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Predicting Spread, Recovery and Death Due to COVID-19 using a Time-Series Model (Prophet)

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***Abstract*—The world is facing its biggest challenge since 1920 due to spread of COVID-19 virus. Identified in China in December 2019, the virus has spread more than 200 countries in the world. Scientists have named the virus as Novel Corona Virus (belongs to SARS group virus). The virus has caused severe disruption to our world. Educational institutions, financial Services, government services and many other sectors are badly affected by this virus. More importantly, the virus has caused a massive amount of human deaths around the world and still its infecting people every day. Scientist around the world are trying to find a solution to stop the COVID-19. Their solutions include identifying possible effective vaccine, computer-aided modelling to see the pattern of spread etc. Using Machine Learning techniques, it is possible to forecast the spread, death, and recovery due to COVID-19. In this article, we have shown a machine learning model named as Prophet Time Series Analysis to forecast the spread, death, and recovery in different countries. We train the model using the available historical data on COVID-19 from John Hopkins University's COVID-19 site. Then we forecast spread, death, and recovery for seven days using a well known forecasting model called Prophet. This interval can be increased to see the effect of COVID-19. We chose 145 days of historical data to train the model then we predict effect for seven days (15 June 2020 to 22 June 2020). To verify out result, we compare the predicted value with actual value of spread, death and recovery. The model provides accuracy over 92% in all the cases. Our model can be used to identify the effect of COVID-19 in any countries in the world. The system is developed using Python language and visualization is also possible interactively. By using our system, it will be possible to observe the effect of spread, death and recovery for any countries for any period of time.**

***Index Terms*—COVID-19, Machine Learning, Prediction, Prophet, Time-Series, Python**

I. Introduction

The world has been encountering the global threat of COVID-19 or Coronavirus Disease – 2019 outbreak which began from the Wuhan city of the Hubei province of China during December 2019. Later, the cause of the disease has been identified as SARS-CoV-2, a novel Coronavirus having the capability of human transmission[1], [2]. Figure 1 shows the time-line of COVID-19 [3].

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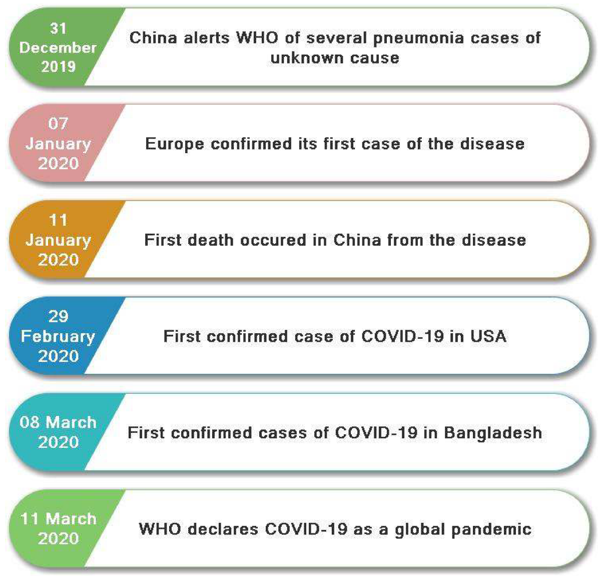

Fig. 1. Time-line of COVID-19 [3]

This global pandemic has also demonstrated that there is no geographical restraint of the disease spread. Responses to COVID-19 in each country depend on the country's resources, influencing the altered case detection rate [4], [5]. The very high number of encounters, high rate of transmission and critical challenges that COVID-19 poses demand the urgency for newer public health initiatives, accurate technical approaches for monitoring and predicting disease course and other preventive measures. Several reports show that many highly populated underdeveloped and developing countries of South Asia, Africa and South America, COVID-19 can be a threat, which can potentially paralyze the health and economic systems [6], [7], [5]. These disastrous effects can be prevented only through adequate and appropriate preparedness. Using a time-series predictive model the disastrous effects can be handled. In this article we have shown the prediction of spread, recovery rate and number of deaths due to COVID-19 disease using the Prophet Forecasting Model.

II. Background & Related Work

Discovered in 1966, Coronavirus is a group of enveloped, positive-stranded large RNA viruses that have the potential to infect human and other animals [8]. COVID-19 timeline shows that the World Health Organization (WHO) was alerted by the China Health Authority about cases of pneumonia with unknown origin on 31 December 2019 [8]. Observing the danger of this highly contagious disease spread, WHO declared COVID-19 a Public Health Emergency of International Concern (PHEIC) on 30 January, 2020[8], [9]. Respiratory droplets have been identified as the major source of SARS-CoV-2 transmission among human contacts, along with fecal-oral, aerosol and in few cases, possible vertical transmission [10]. These confirm that any individual of any age and sex can be infected by it. Due to fast spread of COVID-19, many studies have been carried out for prediction of trend and its impact. This section briefs about recent studies which are primarily related to predictive analytics. In Italy, a research conducted by Giulia Giordano et al shows an epidemic prediction model. It compares infected density and the degree of symptoms. A SIDARTHE Model is used by the authors and data from 20 February 2020 (day 1) to 5 April 2020 (day 46) shows how the progressive restrictions, including the most recent lockdown progressively enforced since 9 March 2020, have affected the spread of the epidemic [11], [9]. Also, it shows the effects of social distancing to minimize the spread of the disease. Melanie Bannister et al shows the correlation of temperature and evidence of COVID-19 in Europe. The Study suggest that a higher temperature may reduce the spread of COVID-19. However, the study conflicts with current spread rate of COVID-19 in the higher temperature region [12]. Lucia Russo et al demonstrated a technique to identify the first day of infections and predictions of COVID-19 in Italy. The study was able to estimate that the actual count of confirmed cases of COVID-19 [13]. The author used Susceptible-Infectious-Recovered-Dead (SIDR) model to predict the outbreak at the epicenter three weeks ahead. The trend analysis of COVID-19 pandemic in China using globally accepted SIR model developed by Albertine Weber et al [14]. The primary goal of the study showed by Feng Zhang et al is to provide control measures to be considered internationally for global control of this pandemic [15]. The time frame of dataset is from 3-10 February, 2020 and authors used a time-series model to predict number of confirmed cases and the turning point where the spread is at peak [15]. A probabilistic model proposed by Joel Hellewell et al showed feasibility analysis of controlling the spread of COVID-19. The model considered infections, basic reoccur number, and probability of contacts traced and rate of clinical infections. Results from the study show that, isolation of infected people and contact tracing is not just enough to minimize the rate of spread [16]. Vitaly Volpert et al showed the effect of quarantine model on the spread of virus infection using data analytics. The goal of this work is to present the assessment of placed quarantine mechanism using mathematical modeling [17].

Based on the recent studies on COVID-19 [18], [19], [20], we use a time-series predictive model known as *Prophet* to predict the spread, recovery rate and number of deaths due to COVID-19 in Brazil, USA, Canada, UK, Spain, Italy, Singapore, Japan, China and South Korea.

III. Materials and Method

In this section, we have shown forecasting of spread, recovery and death due to COVID-19 diseases.The forecasting is done by using a model called Prophet, originally developed by Facebook in 2017. Prophet Forecasting model is known for predicting non-linear time-series data [21]. The trends can be fit with yearly, weekly, and daily seasonality, plus holiday effects [21]. In our research, we have used this forecasting model to predict the spread, recovery and death of COVID-19 disease for different countries of the world. We used a decomposable time series model with three main model components: trend, seasonality, and holidays [22], [23]. They are combined in the following equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t) \tag{1}$$

In the above equation, $g(t)$ is piecewise linear or logistic growth curve for modelling non-periodic changes in time series, $s(t)$ is periodic changes (e.g. weekly seasonality), $h(t)$: effects of holidays with irregular schedules and $\varepsilon(t)$ is error term accounts for any unusual changes not accommodated by the model [24].

Using time as a regressor, Prophet is trying to fit several linear and non linear functions of time as components. We are, in effect, framing the forecasting problem as a curve-fitting exercise rather than looking explicitly at the time-based dependence of each observation within a time series.

Trend: Trend is modelled by fitting a piece wise linear curve over the trend or the non-periodic part of the time series. The linear fitting exercise ensures that it is least affected by spikes/missing data.

$$g(t) = (k + a(t)^T \delta)t + (m + a(t)^T \delta) \tag{2}$$

Here, k is the growth rate; δ has the rate adjustments and m is the offset parameter.

To fit and forecast the effects of seasonality, prophet relies on Fourier series to provide a flexible model. Seasonal effects $s(t)$ are approximated by the following function:

$$s(t) = \sum_{n=1}^{N} (a_n cos(\frac{2\pi nt}{P}) + b_n sin(\frac{2\pi nt}{P}))) \tag{3}$$

P is the period (365.25 for yearly data and 7 for weekly data) Parameters $a_1, b_1, \ldots.., a_N, b_N$ are estimated for a given N to model seasonality.

Prophet allows the analyst to provide a custom list of past and future events. A window around such days are considered separately and additional parameters are fitted to model the effect of holidays and events. In our research, there is no use of holidays and events.

IV. Results

The dataset is collected from GitHub repository published by "John Hopkins University" titled "COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University". From the repository, we have taken three COVID-19 time series datasets for confirmed cases, deaths and recovery for different countries.

These datasets have worldwide date wise data starting from 22 January, 2020. We have collected data up to 14 June, 2020. Then we use the Prophet model to predict next 7 days result based on previous data.

From dataset, we have used columns named 'Country/Region' and all above mentioned dates. Therefore each row specifies date wise confirmed/deaths/recovered number of people. We have considered data of total 145 days and analyzed for future predictions. At the same time, we trained other machine learning, time-series and deep-learning models such as Support Vector Machine (SVM), LSTM and ARIMA. The accuracy of SVM was measured as 76.5%; for LSTM accuracy was below 50% and for ARIMA it was 70.8%. The following equations are used to calculate accuracy, precision and recall score of different models [25].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

. where,

- TP: True Positive: Predicted values correctly predicted as actual positive
- FP: Predicted values incorrectly predicted an actual positive. i.e., Negative values predicted as positive
- FN: False Negative: Positive values predicted as negative
- TN: True Negative: Predicted values correctly predicted as an actual negative

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

.

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

. Table 1 below shows the performance optimization for Prophet, SVM, LSTM and ARIMA.

TABLE I
PERFORMANCE OPTIMIZATION OF DIFFERENT MODELS

Model	Precision (%)	Recall (%)	Accuracy (%)	F-Measure (%)
Prophet	89.2	0.4	93.2	3.66
SVM	68.4	4.3	76.5	8.2
LSTM	44.6	45.9	45.32	45.8
ARIMA	58.2	62.7	70.81	60.48

The highest accuracy was achieved by using Prophet Forecasting model. We use this model for spread, recovery and death prediction due to COVID-19 for different countries. The results obtained from the model was further verified by comparing with actual number of cases, recovery and deaths in different countries. 2020. Table 2 and 3 show the calculation of R2 and RMSE (Root Mean Squared Error) score of spread, death and recovery for different countries.

TABLE II
R2 SCORE FOR SPREAD, DEATH AND RECOVERY

Country	Spread	Recovery	Death
Brazil	0.9980	0.9707	0.9998
Canada	0.9993	0.9999	0.9994
China	0.9983	0.9999	0.9981
Italy	0.9999	0.9994	0.9999
Japan	0.9998	0.9917	0.9979
Singapore	0.9995	0.9954	0.9986
South Korea	0.9998	0.99965	0.9998
Spain	0.9999	0.9998	0.9995
UK	0.9996	0.9968	0.9998
USA	0.9999	0.9983	0.9999

TABLE III
ROOT MEAN SQUARED ERROR FOR SPREAD, DEATH AND RECOVERY

Country	Spread	Recovery	Death
Brazil	115903823.54	445864545.44	26273.84
Canada	902833.64	22264.29	4868.61
China	938580.02	31771.01	3949.80
Italy	509480.90	6031080.77	4950.47
Japan	8260.20	258851.42	259.49
Singapore	88342.60	346991.37	0.09
South Korea	2961.80	6204.06	1.13
Spain	988296.94	499260.64	55128.29
UK	4025634.49	760.03	24718.45
USA	13533542.91	51500933.29	154675.23

In figure 2-4, we have shown prediction of no. of confirmed cases, deaths and recovery in Brazil. We fit data dated from 22 January 2020 to 14 June 2020 and predicted the confirmed cases from 15 June 2020 to 22 June 2020 (highlighted in red in figures). Then, we compare with actual confirmed cases, deaths and recovery for 7 days (15 June to 22 June) in Brazil. The comparison with actual numbers of confirmed cases in Brazil from 15 June to 22 June shows an accuracy over 90% using Prophet Forecasting Model.

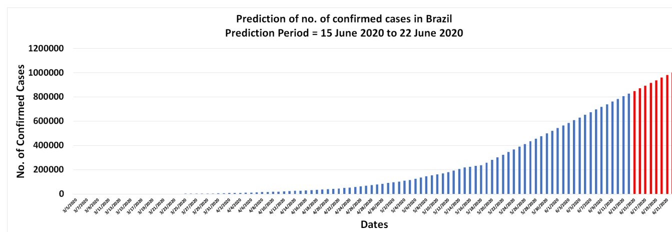

Fig. 2. Prediction of no of Confirmed Cases in Brazil using Prophet Forecasting Model

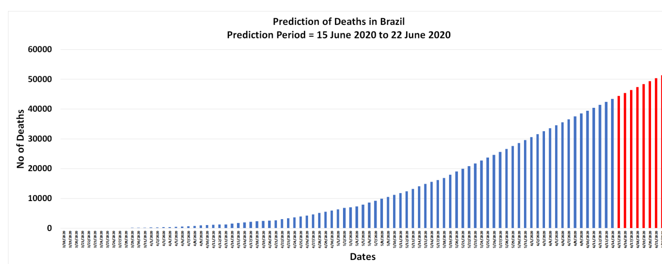

Fig. 3. Prediction of no of Deaths in Brazil using Prophet Forecasting Model

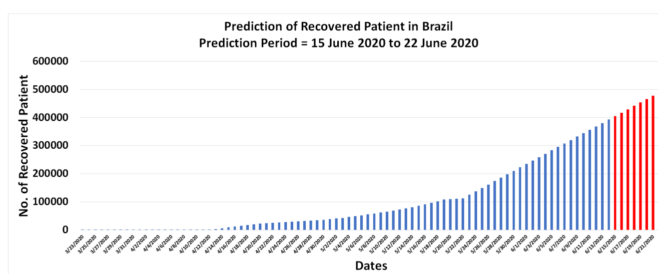

Fig. 4. Prediction of no of Recovery in Brazil using Prophet Forecasting Model

Table 4 shows accuracy of prediction for number of confirmed cases in Brazil for seven days. The average accuracy for seven days is calculated as 92.38%. We follow the similar approach to calculate spread, recovery and death for USA, Canada, UK, Spain, Italy, Singapore, Japan, China and South Korea for seven days. These results are summarized in table 7-9 and shown in figure 5-7. Table 5 and 6 shows death and recovery prediction for seven Days in Brazil. The average accuracy of seven days for Death is calculated as 99.38% and 82.59% for recovery.

TABLE IV
COMPARISON OF DAILY CONFIRMED CASES IN BRAZIL

Date	Predicted Value	Actual Value	Accuracy
6/15/2020	849817.86	888271	95.67%
6/16/2020	871691.03	923189	94.42%
6/17/2020	893564.21	955377	93.53%
6/18/2020	915437.38	978142	93.59%
6/19/2020	937310.56	1032913	90.74%
6/20/2020	959183.73	1067579	89.85%
6/21/2020	981056.90	1083341	90.56%
6/22/2020	1002930.08	1106470	90.64%

TABLE V
COMPARISON OF DAILY DEATH CASES IN BRAZIL

Date	Predicted Value	Actual Value	Accuracy
6/15/2020	44435.68	43959	98.93%
6/16/2020	45423.29	45241	99.60%
6/17/2020	46410.90	46510	99.79%
6/18/2020	47398.51	47748	99.27%
6/19/2020	48386.13	48954	98.84%
6/20/2020	49373.74	49976	98.79%
6/21/2020	50361.35	50591	99.55%
6/22/2020	51348.97	51271	99.85%

TABLE VI
COMPARISON OF DAILY RECOVERY CASES IN BRAZIL

Date	Predicted Value	Actual Value	Accuracy
6/15/2020	405053.09	477709	84.79%
6/16/2020	417225.03	490005	85.15%
6/17/2020	429396.97	521046	82.41%
6/18/2020	441568.91	534580	82.60%
6/19/2020	453740.85	551631	82.25%
6/20/2020	465912.79	576779	80.78%
6/21/2020	478084.73	588118	81.29%
6/22/2020	490256.67	601736	81.47%

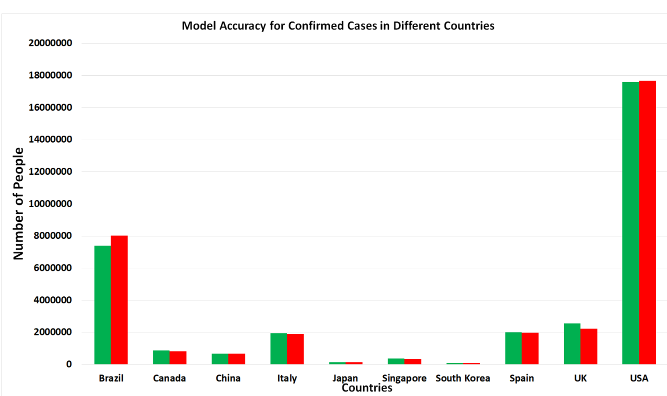

Fig. 5. Model Accuracy for Confirmed Cases in Different Countries

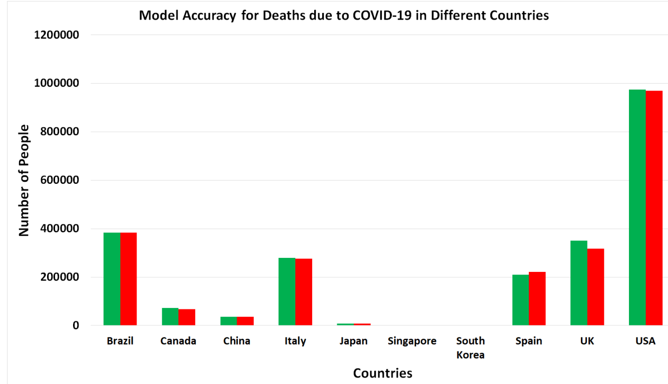

Fig. 6. Model Accuracy for Deaths in Different Countries

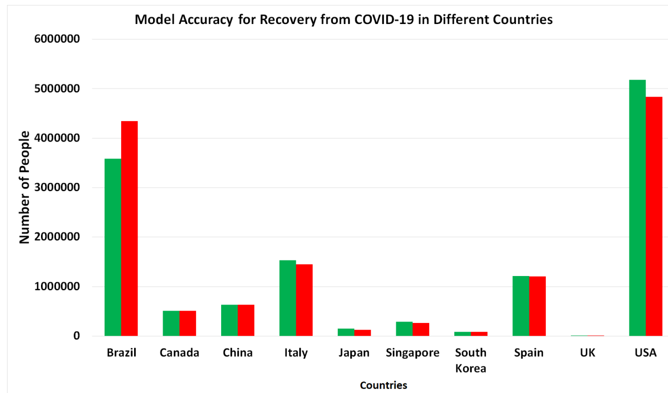

Fig. 7. Model Accuracy for Recovery in Different Countries

TABLE VII
MODEL ACCURACY OF COVID-19 SPREAD IN DIFFERENT COUNTRIES

Country	Confirmed Cases for 7 Days		Accuracy in (%)
	Predicted Value	Actual Value	
Brazil	7410991.79	8035282	92.23
Canada	801892.25	816734	98.18
China	674075.80	675995	99.71
Italy	1879459.60	1904282	98.70
Japan	140286.15	141024	99.47
Singapore	315475.53	332332	94.92
South Korea	96720.19	98632	98.06
Spain	1931120.82	1962677	98.39
UK	2161658.52	2217853	97.46
USA	17601574.44	17678123	99.56

TABLE VIII
MODEL ACCURACY OF COVID-19 DEATH IN DIFFERENT COUNTRIES

Country	Death Cases for 7 Days		Accuracy (%)
	Predicted Value	Actual Value	
Brazil	383138.61	384250	99.71
Canada	62152.31	67022	92.73
China	37106.56	37107	99.99
Italy	272289.66	276200	98.58
Japan	7398.75	7549	98.00
Singapore	206.52	208	99.28
South Korea	2225.28	2238	99.43
Spain	210173.54	221828	94.74
UK	300123.36	318299	94.28
USA	964340.44	969781	99.43

TABLE IX
MODEL ACCURACY OF COVID-19 RECOVERY IN DIFFERENT COUNTRIES

Country	Recovery Cases for 7 Days		Accuracy (%)
	Predicted Value	Actual Value	
Brazil	3581239.08	4341604	82.48
Canada	507412.89	510541	99.38
China	634386.50	636138	99.72
Italy	1418952.62	1446214	98.11
Japan	122504.29	126422	96.90
Singapore	262564.90	264394	99.30
South Korea	85931.51	86682	99.13
Spain	1195831.32	1203008	99.40
UK	10458.66	10473	99.86
USA	4675436.06	4837649	96.64

V. CONCLUSION

In this article, we have shown forecast of spread, death and recovery due to COVID-19 using Prophet Time Series Model. The accuracy score shows the effectiveness of our model. By using this model, it is possible to visualize the impact of COVID-19 in any countries. We have also shown a forecasting for seven days but our model can estimate the effect after 15, 30 and 45 days respectively. We have observed the accuracy for different time interval and the accuracy score remains above 90% in all three cases (Spread, Death and Recovery). Machine Learning techniques are widely used to predict several outcomes such as disease diagnosis, patient's diet, health information etc. These predictions are done by using historical data or survey questionnaires. We have followed the same protocol and used historical data for COVID-19 to train the model. Then we apply the model for forecasting values. Performance optimization of several models have considered and among the models, Prophet's accuracy remain higher.

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