Intelligent Forecasting Model of COVID-19 Novel Coronavirus Outbreak Empowered with Deep Extreme Learning Machine

Muhammad Adnan Khan[1, *], Sagheer Abbas[2], Khalid Masood Khan[1], Mohammed A. Al Ghamdi [3] and Abdur Rehman[2]

Abstract: An epidemic is a quick and widespread disease that threatens many lives and damages the economy. The epidemic lifetime should be accurate so that timely and remedial steps are determined. These include the closing of borders schools, suspension of community and commuting services. The forecast of an outbreak effectively is a very necessary but difficult task. A predictive model that provides the best possible forecast is a great challenge for machine learning with only a few samples of training available. This work proposes and examines a prediction model based on a deep extreme learning machine (DELM). This methodology is used to carry out an experiment based on the recent Wuhan coronavirus outbreak. An optimized prediction model that has been developed, namely DELM, is demonstrated to be able to make a prediction that is fairly best. The results show that the new methodology is useful in developing an appropriate forecast when the samples are far from abundant during the critical period of the disease. During the investigation, it is shown that the proposed approach has the highest accuracy rate of 97.59% with 70% of training, 30% of test and validation. Simulation results validate the prediction effectiveness of the proposed scheme.

Keywords: Coronavirus, nCoV, DELM, Mis rate, SERS-CoV, WHO, COVID-19.

1 Introduction

Since December 2019, China has undergone an unprecedented outbreak due to new coronavirus (COVID-19). The COVID-19 disease currently represents the legal class B infectious disease under PRC Law on Infectious Disease Prevention and Treatment, and Infections prevention and management procedures controlled as class A infectious disease. The first cases of a new (unknown and new) virus human infection, once known as Wuhan and Coronavirus, were identified and labeled as COVID-19, respectively [WHO (2020)]. The possibility that COVID-19 emerged from a single wild animal traded

[1] Department of Computer Science, Lahore Garrison University, Lahore, 54000, Pakistan.

[2] Department of Computer Science, National College of Business Administration & Economics, Lahore, 54000, Pakistan.

[3] Department of Computer Science, Umm Al-Qura University, Makkah, 23500, Saudi Arabia.

[*] Corresponding Author: Muhammad Adnan Khan. Email: madnankhan@lgu.edu.pk.

Received: 22 April 2020; Accepted: 30 April 2020.

on a busy market place was hypothesized [Cohen (2020)]. In the city, Wuhan, the mass of infected people spread rapidly to other Chinese cities, and in one month became a global epidemic [Chan, Yuan, Kok et al. (2020)]. COVID-19 is extremely contagious by body air droplets and can live on a touching surface for up to two days [Zhu, Zhang, Wang et al. (2020)]. Recently, the transition between human beings has been observed and the toll of the infested in this initial stage has risen steadily. On 30 January 2020, the World Health Organization released a global health emergency warning, designating COVID-19 as a global emergency Early on, the death rates resulting from COVID-19 disease are unknown especially for young children and the old aged groups.

In Wuhan, Hubei Province of China, some viral pneumonia patients were found to be epidemiologically associated with the maritime market for Huanan at the end of December 2019 and were sold also before the outbreak for several non-aquatic animals including birds and rabbit [Munster, Koopmans and van Doremalen (2020); Carlos, Dela Cruz, Cao et al. (2020)]. A novel human coronavirus has been detected using next-generation sequencing and is provisionally referred to as the 2019 novel coronavirus (2019-nCoV). China has registered over 5,900 confirmed cases and over 9,000 suspected cases of COVID-19 in 33 Chinese provinces or municipalities as of Jan 28, 2020, with 106 deaths. However, in Thailand, Japan, South Korea, Malaysia, Singapore, and the United States COVID-19 has been registered. Health and family cluster infections have also been identified and the transmission from human to human has been confirmed. Some affected patients have a high fever and some have dyspnea, with chest X-rays that indicate abnormal lesions of the lungs [Paules, Marston and Fauci (2020); Huang, Wang, Li et al. (2020); Song, Shi, Shan et al. (2020)].

Preventive measures were taken to cordon off infected cities to monitor the large and rapid spread of the virus [Wang, Horby, Hayden et al. (2020)]. These include, until further notice, closing borders, halting community services and colleges, minimizing both domestic and international travel, etc. The goal is to reduce the probability of physical interaction between people to prevent the spread of the new virus. Every day the curfew put on China and other countries will cost enormous economic loss. As this virus is new, its magnitude is unpredictable, although its infectious nature is very high and its incubation is comparatively longer than that of other viruses [Wu, Zhao, Yu et al. (2020)]. The ban should be lifted too soon; the epidemic may not be completely subsidized; expanded restrictions would lead to greater economic losses. In this initial stage, time is very unpredictable, as long as the virus is new and all of us have no understanding of its characteristics. Officials would like to know if this outbreak will end and if it keeps getting worse [Xu, Chen, Wang et al. (2020)].

Among the various human pathogenic coronaviruses, the majority are related to mild clinical signs [Su, Wong, Shi et al. (2016)], with two notable exceptions: SERS-CoV (SARS), a novel beta-CoV in Guangdong, Southern China, which appeared in November 2002 [Peiris, Guan and Yuen (2004)], More than 8000 human infections and a death toll of 774 was reported in 37 countries in 2002-2003 as well as the Middle East Respiratory Syndrome (MERS-CoV) (MERS) coronavirus, first identified in Saudi Arabia in 2012, in which 2494 laboratory-confirmed cases and 858 deaths have been reported since September 2012, particularly 38 deaths following a single introduction into South Korea

[Lee, Chowell and Jung (2017); Lee, Kim, Chung et al. (2017)].

Therefore, even for the smallest hints for multiple characteristics, forecasting is extremely important for other individual and social health factors. The most accurate forecast is necessary in this case. This is a complicated computational problem in machine learning [Hyndman and Kostenko (2007); Croda, Romero and Morales (2019)]. How can a precise forecasting model be generated with only a few early training data? The literature provides three common approaches to building prediction models of a small dataset [Pasini (2015); Ingrassia and Morlini (2005)]. One approach is to extend the training data collection by adding more data to the data available [Andonie (2010); Lateh, Muda, Yusof et al. (2017)]. The second way consists of a collection for collective prediction results and one of the algorithms with the lowest error is chosen to use the forecast results [Shaikhina and Khovanova (2017)]. The results of the other candidates will be denied. The third method is to rely on a single prediction algorithm, often with multiple customizable parameters. The exactness of the resulting model is very prone to parameters. For such an algorithm, the default parameter values often do not provide the highest performance, so that the accuracy of the parameter values can be improved.

Many works have been proposed to tackle medical problems utilizing various areas of artificial intelligence. Jiang et al. [Jiang, Coffee, Bari et al. (2020)] purposed a first step towards developing an artificial intelligence system with predictive computational technologies implemented to real patient information in order to provide fast clinical decision-making help. Hossain et al. [Hossain, Morooka, Okuno et al. (2020)] proposed a framework for predicting postoperative knee functions of a new patient prior to total knee arthroplasty (TKA) surgery using machine learning, as these predictions are important for surgical preparation and for patients to better understand the overall knee arthroplasty results. Yuan et al. [Yuan, Yao and Tan (2018)] suggests a system focused on machine learning, which can automatically and precisely identify certain occurrences in biomedical imaging.

DELM approach should be viewed as an alternative to current methods to draw on the best model of a few training data given the severity associated with decisions on the epidemic. In this paper, a deep extreme learning machine for the forecasting of novel coronavirus outbreak is investigated to achieve the highest accuracy. In the training and testing, for predication of coronavirus outbreak with deep learning, data instances are used, so that each instance includes different and diverse characteristics. This paper integrates the merits of the three methods in the proposed approach with these characteristics: First, the group prediction includes multiple candidate forecast algorithms, choose the one with the lowest error. In the second one, most appropriate parameter values are used in each prediction model, and third, in a multiple regression system of prediction models, relevant information about the prediction target is introduced as a candidate of the group selection.

The remainder of this paper is organized as follows. Section 2 presents the method to carry out a comprehensive evaluation for the forecasting of a novel coronavirus outbreak. Section 3 discusses the simulation and results of the DELM approach. Section 4 discuss the conclusions from the study.

2 Experimental

2.1 System model

During the early phase of decision making on the rapid development of an outbreak, little data is available. It is supposed to be a new virus and human experts will be consulted after a scientific assessment is made similar to the decision taken at Delphi. A DELM approach using a limited dataset is expected in light of three main aims-the forecast model that has been approved needs to be more efficient than its counterparts (with the lowest error), the winning model itself requires maximum efficiency and it has the flexibility to include certain appropriate time intervals for regression. Our proposed approach aims to ensure maximum predictive precision under the limitations of the limited availability of data and information. The objective of the project is on community prediction with a series of adaptive prediction models, some of which can use several information sources as inputs.

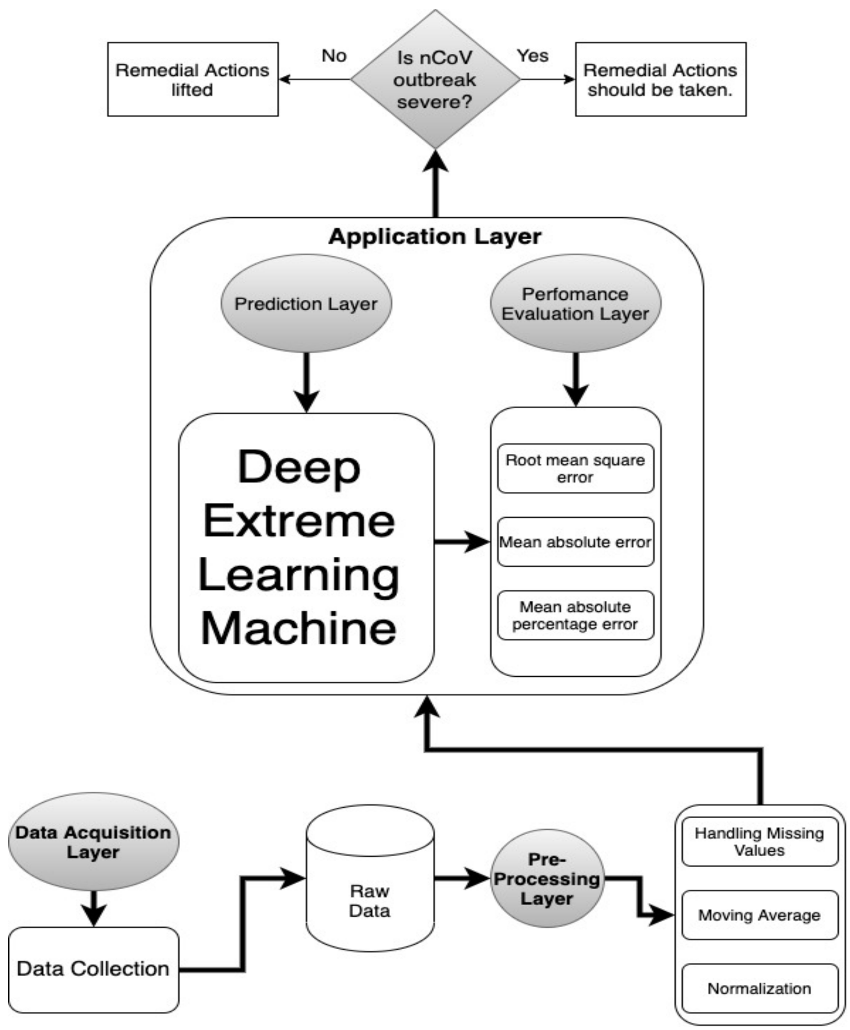

Figure 1: Proposed model for prediction of novel coronavirus outbreak

Finding an early forecasting model of 2019 novel Coronavirus outbreak in a human being is extremely important. However, correct forecasting is a challenging task. In this research, a system for accurate forecasting model of 2019 novel Coronavirus based on DELM is proposed. The proposed method has been divided into three main layers that are data acquisition layer, pre-processing layer, and application layer. The data acquisition layer deals with the appropriate data collection for investigation. In the preprocessing layer, standard data processing approaches are used to eliminate anomalies in the data. In the application layer, there are two sub-layers namely the prediction and performance assessment layers, respectively. The proposed DELM is investigated in the application layer to improve the forecasting model of the 2019 novel Coronavirus.

Fig. 1 depicts the components and detail of the proposed forecasting approach. It shows that the data acquisition layer contains the input parameters to the neural system, where a training algorithm has been used to forecast the novel Coronavirus outbreak. Applications of artificial neural networks (ANNs) in various fields need no introduction. The ANNs comprise of a set of neurons which are the fundamental unit of information processing characterized by a layered arrangement, mainly, input, output and hidden layers [Nasser and Abu-Naser (2019); Sa'di, Hashemi, Abdollapour et al. (2015); Gentiluomo, Roessner, Augustijn et al. (2019)].

In this research work, the deep extreme learning machine technique is being unified to forecast the coronavirus outbreak. Fig. 2 demonstrates that in deep extreme learning machines diverse amounts of hidden layers, different hidden neurons, and numerous kinds of activation functions have been used to attain the finest structure of DELM for forecasting of the outbreak. In the application layer, Deep extreme learning machine has been used for forecasting of the novel coronavirus. The DELM takes the benefits of both extreme learning and deep learning techniques.

The complete system procedure is shown in Fig. 1. In which layer of data acquisition contains the parameters of input, they will go to the neural system, where an algorithm has been trained to predict the correct prediction of the outbreak. In all sectors, artificial neural networks can now be used. The artificial neural network contains a group of neurons that are specially organized. Neurons and connections between them are the main parts of an artificial neural network. A neuron is the fundamental unit of processing information that forms the foundation for the performance of ANN. Neurons are mutual processing components that solve a problem.

2.2 Deep extreme learning machine

The deep extreme learning machine (DELM) is a well-known method used in various areas for predicting health problems, energy consumption predictions, transportation and traffic management, etc. The conventional ANN algorithms need more measurements and slow learning times and can override the learning model [Lee, Kim, Chung et al. (2017)]. The idea of an extreme machine as defined by Huang et al. [Huang, Wang and Lan (2011)]. The DELM can be commonly used for classification and regression purposes in different domains because DELM learns rapidly and it is effectual in the rate of computational convolution. Extreme learning machine is feedforward neural network which means data only goes one way through the series of layers but we have used backpropagation method in this proposed model during training phase where information flows back through the network and in backpropagation method network adjust the weights to achieve high accuracy with minimum error rate. During validation phase weights of the network are constant in which we import the trained model and predict the real data. The input layer, multiple hidden layers, and one output layer are included in the DELM model. The DELM concept is implemented in the structural form is shown in Fig. 2.

In the application layer, a deep extreme learning machine method will be considered for the prediction of the deadly coronavirus outbreak in danger zones. In the evaluation layer, two parameters accuracy and Mis rate will be observed to predict novel coronavirus outbreak as remedial actions in the city should be taken or not. An early forecasting of coronavirus outbreak is affected by four primary parameters that are used in the dataset as input factors, such as date, State, country, and last update. These parameters influence the remedial action for danger zone, which are termed the target variables such as deaths, recovered, and danger. In the data acquisition layer, inputs will be taken from the collection of data. These variables forecast the novel coronavirus outbreak. In the pre-processing layer, cleaning abnormalities in data and data reduction will be used for quality data in machine learning. In the application layer, a deep extreme learning machine method will be considered for outbreak prediction. In this article, DELM was used to train and fit 1719 sets of data. This data arbitrarily divides into 70% of training (1204 samples), 30% of data is used for validation and testing (515 samples).

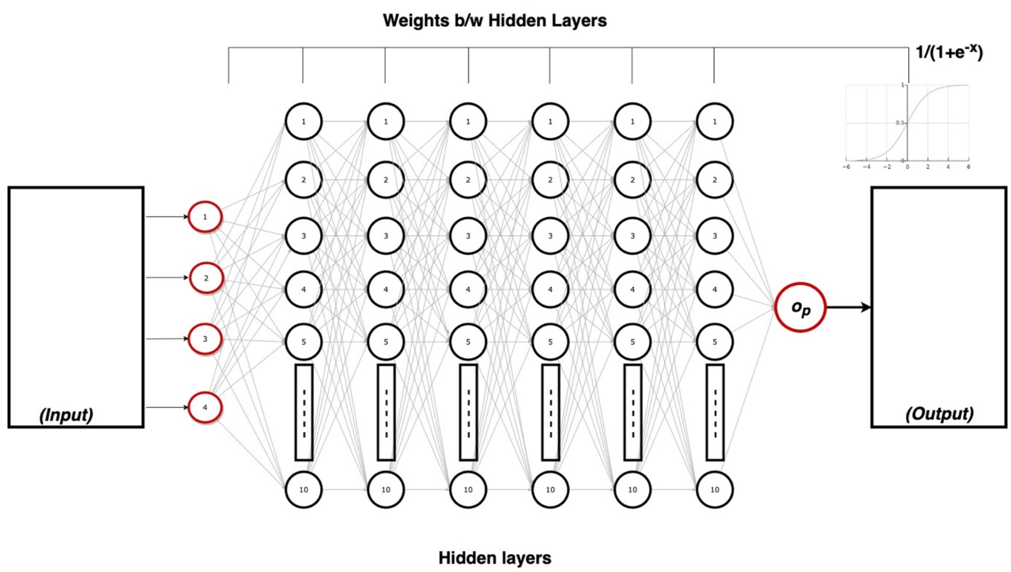

Figure 2: Structural diagram of a deep extreme learning machine

In the DELM framework, the n-th input node, the i^{th} hidden node, and the m^{th} output node can be characterized as a_n, p_i, and g_m, respectively, although all the N input nodes, l hidden nodes, and M output nodes can be characterized as $a = [a_1, a_2 \dots \dots a_N]^T \in R^N$, $p = [p_1, p_2 \dots \dots p_l]^T \in R^l$, $g = [g_1, g_2 \dots \dots g_M]^T \in R^M$, respectively. The DELM model will accordingly be represented compactly as;

$$p = f\ (B_a + c) \quad (1)$$

and

$$G = QB \quad (2)$$

where $B = [b_{in}] € R^{lxN}$, $c = [c_1,\ c_2 \dots \dots c_l]^T € R^l$, $Q = [q_{mi}] € R^{mxl}$, and the activation function $f(\ )$ could be used as sigmoid, linear Gaussian models, etc.

Suppose that there are only V distinct training samples, and let $a_v € R^N$ and $g_v € R^M$ and denote the v^{th} training input and the resultant v^{th} training output, respectively, where $v = 1, 2, \dots, V$. In the training set the input sequence and output sequence can be shown as;

$$A = [a_1, a_2 \dots \dots a_V]^T € R^{N\text{x}V} \quad (3)$$

and

$$G = [g_1, g_2 \dots \dots g_V]^T € R^{M\text{x}V} \quad (4)$$

respectively. We can substitute (3) into (1) to obtain

$$P = f(BA + 1^T \otimes \text{c}\ ), \quad (5)$$

where $P =\ [p_1, p_2 \dots \dots p_V]^T € R^{lxV}$ is the value classification of all l hidden nodes, and $\otimes$ Kronecker product. Then we can overwrite (5) and (4) in (2) to achieve the actual training performance series.

$$G = QP \quad (6)$$

In DELM, just the output weight Q is flexible, while B (i.e., the input weights) and c (i.e., the biases of the hidden nodes) are arbitrarily addressed. Designate the anticipated output as Y. Then DELM merely minimalizes the assessment error;

$$E = Y - G = Y - QP \quad (7)$$

By finding the least-squares solution Q for the problem

$$\min_{Q} \|E\|_F^2 = \min_{Q} \|Y - QP\|_F^2 \quad (8)$$

where $\|.\|_F$ indicates the Frobenius norm.

For the problematic (8), the exceptional minimum norm least-squares solution is;

$$Q = YP^T(PP^T)^{-1} \quad (9)$$

To avoid overfitting, the popular Tikhonov regularization can be utilized to modify Eq. (9) into

$$Q = YP^T(PP^T + v_0^2 I)^{-1}, \quad (10)$$

where $v_0^2 > 0$ signify the regularization term. Apparently, Eq. (9) is only the particular case of (10) with v_0^2=0. Therefore, we find only Eq. (10) the regularization of Tikhonov for the DELM. Machine learning is a common strategy for gradually increasing the number of hidden layers to the desired precision. When this technique is applied directly in DELM, however, in Eq. (10) the reverse matrix operation for standard ELM is required when some or only another hidden node is added, and the algorithm is therefore prohibitive to computation. The back-propagation algorithm includes weight initialization, feedforward propagation, back error propagation, and update of weight and distinctiveness. An activation function like $g(x) = sigmoid$ exists on each neuron in the hidden layer. This allows the sigmoid input feature and the DELM hidden layer to be composed in this way;

$$E = \frac{1}{2}\sum_j (sj - wp_j)\, 2 \tag{11}$$

s_j=Desired output

wp_j=calculated output

Eq. (11) indicates a back-propagation error that can be calculated by dividing the sum of the square from the desired output by 2. The weight change is required to reduce the general error. The rates of weight change for the output layer are shown in Eq. (12).

$$\Delta \mathrm{H}_{i,j}^{l=6} \propto -\frac{\partial \mathrm{R}}{\partial \mathrm{H}^{l=6}} \tag{12}$$

where $i = 1,2,3 \ldots \ldots \ldots 10(\text{Neurons})$

and j= output Layer

$$\Delta \mathrm{H}_{i,j}^{l=6} = -\text{const}\frac{\partial \mathrm{R}}{\partial \mathrm{H}^{l=6}} \tag{13}$$

writing Eq. (13) by using the chain rule method

$$\Delta \mathrm{H}_{i,j}^{l=6} = -\text{const}\frac{\partial \mathrm{R}}{\partial wp_j^l} \times \frac{\partial wp_j^l}{\partial NhH_j^l} \times \frac{\partial NhH_j^l}{\partial H_{i,j}^l} \tag{14}$$

The value of change weight can be achieved after substituting the values in Eq. (13) as shown in Eq. (14).

$$\Delta H_{i,j}^{l=6} = \text{const}(\text{sj} - wp_j) \times (\, wp_j^l(1 - wp_j^l) \times wp_j^l) \tag{15a}$$

From wp to H_6

$$\Delta H_{i,j}^{l=6} = \text{const}\,\ni_j wp_j^l \tag{15b}$$

In the next step, the calculation for the appropriate weight adjustment to the hidden weight is shown. This is more complex because it can lead to errors on every node by weighted connection.

From H_6 to H_1 or H_n

where $n = 5,4,3,2,1$

$$\Delta \mathrm{H}_{i,n}^{l} \propto -\left[\sum_{j} \frac{\partial \mathrm{R}}{\partial \mathrm{wp}_{j}^{l}} \times \frac{\partial \mathrm{wp}_{j}^{l}}{\partial \mathrm{NhH}_{j}^{l}} \times \frac{\partial \mathrm{H}_{j}^{l}}{\partial \mathrm{wp}_{n}^{l}}\right] \times \frac{\partial \mathrm{wp}_{n}^{l}}{\partial \mathrm{NhH}_{n}^{hl}} \times \frac{\partial \mathrm{NhH}_{n}^{l}}{\partial \mathrm{H}_{i,n}^{l}} \tag{15a}$$

$$\Delta \mathrm{H}_{i,n}^{l} = R\left[\sum_{j} \ni_{j}(H_{n,j}^{l})\right] \times \mathrm{wp}_{n}^{l}(1 - \mathrm{wp}_{j}^{l}) \times Z_{i,n} \tag{15b}$$

$$\Delta \mathrm{H}_{i,n}^{l} = R \ni_{n} Z_{i,n} \tag{15c}$$

where

$$\ni_{n} = \left[\sum_{j} \ni_{j}(H_{n,j}^{l})\right] \times wp_{n}^{l}(1 - wp_{n}^{l}) \tag{15d}$$

The mechanism to improve the weight and bias between the output and the hidden layer is shown in Eq. (15e).

$$H_{i,j}^{l=6}(t) = H_{i,j}^{l=6}(t) + \lambda \Delta H_{i,j}^{l=6} \tag{15e}$$

Eq. (16) shows how updating the weight and bias among the input and the hidden layer.

$$H_{i,n}^{l}(t) = H_{i,n}^{l}(t+1) + \lambda \Delta H_{i,j}^{l} \tag{16}$$

3 Results and discussion

In particular, the early stage forecast of the COVID-19 outbreak is tested to validate the reliability of the current DELM methodology. Inferential statistics collected from the Chinese health officials' archives are used [WHO (2020)]. The statistics on the average rise of the number of infected people in China are revised daily after 21 Jan 2020. The patterns are classed as having the complete post-infection case cycle: confirmed, recovered, dead, suspicious, crucial. A patient is called suspicious when he or she is showing signs of a viral infection and is then proven or consistent with a medical diagnosis. The patient may then become vital and be either treated or died. Such statistics show the routine pattern of the epidemic. The pattern in epidemics has been increasing until the time of writing, but only data from 21 Jan-3 Feb 2020 will be used for studies. The officials become worried at any moment during the development of the outbreak for future days. The situations are a difficult scenario of the current solution to small data.

In the proposed article, the deep extreme learning machine algorithm has been applied to the dataset and in this regard, the MATLAB tool has been performed for simulation. In MATLAB, a python script was implemented to train data. In this article, DELM was used to train and fit 1719 sets of data. This data arbitrarily divides into 70% of training (1204 samples), 30% of data is used for validation and testing (515 samples). Data were previously processed to remove data abnormalities and free the data from error. DELM has attempted to discover the finest configuration model for novel coronavirus outbreak prediction in different hidden layers, hidden neurons, and combinations of Activation Functions. Therefore, we have tried the same number of neurons, different types of active functions in hidden layers. In this work, we used the proposed DELM for prediction to properly test the effectiveness of this algorithm. To measure the performance of this DELM algorithm together with the counterpart algorithms, we used different statistical measures written in Eqs. (17) and (18). In Eq. (17), O represent the predictive output of coronavirus outbreak, and T represents the actual output. O_0 and T_0 represent that there is no change in predictive and forecast in coronavirus outbreak respectively from the previous cycle. O_k and T_k represents the change in prediction from the previous cycle of the predictive and actual prediction respectively. ${O_k}/{T_k}$ represents predictive and actual output is the same. Similarly, ${O_k}/{T_{j\neq k}}$ represents an error, in which predictive and actual output of coronavirus outbreak are varied.

$$\text{Miss rate} \quad = \frac{\sum_{k=0}^{2}({O_k}/{T_{j\neq k}})}{\sum_{k=0}^{2}(T_k)}, \text{ where j=1,2,3} \tag{17}$$

$$\text{Accuracy} = \frac{\sum_{k=0}^{2}({O_k}/{T_k})}{\sum_{k=0}^{2}(T_k)} \tag{18}$$

Tab. 1 shown the proposed DELM system model prediction of coronavirus outbreak during the training phase. A total of 1719 number of samples are used during training which is further divided into 9, 995, and 200 samples of deaths, recovered and danger respectively. In training 9 samples of deaths, 995 samples of recovered, and 200 samples of danger zone reports are put into the proposed DELM framework for prediction. Similarly, a total of 200 samples are taken in the case of the danger zone, in which 193 samples are correctly predicted as a danger zone and 7 samples are invalid predict as a recovered while danger zone exists there.

Table 1: Training performance of the proposed deep extreme learning machine system model during the prediction of coronavirus outbreak

Input	Output		
(1204)	O_0	O_1	O_2
I_0=9	9	0	0
I_1=995	9	976	10
I_2=200	0	7	193

While Tab. 2 shown the proposed DELM system model prediction of coronavirus outbreak during the validation phase. A total of 1719 numbers of samples are used during validation which is further divided into 9, 338 and 168 samples of deaths, recovered and danger respectively. During validation 9 samples of deaths, 338 samples of recovered, and 167 samples of danger zone reports are put into the proposed DELM framework for prediction. Similarly, a total of 168 samples are taken in the case of the danger zone, in which 160 samples are correctly predicted as a danger zone and 8 samples are invalid predict as a recovered while danger zone exists there.

Table 2: Validation performance of the proposed deep extreme learning machine system model during the prediction of coronavirus outbreak

Input	Output		
(515)	O_0	O_1	O_2
I_0=9	7	2	0
I_1=338	4	325	9
I_2=168	0	8	160

Tab. 3 shown the proposed DELM system model performance in terms of accuracy and miss rate during the training and validation phase. It clearly shown that the Proposed DELM framework during training gives 97.59% and 2.41 % accuracy and miss rate respectively. And during validation, the proposed DELM framework gives 95.53% and 4.47% accuracy and miss rate respectively.

Table 3: Performance evaluation of proposed deep extreme learning machine during validation & training

	Training	Validation
Accuracy	97.59%	95.53%
Miss Rate	2.41%	4.47%

4 Conclusion

Modeling, analysis, and prediction of novel coronavirus outbreak is a challenging task. In this research, a model for prediction of novel coronavirus outbreak in different zones has been proposed to improve the prediction accuracy of the outbreak to take the emergency remedial actions. The proposed model is an expert system based on an artificial neural system (ANN) with a deep extreme learning machine (DELM) possessing a high level of potential to predict novel coronavirus outbreak in different zones to take necessary actions to fight this deadly virus. Various numbers of the hidden layer neurons were defined, and diverse activation functions and features were used for the ideal arrangement of different DELM parameters to obtain an optimized structure.

For measuring the performance of the proposed approach, various statistical measures have been used. These measuring figures show that proposed DELM in contrast to other algorithms is way better in terms of accuracy. The proposed DELM technique produces attractive results. The proposed technique exhibits 97.59% accuracy. Moreover, it is observed that the proposed approach exhibits an affordable computational complexity. DELM has been used in the proposed work to encapsulate the benefits of ELM as well as deep learning. We are confident in initial results and intended to expand this work in the future by investigating different datasets, learning machines, structures, and algorithms.

Acknowledgment: Thanks to our families & colleagues who supported us morally.

Funding Statement: The author(s) received no specific funding for this study.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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