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Modelling and forecasting of COVID-19 spread using wavelet-coupled random vector functional link networks

Barenya Bikash Hazarika, Deepak Gupta *

Department of Computer Science & Engineering, National Institute of Technology Arunachal Pradesh, India

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ABSTRACT

Researchers around the world are applying various prediction models for COVID-19 to make informed decisions and impose appropriate control measures. Because of a high degree of uncertainty and lack of necessary data, the traditional models showed low accuracy over the long term forecast. Although the literature contains several attempts to address this issue, there is a need to improve the essential prediction capability of existing models. Therefore, this study focuses on modelling and forecasting of COVID-19 spread in the top 5 worst-hit countries as per the reports on 10th July 2020. They are Brazil, India, Peru, Russia and the USA. For this purpose, the popular and powerful random vector functional link (RVFL) network is hybridized with 1-D discrete wavelet transform and a wavelet-coupled RVFL (WCRVFL) network is proposed. The prediction performance of the proposed model is compared with the state-of-the-art support vector regression (SVR) model and the conventional RVFL model. A 60 day ahead daily forecasting is also shown for the proposed model. Experimental results indicate the potential of the WCRVFL model for COVID-19 spread forecasting.

1. Introduction

The coronavirus disease-2019 or simply COVID-19 eruption has not only disrupted the global healthcare networks but also it has demised the world economy. More than 690000 people died till date, and the total infected people are growing exponentially day by day as per reports. COVID-19 leads to a rigorous respiratory symptom, and it is linked with highly Intensive Care Unit (ICU) admissions and death. Individuals can turn out to be ill with the infection for 1 to 14 days before symptoms develop. The most widely recognized indications of COVID-19 ailment are fever, exhaustion and dry hack. The malady can be all the more once in a while extreme and even deadly. Older individuals, just as individuals with underlying disease, including hypertension, respiratory system disease and cardiovascular disease, may turn out to be progressively defenceless to extreme illness [1]. Machine learning (ML) methods have been extensively implemented for diagnosis and prediction of the most common illness, commonly diabetes, hepatitis, cancer, tumours, Parkinson and many more. Hence, the ML models can be a good alternative for the reverse transcription-polymerase chain reaction (RT-PCR) approach for early COVID-19 prediction. However, limited pieces of literature are available to our prior knowledge for COVID-19 prediction. The virus is novel, and we all have a little information about its characteristics. The authorities would like to know when this epidemic will come to an end and whether it is going to get worse. Forecasting is therefore very essential, even at the very least indications for consideration of multiple attributes over other societies and the public factors of health. In this case, the forecast using a single model is not enough. Therefore several prediction models need to be implemented so that the most reliable model can be chosen for the forecast [2].

1.1. Literature survey

A short time ago, Herlawati [3] tried to estimate the spread pattern of COVID-19 using the popular support vector regression (SVR) model with three different kernel functions that include the linear, radial basis function (RBF) and polynomial kernels. Experimental results reveal that the SVR model with RBF kernel was able to predict the pattern of spread of the global epidemic accurately. Al-Qaness et al. [4] used a hybrid ML model using adaptive neuro-fuzzy inference system (ANFIS) coupled with the improvised flower pollination algorithm (FPA) and salp swarm algorithm (SSA) called FPASSA-ANFIS for confirmed case prediction in China. The model showed excellent performance based on a few performance evaluation measures. Ardabili et al. [5] effectively predicted the COVID-19 outbreak using the multi-layer perceptron (MLP) and ANFIS model. Wang et al. [6] used a patient information based algorithm (PIBA) for real-time COVID-19 estimation. Very recently, Javid et al. [7] used the ELM model [8] using a sliding window method for COVID-19 time-series

* Corresponding author.
E-mail addresses: barenya1431@gmail.com (B.B. Hazarika), deepak@nitap.ac.in (D. Gupta).

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Table 1
Few prominent works for COVID-19 prediction using machine learning/AI models.

Sl no	Reference	Country	Machine learning / AI Models	Merits	Demerits/Limitations
1.	Herlawati [3]	Indonesia	SVR	High generalization ability and can handle the non-linearity using kernels.	Not suitable for large scale datasets
2.	Al-Qaness et al. [4]	China	FPASSA-ANFIS	High prediction ability	High computational cost
3.	Ardabili et al. [5]	Italy, Germany, Iran, USA and China	MLP and ANFIS	High generalization ability for long term prediction.	High computational cost
4.	Chakraborty and Ghosh [17]	India, UK, Canada, France and South Korea	Wavelet-ARIMA-Regression tree hybrid model	High prediction ability.	Long term prediction yet to be tested
5.	Wang et al. [6]	China	PIBA	Good prediction performance.	Dependent on accurate patient information at the beginning of the epidemic
6.	Javid et al. [7]	Sweden, Denmark, Finland, Norway, France, Italy, Spain, UK, China, India, Iran, USA	ELM	Fast and efficient. Able to handle the stationarity of datasets.	Long term prediction yet to be tested
7.	Pinter et al. [9]	Hungary	MLP-ICA and ANFIS based hybrid models	Good generalization ability.	If the prevention regime changes, the MLP-ICA model will not maintain its accuracy
8.	Zheng et al. [10]	China	LSTM based hybrid model	Significantly reduces the error of prediction.	Long term prediction yet to be tested
9.	Tomar and Gupta [11]	India	LSTM and curve fitting	High prediction ability.	Limited data availability
10.	Ribeiro et al. [12]	Brazil	ARIMA,CUBIST,RF,RR, SVR and SEL	Good prediction performance.	Long term prediction yet to be tested
11.	Rafiq et al. [13]	India	SISO	The disease variations are accurately captured.	Limited data availability
12.	Chimmula and Zhang [18]	Canada	LSTM	Can handle the nonlinearity, high prediction performance.	Limited data availability

forecasting to avoid the overfitting of data. A sliding window approach is also used to handle the non-stationarity of data. Pinter et al. [9] tried to predict the COVID-19 pandemic using ANFIS as well as MLP-imperialist competitive algorithm (MLP-ICA) models. Zheng et al. [10] and Tomar and Gupta [11] used hybrid long short term memory (LSTM) models for COVID-19 prediction. Ribeiro et al. [12] implemented several machine learning models for estimating COVID-19. They are autoregressive integrated moving average (ARIMA), ridge regression (RR), cubist (CUBIST), random forest (RF), SVR and stacking-ensemble learning (SEL) model. Rafiq et al. [13] used a single input single output (SISO) based machine learning model for COVID-19 estimation. One can find a few relevant pieces of literature in Fong et al. [14], Mahalle et al. [15] and Lalmuanawma et al. [16]. Table 1 shows selected works on the prediction of COVID-19 using machine learning/ artificial intelligence (AI) models.

There are limited data available on outbreaks of COVID-19 epidemics, making predictions widely uncertain. It was evident from the recent studies that the timing and location of the outbreak enabled the virus' fast transmission within an extremely mobile population [19]. In highly affected countries, in subsequent days of initial transmission of the virus, the governments enforced a lockdown and in hospitals, patients who satisfy the clinical and epidemiological characteristics of COVID-19 are isolated immediately. Various machine learning models have been applied to provide both short term and long term forecast of reported cases to tackle the epidemic. These models prediction shows a high level of variations [17]. Since the COVID-19 time series data contain both nonlinear and non-stationary trends, it would be critical to make decisions based on a single model. This motivated us to propose an alternative hybridization-based forecasting system. Through incorporating the strengths of two different models, i.e., wavelets and RVFL, the proposed method eliminates the weaknesses of conventional techniques. To handle the nonlinearity and non-stationary trends in datasets, wavelets are very efficient model [20,21]. On the other hand, the RVFL is a powerful ML model that adapts the empirical risk minimization principle and shows a high generalization performance. Hence, the main contributions of this work are:

- A wavelet coupled random vector functional link network (WCRVFL) model is proposed.
- The wavelet decomposed time-series data is directly provided as an input to the RVFL model.
- The time-series of top 5 worst-hit countries with the most number of cases as on 10th July 2020 are provided as an input to the model.
- A 60-day ahead prediction is portrayed for each country using both, RVFL and the WCRVFL model to show the forecasting of the disease spread.

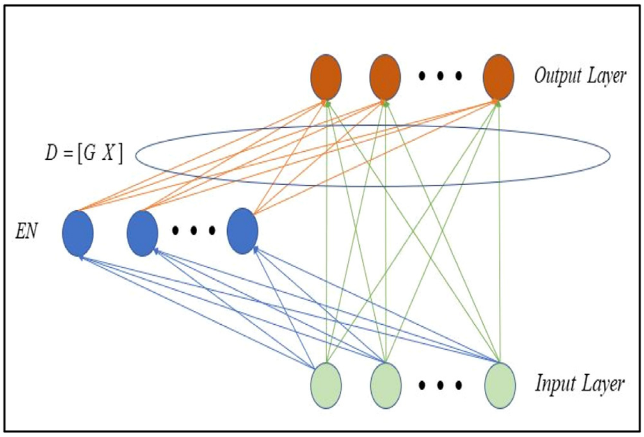

Fig. 1. Structure of the RVFL network with direct links [26]. Here, the green line from input to the output layer indicates the direct link.

Table 2
R^2 values obtained by SVR, RVFL and the best WCRVFL models for the reported countries (Best results are bolded).

Country	SVR	RVFL		Best WCRVFL	
		RELU	Sigmoid	RELU	Sigmoid
BRAZIL	0.99733	0.99909	0.99891	0.99955	**0.99975**
INDIA	0.94149	0.99995	0.99993	**0.99996**	0.99994
PERU	0.99277	0.99874	0.99849	**0.99986**	0.99975
RUSSIA	0.99818	0.99909	**0.99999**	0.99941	0.99873
USA	0.99923	0.99988	0.99986	**0.9999**	0.99989

Table 3
RMSE values obtained by SVR, RVFL and the best WCRVFL models for the reported countries (Best results are bolded).

Country	SVR	RVFL		Best WCRVFL	
		RELU	Sigmoid	RELU	Sigmoid
BRAZIL	0.03011	0.0702	0.03048	0.00602	**0.00323**
INDIA	0.01519	**0.00147**	0.00381	0.0021	0.00198
PERU	0.04647	0.03173	0.01307	0.00243	**0.00197**
RUSSIA	0.03202	0.00469	0.00036	0.0003	**0.00029**
USA	0.06403	0.01654	0.01539	0.00617	**0.00524**

Section 2 describes the related works. In Section 3, the proposed WCRVFL model is explained. The experimental study and datasets are explained in Section 4. Finally, Section 5 describes the conclusion of this work in brief.

2. Related works

2.1. Random vector functional link networks

RVFL [22–24] is a special single hidden layer feed-forward neural network (SLFN) that was proposed by Pao et al. [22], where the output weights are chosen as an adaptable parameter [25]. The structure of the RVFL network is presented in Fig. 1. Here, the input layer neurons have direct links to the output layer. In addition to the input layer nodes and the output node, there exists some special type of nodes known as the enhancement nodes (ENs) which composite the hidden layer of RVFL network. A suitable activation function $a(.)$ maps the input data to the ENs.

Now let us consider an SLFN with training samples N such that $X = \{(x_i, y_i)\}_{i=1}^{N}$ where $x_i \in \Re^d$ and $y_i \in \Re^e$ are d and e dimensional input and output vectors respectively. Let $\beta = \Re^{N_g \times e}$ represents the output weight matrix and $Y = \Re^{N \times e}$ is the output target matrix. g denotes the hidden layer output. The RVFL model that has been used in this work solves the following optimization problem:

$$\min_{\beta} \|D\beta - Y\|^2, \tag{1}$$

where $D = [GX]$ is the augmentation of input and hidden features. The hidden layer output matrix $G \in \Re^{N \times N_g}$ can be represented by:

$$G = \begin{bmatrix} g_1(x_i)\ldots & g_{N_g}(x_1) \\ g_1(x_2)\ldots & g_{N_g}(x_2) \\ . \quad . & . \\ . \quad\quad . & . \\ . \quad\quad\quad . & . \\ g_1(x_N)\ldots & g_{N_g}(x_N) \end{bmatrix}. \tag{2}$$

The hidden layer weights are randomly generated. Only the output layer weight vector β is needed to be learned. Typically the above equation can be solved by using the Moore–Penrose pseudo inverse (MPPI). Hence, after applying the MPPI, the required solution can be obtained as:

$$\beta = D^{\dagger} Y, \tag{3}$$

where $D^{\dagger}$ is the MPPI of D.

2.2. Wavelet analysis

Due to its multi-resolution and localization ability in both, time and frequency domain, wavelet analysis presents a more balanced way of decomposing signals. Wavelet analysis helps in localizing the several features of a signal in time. In wavelet transform, the analysing functions known as wavelets adjust the time width to the respective frequencies in such a way that higher frequency will be narrow while the low-frequency components are wide [20]. Therefore it can be considered as a more powerful tool compared to Fourier transform (FT) for analysing the time series data. WT can be majorly classified into two types: (a) Continuous WT and (b) Discrete WT.

2.2.1. Continuous WT (CWT)

The CWT of a continuous-time signal $x(t)$ may be expressed as:

$$C(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} \psi^* \left(\frac{t-b}{a}\right) x(t).dt \tag{4}$$

where * indicates the complex conjugate and $\psi(t)$ indicates the mother wavelet function [27,28]. The dilation factor is represented by a while b is the temporal translation of $\psi(t)$. The inverse CWT can be used to reconstruct the signal as,

$$x(t) = \frac{1}{c_\psi} \int_{-\infty}^{\infty} \int_{0}^{\infty} \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a}\right) C(a, b) \frac{da.db}{a \times a} \tag{5}$$

2.2.2. Discrete WT (DWT)

The DWT of a discrete-time signal has the form:

$$\psi_{p,q}(t) = \frac{1}{\sqrt{a_0^p}} \psi \left(\frac{t - qb_0 a_0^p}{a_0^p}\right) \tag{6}$$

The p and q are parameters that control a and b. Here $a_0 > 0$ and $b_0 > 1$ are the localization parameter and user-specified dilation step respectively. The original signal can be recreated using the inverse DWT as:

$$x_i = \overline{D} + \sum_{p=1}^{P} \sum_{q=0}^{2^{P-p}-1} D_{p,q} 2^{-p/2} \psi(2^{-p} i - q) \tag{7}$$

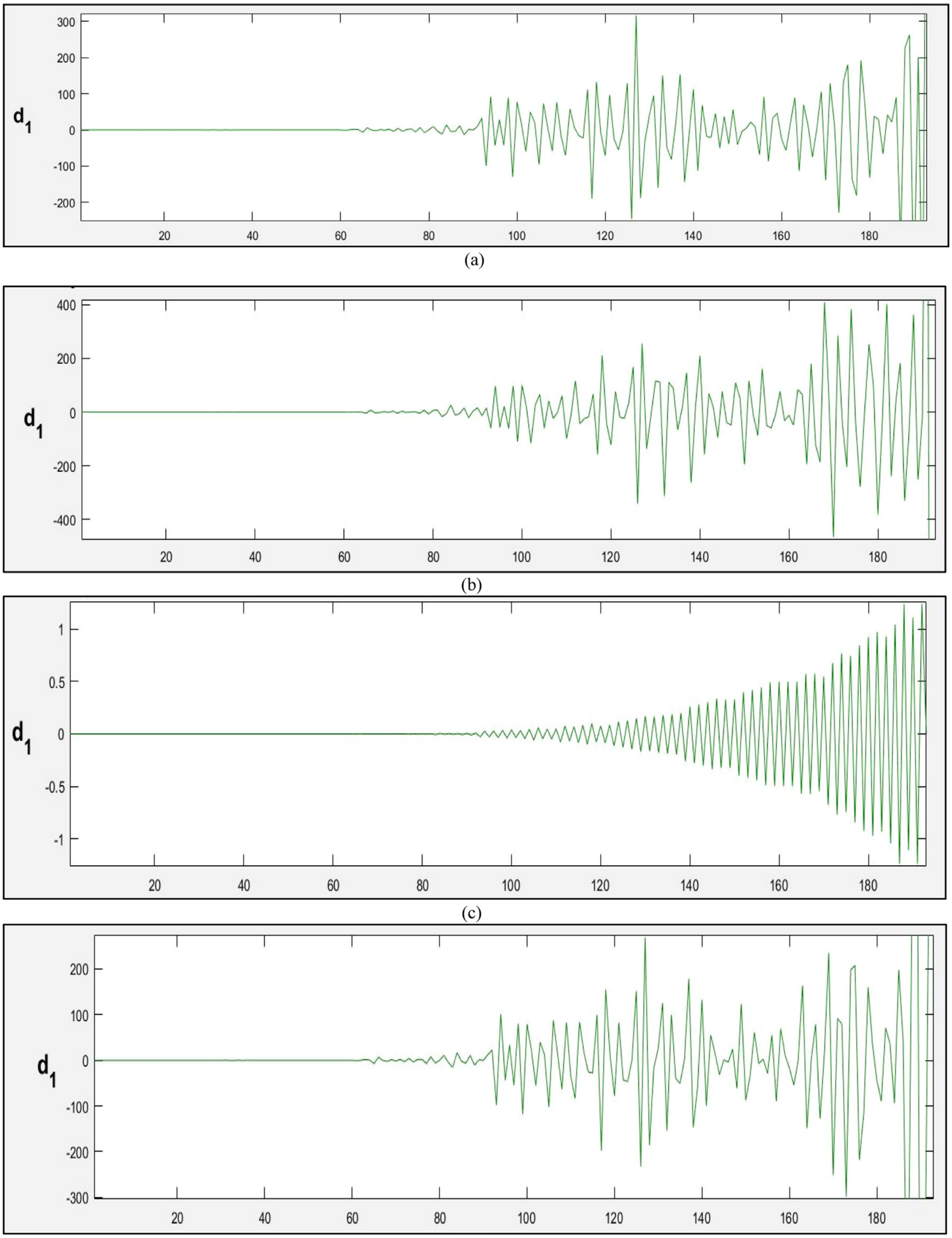

Fig. 2. Decomposition at level 1 using db8, coif2, haar and sym5 wavelet.

Eq. (7) can be rewritten in a simplified form as :

$$x_i = \overline{D}(t) + \sum_{p=1}^{P} \sum_{q=0}^{2^{P-p}-1} W_p(t) \tag{8}$$

$\overline{D}(t)$ indicates the approximation sub-signal of D and level 2^P and $W_p(t)$ is the detailed sub-signal at levels $p = 1, 2, \ldots, P$. The dyadic wavelet transform D that can be represented as [29]:

$$D_{p,q} = 2^{-p/2} \sum_{i=0}^{2^P-1} \psi(2^{-p}i - q)x_i \tag{9}$$

where $i = 0, 1, 2, \ldots, 2^P$.

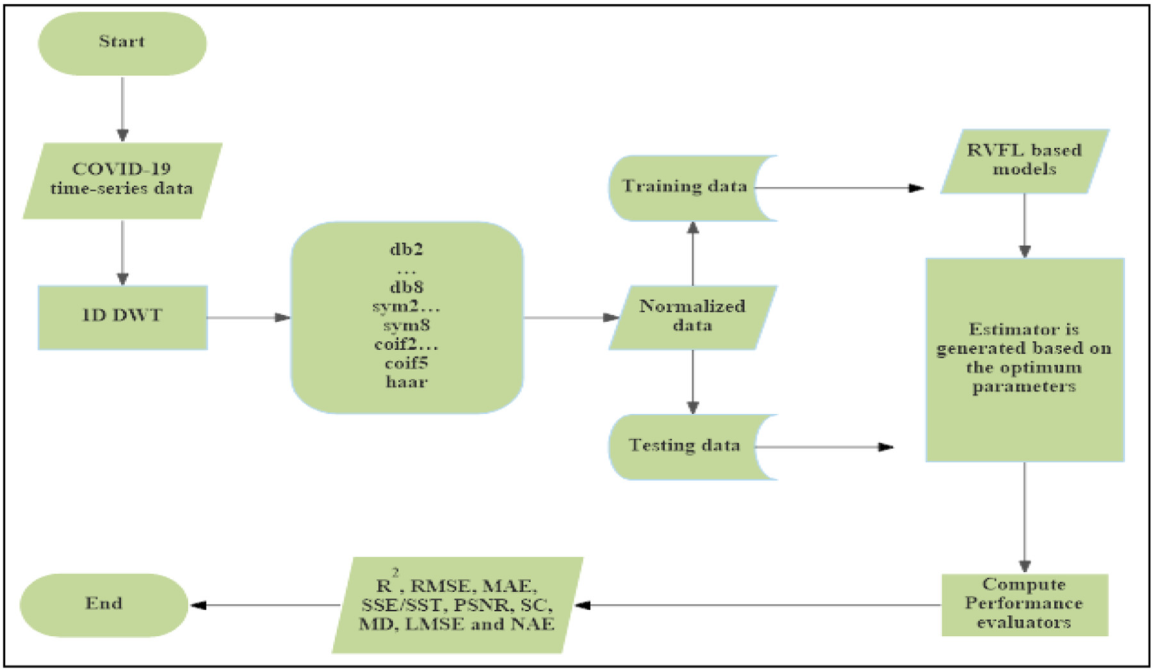

Fig. 3. Schematic diagram of the proposed WCRVFL.

There are several types of mother wavelets such as Daubechies (Db), Coiflet (Coif), Symlets (Sym), Haar etc. Because of its inherent capability in discovering the time localization information, Db achieves good results in several regression processes such as sediment transport [20]. On the other hand, the Coif is more symmetrical compared to Db wavelet. Moreover, Sym is the modified version of Db with increase symmetry. Hence the appropriate selection of mother wavelet is dependent on the characteristics and the type of application.

3. Proposed wavelet-coupled RVFL network

This section expresses the proposed WCRVFL network. In the proposed WCRVFL, the time series data based on a daily number of COVID-19 infected people are decomposed using a 1-dimensional discrete wavelet transform (1D DWT). For decomposition, we have used 19 types of wavelets. They are db2, db3, db4, db5, db6, db7, db8, coif2, coif3, coif4, coif5, haar, sym2, sym3, sym4, sym5, sym6, sym7 and sym8. The decomposed data for INDIA dataset using db8, coif2, haar and sym5 are portrayed in Fig. 2. In Fig. 2, the $x-$axis indicates the day-wise decomposition while in the $y-$axis, $d_1$indicates the decomposition at level 1. The level 1 approximation obtained after decomposing the data are provided as an input to the conventional RVFL model (Eqs. (1)–(3)). The estimator of the RVFL model is obtained based on the optimum parameter. The model performance is evaluated using 9 different performance evaluators. The descriptions of the evaluators are explained in Section 4. The developed schematic diagram of the proposed model is shown in Fig. 3.

4. Experimental study and datasets

All the experiments are performed in a Windows 7 OS computer with 8 GB RAM and 1 TB ROM enriched with i5 processor with a processing speed of 1 GHz/second. The institutional licenced MATLAB-2019 software has been used for these experiments. The 10-fold cross-validation method is considered for optimal parameter selection. In 10-fold cross-validation, the dataset is split into 10 parts. One part is for training and remaining parts for testing. This process is repeated for 9 more times until all the parts are trained at least once. Moreover, the MATLAB wavelet toolbox was used for implementing the various wavelets. Let x be an input sample. The datasets are also normalized by considering $\bar{x}_{lm} = \frac{x_{lm}-x_m^{\min}}{x_l^{\max}-x_m^{\min}}$, $\bar{x}_{lm}$ is the normalized value of x_{lm}. $x_l^{\max}$ and $x_m^{\max}$ are the maximum and minimum values respectively. As per the selection of the activation function, 2 popular activation functions i.e., RELU and Sigmoid are used. These activation function definitions can be expressed as:

(a) *RELU function:* $f(x) = \max(0, x)$
(b) *Sigmoid function:*$f(x) = \frac{1}{1+e^{-x}}$

where $f(x)$ depicts the output function for the input sample x. To validate the efficiency of the RVFL and the wavelet coupled RVFL model, 4 performance evaluators has been used. They are: coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), the ratio between the sum of squared error and the total sum of squares (SSE/SST), peak signal to noise ratio (PSNR), structural content (SC), the maximum difference (MD), Laplacian mean squared error (LMSE) and normalized absolute error (NAE). Their definitions can be given as:

- $R^2 = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}(o_i-\hat{o}_i)^2}{\frac{1}{N}\sum_{i=1}^{N}(o_i-\bar{o}_i)^2}$,
- $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(o_i - p_i)^2}$,
- $MAE = \frac{1}{N}\sum_{i=1}^{N}|o_i - p_i|$,
- $SSE/SST = \frac{\frac{1}{N}\sum_{i=1}^{N}(o_i-\hat{o}_i)}{\frac{1}{N}\sum_{i=1}^{N}(o_i-\bar{o}_i)}$,
- $PSNR = 10\log 10\left(\frac{\max_i^2}{\sqrt{(o_i-p_i)}}\right)$,
- $SC = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}o_i^2}{\frac{1}{N}\sum_{i=1}^{N}p_i^2}$,
- $MD = \frac{1}{N}\max\left(\sum_{i=1}^{N}(o_i - p_i)\right)$,
- $LMSE = \frac{\frac{1}{N}\sum_{i=1}^{N}(o_i-p_i)^2}{\frac{1}{N}\sum_{i=1}^{N}(o_i)^2}$,
- $NAE = \frac{1}{N}\sum_{i=1}^{N}\frac{|o_i-p_i|}{o_i}$,

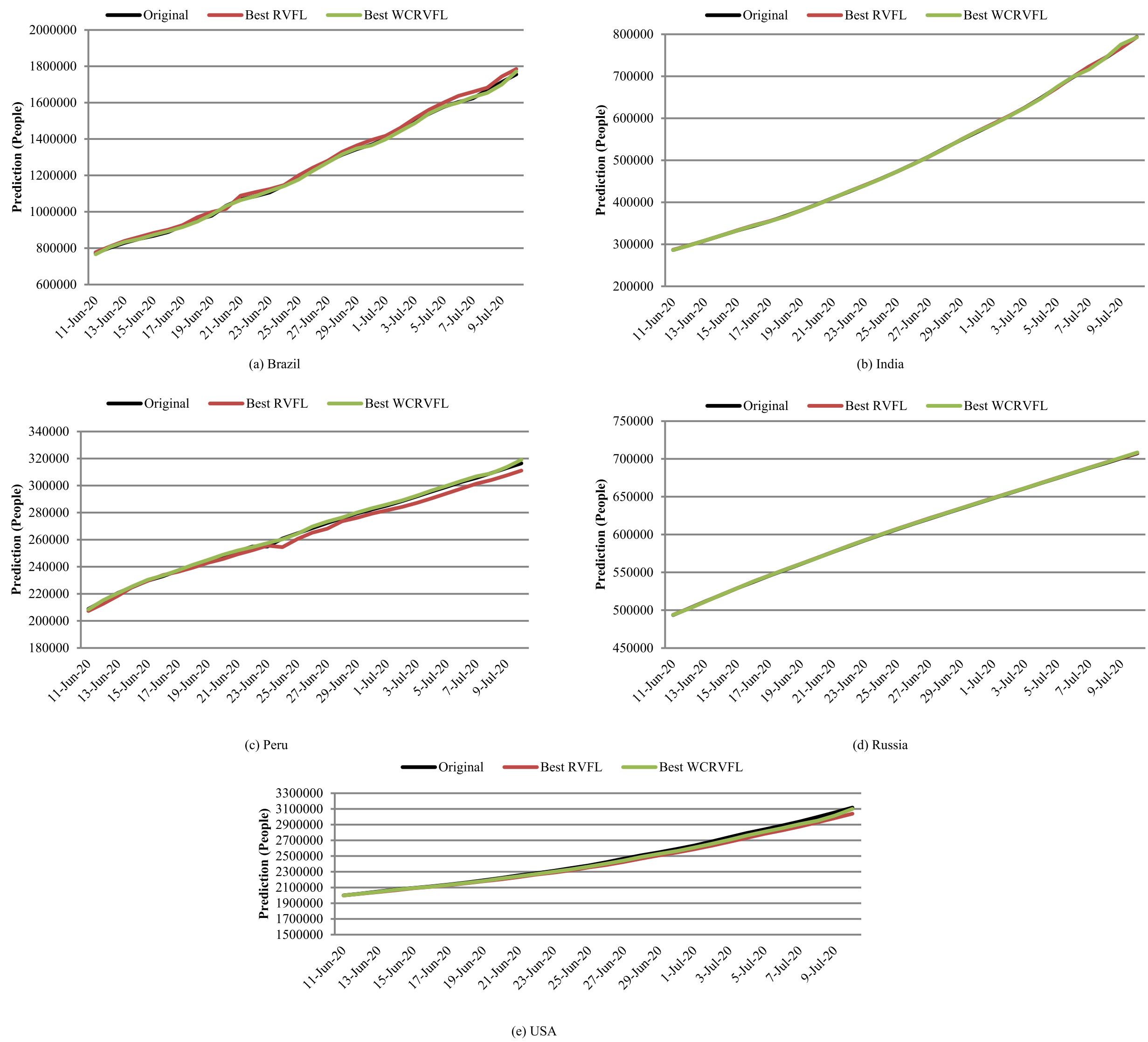

Fig. 4. Daily prediction over the testing sample from 11th June 2020 to 10th July 2020 using RVFL and WCRVFL models.

where,
p = predicted values,
o= *observed values,*
$\overline{o}$ = Average of o,
$\hat{o}$ = Estimated value of o,
max= maximum possible value,
N= total number of samples.

4.1. Experiment on COVID-19 time series dataset

The COVID-19 time series dataset is obtained from https://ourworldindata.org/coronavirus-source-data. The dataset consists of the cumulative number of cases reported daily for different countries. In this work, we used the data for the top 5 worst-hit countries as per the report on 10th July 2020. They are Brazil, India, Peru, Russia and the USA. Given the current day, the index is d, the number of cases for $d + \tau$ days is predicted by considering input from past ν days, i.e., for $d - \nu + 1$ to d days.

4.1.1. Modelling based on time-series data from 11th April 2020 to 10th July 2020

Ninety days cumulative data starting from 11th April 2020 to 10th July 2020 is considered for modelling the COVID-19 spread in 5 countries. For this purpose, the first 60 days data is considered for training and the remaining 30 days for testing. The experimental results of the WCRVFL model are compared with conventional SVR and RVFL models and are exhibited in Tables 2 and 3 respectively based on R^2 and RMSE. It is revealed from Tables 2 and 3 that the proposed WCRVFL model shows the best performance in 4 and 4 cases respectively out of the total 5 cases based on R^2 and RMSE respectively. Further the original versus the predicted values over testing data are also portrayed in Table 4 daily for the best RVFL model and the best WCRVFL model. Further to visualize the predicted values over testing data, the original versus predicted data are shown in Fig. 4 for each country. One can say from Table 4 and Fig. 4 that the proposed WCRVFL model has a close relationship with the original data which reveals the efficiency of the WCRVFL model.

4.1.2. A 60 days ahead forecasting based on data from 31st December 2019 to 10th July 2020

Moreover, Table 5 reveals the prediction errors using 9 performance evaluators for the WCRVFL models. Table 6 shows the average ranks based on various evaluators for the WCRVFL network. One can say from Tables 5 and 6 that the DB8 wavelet shows the best results for 7 evaluators except for MD and LMSE

Table 4
Original versus predicted values obtained by the best RVFL model and the best WCRVFL model (Based on RMSE) daily from 11 June 2020 to 10 July 2020.

Date	Brazil (People)			India (People)			PERU (People)			RUSSIA (People)			USA (People)		
	Original	Best RVFL	Best WCRVFL	Original	Best RVFL	Best WCRVFL	Original	Best RVFL	Best WCRVFL	Original	Best RVFL	Best WCRVFL	Original	Best RVFL	Best WCRVFL
11-Jun-20	772416	777399	766135	286579	287164	286478	208823	207301	208467	493657	494042	493850	2000464	1998276	1999357
12-Jun-20	802828	809528	806683	297535	297252	297170	214788	212619	215258	502436	502208	502066	2023347	2019825	2021393
13-Jun-20	828810	839429	833386	308993	308857	309234	220749	218606	220538	511423	511164	511273	2048986	2042262	2044923
14-Jun-20	850514	861631	850075	320922	320944	320808	225132	225300	225778	520129	520424	520272	2074526	2066338	2071958
15-Jun-20	867624	883287	872433	332424	333312	332543	229736	229648	230455	528964	529034	528972	2094069	2090286	2093165
16-Jun-20	888271	901159	892923	343091	344770	344086	232992	233850	233527	537210	537837	537790	2114026	2108927	2110203
17-Jun-20	923189	926394	915765	354065	354920	353838	237156	236210	237333	545458	545792	545729	2137731	2129082	2133155
18-Jun-20	955377	969258	945566	366946	365990	365848	240908	239339	241441	553301	553858	553641	2163290	2154459	2158091
19-Jun-20	978142	998116	984350	380532	380202	380669	244388	242911	244968	561091	561489	561369	2191052	2179307	2184218
20-Jun-20	1032913	1016758	1031320	395048	394758	394723	247925	245656	248793	569063	569141	568878	2220961	2204834	2214429
21-Jun-20	1067579	1088262	1063837	410461	409995	410092	251338	249222	251962	576952	577223	577060	2255119	2233012	2243309
22-Jun-20	1085038	1107601	1085728	425282	426278	425928	254936	252231	254560	584680	585146	585026	2280912	2265165	2271580
23-Jun-20	1106470	1124089	1114255	440215	441065	439968	254936	255586	257473	592280	592754	592543	2312302	2289996	2301591
24-Jun-20	1145906	1146836	1140963	456183	456000	455767	260810	254488	260248	599705	600229	600092	2347022	2319532	2332025
25-Jun-20	1188631	1199788	1176934	473105	472782	473073	264689	260538	264339	606881	607524	607270	2381361	2355993	2366536
26-Jun-20	1228114	1243488	1226081	490401	490643	490162	268602	265147	269670	613994	614513	614355	2422310	2387848	2404396
27-Jun-20	1274974	1280490	1270939	508953	508479	508634	272364	268115	273404	620794	621524	621217	2467837	2426100	2445015
28-Jun-20	1313667	1329682	1315840	528859	527964	528233	275989	273616	276421	627646	628141	627920	2510323	2469932	2489965
29-Jun-20	1344143	1364092	1348137	548318	549129	548714	279419	276157	280107	634437	634937	634764	2548996	2509115	2529139
30-Jun-20	1368195	1394214	1364456	566840	568767	568047	282365	279297	283285	641156	641729	641439	2590552	2545788	2564008
1-Jul-20	1402041	1417477	1398589	585493	586731	585241	285213	281783	286024	647849	648400	648148	2634432	2587876	2608818
2-Jul-20	1448753	1460628	1442932	604641	605435	604528	288477	284169	288987	654405	655060	654776	2686480	2632352	2658005
3-Jul-20	1496858	1514128	1486385	625544	625119	624785	292004	287182	292506	661165	661537	661439	2739879	2681833	2707503
4-Jul-20	1539081	1561805	1540725	648315	647312	646860	295599	290586	296350	667883	668380	668054	2794321	2732534	2761961
5-Jul-20	1577004	1600180	1578370	673165	671767	674537	299080	294224	299817	674515	675152	674819	2839542	2782716	2810245
6-Jul-20	1603055	1636815	1599729	697413	698394	698627	302718	297793	303483	681251	681722	681558	2888635	2827115	2855721
7-Jul-20	1623284	1659445	1630333	719665	722939	716028	305703	301408	306881	687862	688490	688174	2938625	2875669	2906090
8-Jul-20	1668589	1682057	1653695	742417	743982	742260	309278	304114	309141	694230	695072	694813	2996098	2928107	2949038
9-Jul-20	1713160	1743608	1699748	767296	766788	775379	312911	307454	313566	700792	701261	701714	3055004	2983053	3015773
10-Jul-20	1755779	1784987	1771436	793802	793348	792866	316448	311088	319128	707301	707862	708595	3118008	3039759	3100233

Table 5
Performance evaluators obtained for various countries using WCRVFL model (Best results are bolded).

	Dataset	Activation function	DB2	DB3	DB4	DB5	DB6	DB7	DB8	HAAR	COIF2	COIF3	COIF4	COIF5	SYM2	SYM3	SYM4	SYM5	SYM6	SYM7	SYM8
RMSE	BRAZIL	RELU	0.02866	0.0247	0.04669	0.05256	0.01666	0.04674	0.06146	0.02876	0.04117	0.09416	0.07467	0.03977	**0.00787**	0.01268	0.00848	0.03933	0.15719	0.02837	0.10706
		SIGMOID	0.00828	0.0067	0.01809	0.01768	0.01307	0.01249	0.00704	0.01733	0.00672	0.01582	0.01311	0.00662	0.01825	0.00936	0.00715	0.00818	0.00649	0.00998	**0.00619**
	INDIA	RELU	0.02935	0.00488	0.00374	0.02925	0.01579	0.06699	0.01486	0.04276	0.05389	0.09528	0.02945	0.03851	0.02623	0.09798	0.00374	0.00949	0.03367	0.04584	**0.00349**
		SIGMOID	0.00247	0.00325	0.00273	0.0023	0.00417	0.002	0.00195	0.00335	0.00237	0.00616	0.00214	0.00416	0.00237	0.00397	0.00572	**0.00156**	0.00419	0.00313	0.00385
	PERU	RELU	0.04414	0.06863	0.12994	0.01069	0.02503	0.11371	0.10888	0.0061	0.01719	**0.00452**	0.01729	0.19487	0.02791	0.03794	0.06914	0.00871	0.1022	0.01196	0.18366
		SIGMOID	0.01546	0.0323	0.00421	0.01102	0.00424	0.01532	0.01381	0.00994	0.00332	0.00262	0.01635	0.0055	0.01095	0.05982	0.00525	0.07387	**0.00247**	0.00531	0.00681
	RUSSIA	RELU	0.00712	0.02445	0.04919	0.09504	0.02658	0.01571	0.0072	0.00643	0.01551	0.01403	0.01435	0.1303	0.0447	**0.00513**	0.06249	0.07127	0.06244	0.01369	0.00972
		SIGMOID	0.02551	0.00818	0.02901	0.03111	0.00566	0.00517	**0.00508**	0.03269	0.02669	0.0344	0.02301	0.02475	0.03339	0.03085	0.00549	0.00594	0.03229	0.00741	0.03083
	USA	RELU	0.00416	0.03952	0.01972	0.0791	0.00127	0.01588	0.01289	0.01372	0.02157	0.08242	0.01524	0.02359	0.04978	0.03139	0.01061	**0.00087**	0.05299	0.00122	0.01627
		SIGMOID	0.00208	0.00224	0.00177	0.00168	0.00162	0.00105	**0.00073**	0.00186	0.00161	0.00196	0.00163	0.00161	0.00179	0.00206	0.00148	0.00129	0.00167	0.00128	0.00139
SSE/SST	BRAZIL	RELU	0.0116	0.00864	0.03111	0.03968	0.004	0.03142	0.05414	0.01188	0.02444	0.12763	0.08019	0.02274	**0.00087**	0.00228	0.00104	0.02221	0.35596	0.01149	0.16495
		SIGMOID	0.00097	0.00064	0.00467	0.00449	0.00246	0.00224	0.00071	0.00432	0.00065	0.0036	0.00247	0.00063	0.0047	0.00124	0.00074	0.00096	0.00061	0.00142	**0.00055**
	INDIA	RELU	0.01285	0.00035	0.00021	0.0127	0.00372	0.06697	0.00328	0.02728	0.04342	0.13548	0.01293	0.0221	0.01002	0.14019	0.00021	0.00134	0.01695	0.03091	**0.00018**
		SIGMOID	0.00009	0.00015	0.00011	0.00008	0.00026	0.00006	0.00006	0.00017	0.00008	0.00057	0.00007	0.00026	0.00008	0.00023	0.00049	**0.00004**	0.00026	0.00014	0.00022
	PERU	RELU	0.03821	0.0925	0.33241	0.00226	0.0124	0.2557	0.23415	0.00074	0.00585	**0.00041**	0.00591	0.75073	0.01527	0.02826	0.09467	0.0015	0.20666	0.00282	0.66722
		SIGMOID	0.00469	0.02049	0.00035	0.0024	0.00036	0.00464	0.00377	0.00195	0.00022	0.00014	0.00529	0.0006	0.00235	0.07026	0.00055	0.10783	**0.00012**	0.00056	0.00092
	RUSSIA	RELU	0.00141	0.01665	0.06754	0.25265	0.01979	0.00691	0.00145	0.00115	0.00674	0.00551	0.00577	0.47533	0.05558	**0.00073**	0.1095	0.1422	0.10925	0.00523	0.00265
		SIGMOID	0.01811	0.00187	0.02348	0.02708	0.0009	0.00075	**0.00072**	0.02988	0.01996	0.03315	0.01483	0.01715	0.03102	0.02651	0.00084	0.00099	0.02921	0.00153	0.02662
	USA	RELU	0.00077	0.06989	0.01748	0.28243	0.00007	0.01141	0.00751	0.00852	0.02108	0.30745	0.01051	0.02515	0.11071	0.04407	0.00511	**0.00003**	0.12721	0.00007	0.01198
		SIGMOID	0.00019	0.00022	0.00014	0.00013	0.00012	0.00005	**0.00002**	0.00016	0.00012	0.00017	0.00012	0.00012	0.00014	0.00019	0.0001	0.00007	0.00013	0.00007	0.00009
MAE	BRAZIL	RELU	0.02214	0.01813	0.02862	0.03586	0.0112	0.03186	0.03712	0.02183	0.02767	0.07302	0.0585	0.02686	**0.00567**	0.01065	0.00758	0.02502	0.11424	0.02072	0.07576
		SIGMOID	0.00606	**0.00488**	0.01434	0.01427	0.00797	0.00802	0.00536	0.01116	0.00527	0.00938	0.01096	0.00547	0.0111	0.00753	0.00547	0.00602	0.00526	0.00818	0.00496
	INDIA	RELU	0.0163	0.00301	**0.00229**	0.01473	0.00975	0.04336	0.00873	0.02865	0.03335	0.06254	0.02003	0.02789	0.0176	0.07375	0.0027	0.00608	0.02501	0.03037	0.00239
		SIGMOID	0.00155	0.00194	0.00168	0.00159	0.00236	0.00149	0.00146	0.00209	0.00166	0.00347	0.00145	0.00232	0.00156	0.00249	0.00323	**0.00115**	0.00235	0.00211	0.0027
	PERU	RELU	0.0347	0.04777	0.10876	0.00931	0.02268	0.09211	0.08373	0.00491	0.01445	**0.00381**	0.01597	0.15572	0.02532	0.03394	0.05747	0.007	0.0867	0.00979	0.15697
		SIGMOID	0.0128	0.02525	0.00341	0.00901	0.00373	0.01165	0.01062	0.00856	0.00285	0.00213	0.0125	0.00473	0.00945	0.04735	0.00469	0.05896	**0.00203**	0.00408	0.00596
	RUSSIA	RELU	0.00602	0.01776	0.03864	0.08267	0.02007	0.01327	0.00622	0.00551	0.01423	0.01262	0.01202	0.1105	0.03366	**0.0039**	0.05592	0.06059	0.04992	0.01204	0.00888
		SIGMOID	0.02104	0.00704	0.02355	0.02526	0.00513	0.00465	**0.00454**	0.02696	0.02182	0.02784	0.01886	0.02016	0.02718	0.02498	0.00495	0.00525	0.02611	0.00642	0.02501
	USA	RELU	0.003	0.0338	0.01196	0.06417	0.00095	0.01092	0.01042	0.01167	0.01705	0.06736	0.01319	0.01794	0.04277	0.02209	0.00593	**0.00069**	0.0396	0.00079	0.01066
		SIGMOID	0.0014	0.00123	0.00103	0.00101	0.00104	0.00075	**0.00057**	0.00125	0.00104	0.00139	0.00101	0.00091	0.00104	0.00119	0.00098	0.00093	0.0011	0.00085	0.00084
R^2	BRAZIL	RELU	0.9884	0.99136	0.96889	0.96032	0.996	0.96858	0.94586	0.98812	0.97556	0.87237	0.91981	0.97726	**0.99913**	0.99772	0.99896	0.97779	0.64404	0.98851	0.83505
		SIGMOID	0.99903	0.99936	0.99533	0.99551	0.99754	0.99776	0.99929	0.99568	0.99935	0.9964	0.99753	0.99937	0.9953	0.99876	0.99926	0.99904	0.99939	0.99858	**0.99945**
	INDIA	RELU	0.98715	0.99965	0.9998	0.9873	0.99628	0.93303	0.99672	0.97272	0.95658	0.86452	0.98707	0.9779	0.98998	0.85981	0.99979	0.99866	0.98305	0.96909	**0.99982**
		SIGMOID	0.99991	0.99985	0.99989	0.99992	0.99974	0.99994	0.99994	0.99983	0.99992	0.99943	0.99993	0.99974	0.99992	0.99977	0.99951	**0.99996**	0.99974	0.99986	0.99978
	PERU	RELU	0.96179	0.9075	0.66759	0.99774	0.98761	0.74431	0.76585	0.99926	0.99415	**0.9996**	0.99409	0.24927	0.98473	0.97174	0.90533	0.9985	0.79334	0.99718	0.33278
		SIGMOID	0.99531	0.97951	0.99965	0.9976	0.99964	0.99536	0.99623	0.99805	0.99978	0.99986	0.99471	0.9994	0.99765	0.92974	0.99945	0.89217	**0.99988**	0.99944	0.99908
	RUSSIA	RELU	0.99859	0.98335	0.93246	0.74735	0.98021	0.99309	0.99855	0.99885	0.99326	0.99449	0.99423	0.52467	0.94442	**0.99927**	0.89051	0.85781	0.89075	0.99477	0.99735
		SIGMOID	0.98189	0.99814	0.97652	0.97292	0.9991	0.99925	**0.99928**	0.97012	0.98004	0.96685	0.98517	0.98285	0.96898	0.97349	0.99916	0.99901	0.97079	0.99847	0.97338
	USA	RELU	0.99923	0.93011	0.98252	0.71757	0.99993	0.98859	0.99249	0.99148	0.97892	0.69256	0.98949	0.97485	0.88929	0.95593	0.99489	**0.99997**	0.87279	0.99993	0.98802
		SIGMOID	0.99981	0.99978	0.99986	0.99987	0.99988	0.99995	**0.99998**	0.99984	0.99988	0.99983	0.99988	0.99988	0.99986	0.99981	0.9999	0.99993	0.99987	0.99993	0.99991
PSNR	BRAZIL	RELU	77.2222	72.6417	90.3719	70.6091	74.657	68.0834	72.2595	80.3823	82.0025	73.9498	76.407	89.2564	66.1399	**90.3868**	75.3598	88.9994	74.7832	79.4713	66.5262
		SIGMOID	87.3324	90.5922	91.6296	91.7009	91.3709	87.7036	84.7542	88.3305	88.3014	90.7744	**93.0019**	87.0281	89.7045	89.3644	89.595	91.7658	91.9637	91.893	86.0185
	INDIA	RELU	91.9479	74.5817	79.8778	79.0809	71.1813	69.7549	89.6223	74.5271	80.9053	91.6203	68.2174	77.9468	90.9475	86.9491	66.4774	81.5632	69.8243	**96.0934**	63.2181
		SIGMOID	99.5148	95.5094	95.4381	97.7427	98.4782	97.9321	**103.832**	99.3556	100.297	92.8147	96.4682	100.103	100.912	95.2571	92.571	98.3075	101.215	96.0677	99.7727
	PERU	RELU	77.6603	89.3875	73.4547	56.4982	89.0619	69.8998	**91.375**	74.4167	66.8389	79.1267	86.9136	67.1247	89.0395	88.1313	71.3348	87.4908	66.2178	70.6565	77.5593
		SIGMOID	86.21	96.2414	91.5502	86.4655	91.3333	92.9706	**98.4921**	85.4834	89.838	94.9392	93.0807	96.7118	78.3656	83.1218	86.25	76.3774	84.7984	91.7502	98.4149
	RUSSIA	RELU	95.2979	99.7821	70.9362	80.1133	79.2595	107.301	86.2218	69.7298	91.0856	87.3098	87.7416	**107.4**	85.1455	81.1854	92.0956	85.2412	67.0613	81.9816	73.0174
		SIGMOID	95.3972	100.807	76.8771	81.0473	95.2673	84.3352	73.5401	**103.034**	82.7388	82.0058	78.0391	81.9525	77.6814	83.255	93.1311	97.675	75.8037	84.6255	94.0349
	USA	RELU	78.9712	90.1113	92.6613	79.535	87.5491	78.8601	91.0289	77.012	**98.555**	76.9741	80.1679	78.4418	85.4196	85.1016	77.9844	82.0147	89.2	81.2374	80.2273
		SIGMOID	103.27	99.9637	103.134	103.253	101.314	104.781	**108.239**	102.881	103.615	104.916	100.909	104.45	103.521	100.273	105.056	104.82	105.736	106.77	105.383
SC	BRAZIL	RELU	1.11931	1.24364	0.97976	1.30385	1.161	1.438	**0.81432**	0.92186	1.07407	0.84573	1.12139	0.98184	1.55693	0.98386	1.16197	1.02955	1.16474	1.04502	1.58385
		SIGMOID	0.96741	0.98369	0.98638	0.98303	0.9827	1.02129	**0.95084**	0.97501	0.96841	0.97858	0.98984	0.96238	1.00141	1.0105	0.9743	0.99556	0.99519	0.99721	0.95728
	INDIA	RELU	0.977747	1.18654	**0.90954**	1.06693	1.34137	1.40625	0.968892	1.21094	1.08835	1.02578	1.52676	1.13308	0.975048	1.04481	1.66116	1.07933	1.38724	0.986694	2.20579
		SIGMOID	0.99463	1.01197	**0.98627**	0.99006	0.99066	0.98918	0.99762	0.9941	1.00276	1.01779	0.98739	0.99456	0.999	0.9863	1.01953	0.98924	0.9956	1.01146	0.99293
	PERU	RELU	1.09625	1.02121	0.87718	4.4338	0.97561	0.80825	0.99054	1.14587	1.42069	1.08379	1.01706	1.39407	0.9886	0.97379	1.21628	1.02416	**0.72383**	1.25074	0.91492
		SIGMOID	0.96717	0.99273	0.98264	1.03174	1.01671	0.98461	0.99398	**0.96433**	0.97791	1.00871	0.985	0.99055	1.08581	1.04718	0.96657	1.11203	1.03948	0.98315	1.00464
	RUSSIA	RELU	1.0079	1.00675	1.20391	1.06976	1.07859	0.99717	1.03164	1.24853	1.01942	1.0302	0.97732	0.9975	1.03409	1.03909	1.01707	1.03837	1.36952	**0.95725**	1.16561
		SIGMOID	1.07728	1.02118	1.01594	1.07212	1.02862	1.07816	1.01919	1.09911	**1.00804**	1.09832	1.06707	1.0825	1.03633	1.03759	1.08686	1.05412	1.02368	1.05898	1.06665
	USA	RELU	0.9888	0.9969	1.09219	1.0629	1.00995	1.03637	**0.8733**	1.0008	0.95227	0.95102	1.08725	1.05108	1.08557	1.04472	1.01361	1.0067	0.90157	0.96334	1.01143
		SIGMOID	1.00149	0.99614	1.00131	1.00226	**0.99527**	0.99691	0.99806	1.00076	0.99792	1.00126	0.99548	0.99829	0.99999	0.99597	0.99812	0.99694	0.99887	1.00112	0.99826

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Table 5 (*continued*).

	Dataset	Activation function	DB2	DB3	DB4	DB5	DB6	DB7	DB8	HAAR	COIF2	COIF3	COIF4	COIF5	SYM2	SYM3	SYM4	SYM5	SYM6	SYM7	SYM8
MD	BRAZIL	RELU	0.08559	0.1195	0.02917	0.179	0.11151	0.22603	0.13476	0.05	0.04002	0.10994	0.09842	0.02155	0.28417	**0.02041**	0.10572	0.02291	0.11002	0.07137	0.26182
		SIGMOID	0.02659	0.01804	0.01606	0.0137	0.0137	0.03232	0.02805	0.02994	0.01714	0.01426	**0.01223**	0.01919	0.02637	0.03034	0.01715	0.01713	0.01683	0.01853	0.023
	INDIA	RELU	0.02753	0.12248	0.04724	0.08296	0.14849	0.19416	0.01795	0.11059	0.06899	0.01916	0.21536	0.08258	0.02984	0.02992	0.29014	0.05693	0.20527	**0.01678**	0.42751
		SIGMOID	0.0141	0.01554	0.01944	0.01118	0.00987	0.01149	**0.00398**	0.01423	0.01143	0.024	0.01252	0.00816	0.01065	0.02246	0.02045	0.00841	0.00846	0.01353	0.01011
	PERU	RELU	0.06544	0.01833	0.09554	0.62868	0.01717	0.1452	**0.01621**	0.08752	0.1948	0.04347	0.03273	0.19848	0.02236	0.02138	0.12813	0.02839	0.20699	0.10809	0.0611
		SIGMOID	0.02484	0.01258	0.01431	0.02826	0.01822	0.00902	0.00747	0.02604	0.01561	0.01425	0.01241	**0.00732**	0.06236	0.03832	0.02241	0.07847	0.03356	0.01271	0.01018
	RUSSIA	RELU	0.00945	0.00489	0.13455	0.04389	0.04645	**0.00236**	0.02665	0.15373	0.01341	0.01991	0.02508	0.00379	0.02759	0.05492	0.01163	0.02259	0.20199	0.03632	0.09387
		SIGMOID	0.05422	0.01475	0.0113	0.05319	0.02112	0.05672	0.01298	0.06685	**0.00527**	0.07106	0.0495	0.0598	0.02517	0.02685	0.06305	0.03802	0.01776	0.04162	0.04897
	USA	RELU	0.01398	0.00928	0.08973	0.05032	0.01443	0.03817	0.11563	**0.00646**	0.04583	0.04948	0.07428	0.05157	0.07628	0.04119	0.017	0.00908	0.09367	0.03023	0.01502
		SIGMOID	0.00775	0.01485	0.0075	0.00806	0.00904	0.00528	**0.00357**	0.00687	0.00688	0.00794	0.0108	0.0081	0.00896	0.0142	0.00435	0.00525	0.00527	0.0054	0.00646
LMSE	BRAZIL	RELU	1.9592	1.51638	1.65758	1.61344	1.56344	1.19301	1.35594	**0.16029**	1.6354	1.54353	1.25457	1.21928	1.52869	1.44633	1.94341	2.79724	1.7816	0.86485	1.34554
		SIGMOID	1.98615	1.43143	1.62054	2.02656	1.65035	1.27011	1.54103	**0.1628**	2.45645	2.09644	1.6881	1.53025	1.97211	1.3593	2.3996	2.84463	2.12371	1.10525	1.81776
	INDIA	RELU	**0.03022**	1.18593	1.46971	1.85715	2.69832	2.75105	3.67076	0.24736	2.86583	2.63142	2.79089	2.31862	1.238	1.29772	2.8215	1.07686	3.1414	0.899256	2.28136
		SIGMOID	0.02995	1.20692	1.59181	2.09763	2.87518	3.7112	3.60436	**0.02981**	3.22094	2.9384	2.82077	2.74866	1.20943	1.24715	4.04946	1.16252	3.38315	1.05892	3.28908
	PERU	RELU	2.70754	1.84011	1.15015	1.47043	2.76412	1.18878	1.58895	**0.08235**	3.84676	3.41821	1.64768	1.42215	1.62038	2.23494	3.40041	2.19123	3.43757	1.54283	1.72623
		SIGMOID	3.05547	2.12135	1.69593	2.05716	2.55036	2.28687	2.12045	**0.12124**	4.10484	4.12302	2.05402	1.5896	2.89882	2.07387	4.95309	2.20615	3.42778	1.98968	2.75955
	RUSSIA	RELU	1.16522	0.96089	1.22561	2.01942	3.1303	4.25083	3.17265	**0.01567**	4.2269	3.78776	2.76609	2.88787	1.0765	0.99987	5.37363	2.20785	5.1298	0.55564	4.04187
		SIGMOID	1.162	1.01433	1.33827	1.86986	3.03096	4.07778	3.25323	**0.01326**	4.69482	3.50167	3.04166	2.64205	1.17759	1.01077	6.9593	2.11957	4.93047	0.4034	4.13115
	USA	RELU	0.96104	0.80102	0.79092	1.84075	2.68277	2.13947	1.40724	**0.02383**	4.32197	4.01089	2.17031	1.50677	0.77241	0.56761	7.45131	2.17607	5.97374	0.42201	3.11836
		SIGMOID	1.10998	0.81694	1.02027	2.00281	3.18338	2.94843	1.3748	**0.02485**	6.90076	4.01421	2.71294	2.09892	1.11762	0.75341	11.9694	3.04973	6.31992	0.55929	4.22307
NAE	BRAZIL	RELU	0.04451	0.09382	**0.01115**	0.10572	0.06462	0.13931	0.09455	0.04437	0.0324	0.07689	0.04903	0.01254	0.1655	0.01134	0.06126	0.01344	0.06249	0.04064	0.17966
		SIGMOID	0.01771	0.01187	0.01073	0.01106	0.01151	0.01418	0.02445	0.01518	0.01686	0.01265	**0.00923**	0.01945	0.01235	0.01224	0.01435	0.01042	0.01053	0.0098	0.02158
	INDIA	RELU	0.01002	0.064	0.04576	0.04389	0.12445	0.13439	0.01541	0.07959	0.03337	0.01235	0.17074	0.05174	0.01091	0.02033	0.188728	0.030152	0.124176	**0.00612**	0.28217
		SIGMOID	0.00391	0.0056	0.00642	0.00525	0.00488	0.00526	**0.00285**	0.00403	0.00349	0.00738	0.00608	0.00409	0.00338	0.00631	0.00786	0.00534	0.00357	0.00531	0.00406
	PERU	RELU	0.04041	0.0116	0.06801	0.50116	0.01168	0.10072	**0.00857**	0.05935	0.1489	0.03795	0.01291	0.13999	0.01067	0.01272	0.08361	0.01082	0.16127	0.10153	0.04048
		SIGMOID	0.0161	0.00481	0.00868	0.01404	0.00784	0.00778	0.00382	0.0176	0.01059	0.00518	0.00732	0.00495	0.03612	0.02067	0.01591	0.04602	0.01716	0.00852	**0.00359**
	RUSSIA	RELU	0.005	0.00326	0.07888	0.03077	0.03499	0.00142	0.01387	0.09521	0.00911	0.01401	0.00974	**0.00128**	0.01522	0.02195	0.0079	0.01758	0.13401	0.02421	0.06768
		SIGMOID	0.0331	0.00967	0.00744	0.03094	0.01294	0.03335	0.0088	0.04201	**0.00405**	0.04137	0.02893	0.03517	0.01621	0.0167	0.03681	0.02365	0.01079	0.02559	0.02877
	USA	RELU	0.00545	0.00269	0.03761	0.02748	0.00432	0.01576	0.06236	**0.00174**	0.02278	0.02229	0.03677	0.02149	0.03528	0.01912	0.0059	0.00321	0.0469	0.01695	0.0049
		SIGMOID	0.00154	0.00209	0.00157	0.00157	0.00225	0.00152	**0.00106**	0.00179	0.00156	0.00127	0.00217	0.00129	0.00141	0.0021	0.0014	0.00154	0.00122	0.00116	0.00123

Table 6
Ranks obtained using 9 performance evaluations for the countries using WCRVFL (Best results are bolded).

Evaluators	Dataset	Activation function	DB2	DB3	DB4	DB5	DB6	DB7	DB8	HAAR	COIF2	COIF3	COIF4	COIF5	SYM2	SYM3	SYM4	SYM5	SYM6	SYM7	SYM8
RMSE	BRAZIL	RELU	7	5	12	14	4	13	15	8	11	17	16	10	1	3	2	9	19	6	18
		SIGMOID	9	4	18	17	13	12	6	16	5	15	14	3	19	10	7	8	2	11	1
	INDIA	RELU	10	4	2.5	9	7	17	6	14	16	18	11	13	8	19	2.5	5	12	15	1
		SIGMOID	8	11	9	5	16	3	2	12	6.5	19	4	15	6.5	14	18	1	17	10	13
	PERU	RELU	11	12	17	4	8	16	15	2	6	1	7	19	9	10	13	3	14	5	18
		SIGMOID	15	17	4	12	5	14	13	10	3	2	16	8	11	18	6	19	1	7	9
	RUSSIA	RELU	3	11	14	18	12	10	4	2	9	7	8	19	13	1	16	17	15	6	5
		SIGMOID	10	7	12	15	4	2	1	17	11	19	8	9	18	14	3	5	16	6	13
	USA	RELU	4	15	11	18	3	9	6	7	12	19	8	13	16	14	5	1	17	2	10
		SIGMOID	18	19	13	12	9	2	1	15	7.5	16	10	7.5	14	17	6	4	11	3	5
AVERAGE RANK			9.5	10.5	11.25	12.4	8.1	9.8	**6.9**	10.3	8.7	13.3	10.2	11.65	11.55	12	7.85	7.2	12.4	7.1	9.3
SSE/SST	BRAZIL	RELU	7	5	12	14	4	13	15	8	11	17	16	10	1	3	2	9	19	6	18
		SIGMOID	9	4	18	17	13	12	6	16	5	15	14	3	19	10	7	8	2	11	1
	INDIA	RELU	10	4	2.5	9	7	17	6	14	16	18	11	13	8	19	2.5	5	12	15	1
		SIGMOID	8	11	9	6	16	2.5	2.5	12	6	19	4	16	6	14	18	1	16	10	13
	PERU	RELU	11	12	17	4	8	16	15	2	6	1	7	19	9	10	13	3	14	5	18
		SIGMOID	15	17	4	12	5	14	13	10	3	2	16	8	11	18	6	19	1	7	9
	RUSSIA	RELU	3	11	14	18	12	10	4	2	9	7	8	19	13	1	16	17	15	6	5
		SIGMOID	10	7	12	15	4	2	1	17	11	19	8	9	18	13	3	5	16	6	14
	USA	RELU	4	15	11	18	2.5	9	6	7	12	19	8	13	16	14	5	1	17	2.5	10
		SIGMOID	17.5	19	13.5	11.5	8.5	2	1	15	8.5	16	8.5	8.5	13.5	17.5	6	3.5	11.5	3.5	5
AVERAGE RANK			9.45	10.5	11.3	12.45	8	9.75	**6.95**	10.3	8.75	13.3	10.05	11.85	11.45	11.95	7.85	7.15	12.35	7.2	9.4
MAE	BRAZIL	RELU	8	5	12	14	4	13	15	7	11	17	16	10	1	3	2	9	19	6	18
		SIGMOID	9	1	19	18	11	12	5	17	4	14	15	6.5	16	10	6.5	8	3	13	2
	INDIA	RELU	9	4	1	8	7	17	6	14	16	18	11	13	10	19	3	5	12	15	2
		SIGMOID	5	10	9	7	15	4	3	11	8	19	2	13	6	16	18	1	14	12	17
	PERU	RELU	11	12	17	4	8	16	14	2	6	1	7	18	9	10	13	3	15	5	19
		SIGMOID	16	17	4	11	5	14	13	10	3	2	15	8	12	18	7	19	1	6	9
	RUSSIA	RELU	3	11	14	18	12	9	4	2	10	8	6	19	13	1	16	17	15	7	5
		SIGMOID	10	7	12	15	4	2	1	17	11	19	8	9	18	13	3	5	16	6	14
	USA	RELU	4	15	10	18	3	8	6	9	12	19	11	13	17	14	5	1	16	2	7
		SIGMOID	19	16	10	8.5	12	2	1	17	12	18	8.5	5	12	15	7	6	14	4	3
AVERAGE RANK			9.4	9.8	10.8	12.15	8.1	9.7	**6.8**	10.6	9.3	13.5	9.95	11.45	11.4	11.9	8.05	7.4	12.5	7.6	9.6
R^2	BRAZIL	RELU	7	5	12	14	4	13	15	8	11	17	16	10	1	3	2	9	19	6	18
		SIGMOID	9	4	18	17	13	12	6	16	5	15	14	3	19	10	7	8	2	11	1
	INDIA	RELU	10	4	2	9	7	17	6	14	16	18	11	13	8	19	3	5	12	15	1
		SIGMOID	8	11	9	6	16	2.5	2.5	12	6	19	4	16	6	14	18	1	16	10	13
	PERU	RELU	11	12	17	4	8	16	15	2	6	1	7	19	9	10	13	3	14	5	18
		SIGMOID	15	17	4	12	5	14	13	10	3	2	16	8	11	18	6	19	1	7	9
	RUSSIA	RELU	3	11	14	18	12	10	4	2	9	7	8	19	13	1	16	17	15	6	5
		SIGMOID	10	7	12	15	4	2	1	17	11	19	8	9	18	13	3	5	16	6	14
	USA	RELU	4	15	11	18	2.5	9	6	7	12	19	8	13	16	14	5	1	17	2.5	10
		SIGMOID	17.5	19	13.5	11.5	8.5	2	1	15	8.5	16	8.5	8.5	13.5	17.5	6	3.5	11.5	3.5	5
AVERAGE RANK			9.45	10.5	11.25	12.45	8	9.75	**6.95**	10.3	8.75	13.3	10.05	11.85	11.45	11.95	7.9	7.15	12.35	7.2	9.4
PSNR	BRAZIL	RELU	8	14	2	16	12	17	15	6	5	13	9	3	19	1	10	4	11	7	18
		SIGMOID	16	9	6	5	7	15	19	13	14	8	1	17	10	12	11	4	2	3	18
	INDIA	RELU	2	12	9	10	14	16	5	13	8	3	17	11	4	6	18	7	15	1	19
		SIGMOID	7	15	16	12	9	11	1	8	4	18	13	5	3	17	19	10	2	14	6
	PERU	RELU	9	2	12	19	3	15	1	11	17	8	7	16	4	5	13	6	18	14	10
		SIGMOID	14	4	9	12	10	7	1	15	11	5	6	3	18	17	13	19	16	8	2
	RUSSIA	RELU	4	3	17	14	15	2	9	18	6	8	7	1	11	13	5	10	19	12	16
		SIGMOID	14	4	2	13	6	15	3	18	1	19	12	16	7	8	17	9	5	10	11
	USA	RELU	4	2	17	14	5	9	19	1	11	12	15	13	16	10	7	3	18	8	6
		SIGMOID	12	19	14	13	16	8	1	15	10	6	17	9	11	18	5	7	3	2	4
AVERAGE RANK			9	8.4	10.4	12.8	9.7	11.5	**7.4**	11.8	8.7	10	10.4	9.4	10.3	10.7	11.8	7.9	10.9	7.9	11

(*continued on next page*)

Table 6 (*continued*).

Evaluators	Dataset	Activation function	DB2	DB3	DB4	DB5	DB6	DB7	DB8	HAAR	COIF2	COIF3	COIF4	COIF5	SYM2	SYM3	SYM4	SYM5	SYM6	SYM7	SYM8
SC	BRAZIL	RELU	10	15	4	16	12	17	1	3	9	2	11	5	18	6	13	7	14	8	19
		SIGMOID	4	11	12	10	9	19	1	7	5	8	13	3	17	18	6	15	14	16	2
	INDIA	RELU	4	12	1	8	14	16	2	13	10	6	17	11	3	7	18	9	15	5	19
		SIGMOID	11	17	1	6	7	4	13	9	15	18	3	10	14	2	19	5	12	16	8
	PERU	RELU	13	10	3	19	6	2	8	14	18	12	9	17	7	5	15	11	1	16	4
		SIGMOID	3	10	5	15	14	7	11	1	4	13	8	9	18	17	2	19	16	6	12
	RUSSIA	RELU	6	5	17	14	15	3	10	18	8	9	2	4	11	13	7	12	19	1	16
		SIGMOID	14	4	2	13	6	15	3	19	1	18	12	16	7	8	17	9	5	10	11
	USA	RELU	6	7	19	16	10	13	1	8	4	3	18	15	17	14	12	9	2	5	11
		SIGMOID	18	4	17	19	1	5	8	14	7	16	2	11	13	3	9	6	12	15	10
AVERAGE RANK			8.9	9.5	8.1	13.6	9.4	10.1	**5.8**	10.6	8.1	10.5	9.5	10.1	12.5	9.3	11.8	10.2	11	9.8	11.2
MD	BRAZIL	RELU	8	14	4	16	13	17	15	6	5	11	9	2	19	1	10	3	12	7	18
		SIGMOID	15	10	5	2.5	2.5	19	16	17	8	4	1	12	14	18	9	7	6	11	13
	INDIA	RELU	4	13	7	11	14	15	2	12	9	3	17	10	5	6	18	8	16	1	19
		SIGMOID	13	15	16	8	5	10	1	14	9	19	11	2	7	18	17	3	4	12	6
	PERU	RELU	10	3	12	19	2	15	1	11	16	8	7	17	5	4	14	6	18	13	9
		SIGMOID	13	6	9	15	11	3	2	14	10	8	5	1	18	17	12	19	16	7	4
	RUSSIA	RELU	4	3	17	13	14	1	10	18	6	7	9	2	11	15	5	8	19	12	16
		SIGMOID	14	4	2	13	6	15	3	18	1	19	12	16	7	8	17	9	5	10	11
	USA	RELU	4	3	17	13	5	9	19	1	11	12	15	14	16	10	7	2	18	8	6
		SIGMOID	11	19	10	13	16	5	1	8	9	12	17	14	15	18	2	3	4	6	7
AVERAGE RANK			9.6	9	9.9	12.35	8.85	10.9	7	11.9	8.4	10.3	10.3	9	11.7	11.5	11.1	**6.8**	11.8	8.7	10.9
LMSE	BRAZIL	RELU	13	5	8	14	9	3	7	1	18	15	10	6	12	4	17	19	16	2	11
		SIGMOID	1	5	8	9	13	14	19	2	17	12	15	11	6	7	16	4	18	3	10
	INDIA	RELU	2	5	8	9	12	18	17	1	14	13	11	10	6	7	19	4	16	3	15
		SIGMOID	14	11	2	5	15	3	7	1	19	17	9	4	8	13	16	12	18	6	10
	PERU	RELU	15	9	3	6	12	11	8	1	17	18	5	2	14	7	19	10	16	4	13
		SIGMOID	6	3	7	8	12	17	13	1	16	14	10	11	5	4	19	9	18	2	15
	RUSSIA	RELU	5	4	7	8	11	15	13	1	17	14	12	10	6	3	19	9	18	2	16
		SIGMOID	5	4	7	8	11	15	13	1	17	14	12	10	6	3	19	9	18	2	16
	USA	RELU	7	6	5	10	14	11	8	1	17	16	12	9	4	3	19	13	18	2	15
		SIGMOID	13	5	8	14	9	3	7	1	18	15	10	6	12	4	17	19	16	2	11
AVERAGE RANK			8.1	5.7	6.3	9.1	11.8	11	11.2	**1.1**	17	14.8	10.6	7.9	7.9	5.5	18	10.8	17.2	2.8	13.2
NAE	BRAZIL	RELU	8	14	1	16	12	17	15	7	5	13	9	3	18	2	10	4	11	6	19
		SIGMOID	16	8	5	6	7	12	19	14	15	11	1	17	10	9	13	3	4	2	18
	INDIA	RELU	2	12	10	9	15	16	5	13	8	4	17	11	3	6	18	7	14	1	19
		SIGMOID	5	14	17	10	9	11	1	6	3	18	15	8	2	16	19	13	4	12	7
	PERU	RELU	9	4	12	19	5	14	1	11	17	8	7	16	2	6	13	3	18	15	10
		SIGMOID	14	3	10	12	8	7	2	16	11	5	6	4	18	17	13	19	15	9	1
	RUSSIA	RELU	4	3	17	14	15	2	8	18	6	9	7	1	10	12	5	11	19	13	16
		SIGMOID	14	4	2	13	6	15	3	19	1	18	12	16	7	8	17	9	5	10	11
	USA	RELU	6	2	17	14	4	8	19	1	13	12	16	11	15	10	7	3	18	9	5
		SIGMOID	10.5	16	13.5	13.5	19	9	1	15	12	5	18	6	8	17	7	10.5	3	2	4
AVERAGE RANK			8.85	8	10.45	12.65	10	11.1	**7.4**	12	9.1	10.3	10.8	9.3	9.3	10.3	12.2	8.25	11.1	7.9	11

Table 7
R^2 values obtained by SVR, RVFL and the best WCRVFL models for the reported countries.

Evaluators	SVR	RVFL		Best WCRVFL	
		RELU	Sigmoid	RELU	Sigmoid
BRAZIL	0.99711	0.97965	**0.99949**	0.99913	0.99945
INDIA	0.93156	0.99905	0.99995	0.99982	**0.99996**
PERU	0.92535	0.99889	0.99726	0.9996	**0.99988**
RUSSIA	0.99744	0.99929	**0.99942**	0.99927	0.99928
USA	0.99225	0.99992	0.99994	0.99997	**0.99998**

Table 8
RMSE values obtained by SVR, RVFL and the best WCRVFL models for the reported countries.

Evaluators	SVR	RVFL		Best WCRVFL	
		RELU	Sigmoid	RELU	Sigmoid
BRAZIL	0.08584	0.11573	0.00699	0.00787	**0.00619**
INDIA	0.18848	0.05224	0.00189	0.00349	**0.00156**
PERU	0.18303	0.08209	0.05809	0.00452	**0.00247**
RUSSIA	0.02281	0.01997	0.0344	0.00513	**0.00508**
USA	0.04927	0.05115	0.00119	0.00087	**0.00073**

Table 9
Ranks obtained by SVR, RVFL and the best WCRVFL models based on R^2 (Best average rank is bolded).

Country	SVR	RVFL		Best WCRVFL	
		RELU	Sigmoid	RELU	Sigmoid
BRAZIL	4	5	1	3	2
INDIA	5	4	2	3	1
PERU	5	3	4	2	1
RUSSIA	5	2	1	4	3
USA	5	4	3	2	1
Average rank	4.8	3.6	2.2	2.8	**1.6**

where the best rank is observed in SYM5 and HAAR respectively. To validate the prediction performance of the proposed WCRVFL network, its prediction performance is compared with the conventional SVR and RVFL models. For comparison, we have used the best WCRVFL model for each country based on R^2 and RMSE. The results are shown in Tables 7 and 8 based on R^2 and RMSE respectively. It is noticeable from Tables 7 and 8 that the proposed WCRVFL model shows the best performance in 3 and 5 cases respectively out of the total 5 cases based on R^2 and RMSE respectively. Further a statistical analysis is carried out based on the average ranks of the reported models that are tabulated in Tables 9 and 10 based on R^2 and RMSE respectively.

4.1.2.1. Friedman test with post-hoc analysis. From Table 9, the null hypothesis can be formulated as:

$$\chi_F^2 = \frac{12 \times 5}{5 \times 6}\left[4.8^2 + 3.6^2 + 2.2^2 + 2.8^2 + 1.6^2 - \frac{5 \times 6^2}{4}\right] = 12.48$$

,

$$F_F = \frac{(5-1) \times 12.48}{5 \times (5-1) - 12.48} = 6.6383.$$

F_F is distributed to $(5-1)$ and $(5-1) \times (5-1) = 16$ degrees of freedom. The critical value C_V for F_F is 3.007 for $\alpha = 0.05$. Since $F_F > C_V$ therefore the null hypothesis can be rejected. Therefore, we can proceed with the post-hoc Nemenyi test to pairwise compare the models. According to Demšar [30], the critical difference (CD) considering $p = 0.10$ may be calculated as:

$$CD = 2.49\sqrt{\frac{5 \times (5+1)}{6 \times 5}} = 2.49.$$

It is revealed from the test that the average rank difference between the best-proposed model, i.e., WCRVFL sigmoid activation function with SVR is $3.2 > CD$, hence it can be concluded that WCRVFL shows significantly better performance compared to SVR based on R^2. It can be also observed from Table 9 that WCRVFL shows the best performance in 3 out of 5 cases.
Moreover, from Table 10, the null hypothesis can be expressed as:

$$\chi_F^2 = \frac{12 \times 5}{5 \times 6}\left[4.4^2 + 4.2^2 + 3^2 + 2.4^2 + 1^2 - \frac{5 \times 6^2}{4}\right] = 15.52$$

Table 10
Ranks obtained by SVR, RVFL and the best WCRVFL models based on RMSE (Best average rank is bolded).

Country	SVR	RVFL		Best WCRVFL	
		RELU	Sigmoid	RELU	Sigmoid
BRAZIL	4	5	2	3	1
INDIA	5	4	2	3	1
PERU	5	4	3	2	1
RUSSIA	4	3	5	2	1
USA	4	5	3	2	1
Average rank	4.4	4.2	3	2.4	**1**

$$F_F = \frac{(5-1) \times 15.52}{5 \times (5-1) - 15.52} = 13.8571.$$

F_F is distributed to$(5-1)$ and $(5-1) \times (5-1) = 16$ degrees of freedom. The critical value C_V for F_F is 3.007 for $\alpha = 0.05$. Since $F_F > C_V$ therefore the null hypothesis can be rejected. Therefore, we can proceed with the posthoc Nemenyi test to do a pairwise comparison of the models. It is noticeable from Table 10 that WCRVFL shows the best performance in 5 out of 5 cases. It is noticeable from the test that the average rank difference between WCRVFL sigmoid with SVR and RVFL RELU are 3.4 and 3.2 which are greater than the CD. Hence one can say that WCRVFL shows significantly better performance compared to SVR and RVFL RELU models.

Further, the 60 days ahead daily prediction values are plotted in Fig. 5 for the best RVFL model and the best WCRVFL model as a form of a line graph. The best models are chosen based on the best R^2 values obtained from Table 7. It is distinct from the graph that the Brazil graph (RVFL model) crosses the USA graph (RVFL model) after 7 September which indicates that Brazil might cross the total number of infected people compared to the USA after 7th September. Also, it is observable that the Brazil line (RVFL model) crosses the USA (WCRVFL model) line after 25th August which suggests that Brazil might cross the total number of infected people compared to the USA after 25th September. However, downfall in the line of RUSSIA (Using both RVFL and WCRVFL) and PERU (Using both RVFL and WCRVFL) is noticeable. The line for INDIA (Both RVFL and WCRVFL) shows an increase in the number of infected people on a daily basis. Furthermore, 60 days ahead of daily future prediction values that are obtained by both RVFL and WCRVFL models are tabulated in Table 11.

Additionally, the original data and the 60 days ahead forecast using the best RVFL model based on R^2 value are portrayed in Fig. 6. The following implications can be obtained from Fig. 6 for different countries using the RVFL networks:

a. Brazil: It is observed that the prediction curve grows exponentially which indicates that the number of infected people grows exponentially.
b. India: Similar to the Brazil curve, the India curve also shows exponential growth.
c. Peru: Growth can be noticed in the graph; however, it is not exponential.
d. Russia: It is noticeable from the 60 days ahead prediction curve that the limb gradually decreases from mid-August 2020.
e. USA: Similar to the Brazil curve the USA curve also shows exponential growth in the number of infected people.

Also, the original and the 60 days ahead prediction line graphs for the best WCRVFL network are shown in Fig. 7 for Brazil, India, Peru, Russia and the USA respectively. The following implications can be drawn from these figures:

a. Brazil: It is observed that the graph grows almost exponentially for both WCRVFL RELU Network and WCRVFL Sigmoid Network.

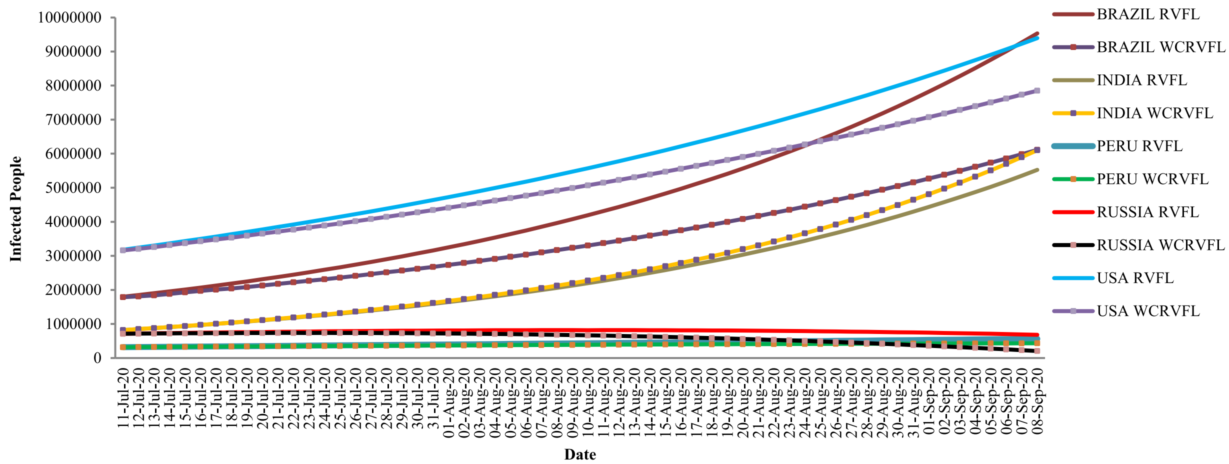

Fig. 5. 60 days ahead of the day by day prediction from 11th July to 8th September of corresponding best RVFL models and the best WCRVFL models.

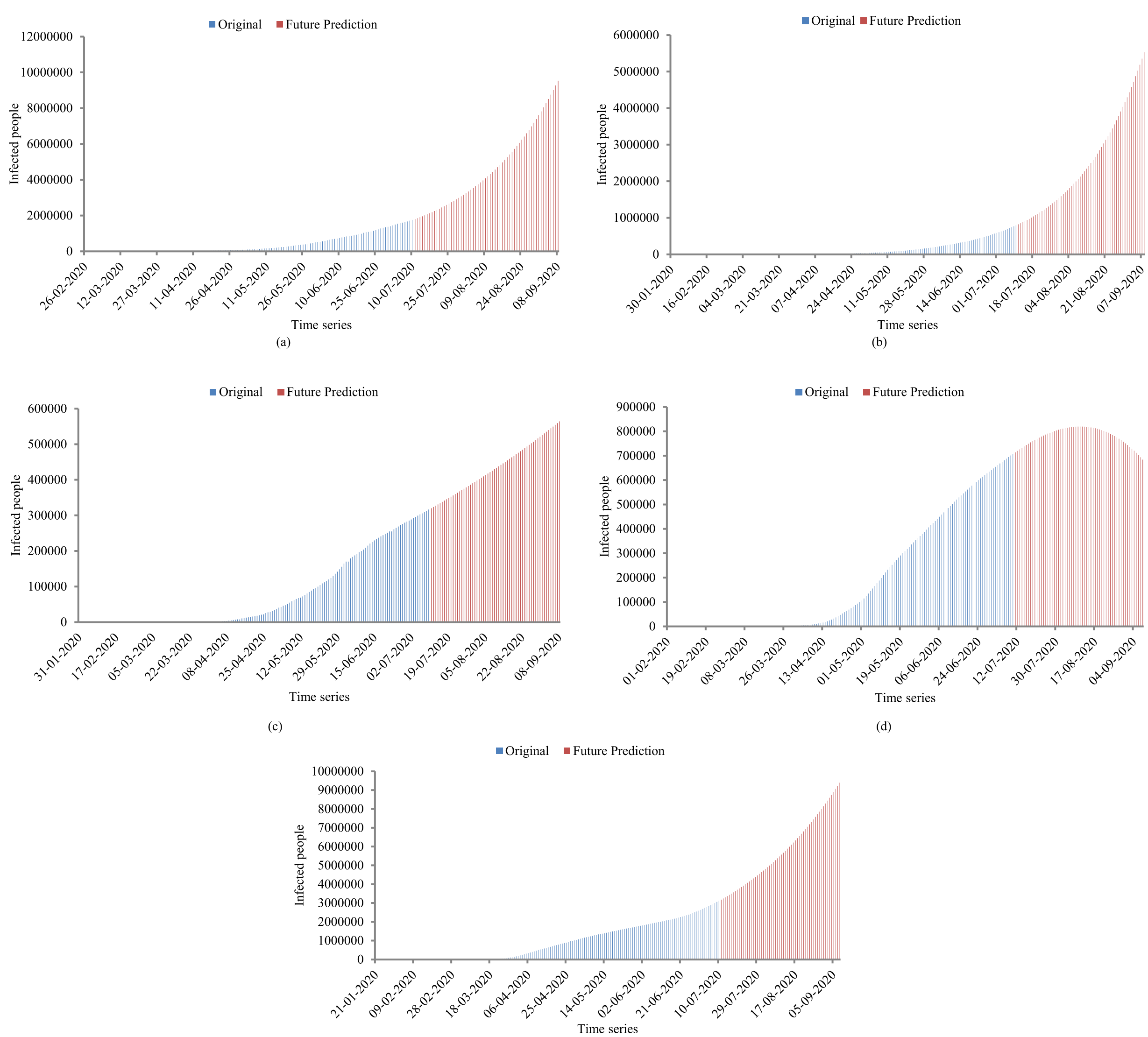

Fig. 6. 60 days ahead prediction using the best RVFL Network for (a) Brazil, (b) India, (c) Peru, (c) Russia and (e) USA.

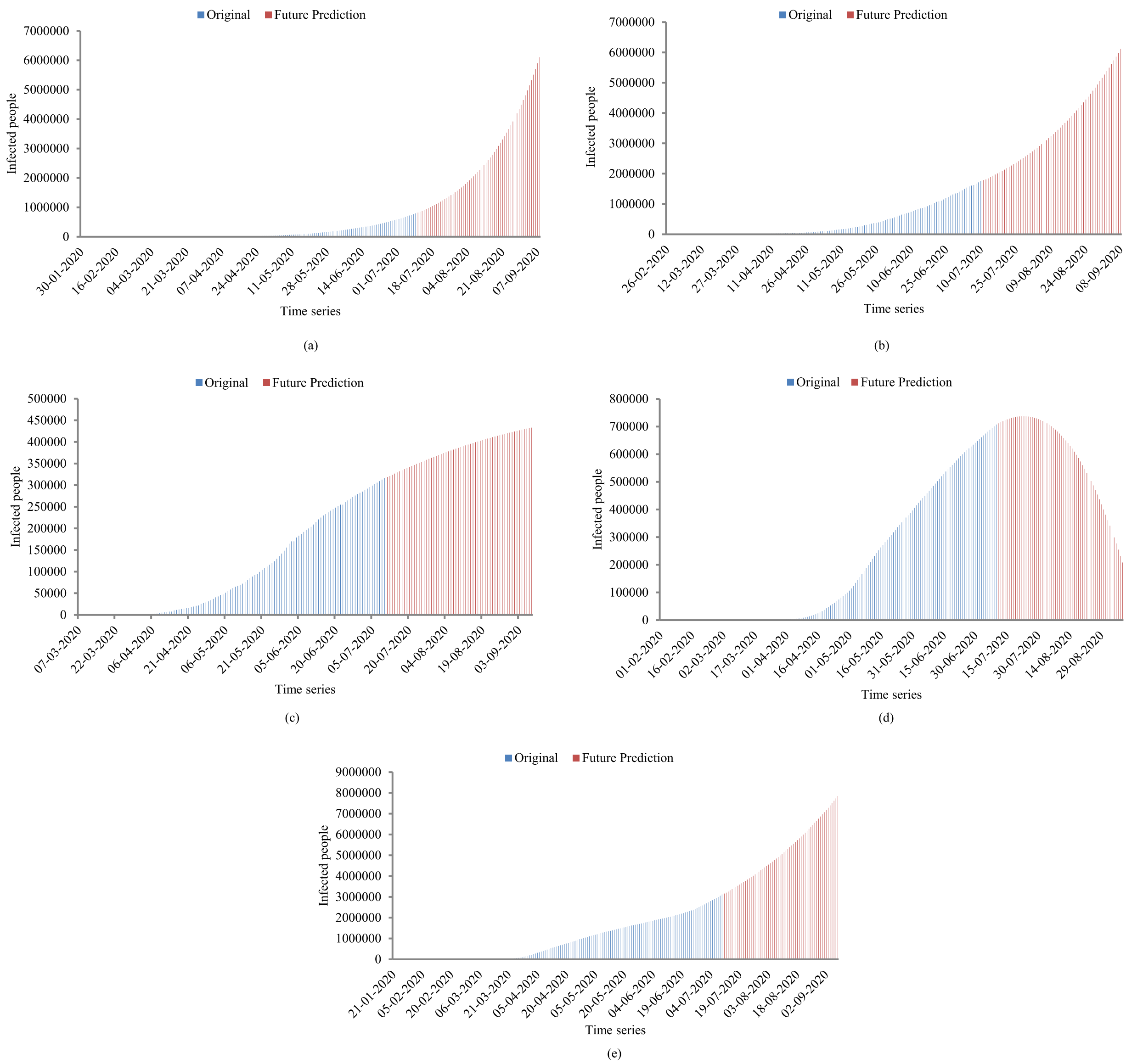

Fig. 7. 60 days ahead prediction for (a) Brazil, (b) India, (c) Peru, (d) Russia and (e) USA respectively using the best WCRVFL network.

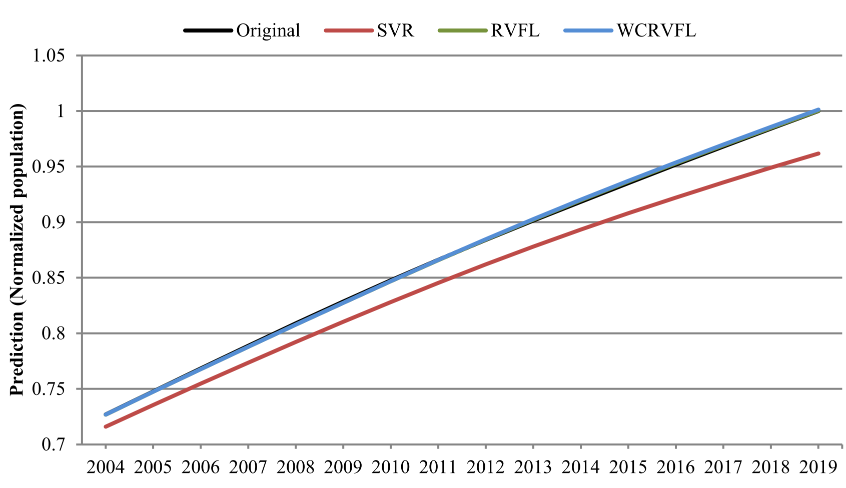

Fig. 8. Prediction performance over the testing sample for POPULATION dataset.

Table 11
Predicted values obtained by the RVFL models and the best WCRVFL (Based on R^2) on a daily basis.

Date	BRAZIL (People)		INDIA (People)		PERU (People)		RUSSIA (People)		USA (People)	
	Best RVFL	Best WCRVFL	Best RVFL	Best WCRVFL	Best RVFL	Best WCRVFL	Best RVFL	Best WCRVFL	Best RVFL	Best WCRVFL
11-Jul-20	1801460	1786560	821387	821407	319922	318930	713694	711629	3178460	3160420
12-Jul-20	1851040	1809310	849552	850092	323512	321150	719971	715547	3240570	3205060
13-Jul-20	1902600	1839830	878250	879132	327096	323844	726103	719289	3302990	3256440
14-Jul-20	1955550	1881990	907786	909006	330668	326723	732089	722825	3367780	3314290
15-Jul-20	2010400	1929160	938431	940148	334259	329417	737919	725923	3432990	3372640
16-Jul-20	2067330	1972040	970213	972614	337876	331925	743589	728546	3499520	3427530
17-Jul-20	2126120	2008220	1002980	1006250	341499	334421	749094	730801	3566700	3480340
18-Jul-20	2186700	2042970	1036740	1040960	345135	336971	754429	732749	3635330	3534870
19-Jul-20	2249140	2082780	1071590	1076800	348788	339521	759589	734362	3704950	3592800
20-Jul-20	2313490	2129000	1107670	1113900	352457	342014	764570	735599	3775860	3652660
21-Jul-20	2379770	2177620	1144860	1152330	356140	344457	769368	736453	3847810	3712270
22-Jul-20	2448000	2224140	1183320	1192120	359840	346877	773977	736934	3921030	3771130
23-Jul-20	2518230	2267940	1223010	1233290	363557	349285	778393	737048	3995420	3830420
24-Jul-20	2590500	2312080	1263810	1275880	367290	351672	782611	736781	4071110	3891360
25-Jul-20	2664870	2359710	1305920	1319950	371040	354031	786626	736120	4148030	3953950
26-Jul-20	2741390	2411090	1349580	1365550	374809	356358	790434	735055	4226260	4017400
27-Jul-20	2820130	2463960	1394570	1412740	378595	358657	794031	733588	4305790	4081120
28-Jul-20	2901150	2516160	1441110	1461570	382400	360931	797411	731713	4386670	4145290
29-Jul-20	2984490	2567720	1489240	1512100	386224	363180	800569	729418	4468910	4210470
30-Jul-20	3070250	2620360	1538740	1564380	390068	365400	803502	726696	4552550	4276900
31-Jul-20	3158460	2675590	1589760	1618480	393931	367589	806204	723544	4637590	4344420
01-Aug-20	3249210	2733320	1642380	1674450	397814	369752	808670	719952	4724090	4412740
02-Aug-20	3342560	2792300	1696410	1732370	401718	371893	810897	715914	4812050	4481770
03-Aug-20	3438610	2851570	1752370	1792290	405643	374010	812878	711425	4901510	4551690
04-Aug-20	3537430	2911300	1810180	1854300	409590	376100	814611	706481	4992500	4622680
05-Aug-20	3639070	2972450	1869950	1918450	413558	378164	816089	701077	5085030	4694780
06-Aug-20	3743640	3035730	1931350	1984830	417549	380207	817309	695206	5179150	4767880
07-Aug-20	3851200	3100990	1994540	2053510	421562	382227	818266	688852	5274880	4841920
08-Aug-20	3961840	3167570	2059780	2124580	425599	384224	818954	682008	5372250	4916920
09-Aug-20	4075690	3235060	2127590	2198100	429658	386192	819371	674672	5471300	4992970
10-Aug-20	4192800	3303650	2197380	2274180	433742	388131	819510	666843	5572040	5070140
11-Aug-20	4313280	3373860	2269320	2352890	437849	390043	819367	658513	5674520	5148410
12-Aug-20	4437200	3446030	2343160	2434330	441982	391929	818939	649678	5778760	5227750
13-Aug-20	4564690	3520030	2419420	2518590	446139	393787	818219	640334	5884810	5308170
14-Aug-20	4695820	3595540	2498610	2605770	450322	395620	817205	630483	5992680	5389710
15-Aug-20	4830710	3672410	2581190	2695970	454530	397429	815891	620120	6102410	5472400
16-Aug-20	4969500	3750790	2666610	2789290	458765	399216	814273	609241	6214050	5556280
17-Aug-20	5112270	3830970	2754590	2885850	463026	400979	812346	597835	6327610	5641330
18-Aug-20	5259180	3913120	2844330	2985760	467315	402717	810107	585898	6443150	5727560
19-Aug-20	5410270	3997160	2936920	3089120	471630	404424	807551	573426	6560680	5815000
20-Aug-20	5565700	4082950	3032760	3196070	475974	406101	804674	560415	6680260	5903680
21-Aug-20	5725590	4170450	3131130	3306720	480345	407744	801471	546865	6801920	5993610
22-Aug-20	5890080	4259790	3232180	3421200	484745	409357	797938	532768	6925690	6084820
23-Aug-20	6059300	4351130	3335780	3539650	489174	410944	794071	518121	7051620	6177310
24-Aug-20	6233400	4444560	3442500	3662210	493632	412502	789867	502924	7179740	6271110
25-Aug-20	6412470	4540050	3552970	3789000	498120	414038	785320	487172	7310090	6366230
26-Aug-20	6596650	4637570	3667190	3920190	502638	415558	780428	470866	7442710	6462710
27-Aug-20	6786150	4737110	3785110	4055920	507187	417051	775186	454010	7577650	6560550
28-Aug-20	6981080	4838790	3907000	4196360	511766	418515	769591	436601	7714950	6659790
29-Aug-20	7181590	4942710	4033460	4341650	516377	419957	763638	418634	7854640	6760430
30-Aug-20	7387860	5048930	4163600	4491980	521019	421384	757324	400105	7996780	6862500
31-Aug-20	7600080	5157460	4297000	4647510	525694	422786	750645	381017	8141400	6966030
01-Sep-20	7818420	5268300	4433690	4808430	530401	424157	743597	361371	8288550	7071030
02-Sep-20	8043020	5381500	4576450	4974920	535141	425501	736177	341172	8438290	7177530
03-Sep-20	8274040	5497140	4723370	5147180	539914	426821	728382	320424	8590640	7285550
04-Sep-20	8511710	5615300	4872560	5325400	544721	428120	720207	299118	8745670	7395120
05-Sep-20	8756210	5736030	5025460	5509790	549562	429399	711650	277257	8903420	7506240
06-Sep-20	9007750	5859380	5185610	5700570	554437	430654	702707	254836	9063930	7618960
07-Sep-20	9266510	5985360	5353210	5897950	559348	431885	693376	231856	9227270	7733280
08-Sep-20	9532680	6114040	5526650	6102170	564293	433091	683653	208334	9393470	7849250

b. India: An exponential growth can be observed in the prediction curve of India.
c. Peru: In case of WCRVFL RELU as well as the WCRVFL Sigmoid network, the increase in the number of infected people can be observed.
d. Russia: A gradually decreasing curve can be observed from the last days of July 2020 for both cases.
e. USA: Similar to the Brazil curve, the USA curve also shows growth in the number of infected people if not exponential for both; WCRVFL RELU and WCRVFL Sigmoid networks.

4.2. Experiment on time series dataset

Further, to test proposed WCRVFL's applicability in application areas with time-series datasets, we have experimented on a real world time series dataset. The dataset, called "POPULATION", is originally a collection of the total population in India from 1961 to 2019, i.e., a total collection of 60 samples. Out of which, 70% of the total samples are used for training while the rest are used for testing. The dataset is obtained from https://data.worldbank.org/. The experimental results of WCRVFL model in time series prediction are tabulated in Table 12. Further, the best WCRVFL model is compared with the conventional RVFL and SVR models which are shown in Table 13. Moreover, the prediction performance plot is shown in Fig. 8. It is noticeable that WCRVFL could achieve convincing prediction performance in time-series prediction for the reported dataset.

5. Conclusion

We studied the prediction ability of the RVFL network to model and forecast the spread of the COVID-19 pandemic. The non-stationarity of the time-series datasets is handled by using numerous types of mother wavelets. It is noticeable that the RVFL network that is embedded in the wavelet provides consistent prediction performance. The 60 days ahead prediction is also employed by using both, RVFL and the proposed WCRVFL. Overall it can be concluded that the wavelet-based hybrid models might be helpful for society so that early prevention can be taken. However, our research has limitations like the optimal number of nodes in the hidden layer, tuning the scaling of the uniform randomization range, accurate data availability etc. The RVFL network presently uses the only samples of the time-series data for prediction. A prospective future direction to add more attributes in the time series data so that maximum information can be gathered from the data, as well as the prediction performance, may be improved. In addition to that Lagrangian twin RVFL model can be coupled with wavelets and wavelet coupled ARIMA models are suggested for forecasting the COVID-19 spread worldwide.

Table 12
Experimental results obtained by the WCRVFL model for POPULATION dataset for 9 different evaluators (Best results are bolded).

Evaluators	Activation	DB2	DB3	DB4	DB5	DB6	DB7	DB8	HAAR	COIF2	COIF3	COIF4	COIF5	SYM2	SYM3	SYM4	SYM5	SYM6	SYM7	SYM8
RMSE	RELU	0.00103	**0.00086**	0.00126	0.00325	0.00222	0.00347	0.00614	0.00112	0.00482	0.00254	0.00444	0.00088	0.00685	0.00132	0.00232	0.00349	0.00202	0.00271	0.00185
	SIGMOID	0.00099	0.00068	**0.00055**	0.00074	0.00117	0.00208	0.00156	0.0029	0.00197	0.00154	0.00106	0.00098	0.001	0.00064	0.00187	0.00282	0.00147	0.00131	0.00186
MAE	RELU	0.00069	0.00064	0.00113	0.00275	0.00162	0.0028	0.00507	0.00094	0.00379	0.00201	0.00373	**0.0006**	0.00549	0.00102	0.00158	0.00249	0.00139	0.00204	0.00138
	SIGMOID	0.00077	0.00047	**0.00043**	0.00055	0.00072	0.00133	0.00106	0.00237	0.00124	0.00098	0.00073	0.00065	0.00076	0.00048	0.00107	0.00187	0.00086	0.00085	0.00117
R^2	RELU	0.99989	0.99987	0.99987	0.99993	0.99988	0.9998	0.99993	0.98779	**0.99996**	0.99995	0.99995	0.99993	0.99992	0.99987	0.99995	0.99987	0.99989	0.99985	0.99987
	SIGMOID	0.99989	0.99987	0.99987	0.99993	0.99988	0.9998	0.99993	0.98779	**0.99996**	0.99995	0.99995	0.99993	0.99992	0.99987	0.99995	0.99987	0.99989	0.99985	0.99987
SSE/SST	RELU	0.00014	**0.0001**	0.00021	0.00141	0.00066	0.0016	0.00502	0.00017	0.00309	0.00086	0.00263	0.0001	0.00624	0.00023	0.00072	0.00162	0.00055	0.00098	0.00046
	SIGMOID	0.00013	0.00006	**0.00004**	0.00007	0.00018	0.00058	0.00032	0.00113	0.00051	0.00032	0.00015	0.00013	0.00013	0.00006	0.00046	0.00106	0.00029	0.00023	0.00046
PSNR	RELU	107.859	**109.479**	106.111	97.9012	101.186	97.3242	92.3692	107.138	94.472	100.046	95.1753	109.25	91.422	105.733	100.827	97.2766	102.007	99.4579	102.791
	SIGMOID	108.211	111.49	**113.359**	110.708	106.756	101.772	104.269	98.8794	102.261	104.371	107.638	108.298	108.153	111.949	102.704	99.1293	104.772	105.814	102.722
SC	RELU	1.00109	0.99948	0.9989	0.99343	0.99679	1.00674	0.98787	0.99872	0.99087	0.99521	0.99111	0.99946	**0.9867**	1.00228	0.99682	0.994	0.99756	0.99529	0.99679
	SIGMOID	0.99846	1.00048	1.00042	1.00099	0.99963	0.99694	0.99871	**0.99439**	0.99737	0.99824	1.00068	0.99989	0.99839	1.00059	0.99887	0.99572	0.99954	1.00203	0.99744
MD	RELU	0.00317	**0.00183**	0.00194	0.00674	0.00571	0.00875	0.01255	0.00193	0.01178	0.00671	0.0098	0.00236	0.01072	0.00273	0.0076	0.00771	0.00568	0.00533	0.00421
	SIGMOID	0.00175	0.00199	**0.00108**	0.00195	0.00397	0.0065	0.0045	0.00454	0.00661	0.00515	0.00257	0.00298	0.00176	0.00181	0.00658	0.00877	0.00468	0.00447	0.00593
LMSE	RELU	0.65231	0.69812	0.25447	0.49999	0.92683	1.07027	1.15043	**0.00044**	0.65701	0.55	0.63212	0.92651	1.45533	0.76255	0.93499	1.10498	0.85122	1.16987	0.85343
	SIGMOID	1.85611	1.79023	0.1693	0.34123	0.66743	1.00152	1.23496	**0.00218**	0.5866	0.52683	0.53954	0.59205	1.84227	1.62474	0.75179	1.34249	0.62161	2.21191	0.61719
NAE	RELU	0.00079	0.00073	0.0013	0.00315	0.00186	0.00321	0.00582	0.00108	0.00434	0.00231	0.00427	**0.00068**	0.00632	0.00118	0.00181	0.00286	0.00159	0.00234	0.00158
	SIGMOID	0.00089	0.00054	**0.00049**	0.00064	0.00082	0.00152	0.00121	0.0027	0.00142	0.00113	0.00083	0.00075	0.00087	0.00055	0.00123	0.00214	0.00098	0.00098	0.00134

Table 13
Prediction error based on RMSE and R^2 for the POPULATION dataset (Best results are bolded).

Evaluators	SVR	RVFL		Best WCRVFL	
		RELU	Sigmoid	RELU	Sigmoid
RMSE	0.02386	0.00088	0.0010	0.00086	**0.00055**
R^2	0.99958	0.99951	0.99995	**0.99996**	**0.99996**

CRediT authorship contribution statement

Barenya Bikash Hazarika: Formal analysis, Validation, Visualization, Writing - editing. **Deepak Gupta:** Conceptualization, Investigation, Writing - original draft.

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.

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