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RESEARCH ARTICLE

Assessing the Efficacy of Lockdown 2020 to Curb COVID-19 Growth in India

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ABSTRACT

We consider the control of the COVID-19 pandemic through a traditional SIR Compartmental model. Due to unavailability of vaccines or any drugs, most countries including India have adopted mitigation strategies like a lockdown. This lockdown can be complete or moderated. The effectiveness of a lockdown or any social distancing measure is gauged by the change in reproductive growth factor R_0.R_0 values of pre and during lockdown were compared to quantify the extent to which total confirmed cases were reduced. Predictive analysis was done using Holt's Linear Model and Facebook's prophet feature to anticipate further cases of the COVID-19. The study analysed and interpreted India's national lockdown(s).

Keywords: Lockdown, COVID-19, SIR Model, Reproductive Growth Factor, Linear Regression, Holt's Linear Model, Facebook Prophet

Introduction

COVID-19 outbreak was instigated in Wuhan, China. It is estimated that the disease was transmitted from a bat to human. The symptoms include as cough, fever and difficulty in breathing. Currently, COVID-19 has affected more than 1,22,917 people in the world and 8,392 in India. Due to paucity of vaccines, the only putative solution to enfeeble the spread of the disease is practicing social distancing measures. India imposed its first national lockdown on 25th March at the then total confirmed cases of 571.The first lockdown lasted for 21 days but was eventually extended till 3rd May.

After a third national lockdown, the Indian economy recommenced businesses on 31st May. The majority of this work considers the three lockdowns singular. A lockdown can have various consequences, there have been outbreaks observed even after its imposition. It's extremely important to evaluate the credibility of a lockdown. In this paper, we build mathematical models stimulating the spread of the pandemic. There are multiple variables and factors involved in the SIR model. These are elaborated in the later section.

The SIR Model

The dynamics of the pandemic are modelled by SIR(Susceptible-Infected-Recovered). In this design, a population is separated into susceptible, infective and recovered individuals, with the functions $S(t)$, $I(t)$ and $R(t)$ denoting their respective fractions in the populations at time t (measured, for example, in days). let R(t) be the number of individuals who have died or recovered. We assume that those individuals who have recovered from the disease cannot become susceptible again. The evolution of these quantities is described by the differential equations:

$$\frac{dS}{dt} = -\beta SI$$

$$\frac{dI}{dt} = \beta SI - \Upsilon I$$

$$\frac{dR}{dt} = \Upsilon I$$

where the $\frac{dS}{dt}, \frac{dI}{dt}$ and $\frac{dR}{dt}$ measure the rates of change of the quantities $S(t)$, $I(t)$, and $R(t)$.

β = effective contact rate

Υ =recovery rate

The effective contact rate β is the average number of individuals that one infected individual will infect per time unit, assuming that all contacts that this individual makes are with susceptible individuals. A disease with a higher β tends to be more infectious. The product βSI is the segment of total population that will be infected at time t. This can be further elucidated by assuming that if a fraction I (t) of the population is currently infected, then they would infect a fraction β$I(t)$ of the population per unit time if all of their contacts were with susceptible individuals, but as only a fraction $S(t)$ of the population is currently susceptible, they will only infect βSI per unit time. The SIR Model assumes that the total population can only be divided into three segments, so no individual is factionless.

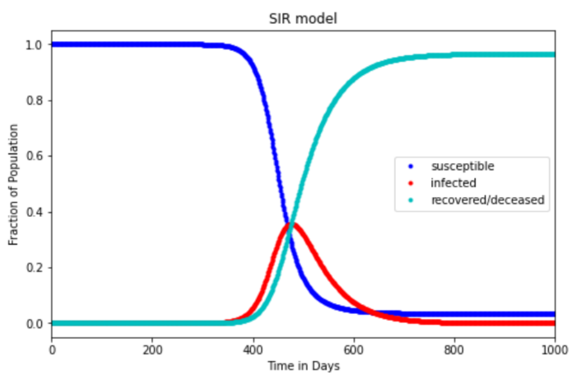

Figure 1: A traditional SIR Model

By codifying the aforementioned differential equations into python, we can obtain Figure by specifying values of β, Υ and susceptible, infected and recovered population. Moreover, analytical tools allow us to draw some general conclusions about the model's solutions. For instance, Figure 2 shows that after approximately 500 days, the number of infected cases abate and a large segment of the population recovered.

The ratio β/γ is also known as the basic reproductive number R_0, this is an important metric to predict the behaviour of the disease. R_0 can be qualitatively defined as the average number of people infected by an infected individual over a time period in a completely susceptible population. Analysing R_0 delineates consequential results. The most important conclusions are as follows:

1. The epidemic threshold: if the inequality $R_0 > 1$ holds, then disease will spread and eventually become worse. If $R_0 < 1$, the disease will gradually stop and die.
2. The size of the epidemic, when it occurs, will not depend on the initial number of infectives, but it will depend on the initial fraction of susceptible, *S*(0), and on R_0. An important point here is that the final size of the epidemic (the fraction of the population infected) will always be strictly smaller than the initial fraction of the population that was susceptible, *S*(0), so that there will always remain a subpopulation of susceptible individuals who have not been infected.

These conclusions, in so far as they apply in reality, have some key implications. Most notably, the epidemic threshold alludes that, if we vaccinate a fraction of the population prior to the arrival of the pathogen, so as to reduce the initial fraction of susceptible to $S\ (0) < \frac{\Upsilon}{\beta}$, then we will have prevented an epidemic. This result underlies the concept of herd immunity, whereby prevention of an epidemic can be achieved if a sufficiently large fraction of the population is vaccinated. If we do not achieve sufficiently high vaccination coverage, then we will have only reduced the size of the epidemic, and not have prevented it. Other ways to achieve the condition $S(0) < \frac{\Upsilon}{\beta}$, and thus to eliminate an epidemic are: (i) reducing the effective contact rate β by isolation of infected individuals or social distancing measures; and (ii) increasing the recovery rate γ by treatment of infectives.

Holt's Linear Trend Method

Holt (1957) extended simple exponential smoothing to allow the forecasting of data with a trend. This method involves a forecast equation and two smoothing equations: one for the level and one for the trend.

$$\begin{aligned} \text{Forecast equation} \quad & \hat{y}_{t+h|t} = \ell_t + hb_t \\ \text{Level equation} \quad & \ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\ \text{Trend equation} \quad & b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}, \end{aligned}$$

where ℓ_t denotes an estimate of the level of the series at time t, b_t denotes an estimate of the trend (slope) of the series at time t, α is the smoothing parameter for the level, $0 \le \alpha \le 1$, and β∗ is the smoothing parameter for the trend, $0 \le \beta^* \le 1$.

As with simple exponential smoothing, the level equation here shows that ℓt is a weighted average of observation y_t and the one-step-ahead training forecast for time t, here given by $\ell_{t-1}+b_{t-1}$. The trend equation shows that b_t is a weighted average of the estimated trend at time t based on $\ell_t-\ell_{t-1}$ and b_{t-1}, the previous estimate of the trend.

The forecast function is no longer flat but trending. The h-step-ahead forecast is equal to the last estimated level plus h times the last estimated trend value. Hence the forecasts are a linear function of h.

India's first nationwide lockdown was imposed by Prime Minister Narendra Modi on 24th March 2020 for 21 days till 14th April. This circumscribed mobility of 1.3 billion people. The announcement on 24th was preceded by a voluntary public curfew on 22nd March. Recognizing the admonitory fingers raised by various state governments, the Prime Minister extended lockdown to 3rd may. Additionally, the second lockdown was protracted to 17th May and then to 31st May. It must be noted that all the lockdowns were arrantly national. Due to the recrudescence in lockdowns, this study considers all 4 lockdowns to be singular. After 17th May, there were some relaxations in different factions: red, orange and green. However, perceptible differences were only observed after 31st May when the national lockdown was finally lifted.

The data was obtained from various sources and hard coded into python. Visualizations were primarily done using plotly followed by pyplot and seaborn.

Situation in India before the First Lockdown

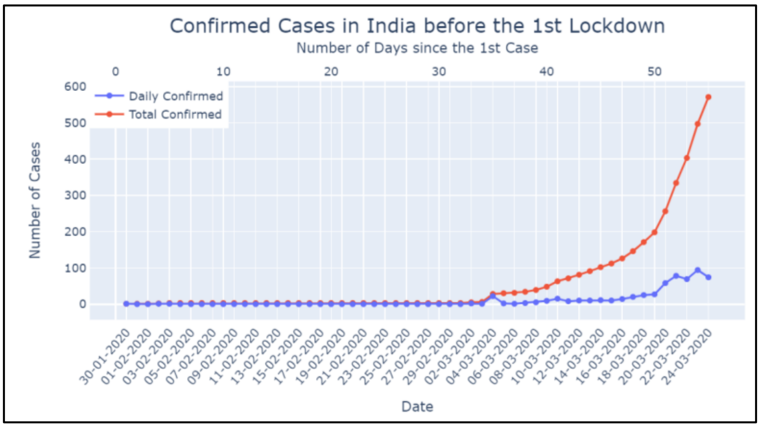

Figure 2: A contrast between total and daily confirmed cases before the first lockdown

It can be inferred from Figure 2 that the total confirmed cases remain constant until the 5th March. On 5h March, test conducted were and fifteen Italian tourist seven Indians tested positive for the virus. Out of the Indians, one had a travel history to Italy. It must be noted that Italy's situation at the time was much more adverse than that of any of the other countries with confirmed COVID-19 cases. The nation had recorded 778 positive cases as of 6th March. This is why most confirmed cases at the time were liked to Italy. The 4th March breakout lead to a dramatic increase in the total number of cases to 28. Following this, the linear graph of daily cases kept on surging. This might have been due to the contacts of infected people. A linear scale does not give an apt representation of the scale of rising cases in the long run. If we take a look at Figure 3, it might be inferred that cases will continue to escalate. The red line can even become vertical and belie that mitigation strategies aren't effective. This is why a logarithm scale is employed as it identifies the rate at which cases double. Figure 3 uses the logarithm scale and provides a greater picture to the rise of the COVID-19 in India.

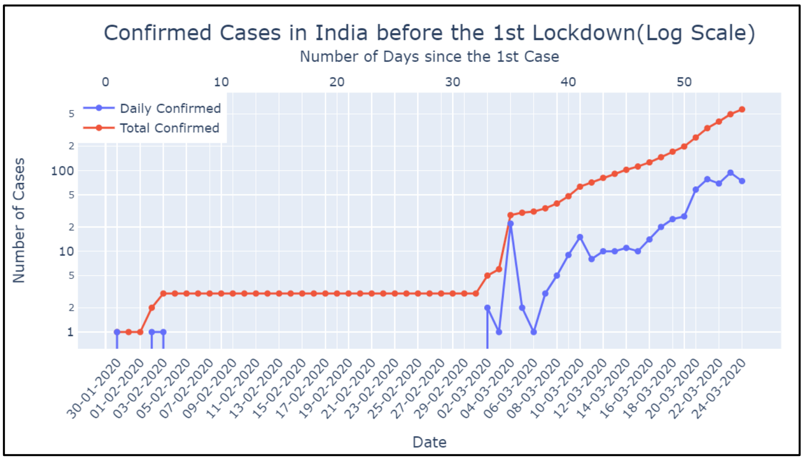

Figure 3: A depiction of total and daily confirmed cases before the lockdown in a log scale

Figure 3 shows the real 'curve' which all the nations are persisting to flatten. As shown,the total confirmed cases of COVID-19 were rising exponentially before imposing the lockdown. This trend might have been the incentive behind the imposition of a national lockdown in India on 25th March. As of 24th March, total reported positive cases of the COVID-19 in India were 571.This is much lower than that of Italy (9179) when it imposed its nationwide lockdown. However, considering the population density of India, government may have decided to opt for it early.

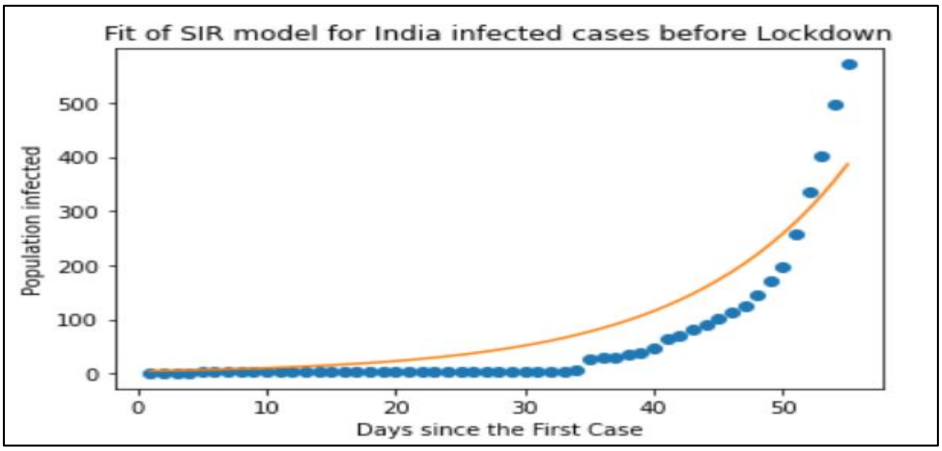

Figure 4: Fit SIR Model of India's confirmed Cases before Lockdown

SIR model was hardcoded for COVID 19 using python and SciPy. A custom loss function was framed and the value of β with minimum loss was taken by applying gradient descent and iterating it over a range of β.The value of β before the lockdown turned out to be 0.364 and that of gamma was 0.287.As a result, the growth factor of COVID-19 before lockdown was 1.268. Clearly, this quantity is greater than 1, which means that the disease was going to spread progressively. This is the average value of R_0. To get a greater extent of the values before the lockdown, a specific algorithm was processed into python. Using Plotly, R_0 values of different days since the first case of COVID-19 in India were calculated.

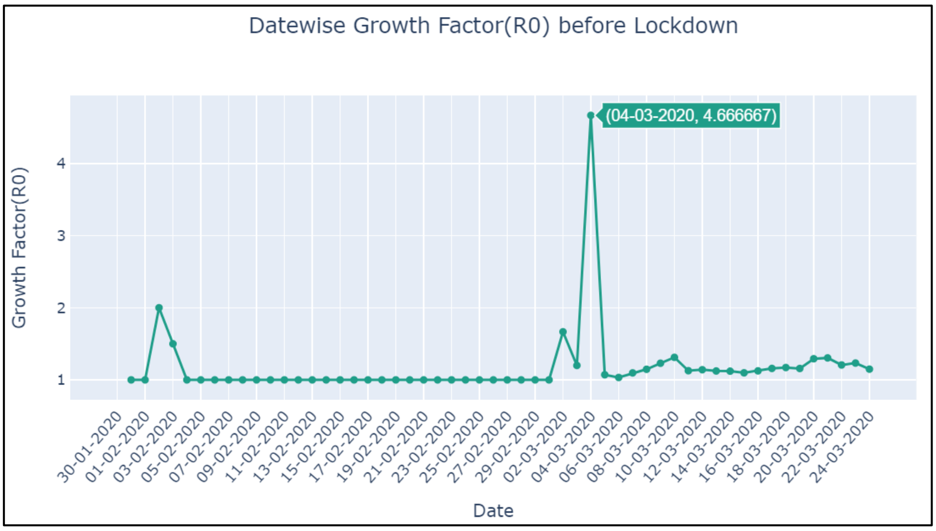

Figure 5: Date wise analysis of the growth factor of COVID-19 before lockdown

It is observed that the median value of R_0 was 1 and the maximum value was 4.67. The greatest value was observed when 15 Italian tourists and seven Indians tested positive. Just a day before the lockdown, value of R_0 was 1.14. The value of growth reproductive factor can plummet if β shrinks as ϒ amplifies, I.e. it is expected that at the onset of imposition of a lockdown, the effective contact rate decreases due to restricted movement. Initially it is anticipated that there will be a rise in cases due to those who came in contact of suspected and later infected COVID-19 cases.

Analysis of India's Lockdown

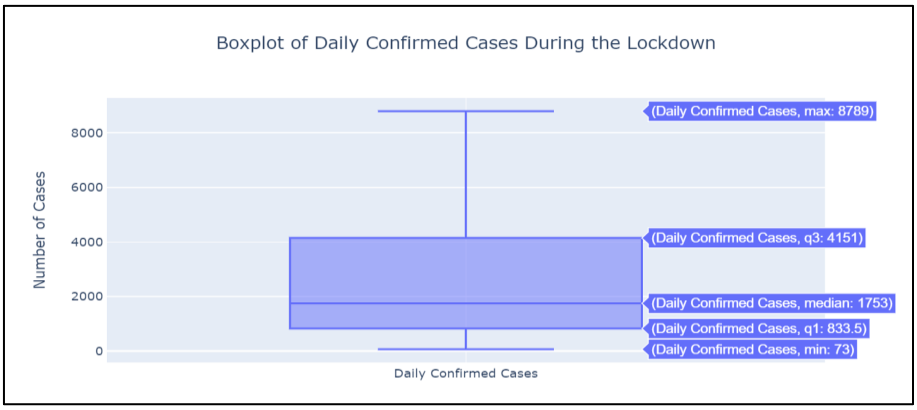

Figure 6: Statistical Analysis of Daily Confirmed Cases during Lockdown

Figure 6 depicts statistical information about daily reported cases of the COVID-19 during the countrywide quarantine period. As portrayed, the median number of cases were 1753.The interquartile range was:

$$Q3 - Q1 = 4151 - 834 = 3317$$

The minimum and maximum number of cases confirmed daily were felicitously on the second and the last day of the shutdown respectively.

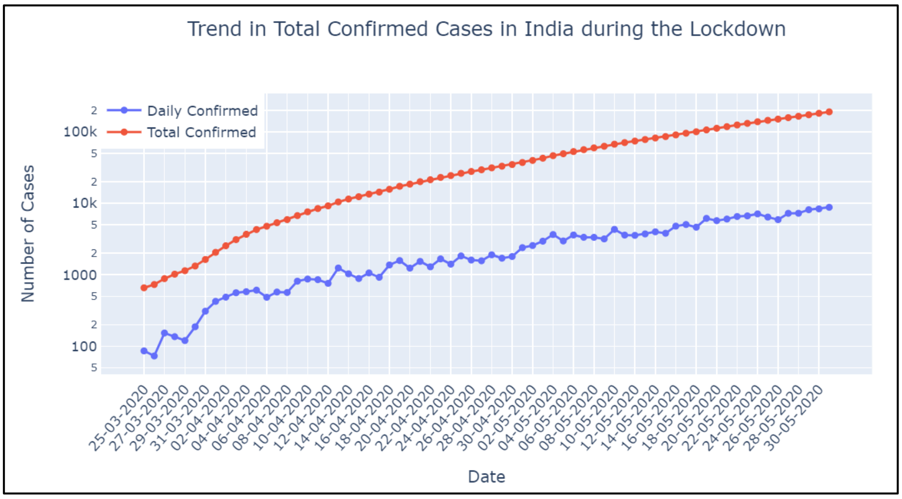

Figure 7: A logarithmic representation of trend in total reported COVID-19 cases during the lockdown

Figure 7 outlines a positive correlation between the rate at which daily reported cases increase and the rate at which total cases proliferate. At first glance, it may appear that the curve is flattening. However, this result is studied better as we take a meticulous look at the graph. The red line in the graph implies that the aggregate number of confirmed individuals are increasing sluggishly in increments of 10. For instance, about 90,000 total infected cases were reported on 16th May. Within 15 days, that number climbed to 180,000, i.e. the infectives doubled. The number of daily reported cases also follow a similar pattern. In Figure 3, the cases doubled in 4 days (20th March:256::24th March:571), a duration relatively less than that observed in the last phase of India's national lockdown. This is a remarkable encumberment.

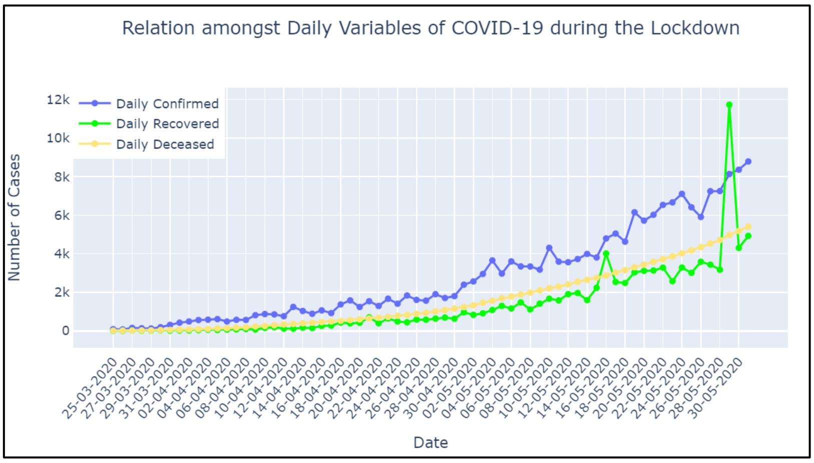

Figure 8: An illustration of trend trailed by daily variables of the disease during the lockdown

It is descried that along with the rise in daily confirmed cases, the number of individuals recovered daily also followed a proportionate increase. For the disease to be slowing down, the number of daily recovered individuals should increase daily while the daily reported cases drop accordingly. However, this linear graph follows the first paradigm.

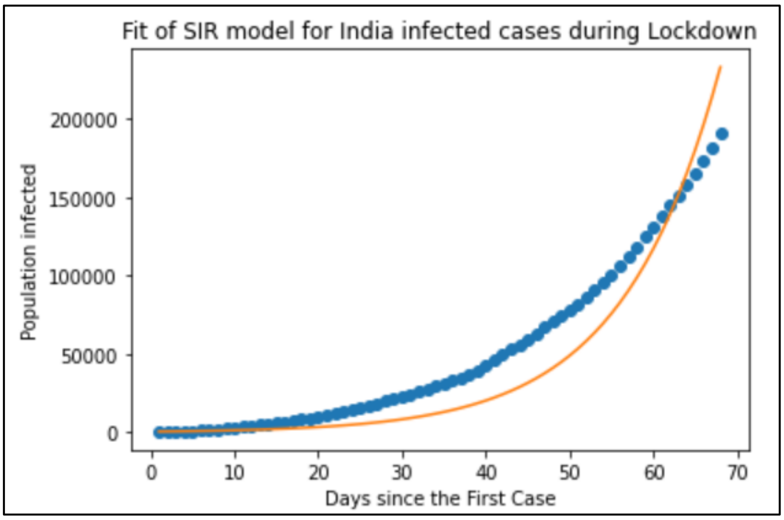

Figure 9: Fit of SIR model for India's total confirmed cases during the lockdown

After methodically devising an SIR model into python and entering necessary numbers, it was discovered that β decreased significantly during the lockdown, to 0. 273.Mean while, ϒ was 0. 265. Ultimately, the value of R_0 was observed to be 1.048. This is a huge accomplishment. The nationwide shutdown reduced the number of latter susceptible to 10% of India's population of 1.3 billion. As a result, hospitals and other medical centres were able to mange and treat COVID-19 patients at the time for a substantial duration and without unforeseen outbreaks. It is ambiguous to gauge the load on hospitals in the long run but according to the study, a low value of gamma indicates that recovery time of COVID-19 patients was reduced. This can also be possible due to the quarantine at home advisory issued by the government of India.

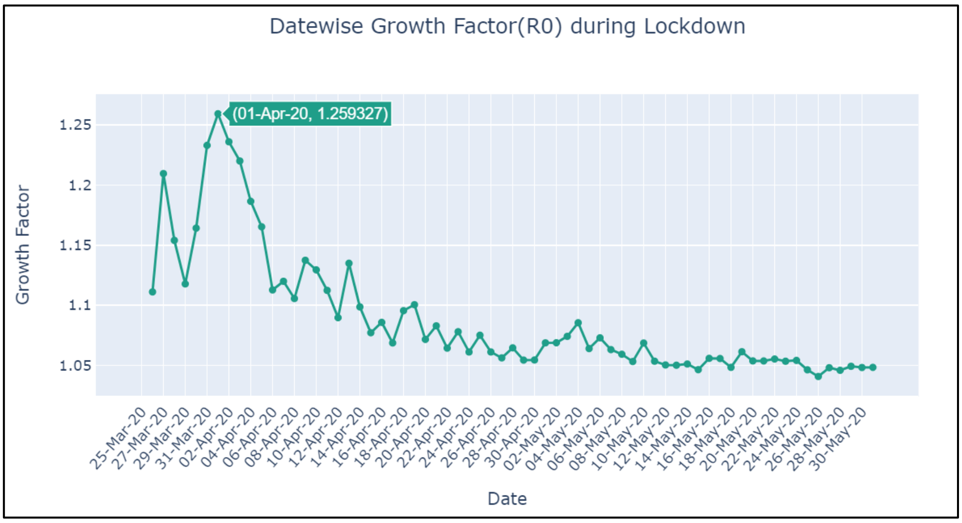

Figure 10: Date wise analysis of the growth factor of COVID-19 during lockdown

We can see from the graph that the initial trend in R_0 was an upsurge. However, it becomes evident that R_0 plunged to great extents as the value of growth factor on 30th May was 1. 048.Thus, the lockdown was highly effective in curbing COVID-19's spread.

Table 1: R_0 values by lockdown dates

Lockdown	Min R_0 Value	Average R_0 Value	Max R_0 Value
1: 25th March- 13th April	1.0896	1.1578	1.2593
2:14th April-3rd May	1.0543	1.0717	1.1004
3:4th May-17th May	1.0464	1.0511	1.0729
4:18th May-31st May	1.0407	1.0506	1.0613

We further elucidate the growth factor by categorising it. Table 1 depicts the minimum, maximum and average R_0 values from the main four nationwide lockdowns of India. Data was obtained by using pandas on python. It is observed that there has been a steady decline in all columns.

Predictive Analysis

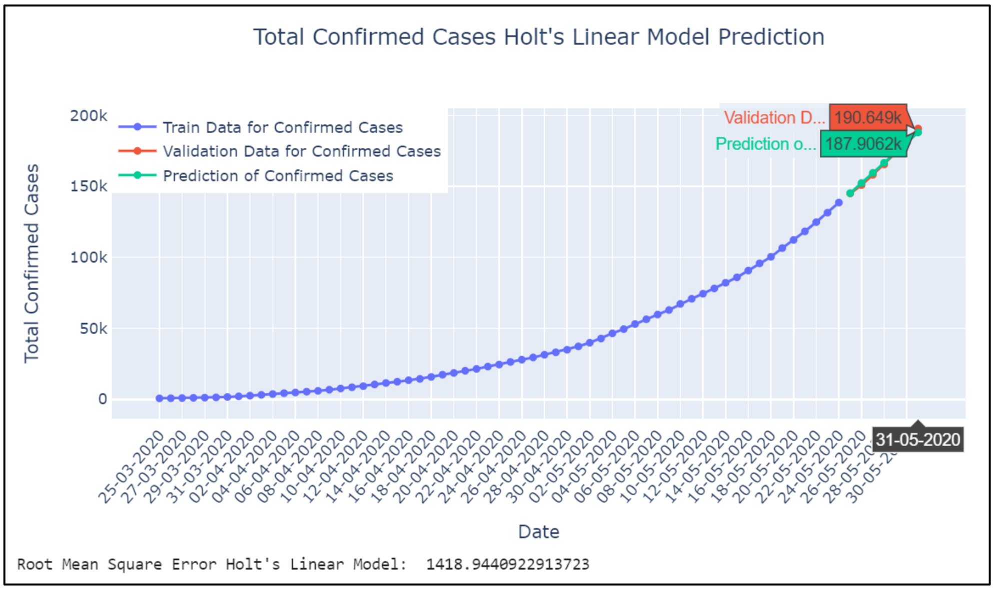

Figure 11: A prediction based out of Holt's Linear Model

A prediction analysis was performed using Holt's Linear Model.90% of India's lockdown dataset was trained. The trained data included total confirmed cases from 25th March to 24th May. The predicted output: 25th-31st May, was also the last of the four countrywide lockdowns. The resulting forecasts were ostensibly practical with increasing trend. The width of prediction intervals in languidly surging, with a difference of 3,000 observed on 31st May. The root mean square error was approximately 1418.944, in relative to a 50,000 range.

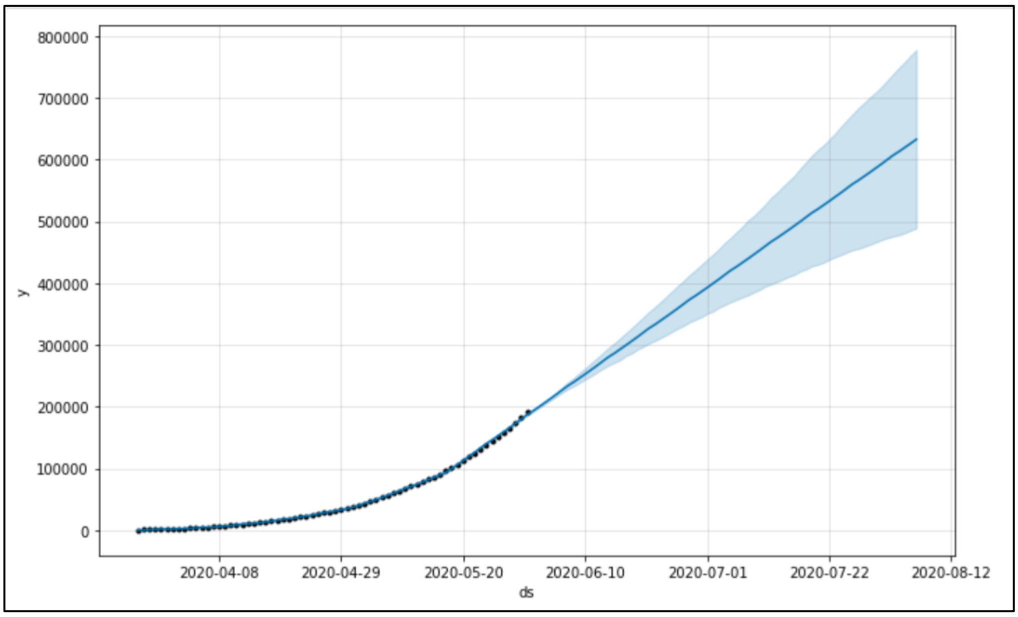

Figure 12: Facebook Prophet's prediction for post-Lockdown period

For further prediction, Facebook Prophet was employed. The data provided was from 30th January to 31st May. Using time series analysis, Prophet was able to produce a value along with its lower and upper limit. Figure 12 reveals that cases are likely to surge to 600,000 by August.

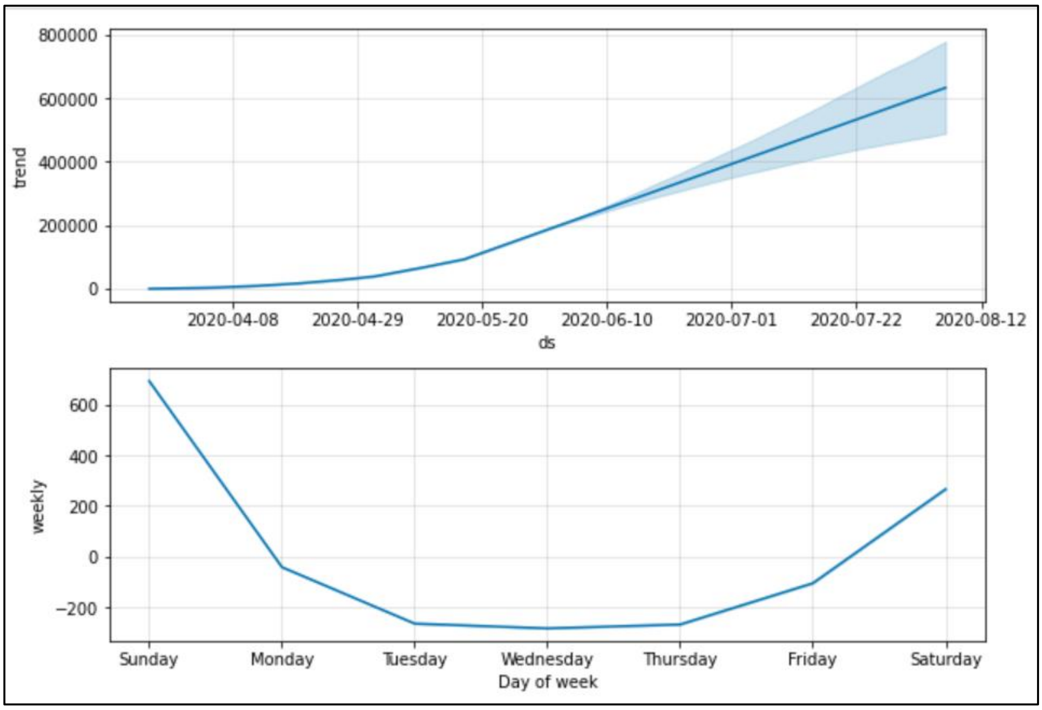

Figure 13: A detailed inspection of Facebook Prophet's Analysis

Results

We culminate that the reproductive growth factor, R_0, was tremendously diminished after the implementation of a lockdown, by an average margin of 0.22. Although the value of R_0 after a brief country wide shutdown period was 1.048, and thus greater than 1, the rate of spread was slackened as shown by the analysis. The study shows that COVID-19 will continue to spread at a slower rate. The research provides a meticulous insight into the contentious decision of imposing a lockdown in India, a densely populated country, by making pragmatic implications. For a greater magnitude in the reduction in the number of cases, there must be an application of stringent social distancing measures until the arrival of a vaccine and its successful distribution.

Limitations

This study should be considered an estimate of gauging effects of a lockdown on a national level. It does not include state wise analysis, only the big picture of a country of 1.3 billion. It is important to highlight that all the 'confirmed' cases only include those which were tested and reported. There are multiple other parameters like testing capacity, role of regional lockdowns and nature of a lockdown which redound to the collective analysis of understanding the growth of COVID-19 through lockdowns. While the research delivers promising outcomes of the impact of a lockdown in curbing a disease, the results must not be overestimated as there might be the existence of standard errors. It is also import to note that there is a lot that we don't yet know about COVID-19, and thus its way of dispersal. Caution is thus suggested in reading these results, which are necessarily also driven by the timing of the measures taken in India. For these reasons, we highlight the importance of and need for further investigations on this topic, which may focus on more specific territorial or climatic subsamples, or on the mobility facilitated by various types of lockdowns.

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