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Optimized Extreme Learning Machine for Forecasting Confirmed Cases of COVID-19

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Abstract: Recently, a new challenge to the researchers has been emerged due to the spread of a new outbreak called novel corona-virus (COVID-19) to portend the confirmed cases. Since discovering the first certain cases in Wuhan, China, the COVID-19 has been widely spreading and expanding to other provinces and other countries via travellers into various countries around the world. COVID-19 virus is not a problem of only developing countries, but also of developed countries. Artificial Intelligence (AI) techniques can be profitable to predict such; parameters, risks and influence of an outbreak. Therefore, accurate prognosis can be helpful to control the spread of such viruses and provide crucial information for identifying the type of virus interventions and intensity. Here are develop an intelligent model depicting COVID-19 transmission and resulting confirmed cases. The epidemic curve of COVID-19 cases was modelled. The main key idea of predicting the confirmed cases is based on two factors 1) cumulative number of confirmed cases and 2) the daily confirmed cases instead of using only one factor as previous research. In this study, a comparison between different intelligent techniques has been conducted. To assess the effectiveness of these intelligent models, a recorded data of 5 months has been used for training in various countries. Results obtained show the superiority of ELM model in accurate prediction and outperforms other intelligent techniques. We have used a Social Spider Optimization (SSO) method to optimize the ELM parameters. The prediction results show the superiority of the proposed intelligent predictors with accuracy greater than 93%. Therefore, medical personnel can take defensive steps earlier.

Keywords: Extreme learning machine, Social spider optimization, COVID-19, Artificial intelligence, World health organization.

1. Introduction

Early of this year, a novel virus related to the corona viruses' family spread widely in Wuhan city of Hubei Province of People's Republic of China (PRC) and rapidly spread to the various countries in the world. In December 2019, infected people attends to local hospitals cause they severe from a pneumonia with unknown reason. Most of the early reported cases had a mutual relation to the Huanan seafood market which also traded animals as well. On December 31st 2019, the Government of PRC sends a report regarding the outbreak to the World Health Organization (WHO), after one day they close the seafood market. Lab testing approves a similarity of the new virus with bat coronavirus in 95% and more than 70% similitude to SARS-Cov. More than 162 countries are currently suffering from the rapid spread of a novel corona virus, called COVID-19 (called previously, 2019-nCoV).

Some authors said that COVID-19 is mostly transferred from bats, since it is very similar to the Coronavirus family. However, it is not assured yet, and need more tests and examinations. A large number of confirmed cases and deaths cases are reported in Wuhan city; therefore, the authorities decide to lockdown the Wuhan city by stopping all public transportation to reduce the spread of COVID-19 virus. The Center for Disease Control and

Prevention (CDC) approved the transmission of the virus between humans at the end of January 2020 and the spread of it is very quick and risky, seeking more firm policies and plans [1]. Therefore, social distance is mandatory. However, incubation period ranges between (2-14) days considered as a big challenge to the medical personnel. Actually, predicting or forecasting the COVID-19 cases, deaths, and recovered is very important to ensure a successful protection plans.

Shi et al [2] derive a mathematical model for the epidemic curve of COVID-19 to predict the actual number of positive cases, while the unreported confirmed cases was determined through maximum likelihood estimation. They claimed that the number of cases reported is increased by 21-fold and they finally estimate the value of reproduction number (R_o). Hiroshi et al [3] suggest an estimation model to predict the incidence rate of the COVID-19 virus in Hubei-China, through collecting a data from 565 Japanese people who were evacuated from China, they predict the death rate in range between (0.3% to 0.6%). Even though, the number of samples from the evacuated Japanese people is small and insufficient. Moreover, By proposing an estimation model to estimate the transmission risk of COVID-19 in Beijing during the outbreak based on clinical progression of the viruses, Tang et al [4] are trying to estimate the importance of Ro, epidemiological status of the people, and intervention measures. Accurate analysis shows that quarantine and isolation with stopping the travel to Beijing decreases the number of people who are infected by one week to less than 91.14%. In addition to, Thompson et al [5] estimate the percentage rate of transmission of COVID-19 from human to human. They estimated the transmission equal to 0.4 and can be reduced to 0.012 if half of the checked samples are hospitalized when symptom are appeared. Unfortunately, the confidence of this conclusion is low since the study is based on 47 patients only. Moreover, Jung et al [6] present an estimation model based on the exported cases of COVID-19 outside China to estimate a model for the probability of death as a result of this virus. Their estimation outcomes with two possibilities as (5.1% and 8.4%), while the predicted R_o for the two scenarios are (2.1% and 3.2%), respectively.

In the last decade, several studies were conducted to forecast and predict various epidemics. As an example, DeFelice et al. [7] suggest an accurate forecast for transmission and human infection by West Nile Virus (WNV) cases. Therefore, the proposed model is based on employing a data assimilation and two observed data method registered in outbreaks of Long Island, in New York, for the period 2001-2014. Moreover, Ture and Kurt [8] compare various time series forecasting models in order to prognosis Hepatitis A Virus (HAV) infection. Data recorded monthly for 13 years (Jan. 1992-Jun. 2004). Seasonal outbreaks of Influenza are mostly repeated every season in most temperature countries in the world. Therefore, Shaman and Karspeck [9] suggest a predicting model based on Kalman filter (KF). Validation of the suggested model is confirmed through utilizing a cumulative data of New York City for 6 years (from 2003- till 2008). While Shaman et al. [10] propose another model except using data for 108 cities in (2012-2013) season.

Outbreak of Ebola which happened in some West African countries such as (Guinea, Sierra Leone, and Liberia) encourages Jeffrey and his group to harness a dynamic model with Bayesian inference to predict the outbreak of Ebola virus [11]. Another epidemic called Severe Acute Respiratory Syndrome (SARS) had been analyzed by [12] through proposing a simple mathematical model to study and investigate the influence of control measures against this infection. This study estimates the reproduction number in different countries (i.e. Canada, and Hong Kong). In [13] a real time model for monitoring and forecasting H1N1-2009 was proposed. Furthermore, Nah et al. [14] proposed a simple statistical model based on the effective distance to predict the international propagation of Middle East Respiratory Syndrome (MERS) related to Coronavirus.

Emergency epidemic forecasting attracts many researchers to use AI capabilities for this reason. Jia et al. [15] suggest a Recurrent Neural Network (RNN) to predict the outbreak of hand-foot-mouth disease (HFMD) caused by entero viruses in China. Machine learning is recently used to predict various outbreaks such as Spatio-Temporal spread of Pathological diseases in [16], predict cardiovascular diseases in [17], or seasonal Influenza in [18], and also Diarrhea virus (PEDV) outbreaks in [19], and predict epidemiological clc's of Ebola virus outbreak (EBOV) in West Africa [20]. However, this type of learning required a large amount of data sets.

Various techniques have been utilized recently including classical Kalman Filtering (KF) and Artificial Intelligence (AI) techniques to predict time series problems. In KF, the state of a linear stochastic model is estimated through efficient computational techniques. Unfortunately, KF and even Extended Kalman Filter (EKF) still have major disadvantages such as:

(1) It is required to a stochastic error model for the intended model which is difficult to obtain for some applications;

(2) It is necessary to gain a prior knowledge for the measurement covariance matrices which different from one model to another;
(3) It suffers from computational intricacy;
(4) It lacks of observability problem for different state variables.

Accurate results and elevated accuracy for some published intelligent techniques show that KF technique outperforms some of these intelligent techniques when the required model of the system and the previous drawbacks are overcome. However, a systematic review of using various AI type to predict different outbreaks is reported in [21]. It can be observed that majority of the algorithms use a combined intelligent with optimization methods to predict the future growth established on a previous recorded data.

Therefore, in order to overcome the mentioned drawbacks of the KF, then Artificial Neural Network (ANN) has been utilized for prediction process in various fields. Several architectures were evaluated through utilizing different types of ANN networks. These networks include Multi-Layer Perceptron Neural Network (MLPNN), Radial Basis Function (RBF), and Input Delay Neural Network (IDNN). An experimental result shows the superiority of RBF in providing a better performance than a classical MLPNN in some prediction and classification problems and functional extrapolations. Unfortunately, ANN is not sufficient since it requires choosing the number of hidden layers and also the number of nodes in each layer. On one hand, RBF contain a single hidden layer but the number of nodes is decided empirically which make it unsuitable for real time implementation. Moreover, IDNN is considered an accurate model but unlikely it requires a lot of time for training computations. Moreover, Artificial based segmented forward predictor (ASFP) has been widely used for achieving forward prediction through using the RBF. However, prosaic accuracy obtained from using the ASFP method opens the door for improving more effective AI techniques. The Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture is extensively utilized in forecasting and prediction problem. ANFIS consists of fixed five-layered feed-forward neural network (FFNN) architecture. It collects the benefits features of two main intelligent techniques named as Artificial Neural Network (ANN) and Fuzzy System (FS) [22]. ANFIS was chosen in solving various problems due to its superiority in dealing with imprecision, uncertainty, and stochastic problem in the input data for the model [23]. Nevertheless, ANFIS structure is restricted to only one output which makes it suitable for the MISO solely.

Anywise, this technique is not recommended in high level of stochastic and arbitrary data [24]. Static ANN technique shows significant results in forecasting problems; however, it has many drawbacks such as its slow convergence to the specified target, and long time elapsed during training phase. Therefore, various researchers extend their efforts to overcome the limitations of the ANN techniques, including Extreme Learning Machine (ELM). ELM is a new and promising type of Feed-Forward Neural Network (FFNN), which contain a single hidden layer and perform an efficient mechanism to determine the hidden nodes in order to computing the output weights [25].

Depending on deriving the mathematical model in order to predict the number of infected cases of COVID-19 is restricted and results in unreliable results. Moreover, most of the previous intelligent techniques predict the number of cases depending on the reported daily cases solely while in the current work utilize the daily and cumulative cases as well. Furthermore, the estimation of reproduction number is influenced by different factors such as the region, race, sex, age and other factors which restrict it to employ in other places. Eventually, the results of the model were based on the daily and cumulative reports in different countries at the beginning of the COVID-19 outbreak. In this study, we intend to (1) test the applicability of the ELM technique to forecasting the certain cases of COVID-19, (2) optimize the ELM structure through employing a Social Spider Optimization (SSO) technique, and (3) examine the performance of our optimized ELM model and compare the results obtained with other optimization techniques.

The remainder of this paper is formulated as follows: section 2 illustrates the utilized Extreme Learning Machine (ELM) while the proposed intelligent predictor is presented in section 3. Section 4 discusses the results obtained from the implemented predictor and finally the main conclusions are drawn in section 5.

2. Extreme learning machine (ELM)

As illustrated in Fig. 1, the training procedure in stage 2 is performed through utilizing Extreme Learning Machine (ELM). ELM is extremely fast which attribute to a gradient descent feed-forward neural network since it outperforms the traditional back-propagation training algorithm in terms of generalization, falling into local minima, and over-fitting. Furthermore, ELM is consistent with commonly all non-linear activation functions.

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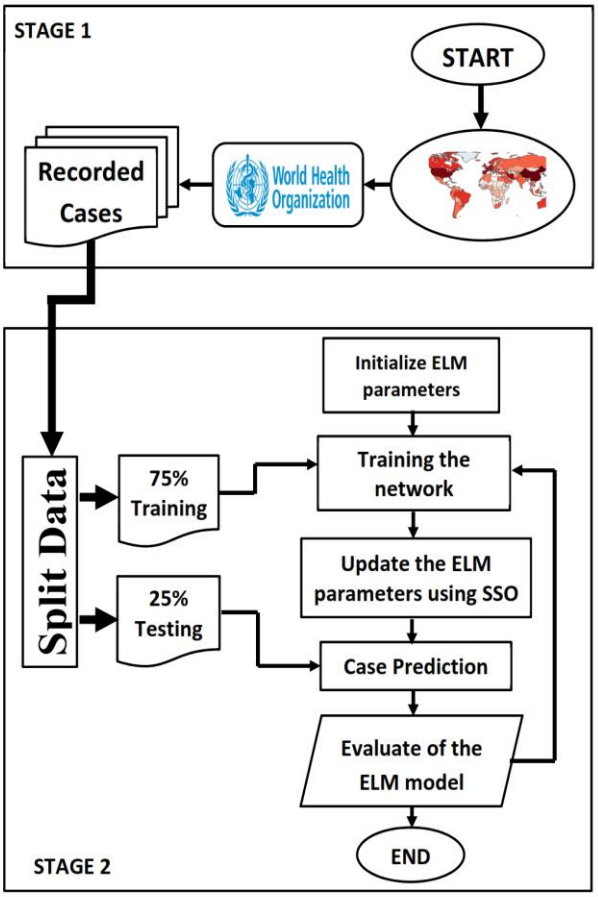

Figure. 1 The proposed SSO-ELM forecasting module

The structure of ELM model is illustrated in Fig. 2, while the details about the ELM structure are given as follows:

Considering N input and target samples (I_i, O_i), where $I_i = [I_{i1}\ , I_{i2}\ , \ldots, I_{in}]^T \in R^n$ and $O_i = [O_{i1}, O_{i2}, \ldots, O_{im}]^T \in R^m$, with $\hat{h}$ hidden nodes, while the activation function $f(x)$ can be expressed as [26]:

$$Activation\ Function = \sum_{i=1}^{h} W_i f_i(I_j) = \sum_{i=1}^{h} W_i\, f(w_{ei} I_j + Th_i) = d_i \quad (1)$$
$$j = 1, \ldots, N;$$

Where $W_i = [w_{ei1}, w_{ei2}, \ldots, w_{ein}]^T$ acts as the connection weights between the input nodes and the i^{th} hidden nodes while $W_i = [W_{i1}, W_{i2}, \ldots, W_{im}]^T$ represent the weight connection between the i^{th} hidden nodes and the output nodes as well, while Th_i is the threshold of the i^{th} hidden node. Here the conventional feed-forward neural network attempts to minimize the difference between d_j (i.e. desired output) and O_j (i.e. Actual output).

$$O_j = \sum_{i=1}^{h} W_i f(w_{ei} I_j + Th_i); \quad j = 1,2, \ldots, N \quad (2)$$

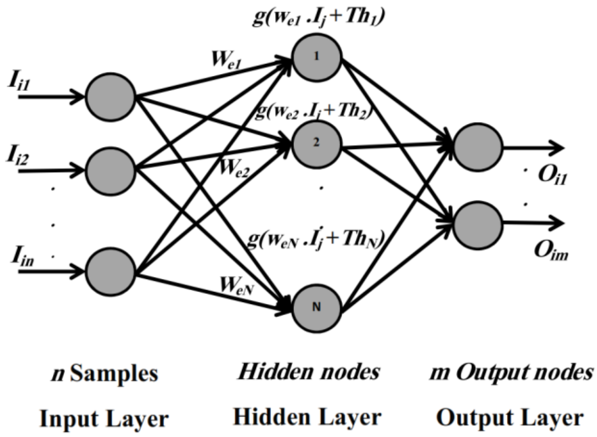

Figure. 2 Extreme learning machine structure [27]

Or can be expressed in matrix form as $HW_i = T$

$$H(w_{e1}, \ldots, w_{e\hat{N}}, Th_1, \ldots, Th_{\hat{N}}, I_1, \ldots, I_N) = \begin{bmatrix} f(w_{e1}I_1 + Th_1) & \cdots & f(w_{e\hat{N}}I_{\hat{N}} + Th_{\hat{N}}) \\ \vdots & \ddots & \vdots \\ f(w_{e1}I_N + Th_1) & \cdots & f(w_{e\hat{N}}I_N + Th_N) \end{bmatrix}_{N\times\hat{N}} \quad (3)$$

$$W = \begin{bmatrix} W_1^T \\ \vdots \\ W_{\hat{N}}^T \end{bmatrix}_{\hat{N}\times m} \quad and \quad T = \begin{bmatrix} O_1^T \\ \vdots \\ O_{\hat{N}}^T \end{bmatrix}_{N\times m} \quad (4)$$

Where H represent the feed-forward neural network output matrix and the i^{th} column of matrix H is defined as the i^{th} hidden node output which corresponds to inputs I_1, I_2, …, I_N. Hopefully, gradient learning algorithm can be utilized to find the minimum of $\|HW = T\|$ even if H is unknown. Actually, the proposed ELM network tries to reach the minimum training error. In addition to achieve smallest norm of output weights [25, 28, 29]. During minimization procedure through utilizing gradient learning algorithm, the vector w_e which includes the weights (w_{ei}, W) and biases (Th_i) parameters could be updated as follows:

$$w_{ek} = w_{e(k-1)} - \gamma \frac{\partial E(w_e)}{\partial w_e} \quad (5)$$

Where γ is the learning rate of the gradient-based algorithm. Back-propagation (BP) learning algorithm is considered as one of the most popular learning algorithm utilized in training the feed-forward neural network. However, it suffers from lack of high convergence, falling into local minima, and generalization issues. At the beginning of learning stage, all parameters are assigned randomly. Such as the weights of the inputs (w_{ei}) with the biases of the hidden layer (Th_i) and the hidden layer output matrix

(H). During the learning stage these parameters are updated in equivalent manner to find a least squares solution of the linear system $HW = T$.

$$\|H(w_{e1}, \dots, w_{e\tilde{N}}, Th_1, \dots Th_N)W - T\| = min_W \|H(w_{e1}, \dots, w_{e\tilde{N}}, Th_1, \dots Th_N)W - T\| \quad (6)$$

Consequently, if the entire number of hidden nodes ($\overline{N}$) is equal to the total number of separate training samples (N), then it results in a sequence and invertible matrix (H). In addition to, random initialization for the input weight vectors (w_{ei}) and the hidden biases (Th_i) ensures an accurate trained for the feed-forward neural network (FFNN) with high accuracy. However, if the number of hidden nodes is less than the number of the training samples (i.e. $\overline{N} < N$) then it results a non-square matrix (H) which will not satisfy the formula $HW = T$, which results in a solution equal to the linear system $W = H^*T$.

Where H^* is represent the Moore-Penrose generalization of the (H) matrix inverse [30]. This inverse matrix can be calculated utilizing various methods such as orthogonalization, iterative, orthogonal projection and singular value decomposition methods [31].

Actually, ELM can be utilized to train the FFNN in two phases; first phase includes the initializations of random feature mapping for the hidden layer in order to mapping the input data to useful features through utilizing a classical nonlinear mapping function. While computing the weights and thresholds of the hidden and output layer are computed through minimizing the approximation error in the squared error.

3. Design of the intelligent predictor

The proposed frame work consists of three modules as shown in Fig. 1. These modules are (1) Data collection, (2) Training phase, and (3) Testing phase. In this section, the proposed SSO-ELM method will be designed for predicting the confirmed cases of the COVID-19.

The SSO-ELM utilizes the Social Spider Optimization (SSO) to train the ELM network through optimizing its parameters. The SSO-ELM has three main layers as conventional ELM network. Layer 1 called the input layer which contains the input variables (Daily Recorded cases and the Accumulated cases), Layer 2 is called the hidden layer (i.e. may be more than one layer), and Layer 3 called the output layer which produces the forecasted values (i.e. predicted confirmed cases) as shown in Fig. 3. During the training phase, the SSO technique is utilized to decide the optimum number of hidden nodes in hidden layer. Besides, the recorded data is portioned into two parts: first part is for training (i.e.75%) and the second part for testing (25%).

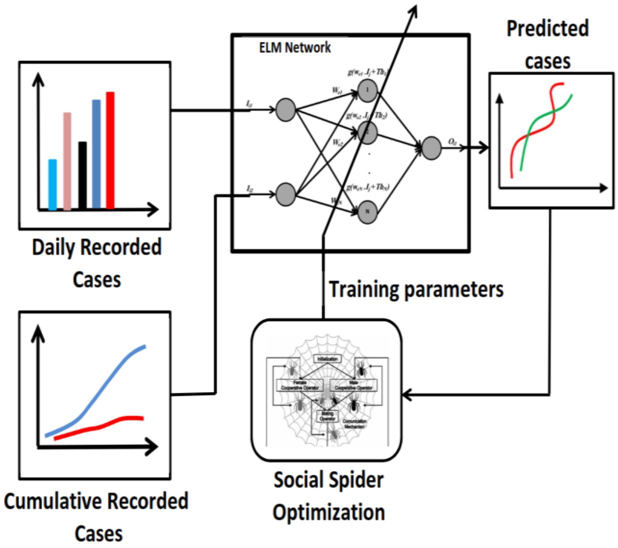

Figure. 3 Training the intelligent predictor

The number of hidden nodes in ELM network is prepared by SSO technique. Hence, in the training phase, the desired performance is calculated based on the error between the actual output and the desired output as shown in Eq. (7).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(A_i - T_i)^2 \quad (7)$$

Where A is the actual output, T is the desired output; N is the number of samples. Actually, the smallest value of the difference relates to better ELM parameters.

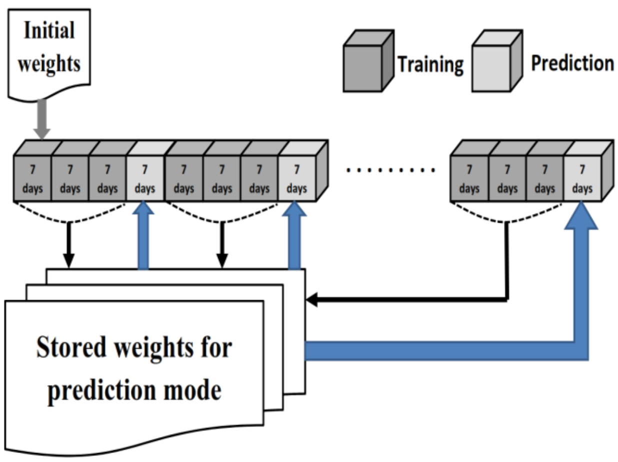

Figure. 4 Window based-ELM parameters updating strategy

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Here, the number of hidden neurons is increased in a range from 2 to 100 and the training procedure is continual until reaching the desired accuracy, which in this paper, is the maximum number of iterations.

Therefore, the optimum number of hidden neurons is passed to train the ELM network. After completing the training phase using data for three weeks, the intelligent predictor started with testing phase utilizing the optimized parameters in order to predict the estimated confirmed cases for the next 7 days as explained in Fig. 4. The performance of the intelligent predictor is evaluated through comparing the recorded cases with the predicted cases. Finally, the SSO-ELM predicts the confirmed cases of COVID-19 in the next few days.

4. Experimental results

The primary data set conducted in this study is COVID-19 recorded data set. This data set is obtained from the World Health Organization (WHO) reports. These reports contain daily confirmed cases including the infected cases, recovered cases, and death cases in most of the registered countries from 21th January 2020 to 7th June 2020. As shown in Fig. 1. 75% of these data is used for training phase and the rest 25% is used for testing phase. The performance assessment for the proposed intelligent predictor is assessed utilizing a set of performance metrics such as using the Root Mean Square Error (RMSE), Standard Deviation (STD), and the coefficient of determination (R^2) as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(A_i - T_i)^2} \tag{8}$$

$$STD = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|A - \mu|^2} \tag{9}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(A_i - T_i)^2}{\sum_{i=1}^{N}(A_i - \bar{A}_i)^2} \tag{10}$$

Where A and T are the forecasted and the original data values, respectively. $\bar{A}$ represent the average of A and μ is the mean value of the data set. Therefore, the lowest values of RMSE, and STD denotes to the optimum prediction method while greater value of R^2 refers to best correlation for the predictor.

The goal of the study is to determine the ability of the proposed SSO-ELM model to prognosis the COVID-19 through matching the obtained results with further optimization techniques, namely Genetic Algorithm (GA), and Particle Swarm Optimization (PSO). The parameters setting for these optimization techniques are listed in Table 1.

Table 1. Calibration parameters of the Optimization Techniques

Technique	Parameter	Values
GA	***Number of iteration***	100
	Population size	20
	Selection	Rank
	Crossover	Two-point crossover
	Crossover probability	0.5
	Mutation	Random
	Mutation probability	0.2
PSO	***Number of iteration***	100
	Population size	20
	Inertia weight factor (w)	0.4
	C1 and C2 acceleration	2
	Random number (R1 and R2)	1
SSO	***Number of iteration***	100
	Population size	50
	Female percent	88
	Male percent	12
	Pf	0.7

Table 2. Comparison results for influenza data sets

Technique	**RMSE**	**STD**	**R^2**	**Elapsed Time (sec)**
ELM	534	507	0.897	10.25
GA-ELM	427	389	0.981	73.47
PSO-ELM	409	377	0.953	29.32
SSO-ELM	351	319	0.985	27.49

As mentioned previously, a data set for influenza in United States of America (USA) from year 1999-2019 was conducted to forecast the new cases using the proposed SSO-ELM compared with other methods. It can be observed from Table 2 that the proposed SSO-ELM method has superior performance compared to other approaches in all measures, although the PSO-ELM is ranked second.

The achieved results show also that GA-ELM is ranked third in terms of RMSE, STD, R^2, and elapsed CPU time. On the other hand, comparison results obtained between the proposed SSO-ELM and other

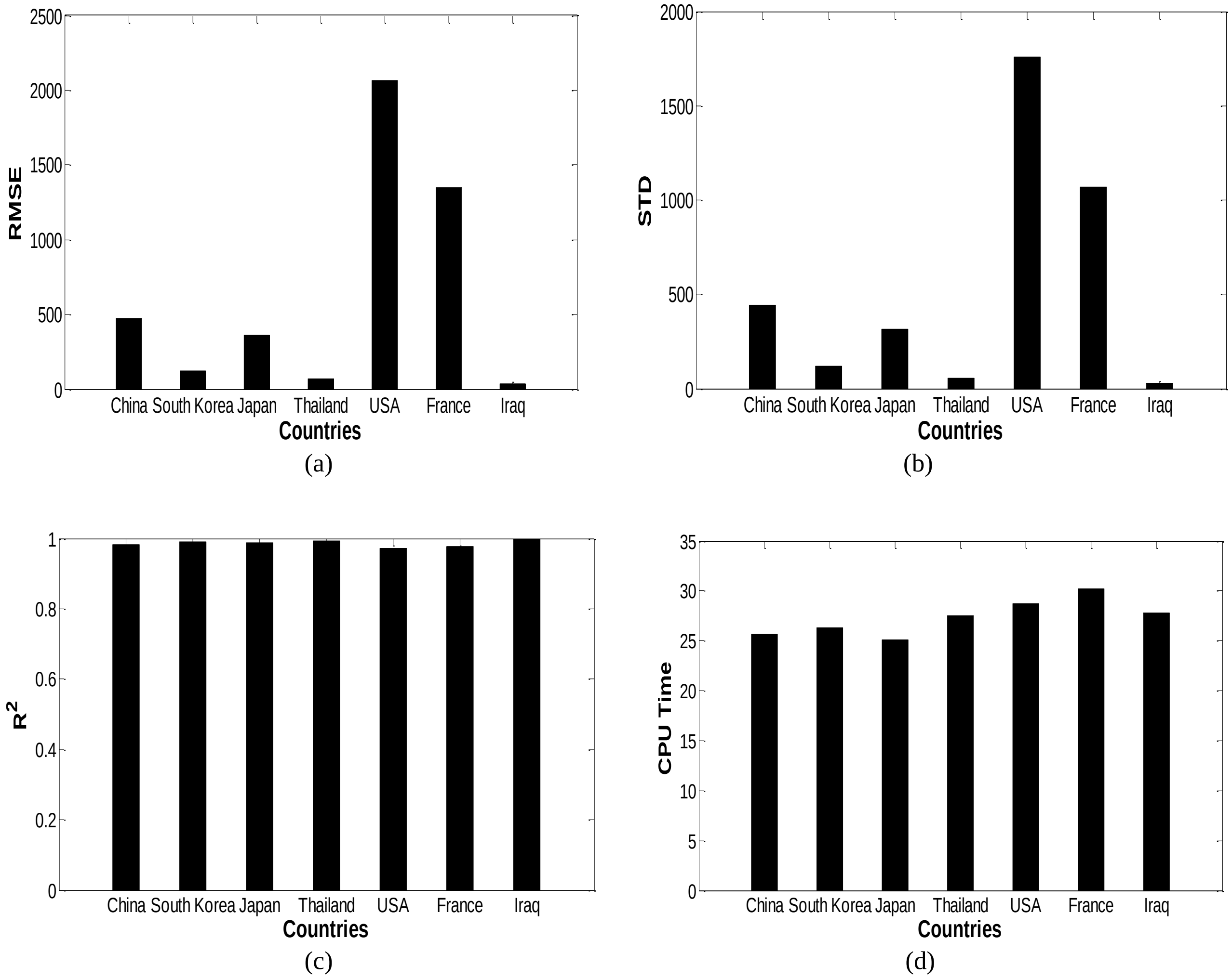

Figure. 5 Performance of the proposed SSO-ELM for various criteria: (a) root mean square error, (b) standard deviation, (c) correlation, and (d) CPU time

methods show that the proposed method outperforms these outcomes in terms of performance measures.

Comparison results for the performance of the proposed SSO-ELM for various countries to predict the confirmed cases of COVID-19 are given in Fig. 5. After analyzing the obtained results of RMSE, STD, R^2, and elapsed CPU time. Some points can be spotted such as SSO-ELM attains the smallest value amongst the compared techniques, and this denotes the high performance of the SSO-ELM. In the meantime, the GA-ELM ranked the second technique in providing better results than the rest of techniques. However, the time elapsed for reaching the target is longer than that of PSO-ELM.

Moreover, the coefficient of determination indicates a high correlation between the desired and predicted output results from the proposed SSO-ELM technique, which has approximately 0.979. In

Table 3. Comparison with previous work

Technique	Average RMSE
MLP [32]	394
ANFIS [33]	492
Proposed technique	351

addition to previous performance comparison, Fig. 6shows the outputs of the proposed technique using the historical data of COVID-19 corresponding to the forecasted cases for 7 days. In addition to previous discussed results. Table 3 shows clearly a comparison in order to assess the proposed technique against existing techniques such as MLP [32] and ANFIS [33].

According to the obtained results, hence, it can be observed that the suggested SSO-ELM has a great ability to predict the COVID-19 cases. The previous results indicate clearly the adequacies of other techniques in predicting COVID-19 cases.

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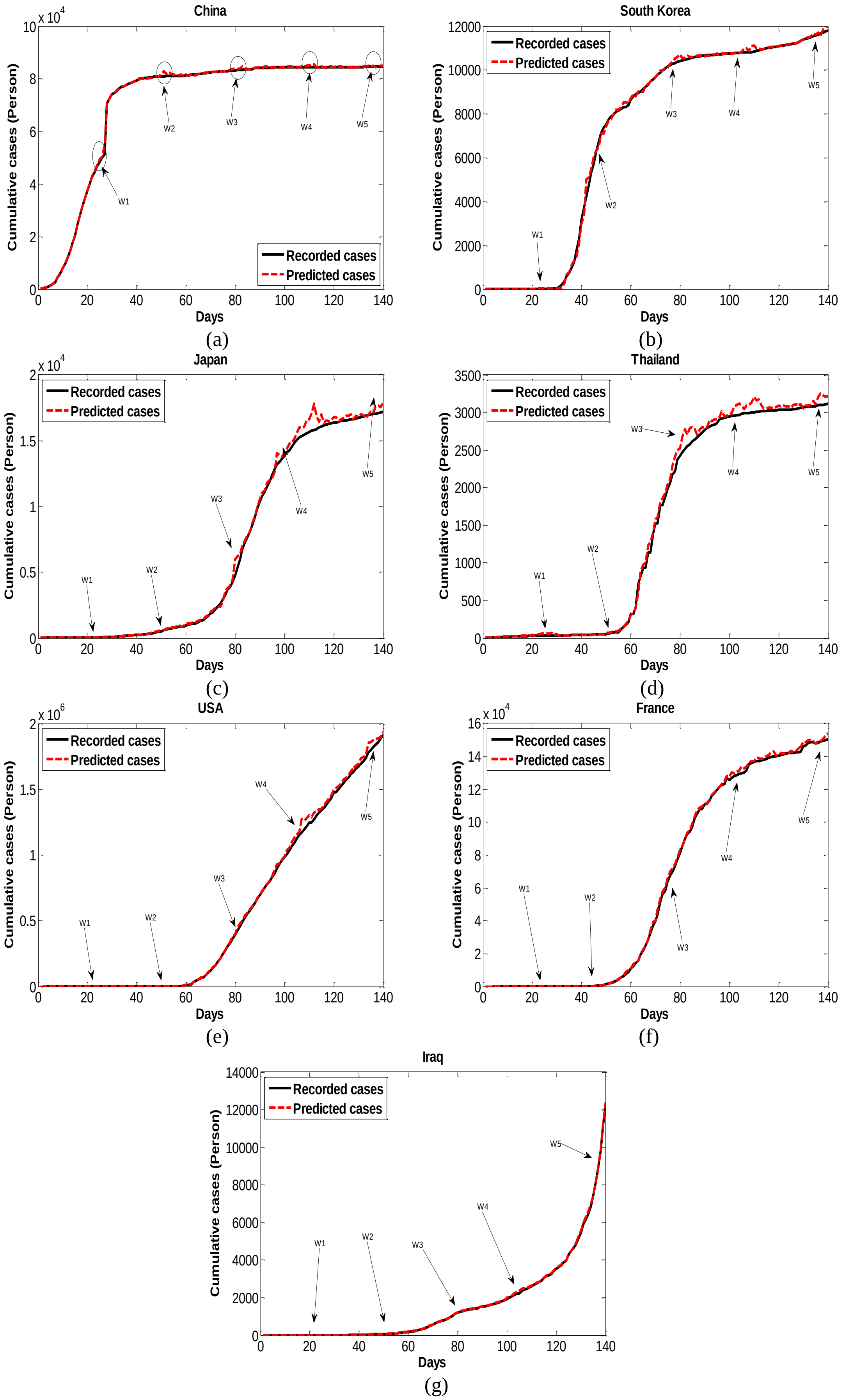

Figure. 6 Comparison between the desired output and actual output of the intelligent technique for different countries such as: (a) China, (b) South korea, (c) Japan, (d) Thailand, (e) USA, (f) France, and (g) Iraq.

5. Conclusions

This paper suggests using the SSO technique in order to optimize the ELM parameters and specifically the number of hidden neurons. The developed SSO-ELM is utilized in order to forecast the COVID-19 cases depending on a history cases recorded for previous five months that was discovered in various countries such as China, South Korea, Japan, Thailand, USA, France, and Iraq. These countries are chosen due to variance in cultural, citizen population, climate environments. The results show that the proposed SSO-ELM technique outperforms other techniques and reduces the estimation error by approximately 52%, 21%, and 16% against the implemented techniques (ELM, GA-ELM, PSO-ELM), respectively and by 12%, and 40% against (MLP and ANFIS) techniques. Therefore, the evaluations outcomes indicate clearly its good performance. Therefore, the promising results ensure the ability of the proposed SSO-ELM to use in other forecasting applications. Finally, COVID-19 outbreak in Wuhan, China, highlights the emergence of global surveillance of henipaviruses in bats, since these bats are the main hosts for this virus and many others. As a future plan of this work is to investigate some factors such as travelers, flight, inside and outside tourists, and business that have a great effect on economic during and after the epidemics for long term.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Ahmed M. Hasan and Zainab M. Hasan; methodology, Ahmed M. Hasan; software, Ahmed M. Hasan and Aseel G. Mahmoud; validation, Ahmed M. Hasan, Aseel G. Mahmoud, and Zainab M. Hasan; formal analysis, Ahmed M. Hasan; investigation, Zainab M. Hasan; resources, Zainab M. Hasan; data curation, Ahmed M. Hasan and Aseel G. Mahmoud; writing—original draft preparation, Ahmed M. Hasan; writing—review and editing, Ahmed M. Hasan and Aseel G. Mahmoud; visualization, Ahmed M. Hasan; supervision, Ahmed M. Hasan and Aseel G. Mahmoud; project administration, Ahmed M. Hasan; funding acquisition, not funded.

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