (SO2) and (SO4) concentrations and (CO) concentration. AOD is the output of the trained and validated model. Effects of changing the number of both hidden layers and number of neurons per layers were evaluated.

The results of increasing the number of neurons per one hidden layer revealed that increasing the number of neurons leads to three main finding (a) leads to faster convergence of loss function. (b) Produces more realistic AOD estimation (c) RMSE is reduced by increasing number of neurons. It was also found that, the model with one hidden layer and 50 neurons is the best model setup with RMSE (0.06).

However, our studies showed also that increasing the number of hidden layers has no dominant effect on model RNN performance. The proposed LSTM model showed a very high level of accuracy with percentage 99.94 %. Future work can include more variables that has direct effect on AOD calculations. Both ensemble algorithms and different datasets can have more positive impact on the current proposed model.

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