International Journal on Advanced Science Engineering Information Technology
Vol.10 (2020) No. 1
ISSN: 2088-5334

Enhancing Prediction Method of Ionosphere for Space Weather Monitoring Using Machine Learning Approaches: A Review

Nor'asnilawati Salleh[#], Siti Sophiayati Yuhaniz[#], Sharizal Fadlie Sabri[*], Nurulhuda Firdaus Mohd Azmi[#]

[#] *Razak Faculty of Technology and Informatics, Universiti Teknologi Malaysia, 54100 Kuala Lumpur, Malaysia*
E-mail: asni@angkasa.gov.my; sophia@utm.my; huda@utm.my

[*] *Development and Operation Space System Division, Malaysia Space Agency, 42700 Banting, Selangor, Malaysia*
E-mail: fadlie@angkasa.gov.my

***Abstract*— This paper studies the machine learning techniques that can be used to enhance the prediction method of the ionosphere for space weather monitoring. Previously, the empirical model is used. However, there is a large deviation of the total electron content of ionosphere data for the areas located in the equatorial and low-latitude regions due to the lack of observation data contributed by these areas during the development of the empirical model. The machine learning technique is an alternative method used to develop the predictive model. Thus, in this study, the machine learning techniques that can be applied are investigated. The aim is to improve the predictive model in terms of reducing the total electron content deviation, increasing the accuracy and minimizing the error. In this review, the techniques used in previous works will be compared. The artificial neural network is found to be a suitable technique and the most favorable from the review conducted. Also, this technique can provide an accurate model for time series data and fewer errors compared to other techniques. However, due to the size and complexity of the data, the deep neural network technique that is an improved artificial neural network technique is suggested. By using this technique, an accurate ionosphere predictive model in equatorial and low region area is expected. In the future, this study will analyze further by using computing tools and real-time data.**

***Keywords*— prediction; ionosphere; space weather; machine learning; data analytic.**

I. INTRODUCTION

The solar phenomenon resulting from solar activity, also known as space weather, can affect the earth's environment. This topic began after researchers surveyed phenomena such as aurora and magnetic interference that occurred due to solar activity [1]. Further research on space weather is continued due to the occurrence of the solar activity, causing disturbances that affect the Earth. Its most significant effect is that it affects the performance and reliability of space-based technology. It can also cause harm to humanity. Among the major disruption that occurs due to space weather is the disruption of the ionosphere layer. The production of electrons generated from the solar activity will cause a disturbance in the ionosphere through fluctuations in electron density and consequently resulting in scintillation effects and ionosphere delay [2]. Thus, the severe ionosphere disturbances may cause electronic space damage, induced currents in power systems, effects on marine communications, navigation and so on.

The empirical model, such as the international reference ionosphere (IRI) Model and NeQuick ionospheric model (NeQuick) have been used by the practitioner to predict the ionosphere condition to monitor the space weather [3]. However, for the areas located in the equatorial and low-latitude region, there is a large deviation of total electron content (TEC) prediction due to lack of observation data contributed from these areas and regions during the development of the model [4]. Thus, an improved model should be considered to enhance the current model for the specific areas and regions that affected. Machine learning is an alternative technique that able to do so. This technique presents different modeling capabilities and predictions. In this study, the previous research on the prediction model that using machine learning will be reviewed and the techniques used will be identified to support this study.

II. MATERIAL AND METHODS

This section presents relevant works related to the predictive model. It also provides an overview of the prediction techniques and elaborates on the criteria used for the comparison analysis.

A. Prediction Techniques

The predictive model is an analysis process that is used to identify future events based on current and historical data.

For space weather, the prediction can predict the incident that may be encountered, and with that, the parties involved able to take appropriate steps such as providing an error correction value, early detection system and much more. To improve the model, different methods are used by the researchers. These methods are ranged from physical to stochastic depending on available data inputs and resources [5]. The machine learning techniques became popular among researchers as it helps researchers or analysts to understand more about the system and it is easy to develop the prediction model [6]. It can provide computer learning rules and automation prediction models [7]. Among the machine learning techniques used in predictive models are artificial neural network (ANN), support vector machine (SVM), autoregressive integrated moving average (ARIMA) and regression [8].

ANN is known as the technique that is widely used in predictive models [8]. It proved to be very helpful in solving non-linear and complex system problems [9]. It also has a better generalization ability for real-time series problems [10]. ANN has been applied in the predictive model for various applications such as a model drug, HVAC system, traffic, and energy. In terms of accuracy, ANN can improve the predictive model by up to 95% [11]. Meanwhile, the root-mean-square error (RMSE) value is less than 5% and the mean absolute percentage error (MAPE) is less than 8.6 % [9], [12]. Anyhow, all these values are still depending on certain conditions and application.

The SVM is a neural network classification technique based on statistical learning theory. It uses a structured risk reduction principle that minimizes the upper bound of the expected risk [13]. It also can provide excellent predictive accuracy and find the optimal global solution [14]. ARIMA is very appropriate and applicable when existing information or data is limited and the data stream acts as a predictor [15]. It is suitable for making predictions for the time series model. While regression analysis is to get the function normally linear to the data and to know how one or more variables differ as one another function [16].

There are also hybrid techniques used as their predictive technique such as joint linear-nonlinear extreme learning network and extreme learning machine with a new switching delayed particle swarm optimization (SDPSO-ELM) [17]. Meanwhile, for time-series prediction methods, the techniques that are usually used are ANN, ARIMA, SVM and linear regression (LR) [18]. The ANN is found to be the most commonly used in time series forecasting tasks and applied in various fields or domains because it is able to facilitate decision-making for various domains [19]. However, for this study, to identify which algorithm is the best, these algorithms will be further analyzed and discussed. The overview of the prediction techniques is illustrated in Figure 1.

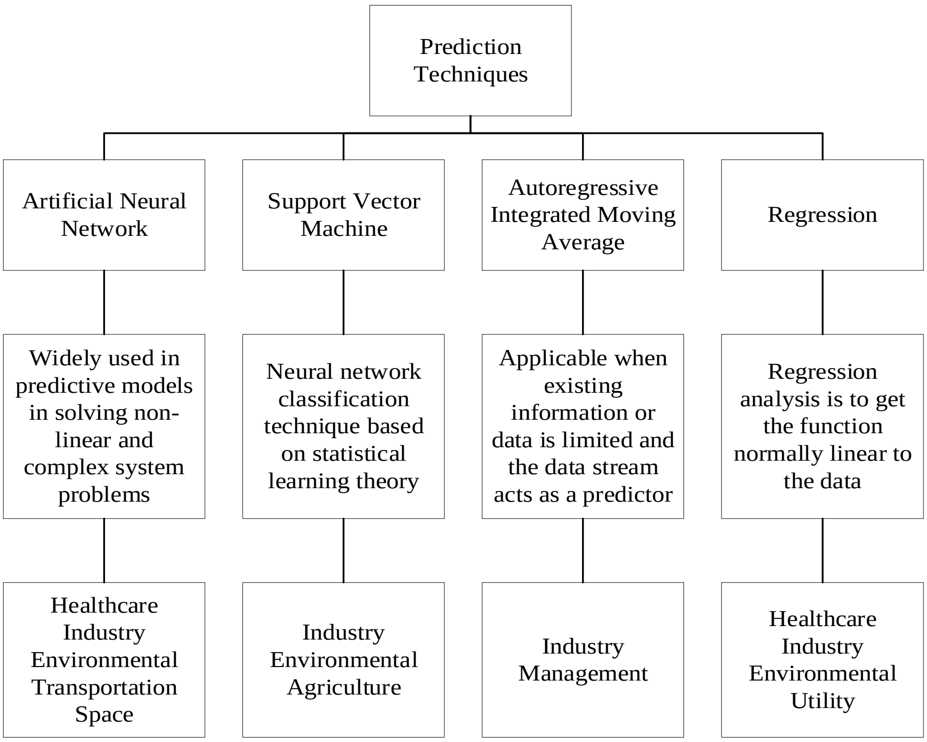


Fig. 1 Prediction Techniques

B. *Comparison Analysis*

RMSE, mean absolute error (MAE) and accuracy are three criteria that have been specified to ensure the most suitable technique is chosen. These criteria will be used to identify the best technique for this study. The following are the equations of these criteria used for the predictive model performance evaluation.

$$R = 1 - \sqrt{\frac{\sum_{i=1}^{N}(y_i - y'_i)^2}{\sum_{i=1}^{N}(y_i)^2}} \tag{1}$$

$$RMSE = 1 - \sqrt{\frac{\sum_{i=1}^{N}(y_i - y'_i)^2}{N}} \tag{2}$$

$$MAE = \frac{\sum_i^N |y_i - y'_i|}{N} \quad (3)$$

Where y_i is the actual value obtained and y_i' is the predicted value. Meanwhile, R measures the fitting degree between the actual and the prediction series with the range of [0, 1]. The closer R to 1, the more effective the predictive model will be. The RMSE represents the error that occurred during prediction. It is the measured average squared deviation of prediction values. A predictive model that has a small RMSE value will have better performance. MAE shows the magnitude of an overall error by measuring the average absolute deviation of predictive values from the actual values. The effects of positive and negative errors are not eliminated. To have a good predictive model, the MAE should be as small as possible. The final criteria, accuracy, defines how precise the technique can improve the model.

III. Results and Discussion

As described in the previous section, there are four (4) techniques that are suitable to be used for time-series data. Therefore, these techniques are compared on the same problem domain that is related to the space weather monitoring using the ionosphere data. Table 1 lists the results of the comparison.

TABLE I
PREDICTIVE TECHNIQUE ANALYSIS RESULTS

Criteria	**Techniques**			
	ANN	**SVM**	**ARIMA**	**Regression**
RMSE	18.38[20], 0.34[21]	0.35[21], 2.02 [22]	4.407 [23]	18.57[20], 3.98[22]
MAE	2.5654 [24]	1.19 [22]	0.73 [25]	2.81[22]
Accuracy	Accuracy over 95% [4]	96.74 [26]	83% [32], 60-83% [25]	84.8 ± 4.3% [27]

From the comparison study that has been done, the RMSE value for ANN is providing a slightly lower value than regression [20]. The ANN is also better than SVM by using the same parameter data [21]. Also, the RMSE value for SVM is better than regression by using the same parameter. Meanwhile, ARIMA not appropriate to be compared due to the different parameters are used. In terms of MAE, SVM is better than regression by using the same parameter.

Meanwhile, ANN and ARIMA are not compared due to the different parameters used. Lastly, in term of accuracy, different parameter value was used. Therefore, it is not appropriate to state that SVM is the best. Nevertheless, there is a study that proved that the ANN model gives a better performance compared to the regression model [20]. Besides that, ARIMA able to predict successfully; however, it is found that the prediction precision result is lower when involving with the longtime series predicting [28]. Thus, it is difficult to identify which technique is the best. However, both ANN and SVM perform better than regression. Thus, ANN and SVM can be considered to be used in this study.

But, as the ANN is mostly being used in ionosphere prediction and it is also has been recommended to be used for solar systems and solar radiation prediction [29]. Thus, for this study, ANN is proposed to be used to improve the prediction of the ionosphere. ANN had been proved able to perform better and more precisely than the IRI Model with the RMSE value of 0.4097 by using ANN and 3.8468 by using IRI Model [4]. It also provides better performance than the NeQuick 2 model for low latitude regions [30]. With that, ANN will be further investigated and analyzed on how it can improve the current ionosphere predictive model which only considers the historically observed data of ionosphere as the data input. Besides that, this proposed technique will be adapted to the in-depth learning approach as it can help ANN to handle large size data and complex data better.

The deep learning is a machine learning algorithm that is able to expose non-linear and complex data. It allows a calculation model comprising multiple layers of processing to study data representation with multiple levels of abstraction [31]. The method used by deep learning is the multiple-stage representation-learning algorithm, which is obtained by arranging delegate modules at one stage (starting with raw inputs) to representations at a higher level. It is one of the fastest-growing learning techniques and capable of processing large-sized data. Research for this technique gets extensive opportunities with the availability of better software infrastructure and more powerful CPUs and GPUs. It is also effective and efficient for real-time detection. Also, it provides high-quality model predictions when combining with ANN [32]. The deep neural network technique had also successfully implemented for solar irradiance and ionosphere prediction [33], [34].

A. *Ionosphere Predictive Model for Space Weather Monitoring*

The ANN is proposed in this study based on the comparative analysis that was done previously. In order to cater to the large and complex data, the deep learning approach will be adopted together with ANN. Also, the data that will be used in this study is the TEC data which is an ionosphere parameter and it can be predicted by using time series analysis [22]. TEC also an important parameter reflecting significant ionosphere characteristics and can be used to analyze ionosphere disturbance and cyclic change.

B. *Predictive Model Framework*

The new predictive model will use the deep learning framework to optimize its performance in handling the complex patterns and large size of ionosphere data. The deep learning allows computational models to have multiple processing layers to learn data representations with varying abstraction levels. It is also well-suited to many problems and has the potential to improve predictive performance [35]. The new proposed model is expected to be more accurate and reliable by implementing a deep learning technique.

Besides that, the established model such as IRI Model will also be used in the study as it globally used by most practitioners. Thus, the prediction result from the improved model can be compared with these models and the obtained result will be more accurate and reliable. The proposed technique will be studied in depth to ensure that it is appropriate and can enhance the predictive ionosphere model. Figure 2 described the process flow of designing the predictive model for this study.

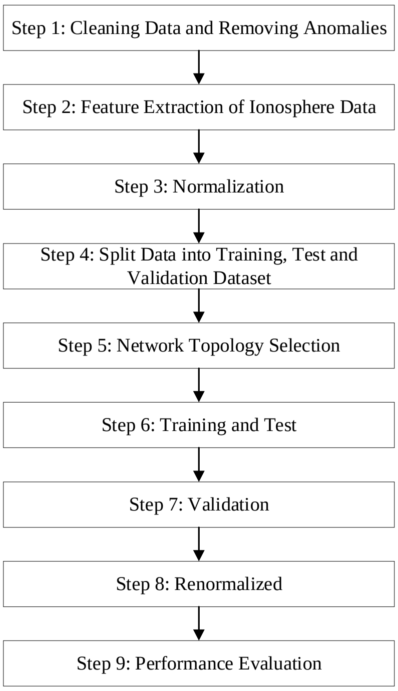


Fig. 2 Design framework

First of all, the most important step is to clear data and remove anomalies from abnormal data. Abnormal data comes from lost reading or incorrect reading collected. Linear interpolation methods can be used to replace the lost data. Meanwhile, the wrong reading can be replaced with theoretical data or the data can be removed. If it is removed, it may be replaced with a maximum limit value if it exceeds the limit or interpolation results.

Next, feature extraction is done to ensure only the required data is extracted. The data will be used as a set of data inputs and some of the data inputs considered for this study are latitude, longitude, and time of day. Then, the next step is normalization, whereby all data will be scaled between zero and one, as stated in Equation 4.

$$y = \frac{(y_{max} - y_{min})(x - x_{min})}{(x_{max} - x_{min})} + y_{min} \qquad (4)$$

Where y is the normalized input, y_{max} is 1, and y_{min} is 0 and x is assumed to have only real values. This normalization is used as a pre-processing step to make the data comparable to the features. As the data flows through a deep network, data is likely to be too large or too small. Therefore, by normalizing data in small groups, this problem can largely be avoided. After the normalization process, the data will be split into three sets: training, testing, and validation. In this study, the data is planned to be split with 70%, 15%, and 15%, respectively. The details of each set are described as follows.

1) *Training set*: These data are utilized for the training of the predictive models. It is the portion of the initial data that will be used to evaluate the performance of the model. The parameters of the model that is being derived are chosen so that the model outcome, for this portion of data, will be very similar to the observed values of the dataset.

2) *Test set*: The test data set is a portion of the initial data, normally smaller than the training set, utilized to test the model performance. After obtaining the model with the training data it is submitted to the inputs of the test set. The model outcome obtained from the test set is then compared with the observed values from the test data. The advantage of this process is that the model is tested with a portion of unseen data that were not utilized to optimize the model parameters during the training process. The test process is important because its results are used to compare different models. Then, a suitable model will be selected to model the problem.

3) *Validation set:* As the test data, the validation data is smaller and unknown by the model set of data obtained using the training set. After testing and choosing the best model the test results need to be validated. The results from the validation process are the ones used to evaluate the model performance and compare it with other models from different analyses.

The data that has been split will be trained and tested to ensure that the optimum value parameter can be identified and can produce the desired prediction model. Then, network topology will be selected to deliver the best network learning results. For this study, the input parameters are based on features that will affect the value of TEC, such as latitude, longitude, year, year and day time. Besides, information on magnetic activity, seasonal and diurnal variations, and solar activities should also be considered. Meanwhile, the number of neurons in hidden layers is a complicated aspect and it can be decided upon neural network training. These are among the factors that affect trained network performance. Typically, several different networks in the number of hidden layer neurons will be trained and then choose the best of them through the performance index. Meanwhile, the output is one neuron that is labeled as VTEC. Figure 3 shown the basic input and output flow.

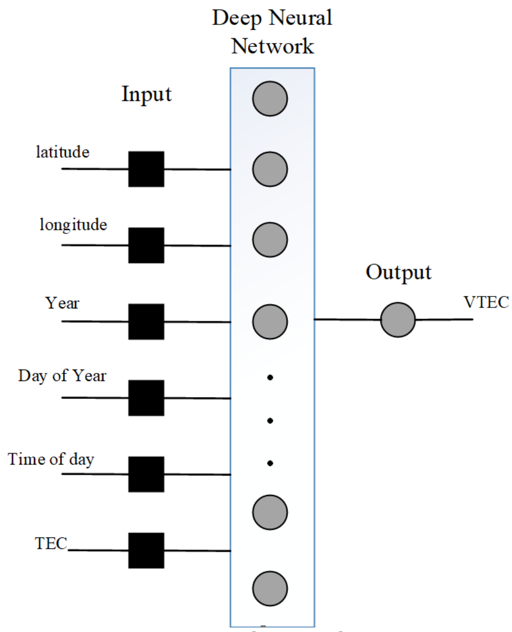


Fig. 3 Input and Output Flow

The results from the predictive models will be compared and the analysis of the results is done. A few tests will be conducted by using different sets of data input in order to ensure the validity of the tests. All findings will be discussed and concluded. With that, the result is determined whether the DNN technique is able to do the improvement of the predictive ionosphere model for equatorial and low latitude regions. The validation will be done using the estimated TEC from the established model which is the IRI-2012 and NeQuick 2 models. The same parameter inputs are compared with the VTEC based on Deep Neural Network. The renormalization process is done to ensure that the predictive model is within the appropriate range. Next, the evaluation of the performance of the new model is done by using MSE, RMSE and main bias error (MBE). Lastly, a newly designed predictive model is expected.

C. Datasets

The ionosphere is the uppermost atmospheric layer comprising a combination of ionized gas, ion, and electron that coat the earth at the height of 60 to 2000 km from the surface of the earth [36]. Ionosphere acts as a protector of the earth and life on it from any threat of space weather phenomena. The ionosphere data can be obtained by using a global navigation satellite system (GNSS). The GNSS that orbit the earth are namely Global Positioning System (GPS), European Galileo System, Russian Glonass System, Japan Regional Navigation Satellite System, China BeiDou System and India Regional Navigation Satellite System [37].

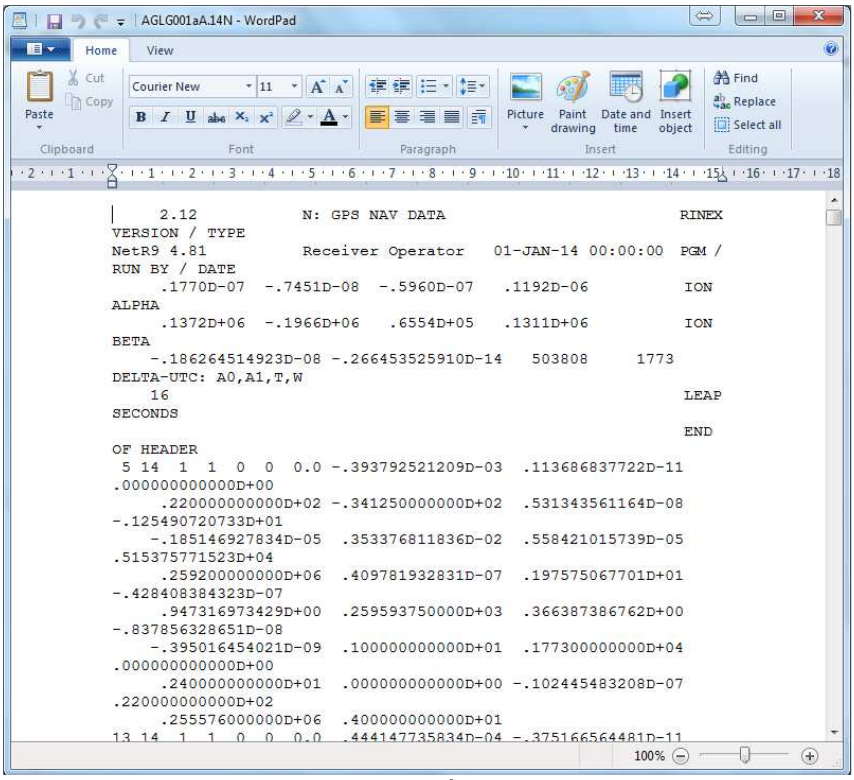
This constellation is able to provide the desired coverage such as regional or global. In this study, the ionosphere data from GPS satellite will be used for the predictive model verification as it is claimed as the most accurate navigation satellite system. In this study, total electron content, TEC, is an ionosphere parameter that will be used as a feature. TEC is obtained by the integration of Ne along the signal path S, as shown in Equation 5. TEC can be expressed in TECU (1 TECU is equivalent to $1\text{x}10^{16}$ electrons/ m2) [38], [39].

$$TEC = \int_S N_e dS \tag{5}$$

Where, electron density (Ne) is the amount of electron in a column of the cross-sectional area of 1 m^2 along the path of the signal through the ionosphere. The TEC also can be used to determine the delay caused by ionosphere refraction. The relationship between time delay, a frequency of the signal and TEC is represented in the following equation.

$$dt = \frac{40.28}{cf^2} \times TEC \tag{6}$$

Where *dt* is the ionosphere time delay, *c* is the velocity of light and *f* is the wave propagation frequency [38], [39]. The sample of data to be collected and analyzed for this study is shown in Figure 4.



```
      2.12           N: GPS NAV DATA                         RINEX
VERSION / TYPE
NetR9 4.81           Receiver Operator   01-JAN-14 00:00:00  PGM /
RUN BY / DATE
     .1770D-07  -.7451D-08  -.5960D-07   .1192D-06           ION
ALPHA
     .1372D+06  -.1966D+06   .6554D+05   .1311D+06           ION
BETA
    -.186264514923D-08 -.266453525910D-14   503808     1773
DELTA-UTC: A0,A1,T,W
    16                                                       LEAP
SECONDS
                                                             END
OF HEADER
 5 14  1  1  0  0  0.0 -.393792521209D-03  .113686837722D-11
.000000000000D+00
     .220000000000D+02 -.341250000000D+02  .531343561164D-08
-.125490720733D+01
    -.185146927834D-05  .353376811836D-02  .558421015739D-05
.515375771523D+04
     .259200000000D+06  .409781932831D-07  .197575067701D+01
-.428408384323D-07
     .947316973429D+00  .259593750000D+03  .366387386762D+00
-.837856328651D-08
    -.395016454021D-09  .100000000000D+01  .177300000000D+04
.000000000000D+00
     .240000000000D+01  .000000000000D+00 -.102445483208D-07
.220000000000D+02
     .255576000000D+06  .400000000000D+01
13 14  1  1  0  0  0.0  .444147735834D-04 -.375166564481D-11
```

Fig. 4 Sample Data

D. The Significance of the Study

The study can streamline the applied research in operational prediction space weather service for the areas located in the equatorial and low-latitude region, which is beneficial to the navigation and satellite positioning communities in the area. The study also plays an important role in predictive model development. It is also expected to enhance the predictive model especially in processing complex and large-sized data. The improvements in this model based on an in-depth learning approach will help the analyst in making a good decision despite their lack of expertise. This will prevent unwanted events from happening. Besides, it will also help to speed up the prevention process as well as costs incurred in the event of any incident.

Meanwhile, this study will be able to produce a reliable ionosphere predictive model for the space weather application. It will provide important information for anyone who may be affected by space weather. Space-based organizations can make their systems more robust and resilient to the effects of space weather. Personnel can prepare themselves for any interruption of communication or electricity supply with emergency plans and so on. The technique used will also benefit in the development of Space 4.0 that intertwined with Industry 4.0. Another important contribution of this study is that it will be able to provide additional inputs to the international regulatory authorities that are monitoring space weather issues such as National Oceanic and Atmospheric Administration (NOAA) and other related international organizations. Meanwhile, the research has some limitations, which is the data gathered might have some error or is corrupted. Thus, filtering and cleaning have to be done before the data can be used. Besides that, the availability of the historical data as the input of the predictive model needs to be considered.

IV. CONCLUSION

As a conclusion, the deep neural network is suggested to be used to enhance the ionosphere predictive model for space weather monitoring. The deep neural network technique is proven to improve predictive model performance and reduces the complexity of predictions. It has been implemented for solar irradiance data and there should not be any problem if it is implemented for ionosphere data specifically for the equatorial ionosphere data. With that, the improved predictive model is targeted and this model can provide an accurate and reliable predictor model that can predict and act as a domain expert on this subject. In the future, the deep neural network will be studied for the predictive ionosphere model with the real data. The simulation will be done using computing tools such as Matlab and the new improved model is targeted.

ACKNOWLEDGMENT

We would like to show our gratitude to the Malaysia Space Agency for allowing us to conduct the study. Also, Universiti Teknologi Malaysia (UTM) for realizing it. This study is funded by UTM with Vot number:14H08.

REFERENCES

[1] M. Lockwood, M. J. Owens, L. A. Barnard, C. J. Scott, C. E. Watt, and S. Bentley, “Space climate and space weather over the past 400 years: 2. Proxy indicators of geomagnetic storm and substorm occurrence,” *J. Sp. Weather Sp. Clim.*, vol. 8, no. 2004, p. A12, 2018.

[2] L. A. Hayes, P. T. Gallagher, J. McCauley, B. R. Dennis, J. Ireland, and A. Inglis, “Pulsations in the Earth’s Lower Ionosphere Synchronized with Solar Flare Emission,” *J. Geophys. Res. Sp. Phys.*, vol. 122, no. 10, pp. 9841–9847, 2017.

[3] R. G. Ezquer, L. A. Scidá, Y. M. Orué, B. Nava, M. A. Cabrera, and C. Brunini, “NeQuick 2 and IRI Plas VTEC predictions for low latitude and South American sector,” *Adv. Sp. Res.*, vol. 61, no. 7, pp. 1803–1818, 2018.

[4] F. Sabzehee, S. Farzaneh, M. A. Sharifi, and M. Akhoondzadeh, “TEC Regional Modeling and prediction using ANN method and single frequency receiver over IRAN,” *Ann. Geophys.*, vol. 61, no. 1, p. 103, 2018.

[5] J. Kleissl, *Solar Energy Forecasting and Resource Assessment*. Elsevier Science, 2013.

[6] J. Strickland, *Predictive Analytics using R*. Lulu.com, 2015.

[7] S. Mohanty, P. K. Patra, and S. S. Sahoo, “Prediction and application of solar radiation with soft computing over traditional and conventional approach--a comprehensive review,” *Renew. Sustain. Energy Rev.*, vol. 56, pp. 778–796, 2016.

[8] C. Voyant *et al.*, “Machine learning methods for solar radiation forecasting: A review,” *Renew. Energy*, vol. 105, pp. 569–582, 2017.

[9] F. Almonacid, E. F. Fernandez, A. Mellit, and S. Kalogirou, “Review of techniques based on artificial neural networks for the electrical characterization of concentrator photovoltaic technology,” *Renew. Sustain. Energy Rev.*, vol. 75, pp. 938–953, 2017.

[10] R. Chandra and S. Chand, “Evaluation of co-evolutionary neural network architectures for time series prediction with mobile application in finance,” *Appl. Soft Comput.*, vol. 49, pp. 462–473, 2016.

[11] M. Čelan and M. Lep, “Bus arrival time prediction based on network model,” *Procedia Comput. Sci.*, vol. 113, pp. 138–145, 2017.

[12] E. Disse *et al.*, “An artificial neural network to predict resting energy expenditure in obesity,” *Clin. Nutr.*, vol. 37, no. 5, pp. 1661–1669, 2018.

[13] J. Wang *et al.*, “Statistical analysis and verification of 3-hourly geomagnetic activity probability predictions,” *Sp. Weather*, vol. 13, no. 12, pp. 831–852, 2015.

[14] G. Najafi *et al.*, “SVM and ANFIS for prediction of performance and exhaust emissions of a SI engine with gasoline–ethanol blended fuels,” *Appl. Therm. Eng.*, vol. 95, pp. 186–203, 2016.

[15] H. Z. Sabzi, J. P. King, and S. Abudu, “Developing an intelligent expert system for streamflow prediction, integrated in a dynamic decision support system for managing multiple reservoirs: A case study,” *Expert Syst. Appl.*, vol. 83, pp. 145–163, 2017.

[16] A. M. Bagirov, A. Mahmood, and A. Barton, “Prediction of monthly rainfall in Victoria, Australia: Clusterwise linear regression approach,” *Atmos. Res.*, vol. 188, pp. 20–29, 2017.

[17] X. Chen, X. Chen, J. She, and M. Wu, “A hybrid time series prediction model based on recurrent neural network and double joint linear–nonlinear extreme learning network for prediction of carbon efficiency in iron ore sintering process,” *Neurocomputing*, vol. 249, pp. 128–139, 2017.

[18] C. Liu, C. Liu, Y. Shang, S. Chen, B. Cheng, and J. Chen, “An adaptive prediction approach based on workload pattern discrimination in the cloud,” *J. Netw. Comput. Appl.*, vol. 80, pp. 35–44, 2017.

[19] A. Stepchenko, J. Chizhov, L. Aleksejeva, and J. Tolujew, “Nonlinear, non-stationary and seasonal time series forecasting using different methods coupled with data preprocessing,” *Procedia Comput. Sci.*, vol. 104, pp. 578–585, 2017.

[20] M. Tshisaphungo, J. B. Habarulema, and L.-A. McKinnell, “Modeling ionospheric foF2 response during geomagnetic storms using neural network and linear regression techniques,” *Adv. Sp. Res.*, vol. 61, no. 12, pp. 2891–2903, 2018.

[21] X. Zhao, B. Ning, L. Liu, and G. Song, “A prediction model of short-term ionospheric foF2 based on AdaBoost,” *Adv. Sp. Res.*, vol. 53, no. 3, pp. 387–394, 2014.

[22] A. Zhukov, D. Sidorov, A. Mylnikova, and Y. Yasyukevich, “Machine learning methodology for ionosphere total electron content nowcasting,” *Int. J. Artif. Intell.*, vol. 16, no. 1, pp. 144–157, 2018.

[23] J. Xin, J. Zhou, S. Yang, X. Li, and Y. Wang, “Bridge structure deformation prediction based on GNSS data using Kalman-ARIMA-GARCH model,” *Sensors*, vol. 18, no. 1, p. 298, 2018.

[24] J. A. Lazzús, P. Vega, P. Rojas, and I. Salfate, “Forecasting the Dst index using a swarm-optimized neural network,” *Sp. Weather*, vol. 15, no. 8, pp. 1068–1089, 2017.

[25] G. Sivavaraprasad and D. V. Ratnam, “Performance evaluation of ionospheric time delay forecasting models using GPS observations at a low-latitude station,” *Adv. Sp. Res.*, vol. 60, no. 2, pp. 475–490, 2017.

[26] M. Nekkaa and D. Boughaci, “A memetic algorithm with support vector machine for feature selection and classification,” *Memetic Comput.*, vol. 7, no. 1, pp. 59–73, 2015.

[27] S. S. Abadeh, P. M. M. Esfahani, and D. Kuhn, “Distributionally robust logistic regression,” in *Advances in Neural Information Processing Systems*, 2015, pp. 1576–1584.

[28] Y. Kong, H. Chai, J. Li, Z. Pan, and Y. Chong, “A modified forecast

method of ionosphere VTEC series based on ARMA model," in *2017 Forum on Cooperative Positioning and Service (CPGPS)*, 2017, pp. 90–95.

[29] A. Qazi, H. Fayaz, A. Wadi, R. G. Raj, N. A. Rahim, and W. A. Khan, "The artificial neural network for solar radiation prediction and designing solar systems: a systematic literature review," *J. Clean. Prod.*, vol. 104, pp. 1–12, 2015.

[30] A. Tebabal, S. M. Radicella, M. Nigussie, B. Damtie, B. Nava, and E. Yizengaw, "Local TEC modelling and forecasting using neural networks," *J. Atmos. Solar-Terrestrial Phys.*, vol. 172, pp. 143–151, 2018.

[31] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, p. 436, 2015.

[32] J. Schmidhuber, "Deep learning in neural networks: An overview," *Neural networks*, vol. 61, pp. 85–117, 2015.

[33] W. Sun, L. Xu, X. Huang, W. Zhang, T. Yuan, and Y. Yan, "Bidirectional LSTM for ionospheric vertical Total Electron Content (TEC) forecasting," in *2017 IEEE Visual Communications and Image Processing (VCIP)*, 2017, pp. 1–4.

[34] A. Alzahrani, P. Shamsi, C. Dagli, and M. Ferdowsi, "Solar irradiance forecasting using deep neural networks," *Procedia Comput. Sci.*, vol. 114, pp. 304–313, 2017.

[35] J. B. Heaton, N. G. Polson, and J. H. Witte, "Deep learning in finance," *arXiv Prepr. arXiv1602.06561*, 2016.

[36] Y. Amerian, M. M. Hossainali, and B. Voosoghi, "Regional improvement of IRI extracted ionospheric electron density by compactly supported base functions using GPS observations," *J. Atmos. Solar-Terrestrial Phys.*, vol. 92, pp. 23–30, 2013.

[37] S.-S. Jan and A.-L. Tao, "Comprehensive comparisons of satellite data, signals, and measurements between the BeiDou navigation satellite system and the global positioning system," *Sensors*, vol. 16, no. 5, p. 689, 2016.

[38] A. A. Ferreira, R. A. Borges, C. Paparini, and S. M. Radicella, "TEC modelling via neural network using observations from the first GLONASS R&D data network in Brazil and the RBMC," *IFAC-PapersOnLine*, vol. 50, no. 1, pp. 12829–12834, 2017.

[39] A. A. Ferreira, R. A. Borges, C. Paparini, L. Ciraolo, and S. M. Radicella, "Short-term estimation of GNSS TEC using a neural network model in Brazil," *Adv. Sp. Res.*, vol. 60, no. 8, pp. 1765–1776, 2017.