Modelling for prediction of the spread and severity of COVID-19 and its association with socioeconomic factors and virus types

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Received date: July 21, 2020; **Accepted date:** August 24, 2020; **Published date:** September 14, 2020

Citation: Shreshth T, Shikhar T, R Vermac and Rakesh T. (2020) Modelling for prediction of the spread and severity of COVID-19 and its association with socioeconomic factors and virus types. Biomedical Research and Clinical Reviews. 1(3); DOI: [10.31579/2692-9406/014](https://doi.org/10.31579/2692-9406/014)

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Abstract

We report the development of a Weibull based Long-Short-Term-Memory approach (W-LSTM) for the prediction of COVID-19 disease. The W-LSTM model developed in this study, performs better in terms of MSE, R2 and MAPE, as compared to the previously published models, including ARIMA, LSTM and their variations. Using W-LSTM model, we have predicted the beginning and end of the current cycle of COVID-19 in several countries. Performance of the model was validated as satisfactory in 82% of the 50 test countries, while asking for prediction for 10 days beyond the period of training. Accuracy of the above prediction with days beyond training was assessed in comparison with the MAPE that the model gave with cumulative global data. The model was applied to study correlation between the growth of infection and deaths, and a number of effectors that may influence the epidemic. The model identified age groups, trade with China, air traffic, country temperature and CoV-2 virus types as the likely effectors of infection and virulence leading to deaths. The predictors likely to promote or suppress the epidemic were identified. Some of the predictors had significant effect on the shape parameters of Weibull distribution. The model has been deployed on cloud, taking inputs in real time to handle large data country wise, at low costs and make predictions dynamically. Such predictions are highly valuable in guiding policy makers, administration and health. Interactive prediction curves generated from the W-LSTM model deployed on cloud platform can be seen at <http://collaboration.coraltele.com/covid2/> (updated daily)

Keywords: COVID-19; coronavirus; machine learning; epidemic prediction; so- cioeconomic predictors

Abbreviations: ML: Machine Learning; SARS-CoV-2: Severe Acute Respiratory Syndrome Coronavirus 2; COVID-19: Coronavirus disease

1. Introduction

Since the first few reports from Wuhan, China in December, 2019, the Coronavirus disease COVID-19 has now spread globally to more than 200 countries and territories. It has been declared a pandemic by WHO. In the absence of a curative drug or vaccine, containing the disease by non-pharmaceutical approaches is the highest priority to guard against its continued outbreak and spread. It is caused by a member of the SARS group of viruses, called novel Coronavirus CoV-2, which is more contagious than the previously known SARS viruses. In a large proportion of the cases, CoV-2 incubates in individuals with no exhibited symptoms, who continue to spread the infection. Within a period of fewer than 6 months, more than six million people have globally been tested as infected by CoV-2, which has claimed some 370000 lives. Containing and managing the spread of COVID-19 requires anticipating well in advance, the magnitude and dimension that a pandemic like this, may take in the coming months.

Mathematical models for simulating the phase-based human transmissibility of the disease, requires detailed knowledge of the

epidemiological parameters related to its infectivity and spread. Systematic data on key epidemiological parameters such as basic reproduction number (a few to several cases to which an individual may pass the disease by direct and indirect contact), incubation period (2 to 14 days and longer when an individual may or may not have symptoms but spreads the disease), sensitivity time (time it takes for a suspected individual to be diagnosed as a confirmed infected case in community), serial transmission time, virus type etc., show large variability (depending upon the socioeconomic, health and environmental factors) and are at early stages of study [1].

Based on such parameters, classical models, like SIR and its variations like SEIQDR [2] and SIDARTHE [3] have been developed for the modelling of COVID-19 disease to guide the implementation of community-level interventions to contain and manage the epidemic. However, the parameters related to such models vary, depending upon the ecosystem. These are not easy to assess and fully accommodated in the models. Hence, the accuracy and predictability of the mathematical models for forecasting the epidemic become limiting, though such

models help take community-level decisions.

A powerful alternative approach to capture the temporal components of the epidemic and deploy those for predicting the future course of action is statistical modelling. With the growth of machine learning methods, it has become possible to utilize the statistical principles and build models after learning the principles and parameters from the data itself. With the availability of real time data on the pandemic from nearly 200 countries, it is immediately desirable to apply deep learning methods that learn from country-wise data and make predictions, without making the core assumptions required in the epidemiological models. Artificial intelligence (AI) based approaches can handle large data in real-time and can utilize global data from the cloud at low costs to make predictions dynamically. Such predictions are highly valuable in guiding policymakers, administration and health departments for data-driven management of the pandemic, at levels varying from communities, territories and countries.

A number of research papers have been published in the last six months on the development of models based on multiple linear regression, Gaussian and Bayesian statistics and time series analysis. Some of the recent publications include the application of ARIMA [4] and its variants [4]. The advent of Deep Learning has shown that Recurrent Neural Networks [5] and Long Short-Term Memory (LSTM) [6, 7, 8] outperform previously used models, due to their ability to generalize to diverse series types and provide much higher prediction accuracy. Yet there is a need to improve the accuracy and duration of prediction by these models. The AI-based models embody the unique feasibility of making quick adjustments in response to any local factors that may impact the course of the epidemic.

This study presents an improved approach to forecast course of the epidemic, compares its performance with other contemporary methods and applies the model to analyze associations between a variety of socioeconomic determinants likely to affect the spread of the infection and the resultant deaths. The prediction model was used to forecast dimensions of the epidemic in 30 countries. A number of socioeconomic predictors that influence infection and death were identified. The model was also applied to predict if the global data on the infections suggests the evolution of COV-2 virus into variants that differed in their degree of virulence. The

model was applied to make predictions at desired time points. Once connected to real time data, it can take inputs in real time to re-learn and make autocorrections in short and long-term predictions for future dates.

2. Methods

2.1. Prediction Model

We have earlier reported that the growth of the COVID-19 epidemic fits Weibull distribution better than the Gaussian, Beta 4, Fisher-Tippett and Normal Logarithmic distributions [9]. For several countries, the number of daily new infections and deaths was modeled by an improved “Robust Weibull” machine learning approach that fits a Generalized Weibull Distribution (GIW) as shown below:

$$f(x) = k \cdot \gamma \cdot \beta \cdot \alpha^\beta \cdot x^{-1-\beta} \cdot \exp\left(-\gamma\left(\frac{\alpha}{x}\right)^\beta\right) \quad (1)$$

The above model uses an iterative weighting strategy, calculating weights using residuals from the fit curve, to prevent outliers and noisy data that lead to poor curve fits using the Levenberg-Marquardt (LM) method [10] as shown in Algorithm 1. However, this model faces a serious limitation of being very sensitive to new data that may differ even marginally from the data used for building the model. Whenever new data is added, the earlier model is trained from the very beginning. This does not allow predictions to be made with high confidence as they fit curve itself changes significantly with even a single day's new data. To improve the model in this respect, we developed a time series model to capture the temporal dependence of the model parameters (k, α, β, γ) and predict the appropriate parameter set.

Series analysis has been used abundantly in the past for various activities like weather forecasting, language translation, etc. Models like ARIMA [4] have prominently been used in the past. However, the advent of Deep Learning has shown that Recurrent Neural Networks [5] and Long Short-Term Memory (LSTM) [11] outperform previously used models mostly due their ability to generalize to diverse series types and provide much higher prediction accuracy

Algorithm 1 Robust Curve Fitting using Iterative weighting

Require:

x : Input sequence of days from first case

y : Number of cases for each day in x

ϵ : Threshold parameter

procedure ROBUST CURVE FITTING

$w^0 \leftarrow$ Unit vector $[1] \times \text{size}(x)$

for iteration n from 0, step 1 **do**

$f \leftarrow$ LM(input = x , target = y , weights = w^n)

$d_i \leftarrow |f(x_i) - y_i| \forall i$

$$w_i^{n+1} \leftarrow \frac{\exp\left(1 - \frac{d_i^n - \tanh(d_i^n)}{\max_i d_i^n - \tanh(d_i^n)}\right)}{\sum_i \exp\left(1 - \frac{d_i^n - \tanh(d_i^n)}{\max_i d_i^n - \tanh(d_i^n)}\right)}$$

if $\sum_i |w_i^n - w_i^{n+1}| < \epsilon$ **then**

break

end for

end procedure

We use LSTM to analyze and predict the best GIW parameters $(k, \alpha, \beta, \gamma)$. LSTM models use three types of "gates" to analyze the data sequence: input, forget and output gates. A single LSTM cell takes as input the sequence data corresponding to each time-step and a hidden state. Now, for an input at x_t at time t :

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \quad (2)$$

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \quad (3)$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o), \quad (4)$$

Where i_t corresponds to the input gate, f_t forget gate and o_t output gate. Here, each gate has its weight matrix w and bias value b . Moreover, h_{t-1} is the output for the previous time-step. To output h_t and hidden state c_t are calculated as follows:

$$c_t = f_t \times c_{t-1} + i_t \times \tanh(w_c[h_{t-1}, x_t] + b_c) \quad (5)$$

$$h_t = o_t \times \tanh(c_t), \quad (6)$$

Where c_{t-1} is the hidden state of the previous type step. The Equations 2

to 6 can be written compactly as:

$$h_t, c_t = \text{LSTM}(x_t, h_{t-1}, c_{t-1}). \quad (7)$$

The LSTM model can be applied to a complete time sequence to predict the output at the end of the sequence. Main features of the model are given in Figure 1. The time-series LSTM model is applied to the parameters of the Weibull distribution $(k, \alpha, \beta, \gamma)$. The "iterative" optimization, provided by the LSTM, helps in an under-fitted model to be transformed into a model optimally fitted to the data. The resultant hybrid model is named here as Weibull-LSTM (W-LSTM).

Model Training: To train the W-LSTM model, we use a sequence of 10 curve fits obtained from Robust-Weibull Curve fitting (Algorithm 1). The curve parameters of each of these curves is given as input to the LSTM network in the order of increasing data size as shown in Figure 1. The loss corresponding to each input set is calculated as the Mean Square Error (MSE) between the prediction and the actual $(k, \alpha, \beta, \gamma)$ values. This is then weighted by the normalized inverse error $(1 - \frac{MAPE}{100})$, where MAPE corresponds to the error of the curve corresponding to the input shape parameters. This gives higher weight to those parameter sets which have lower MAPE scores, allowing the model to converge to better parameter values. Detailed description of the training process is given in Algorithm 2.

Figure 1: LSTM Model

Prediction: To predict the best set of parameters for a given data of countries (number of daily new cases/deaths), we use Algorithm 3. Again, the data is used to generate 10 curves. The 10 curves use a subset of original data with last n datapoints removed, where n decreases from 9 to 0 (m in Algorithm 3 is 10 in our case). The LSTM network (trained

using Algorithm 2) is given the sequence of curve parameters fit by Algorithm 1 for the 10 curves in a sequence. The final output is used as the parameters of the GIW curve and predictions are made using this distribution.

Algorithm 2 W-LSTM Training**Require:**

countries : List of all countries with data
data : dictionary of data for each country in *countries*
 $\epsilon_{training}$: Threshold parameter for training
m : Sequence length for training

procedure TRAIN LSTM MODEL

```

     $t \leftarrow 0$ 
    Initialize new LSTM model
    while True do
         $h_0 \leftarrow 0$ 
         $c_0 \leftarrow 0$ 
         $loss_t \leftarrow 0$ 
         $MAPE \leftarrow [0] * m$ 
         $lossvec \leftarrow [0] * m$ 
        for country in countries do
            if  $\sum data[country] < 2000$  then
                continue
            for i from 1 to m do
                 $output \leftarrow \text{ROBUSTCURVEFITTING}(data[country][0 : n - m - 1 + i])$ 
                 $h_i, c_i \leftarrow \text{LSTM}(output, h_{i-1}, c_{i-1})$ 
                 $lossvec_i \leftarrow \text{MSE}(output, h_i)$ 
                 $k, \alpha, \beta, \gamma \leftarrow output$ 
                 $pred \leftarrow k \cdot \gamma \cdot \beta \cdot \alpha^\beta \cdot x^{-1-\beta} \cdot \exp\left(-\gamma\left(\frac{\alpha}{x}\right)^\beta\right) \forall x \in data[country]$ 
                 $MAPE_i \leftarrow \text{MAPE}(pred, data[country])$ 
            end for
             $loss_t \leftarrow loss_t + (1 - \frac{MAPE}{100}) \odot lossvec$ 
             $\text{BACKPROP}(\text{LSTM}, loss_t)$ 
            if  $t > 0$  and  $|loss_t - loss_{t-1}| < \epsilon_{training}$  then
                break
             $t \leftarrow t + 1$ 
        end for
    end while
end procedure

```

2.2. Cloud Framework

To provide a fail-safe computation and quick data analysis, we propose a framework to deploy the W-LSTM model on cloud data-centers. In a cloud-based environment, the government hospitals and private health-centers continuously send their positive patient count. For this case study,

we used three instances of single-core *Azure B1s* virtual machines with 1-GiB RAM, SSD Storage and 64-bit Microsoft Windows Server 2016¹. We used the FogBus [12] framework to deploy the W-LSTM model and generate prediction plots daily². We analyzed that the cost of tracking patients daily, amortized CPU consumption and Cloud execution is 57% and only 2.9 USD per day. As the dataset size increases, computationally more powerful resources would be needed.

Algorithm 3 W-LSTM Curve Fitting**Require:***countries* : List of all countries with data*data* : dictionary of data for each country in *countries**m* : Sequence length for training**procedure LSTM ROBUST WEIBULL CURVE FITTING**

Use pretrained LSTM model

while True **do** $h_0 \leftarrow 0$ $c_0 \leftarrow 0$ **for** *country* in *countries* **do****if** $\sum data[country] < 2000$ **then****continue****for** *i* from 1 to *m* **do** $output \leftarrow \text{ROBUSTCURVEFITTING}(data[country][0 : n - m - 1 + i])$ $h_i, c_i \leftarrow \text{LSTM}(output, h_{i-1}, c_{i-1})$ **end for** $k, \alpha, \beta, \gamma \leftarrow h_k$ $pred \leftarrow k \cdot \gamma \cdot \beta \cdot \alpha^\beta \cdot x^{-1-\beta} \cdot \exp(-\gamma(\frac{\alpha}{x})^\beta) \forall x \in data[country]$ **end for****end while****end procedure****2.3. Inferential Statistics**

Inferential statistics was applied through Pearson correlation and step-wise multiple linear regression analysis. After fitting a regression model, the p-values were used at 5% ($p < 0.05$, highly significant) and 10% ($p < 0.1$, significant) level of significance to identify the statistically significant relationships, and hence most likely influential. To identify the population variables that had a highly significant correlation with the disease, only those cases were considered whose r-value fell beyond the Critical Value (less than the lower limit and more than the upper limit), as applied to two-tailed test at n-2 degrees of

freedom and 0.05 or 0.1 level of significance. Numerical values of the regression coefficients represent the mean change that the disease (response variable/ dependent variable) will have with a one-unit change in the corresponding predictor variable (independent variable), keeping all other factors that influence growth of the disease at constant. Only those independent variables were considered significant whose regression coefficients had p below 0.1, or preferentially below 0.05. Only the variables that were significant at $p < 0.1$ and had a high R^2 were listed as the important predictors of the disease and its severity. The residual plots were examined for unbiased scatter.

2.4. Data Sources

Epidemic data: The data related to daily new cases of confirmed infections and deaths as a consequence of covid-19 in different countries was downloaded from Our World in Data COVID-19 Dataset at <https://ourworldindata.org/coronavirus>. The site updates its data on daily basis from European Centre for Disease Prevention and May 19, 2020 was used for learning the model based on W-LSTM. Predictions were made the numeral value for daily new infections came down to one.

Socioeconomic data: The data related to country wise socioeconomic parameters were taken from a number of open source public resources. These include Index Mundi and World Bank at the following links. <https://www.indexmundi.com/facts/indicators/SH.MLR.TRET.ZS>; and <https://wits.worldbank.org/CountryProfile/en/Country/CHN/Year/2018/>.

Virus Type data: The data related to the eleven different types of COV-2 virus strains (technically, clades) was taken from <https://www.biorxiv.org/content/10.1101/2020.05.04.075911v1.supplementary-material> [13]. The frequency of the type of COV-2 was determined by the authors in 62 countries, based on the 6181 nucleotide sequences of the genomes sequenced in those countries by April 16, 2020. The frequency data were smoothed by Laplace transform. The original data is given in Supplementary Table 1A. The frequency data before and after smoothing is given in Supplementary Tables 1B and 1C respectively. The Laplace transform data (Supplementary Table 1C) was used in the analysis here.

Government Stringency Index: The daily score was calculated as in Oxford Government Response Tracker (<https://www.bsg.ox.ac.uk/sites/default/files/Calculation%20and%20presentation%20of%20the%20Stringency%20Index.pdf>) and was taken from *Our World in Data*. The score is based on several factors including the closure of schools, market places, works, public gatherings etc. taken as emergency intervention measures to implement social distancing.

Country	MSE					R^2					MAPE				
	W-LSTM	W-ARIMA	Weibull	Gaussian	LSTM	W-LSTM	W-ARIMA	Weibull	Gaussian	LSTM	W-LSTM	W-ARIMA	Weibull	Gaussian	LSTM
World	3.13E+05	3.25E+05	3.95E+05	4.16E+05	3.99E+07	0.93	0.95	0.95	0.95	0.95	39.29	40.12	49.12	42.58	60.29
India	1.93E+01	1.96E+01	1.98E+01	2.08E+01	2.19E+03	0.91	0.96	0.94	0.94	0.93	22.00	22.13	23.44	37.03	38.44
United States	1.02E+05	1.15E+05	1.20E+05	1.25E+05	1.33E+05	0.86	0.87	0.86	0.86	0.80	26.09	104.38	27.55	134.66	149.52
United Kingdom	9.92E+03	9.96E+03	9.96E+03	1.21E+04	1.12E+05	0.90	0.91	0.92	0.91	0.90	14.93	14.99	15.13	104.86	93.03
Italy	2.11E+03	2.51E+03	2.53E+03	5.93E+03	3.10E+05	0.89	0.91	0.97	0.93	0.90	12.78	12.66	12.53	214.29	58.23

Table 1: Evaluation of different models on 5 representative countries, for predicting COVID-19 infections. W-LSTM performs significantly better than other distributions. The lowest value of MSE/MAPE and highest values of R^2 are shown in bold.

COUNTRY	O	B	B1	B2	B4	A3	A6	A7	A1A	A2	A2A	TOTAL
ALGERIA											3	3
ARGENTINA											3	3
AUSTRALIA	39	34	42	1	5	33	1		59		174	388
AUSTRIA	3					1			1		16	21
BELGIUM	13	10					10		8	1	258	300
BRAZIL	2	1							2		13	18
COMBODIA	1											1
CANADA	9		40			17			2		52	120
CHILE		6									1	7
CHINA	140	63	5	10	5	12			1		6	242
COLOMBIA		1									1	2
CZECH REPUBLIC											4	4
DR CONGO					1	1			1		29	32
DENMARK											9	9
ECUADO	2						1				1	4
FINLAND	3						1		4		32	40
FRANCE	9	1							1		187	198
GEORGIA	3	1				2					6	12
GERMANY	15	1		1		2			2		54	75
GHANA					2				1		3	6
GREECE		1									2	3
HONG KONG	55	3										58
HUNGARY											3	3
ICELAND	26		14				3		80	1	377	501
INDIA	1	1				13					11	26
IRAN						1						1
IRELAND	1								2		9	12
ISRAEL	1										1	2
ITALY	2										35	37
JAPAN	9			4							18	31
KUWAIT						4					4	8
LATVIA	3										6	9
LUXEMBOURG		1							5		80	86
MALAYSIA	6	1	1									8
MEXICO		2	2								5	9
NETHERLANDS	17	4			3	2	106		49	1	329	511
NEW ZEALAND		2				2	1		1		2	8
NIGERIA											1	1
NORWAY	7					1			2		15	25
PAKISTAN	1					1						2
PANAMA											1	1
PERU											1	1
POLAND	1											1
PORTUGAL	4	3					2		5		85	99
RUSSIA											4	4

SAUDI ARABIA	1									2	3
SENEGAL	1	1			2					18	22
SINGAPORE	30	9	1		1				1	3	45
SLOVAKIA							1			3	4
SLOVENIA									1	2	3
SOUTH AFRICA	1	19							1	1	22
SOUTH KOREA	7	66							3		76
SPAIN	4								2	71	77
SWEDEN	2										2
SWITZERLAND									1	47	48
TAIWAN	7	3				9			2	27	48
THAILAND		1								4	5
TURKEY						1					1
UNITED KINGDOM	339	26	1			3	14		230	4	802
UNITED STATES	31	28	446	1	27	3	2	4	42		882
VIETNAM	2	3								3	8
WORLD	798	292	552	17	46	108	142	4	509	7	3706

Supplementary Table 1A.

COUNTRY	O	B	B1	B2	B4	A3	A6	A7	A1A	A2	A2A
ALGERIA	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
ARGENTINA	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
AUSTRALIA	1.01E-01	8.76E-02	1.08E-01	2.58E-03	1.29E-02	8.51E-02	2.58E-03	0.00E+00	1.52E-01	0.00E+0 0	4.48E-01
AUSTRIA	1.43E-01	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	4.76E-02	0.00E+0 0	0.00E+00	4.76E-02	0.00E+0 0	7.62E-01
BELGIUM	4.33E-02	3.33E-02	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	3.33E-02	0.00E+00	2.67E-02	3.33E-03	8.60E-01
BRAZIL	1.11E-01	5.56E-02	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	1.11E-01	0.00E+0 0	7.22E-01
COMBODIA	1.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+00
CANADA	7.50E-02	0.00E+0 0	3.33E-01	0.00E+00	0.00E+0 0	1.42E-01	0.00E+0 0	0.00E+00	1.67E-02	0.00E+0 0	4.33E-01
CHILE	0.00E+0 0	8.57E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.43E-01
CHINA	5.79E-01	2.60E-01	2.07E-02	4.13E-02	2.07E-02	4.96E-02	0.00E+0 0	0.00E+00	4.13E-03	0.00E+0 0	2.48E-02
COLOMBIA	0.00E+0 0	5.00E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	5.00E-01
CZECH REPUBLIC	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
DR CONGO	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	3.13E-02	3.13E-02	0.00E+0 0	0.00E+00	3.13E-02	0.00E+0 0	9.06E-01
DENMARK	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
ECUADO	5.00E-01	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	2.50E-01	0.00E+00	0.00E+0 0	0.00E+0 0	2.50E-01
FINLAND	7.50E-02	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	2.50E-02	0.00E+00	1.00E-01	0.00E+0 0	8.00E-01
FRANCE	4.55E-02	5.05E-03	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	5.05E-03	0.00E+0 0	9.44E-01
GEORGIA	2.50E-01	8.33E-02	0.00E+0 0	0.00E+00	0.00E+0 0	1.67E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	5.00E-01
GERMANY	2.00E-01	1.33E-02	0.00E+0 0	1.33E-02	0.00E+0 0	2.67E-02	0.00E+0 0	0.00E+00	2.67E-02	0.00E+0 0	7.20E-01
GHANA	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	3.33E-01	0.00E+0 0	0.00E+0 0	0.00E+00	1.67E-01	0.00E+0 0	5.00E-01

GREECE	0.00E+0 0	3.33E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	6.67E-01
HONG KONG	9.48E-01	5.17E-02	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+00
HUNGARY	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
ICELAND	5.19E-02	0.00E+0 0	2.79E-02	0.00E+00	0.00E+0 0	0.00E+0 0	5.99E-03	0.00E+00	1.60E-01	2.00E-03	7.52E-01
INDIA	3.85E-02	3.85E-02	0.00E+0 0	0.00E+00	0.00E+0 0	5.00E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	4.23E-01
IRAN	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	1.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+00
IRELAND	8.33E-02	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	1.67E-01	0.00E+0 0	7.50E-01
ISRAEL	5.00E-01	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	5.00E-01
ITALY	5.41E-02	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	9.46E-01
JAPAN	2.90E-01	0.00E+0 0	0.00E+0 0	1.29E-01	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	5.81E-01
KUWAIT	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	5.00E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	5.00E-01
LATVIA	3.33E-01	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	6.67E-01
LUXEMBOURG	0.00E+0 0	1.16E-02	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	5.81E-02	0.00E+0 0	9.30E-01
MALAYSIA	7.50E-01	1.25E-01	1.25E-01	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+00
MEXICO	0.00E+0 0	2.22E-01	2.22E-01	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	5.56E-01
NETHERLANDS	3.33E-02	7.83E-03	0.00E+0 0	0.00E+00	5.87E-03	3.91E-03	2.07E-01	0.00E+00	9.59E-02	1.96E-03	6.44E-01
NEW ZEALAND	0.00E+0 0	2.50E-01	0.00E+0 0	0.00E+00	0.00E+0 0	2.50E-01	1.25E-01	0.00E+00	1.25E-01	0.00E+0 0	2.50E-01
NIGERIA	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
NORWAY	2.80E-01	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	4.00E-02	0.00E+0 0	0.00E+00	8.00E-02	0.00E+0 0	6.00E-01
PAKISTAN	5.00E-01	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	5.00E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+00
PANAMA	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
PERU	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
POLAND	1.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+00
PORTUGAL	4.04E-02	3.03E-02	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	2.02E-02	0.00E+00	5.05E-02	0.00E+0 0	8.59E-01
RUSSIA	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	1.00E+00
SAUDI ARABIA	3.33E-01	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	6.67E-01
SENEGAL	4.55E-02	4.55E-02	0.00E+0 0	0.00E+00	9.09E-02	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	8.18E-01
SINGAPORE	6.67E-01	2.00E-01	2.22E-02	0.00E+00	2.22E-02	0.00E+0 0	0.00E+0 0	0.00E+00	2.22E-02	0.00E+0 0	6.67E-02
SLOVAKIA	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	2.50E-01	0.00E+00	0.00E+0 0	0.00E+0 0	7.50E-01
SLOVENIA	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	3.33E-01	0.00E+0 0	6.67E-01
SOUTH AFRICA	4.55E-02	8.64E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	4.55E-02	0.00E+0 0	4.55E-02
SOUTH KOREA	9.21E-02	8.68E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	3.95E-02	0.00E+0 0	0.00E+00
SPAIN	5.19E-02	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	2.60E-02	0.00E+0 0	9.22E-01
SWEDEN	1.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+00
SWITZERLAND	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	2.08E-02	0.00E+0 0	9.79E-01
TAIWAN	1.46E-01	6.25E-02	0.00E+0 0	0.00E+00	0.00E+0 0	1.88E-01	0.00E+0 0	0.00E+00	4.17E-02	0.00E+0 0	5.63E-01

THAILAND	0.00E+0 0	2.00E-01 0	0.00E+0 0	0.00E+00 0	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00 0	0.00E+0 0	0.00E+0 0	8.00E-01
TURKEY	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00 0	0.00E+0 0	1.00E+0 0	0.00E+0 0	0.00E+00 0	0.00E+0 0	0.00E+0 0	0.00E+00
UNITED KINGDOM	2.39E-01	1.83E-02	7.05E-04	0.00E+00	0.00E+0 0	2.11E-03	9.87E-03	0.00E+00	1.62E-01	2.82E-03 0.00E+0	5.65E-01
UNITED STATES	2.11E-02	1.91E-02	3.04E-01	6.82E-04	1.84E-02	2.05E-03	1.36E-03	2.73E-03	2.86E-02	0	6.02E-01
VIETNAM	2.50E-01	3.75E-01	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	0.00E+0 0	0.00E+00	0.00E+0 0	0.00E+0 0	3.75E-01
WORLD	1.29E-01	4.72E-02	8.93E-02	2.75E-03	7.44E-03	1.75E-02	2.30E-02	6.47E-04	8.23E-02	1.13E-03	6.00E-01

Supplementary Table 1B.

COUNTRY	O	B	B1	B2	B4	A3	A6	A7	A1A	A2	A2A
ALGERIA	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	1.0000
ARGENTINA	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	1.0000
AUSTRALIA	0.1028	0.0900	0.1105	0.0051	0.0154	0.0874	0.0051	0.0026	0.1542	0.0026	0.4499
AUSTRIA	0.1818	0.0455	0.0455	0.0455	0.0455	0.0909	0.0455	0.0455	0.0909	0.0455	0.7727
BELGIUM	0.0465	0.0365	0.0033	0.0033	0.0033	0.0033	0.0365	0.0033	0.0299	0.0066	0.8605
BRAZIL	0.1579	0.1053	0.0526	0.0526	0.0526	0.0526	0.0526	0.0526	0.1579	0.0526	0.7368
COMBODIA	1.0000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
CANADA	0.0826	0.0083	0.3388	0.0083	0.0083	0.1488	0.0083	0.0083	0.0248	0.0083	0.4380
CHILE	0.1250	0.8750	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.1250	0.2500
CHINA	0.5802	0.2634	0.0247	0.0453	0.0247	0.0535	0.0041	0.0041	0.0082	0.0041	0.0288
COLOMBIA	0.3333	0.6667	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.6667
CZECH REPUBLIC	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	1.0000
DR CONGO	0.0303	0.0303	0.0303	0.0303	0.0606	0.0606	0.0303	0.0303	0.0606	0.0303	0.9091
DENMARK	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	1.0000
ECUADO	0.6000	0.2000	0.2000	0.2000	0.2000	0.2000	0.4000	0.2000	0.2000	0.2000	0.4000
FINLAND	0.0976	0.0244	0.0244	0.0244	0.0244	0.0244	0.0488	0.0244	0.1220	0.0244	0.8049
FRANCE	0.0503	0.0101	0.0050	0.0050	0.0050	0.0050	0.0050	0.0050	0.0101	0.0050	0.9447
GEORGIA	0.3077	0.1538	0.0769	0.0769	0.0769	0.2308	0.0769	0.0769	0.0769	0.0769	0.5385
GERMANY	0.2105	0.0263	0.0132	0.0263	0.0132	0.0395	0.0132	0.0132	0.0395	0.0132	0.7237
GHANA	0.1429	0.1429	0.1429	0.1429	0.4286	0.1429	0.1429	0.1429	0.2857	0.1429	0.5714
GREECE	0.2500	0.5000	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.7500
HONG KONG	0.9492	0.0678	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169	0.0169
HUNGARY	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	1.0000
ICELAND	0.0538	0.0020	0.0299	0.0020	0.0020	0.0020	0.0080	0.0020	0.1614	0.0040	0.7530
INDIA	0.0741	0.0741	0.0370	0.0370	0.0370	0.5185	0.0370	0.0370	0.0370	0.0370	0.4444
IRAN	0.5000	0.5000	0.5000	0.5000	0.5000	1.0000	0.5000	0.5000	0.5000	0.5000	0.5000
IRELAND	0.1538	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.0769	0.2308	0.0769	0.7692
ISRAEL	0.6667	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.6667
ITALY	0.0789	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.0263	0.9474
JAPAN	0.3125	0.0313	0.0313	0.1563	0.0313	0.0313	0.0313	0.0313	0.0313	0.0313	0.5938
KUWAIT	0.1111	0.1111	0.1111	0.1111	0.1111	0.5556	0.1111	0.1111	0.1111	0.1111	0.5556
LATVIA	0.4000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.7000
LUXEMBOURG	0.0115	0.0230	0.0115	0.0115	0.0115	0.0115	0.0115	0.0115	0.0690	0.0115	0.9310
MALAYSIA	0.7778	0.2222	0.2222	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111
MEXICO	0.1000	0.3000	0.3000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.1000	0.6000
NETHERLANDS	0.0352	0.0098	0.0020	0.0020	0.0078	0.0059	0.2090	0.0020	0.0977	0.0039	0.6445

NEW ZEALAND	0.1111	0.3333	0.1111	0.1111	0.1111	0.3333	0.2222	0.1111	0.2222	0.1111	0.3333
NIGERIA	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	1.0000
NORWAY	0.3077	0.0385	0.0385	0.0385	0.0385	0.0769	0.0385	0.0385	0.1154	0.0385	0.6154
PAKISTAN	0.6667	0.3333	0.3333	0.3333	0.3333	0.6667	0.3333	0.3333	0.3333	0.3333	0.3333
PANAMA	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	1.0000
PERU	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	1.0000
POLAND	1.0000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000
PORTUGAL	0.0500	0.0400	0.0100	0.0100	0.0100	0.0100	0.0300	0.0100	0.0600	0.0100	0.8600
RUSSIA	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	1.0000
SAUDI ARABIA	0.5000	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.7500
SENEGAL	0.0870	0.0870	0.0435	0.0435	0.1304	0.0435	0.0435	0.0435	0.0435	0.0435	0.8261
SINGAPORE	0.6739	0.2174	0.0435	0.0217	0.0435	0.0217	0.0217	0.0217	0.0435	0.0217	0.0870
SLOVAKIA	0.2000	0.2000	0.2000	0.2000	0.2000	0.2000	0.4000	0.2000	0.2000	0.2000	0.8000
SLOVENIA	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.2500	0.5000	0.2500	0.7500
SOUTH AFRICA	0.0870	0.8696	0.0435	0.0435	0.0435	0.0435	0.0435	0.0435	0.0870	0.0435	0.0870
SOUTH KOREA	0.1039	0.8701	0.0130	0.0130	0.0130	0.0130	0.0130	0.0130	0.0519	0.0130	0.0130
SPAIN	0.0641	0.0128	0.0128	0.0128	0.0128	0.0128	0.0128	0.0128	0.0385	0.0128	0.9231
SWEDEN	1.0000	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333	0.3333
SWITZERLAND	0.0204	0.0204	0.0204	0.0204	0.0204	0.0204	0.0204	0.0204	0.0408	0.0204	0.9796
TAIWAN	0.1633	0.0816	0.0204	0.0204	0.0204	0.2041	0.0204	0.0204	0.0612	0.0204	0.5714
THAILAND	0.1667	0.3333	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.1667	0.8333
TURKEY	0.5000	0.5000	0.5000	0.5000	0.5000	1.0000	0.5000	0.5000	0.5000	0.5000	0.5000
UNITED KINGDOM	0.2394	0.0190	0.0014	0.0007	0.0007	0.0028	0.0106	0.0007	0.1627	0.0035	0.5655
UNITED STATES	0.0218	0.0198	0.3047	0.0014	0.0191	0.0027	0.0020	0.0034	0.0293	0.0007	0.6019
VIETNAM	0.3333	0.4444	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.1111	0.4444
WORLD	0.1292	0.0474	0.0895	0.0029	0.0076	0.0176	0.0231	0.0008	0.0825	0.0013	0.5996

Supplementary Table 1C.

3. Results

3.1. Testing of the W-LSTM model on representative countries

As reported earlier [9] the Robust Weibull curve fitting technique performs superior to other fitting models including - Gaussian, Beta 4, Fisher-Tippet and Log-Normal. In this paper, we have developed an LSTM-based Robust Weibull approach (W-LSTM) and compared it with other published methods for the accuracy of prediction based on different estimates of error. We analyzed results obtained from COVID-19 infection data from 5 representative countries: world, India, USA, UK and Italy. Table 1 gives a comparison of the fitness accuracy of the W-LSTM model. It gives distinctly better results, as compared to the other distributions, and also the previously used ARIMA [5] and Simple LSTM [6, 7] models that have been applied to COVID-19 infection data. The W-LSTM-based approach developed in this study performs better in terms of MSE, R^2 and MAPE, as compared to the previously published models. This model was therefore applied to several countries for further analysis. The daily new infection and death curves based on W-LSTM model are plotted for 30 countries in Supplementary Figure 1 from the beginning to the predicted end of the current epidemic cycle. Curves for the world and a few countries with the highest cases are reproduced in Figure 2. Data giving the analysis of infections, deaths etc. and shape parameters (k, α, β, γ) are given in Supplementary Table 2.

3.2. W-LSTM prediction of infections and deaths till end

of the epidemic cycle

The W-LSTM model was applied to publicly available data on daily new cases of infections and deaths from several countries as per the data available till May 19, 2020. Raw data from different countries have lots of missing, incomplete and inconsistent entries, and therefore does not fit any distribution satisfactorily. Out of the 50 countries where sufficient data (for at least 3 months) is available for public view, the W-LSTM model, fits well on 30 countries. These countries were selected for further analysis. Supplementary Figure 1 shows the actual daily values as bars and compares those with the best fitting daily infection and death curves for the predicted values for these 30 countries. Unlike what we had expected, the peak positions of the infection and death curves for the 30 countries, do not show consistency in the survival time indicated by the time difference between the peaks of the curves. This difference should represent the average survival time of population from infection to fatality. In hospital based epidemiological studies, the survival time from disease onset to death varies from 14 to 22 days [14]. As noticed in Supplementary Figure 1, in case of some countries, the deaths data begins and reach the peak height before the infection curve. This is obviously because of late start and large under reporting of infections in several countries, due to insufficient screening of population, unavailability of diagnostic kits in required numbers, inconsistent quality of the diagnostic kits and their high costs [15]. The limitations of diagnostics, along with ambiguities in the interpretation of COVID as the cause of death, differences in average population age and other

metabolic disorders etc., also effect the calculations. Due to these reasons, the fatality rates reported from different countries vary from 1 to 7% and more [16]. The survival time difference as indicated by the infection and death curves for the 30 countries varied from 8 to 20 days

(Table 2), with an average at 6 days. The small-time difference is obviously because in many cases, the infection curve rises slower largely due to under reporting.

Country	R^2 for cumulative infections WLSTM predicted	MAPE for cumulative infections WLSTM predicted	R^2 for cumulative Deaths WLSTM predicted	MAPE for cumulative Deaths WLSTM predicted	Predicted date for 97 % Infections	Predicted date for 97 % Deaths	Predicted Cumulative Infections on June 30	Predicted cumulative Deaths on June 30	Cumulative infection cases at end of epidemic	Cumulative deaths at end of epidemic	Cumulative infected cases/pop at end of epidemic	Cumulative deaths per population at end of infection	Mortality at end of epidemic	Days difference between the peaks of predicted infection & death curves
United Arab Emirates	0.83	720.63	0.75	19.47	28 Oct 20	05 Jun 20	39,625	286	50,544	276	5.33E-03	2.91E-05	5.46E-01	-1
Australia	0.81	39.10	0.54	22.25	09 May 20	15 Apr 20	7,099	103	7,095	101	2.88E-04	4.11E-06	1.43E+00	12
Austria	0.91	29.16	0.77	36.31	14 May 20	18 May 20	16,404	666	16,394	653	1.86E-03	7.42E-05	3.98E+00	12
Azerbaijan	0.13	28.59	0.02	13.86	24 May 20	22 Apr 20	3,960	46	3,959	46	4.02E-04	4.67E-06	1.16E+00	5
Belgium	0.88	20.52	0.87	15.55	19 Jun 20	02 Jun 20	60,577	9,653	61,783	9,697	5.43E-03	8.52E-04	1.57E+01	6
Belarus	0.92	872.45	0.84	12.56	11 Oct 20	05 Jul 20	55,917	271	72,315	286	7.61E-03	3.01E-05	3.96E-01	-8
Canada	0.94	22.60	0.93	15.60	14 Oct 20	01 Sep 20	109,000	9,028	131,946	10,592	3.61E-03	2.90E-04	8.03E+00	11
Czech Republic	0.83	25.00	0.72	18.21	24 May 20	01 May 20	9,051	320	9,079	313	8.57E-04	2.95E-05	3.44E+00	9
Denmark	0.81	19.24	0.86	19.39	13 Jul 20	17 May 20	12,503	600	13,079	588	2.27E-03	1.02E-04	4.50E+00	2
Finland	0.72	114.54	0.44	21.38	01 Sep 20	20 May 20	7,910	320	8,914	309	1.62E-03	5.61E-05	3.47E+00	11
France	0.81	34.88	0.78	26.25	28 May 20	24 May 20	148,936	29,043	149,860	29,121	2.24E-03	4.36E-04	1.94E+01	7
United Kingdom	0.93	2213.72	0.90	17.29	22 May 20	02 Jul 20	323,856	40,635	372,999	41,944	5.65E-03	6.35E-04	1.12E+01	-4
Greece	0.65	124.62	0.56	28.24	28 Apr 20	19 Apr 20	2,982	175	2,989	169	2.78E-04	1.57E-05	5.67E+00	6
Croatia	0.87	26.14	0.46	21.47	15 May 20	22 Apr 20	2,291	117	2,281	100	5.53E-04	2.42E-05	4.38E+00	20
India	0.84	33.12	0.93	17.03	26 Sep 22	22 Jan 22	270,235	9,632	1,105,411	35,758	8.26E-04	2.67E-05	3.23E+00	-5
Ireland	0.83	27.87	0.47	45.28	04 Jun 20	04 May 20	25,801	1,750	25,983	1,755	5.40E-03	3.65E-04	6.75E+00	7
Israel	0.80	73.53	0.71	19.94	21 May 20	28 Apr 20	17,103	291	17,151	280	1.97E-03	3.21E-05	1.63E+00	9
Italy	0.96	15.80	0.96	13.02	28 Jun 20	29 Jun 20	243,441	35,035	250,367	36,061	4.14E-03	5.96E-04	1.44E+01	4
South Korea	0.87	60.90	0.62	37.48	02 Apr 20	02 Apr 20	11,165	284	11,165	267	2.17E-04	5.19E-06	2.39E+00	16
Luxembourg	0.84	49.68	0.44	29.22	10 May 20	16 Apr 20	3,999	113	3,987	109	6.69E-03	1.83E-04	2.74E+00	10
Malaysia	0.86	32.57	0.65	19.56	08 Jun 20	22 Apr 20	7,473	117	7,555	115	2.43E-04	3.70E-06	1.52E+00	2
Nigeria	0.89	21.11	0.65	14.36	26 Aug 20	14 Jun 20	12,278	287	14,635	280	7.67E-05	1.47E-06	1.91E+00	-8
Netherlands	0.93	19.98	0.88	21.14	23 Jun 20	21 Jun 20	48,264	6,296	49,414	6,425	2.88E-03	3.75E-04	1.30E+01	4
Norway	0.80	226.03	0.58	40.59	19 Apr 20	19 Apr 20	8,530	244	8,563	236	1.62E-03	4.47E-05	2.75E+00	15
Philippines	0.59	470.46	0.58	44.38	02 Apr 20	21 Jun 20	15,492	971	16,494	984	1.57E-04	9.36E-06	5.97E+00	4
Romania	0.90	17.13	0.82	22.98	20 Aug 20	13 Aug 20	21,481	1,524	23,770	1,733	1.21E-03	8.85E-05	7.29E+00	7
Russia	0.97	26.28	0.94	10.20	18 Dec 20	14 Oct 20	671,288	5,866	1,067,281	8,072	7.39E-03	5.59E-05	7.56E-01	-5
Singapore	0.68	123.92	0.01	6.31	24 May 20	24 Mar 20	31,076	23	31,090	23	5.54E-03	4.10E-06	7.40E-02	10
Thailand	0.64	340.08	0.57	12.87	02 Apr 20	08 Apr 20	3,059	56	3,047	56	4.40E-05	8.09E-07	1.84E+00	9
United States	0.93	26.67	0.83	26.02	17 Aug 20	26 Jun 20	1,906,544	106,752	2,088,445	109,515	6.43E-03	3.37E-04	5.24E+00	3
World	0.93	42.94	0.93	44.32	29 Dec 20	27 Aug 20	6,826,875	412,857	8,928,895	460,366	1.19E-03	6.13E-05	5.16E+00	-3

Table 2: Prediction results for select 30 countries + World.

	Country	R2 for W- LSTM predictions on daily new infections	MAPE for W- LSTM predictions on daily new infection	R2 for W- LSTM predictions on daily new Deaths	MAPE for W- LSTM predictions on daily new Deaths	Peaks difference W-LSTM (survival time)	Cumulative cases of infection at end of epidemic	Cumulative deaths at end of epidemic	Cases of infections/coun by population at the end of epidemic	Cases of deaths/ country population at end of epidemic	Mortality at end of epidemic	k for W-LSTM model for daily infections	a for W- LSTM model for daily infection	b for W- LSTM model for daily infection	g for W- LSTM model for daily infection	k for W- LSTM model for deaths-Q2-T 32	a for W- LSTM model for daily deaths	b for W- LSTM model for daily deaths	g for W- LSTM model for daily deaths
0	United Arab	0.8268	720.6292	0.7505	19.4690	-1.0000	50544.1914	276.1341	0.0053	0.0000	0.5463	46331.3074	20.8362	3.9891	1533.5662	261.6636	68.3253	10.4035	514.3259
1	Australia	0.8118	39.0999	0.5361	22.2529	12.0000	7095.3885	101.1577	0.0003	0.0000	1.4257	6502.5095	49.4747	14.3057	2903.8754	89.0447	59.3357	9.2671	112.4830
2	Austria	0.9124	29.1620	0.7693	36.3112	12.0000	16394.3656	652.8683	0.0019	0.0001	3.9823	15215.0905	42.6615	11.2739	2882.0553	686.7958	55.5906	7.7644	92.5993
3	Azerbaijan	0.1346	28.5945	0.0227	13.8622	5.0000	3959.4264	46.0206	0.0004	0.0000	1.1623	2228.7944	33.3926	8.0157	7332.1114	19.6184	68.6047	14.3427	492.8503
4	Belgium	0.8760	20.5243	0.8657	15.5524	6.0000	61782.8723	9697.9932	0.0054	0.0009	15.6954	61330.7757	34.3766	6.4971	1021.4868	9533.3878	58.7737	9.0844	193.2641
5	Belarus	0.9197	872.4489	0.8356	12.5587	-8.0000	72315.2948	286.1932	0.0076	0.0000	0.3958	71584.1479	26.5016	4.6708	2097.4572	314.4003	37.8553	4.7955	273.2060
6	Canada	0.9357	22.6004	0.9325	15.5978	11.0000	131945.7350	10592.3927	0.0036	0.0003	8.0278	132587.1498	19.4478	3.9289	1239.5359	10815.9068	44.2165	5.1063	221.3912
7	Czech Repub	0.8291	25.0039	0.7232	18.2125	9.0000	9078.9085	312.5876	0.0009	0.0000	3.4450	8617.4151	30.3219	7.5111	4262.3499	287.0423	56.2406	9.5467	227.1361
8	Denmark	0.8055	19.2352	0.8573	19.3859	2.0000	13078.9309	586.1186	0.0023	0.0001	4.4867	12729.5272	25.1045	5.0749	1167.9286	601.3233	53.7136	6.7481	69.8198
9	Finland	0.7201	114.5429	0.4417	21.3807	11.0000	8914.2875	309.1528	0.0016	0.0001	3.4681	9079.1072	10.9717	3.9695	8807.0416	272.4321	67.3104	12.1271	581.9845
10	France	0.8101	34.8803	0.7790	26.2542	7.0000	149860.0059	29120.5892	0.0022	0.0004	19.4319	143063.3272	35.0022	7.5899	1791.0309	27629.8388	59.4165	9.5111	147.5086
11	United Kingd	0.9282	2213.7190	0.9004	17.2941	-4.0000	372999.0463	41944.3027	0.0056	0.0006	11.2452	378899.9677	20.1955	4.3523	1970.9041	41531.3254	46.8546	6.5523	236.7091
12	Greece	0.6504	124.6234	0.5630	28.2379	6.0000	2988.8016	169.3720	0.0003	0.0000	5.6669	2922.8930	21.8394	6.2947	7418.3709	159.4448	48.8779	7.2518	130.2639
13	Croatia	0.8684	26.1400	0.4633	21.4724	20.0000	2281.0667	99.9668	0.0006	0.0000	4.3788	2263.8235	28.8129	8.1953	13973.9479	111.4751	48.5305	6.1620	193.8431
14	India	0.8380	33.1183	0.9302	17.0257	-5.0000	1105410.5718	35757.7622	0.0008	0.0000	3.2348	1079625.6523	11.8370	2.0927	452.3355	36202.8580	37.0022	2.3868	59.2344
15	Ireland	0.8337	27.8673	0.4681	45.2844	7.0000	25982.9705	1755.0414	0.0054	0.0004	6.7546	24402.6262	46.3459	8.8180	1438.5771	1728.6415	59.9736	8.8494	268.3517
16	Israel	0.8024	73.5301	0.7109	19.9428	9.0000	17151.1125	279.8326	0.0020	0.0000	1.6316	17302.3036	36.7530	8.4537	3016.2269	275.5955	56.4546	8.8743	224.3308
17	Italy	0.9603	15.7996	0.9603	13.0155	4.0000	250366.9807	36061.1041	0.0041	0.0006	14.4033	251654.3010	22.3758	5.1107	1250.7109	35873.6081	38.5724	5.3012	112.8859
18	South Korea	0.8718	60.9040	0.6224	37.4764	16.0000	11165.0262	266.7959	0.0002	0.0000	2.3867	8850.0898	33.2837	11.9840	1634.3794	301.4848	49.4534	3.8763	7.1336
19	Luxembourg	0.8355	49.6777	0.4427	29.2229	10.0000	3986.7925	109.2661	0.0067	0.0002	2.7407	3847.4408	37.4656	10.4983	7187.7151	104.6176	50.8796	7.6966	159.5584
20	Malaysia	0.8379	32.5709	0.6507	19.5581	2.0000	7555.3709	115.1174	0.0002	0.0000	1.5237	7200.0590	22.2183	5.9790	4747.8261	110.4967	52.5115	8.9490	155.3038
21	Nigeria	0.8892	21.1055	0.6500	14.3593	-8.0000	14634.5938	280.0475	0.0001	0.0000	1.9136	13857.9716	34.6774	6.0983	4626.2157	252.0207	62.5668	8.5123	469.3944
22	Netherlands	0.9344	19.9845	0.8785	21.1400	4.0000	49414.4675	6424.6050	0.0029	0.0004	13.0015	49648.7930	37.6859	6.0293	319.6376	6538.8414	46.5104	6.3540	149.7357
23	Norway	0.7953	226.0318	0.5826	40.5920	15.0000	8562.6260	235.6253	0.0016	0.0000	2.7518	8448.7860	31.2358	6.7214	1005.8500	231.8488	58.5401	8.8391	140.5385
24	Philippines	0.5933	470.4551	0.5834	44.3848	4.0000	16494.4344	984.1315	0.0002	0.0000	5.9664	14363.5500	14.6316	4.7983	13685.4365	911.7197	46.4814	5.7770	135.3554
25	Romania	0.8995	17.1341	0.8154	22.9776	7.0000	23769.5433	1732.6586	0.0012	0.0001	7.2884	23559.6250	21.4965	4.5896	1885.9959	1779.0998	36.4898	4.3499	174.9952
26	Russia	0.9725	26.2776	0.9423	10.1956	-5.0000	1067280.8878	8072.2494	0.0074	0.0001	0.7563	107782.8875	27.2520	4.0876	1065.4560	7946.0039	43.8412	4.5573	220.5726
27	Singapore	0.6782	123.9151	0.0081	6.3067	10.0000	31089.7944	23.0000	0.0055	0.0000	0.0740	20936.6469	73.2337	14.4158	590.2410	4.2366	114.0739	91.6555	971.6679
28	Thailand	0.6405	340.0815	0.5741	12.8675	9.0000	3046.8814	56.0048	0.0000	0.0000	1.8381	3007.4973	35.9629	9.9820	7377.0439	46.3190	70.2435	17.2513	233.0663
29	United State	0.9250	26.6700	0.8256	26.0208	3.0000	2088444.8701	109514.8775	0.0064	0.0003	5.2438	2001405.8730	22.7324	4.7074	1685.0300	99471.9816	49.9525	7.1612	294.6380

Supplementary Table 2

Coefficient of correlation and level of significance at $p < 0.05$, CV 0.361 (highly significant **); $p < 0.1$, CV 0.306 (significant *)														
Predictor variable		Indicators of Covid-19 epidemic by end of infection cycle as per model					Parameters of W-LSTM model for cumulative infections by end of epidemic cycle				Parameters of W-LSTM model for cumulative deaths by end of epidemic cycle			
S.No	CoV-2 type	Total cases	Total deaths	Total Infections/ population	Total Deaths/ population	Mortality	k	α	β	γ	k	α	β	γ
1	% of population aged 65 years and more	(-) 0.040	0.134	0.113	0.432**	0.516**	(-) 0.038	(-) 0.020	0.034	(-) 0.100	0.137	(-) 0.257	(-) 0.152	(-) 0.328*
2	% population 15-64 years	(-) 0.029	(-) 0.133	0.271	(-) 0.231	(-) 0.361**	(-) 0.031	0.181	0.212	(-) 0.139	(-) 0.137	0.350*	0.386**	0.316*
3	% population 0 to 14 years	0.059	(-) 0.012	(-) 0.322*	(-) 0.198	(-) 0.167	0.059	(-) 0.129	(-) 0.203	0.202	(-) 0.011	(-) 0.056	(-) 0.178	0.035
4	Trade with China	0.749**	0.760**	0.161	0.097	(-) 0.026	0.741**	(-) 0.040	0.035	(-) 0.217	0.742**	(-) 0.063	(-) 0.014	(-) 0.065
5	Air passenger traffic	0.859**	0.886**	0.322*	0.214	0.038	0.850**	(-) 0.134	(-) 0.174	(-) 0.205	0.869**	(-) 0.088	(-) 0.060	0.017
6	Average yearly temperature	(-) 0.155	(-) 0.107	(-) 0.371**	(-) 0.297	(-) 0.240	(-) 0.163	0.198	0.247	0.210	(-) 0.107	0.372**	0.325*	0.227
7	Social stringency score	0.043	(-) 0.012	(-) 0.392**	(-) 0.023	0.150	0.046	(-) 0.153	(-) 0.139	0.350*	(-) 0.005	(-) 0.012	(-) 0.100	(-) 0.065

Table 3: Correlation of COVID-19 infections and deaths (at end of the epidemic as per W-LSTM model) and the parameters of the Model with socio-economic predictor variables. The level of significance of the correlation is indicated by ** for $p < 0.05$ and * for $p < 0.1$. The significance was determined based on Critical Values (CV) for Pearson Correlation, applied to data on Infections and deaths in 30 countries that gave a good fit in the W-LSTM model (DF 28, $p < 0.05$, CV is 0.361; $p < 0.1$ CV is 0.306). The table gives the values of Pearson's Correlation.

30 Countries on which W-LSTM was trained till May 19, 2020	MAPE Prediction (daily infections) May 19 to May 29	MAPE Prediction (deaths) May 19 to May 29	50 Countries, including 20 beyond training	MAPE Prediction (daily infections) May 19 to May 29	MAPE Prediction (deaths) May 19 to May 29
United Arab Emirates	744.78	19.47	Afghanistan	240.63	26.77
Australia	37.63	22.25	United Arab Emirates	744.78	19.47
Austria	27.23	36.31	Armenia	133.96	15.71
Azerbaijan	26.72	13.86	Australia	37.63	22.25
Belgium	20.76	15.55	Austria	27.23	36.31
Belarus	903.52	12.56	Azerbaijan	26.72	13.86
Canada	23.06	15.60	Belgium	20.76	15.55
Czech Republic	23.39	18.21	Bahrain	65.81	3.45
Denmark	19.06	19.39	Belarus	903.52	12.56
Finland	115.77	21.38	Brazil	42.68	13.84
France	35.25	26.25	Canada	23.06	15.60
United Kingdom	17.98	17.29	Switzerland	342.95	63.35
Greece	125.97	28.24	China	118.80	55.59
Croatia	25.76	21.47	Czech Republic	23.39	18.21
India	32.76	17.03	Germany	885.54	125.60
Ireland	26.99	45.28	Denmark	19.06	19.39
Israel	49.68	19.94	Dominican Republic	287.91	30.82
Italy	15.23	13.02	Algeria	58.80	22.02
South Korea	59.70	37.48	Egypt	445.99	41.14
Luxembourg	49.64	29.22	Spain	1946.37	234.14
Malaysia	31.87	19.56	Finland	115.77	21.38
Nigeria	21.30	14.36	France	35.25	26.25
Netherlands	19.44	21.14	United Kingdom	17.98	17.29
Norway	222.34	40.59	Greece	125.97	28.24

Philippines	485.41	44.38		Croatia	25.76	21.47
Romania	17.12	22.98		Indonesia	45.60	24.57
Russia	26.35	10.20		India	32.76	17.03
Singapore	125.50	6.31		Ireland	26.99	45.28
Thailand	350.17	12.87		Iran	1551.40	111.18
United States	26.38	26.02		Iraq	275.78	29.51
World	43.18	44.32		Israel	49.68	19.94
				Italy	15.23	13.02
	19/30 have MAPE less than that for world; hence 63% good predictions 9/30 have MAPE less than 25 = 30% predictions very good	28/30 have mAPE less than world; hence 93% good predictions 21/30 MAPE less than 25 ; hence 70 % countries very good		Japan	142.14	47.66
				South Korea	59.70	37.48
				Kuwait	37.14	11.59
				Luxembourg	49.64	29.22
				Mexico	15.22	17.46
				Malaysia	31.87	19.56
				Nigeria	21.30	14.36
				Netherlands	19.44	21.14
				Norway	222.34	40.59
				Oman	154.62	6.30
				Pakistan	865.98	29.45
				Philippines	485.41	44.38
				Qatar	77.43	4.28
				Romania	17.12	22.98
				Russia	26.35	10.20
				Singapore	125.50	6.31
				Sweden	19.70	60.62
				Thailand	350.17	12.87
				United States	26.38	26.02
				World	43.18	44.32
					23/50 are with MAPE less than world = 46%	41/50 are with MAPE less than world = 82%
					11/50 are less than MAPE 25 = 22%	30/52 are with MAPE less than 25 = 58%

Supplementary Table 3.

Figure 2: New daily cases and deaths curves for world and a few of the highest affected countries

Supplementary Figure 1.

Table 2 gives the predicted total (cumulative) number of cases for each of the 30 countries as per the W-LSTM model, till the date when the daily new case count is predicted to fall down to single infection. The cumulative number of predicted infections and deaths at end of the epidemic are given in Table 2 along with the country wise dates when 97% of the epidemic will be over. The results show, that out of the 30 countries, India will continue to report cases till as late as the beginning of 2022. The W-LSTM model curve for India (Supplementary Figure 1 and the link <http://collaboration.coraltele.com/covid2/>) also shows that the country is yet to reach its plateau. As a representative case, Table 2 gives the total number of infections and deaths predicted on June 30th viz., 42 days after the date till when the model was trained.

A validation of the model is given in Supplementary Table 3 where the model trained on data till May 19th was tested for 10 days beyond the period of training on 50 countries. The analysis shows that the predictions by the model trained on data till May 19th matched well with the actual values reported during 10 days following the period of training. The MAPE for the predicted vs actual data on daily deaths to happen during the 10 days after the period of training was less than that for the world (44.32) in 93% of the countries, when the selected 30 countries on which W-LSTM gave good fit were used. At a higher level of stringency viz., MAPE less than 25, the predictions were very good for 70% of the countries (Supplementary Table 3, column C). When additional 20 countries were included, the predictions for daily deaths during the next 10 days beyond the period of training continued to be good. In this case, the MAPE for prediction of deaths during the next 10 days for the 50 countries was less than that for the world in 82% of the countries (Column G). It was less than 25 in case of 58% of the 50 test countries. Quite understandably, the predictions for new infections had higher error rate than those for deaths (Columns B and F), because, as explained earlier, the infections data are highly variable from country to country and have larger proportion of outliers, due to variable approaches to diagnosis of daily new infections.

3.3. Identification of likely effectors of infections and deaths

The W-LSTM model was applied on likely factors to have a preliminary analysis of the factors that may influence the growth of the pandemic across countries. To identify such effectors, Pearson correlation was computed between parameters of the epidemic and the likely effectors. The 5 parameters selected for the study were total

(cumulative) cases of infection as predicted by W-LSTM till the end of infection cycle, total (cumulative) deaths till the predicted end of cycle, total infections/ population of the country, total deaths/ population of the country and mortality (deaths/infections). The correlations between these 5 parameters and 7 likely effectors are shown in Table 3. Besides the 5 population-based parameters, the likely relationship of the effectors was also estimated in terms of correlation with the 4 parameters (k, α, β, γ) related to shape of the Weibull curve. The correlations with k, α, β , and γ were computed for both the infection and the deaths curves modelled from the beginning of infection to the end of the cycle. As seen in Table 3, a number of highly significant (***) and significant (*) associations are suggested by the correlations. Also, the associations are both in form of promoting the parameter related to the epidemic (positive correlation) and in suppressing the epidemic (Negative correlation). For example, elderly population beyond 65 years in age showed a highly significant positive correlation with mortality. This suggests, the elderly is more likely to get more severe disease and die, as compared to the younger population across the globe. Hence, the countries with more proportion of elderly population are more likely to see deaths. The absence of significant correlation of the above-65 age group with total infections per population suggests that the elderly are likely not more prone to getting infected as compared to others, but are more likely to get a severe disease. The elderly age group shows a negative correlation ($p < 0.1$) with the γ of death curve, thus making the curve less sharp in rise. In contrast, the adult population (15 to 64 years age) shows highly significant ($p < 0.05$) negative correlation with mortality, thus suggesting the adults to endure COVID-19 infection and not allow the disease to become severe, hence lower likelihood of leading to death. The endurance of the adult population is reflected in the model by the curve becoming flatter due to higher α and β (significant positive correlation), besides γ of the death curve. The analysis also shows that the young age group (0 to 14 years) is tolerant to infection by the CoV-2 virus and shows a negative correlation with infection at population level. Hence, the three age groups in population are likely to show different sensitivity and response to different stages of the infection and disease cycle. Figure 3 illustrates how the lower values of α and β lead to flatter curves compared to higher values for the constants k and γ . In this model, k increases the peak of the distribution at the same x-coordinate value. On the other hand, increasing α and γ moves the curve forward and flattens it.

However, this behavior is observed on reducing β . In that context, α and γ have opposite effect on the curve shape compared to β . If k and γ are held constant, it is clear from the figure that lower values of α and β lead to a flattened and elongated curve (purple) compared to the case

with higher values of α and β (red). Thus, a positive correlation with α and β and a negative correlation with k would mean a higher peak with a more prolonged effect of the disease.

Figure 3: Death cases for constant $k = 10000$ and $\gamma = 2500$ with (a) higher values of $\alpha = 38.5$, $\beta = 4.6$ in red and (b) lower values of $\alpha = 22$, $\beta = 3.4$ in purple.

Coefficient of correlation and level of significance at $p < 0.05$, CV 0.361 (highly significant **); $p < 0.1$, CV 0.306 (significant *)														
Predictor variable		Indicators of Covid-19 epidemic by end of infection cycle as per model					Parameters of W-LSTM model for cumulative infections by end of epidemic cycle				Parameters of W-LSTM model for cumulative deaths by end of epidemic cycle			
S.No	CoV-2 type	Total cases	Total deaths	Total Infections/ population	Total Deaths/ population	Mortality	k	α	β	γ	k	α	β	γ
1	O	@			(-) 0.315*	(-) 0.373**	0.334*					0.437**	0.471**	0.358**
2	B			(-) 0.390**	(-) 0.418**	(-) 0.360**			0.316*					
3	B1					(-) 0.327*								
4	B2				(-) 0.414**	(-) 0.363**								
5	B4				(-) 0.419**	(-) 0.374**								
6	A3			(-) 0.364*	(-) 0.424**	(-) 0.357*								
7	A6				(-) 0.321*						(-) 0.311			
8	A7				(-) 0.413**	(-) 0.362**								
9	A1a					(-) 0.324*								
10	A2				(-) 0.409**	(-) 0.359**								
11	A2a				0.359**	0.334*								

Table 4: Predicted association of CoV-2 virus types with the WLSTM predicted growth of COVID-19 pandemic across countries. @: Blank cells indicate the absence of predictions in favor of significant influence.

3.4 Prediction of likely effect of CoV-2 virus type on the pandemic

The various parameters of infection at the population level, as predicted by W-LSTM and the parameters related to shape of the curve were examined for correlation with virus types that have evolved and spread across countries, since initiation of the pandemic in Wuhan in December 2019. The virus types described here, are technically the clades that show differences in the nucleotides in the RNA genome of the virus. The SARS-CoV-2 virus has a =29926 nucleotide long genome. By now more than 37000 viruses isolated from human patients from different countries have been sequenced across the globe and the sequences deposited at GISAID Database (<https://www.gisaid.org>). These viruses show about 87% similarity that can be used to cluster them into distinct groups called, clades. Bhattacharya et al.[11] deployed 6181 of the CoV-2 genome

sequences and clustered those into 11 groups that are shown in Supplementary Table 1A as the virus types. The frequency of these virus types reported from 61 countries was smoothed by Laplace transform (Supplementary Table 1C) and applied to the group of 30 countries used for modelling the epidemic by W-LSTM. The correlations (Table 4) suggest that the virus type A2a has a highly significant association with deaths / population. Hence this may be the most virulent strain with respect to causing mortality at the end of the current cycle of the epidemic. A number of strains show a negative correlation with deaths, and thus are infective but less likely killing. Two strains, B and A3 show a negative correlation with infections per population, thus suggesting that the countries with a prevalence of B and A3 may more likely get a milder disease.

Predictor variables that influence the spread of infection		Predictor variables that influence intensity of disease/ mortality		Effect of predictor on shape parameters of W-LSTM model
Promoter (+ve correlation)	Suppressor (-ve correlation)	Promoter (+ve correlation)	Suppressor (-ve correlation)	
		Elderly (>65 years) population		Reduces γ of death curve
			Adult (15 – 64 years) population	Increases α, β and γ of death curve
	Young (<14 years) population			
Trade with China		Trade with China		Increases k of infection curve as well as death curve
Air passenger traffic		Air passenger traffic		Increases k of infection curve as well as death curve
	Average yearly temperature			Increases α and β of death curve
	Social stringency score			Increases γ of infection curve
	Virus types B, A3	Virus types B, A3	Virus types O, B, B1, B2, B4, A3, A6, A7, A1a, A2	O increases α of infections curve O increases α, β and γ of death curve B increases β of infection curve A6 reduces k of death curve

Table 5: Predictor variables that significantly influence the growth of infection and intensity of disease caused by CoV-2. The inference is drawn from Tables 3 and 4

4. Discussion

The novel coronavirus CoV-2 continues to be leaving a death trail, midst devastating sweep of infection, fear and economic loss across the globe. The only strategy to manage the pandemic currently is the non-pharmaceutical approaches. The first need is to have preparedness of the hospitals to manage patients for the least distress to patients, quick recovery and minimal mortality. The second important need is to prepare the society for sufficient isolation wards, quarantine centers and social distancing to contain the spread of the infection. Identifying infected cases is central to such containment, but non-availability and non-affordability of quality diagnostic kits is a serious limitation. Whole population screening is a utopian thought and the savaging character of CoV-2 to continue to be incubated in a large proportion of the population without causing any symptoms, weakens all management strategies.

Management of COVID-19 requires a robust prediction of the size, duration and dimensions of the ensuing epidemic. As discussed in the background, machine learning methods, backed by good statistical modelling provide a good opportunity to develop on line dynamic systems to prepare the society for managing such an epidemic. Because the time series models are based on original numbers from a country, these models may be better predictions of the trend, rather than mathematical models based on epidemiological parameters whose values are often variable, do not account for a variety of socioeconomic, managerial and environmental interventions and involve certain assumptions. The hybrid model developed by us utilizes Weibull distribution as the best fit to the disease data on population and integrates the advantage of self-learning to smooth outliers and train itself in response to shifting trends and fluctuations in data. We have given error based analysis to establish that W-LSTM is superior to other Gaussian and Bayesian distributions used by others. Our model is also superior to other time series applications, including the variations of ARIMA and LSTM. Our analysis shows that W-LSTM trains itself well on country data and makes good predictions with low MAPE for data beyond the period on which the model was trained, as well as for countries that were not part of the constituent data. We have shown that the predictions hold good for 10 days beyond the period of training. We have given predictions for the 42nd day (June 30th, 2020) after the last date of training and for the day when the model predicts the current cycle of the epidemic to end. The latter two predictions for future will establish the power and applicability of the model, provided the socioeconomic, environmental and administrative factors remain fairly similar to the conditions as

prevailing at the time of the training dataset.

Various population and shape parameters of W-LSTM based modelling of total infections and deaths at end of the epidemic in 30 countries were used to study correlations with a variety of effectors that may influence the spread and severity of the epidemic. Table 5, summarizes several variables/ effectors that are likely to exercise significant influence in determining the course of the epidemic. Some of the predictors have a positive influence, while others have suppressing influence. Different age groups respond to CoV-2 infection in different ways. The 65 plus age group is vulnerable to getting the disease in its severe form, though not particularly vulnerable to getting infected. Old age has been suggested as an independent risk factor associated with individuals getting clinically infected with COVID-19 [17]. Meta-data analysis suggesting lower vulnerability of children to falling clinically sick with COVID-19 has also been reported [18, 19].

Countries with higher trade with China and higher air passenger traffic show the likelihood of getting higher level of infections. The average yearly temperature in a country, and effective social distancing are likely to have a significant suppressive effect on the spread of COVID-19. Interestingly, the strains of the causative virus CoV-2 show differential association with the growth of infection and severity of the disease. In a recent analysis, high temperature and humidity were reported to reduce the daily new cases and new deaths [20]. One strain, namely A2a particularly is likely to be associated with severity of the disease. A number of strains are likely to cause infection but not likely to lead to the severity of the disease. The corresponding effect on shape parameters of the model is seen in some cases, as shown in Table 5.

COVID-19 pandemic is being handled differently in different countries. The government policies related to screening of the population, isolation of confirmed infectious individuals, quarantine of likely infected individuals based on contact tracking, hospital and health care facilities, social distancing measures, the socio-economic structure of communities, lockdown extent and measures etc., will determine the future development of new cases, recoveries and deaths. In response to government measures, the transmission and growth of the epidemic will change dynamically [21].

Currently, a majority of the countries are tapering down closures and lockdowns and are opting for partial lockdown as a strategy to phase out lifting of the lockdown. In some cases, primarily because of unawareness or misinformation, pockets of infected individuals stay unnoticed, and are discovered following a search campaign by the government. In other

cases, unplanned migration of workers from cities to rural homelands may shift the territory of infection. Each of these actions affects the distribution of infected and deceased cases in populations differently. This calls for a model to be agile and able to adapt to changing patterns. This can be accommodated in the LSTM-based approach proposed by us. The ARIMA models perform well for stationary time series. LSTMs are beneficial due to the fact that they can store the features of the data for long periods of time. The "iterative" optimization, provided by an LSTM, helps in an under-fitted model to be transformed into a model optimally fitted to the data.

When applying LSTM directly on the number of cases or deaths data (Simple LSTM in Table1), the model is not able to utilize the underlying temporal distribution followed by the data and hence performs poorly. Hence, W-LSTM outperforms approaches trying to model the time-series distribution of cases/deaths directly using LSTM [6, 7]. On the other hand, the W-ARIMA, applies ARIMA on the distribution parameters and only performs well for stationary time series. Further, LSTMs are beneficial due to the fact that they can store the features of the data for long periods of time. The model proposed here can be operated on cloud and linked to global databases to be updated on real-time basis [22]. The model is made to respond appropriately to any temporal changes and learn to modify its forecast. A static version of the model is available on <http://collaboration.coraltele.com/covid2/>.

Software Availability

Our prediction model is available online at <https://github.com/shreshthtuli/covid-19-prediction>. Few interactive graphs can be seen at <https://collaboration.coraltele.com/covid2/> wherein the W-LSTM model has been deployed on cloud platform using FogBus [12] framework.

Acknowledgements

R. Tuli acknowledges the grant provided by Science Engineering Research Board, Department of Science Technology, Government of India towards the JC Bose National Fellowship. Authors acknowledge Coral Telecom Ltd., Noida, India for hosting the model on their server.

Declaration of Interests

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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