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Forecasting of Fires Hotspot in Tropical Region Using LSTM Algorithm Based on Satellite Data

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***Abstract* — Raising of temperature due to global warming impacted to the number of fires hotspot globally, in tropical region some of the places a high risk such as wildfire. Fire in Indonesia is one of the big disasters because of forestry region and peat land that highly risk to wildfire especially in dry season. This research aims to do a forecasting number of fires hotspot in future time based on training data collected in previous years. Long Short-Term Memory (LSTM) algorithm applied in this forecasting, the advantages of LSTM model to forecast a timeseries data make the high prediction accuracy. Fires hotspot data was collected since year 2010 to 2021 with total number of datasets more than 700,000 hotspot and forecast for the future year 2022. Collected datasets analyzed use LSTM model divided into two classification which are training and test data with 70% and 30% respectively. Results shows a similar pattern of forecasting fires hotspot in 2022 compared into previous last 2 years which 2021 and 2020. Furthermore, to proof proposed algorithm is working fine then a forecast number of fire hotspot for year 2021 have been done which compared actual and forecasting data and percentage of error 4.56%. LSTM Algorithm is one of the models suitable to use in data forecasting in high volume time series data.**

***Keywords*—Fires Hotspsot, Forecasting, LSTM, Tropical Region**

I. Introduction

Fires are one of the common issues in many countries and regions that potential to get disaster, generally the sources of fires getting high and bad impact to the community is from forest and wildfire. In the tropical region that only has two seasons which are the rain and dry season and the most common sources of fires from forests because of typical land which is forestry and wild as well as some of the areas with peatland that easy to get fires especially in the dry season. Indonesia is one of the regions in the tropical area that has a major issue in forest and wildfire, located in southeast Asia with large forest area and most of every year fires happen in summer due to typical land and some of the cases local people traditionally fire the land to create a new farming area. Furthermore, the impact of the forest fires is very bad on the environment, for example, air pollution with high carbon concentration and low level of oxygen makes human difficult to breathe and respiratory issue especially for the children as well as for the flora and fauna in the fired forest area.

Many research in fires hotspot prediction and spreading forecasting has been done by other researchers for example as discussed by [1-5]. The method and data analyzed to do a prediction used machine learning with many kinds of models and approaches. Characteristic and typical sources of fire data influenced by climate change and environmental aspects considered as well by those studies. Meteorological factors in the prediction process of fire hotspot data are one of the factors that influence the accuracy of prediction. Forest and wildfire are major issues in some counties with a large forest area, especially in tropical countries. A comprehensive data analysis of fire hotspot by measuring the size and fire concentration according to the color of fire to do a prediction how the potential of spreading scale as elaborated in [6-10]. A fires hotspot occurs become a potential to create forest and wildfire especially in the tropical region and the sizes of fires hotspot determine how the potential level to become a fire and its spread rate.

Early analysis of fires hotspot by identifying the smoke spread from the wild and forest is one of the methods used and discussed to identify how the potential getting fire and spread area as well direction mention in [11-13]. The method in early identification used the LSTM model to refer to the previously collected fire data in a city with a small size that only do a prediction in a dedicated area. An investigation of forest and wildfire to forecasting by considering dependencies of fires data using computerized reasoning was discussed as well. A time-series technique to do a prediction of fires hotspot used Recurrent Neural Network (RNN) which is capable of forecasting fire propagation more accurately and LSTM network in the analysis. The use of sensor and remote sensing including wireless sensor network (WSN) to detect forest and wildfire hotspots is one of the proposed solutions as discussed in [14-19]. To detect the impact and rising of global temperature due to forest fires many efforts have done including prediction of the number and spreading of fires. The advantages of the ground sensing system to detect the number of fires hotspot are one of the techniques to achieve high accuracy data analysis and prediction, in the others hand the ground sensing system has limited covered area because of the limited reading range of sensors.

This research proposes a technique to do forecast the number of fires hotspot for future time using the LSTM algorithm in RNN deep learning. Analyzed data based on Moderate Resolution Imaging Spectroradiometer (MODIS) fires hotspot provided by National Aeronautics and Space Administration (NASA) from the year 2010 to 2021 and doing forecasting for the future year which is 2022 [20]. Available fires hotspot data is split into two categories which is training and testing data in the analyzed to achieve accurate results in the deep learning process. This case of fire forecasting narrowing the region which only in Indonesia territory.

II. METHOD AND FIRES DATA

Fire is a natural phenomenon that can be a disaster for humans and the environment with high scale and massive size. Forest and wildfire are the most disasters that happened in many areas with forestry regions, some of the area uncontrolled because of size and type of land and trees. Many techniques have been proposed to prevent forest fires and prediction the occurrence including install number of sensors or detectors to send an alert signal while fires incident. Previous fires data is very important in the analysis and prediction for the future of number fires hotspot or potential to become a big fire, with high number fires data determine the accuracy in the prediction for the future times.

A. LSTM Algorithm

LSTM algorithm is an evolution of deep learning called RNN, first introduced by Hochreiter and Schmidhuber [21] in order to address problems of the aforementioned drawbacks of the RNN by adding additional interactions per module or cell. LSTM is a special model of RNN, that capable of learning in long-term dependencies and remembering information for prolonged periods as a default. Fig. 1 shows an architecture of the RNN-LSTM model of algorithm which consists of several main blocks called cells such as input gate, output gate, and forget gate. In the dense output layer, the sigmoid activation function classifies the values in probabilities for the two predefined classes.

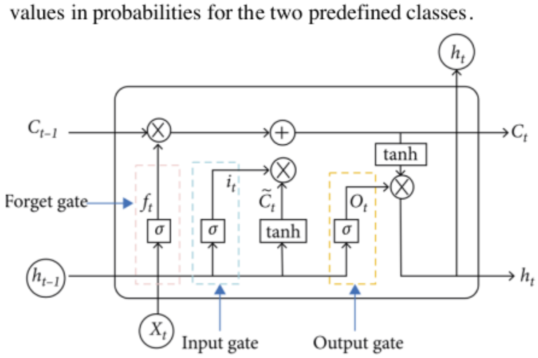


Fig. 1. The structure of RNN-LSTM algorithm.

LSTM model can be elaborate as short-term memory which acts when the information is being acquired, retains that information for a few seconds, and then destines it to be kept for longer periods, or discards it. Long-term memory, permanently retains information, allowing its recovery or recall. It contains all our autobiographical data and all our knowledge. Refer to the architecture of the LSTM model which consists three major cells and the calculation of each cell and the process can be written as equations (1) to (6).

$$f_t = \sigma\,(W_f\,.\,[h_{t-1}\,, x_t] + b_f) \tag{1}$$

$$i_t = \sigma\,(W_i\,.\,[h_{t-1}\,, x_t] + b_i) \tag{2}$$

$$`C_t = \tanh\,(W_c\,.\,[h_{t-1}\,, x_t] + b_c) \tag{3}$$

$$C_t = f_t\ * C_{t-1} + i_t *\ `C_t \tag{4}$$

$$o_t = \sigma\,(W_o\,[h_{t-1}\,, x_t] + b_o \tag{5}$$

$$h_t = o_t\ * \tanh\,(C_t) \tag{6}$$

LSTM model is able to handle the problem with long-term dependencies of RNN which the RNN algorithm cannot do in the prediction of the information stored in the long-term memory but can give more accurate prediction from the recent information. LSTM can use by default to retain the data in a long-term period of time. Normally used for predicting, processing, and classifying on the basis of time-series data [22].

B. Fires Data

Fire hotspot data available on NASA earth data database, MODIS type of fires data refer to the detection of active fires hotspot used satellite imaging. The strategy in data detection is based on absolute fire and when the image relatively sufficient background in the amount to consider as a fire hotspot also considers the average and variability of earth surface temperature reflection by sunlight. The data collected in this case of prediction start from 2010 to 2021 and forecasting for the year 2022 [20]. Table 1 shows the fires dataset obtained only for the Indonesia region, the dataset normalized to the related field in analysis which dates and the total number of fire while table 2 shows the original data.

TABLE I. FIRES HOTSPOT DATASET 2010 TO 2021

	Lati	Long	Date	Total
0	0.02110	116.87390	2010-01-01	42
1	0.48080	116.08060	2010-01-01	66
11	2.15090	117.49680	2010-01-01	0
10	-8.10890	118.07430	2010-01-01	0
8	-8.15960	117.58570	2010-01-01	43
...	...	...	...	...
14208	-7.22331	110.42920	2021-12-31	67
14209	-6.96059	110.45844	2021-12-31	55
14210	-5.80178	139.61118	2021-12-31	65
14211	-4.51654	136.84802	2021-12-31	56
14213	-4.54666	136.77507	2021-12-31	52

703116 rows × 4 columns

TABLE II. DETAIL ORIGINAL OF FIRES HOTSPOT DATASET FROM YEAR 2010 TO 2021

	latitude	longitude	brightness	scan	track	acq_date	acq_time	satellite	instrument	confidence	version	bright_t31	frp	daynight	type
0	0.02110	116.87390	315.30	1.10	1.10	2010-01-01	251	Terra	MODIS	42	6.2	295.60	8.70	D	0.0
1	0.48080	116.08060	312.30	1.00	1.00	2010-01-01	251	Terra	MODIS	66	6.2	295.00	6.90	D	0.0
11	2.15090	117.49680	320.60	1.00	1.00	2010-01-01	550	Aqua	MODIS	0	6.2	297.50	10.60	D	0.0
10	-8.10890	118.07430	319.30	1.00	1.00	2010-01-01	547	Aqua	MODIS	0	6.2	300.80	9.10	D	0.0
8	-8.15960	117.58570	319.60	1.00	1.00	2010-01-01	547	Aqua	MODIS	43	6.2	297.70	9.10	D	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
14208	-7.22331	110.42920	316.80	1.00	1.00	2021-12-31	300	Terra	MODIS	67	6.1NRT	293.06	8.56	D	NaN
14209	-6.96059	110.45844	318.84	1.00	1.00	2021-12-31	300	Terra	MODIS	55	6.1NRT	291.66	6.42	D	NaN
14210	-5.80178	139.61118	309.57	1.00	1.00	2021-12-31	418	Aqua	MODIS	65	6.1NRT	283.90	5.50	D	NaN
14211	-4.51654	136.84802	313.68	1.21	1.09	2021-12-31	418	Aqua	MODIS	56	6.1NRT	291.74	7.84	D	NaN
14213	-4.54666	136.77507	309.21	1.22	1.10	2021-12-31	418	Aqua	MODIS	52	6.1NRT	287.79	5.59	D	NaN

703116 rows × 15 columns

Table 3 shows the fires dataset has been normalized and grouped into a single date of fire occurrence, the total number of data based on days in 12 years which is from the year 2010 to 2021. The total number of the dataset will be used in data training and testing for fire forecasting, while the number of fire hotspot accumulate every single day.

TABLE III. NORMALIZED FIRES HOTSPOT DATASET 2010 TO 2021

	Date	Total
0	2010-01-01	12
1	2010-01-02	12
2	2010-01-03	5
3	2010-01-04	14
4	2010-01-05	36
...	...	...
4360	2021-12-27	7
4361	2021-12-28	6
4362	2021-12-29	4
4363	2021-12-30	30
4364	2021-12-31	7

4365 rows × 2 columns

III. FIRES DATA FORECASTING

A memory working in the long with a short-term network called LSTM is a special type of RNN network with the capability of learning in long-term connections. The LSTM model has an incredible way to do forecasting and works well in time series data as well as in a wide range of problems, thus many applications used this model to analyse data and predict the trend in the future time. Furthermore, this model can organize in the form of a chain structure and has four interacting layers with a unique method of communication with each other in the data processing. Fig. 2 shows an analysis block diagram of how the forecasting process of the fires hotspot in the future times.

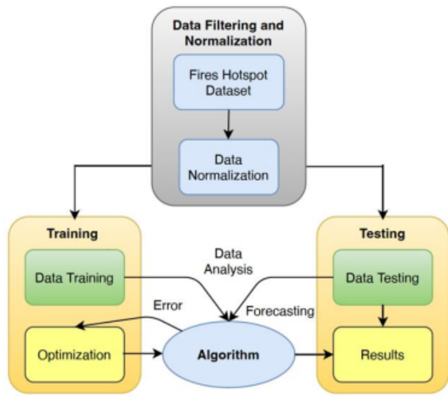


Fig. 2. Analysis diagram of real-time sensor data to forecasting number.

The first step in data processing in forecasting is to construct an LSTM network model to identify the input or information that is not necessary and will be denied in the cell in the current step. The process of identification and excluding of data decide by the sigmoid function, which takes the output of the last LSTM unit h_{t-1} at time $t-1$ and the current input X_t at time t. Additionally, the sigmoid function determines which part from the old output should be eliminated. This gate is called the forget gate f_t; where f is a vector with values ranging from 0 to 1, corresponding to each number in the cell state, C_{t-1} as written in equation (1).

According to the collected dataset, there is more than 700,000 fire hotspot within 12 years and after normalization becomes 4365 datasets of fires grouped in each day are shown in table 3. The basic machine learning process in the forecasting of data which divided into two sections as shown in Fig. 2 training and testing data, this is very important to make sure algorithm and machine learning current data trend and behaviour before doing a test. Optimization process to evaluate results obtained and increasing the performance by enhancing the accuracy which minimizes the error, final result of data analysis and forecasting check in the error analysis. While a LSTM cell with sigmoid function W_f and b_f are the weight matrices and bias respectively of the forget gate. This step decide and store input data from the new information in the cell state as well as to update the cell state. Then, the sigmoid layer decide whether the a new data should updated or ignored (0 or 1), and the tanh function gives weight to the values which passed by decide their level of importance (1 to 1). The two values are multiplied to update the new cell state. This new memory is then added to old memory C_{t-1} resulting in C_t as written in equation (2), (3), and (4). Fig. 3 shows how the neuron process of the LSTM model [23].

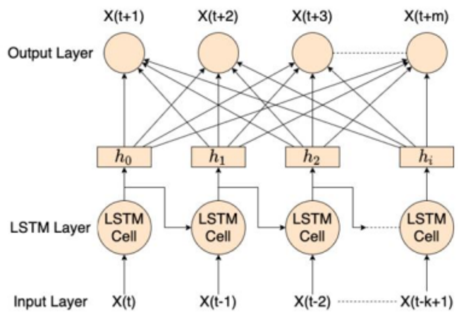


Fig. 3. Internal cell of LSTM model neuron process.

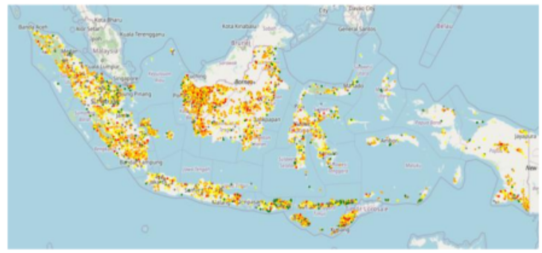
The next step is C_{t-1} and C_t are the cell states in the LSTM cell at time C_{t-1} and t while W and b are the weight matrices and bias of the cell state. In the last step, the value of h_t is based on the output cell state o_t, a sigmoid layer decide which parts of the cell state make it to the output. Next, the output of the sigmoid gate o_t is multiplied by the new values created by the *tanh* layer from the cell state C_t, with a value ranging between 1 and 1 as written in equation (5) and (6) previously.

Evaluation of the performance in forecasting results is required to fire hotspot data, Root Mean Square Error (RMSE) is one of the methods statistically usually applied to compare prediction and actual data values. The RMSE is frequently used to evaluate how closely the predicted values match the forecast values, based on the relative range of the data. Equations (7) which X_i and X'_i are actual fires hotspot data compare to forecasting fires data at the time t. X_i is the mean of actual values fire data and n is the total number of data. The RMSE values equal to zero mean implies perfect results that the LSTM algorithm produce reliable results when the values of RMSE go to a small number to zero.

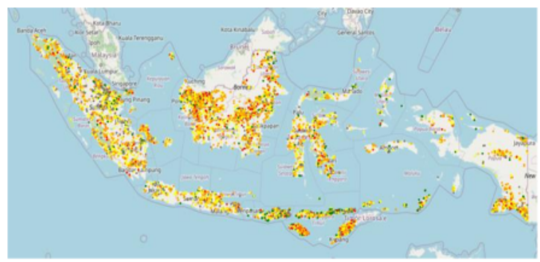
$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(X_i - \widehat{X}_i\right)^2}{n}} \qquad (7)$$

IV. Results and Discussion

The fires dataset collected consists of several parameters such as coordinate or location of fires occurrence, date and time, confidence level, brightness, day or night time, etc. as shown in gable 2. This analysis used four parameters that have a major impact and are impotent to forecasting which coordinates (latitude and longitude), acquisition date (acq_date), and confidence level. Fig. 4 shows the mapping of fires hotspot distribution in the Indonesia region while Fig. 4(a) mapping of fires hotspot year 2021 and Fig. 4(b) for the year 2020. The distribution of fire hotspot classifies into five levels of confidence since the level starts from 0 with the lowest impact and less potential to spread out until 100 which high probability to get spreading and potentially becoming a big fire. The five-level of classifications which from 0-20 as low level indicated with a blue dot, level 21-40 as a green dot, and confidence level 41-60 indicate as yellow dot, while level 61-80 indicates as orange and the last is confidence level 81-100 is the highest level indicate with a red dot as shown.



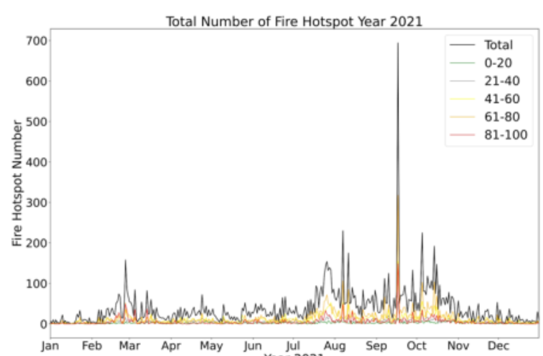
(a)



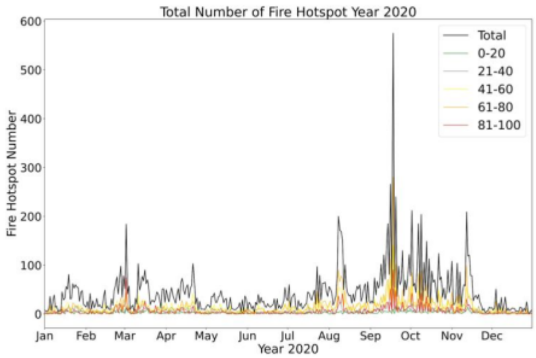
(b)

Fig. 4. Mapping of fires hotspot in Indonesia (a) 2021 (b) 2020.

The number of fires hotspot refers to the data collected and based on confidence level, the total number in every year with thousand of fire hotspots. The distribution-based of the month which a high number of fire as well as month with low fire hotspot as shows in fig. 5, while fig. 5(a) plotting of distribution in the year 2021 and fig. 5(b) distribution of fire hotspot for the year 2020.



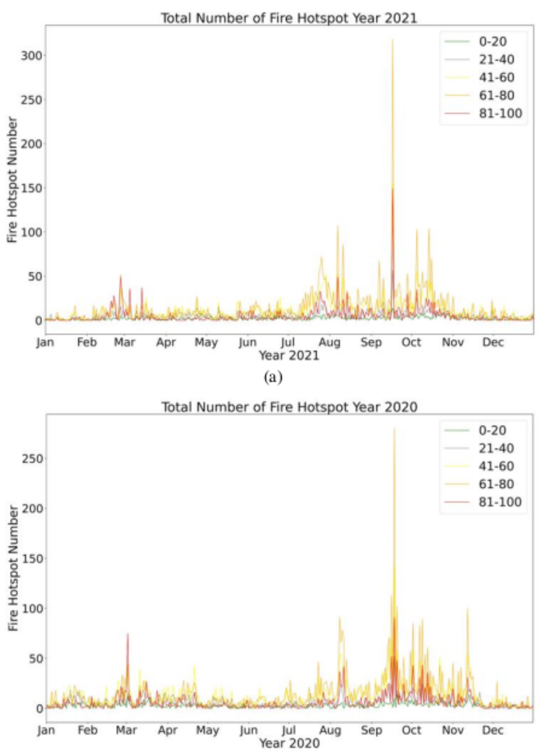
(a)



(b)

Fig. 5. Distribution of fires hotspot in Indonesia region for a year from January to December (a) 2021 (b) 2020.

Generally, the pattern and number of fire hotspot incidents are similar distribution with the maximum number of fire hotspots 600 to 700 in each day but only a few days which the pick of number. Referring to the graph in fig. 5 the highest month of occurrence is from September to November. Fig. 6 shows more detail of data after breaking out the confidence level into five-level as mentioned in early, fig. 6 (a) plotting of fire number based on confidence level year 2021, and fig. 6 (b) plotting fire data in the year 2020.



(a)

(b)

Fig. 6. Distribution of fires hotspot in Indonesia region based on confidence level which clasify into 5 level (a) year 2021 (b) year 2020.

Data analysis used machine learning have to classify data into two types which data for training and data for testing. Normally, training data is larger in quantity compare to testing data to achieve highly accurate results. Fig. 7 shows training data for the forecasting of fire hotspots, the distribution from the year 2010 to 2021.

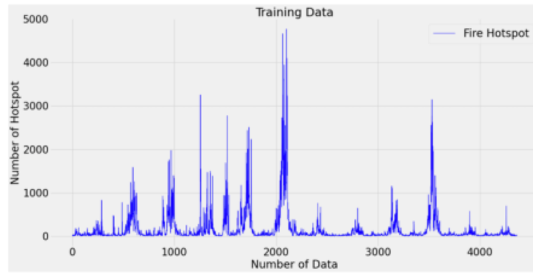


Fig. 7. Training data for fire forecasting from year 2010 to 2021.

The proposed LSTM algorithm to do forecasting of fires hotspot in the Indonesia region has been tested and compared to the actual data available. Preliminary forecasting by testing data from 2010 to 2021 and do predictions for the year 2021. Fig. 8 shows the comparison of actual fires hotspot data and forecasting results year 2021, the results show a good agreement both of graph with RMSE is 4.56 %.

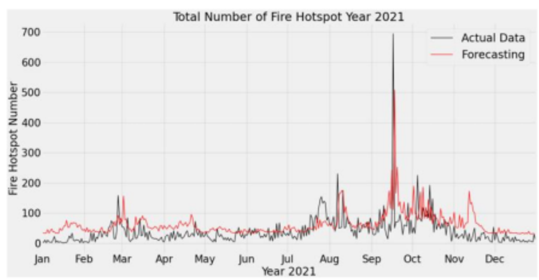


Fig. 8. Comparison of actual and forecasting data for year 2021.

Forecasting results have been achieved for the year 2022, by calculating the distribution of data training more than 4000 datasets and 30% of data testing to plot a new forecasting graph. Fig. 9 shows a good similar pattern for all of year started from the year 2010 graph shows a normal distribution of fire hotspot and rise in the end of the year, similar to the next year 2021 as well as forecasting results data 2022.

Fig. 9. Forecasting data of fires hotspot in year 2022 (red color) and actual data of fires in year 2020-2021 (blue color).

The use of LSTM model in RNN algorithm as results show running successfully with minimum error, time-series fires data obtained suitable analyzed by this algorithm and prediction the data in future time. The proposed model has been proof by analyzing the previous dataset then comparing it to available data which fire hotspots in the year 2021, results show in fig. 8 good matching among both of actual dan forecasting data, mean developed model of forecasting fire data perfume well in analysis and prediction. Forecasting results in the year 2022 shows good agreement and a similar pattern of fires data which the trend of rising number at the end of the year from month August to November while other not much significant data occur.

V. CONCLUSION

Forecasting of fires data have been done and the results achieves in good performance analyzed use LSTM model. Fires data collected from the year 2010 to 2021 from NASA satellites (Aqua and Terra) for the Indonesia region have been mapping and plotted within the last 2 years. The forecasting data for the year 2021 as proof of model have been obtained with high accuracy and percentage error is 4.56%, mean analysis performance up to 95% successful which categories good performance. Forecasting in a future year which is the year 2022 has been done as well as results show the graph a similar trend for the entire year from January to December. The major number of hotspots increase at the end of the year because in this time summer season and dry environment in case of area Indonesia, while in the early year not significantly shows the rising of the hotspot as rainy season.

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