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Study on Mathematical Model For Forecasting of Novel Coronavirus in India

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Abstract
This paper reveals that the new coronavirus (Covid-19) is the biggest challenge for the whole world. The World Health Organization (WHO) has declared it an epidemic. The data was collected from 209 different individual WHO situation reports for COVID-19 in India. First, prognostic models were compared based on minimum AIC, MAPE, and MAE. Then the best forecasting models were used on the epidemiologic data of India to predict the epidemiologic pattern of prevalence. New and Total Covid-19 Deaths and Incidence ARIMA and SARIMA have been found suitable and predicted for September 1, 2020. Also, the prophet model is used for accuracy and prediction of the total number of coronavirus cases in India. The predicted values are checked against the past observed values so that the two values are very close. Using such time series models we can forecast for the next 15-20 days and plan accordingly. This kind of projection helps in planning for the future.

Keywords: Covid-19, India, ARIMA, SARIMA, Prophet, Forecasting

1. Introduction

Coronaviruses are a large family of viruses that cause illnesses ranging from the common cold to more serious illnesses. Coronaviruses were first discovered in the 1930s when an acute respiratory infection of domesticated chickens was shown to be caused by the infectious bronchitis virus (IBV). Arthur Schalk and M.C. Hawn described a new respiratory infection of chickens in North Dakota in 1931. Infection of newborn chicks was characterized by panting and lethargy. Human coronaviruses were discovered in the 1960s. Since then, other human coronaviruses have been identified, including SARS-CoV in 2003, HCoV NL63 in 2004, HCoV HKU1 in 2005, MERS-CoV in 2012, and SARS-CoV-2 in 2019. There have also been a large number of animal coronaviruses identified since 1960 [1].
Covid-19 is an infectious disease caused by the most recently discovered coronavirus. This new virus and disease were unknown before the outbreak in Wuhan, China in December 2019. The story of the origin of the coronavirus appears to be well settled: In late 2019, someone at the now world-famous human seafood market in Wuhan was infected with the virus. From an animal. The number of coronavirus cases in India has crossed 3,239,096 as major cities grapple with the surge. Infections in India approached 32 million as of 26 Aug 2020 20:01:28, with 66,873 new cases reported in the last 24 hours [1]. Currently, India has achieved a usage rate of 76.29% as of 26 August 2020 [1].
After the United States, Brazil, and Russia, India has the fourth-highest outbreak of the virus that causes Covid-19 in the world. The number of infected people in India is expected to continue to rise steadily. India has recorded more than 9.7 million cases. According to the latest global statistics as of 26 August

2020, 14:47 GMT published by Johns Hopkins University, there have been 24,090,241 cases of COVID-19 worldwide, with 824,160 deaths and 16,632,246 recoveries. On January 30, 2020, the WHO declared the outbreak of the new coronavirus a public health emergency of international concern. On March 11, 2020, the WHO declared the COVID-19 epidemic a pandemic after the disease continued to spread outside of China [1]. Public health measures, such as those in place in China and now around the world, will hopefully limit the spread of the virus while treatments and a vaccine are developed to stop it.

COVID-19 has no specific treatment and spreads rapidly; it is essential to create health services for future cases [2]. Machine learning and approximation algorithms have been used to solve problems in areas such as healthcare [3], industry [4], cloud computing [5,6], human activity recognition [7], and brain tumor classification [8]. Machine learning models are certainly useful for predicting future cases to take control of this global pandemic [9-11]. ARIMA was used to predict the spread of SARS-CoV-2 [11].

Tiwari & Rizwan tried to use machine learning to analyze the current situation caused by Covid-19 and tell its impact in future days. They analyzed that the case of Covid-19 in India will be the same as in Italy or South Korea. India may face worse days in the future if we look at the pattern of these countries and India [12]. Shawni et al. use a machine learning approach to build a model that will help clinicians verify the disease in a short time and also the paper attempts to predict the growth of the disease shortly in the world. Experimental results indicate that the combined CNN-LSTM approach significantly outperforms other models [13]. Ranjan and Rajesh used susceptible-infected-recovered (SIR) models based on available data to make short-term and long-term predictions daily. Based on the SIR model, India is estimated to break even by the end of May 2020 [14].

Our goal is to develop the best model using a prediction model for India. Forecasting daily total deaths and confirmed cases helps plan the fight against Covid-19. The remainder of the paper is organized as follows: Section 4 explains the material and methods, including the COVID-19 dataset, the prediction algorithm, and model accuracy metrics. Section 5 describes our results and discussion. Section 4 presents conclusions and suggestions for future work.

2. Material and Methods

We describe the dataset used to estimate the work, prediction algorithms, and model accuracy metrics.

Covid-19 dataset

The dataset used in this study includes the total daily number of confirmed COVID-19 deaths in India, collected from the official website of Our World in data [15] between 30 January 2020 and 22 August 2020. It includes 206 time series cases, from which we build our model, which we compare with other predictive models. Descriptive statistics tell about the nature of the data. Know information about data tools for summary statistics such as mean, standard error, minimum and maximum, skewness, and kurtosis.

Prediction algorithm

There are various time series prediction models like ARIMA, SARIMA, GARCH, Prophet LSTM, etc. Here we use ARIMA, SARIMA, and one machine-learning model Prophet.

ARIMA: Time series analysis provides fundamentals about forecasting. Recent literature has shown the importance of ARIMA (Autoregressive Integrated Moving Average) models in terms of their simplicity in determining trends [16-19]. ARIMA-based modeling prescribes three unique processes: Autoregressive (AR) is foremost, followed by differentiation and moving average (MA). These three processes are constant when it comes to using ARIMA in univariate time series analysis.

We modeled the order of each of the three processes that cumulatively make up the ARIMA model. The first process, which is AR, has order p, has the form AR.
(p) : $X_t = c + a_1 x_{t-1} + a_2 x_{t-2} ... + a_p x_{t-p} + \varepsilon_t$, $t = 1, 2,...T$.
The variables which are considered random are depicted by the error term (ε_t). The expectation is that ε_t shall comply with $E(\varepsilon_t) = 0$, $V(\varepsilon_t) = \sigma^2$. The axiom is that past values shall impact on X_t. In addition, the procedure concerning the MA takes an order q. The intuition behind this is that errors that emanate from q shall have an impact while errors that are considered to be huge will not have an impact on X_t. The MA (q) produces $X_t = \varepsilon_t - \theta_1 x_{t-1} - \theta_2 x_{t-2} ...- \theta_p x_{t-p}$. The permutation of both AR of order p and MA of order q produces the Autoregressive Moving-Average (ARMA) model of order p and q. The ARMA Model proves robust for univariate time series modeling. Since, the ARMA model is the combination of both AR and MA, the AR (p) model takes into account past values of the series whereas MA (q) model considers past errors as explanatory variables (Ratnadip and Agrawal, N.d). Thus, a typical ARMA (p,q) is: $X_t = c + \varepsilon_t + \sum \phi_i x_{t-i} + \sum \vartheta_j \varepsilon_{t-j}$, i = 1., $j = 1$.
The ARMA models are used when the time series data is stationary. This is usually a robust opportunity for these models. However, not all time series data are stationary. As Ratnadip and Agrawal, (N.d) put it, the existence of trends and seasonal patterns makes time series data non-stationary, and therefore, ARMA models are insufficient to address the model-ling process. Therefore, ARIMA models in this case prove to be efficient and robust. The introduction of differencing provides leverage for ARIMA models to be generalized to non -stationary time series. ARIMA (p, d, q). The (p, d, q) within the model for autoregressive, integrated, and moving averages are integers whose expectations are greater than or equal to zero. The special case of ARIMA (p, 1, q) called the random walk model proscribes for the model to be written as:
$\Delta X_t = c + a_1 \Delta x_{t-1} + a_2 \Delta x_{t-2} ... + a_p \Delta x_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_q x\varepsilon_{t-q}$.
By inference, $\Delta X_t = X_t - X_{t-1}$.
The data for this paper takes into account descriptive analysis, which allows easy and convenient forecasting, and the ARI-MA (p, 1, q) procedure is considered effective due to the trend of the COVID-19 data. ARIMA models are a widely used method for time series forecasting, showing autocorrelation in data. The model is to decide whether the data is stationary or not. If non-stationarity exists, it is demonstrated by its resolution to a suitable degree of resolution.
SARIMA: Considering the characteristics of seasonal variation, the Seasonal ARIMA Model (SARIMA) was developed. The SARIMA (p, d, q) (P, D, Q) model is created from the ARIMA model. The SARIMA model has seven basic parameters: Demand for autoregressive (p) and seasonal autoregressive (P), order of regular difference (d) and seasonal difference (D) and order of moving average (q) and seasonal moving average (Q), and finally length seasonal period (s). Stationarity is an important condition in building a SARIMA model, and differentiation is often used to balance time series data. The basic techniques for checking the stationarity of time series include the end-of-series plot, autocorrelation function (ACF), partial autocorrelation function (PACF), and extended Dickey-Fuller (ADF) test [20,21].
Prophet Model: Machine learning techniques for algorithm prediction are a branch of computer science that is trained from past data, such as artificial neural networks, deep learning, decision trees, and Bayesian networks [22,23]. The idea behind the algorithm is to select an appropriate training model based on the characteristics of past data and use it to predict future observation results. We used this method to predict COVID-19 in India. Prophet is Facebook's open-source framework for time series prediction based on an additive model, open to the public in 2017 [24,25].

Prophet's non-linear trends are equipped with annual, weekly, and daily holiday effects. The perfect Prophet function can not only predict the future but also fill in missing values and detect anomalies.
In Prophet, the prediction model $x(t) = g(t) + s(t) + h(t) + \delta_t$, where, $g(t)$ is a trend function used to analyze the non-periodic changes of time series, $s(t)$ a periodic term, reflecting the periodic change, such as the periodicity of a week or a year. $h(t)$ is the influence of an occasional day or day, such as a holiday. δ_t is an error term. In our research, we only consider the non-periodic changes of time series. We create an occurrence of the Prophet class and then fit and predict methods. The input to Prophet is always a time series with two features: date dt and value x. In our study, it is the date of day and x is the accumulated values of a country in India.

Model accuracy metrics

The modeling errors were used to compare the fitness and prediction performance of the ARIMA, SARIMA, and Prophet models. These criteria include the Akaike information criterion (AIC), Schwarz criterion (SC), Root mean square error (RMSE), Mean absolute error (MAE), Mean absolute percentage error (MAPE), and Theil inequality coefficient (Theil's U).
The study is about COVID-19 predictions in India. This virus has proven a potential threat to human life. To control this pandemic situation, this study is based on future predictions of confirmed cases in the upcoming months. The forecasting has been done by using the best models that are suitable to this framework. The dataset used in this study contains the number of confirmed cases, new cases, total deaths, and daily deaths in India at the start pandemic days. ARIMA and SARIMA models were applied to COVID-19 new cases and new deaths, total cases, and total deaths in India. The Machine learning model Prophet has been used. Firstly, the dataset has been pre.

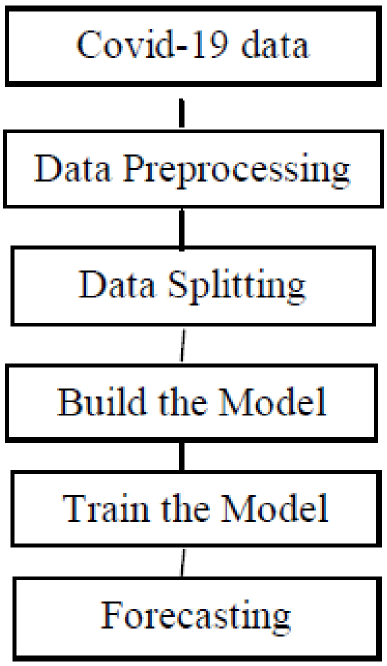

Figure 1: Proposed workflow.

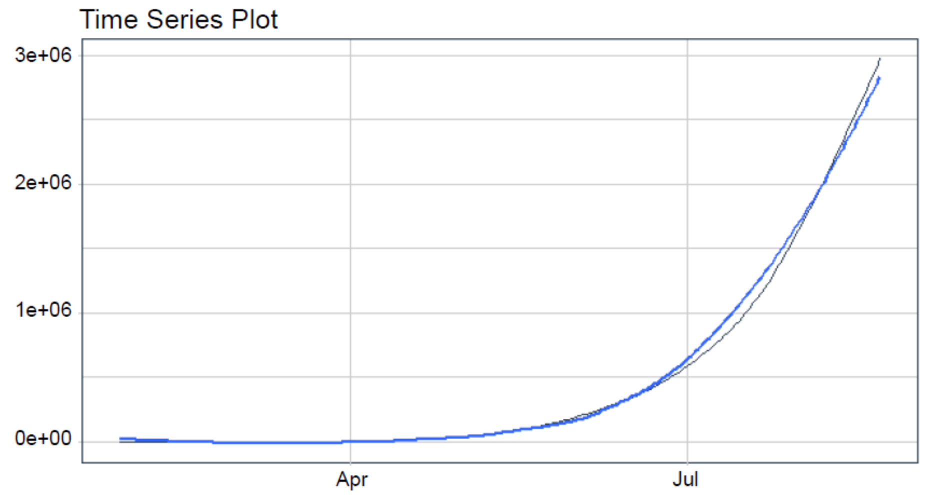

Figure 2: Time series plot of India.

Table 1: Summary statistics.

Variable	Mean	Median	Minimum	Maximum
Total Cases	4.6853e +005	68954.0	1.0000	2.9757e+006
New Cases	14445.0	3663.0	0.00000	69878.0
Total Deaths	10801.0	2249.5	0.00000	55794.0
New Deaths	270.84	111.50	0.00000	2003.0
Variable	**Std. Dev.**	**C.V.**	**Skewness**	**Ex. kurtosis**
Total Cases	7.5110e+005	1.6031	1.7998	2.2080
New Cases	20481.0	1.4178	1.4177	0.63780
Total Deaths	15362.0	1.4222	1.4075	0.79229
New Deaths	338.68	1.2505	1.4552	2.4505

Processed. Then the data set into a training dataset to train the models and testing dataset (10 days). These models have been trained on date and total cases. The models have been evaluated on metrics. The proposed workflow is shown in Figure 1. Time series plots are shown in Figure 2.

3. Results and Discussion

In this section, Table 1 shows the summary statistics of the Covid-19 data set in India. We found that from January 30, 2020 to August 22, 2020, new cases increased between (0) and (69,878). The average daily number of new cases is (14445). An Ex. A kurtosis value of (0.63) means that the data follows a Leptokurtic distribution that shows heavy tails on both sides, which means that there are outliers in the data. This is followed by a positive skewness value (1.41), indicating that there is some probability of an increase in new cases. The number of new deaths increased from (0) to (2003) during the same period, with the average daily number of new deaths being approximately (270.84). Ex. Kurtosis a value of (2.45) means that the data follows a Leptokurtic distribution that shows heavy tails on both sides, which means that there are large outliers in the data. A positive skewness value (1.45) indicates that there is some probability of an increase in new deaths. The total number of cases increased from (1) to (2975701). The average daily total number of cases is (46853). An Ex. A kurtosis value of (2.2) means that the data follows a Leptokurtic distribution, which shows heavy tails on both sides, which means that there are large outliers in the data, followed by a positive skewness value of (1.79), which indicates that there is some probability of an increase. In total cases. The total number of deaths increased from (0) to (55,794) during the same period, with an average daily total of about (10,801). The value of Ex. Kurtosis (0.79) means that the data follows a Leptokurtic distribution which shows heavy tails on both sides, which means that there are outliers in the data. A positive skewness value (1.40) indicates that there is some probability of an increase in total deaths.

Table 2: Selecting best model for forecasting.

Models	New Deaths	.New Deaths	Total Deaths	Total Deaths
ARIMA(P,D,Q) / SARIMA(P,D,Q)(p,d,q)	**ARIMA (5,2,10)**	**SARIMA (8,2,5)(3,2,2)**	**ARIMA (3,2,3)**	**SARIMA (3,2,3)(2,0,0)**
AIC	-938.8490	-787.8707	-929.0862	-847.4050
SC	-882.4410	-722.9302	-902.5412	-815.0939
RMSE	0.021813	0.022029	0.022909	0.023797
MAE	0.0092537	0.0091518	0.0085919	0.0091842
MAPE	0.83075	0.026914	1.0359	0.037849
THEIL'S U	0.1067	0.0039832	0.013931	0.002315
error is normally distributed	No	No	No	No
no ARCH effect is present	Yes	Yes	Yes	Yes
no autocorrelation in the residuals	Yes	Yes	Yes	Yes
Models	**New Cases**	**.New Cases**	**Total Cases**	**Total Cases**
ARIMA(P,D,Q)/SARIMA(P,D,Q) (p,d,q)	**ARIMA (6,2,10)**	**SARIMA (5,2,3)(1,1,1)**	**ARIMA (10,2,2)**	**SARIMA (7,2,3)(1,1,1)**
AIC	-60.89161	-41.61947	-476.8320	-1045.578
SC	-4.483565	-5.504226	-434.3499	-1003.854
RMSE	0.17977	0.19828	0.066212	0.012949
MAE	0.10122	0.11315	0.032833	0.0078238
MAPE	0.010639	0.010793	0.00014523	5.643e-005
THEIL'S U	0.00074624	0.00060478	1.1487e-005	4.079e-006
error is normally distributed	No	No	No	No
no ARCH effect is present	No	No	Yes	No
no autocorrelation in the residuals	Yes	Yes	No	Yes

Table 3: Prophet accuracy metrics for total cases.

Model	MAE	MAPE	MASE	SMAPE	RMSE	Rsq
Prophet	63345.91	2.24	0.98	2.20	82090.21	1.00

Table 2 shows how ARIMA and SARIMA select the best model forecasts for COVID-19. The parameters of the ARIMA model were estimated using the autocorrelation function ACF plot and the partial autocorrelation PACF correlogram. To determine the best models for Covid-19 in India, ARIMA (5,2,10) was selected as the best ARIMA for new deaths, and ARIMA (3,2,3) for total deaths. Similarly, SARIMA (8,2,5) (3,2,2) selected the best model for new deaths and for total deaths, the best model was SARIMA (3,2,3) (2,0,0). R statistical software was used to perform statistical analysis on the data sets and the significance level was set at 0.05.

In Table 2, the best-fitting models are based on the lowest AIC, SC, RMSE, MAE, MAPE, and Theil's U values along with the highest significant coefficients. Among the specific models, these are the best-equipped models. For series we use HP Filter (New Cases) and (New Deaths), (Total Deaths), and

Exponential Moving Average Filter for series (Total Cases). The Hodrick-Prescott (HP) method was implemented to generate filtered sample data sets to obtain a smoothed curve representation of the series, which could provide substantial advantages for the identification and construction of ARIMA and SARIMA models. Therefore, the Hodrick-Prescott (HP) method was implemented to generate filtered sample datasets. For the Total Deaths series and the New Deaths series and the Total Cases series, we find that the SARI-MA model is better than the ARIMA model, accounting for seasonality in the work series. After evaluating each trend series, we forecast the series for the coming days. For ARIMA (p, d, q) and SARIMA (p, d, q) (P, D, Q) s forecasting purposes, as discussed in the Materials and Methods section. Data for the period from January 30, 2020, to August 22, 2020, were used to build the model. Model validation data was used for the period from May 15, 2020, to August 22, 2020. The best models are used to predict the series for the coming days. Different series are considered equipped with different SARIMA (8,2,5) (3,2,2), SARIMA (3,2,3) (2,0,0), ARIMA (6,2,10), SARIMA (7,2,3) (1,1,1) models individually. These models are considered to be the best-fit forecasting models for the period from August 23, 2020, to September 1, 2020. Table 3 shows the accuracy of the Prophet machine-learning method model.

Table 4: Forecasting for new deaths, total deaths, total cases and new cases in paranthesis (standard errors) with 95% intervals.

	New Deaths	Total Deaths	Total Cases	New Cases
2020-08-23	1020.12 0.0220291 (1020.08, 1020.17)	56121.9 0.0237968 (56121.9, 56122.0)	2.70463e+006 0.0129489 (2.70463e+006, 2.70463e+006)	69296.5 0.179770 (69296.2, 69296.9)
2020-08-24	1029.24 0.0842620 (1029.07, 1029.40)	57034.2 0.116310 (57034.0, 57034.5)	2.76136e+006 0.0844171 (2.76136e+006, 2.76136e+006)	70012.6 0.837070 (70010.9, 70014.2)
2020-08-25	1038.38 0.205086 (1037.97, 1038.78)	57946.5 0.346118 (57945.8, 57947.2)	2.81814e+006 0.312682 (2.81814e+006, 2.81814e+006)	70728.4 2.32212 (70723.8, 70732.9)
2020-08-26	1047.55 0.399667 (1046.76, 1048.33)	58858.8 0.803668 (58857.3, 58860.4)	2.87497e+006 0.870862 (2.87497e+006, 2.87497e+006)	71442.6 5.07548 (71432.7, 71452.6)
2020-08-27	1056.73 0.679429 (1055.40, 1058.07)	59771.4 1.60024 (59768.3, 59774.5)	2.93184e+006 2.03098 (2.93184e+006, 2.93185e+006)	72153.1 9.61226 (72134.2, 72171.9)
2020-08-28	1065.95 1.05312 (1063.89, 1068.02)	60684.4 2.86621 (60678.8, 60690.0)	2.98877e+006 4.18495 (2.98876e+006, 2.98878e+006)	72857.7 16.4711 (72825.4, 72890.0)
2020-08-29	1075.21 1.52593 (1072.22, 1078.20)	61598.1 4.74891 (61588.8, 61607.5)	3.04575e+006 7.86483 (3.04573e+006, 3.04577e+006)	73555.6 26.2287 (73504.2, 73607.1)
2020-08-30	1084.51 2.10082 (1080.39, 1088.63)	62513.0 7.41030 (62498.4, 62527.5)	3.10281e+006 13.7682 (3.10278e+006, 3.10283e+006)	74247.1 39.5463 (74169.6, 74324.6)
2020-08-31	1093.87 2.77868 (1088.42, 1099.31)	63429.2 11.0243 (63407.6, 63450.8)	3.15996e+006 22.7858 (3.15991e+006, 3.16000e+006)	74933.2 57.1469 (74821.2, 75045.2)
2020-09-1	1103.28 3.55768 (1096.31, 1110.25)	64347.3 15.7739 (64316.4, 64378.2)	3.21724e+006 36.0276 (3.21717e+006, 3.21731e+006)	75614.8 79.7643 (75458.4, 75771.1)

In Table 4 we find that in India: The number of new deaths will increase from 1020 to 1103 during the period 23-8-2020 to 1-9-2020. The total number of deaths will increase from 56122 to 64347 during the period 23-8-2020 to 1-9-2020. The total number of cases will increase from 2704630 to 3217240 during the period 23-8-2020 to 1-9-2020. The number of new cases will increase from 69296 to 75615 during the period from 23/08/2020 to 01/09/2020. Figure 3 shows the pattern or total number and new cases and deaths in Covid-19. Figure 4,

Figure 5, Figure 6, and Figure 7 show the forecast graph for new COVID-19 cases, total cases, total deaths, and new deaths. Figure 8 shows the prediction graph of the prophet model. Figure 9 shows the correlogram of the forecasting models.

4. Conclusion

India is one of the most populous regions in the world. Stopping Covid-19 is the biggest challenge for a district like India. But today's date (August 26, 2020); India's spread of coronavirus to a great extent. Times forecast values show that India would reach more than 32,000,000,000 dead with 64,213 deaths by 1 September 2020. Now after closing all the cases the number of cases is increasing day by day. India has increasing testing every day which is helping to get more information about the spread of Covid-19.

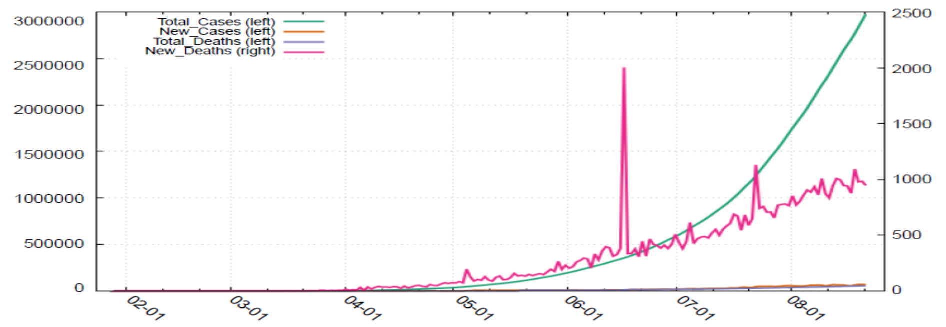

Figure 3: Pattern for total, new cases and deaths in India.

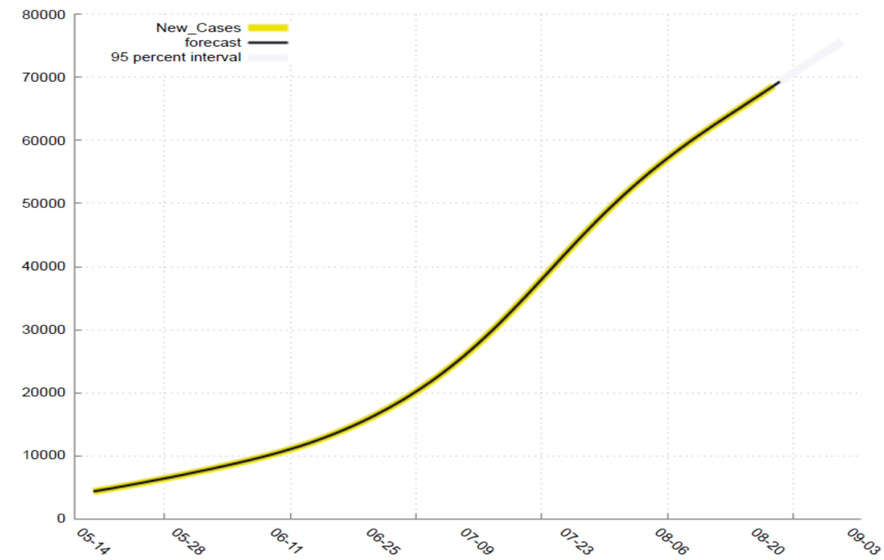

Figure 4: Forecast graph for new cases in India.

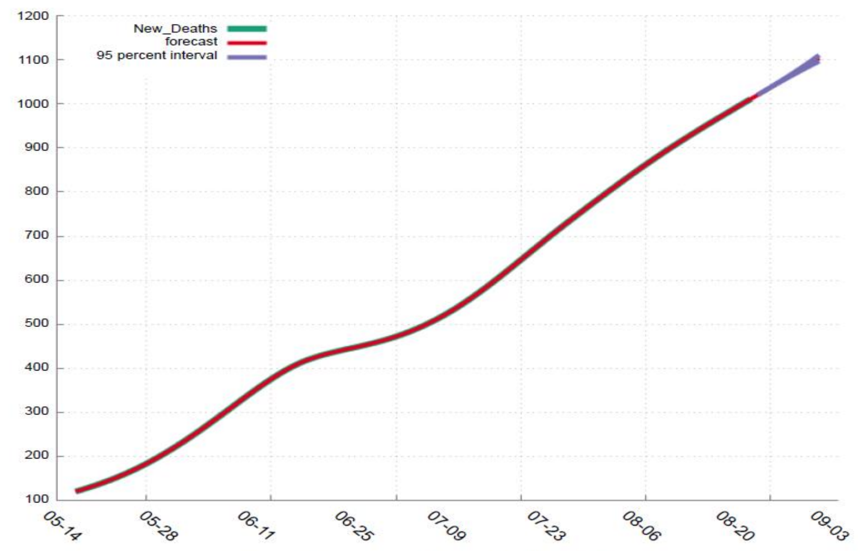

Figure 5: Forecast graph for new deaths in India.

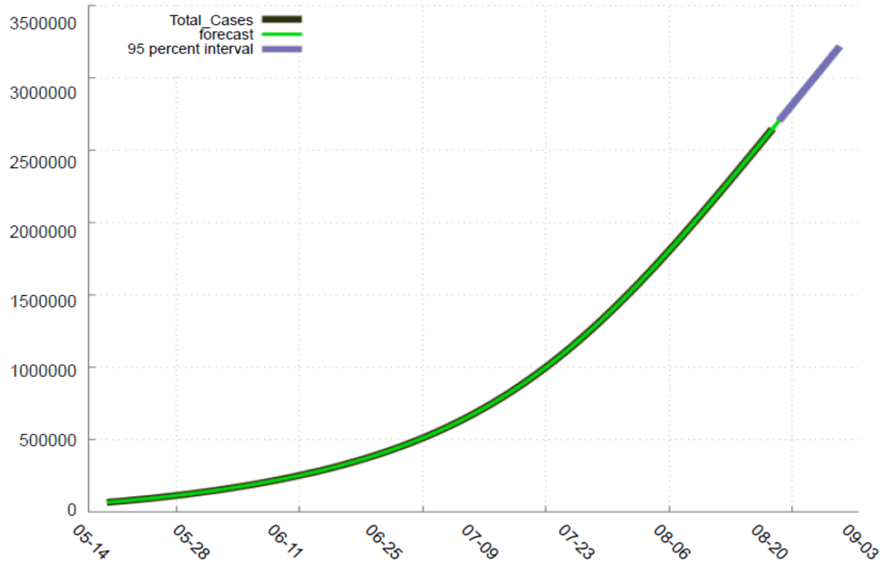

Figure 6: Forecast graph for total cases in India.

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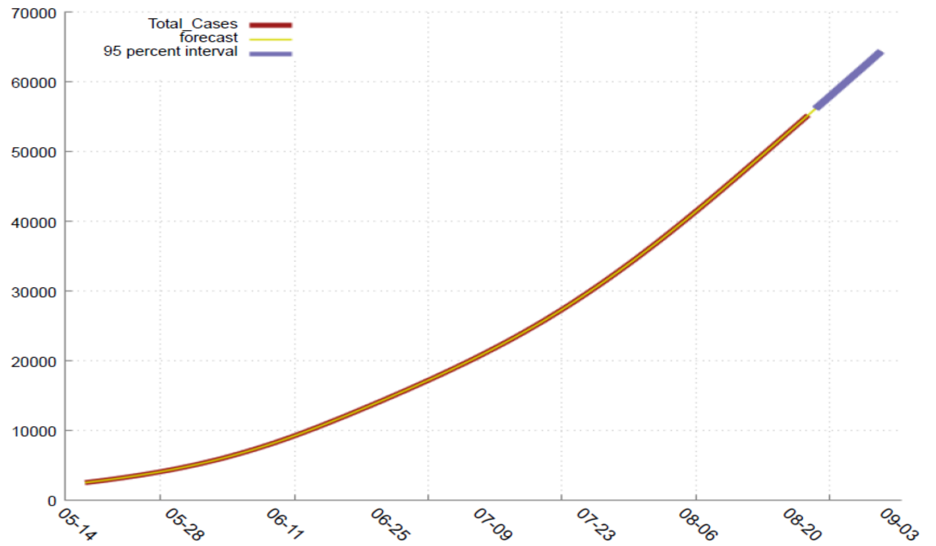

Figure 7: Forecast graph for total deaths in India.

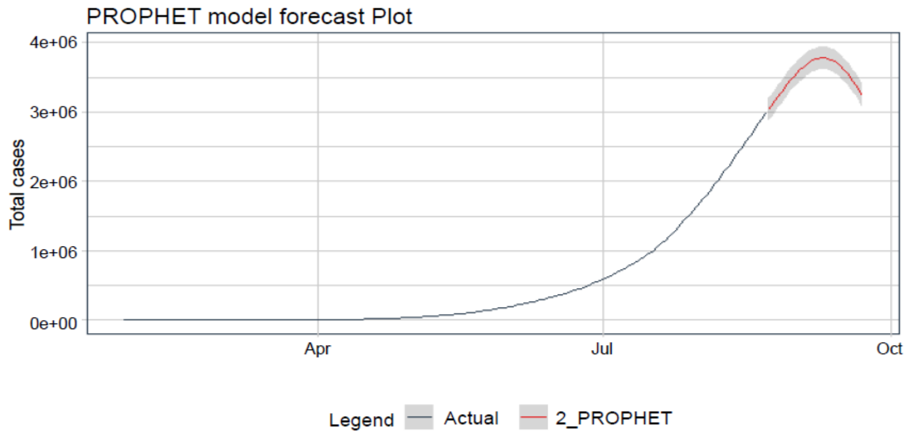

Figure 8: Prophet model forecast plot for total cases.

Also, India is working on small trials of plasma therapy. India has developed aarogya setu to create more awareness about COVID-19.

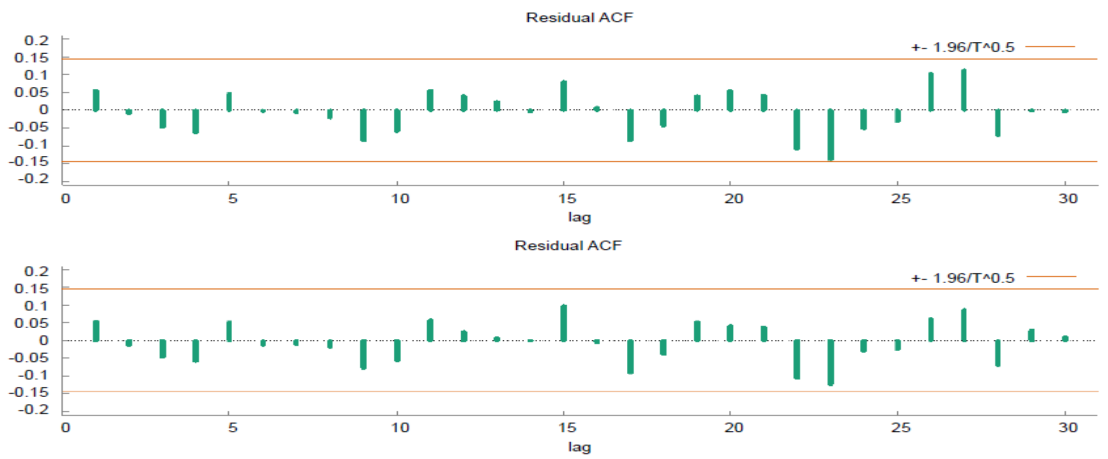

Figure 9: Correlogram and partial correlogram of the residuals.

Due to the lockdown spread of COVID-19 is controlled and cases are less as compared to other countries. After the lockdown, the biggest is challenge maintaining social distancing in society. But actually, medicine is required to completely stop the spread of Covid-19. This projection helps the government to make strategies against Covid-19.

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