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An application of deep learning for lightning prediction in East Coast Malaysia

Mohd Herwan Sulaiman [a,*], Amir Izzani Mohamed [a], Zuriani Mustaffa [b]

[a] Faculty of Electrical & Electronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA), 26600 Pekan Pahang, Malaysia

[b] Faculty of Computing, Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA), 26600 Pekan Pahang, Malaysia

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ABSTRACT

This paper presents the application of deep learning (DL) approach namely Feed-Forward Neural Networks (FFNN) in predicting the location of lightning occurrences within 100 km radius from Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) Pekan, Pahang Malaysia. The recorded data were obtained from Malaysia Meteorology Department (MET Malaysia), where the inputs of the DL are the intensity of the lightning in kilo Ampere, direction in degrees, distance and major axis that measures in km, while the output is the latitude and longitude of the lightning occurrences. The data are divided into training, validation and testing to measure the performance of the developed DL model. The findings of the study demonstrated the promising results of FFNN in terms of obtaining the minimum error which significantly increasing the accuracy of the predictions. To show the effectiveness of FFNN, the comparison study has been conducted with Long Short-Term Memory (LSTM) networks. From the simulation, it can be seen that FFNN can be used as an effective tool for predicting the location of lightning occurred better than the LSTM.

1. Introduction

Lightning is a natural phenomenon that is initiated in the cloud and may strike the ground or the air. It is a type of electrical breakdown that has positive consequences such as the generation of a nitrogen-based compound that may help in the agriculture sector. On the negative side, it may cause catastrophic accidents, especially to power systems eventually causing power shortages. Malaysia Meteorology Department (MET Malaysia) has installed a system known as Safir3000 with 8 antennas installed around Peninsular Malaysia, that is able to detect intra-cloud (IC), cloud-to-ground (CG) and the peak current with their very high frequency (VHF) interferometry antenna system. The SAFIR3000 system is equipped with eight antennas distributed around Peninsular Malaysia, with sensor distances ranging from 160 km to 220 km. The system's proprietary algorithm ensures precise location calculations, and it employs a comprehensive counting method to record and analyze lightning events. The utilization of such advanced measurement and observation methods from the SAFIR3000 system enhances the accuracy and reliability of our lightning prediction model. An analysis of data 100 km radius from Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) Pekan reveals that in 2015, total of 201,296 events occurs which comprise of 78 % of –CG lightning and 22 % of +CG lightning [1].

A lightning prediction model based only on past lightning might be useful. A model that is purely based on historical time series is less costly and may be utilized for real-time forecasting. Three common machine learning models for univariate time-series models are the Auto Regressive (AR), Auto Regressive Integrated Moving Average (ARIMA), and Long-Short-Term-Memory Recurrent-Neural Network (LSTM) which have been discussed in [2]. The model predicts future values based on historical values of the same series using the AR parameters as coefficients. The approach of LSTM and interpolation method with spatio-temporal localization of lightning has been proposed in [3], where the electric potential distribution in Guangzhou city was obtained by interpolating the data from network stations using ordinary Kriging (OK). The approach was then being utilized to determine the approximate region where the lightning may occur.

M. Lu *et al.* [4] proposed the Lightning Monitoring Residual network (LM-ResNet) based on Deep Learning (DL) with multisource spatial data and the performances were compared with GooLeNet and DenseNet. The proposed system shows a significant output with stepwise sensitivity

* Corresponding author.
E-mail address: herwan@umpsa.edu.my (M.H. Sulaiman).

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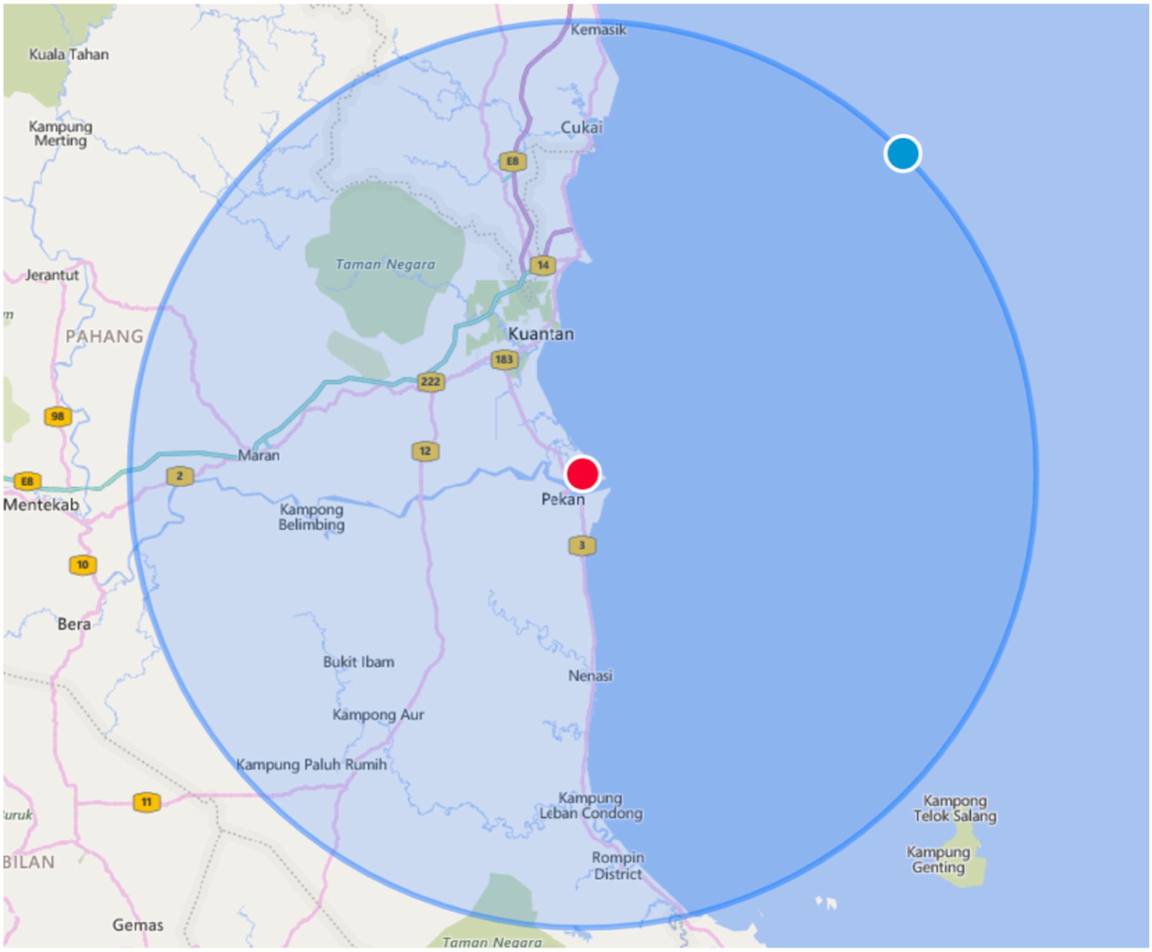

Fig. 1. Covered area within 100 km radius from UMPSA Pekan Campus.

analysis and single factor sensitivity analysis are applied. Similar work has been proposed in [5], where the prediction of the location of lightning strike by using lightning electric field time series measurement data and Resnet50 has been proposed. The different approach has been discussed, where the combination of the improved ResNet50 model and multi-layer-perceptron (MLP) neural network has been used for a lightning spatio-temporal localization method. An application of Artificial Neural Network (ANN) for identifying the lightning strike coordinate for Southern Malaysia has been proposed in [6]. The usage of time difference of arrival (TDOA) technique to determine lightning strike location has been employed in a lightning locating system (LLS).

The influence of initial circumstances on forecasting lightning activity combining the Weather Research and Forecasting (WRF) extra package with the electrification (ELEC) additional package, known as the WRF-ELEC model, has been investigated in [7]. The severity, frequency, and certain physical and dynamical features of lightning strikes happened throughout an 11-year period (2004–2014) have been used and four thundercloud episodes with unusual features over the Tehran area were selected for the investigation. Data mining techniques for lightning prediction based on decision tree and ANN have been proposed in [8]. Lightning prediction considered as a binary classification problem with imbalanced dataset of northeast of Iran has been used and studied. Other related works in predicting the lightning activity in Iran based on Lightning Potential Index (LPI) and electric POTential difference (POT) have been discussed in [9]. Numerical simulation of a widespread lightning event over north India based on an ensemble of Weather Research and Forecasting (WRF) modeling configurations also has been performed in [10]. The implementation of Very Low Frequency signal feature extraction that classify the lightning severity and intensity have been discussed in [11,12].

Other machine learning approaches that have been used in lightning prediction are such as Support Vector Machines (SVM) [13], general regression neural networks (GRNN) for lightning outages prediction by [14], ensemble deep learning [15], discrete wavelet transform (DWT) algorithm [16], variants of LSTM models [17], LightNet+ based on deep neural networks [18], Deep Learning Model Based on Bayesian Optimization [19] and Recurrent-Convolutional Deep Learning [20].

There are massive applications of DL that have been implemented in various fields such as in medical applications of diffusion MRI data [21] and disease prediction [22], time series electric energy consumption prediction [23], brain tumor classification[24], fake news detection [25], seasonal-customized occupancy prediction (SCOP) [26], job cycle time prediction [27], human motion modeling [28], swirling flow field prediction in combustor [29], anomaly detection framework for security in smart building with the IoT-Smart environment network [30], air pollutant concentration prediction [31], prediction of explosive

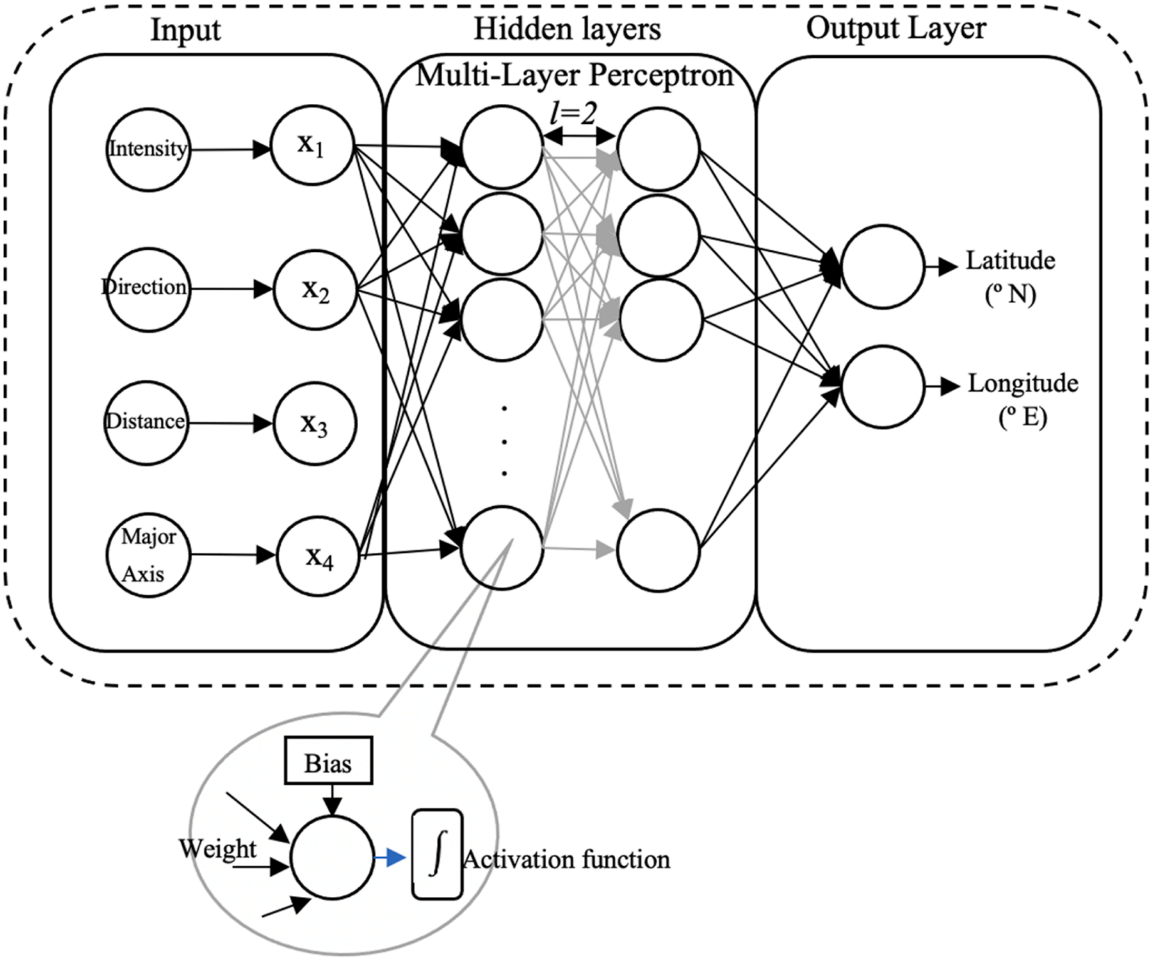

Fig. 2. Feed-Forward Neural Networks for lightning prediction.

Table 1
Properties of Training, Validation and Testing for lightning prediction for 100 km radius from UMP Pekan.

Properties	
Used Profiles	Data from MET Malaysia for 100 km radius from UMP Pekan
Training	140, 910 instances (70 %)
Validation	6000 instances (3 %)
Testing	54, 386 instances (27 %)
Input	Intensity of lightning, direction from UMP, distance from UMP & major axis
Hidden layer	2 (15 neurons for hidden layer 1 & hidden layer 2)
Output	Latitude (°N) and longitude (°E)

detonation properties [32], remaining useful life (RUL) prediction of aero-engine [33] and stream water quality prediction [34].

From the mentioned approaches, it can be noticed that the usage of machine learning or DL is still become the choices of researchers to solve the prediction problems. Thus, this paper takes the initiative to propose the lightning prediction occurrences within 100 km radius from Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) Pekan, Pahang Malaysia based on real data recorded by MET Malaysia on 5 January 2015 to 31 December 2015 which is obtained in [1]. The covered area of this study is depicted in Fig. 1. The objective is to simulate the real environment data collected from lightning activities recorded input of DL FFNN model for predicting the location of the lightning occurrences. The rest of the paper is organized as follows: Section 2 discusses the brief DL FFNN followed by application of DL FFNN for lightning prediction model in Section 3. Results and discussion are presented in Section 4 and finally, Section 5 states the conclusion of the paper.

2. Deep learning feed-forward neural networks

In this study, a Feed-Forward Neural Network (FFNN) is used to train the datasets of interest. A FFNN is a multi-layer perceptron that does not apply recurrence, instead, it only a forward pass of data to map the non-linearities governed by the data [35]. Fig. 2 illustrates the FNN model which consists of three layers namely input layer, hidden layers, and output layer. Each neurons need to be decided which activation functions to be utilized. In this paper, the activation functions for input, hidden and output neurons based on the developed model from [36], where the following expressions are used for each layer of FFNN:

Input layer: linear function

$$y = u \tag{1}$$

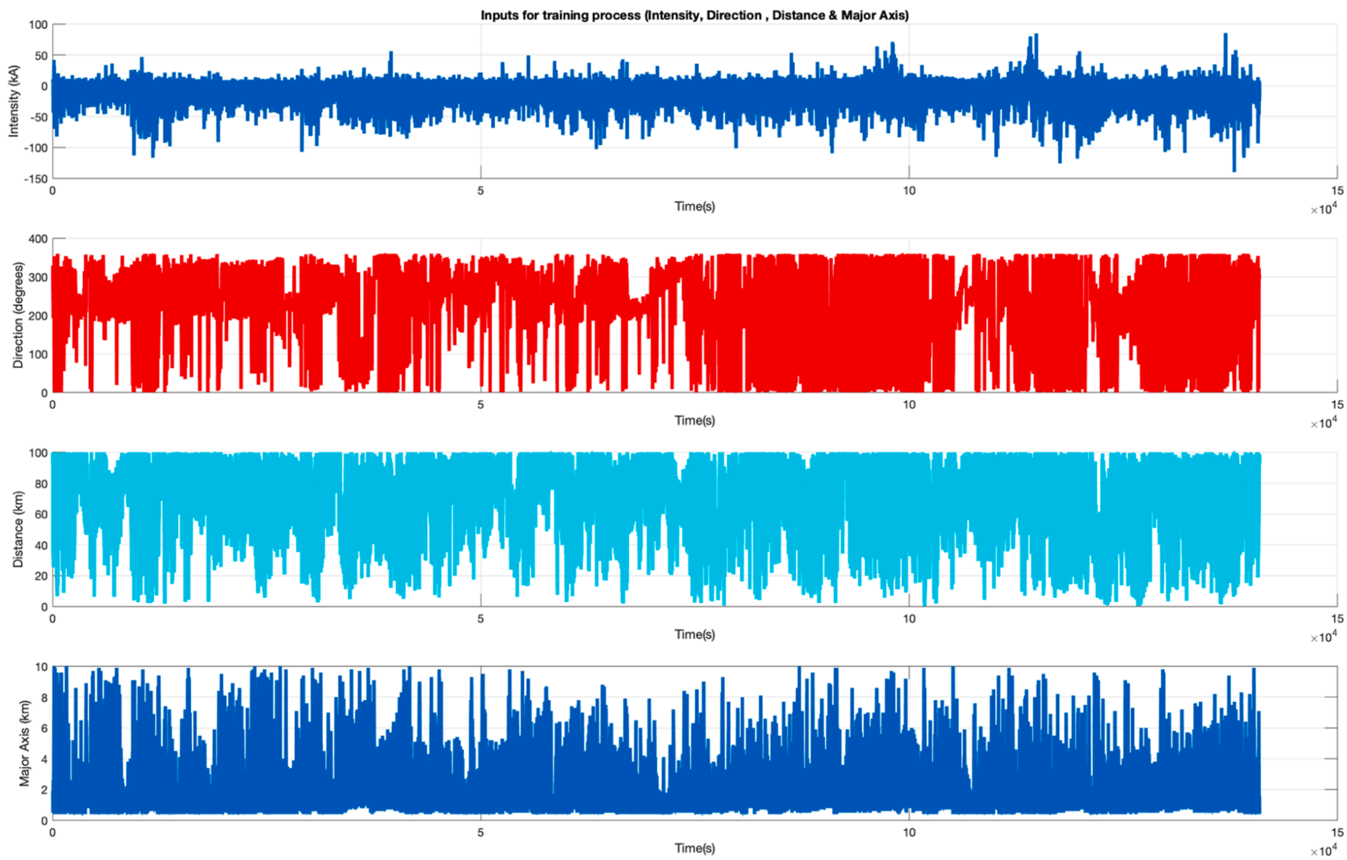

Fig. 3. Input data for training process.

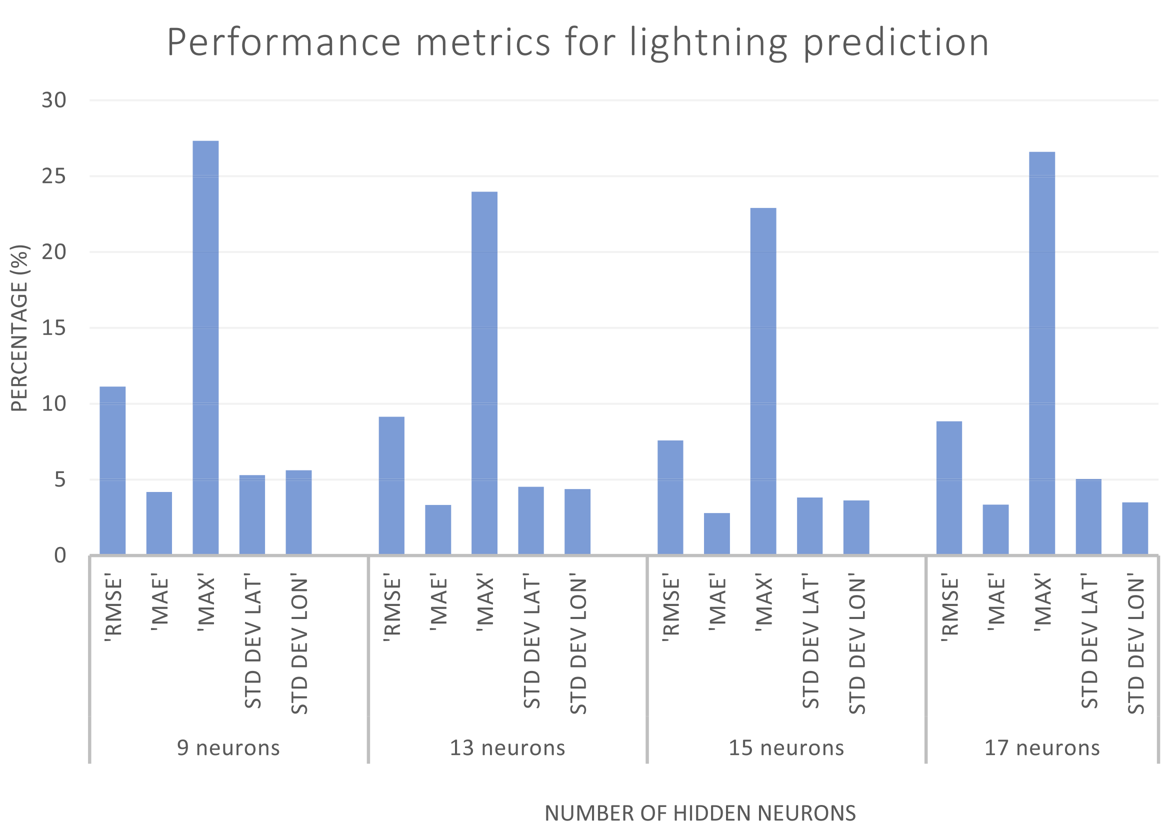

Fig. 4. Performance metrics for 2-hidden layers of FFNN models.

Table 2
The best results obtained by FFNN and LSTM.

ML\Metrics (%)	RMSE	MAE	MAX	STD DEV LAT	STD DEV LON
FFNN	**7.58**	**2.80**	**22.91**	**3.83**	**3.64**
LSTM	25.68	9.40	97.78	13.18	12.03

Hidden layer 1: hyperbolic tangent

$$y = \frac{e^u - e^{-u}}{e^u + e^{-u}} \tag{2}$$

Hidden layer 2: leaky rectified linear unit (ReLU)

$$y = max(0.3 * u, u) \tag{3}$$

Output layer: clipped ReLU

$$y = \begin{cases} 0, & u < 0 \\ u, & 0 \le u \le 1 \\ 1, & u > 1 \end{cases} \tag{4}$$

where y is the output at each neuron and u is the total input before entering the neurons which consist of inputs with the respective weight sum with the bias, as follows:

$$u = \sum_i w_{ij} x_i + b_j \tag{5}$$

where x_i is the output from the i th neuron or node at the previous layer, w_{ij} is the weight of the interconnected layer i-j and b_j is the bias at the present layer j. Adaptive moment estimation (Adam) [37] is used to optimize the weights at each layers.

3. Application of deep learning FFNN for lightning prediction

Since an FFNN is a data-driven approach, the quality of the data may be assessed based on how much of the targeted domain information can be found in the dataset used to train the FFNN as well as how much noise or irrelevant information are included. It is crucial to keep in mind that measurement noise and error, while undesirable in the application, are sometimes impossible to completely eradicate and should be taken into account while training and testing a neural network. In this paper, the real dataset obtained from MET Malaysia which extracted from [1] which consist of 201, 296 data from 5 January 2015 to 31 December 2015 that will be used for the simulation studies. It is worth to highlight that the dataset obtained consist of not a number (*NaN*) elements since the actual extracted data somehow have error or missing values. Thus, the raw data obtained need to be cleaned. The dataset contains of latitude (°N) and longitude (°N) of lightning occurrences where in this study will be used as target or output. The inputs for FFNN on the other hands are intensity of the lightning recorded in kilo Ampere (kA), direction from UMP in degrees (°), distance and major axis in km. The illustration of the lightning prediction of occurrences using FFNN is depicted in Fig. 2 and the detail configuration of data for training, validation and testing are tabulated in Table 1.

Fig. 3 shows the inputs for FFNN which are consist of intensity of lightning, direction from UMP, distance from UMP as well as major axis in km. It can be seen that more than 140 thousand instances used for training which is up to 70 % form overall data, about 3 % for validation

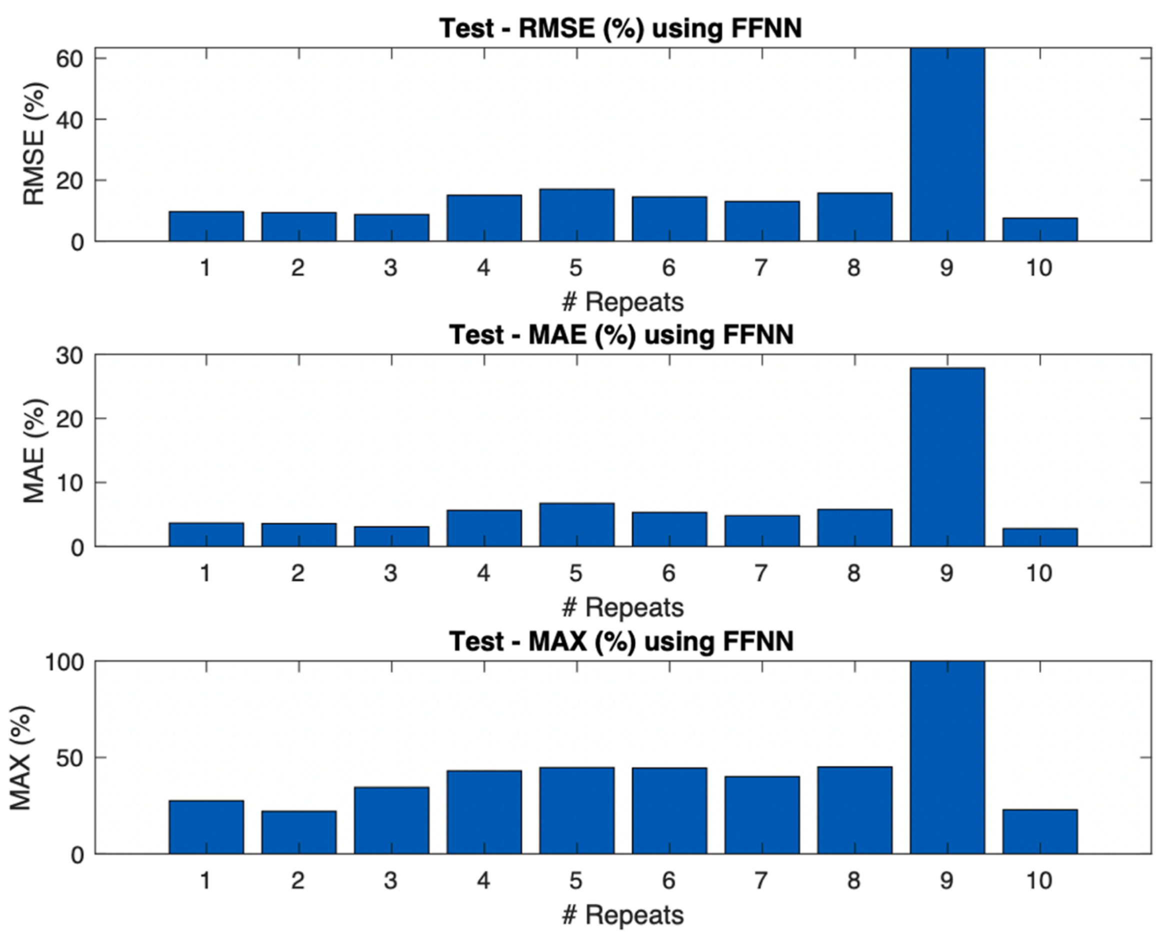

Fig. 5. Performance evaluation for testing process for 10 runs of simulations.

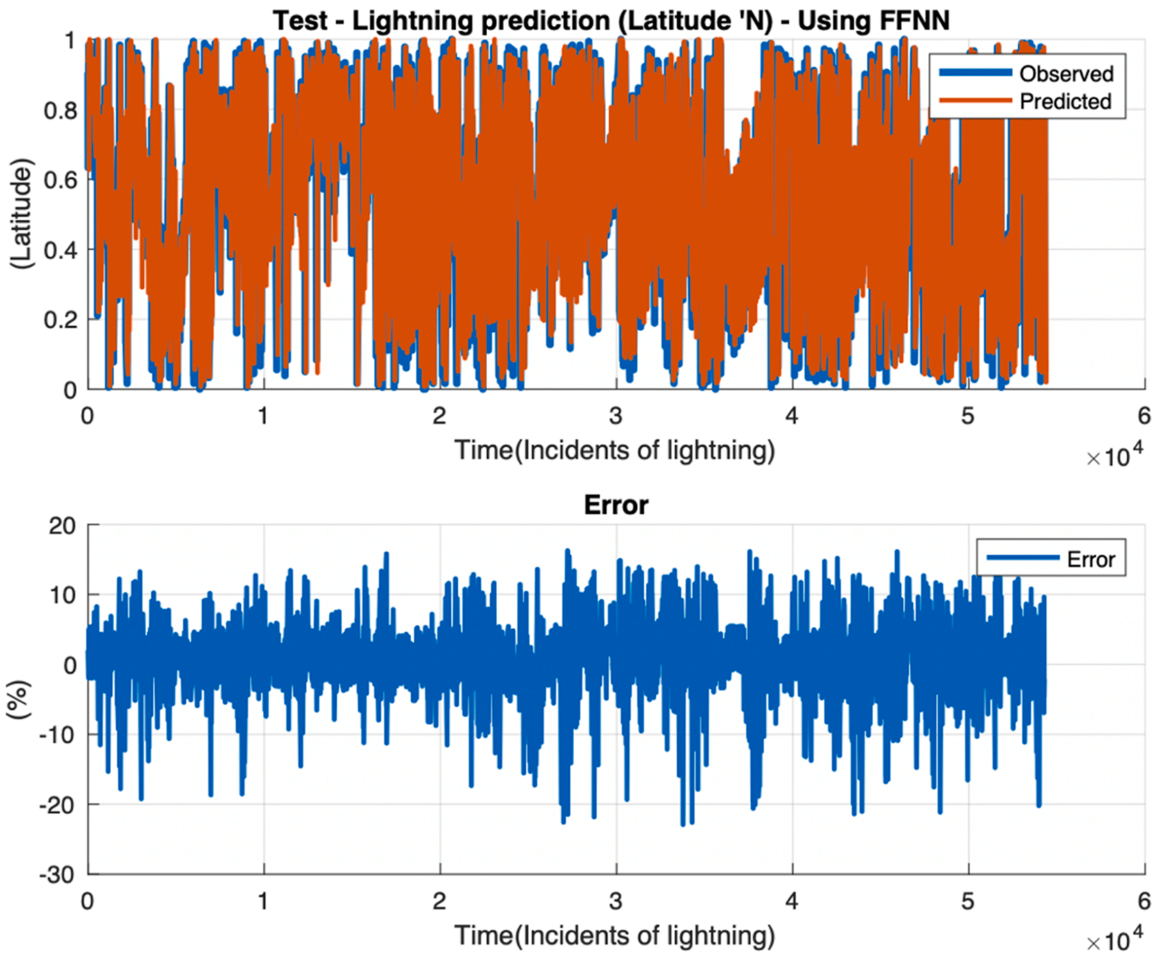

Fig. 6. The best of latitude prediction obtained by FFNN from simulation #10.

and 27% for testing processes. The percentages of training-validation-testing are decided through experimentally. It also can be seen that the intensity of lightning has negative values, and there are a quite large range among all data. Thus, the input and output data will be normalized between 0 and 1.

In order to measure the performance of FFNN together with other machine learning approach, the following metrics were employed, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Maximum Error (MAX ERROR) and Standard Deviation (STD DEV). The definitions of these metrics are as follow:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \quad (6)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (7)$$

where

$\hat{y}_i$- predicted
y_i- actual
n-number of observations

RMSE calculates the standard deviation of the residuals (prediction errors) while MAE is a measure the average magnitude of the errors in a set of predictions, regardless of their direction. STD DEV and MAX ERROR are used to see the robustness of proposed FFNN and the peak error at a particular time, respectively. input

4. Results and discussion

All simulations for this study are executed using MATLAB on a MacBook Pro-Processor 2.40 GHz Quad-Core Intel Core i5, 8 GB RAM. The determination of hidden layers must be carried out experimentally in order to evaluate the performance of FFNN in achieving the reduced RMSE. Two hidden layers are used in this work for the training-testing procedure, and the best results are recorded for comparison. In addition, another machine learning approach: Long Short-Term Memory (LSTM), will be utilized to compare the performances of developed FFNN model.

To identify the number of hidden neurons at each hidden layer, training-testing simulations are run ten times since the initialization phase for improving the weights and bias, which are initially set to random, as well as for assessing the consistency of the built FFNN model. In this paper, 2-hidden layers are selected, and the number of neurons is varied from 9, 13, 15 and 17 at each hidden layer. These simulations are presented in Fig. 4 where the best results obtained by 2-hidden layers that using 15 neurons. Thus,15 hidden neurons at each hidden layer are selected for developing the FFNN model for lightning prediction problem.

As been mentioned, the simulation is executed for ten times for FFNN, while for LSTM, it is executed only once due to heavy computation burden. The best results in terms of RMSE, MAE, MAX ERROR and STD DEV for testing process are tabulated in Table 2. It can be noted that

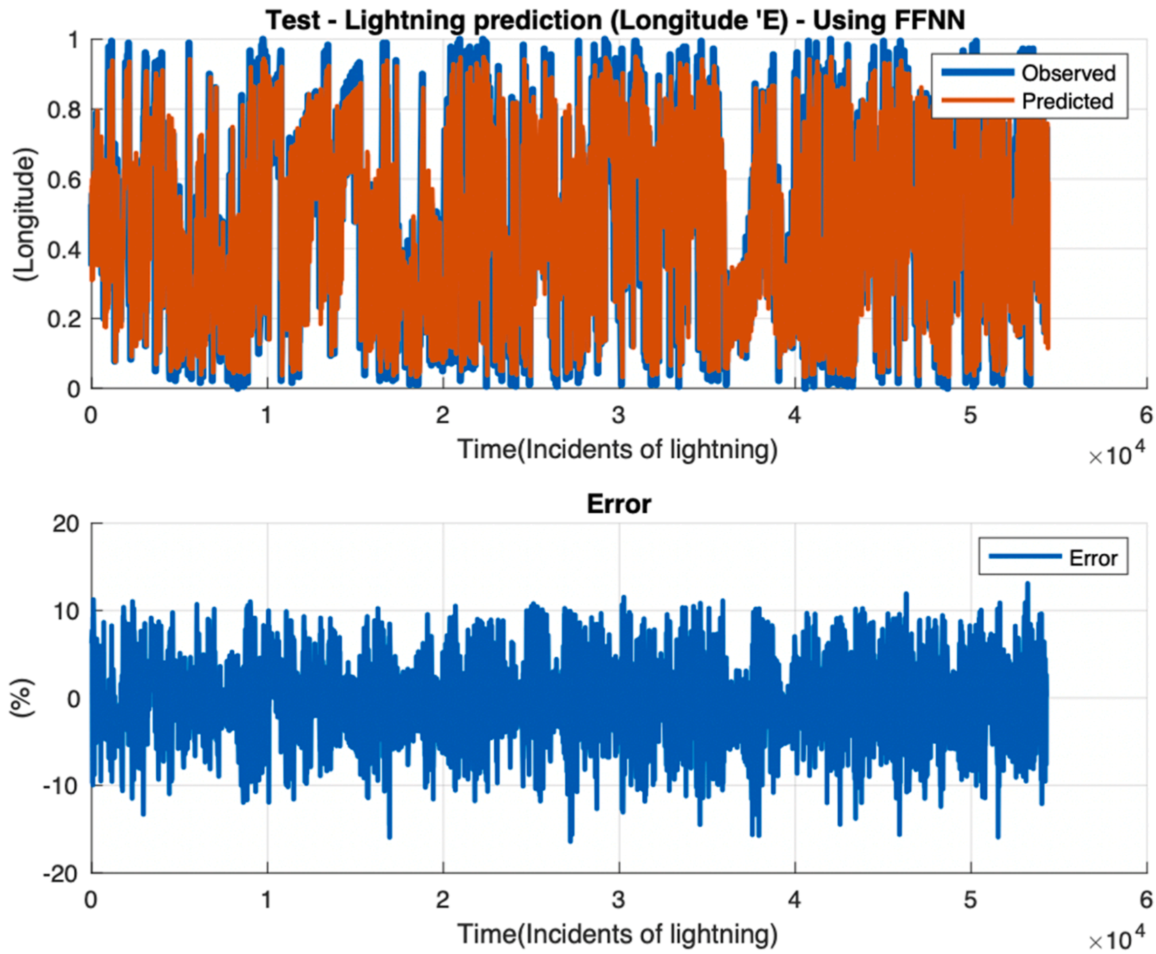

Fig. 7. The best of longitude prediction obtained by FFNN from simulation #10.

there are STD DEV results are for latitude and longitude since there two outputs to be predicted. From this table, FFNN outperformed LSTM by obtaining the best results for all metrics performances.

The detail performance analysis of developed FFNN model for 10 runs of simulations are visualized in Fig. 5, where the RMSE, MAE and MAX ERROR are presented. The best results were obtained at simulation #10, where the detail results matched the data provided in Table 2.

The lightning prediction location that represented by the latitude and longitude obtained by FFNN and ELM are depicted in Figs. 6-9, respectively. From these figures, it can be concluded that FFNN showed the best predicted results where it can follow the pattern of testing data. The maximum error obtained by FFNN is less than 23 % which is occurred at time 33,770 instances as shown in Fig. 6, which is for latitude prediction results. The worst performance is obtained by LSTM that is shown in Fig. 8. It is worth to highlight that the results presented in Figs. 6-9 are in normalization mode which is between 0 and 1.

Due to massive data used in the simulation studies, to show the effectiveness of proposed FFNN in predicting the location of lightning, only 5850 data are tabulated and plotted in the map which is the lightning occurrences in December 2015. The prediction results are exhibited in Fig. 10, where the blue colors indicate the actual location of lightning occurrences while the red colors are the predicted locations. Even though it looks like there are quite misprediction shown in red colors, the detail analysis shows another point of view, which are presented in Table 3, where the predicted locations are quite close to the actual values. This is due to slightly different predicted values of latitude and longitude resulted massive plot in the real map. This can be further investigated in the future with more recent data as well as more features for FFNN to learn in the training process. The results of the deep learning model, though promising, must be interpreted within the model's objectives and limitations. The model's goal was to predict the latitude and longitude of lightning occurrences within a 100 km radius from UMPSA in Pekan, Pahang, Malaysia. Predicting exact coordinates for lightning strikes in such proximity presents challenges due to the inherent complexity and variability of lightning phenomena. Prediction accuracy depends on factors such as input data quality, model features, and the inherent variability of lightning events. The model provides latitude and longitude predictions within a specific range, offering valuable insights into the general locations of lightning occurrences within the specified radius, although it may not pinpoint individual lightning strikes with absolute precision.

5. Conclusion

This paper proposed a deep learning approach namely FFNN to predict the latitude and longitude of lighting occurrences on the real data recorded by MET Malaysia for 100 km radius from UMPSA Pekan. The process of designing the FFNN to lightning prediction requires

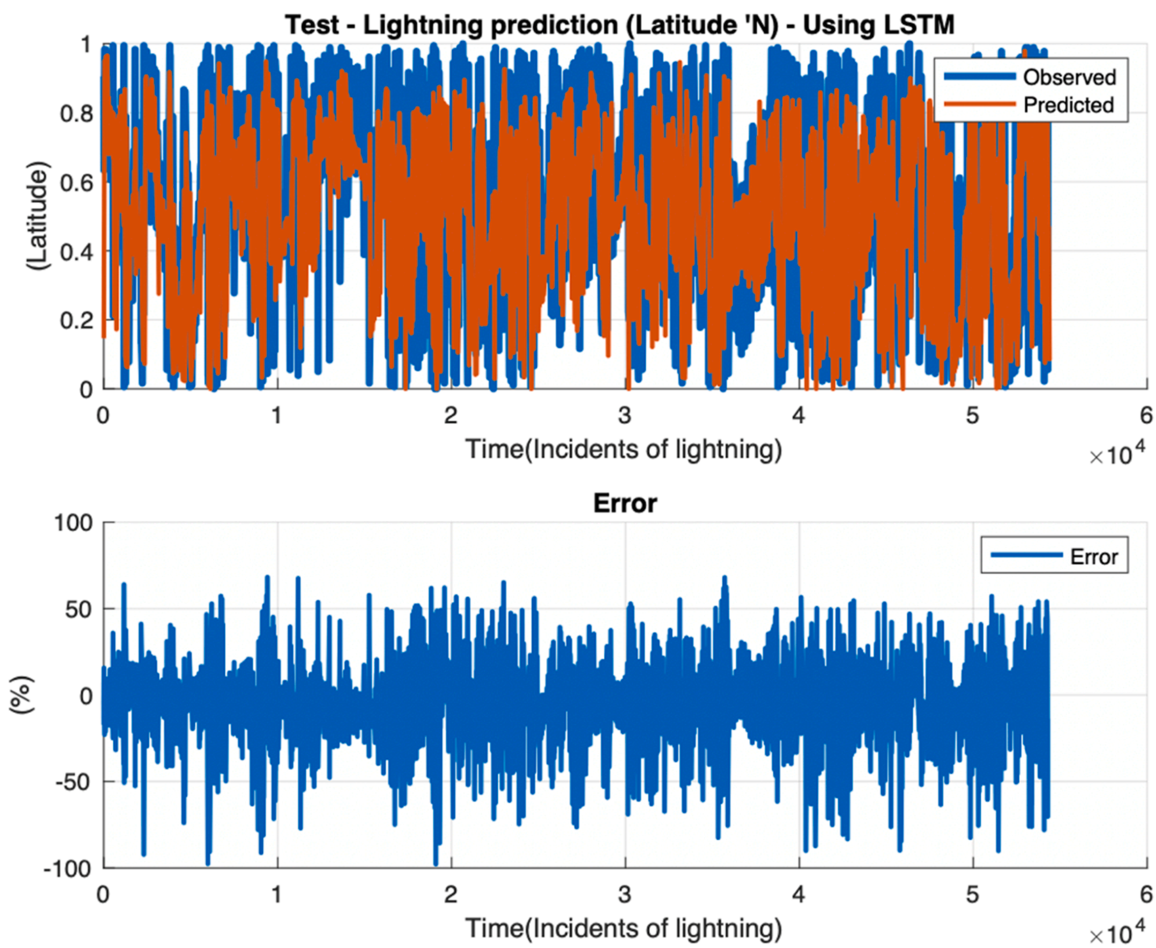

Fig. 8. The latitude prediction obtained by LSTM.

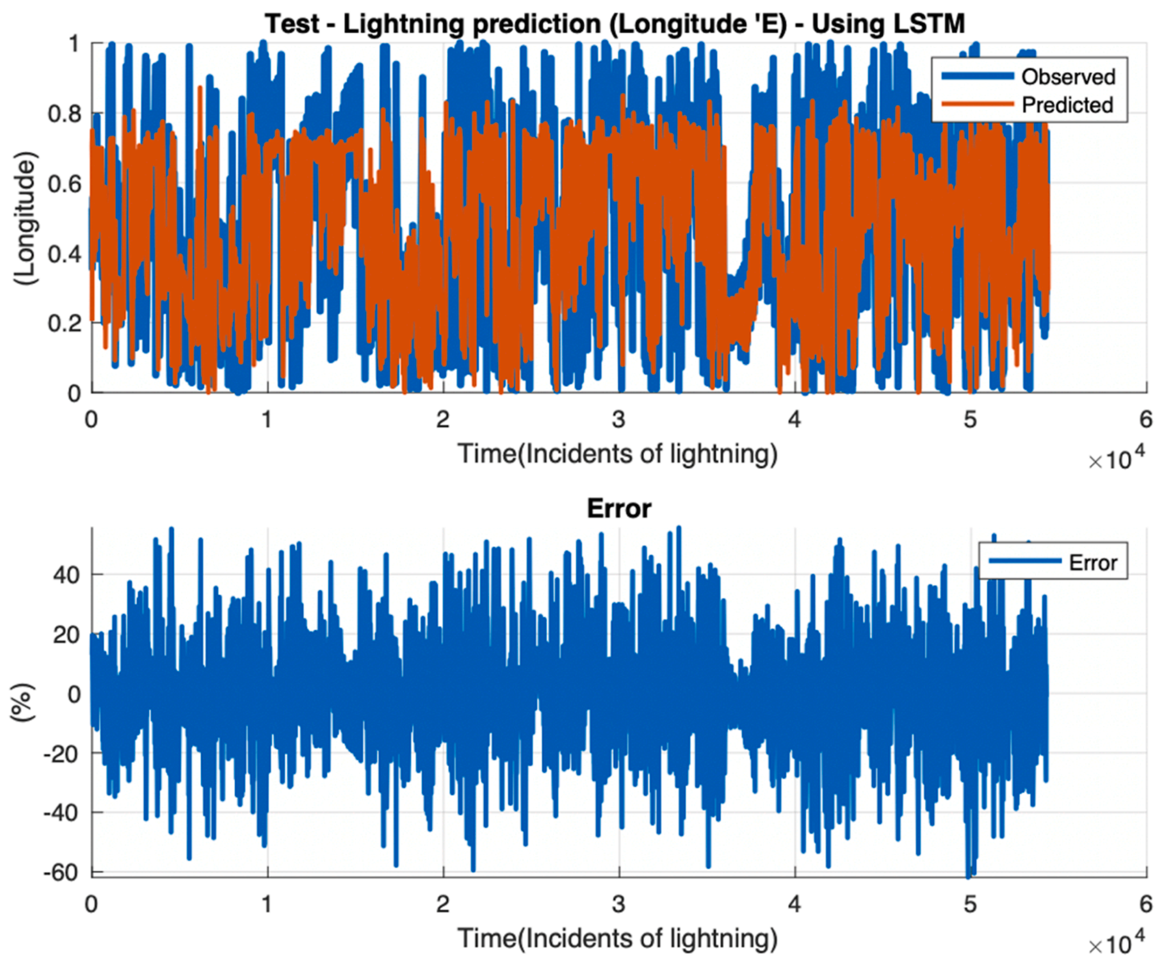

Fig. 9. The longitude prediction obtained by LSTM.

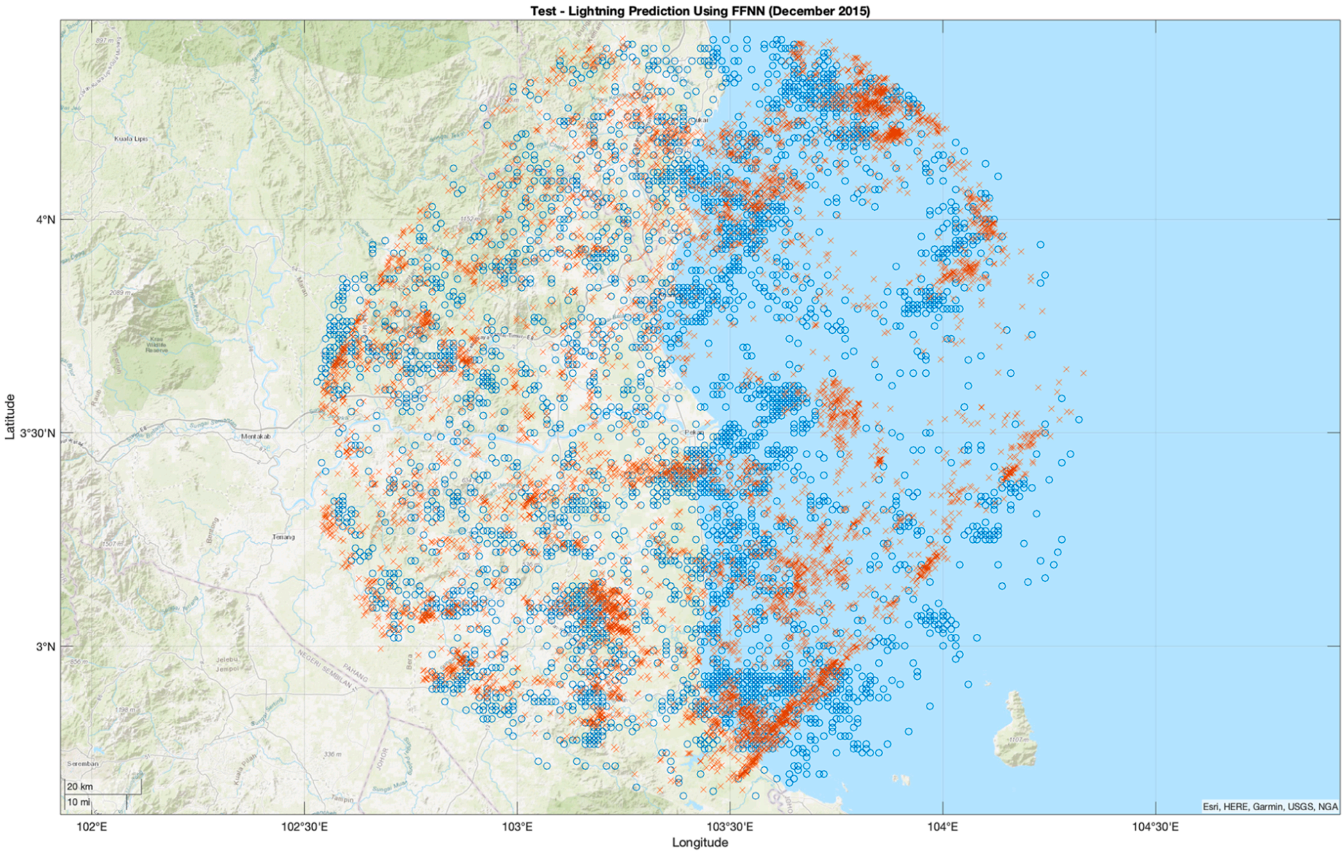

Fig. 10. Lightning occurrence prediction within 100 km radius from UMPSA Pekan Malaysia.

Table 3
20 samples of actual and predicted of lightning occurrences on 1 December 2015.

Date	Time	Actual Latitude (°N)	Longitude (°E)	Prediction by FFNN Latitude (°N)	Longitude (°E)
’01-Dec-15′	’01:02:42 AM’	3.51	103.59	3.3481712	103.79084
’01-Dec-15′	’03:29:04 AM’	3.27	103.82	3.3123302	103.97796
’01-Dec-15′	’08:00:43 AM’	3.06	104.02	3.2269187	104.00277
’01-Dec-15′	’08:37:08 AM’	3.64	103.93	3.7087655	104.03067
’01-Dec-15′	’10:07:46 AM’	3.19	104.04	3.3299627	104.08073
’01-Dec-15′	’10:07:46 AM’	3.19	104.04	3.3312519	104.08252
’01-Dec-15′	’11:10:07 AM’	2.92	103.88	3.0188479	103.81744
’01-Dec-15′	’01:34:39 PM’	3.27	103.94	3.336664	104.04814
’01-Dec-15′	’02:54:58 PM’	3.75	102.71	3.7559817	102.66715
’01-Dec-15′	’02:56:52 PM’	3.73	103.2	3.719491	103.19582
’01-Dec-15′	’02:56:52 PM’	3.72	103.21	3.7028618	103.20572
’01-Dec-15′	’02:56:52 PM’	3.72	103.12	3.6920311	103.10815
’01-Dec-15′	’02:59:45 PM’	3.76	102.69	3.7614477	102.6424
’01-Dec-15′	’02:59:45 PM’	3.74	102.7	3.7422974	102.65865
’01-Dec-15′	’02:59:45 PM’	3.74	102.7	3.7375598	102.65645
’01-Dec-15′	’03:14:33 PM’	3.27	103.95	3.3720758	104.06696
’01-Dec-15′	’03:18:03 PM’	3.57	102.88	3.6539266	102.81854
’01-Dec-15′	’03:18:03 PM’	3.58	102.88	3.6619909	102.82058
’01-Dec-15′	’03:18:03 PM’	3.57	102.88	3.6572104	102.82585
’01-Dec-15′	’03:22:42 PM’	3.56	102.89	3.6399555	102.82599

various parameters or design variables to be optimized such as number of hidden layers, number of neurons as well as how the input-output configuration that need to be set in order to achieve the significant impact to the prediction accuracy. To show the effectiveness of proposed FFNN, LSTM also has been developed and designed with the similar input-output configuration for the performance comparison. From the simulations that have been conducted, the results show that the proposed FFNN outperformed the LSTM for betterment prediction problem. For future works, more recent data and other parameters or features can be included as additional input in order to increase the complexity of lightning prediction and the different configuration arrangement of input-output also can be proposed which offers different performance of the developed DL approach.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Mohd Herwan Sulaiman obtained his B. Eng. (Hons) in Electrical-Electronics, M. Eng (Electrical-Power) and PhD (Electrical Engineering) from Universiti Teknologi Malaysia (UTM) in 2002, 2007 and 2012 respectively. He currently serves as an Associate Professor at Faculty of Electrical & Electronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA). His research interests are power system optimization and swarm intelligence applications to power system studies. He has authored and co-authored more than 150 technical papers in the international journals and conferences and has been invited as a Journal reviewer for several international impact journals in the field of power system, soft computing application and many more. He is also a Senior Member of IEEE.

Amir Izzani Mohamed obtained his B. Eng. (Hons) in Electrical-Electronics, M. Eng (Electrical-Power) and PhD (Electrical Engineering) from Ehime University in 2008, 2010 and 2013 respectively. He currently serves as Senior Lecturer at Faculty of Electrical & Electronics Engineering Technology, Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA). His research interests are lightning and high voltage engineering. He is also a Member of IEEE.

Zuriani Mustaffa is a senior lecturer in the Faculty of Computing, Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA). She holds a PhD in Computer Science from Universiti Utara Malaysia. She also obtained MSc degree in Information Technology and Bachelor of Computer Science (Software Engineering) from Universiti Utara Malaysia and Universiti Teknologi Malaysia respectively. Her research interests include Computational Intelligence (CI) algorithm, specifically in Swarm Intelligence (SI) and machine learning techniques. Her research area focuses on hybrid algorithms which involves optimization and machine learning techniques with particular attention for time series predictive analysis. She has authored and co-authored various scientific articles in the field of interest.