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IEEE TENSYMP 2022

IEEE REGION 10 SYMPOSIUM

1st - 3rd JULY 2022

VMCC, IIT Bombay, Mumbai, INDIA

SOUVENIR

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2022 IEEE Region 10 Symposium (TENSYMP 2022) is being held in Mumbai, India from July 1 to 3, 2022. This is a prestigious flagship technical conference of IEEE Region 10. The theme of TENSYMP 2022 is "Technologies on the horizon for the benefit of humanity" and its aim is to bring together researchers and engineers from academia and industry to overcome the present difficulties and create prosperous future. Bombay Section welcomes you to the 'magical city' of Mumbai for the 10th edition of TENSYMP. It is back to the in-person Symposium after a few years, enabling better networking and fruitful interactions – both during and outside the Symposium sessions. "Aamchi Mumbai" (Our Mumbai) and the !ncredible India are the exciting tourist destinations during any season of the year. Prospective authors are invited to submit full papers using online paper submission system. All accepted and presented papers will be submitted to IEEE Xplore® digital library for review and publication.

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SCHEDULE-AT-A- GLANCE

Day 1: July 1, 2022

Time (IST)	Mode	Activity
08:00 - 09:00	Offline	Registration & Welcome
09:00 - 09:30	Hybrid	Inauguration & Unveiling of new logo of Bombay Section
09:30 - 10:15	Hybrid	Keynote Talk (Inaugural): Prof. K.V.S. Hari
10:15 - 10:30		High Tea
10:30 - 11:00	Hybrid	Parallel Track Invited Talks (IT1/IT2)
11:00 - 13:00	Hybrid	Parallel Technical Sessions (TS1/TS6/TS9/TS15/TS23)
13:00 - 14:00		Lunch
14:00 - 14:30	Hybrid	Parallel Track Invited Talks (IT3/IT4)
14:30 - 16:30	Hybrid	Parallel Technical Sessions (TS2/TS11/TS16/TS20/TS24)
16:30 - 16:45		Tea
16:30 - 18:30	Hybrid	Industry Session (MathWorks Workshop)

SCHEDULE-AT-A- GLANCE

Day 2: July 2, 2022

Time (IST)	Mode	Activity
09:00 - 11:00	Hybrid	Parallel Special (SS1/SS4/SS5) & Physical Poster (PP1) Sessions
11:00 - 11:15		Tea
11:15 - 13:15	Hybrid	Parallel Technical (TS3/TS7/TS10/ TS18/TS25) & Virtual Poster (VP1) Sessions
13:15 - 14:00		Lunch
14:00 - 14:30	Hybrid	Parallel Track Invited Talks (IT5/IT6)
14:30 - 16:30	Hybrid	Parallel Technical (TS4/TS12/TS17/TS21/TS26) &Virtual Poster (VP2) Sessions
16:30 - 16:45		Tea
16:45 - 17:30	Hybrid	Keynote Talk (Evening Talk): Prof. Ashok Jhunjhunwala
17:30 - 19:30	Hybrid	Parallel Special (SS2/SS3/SS6) & Physical Poster (PP2) Sessions
20:00 - 22:00		Gala dinner

SCHEDULE-AT-A- GLANCE

Day 3: July 3, 2022

Time (IST)	Mode	Activity
09:30 - 10:15	Hybrid	Keynote Talk (Virtual): Prof. Anthony Butler
10:15 - 10:45		Parallel Track Invited Talks (IT7/IT8)
10:45 -11:00	Hybrid	Tea
11:00 - 13:00	Hybrid	Parallel Technical Sessions (TS5/TS8/TS14/TS19/TS27)
13:00 - 13:45		Lunch
13:45 - 14:30	Hybrid	Track Invited Talk (IT9) & R10 IRC Session (IT10)
14:30 - 16:30	Hybrid	Parallel Technical Sessions (TS13/TS22/TS28/TS29)
16:30 - 16:45		Tea
16:45 - 17:30	Hybrid	Keynote Talk (Concluding): Prof. Sanghamitra Bandyopadhyay
17:30 - 18:00	Hybrid	Valedictory Session and Awards

TS 20: Sensors and IoT Applications in Health and Agriculture				
Sn.	**Paper ID**	**Paper Title**	**Corresponding Author**	**Registered Author**
1.	1570789015	PUF Based Authentication and Key Sharing Protocol for Smart Water Monitoring System	Sourav Roy (National Institute of Technology Durgapur, India)	Sourav Roy (National Institute of Technology Durgapur, India)
2.	1570789048	Crop Stress Assessment in Cotton with Granular Ambient and Crowd sensed Farm Data	Prachin Jain (Tata Consultancy Services, India)	Prachin Jain (Tata Consultancy Services, India)
3.	1570789224	Forecasting of Fires Hotspot in Tropical Region Using LSTM Algorithm Based on Satellite Data	Evizal Abdul Kadir (Universitas Islam Riau, Indonesia)	Evizal Abdul Kadir (Universitas Islam Riau, Indonesia)
4.	1570789296	A Fuzzy Logic Approach for the Determination of Carabao Mango Ripeness Level and Shelf Life	Christian James Encio (Mapua University, Philippines)	Christian James Y. Encio, Marvin S. Toco (Mapua University, Philippines)
5.	1570789321	Assessing Impact of Carbon-Smart Farming Practices in Rice with Mobile Crowdsensing	Rushikesh Dattatraya Kulat (Tata Consultancy Services, India)	Rushikesh Dattatraya Kulat (Tata Consultancy Services, India)
6.	1570792617	Practical Considerations and Performance Evaluation of an Offset Elimination Scheme for Half-Bridge TMR Angle Sensor	Kishor Bhaskarrao Nandapurkar (Indian Institute of Technology, Indian School of Mines Dhanbad, India)	Kishor Bhaskarrao Nandapurkar (Indian Institute of Technology, Indian School of Mines Dhanbad, India)
7.	1570793016	Addressing DAO Insider Attacks in IPv6-Based Low-Power and Lossy NetworkS	Sachin Verma (PDPM IIITDM, JABALPUR, India)	Sachin Verma (PDPM IIITDM, JABALPUR, India)
8.	1570794136	Oyster Mushroom Cultivation Monitoring and Control with Size QualityPrediction Algorithm via Adaptive Neuro-Fuzzy Inference System (ANFIS)	Glenn C. Virrey (Mapua University, Philippines)	Glenn C. Virrey (Mapua University, Philippines)

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TENSYMP 2022

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

Several research in fires hotspot prediction and spreading forecasting have 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 model and approaching. Characteristic and typical sources of fire data influence by climate change and environmental aspect considered as well by those study. Meteorological factors in prediction process of fire hotspot data are one of factor that influence the accuracy of prediction. Forest and wildfire is a major issue in some counties with a large forest area, especially in a tropical country. A comprehensive data analysis of fire hotspot by measured 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 tropical region and the sizes of fires hotspot determines how the potential level to become a fire and its spread rate.

Early analysis of fires hotspot by identify 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 identify used LSTM model refer to the previous collected fires data in a city with small size that only do a prediction in dedicated area. An investigation of forest and wildfire to forecasting by consider dependencies of fires data using computerized reasoning discussed as well. A time series technique to do a prediction of fires hotspot used Recurrent Neural Network (RNN) which capable of forecasting fire propagation more accurately and LSTM network in the analysis. The used of sensor and remote sensing including wireless sensor network (WSN) to detect forest and wildfire hotspot is one of proposed solution as discussed in [14-19]. In order to detect impact and rising of global temperature due to forest fires many efforts have done including prediction of number and spreading of fires. The advantages of ground sensing system to detect number of fires hotspot is one of techniques to achieve high accuracy data analysis and prediction, in the others hand the ground sensing system has limited covered area because of limited reading range of sensors.

In this research proposed a technique to do a forecasting number of fires hotspot for future time using LSTM algorithm in RNN deep leaning. Analyzed data based on Moderate Resolution Imaging Spectroradiometer (MODIS) fires hotspot provided by National Aeronautics and Space Administration (NASA) from year 2010 to 2021 and doing forecasting for the future year which is 2022 [20]. Available fires hotspot data split into two category 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

Fires is a natural phenomenon that can be disaster for human and environmental with high scale and massive size. Forest and wildfire are the most disaster happened in many areas with forestry region, 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 some 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 of time as a default. Fig. 1 shows an architecture of RNN-LSTM model of algorithm which consist of several main block called cell 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.

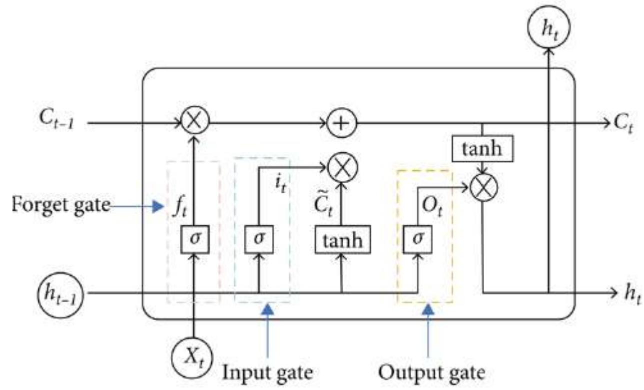


Fig. 1. The structure of RNN-LSTM algorithm

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, which permanently retains information, allowing its recovery or recall. It contains all our autobiographical data and all our knowledge. Refer to the architecture of LSTM model which consist three major cell and the calculation of each cell and the process can be write as equation (1) to (6).

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

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

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

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

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

$$h_t = o_t * \tanh\,(C_t) \quad (6)$$

LSTM model be able to handle the problem with long-term dependencies of RNN in which the RNN algorithm cannot do in prediction of the information stored in the long-term memory but can gives 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 obtained from third party which available on the database of NASA earth data, MODIS type of fires data refer to the detection of active fires hotspot used satellite imaging. The strategy in data detection based on absolute of fire and when the image relative sufficient background in the amount to consider as a fire hotspot also consider the average and variability of earth surface temperature reflection by sunlight. The data collected for this case of prediction start from 2010 to 2021 and forecasting for the year 2022 [20]. Table I shows the fires dataset obtained selected only in Indonesia region, the dataset normalized into use only data to be analyze which date and total number of fire hotspot while Table III shows the original data downloaded.

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

TABLE II. 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

TABLE III. FIRES HOTSPOT DATASET 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

III. FIRES DATA FORECASTING

A memory working in the long with 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 incredible way to do a forecasting and working well in time series data as well as in the wide range of problems, thus many applications used this model to analysis data and prediction 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 each other's in data processing. Fig. 2 shows an analysis diagram how the forecasting process of the fires hotspot in the future times.

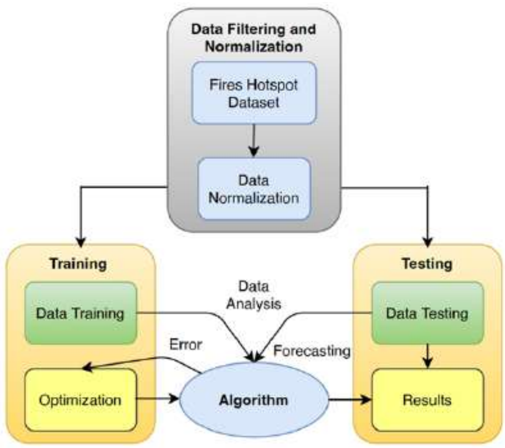


Fig. 2. Analysis diagram forecasting process for fires hotspot

The first step in data processing in a forecasting is construct an LSTM network model to identify the input or information that is not necessary and will be denied in the cell in 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 collected dataset, there is more than 700,000 number of fire hotspot within 12 year and after normalization become 4365 dataset of fires grouping in each day shown in Table III. Basic machine learning process in forecasting of data which divided into two section as shows in Fig. 2 training and testing data, this very important to make sure algorithm and machine learning current data trend and behaviour before doing test. Optimization process to evaluate results obtained and increasing the performance by enhance the accuracy which minimize 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 X_t 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].

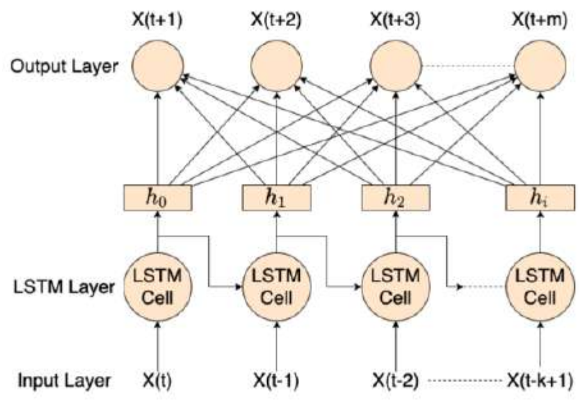


Fig. 3. Internal cell of LSTM model neuon process.

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.

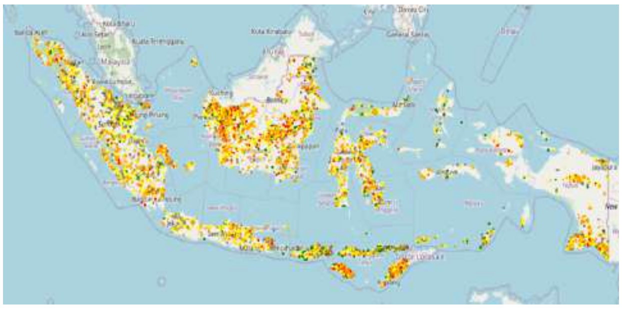
Finally, need to evaluate the performance of forecasting results in fields number of fire hotspot, Root Mean Square Error (RMSE) is one of the method statistically usually apply to compare prediction and actual data values. The RMSE is frequently used to evaluate how closely the predicted values match 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 fires data and n is the total number of data. The RMSE values equal to zero mean implies a perfect results that the LSTM algorithm produce reliable results when the values of RMSE going to small number to zero.

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

IV. Results and Discussion

Fires dataset collected consist of several parameter such as coordinate or location of fires occurrence, date and time, confidence level (probability become a big fire and spread out), brightness, day or night time, etc. as shown in Table II. In this analysis used four parameters that has major impact and impotent to forecasting which coordinate (latitude and longitude), acquisition date (acq_date) and confidence level. Fig. 4 shows the mapping of fires hotspot distribution in 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 level of confidence, since the level start from 0 with lowest impact and less potential to spread out until 100 which high probability to get spread and potential become a big fire. The five level of classifications which from 0-20 as low level indicate with blue dot, level 21-40 as 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 red dot as shown.

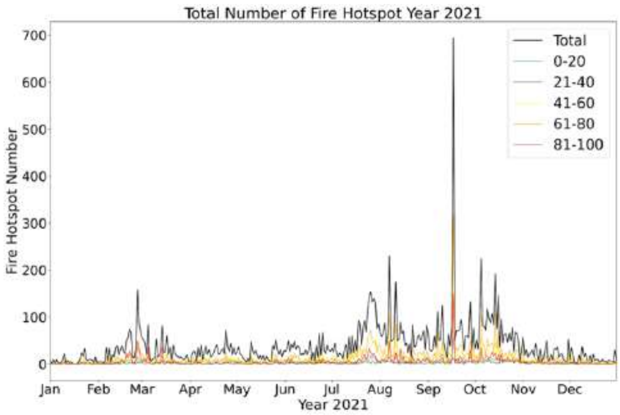
(a)



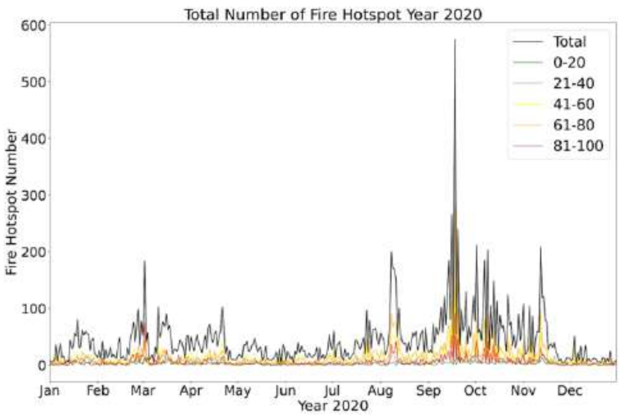
(b)

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

Number of fires hotspot refer to the data collected and based on confidence level, the total number in every year with thousands of fire hotspot. The distribution based of month and which month with 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 year 2021 and fig. 5(b) distribution of fire hotspot for the year 2020.



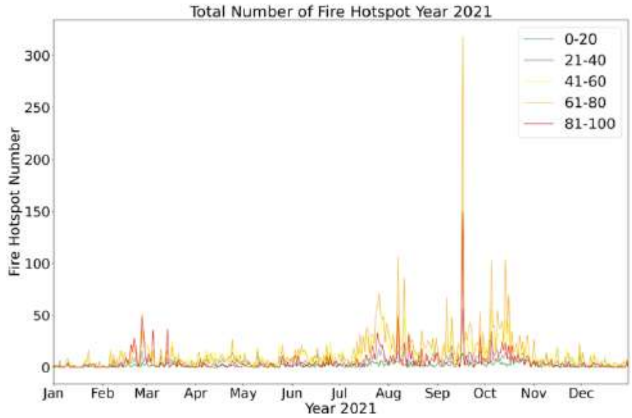
(a)



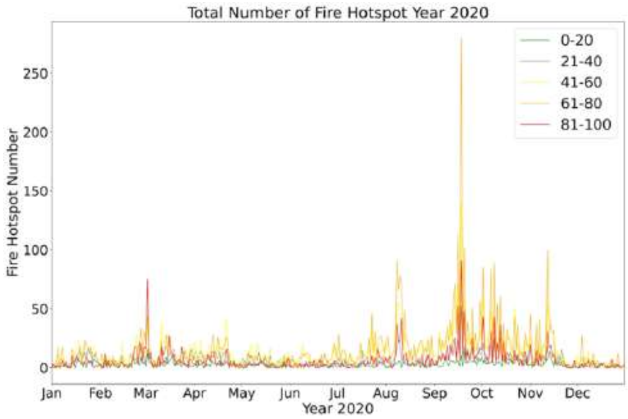
(b)

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 incident similar distribution with maximum number of fire hotspot 600 to 700 in each day but only a few days which the pick of number. Refer to the graph in fig. 5 the highest month of occurrence is from September to November. Fig. 6 shows more detail of data after break out the confidence level into five level as mention in early, fig. 6 (a) plotting of fire number based on confidence level year 2021 and fig. 6 (b) plotting fire data in 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 larger in quantity compare to testing data to achieve high accurate results. Fig. 7 shows a training data for the forecasting of fire hotspot, the distribution from year 2010 to 2021.

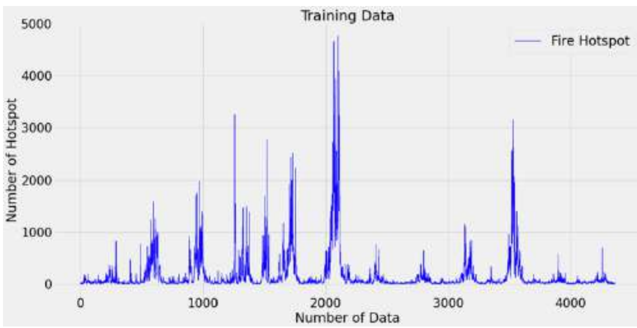


Fig. 7. Training data for fire forecasting from year 2010 to 2021.

Proposed LSTM algorithm to do forecasting of fires hotspot in Indonesia region have been test and compare to the actual data available. Preliminary forecasting by testing data from 2010 to 2021 and do prediction 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 %.

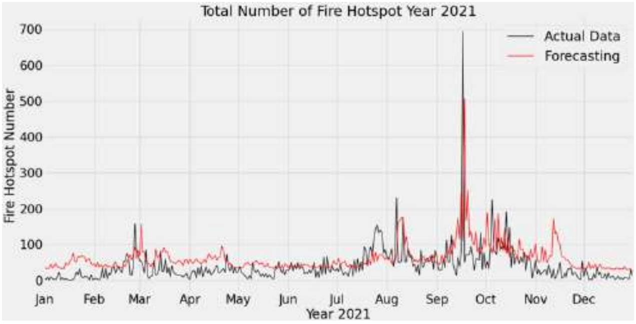


Fig. 8. Comparison of actual and forecasting data for year 2021.

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

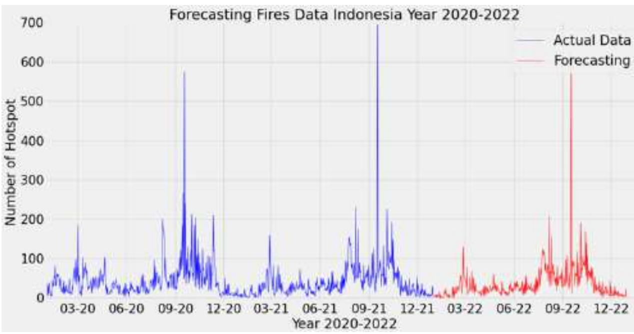


Fig. 9. Forecasting data of fires hotspot in year 2022 (red color) and actual data of fires in year 2020-2021 (blue color).

The used 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. Proposed model has been proof by analyzed previous dataset then compare to available data which fire hotspot in 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 year 2022 shows good agreement and similar pattern of fires data which the trend of rising number in end of year from month August to November while other not much significant data occur.

V. Conclusion

Prediction and forecasting of fires data have been done and the results achieves in good performance analyzed use LSTM model. Fires data collected from year 2010 to 2021 from NASA satellite (Aqua and Terra) for Indonesia region have been mapping and plotting within 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 future year which is year 2022 have been done as well as results shows the graph similar trend for the entire year from January to December. Major number of hotspots increase in the end of year because in this time summer season and dry environment in case area Indonesia, while in early year not significantly shows the rising of hotspot as raining season.

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Certificate

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