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Article

Study of Non-Pharmacological Interventions on COVID-19 Spread

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Abstract: COVID-19 disease has emerged as one of the life threatening threat to the society. A novel beta coronavirus causes it. It began as unidentified pneumonia of unknown etiology in Wuhan City, Hubei province in China emerged in December 2019. No vaccine has been produced till now. Mathematical models are used to study the impact of different measures used to decrease pandemic. Mathematical models have been designed to estimate the numbers of spreaders in different scenarios in the present manuscript. In the present manuscript, three different mathematical models have been proposed with different scenarios, such as screening, quarantine, and NPIs, to estimate the number of virus spreaders. The analysis shows that the numbers of COVID-19 patients will be more without screening the peoples coming from other countries. Since every people suffering from COVID-19 disease are spreaders. The screening and quarantine with NPIs have been implemented to study their impact on the spreaders. It has been found that NPI measures can reduce the number of spreaders. The NPI measures reduce the spread function's growth and provide decision makers more time to prepare with in dealing with the disease.

Keywords: Coronavirus; COVID-19; mathematical modelling; epidemic

1 Introduction

The First Corona case has been reported in Wuhan city of Hubei Province in south China on 31 December 2019, as unidentified pneumonia [1,2]. On 7 January 2020, the Chinese government and the World Health Organization (WHO) have identified the virus as a novel coronavirus (2019-nCoV), which belongs to the same virus family of the Severe Acute Respiratory Syndrome (SARS) that also outbroke in South China in 2002–2003 [3]. Coronavirus is first described in 1966 by Tyrell et al. [4]. It has four family members, namely alpha, beta, gamma and delta. While alpha and beta coronaviruses originate from bats, gamma and delta viruses originate from pigs and birds. Among these, beta coronaviruses may cause severe disease and fatalities, whereas alpha-coronavirus cause asymptomatic or symptomatic infections. Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-COVID-2) belongs to beta-coronaviruses and is closely related to the SARS-COVID-2 virus. SARS-COVID-2 is 96% identical at the whole-genome level to a bat coronavirus. The most common symptoms of COVID-19 are fever, tiredness, and dry cough [5].

Some patients may have aches and pains, nasal congestion, runny nose, sore throat or diarrhea. Around 1 out of every six people who get COVID-19 becomes seriously ill and develops difficulty breathing [6]. People can be infected with COVID-19 disease from others who have the virus. The infection can spread from person to person through small droplets from the nose or mouth, spread when a person with COVID-19 coughs or exhales. People can also catch COVID-19 if they breathe in droplets from a person with COVID-19 who coughs out or exhales droplets. There is an increasing body of evidence to suggest that human–human transmission may be occurring during the asymptomatic incubation period of COVID-19, which has been estimated to be between 2–10 days [7].

On 30 January 2020, the WHO declared the Chinese outbreak of COVID-19 as pandemic [5]. All major counties have suspended all international flights to reduce international travellers to the country to prevent COVID-19 diseases [6]. At present, no effective antiviral treatment or vaccine is available for COVID-19. The countries have taken strong measures to prohibit the virus's transmission, such as warning citizens from going outdoors, suspending the public transport between some big cities, and even taking quarantine for the main infected city. These unprecedented measures were expected to effectively stop virus transmission and buy the necessary time to deploy medical resources to the affected area [7]. The rapid spread of the COVID-19 may be due to multiple causes. One cause is the lacking of information transparency at the early stage of the epidemic outbreak. Releasing the epidemic information in a timely and accurate way is extremely important for the public's anti-epidemic response. The authentic and transparent information could have prohibited the spread of the COVID-19 at the early stage. The other cause is the lacking of the scientific diagnostic criteria for the COVID-19. Rapid developing exact testing techniques for a novel virus is complicated. The symptoms of the COVID-19 are highly similar to those of flu. This aggravated the hardship of diagnosis. Finally, the lack of an epidemic warning and prediction system lost the opportunity to prohibit the epidemic spread at the initial stage.

Mathematical modelling has gained more attention and awareness in epidemiology and the medical sciences [8–11]. It has been used for cancer detection, segmentation and classification [12–15]. These models are useful in cases where disease dynamics are not unclear. It estimates the number of cases in worst and best-case scenarios. It is also helpful in estimating the effect of preventive measures adopted against novel viruses such as COVID-19. One family of these models is the dynamical epidemic model called Susceptible Infected-Removed (SIR) model. The SIR model originated from the study of the plague almost one hundred years ago. Tremendous advance has been achieved in the dynamical epidemic model since the mid-20th century. In recent decades, some realistic factors influencing the epidemic transmission were included in the classic SIR model, such as the model considering the incubation stage, the SEIRS model considering the population age and the population exposed to the epidemic SIS model, including birth and death of the susceptible. Some dynamic models were also designed for a specific epidemic. Researchers have tried to explain the basic understanding of the spread scenario [16–18].

Researchers to study the virus's behavior, people's response, and predictions have used many mathematical and statistical models. Lizarralde-Bejarano et al. [10] have used six regression-based analysis models, i.e., quadratic, cubic, third, fourth, fifth, sixth degrees, and exponential polynomial on India's dataset. It provided a functional analysis of data, and the prediction model is useful for short-term prediction, i.e., only seven days from the study. Yadav et al. [19] have described the regression method carrying out five different analyses, namely predicting spread, analyzing growth rate and types of mitigation, predicting recovery rate, the transmission of the virus, and correlation to weather conditions. An ARIMA model with the Exponential Smoothing and Holt-Winters model has been used for regression analysis of India's COVID-19 growth [20]. The model underestimates the actual observations. It has also predicted slowing in cases in the upcoming days, and proper guidelines and measures accompanied reduction in daily cases with it.

Artificial intelligence and machine learning approaches, such as artificial neural networks and genetic programming, be effective in the near-future prediction of COVID-19 outbreak, trend or potential effect.

Asteris et al. [21]. A short-term model for COVID-19 mortality has been implemented in various countries/states worldwide based primarily on the number of deaths reported. A 3D-epidemic surface for assessing the epidemic phenomenon is proposed based on the derived predicted epidemic curves. For six different countries/states, namely New York, California, the United States, Iran, Sweden and the United Kingdom, the time evolution of COVID-19 is being examined. A 3D epidemic surface is proposed to assess the epidemic's phenomenon at any time of its evolution.

Salgotra et al. [22] performed a time series analysis and prediction of COVID-19 in India and its future behaviour in another study using the predictive technique of gene expression programming. Data from confirmed cases and death counts of the three major states in India, i.e., Maharashtra, Gujarat and Delhi, have been considered and used. A mathematical gene expression programming equation has been developed for each country, which can predict trends in confirmed cases and death counts for the future of a specific state. In addition, they did the same thing for the whole of India, which is the second-most populous country in the world. They found that predictive models/equations are highly reliable in gene expression programming and can be treated as a benchmark for time-series predictions.

Asteris et al. [23] give a global heuristic Gaussian-based algorithm for predicting the trend of the COVID-19 pandemic. The algorithm has been used to obtain predictions at six different locations: California, New York, Iran, Sweden, the United Kingdom, and the United States as a whole, and the prediction has been confirmed in all cases. Their findings show that this algorithm provides a robust and reliable method for discovering SARS-CoV-2 temporal dynamics and disease trends. Asteris et al. [23] analyzed how to model the spread of the outbreak and developed the model based on official source mortality data that are generally more reliable than confirmed cases reported and developed a prediction model based on the number of daily deaths reported from COVID-19.

Due to diversity, the difference in geography, and large population, the study would not be directly beneficial in predicting India's growth rate. Sharma et al. [24] have used linear and polynomial regression models on the datasets of various states of India. It has highlighted a difference in national and state-level models. Pandey et al. [25] and Hamzah et al. [26] have performed analysis during the early onset of the corona. Gupta et al. has used an SEIR and regression model with the data following a linear pattern. It has also predicted that community spread would increase cases exponentially. In the present manuscript, a novel mathematical model is being presented for estimating novel coronavirus patients.

The proposed model also considers Non-Pharmacological interventions (NPIs) such as Social distancing, closure of schools, universities and offices, avoidance of mass gatherings, community-wide containment, etc. [27,28]. In addition, the proposed model has been analyzed with the general population, contacts of cases (Contact tracing, Surveillance, quarantine) and the cases themselves (Early Reporting, Isolation).

In this manuscript, three different novel mathematical models have been proposed, with various scenarios such as screening, quarantine, and NPIs, to estimate the number of virus spreaders. The analysis shows that the number of COVID-19 patients will be higher without screening people from other countries. Since all people suffering from COVID-19 disease are spreaders. Screening and quarantine with NPIs have been carried out to study their impact on spreaders. NPI measures can reduce the number of spreaders. The NPI measures reduce the spread function's growth and give decision-makers more time to prepare to deal with the disease.

The present work is organized as follows. The mathematical model for COVID-19 spread estimation is presented in Section 2. Section 3 discusses the data set used for validating proposed mathematical models. Results ad discussions are presented in Section 4.

1.1 Research Significance

The COVID-19 pandemic has brought unprecedented and swift changes to all of our lives. All our community can do is take preventive measures to suspect an outbreak; we can act quickly. Screening of susceptible cases is essential for the prevention of COVID-19 cases. In addition, if any susceptible case is found to be positive in screening, it is essential to keep it in quarantine to prevent the spread of the disease. In addition, if necessary, lockdown should be put in place to prevent the spread of disease. Our proposed work covers all of these measures and shows the spread scenario of India. In the present manuscript, three mathematical models are being presented to estimate peoples with COVID-19 disease. (1) Mathematical model without screening, quarantine and lockdown, (2) Mathematical model for a spread with screening, and quarantine, and (3) Mathematical model for a spread with screening, quarantine and lockdown. The proposed model also considers Non-Pharmacological interventions (NPIs) such as Social distancing, universities and offices, avoidance of mass gatherings, etc. Moreover, the proposed model has also estimated the number of outbreaks per day in the coming days.

2 Proposed Methodology

In the present manuscript, three mathematical models are being presented for the estimation of Peoples with COVID-19 disease.

(1) Mathematical model without screening, quarantine and lockdown
(2) Mathematical model for a spread with screening and quarantine
(3) Mathematical model for a spread with screening, quarantine and lockdown

2.1 Mathematical Model Without Screening, Quarantine and Lockdown

The mathematical model for estimating COVID-19 patients without screening, quarantine and lockdown is presented in this section. In this model, all the peoples who are suffering from COVID-19 diseases are spreaders. The spreaders are roaming freely around the city and spread coronavirus to a large number of peoples. Hence, the number of estimated peoples with COVID-19 disease will be more. The proposed mathematical model can be defined as:

(case if $m < 14$)

$$\mathrm{MaxCovid19Spreaders} = \mathrm{c} \times \mathrm{n} \times (\mathrm{mf})^{\mathrm{m}}) \tag{1}$$

(case if $m > 14$)

$$\mathrm{MaxCovid19Spreaders} = \mathrm{c} \times \mathrm{n} \times ((\mathrm{mf})^{\mathrm{m}} - (\mathrm{mf})^{\mathrm{m}-14}) \tag{2}$$

Here, c is constant, and n is initial spreaders. mf is the multiplying factor of the disease, and m is the number of days.

2.2 Mathematical Model with Spread with Screening and Quarantine

The mathematical model for estimating COVID-19 patients with screening and quarantine is being presented in this section. In this model, not all the peoples who are suffering from COVID-19 diseases are spreaders. Initial screening of newcomers is being done for testing COVID-19 diseases. The proposed mathematical model is presented in Fig. 1. In Fig. 1, at the top level, COVID-19 screening is being done. At this time, peoples are being tested for COVID-19 diseases. Hence, the peoples are divided into two groups: the peoples with COVID-19 disease and the peoples without COVID-19 disease. The peoples with COVID-19 are quarantined so that they cannot infect other peoples. It is also possible that the COVID-19 symptoms may appear further after initial screening. We are learning more about the virus as it continues to grow over time. It has been considered earlier that only people with high fever, cough or difficulty breathing can spread COVID-19 disease. However, new findings have shown that this was incorrect. It is possible to spread the virus through people who have no disease symptoms. Therefore, keep a safe distance from people who have symptoms of COVID-19 and are also asymptomatic carriers because they can spread the disease. Hence, these peoples are further divided into two groups, namely infectious and non-infectious. The infectious peoples are categorized into three categories based on symptoms such as the peoples having symptoms, the peoples having mild symptoms and the peoples not having any kind of symptoms. The peoples having symptoms are suggested to be self-quarantined. Self-quarantine means separating yourself from others because you have been exposed to someone who may have COVID-19, even though you do not have any signs or symptoms of the disease. This helps to prevent the transmission of the disease. The self-quarantined peoples may be cured or died. The people who are not self-quarantined may die or have sufficient immunity to face COVID-19 and virus died after the completion period. The peoples having mild symptoms are suggested to be self-quarantined. About 80% of individuals diagnosed with coronavirus will develop mild to severe respiratory infections, and they typically recover without further medication.

Nevertheless, this condition can severely affect older people and individuals with chronic medical conditions, such as cardiovascular disease, asthma, lung illness and cancer. Mild symptoms naturally follow quarantine. If they follow quarantine, they may have symptoms that follow the process described previously. The people may die, or the virus may die after completing the virus cycle. The COVID-19 symptoms may be developed further. It is being classified into the peoples with developed symptoms, the peoples with mild and the peoples without any symptoms. These people do not show any symptoms of the disease during the incubation period. This duration can be of 14 days. As a result, they end up transmitting the virus to a large number of people. This is igniting the pandemic rapidly and dangerously. The peoples whose symptoms are not identified may die or survive after completion of the virus cycle. These peoples are spreaders and spread coronavirus in no small number of peoples before they die. Hence, the number of estimated peoples with COVID-19 disease will be more as compared to Model 1 presented in the current section.

$$\begin{aligned} Leakage &= c \times n \times p \times n_3 \times l_3((mf)^m - (mf)^{m-14}) + c \times n \times p \times n_1 \times (1-l)((mf)^m - (mf)^{m-14}) \\ &\quad + c \times n \times p \times n_2 \times (1-a) \times n_3 \times l_3((mf)^m - (mf)^{m-14}) \end{aligned} \tag{3}$$

$$Leakage = c \times n \times p \times (n_3 \times l_3 + n_1 \times (1 - l) + n_2 \times (1 - a))((mf)^m - (mf)^{m-14}) \tag{4}$$
$$MaxCovid19Spreaders = QuarantineCases + Leakage$$

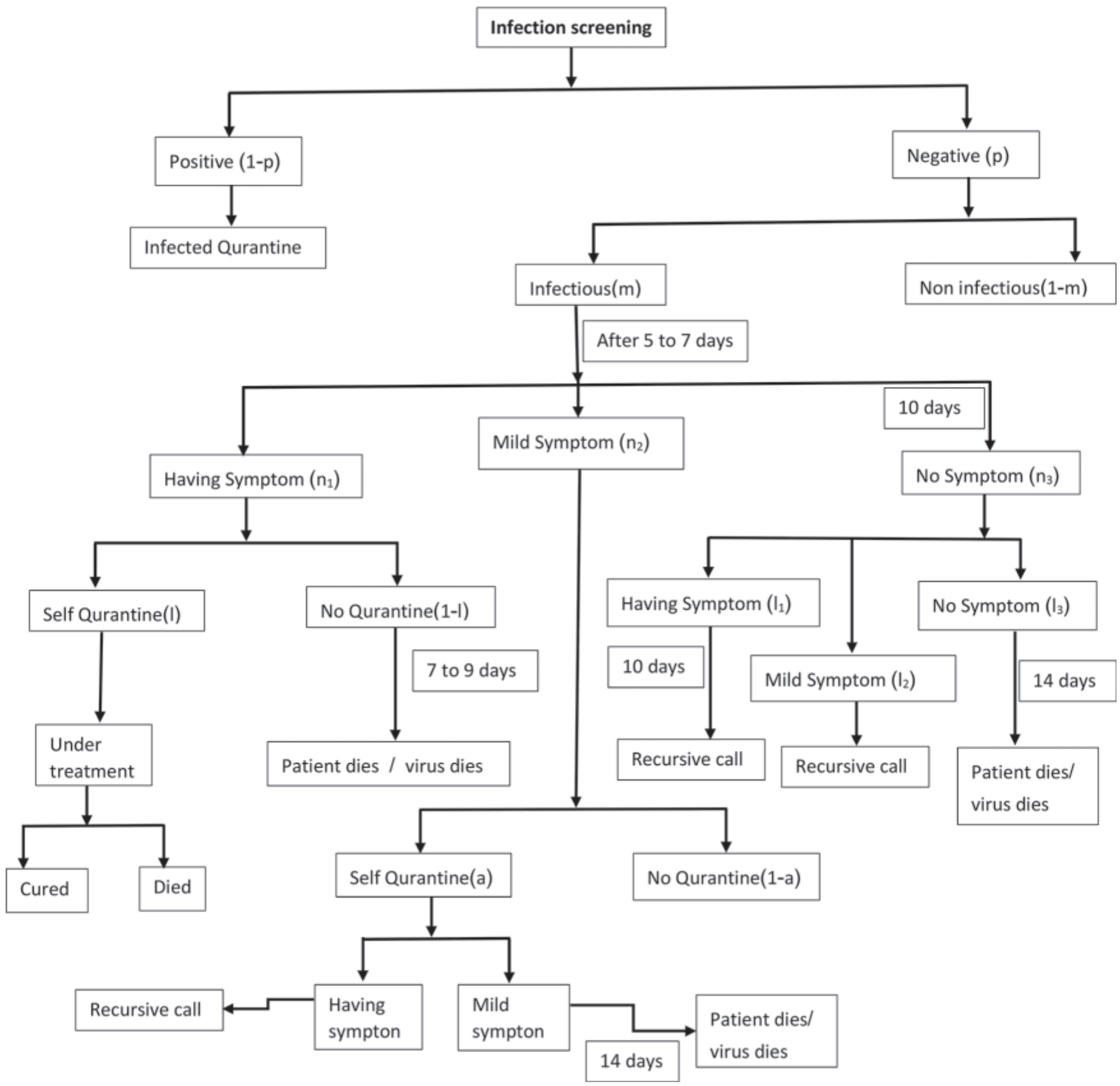


Figure 1: Mathematical model for Corona patient estimation for a spread with screening and quarantine

It is clear advice to avoid the transmission of the infection if you ever find out that you have been near touch with an asymptomatic person. You must give yourself quarantine for fourteen days, even though you do not have any signs of the disease. It will mean that you do not transmit the infection to all those around you.

More than 97 percent of people who contacted any infected people show symptoms of COVID-19 within 11.5 days of exposure. The median incubation period appears to be about five days. This estimation can change, however, as we know more about the virus. In individual patients, the symptoms of COVID-19 start as mild symptoms and slowly worsen over the period. It is important to get immediate medical treatment if the symptoms become worse after a few days of rest.

Here, n, m and mf have the same meaning as in Model 1. p is the fraction of people tested negative in earlier screening. m_1 is the fraction of infectious people. n_1, n_2, n_3 are the fraction of people having symptoms, mild symptoms and no symptoms, respectively, in such a way that the sum of n_1, n_2, and n_3 is one. l is the fraction of people who have followed self-quarantine who have symptoms. a is the fraction of people who have followed self-quarantine having mild symptoms. l_1, l_2, and l_3 are the portion of people initially having no symptoms, but after due time they have been emerged as having symptoms, mild symptoms and no symptoms, respectively.

2.3 Mathematical Model with Spread with Screening, Quarantine with NPIs

The mathematical model for estimating COVID-19 patients with screening, quarantine with complete NPI measures. Non-Pharmacological Intervention (NPI) is intended to reduce the transmission of disease to healthy peoples. The NPI includes distancing measures like no handshaking, working from home, closing educational institutions, cancellation of mass gatherings, partial or total closure of malls/markets, closure of public transportation and voluntary civic shutdown, "Janata curfew," etc. In this model, not all the peoples who are suffering from COVID-19 diseases are spreaders. The proposed mathematical model is the same as presented in the Fig. 1. However, in this model, NPI measures are being implemented to reduce the number of spreaders. The estimated number of peoples with COVID-19 diseases will be less than that of the model presented in Sections 2.1 and 2.2. This model focuses on reducing the leakage term given in Model 2. NPI measures reduce the number of persons, which can contact the spreaders and hence reduce the leakage.

3 Validation Data Set

Tab. 1 tabulates COVID-19 data for India [29]. It has various fields such as date, time, active cases, total cured cases, total death cases, total cases, new cases, daily death cases and daily cured cases. Here, the date and time field describe the COVID-19 cases at a particular date and time. Active cases and cured cases are the number of peoples with COVID-19 disease and cured COVID-19 disease cases, respectively. Total death field describes the number of peoples died due to COVID-19 disease. The total cases field is the sum of active cases, death cases and cured cases. The total death field describes the number of deaths due to COVID-19 disease. The spreaders are affected by external factors such as suspended international flights, curfew, quarantine and gatherings and lockdown.

State-wise COVID-19 disease cases are shown in Fig. 2a [29]. It can be analyzed from the Fig. 2a that the Maharashtra, Gujarat, Delhi, Tamil Nadu, Telangana, Rajasthan, Uttar Pradesh, Madhya Pradesh, Kerala, and Andhra Pradesh are the most suffered state in the country.

Distribution of the disease is shown on the map of India in different geographical states. Looking at the map, it is said how much the disease has spread in the state. Maharashtra, Tamil Nadu, Andhra Pradesh, Karnataka, and Uttar Pradesh are the most affected states.

Table 1: COVID-19 cases in India

Date	Active cases	Total cured	Total death	Total cases	Date	Active cases	Total cured	Total death	Total cases
01-Mar	3	0	0	3	17-May	53946	34109	2872	90927
02-Mar	3	0	0	3	18-May	56316	36824	3029	96169
03-Mar	4	0	0	4	19-May	58802	39174	3163	101139
04-Mar	26	0	0	26	20-May	61149	42298	3303	106750
05-Mar	27	0	0	27	21-May	63624	45300	3435	112359
06-Mar	28	0	0	28	22-May	66330	48534	3583	118447
07-Mar	31	0	0	31	23-May	69597	51784	3720	125101
08-Mar	37	0	0	37	24-May	73560	54441	3867	131868
09-Mar	43	0	0	43	25-May	77103	57721	4021	138845
10-Mar	58	0	0	58	26-May	80722	60491	4167	145380
11-Mar	58	0	0	58	27-May	83004	64426	4337	151767
12-Mar	69	0	1	70	28-May	86230	67520	4527	158277
13-Mar	70	6	2	78	29-May	89987	71106	4706	165799
14-Mar	88	6	2	96	30-May	86422	82370	4971	173763
15-Mar	99	9	2	110	31-May	89995	86984	5164	182143
16-Mar	114	9	2	125	1-Jun	93322	91818	5394	190534
17-Mar	126	10	3	139	2-Jun	97581	95527	5598	198706
18-Mar	152	10	3	165	3-Jun	101497	100303	5815	207615
19-Mar	170	16	4	190	4-Jun	106737	104107	6075	216919
20-Mar	221	19	5	245	5-Jun	110960	109462	6348	226770
21-Mar	282	19	5	306	6-Jun	115942	114073	6642	236657
22-Mar	304	20	7	331	7-Jun	120406	119293	6929	246628
23-Mar	360	30	9	399	8-Jun	125381	124095	7135	256611
24-Mar	446	37	9	492	9-Jun	129917	129214	7466	266597
25-Mar	512	40	9	561	10-Jun	133632	135206	7745	276583
26-Mar	593	42	13	648	11-Jun	137448	141029	8102	286579
27-Mar	640	67	17	724	12-Jun	141842	147195	8498	297535
28-Mar	775	79	19	873	13-Jun	145779	154330	8884	308993
29-Mar	867	87	25	979	14-Jun	149348	162379	9195	320922
30-Mar	942	100	29	1071	15-Jun	153106	169798	9520	332424
31-Mar	1238	124	35	1397	16-Jun	153178	180013	9900	343091
1-Apr	1466	133	38	1637	17-Jun	155227	186935	11903	354065
2-Apr	1764	151	50	1965	18-Jun	160384	194325	12237	366946
3-Apr	2088	157	56	2301	19-Jun	163248	204711	12573	380532
4-Apr	2650	184	68	2902	20-Jun	168269	213831	12948	395048
5-Apr	3030	267	77	3374	21-Jun	169451	227756	13254	410461
6-Apr	3666	292	109	4067	22-Jun	174387	237196	13699	425282
7-Apr	3981	326	114	4421	23-Jun	178014	248190	14011	440215
8-Apr	4643	402	149	5194	24-Jun	183022	258685	14476	456183
9-Apr	5095	473	166	5734	25-Jun	186514	271697	14894	473105

Table 1 (continued).

Date	Active cases	Total cured	Total death	Total cases	Date	Active cases	Total cured	Total death	Total cases
10-Apr	5709	504	199	6412	26-Jun	189463	285637	15301	490401
11-Apr	6565	643	239	7447	27-Jun	197387	295881	15685	508953
12-Apr	7367	716	273	8356	28-Jun	203051	309713	16095	528859
13-Apr	7987	857	308	9152	29-Jun	210120	321723	16475	548318
14-Apr	8988	1036	339	10531	30-Jun	215125	334822	16893	566840
15-Apr	9756	1306	377	11439	1-Jul	220114	347979	17400	585493
16-Apr	10477	1489	414	12380	2-Jul	226947	359860	17834	604641
17-Apr	11201	1749	437	13387	3-Jul	227439	379892	18213	625544
18-Apr	11906	1992	480	14378	4-Jul	235433	394227	18665	648325
19-Apr	12974	2231	507	15712	5-Jul	244814	409083	19268	673165
20-Apr	14175	2547	543	17265	6-Jul	253287	424433	19693	697413
21-Apr	14759	3252	590	18601	7-Jul	259557	439948	20160	719665
22-Apr	15474	3870	640	19984	8-Jul	264944	456831	20642	742417
23-Apr	16454	4258	681	21393	9-Jul	269789	476378	21129	767296
24-Apr	17610	4749	718	23077	10-Jul	276682	495516	21604	793802
25-Apr	18668	5063	775	24506	11-Jul	283407	515386	22123	820916
26-Apr	19868	5804	824	26496	12-Jul	292258	534621	22674	849553
27-Apr	20835	6185	872	27892	13-Jul	301609	553471	23174	878254
28-Apr	21632	6869	934	29435	14-Jul	311565	571460	23727	906752
29-Apr	22629	7696	1007	31332	15-Jul	319840	592032	24309	936181
30-Apr	23651	8325	1074	33050	16-Jul	331146	612815	24915	968876
1-May	25007	8889	1147	35043	17-Jul	342473	635757	25602	1003832
2-May	26167	9951	1218	37336	18-Jul	358692	653751	26273	1038716
3-May	28046	10633	1301	39980	19-Jul	373379	677423	26816	1077618
4-May	29453	11707	1373	42533	20-Jul	390459	700086	27497	1118042
5-May	32138	12727	1568	46433	21-Jul	402529	724578	28084	1155191
6-May	33514	14183	1694	49391	22-Jul	411133	753050	28732	1192915
7-May	35902	15267	1783	52952	23-Jul	426167	782607	29861	1238635
8-May	37916	16540	1886	56342	24-Jul	440135	817209	30601	1287945
9-May	39834	17847	1981	59662	25-Jul	456071	849432	31358	1336861
10-May	41472	19358	2109	62939	26-Jul	467882	885577	32063	1385522
11-May	44029	20917	2206	67152	27-Jul	485114	917568	32771	1435453
12-May	46008	22455	2293	70756	28-Jul	496988	952743	33425	1483156
13-May	47480	24386	2415	74281	29-Jul	509447	988029	34193	1531669
14-May	49219	26235	2549	78003	30-Jul	528242	1020582	34968	1583792
15-May	51401	27920	2649	81970	31-Jul	545318	1057805	35747	1638870
16-May	53035	30153	2752	85940					

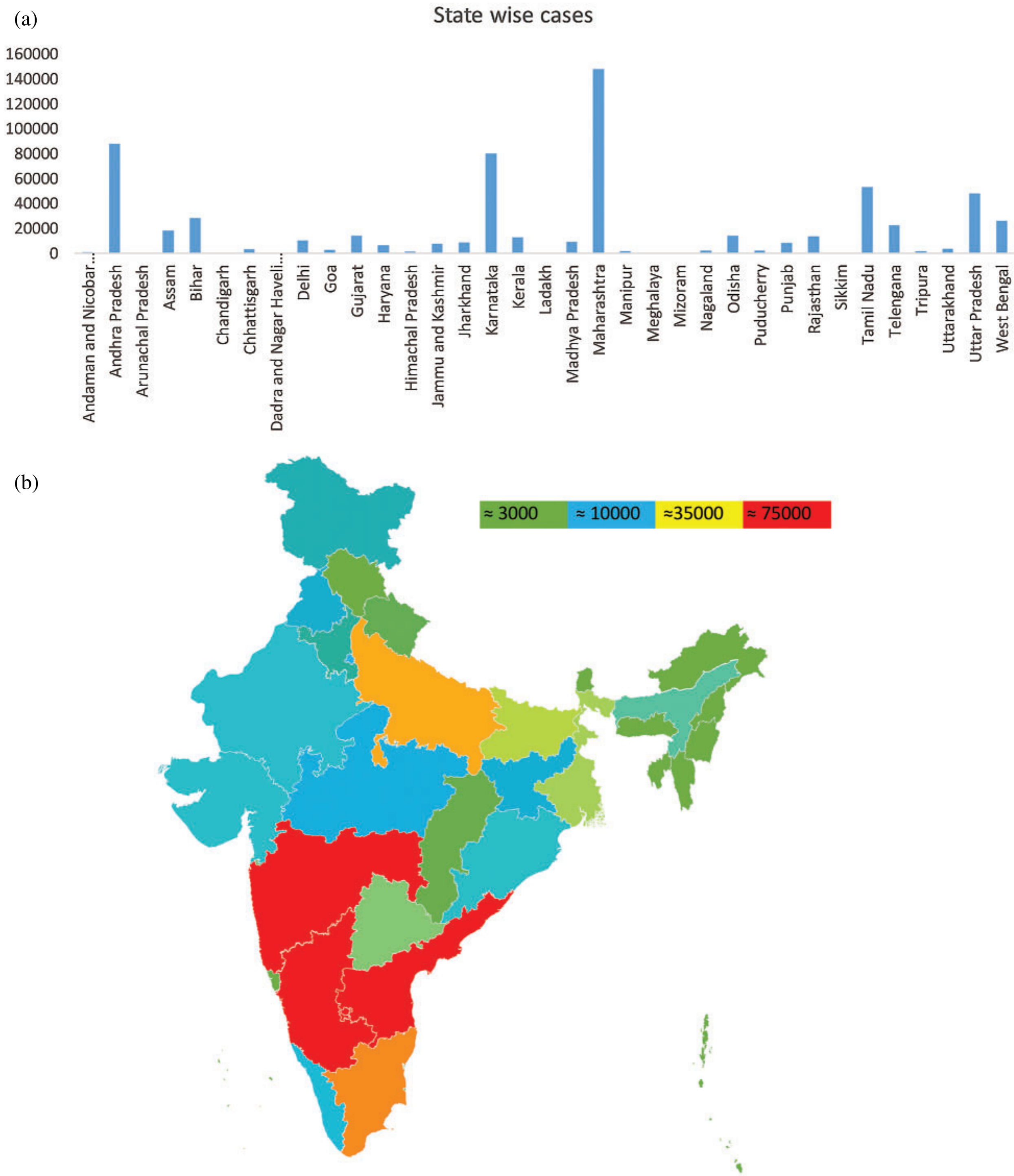


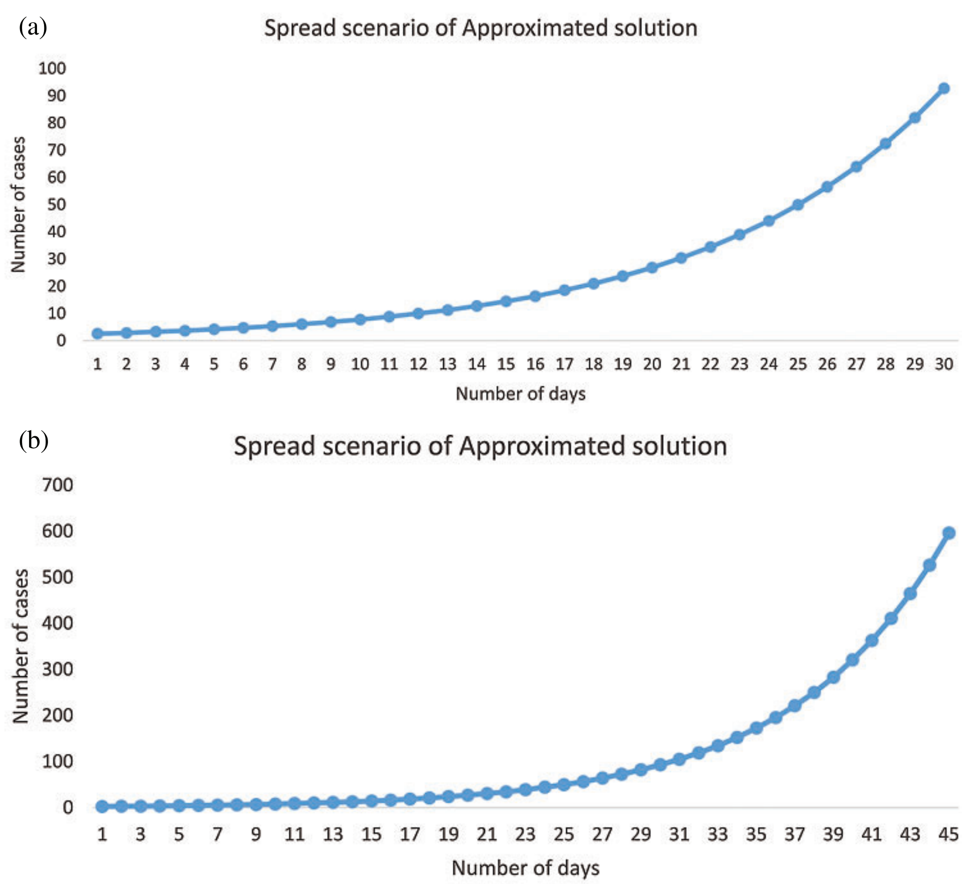
Figure 2: (a) State-wise COVID-19 cases in India (b) Distribution of the disease in all states of India

4 Result and Discussion

Initially, the pandemic's natural evolution affecting the Indian population was modelled, without catering for any NPI or other interventions. We have assumed homogenous distribution of the Indian population for ease of modelling that does not capture variations in population density or the urban-rural variations. It is also being assumed that all the peoples have equal susceptibility to COVID-19.

The mathematical Model 1 has been modelled to implement the natural evolution of the COVID-19 disease in the Indian population was without screening, quarantine and NPI. It has been reported in the literature that the multiplying factor for COVID-19 is approximately 1.3. Hence, the spread scenario has been shown in Figs. 3 and 4 for a different number of days. The growth of COVID-19 cases is exponential in the case of without screening, quarantine and NPI.

India observed a 14-hour voluntary public curfew at the Prime Minister's call on 22 March. Compulsory Lockdowns in COVID-19 hotspots followed in all of the big cities. The Prime Minister decided to order a 21-day national lockdown, affecting India's entire 1.3 billion people on 24 March. The Prime Minister extended the first nationwide lockdown until 3 May. Phase 4 lockdown was applied on 4 May; the Government of India extended the national lockdown by two weeks until 17 May. On 17 May, the National Disaster Management Authority extended the lockdown until 31 May.



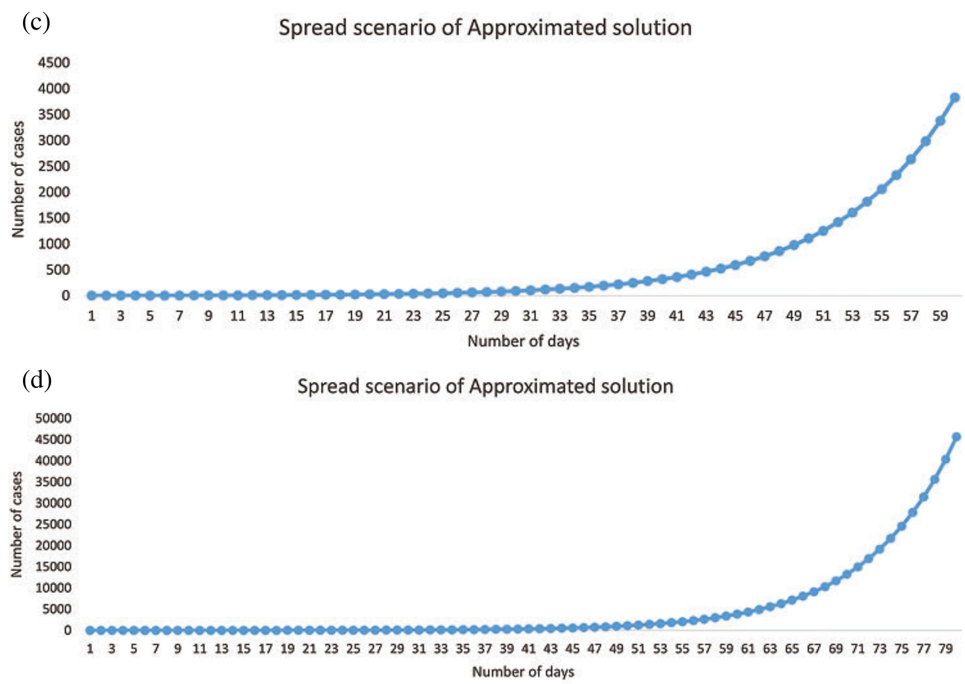


Figure 3: COVID-19 spread scenario without screening, quarantine and Lockdown for (a) 30 days (b) 45 days (c) 60 days (d) 80 days

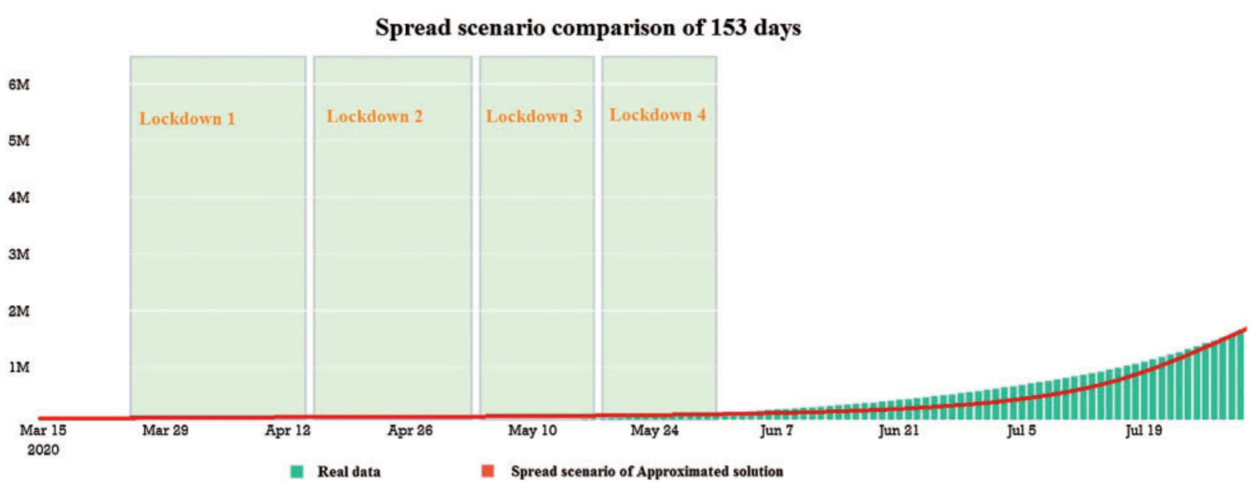


Figure 4: COVID-19 spread scenario with screening, quarantine and lockdown for 153 days

The United Nations and the World Health Organization have appreciated India's approach to the pandemic as lockdown to control the outbreak and develop the essential healthcare infrastructure [30].

Nationwide Lockdown:

Phase 1: 25 March 2020–14 April 2020 (21 days)

Phase 2: 15 April 2020–3 May 2020 (19 days)

Phase 3: 4 May 2020–17 May 2020 (14 days)

Phase 4: 18 May 2020–31 May 2020 (14 days)

These travellers have been further divided into quarantine and normal groups, ending the condition at inspection time. This condition is represented by proposed Model 2. At this stage, NPI interventions were not there or presented in minimal amounts. It can be noticed from Model 2 that the total number of cases is a summation of quarantine cases and leakage. It can also be seen that leakage that exponential behaviour. The multiplication term present in leakage reduces the growth of the function. It can also be noticed from the Figs. 5 and 6. Figs. 5 and 6 are representing the spread scenario before NPI interventions. Only screening and quarantine were in place. The growth shows random behaviour due to a small contribution from the leakage factor. The quarantine cases follow a linear nature and have an enormous impact on total cases and active cases initially. The effect of the leakage factor increases with time, and the graph is also it is showing similar behaviour. Tab. 1 presents the data for India. It has been plotted to have visible results. Fig. 7 shows the total number of infected persons who have been cured of this disease. It can be noticed that the plot shows growth with time, and more people are coming out from this pandemic. Fig. 8 represents total death occurred. It can also be noticed that with the time number of death are also increasing. It has been found that the growth of the death curve is lesser than the growth of total cure. Figs. 9 and 10 present the active cases and total cases of COVID-19 in India, respectively. Curve fitting has been used to obtain the best-fitted equation for the data. It has been reported that exponential curve fitting is providing good results with approximately 96% accuracy. Although active cases and total cases are following exponential behavior, the growth is in the order of 0.17 approximately for active cases and total cases also. This shows that the measures taken by the Indian government have slowed down the growth of COVID-19 spread.

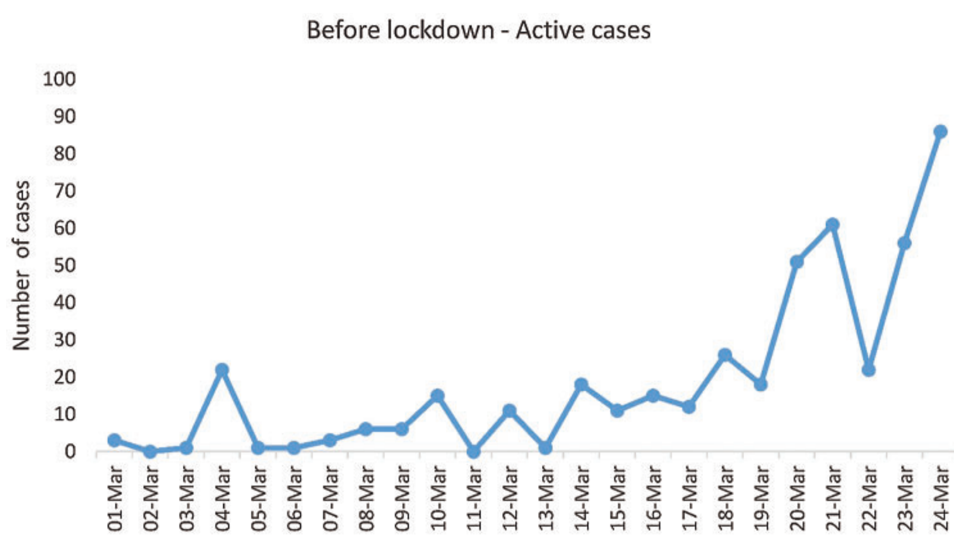


Figure 5: COVID-19 active cases spread scenario for India before lockdown

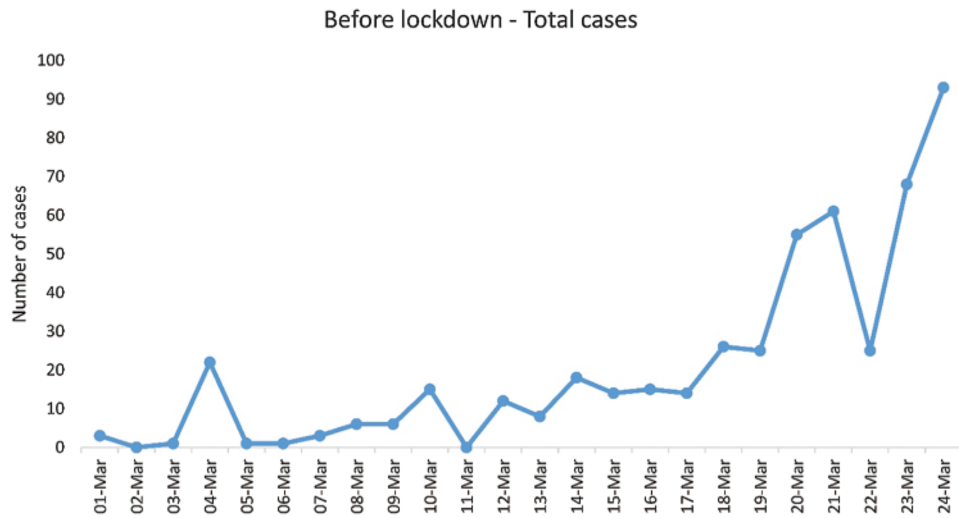


Figure 6: COVID-19 total cases spread scenario for India before lockdown

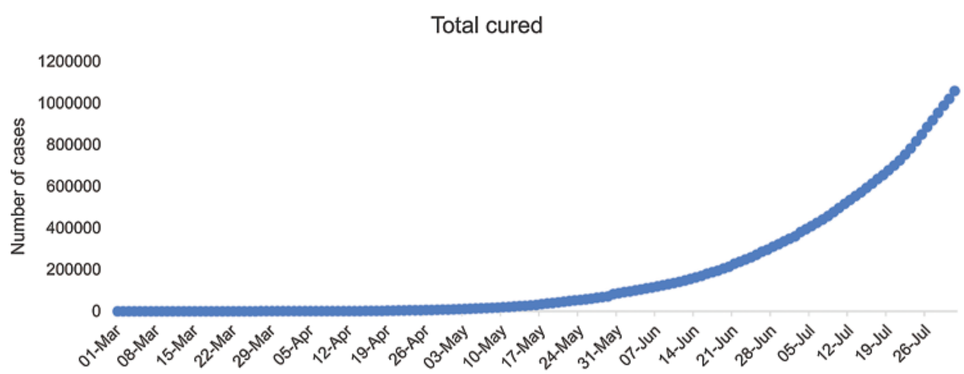


Figure 7: Total COVID-19 cured cases

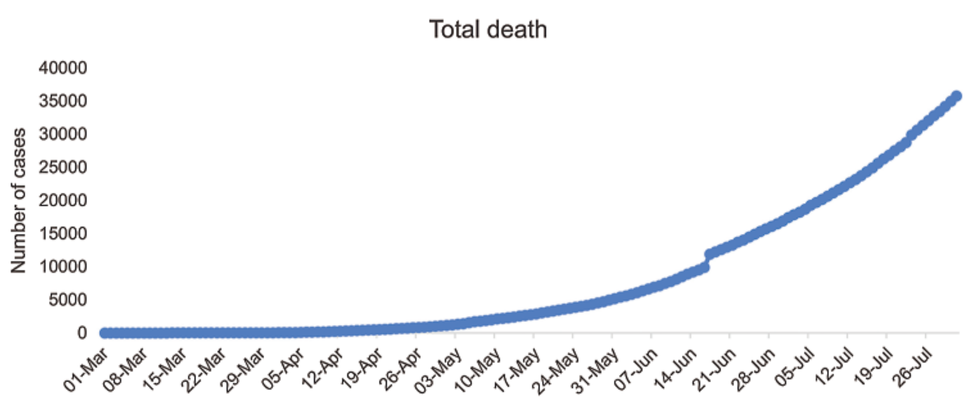


Figure 8: Total COVID-19 death cases

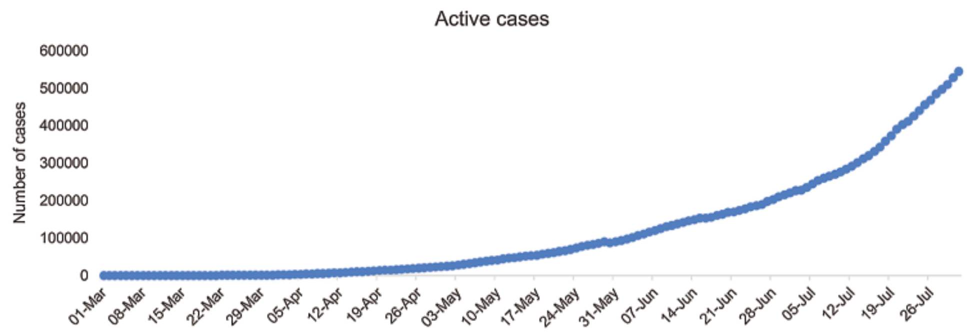


Figure 9: Active COVID-19 cases

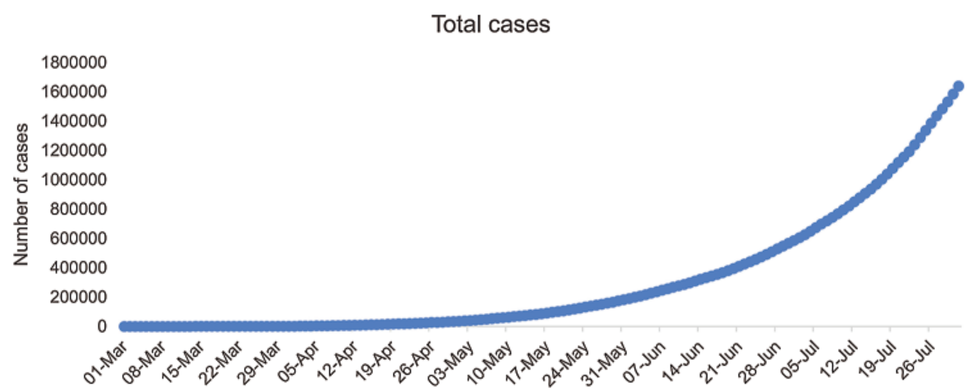


Figure 10: Total cases of COVID-19

The NPI measures have been imposed on the Indian population from March 24, 2020. Hence, the impact of these NPI measures is also of interest for research. This impact has been studied in the current manuscript. The mathematical Model 3 is following screening, quarantine and NPI. Quarantine and NPI measures are being implemented to reduce spreading. The number of freshly infected decreases with the increase in quarantined cases in general. The effectiveness of quarantine depends on the compliance by individuals and public health measures that are instituted. The results obtained by this model are shown in Tab. 2. It shows the number of active cases and total cases after imposing NPI measures. Figs. 11 and 12 represent the active cases and total cases after NPI measures such as lockdown, social distancing, etc. It can be analyzed for Figs. 11 and 12 that lockdown reduces spread exotically.

Tabs. 3 and 4 present the R2 values for different curve fitting methods applied on Figs. 11 and 12 for active and total cases. T has been found that polynomial fitting of order two provides good fitting results for both active and total case scenarios. This indicates that the growth of active and total cases reduces from exponential to polynomial.

Simple linear regression is one of the effective forms of predictive models. It calculates the relationship between two variables by fitting a linear equation to the data. R-squared measures how close the regression line is to the data on which it fits. It appears as if the optimal line has to be curved in, fit data more precisely. That is where the polynomial regression comes in. Polynomial regression models are used to estimate to nth degree to minimize square error and maximize R-squared value. Prediction is one of the significant uses of regression analysis, which estimates the dependent variable values using the prediction equation. We cannot predict the perfect. There might be some error. The error is because of the uncertainty of the estimation and the natural variation of the regression line. The polynomial models are an efficient and flexible curve fitting technique.

Table 2: Active cases and total cases after lockdown

Date	Active cases	Total cases	Date	Active cases	Total cases	Date	Active cases	Total cases
25-Mar	512	561	7-May	35902	52952	19-Jun	163248	380532
26-Mar	593	648	8-May	37916	56342	20-Jun	168269	395048
27-Mar	640	724	9-May	39834	59662	21-Jun	169451	410461
28-Mar	775	873	10-May	41472	62939	22-Jun	174387	425282
29-Mar	867	979	11-May	44029	67152	23-Jun	178014	440215
30-Mar	942	1071	12-May	46008	70756	24-Jun	183022	456183
31-Mar	1238	1397	13-May	47480	74281	25-Jun	186514	473105
1-Apr	1466	1637	14-May	49219	78003	26-Jun	189463	490401
2-Apr	1764	1965	15-May	51401	81970	27-Jun	197387	508953
3-Apr	2088	2301	16-May	53035	85940	28-Jun	203051	528859
4-Apr	2650	2902	17-May	53946	90927	29-Jun	210120	548318
5-Apr	3030	3374	18-May	56316	96169	30-Jun	215125	566840
6-Apr	3666	4067	19-May	58802	101139	1-Jul	220114	585493
7-Apr	3981	4421	20-May	61149	106750	2-Jul	226947	604641
8-Apr	4643	5194	21-May	63624	112359	3-Jul	227439	625544
9-Apr	5095	5734	22-May	66330	118447	4-Jul	235433	648325
10-Apr	5709	6412	23-May	69597	125101	5-Jul	244814	673165
11-Apr	6565	7447	24-May	73560	131868	6-Jul	253287	697413
12-Apr	7367	8356	25-May	77103	138845	7-Jul	259557	719665
13-Apr	7987	9152	26-May	80722	145380	8-Jul	264944	742417
14-Apr	8988	10531	27-May	83004	151767	9-Jul	269789	767296
15-Apr	9756	11439	28-May	86230	158277	10-Jul	276682	793802
16-Apr	10477	12380	29-May	89987	165799	11-Jul	283407	820916
17-Apr	11201	13387	30-May	86422	173763	12-Jul	292258	849553
18-Apr	11906	14378	31-May	89995	182143	13-Jul	301609	878254
19-Apr	12974	15712	1-Jun	93322	190534	14-Jul	311565	906752
20-Apr	14175	17265	2-Jun	97581	198706	15-Jul	319840	936181
21-Apr	14759	18601	3-Jun	101497	207615	16-Jul	331146	968876
22-Apr	15474	19984	4-Jun	106737	216919	17-Jul	342473	1003832
23-Apr	16454	21393	5-Jun	110960	226770	18-Jul	358692	1038716
24-Apr	17610	23077	6-Jun	115942	236657	19-Jul	373379	1077618
25-Apr	18668	24506	7-Jun	120406	246628	20-Jul	390459	1118042
26-Apr	19868	26496	8-Jun	125381	256611	21-Jul	402529	1155191
27-Apr	20835	27892	9-Jun	129917	266597	22-Jul	411133	1192915
28-Apr	21632	29435	10-Jun	133632	276583	23-Jul	426167	1238635
29-Apr	22629	31332	11-Jun	137448	286579	24-Jul	440135	1287945
30-Apr	23651	33050	12-Jun	141842	297535	25-Jul	456071	1336861
1-May	25007	35043	13-Jun	145779	308993	26-Jul	467882	1385522
2-May	26167	37336	14-Jun	149348	320922	27-Jul	485114	1435453
3-May	28046	39980	15-Jun	153106	332424	28-Jul	496988	1483156
4-May	29453	42533	16-Jun	153178	343091	29-Jul	509447	1531669
5-May	32138	46433	17-Jun	155227	354065	30-Jul	528242	1583792
6-May	33514	49391	18-Jun	160384	366946	31-Jul	545318	1638870

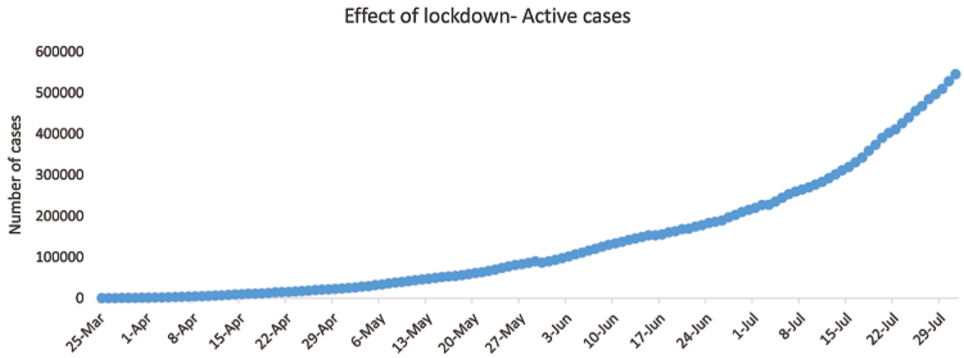


Figure 11: Effect on active Cases on COVID-19 data spread scenario for India after lockdown

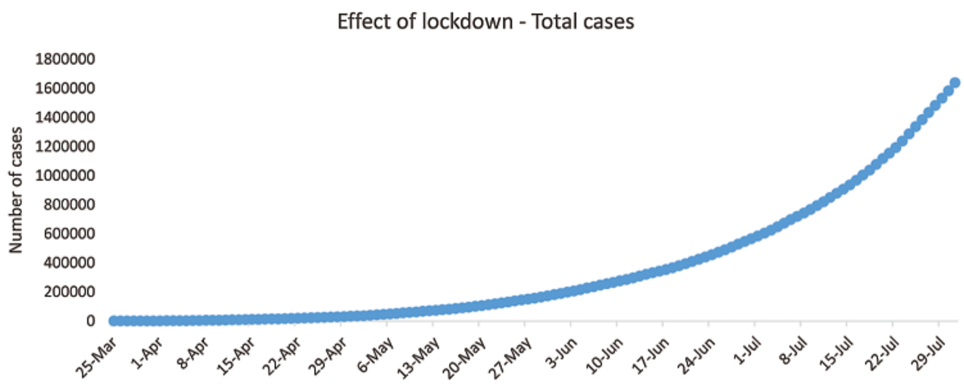


Figure 12: Effect on total Cases on COVID-19 data spread scenario for India after lockdown

Table 3: Active cases after lockdown

Types of curve	Equation	R-squared value (R^2)
Exponential function	$y = 2930.2e^{0.0448x}$	0.909
Linear function	$y = 3519.4x - 92541$	0.8448
Logarithmic function	$y = 107015 \ln(x) - 279615$	0.4928
Polynomial of order 2	$y = 42.682x^2 - 2029.2x + 28604$	0.9826
Polynomial of order 3	$y = 0.3938x^3 - 34.101x^2 + 1978.9x - 15653$	0.9951
Polynomial of order 4	$y = 0.0064x^4 - 1.2655x^3 + 104.93x^2 - 2073.9x + 11604$	0.9986
Polynomial of order 5	$y = 1E - 04x^5 - 0.0252x^4 + 2.3933x^3 - 74.49x^2 + 1310.3x - 3853.8$	0.9995

Table 4: Total cases after lockdown

Types of curve	Equation	R-squared value (R^2)
Exponential function	$y = 2946.3e^{0.0542x}$	0.9375
Linear function	$y = 10205x - 309462$	0.7831
Logarithmic function	$y = 299369\ln(x) - 809412$	0.4252
Polynomial of order 2	$y = 153.25x^2 - 9717.4x + 125501$	0.9792
Polynomial of order 3	$y = 1.46x^3 - 131.45x^2 + 5144.1x - 38599$	0.9974
Polynomial of order 4	$y = 0.0133x^4 - 1.989x^3 + 157.55x^2 - 3280.5x + 18062$	0.9986
Polynomial of order 5	$y = 0.0002x^5 - 0.0395x^4 + 4.1236x^3 - 142.21x^2 + 2373.4x - 7763.8$	0.9992

5 Polynomial Regression Model and Evaluating of its Accuracy

Polynomial regression is a particular case of multiple regression, with only one independent variable X. One-variable polynomial regression model can be expressed as

$$y_i = \beta_0 + \beta_1 x_i + \beta_2 x_i^2 + \cdots + \beta_k x_i^k + e_i, \text{ for } i = 1, 2, \ldots, n$$

Here, k is the degree of the polynomial. The degree of the polynomial is the order of the model.

The R-squared (coefficient of determination) of the curve fit is described as

$$R^2 = 1 - \frac{SSR}{SST} = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} y - \hat{y}^2}$$

Here, SST is the total sum of squares, SSR is the residual sum of squares, and y is the Y variable's arithmetic mean. R-square measures the percentage of variation in the response variable Y explained by the explanatory variable X.

R-squared is an important measure of how well the regression model fits the data. R Square value is always between zero and one, $0 \leq R^2 \leq 1$.

All analyses and calculations have been done using MATLAB and its Curve Fitting Toolbox and using the Solver and Curve Fitting Toolbox and trend line features in Microsoft Excel.

The polynomial of order four fit model outperforms the polynomial of order two and polynomial of order 3 with the lowest error statistics and highest deterministic coefficient. The polynomial of the order 4 model gives a better result. We have found that the polynomial of order five fit or quantic regression model fits the data best. Hence, we have used quantic polynomial fit as an approximate solution.

Hence, NPI measures have reduced or slow down the growth of COVID-19, which has also been indicated in Fig. 6. Complete lockdown represents the full implementation of NPI measures to the entire population. Our model shows that the immediate implementation of effective screening, quarantine and NPIs reduces COVID-19 disease drastically. Hence, the numbers infected peoples with COVID-19 become manageable, reducing from millions to mere thousands.

The overall COVID-19 spread in India has been shown in Fig. 4 and approximation obtained by the proposed method. The lockdown period required by India has been analyzed as per the growth rate obtained. It has been shown in Fig. 15. It can be interpreted from Fig. 15 that there will be no COVID-19 cases after 30-October-2020.

We have fitted the curve first for a linear function, logarithmic function, exponential function, and polynomial of order 2, a polynomial of order 3, a polynomial of order 4, polynomial of order 5 and have calculated the R-squared value for all curves. Polynomial fit results give a better approximate solution as compared to others. The Polynomial of order 4 outperforms the polynomial of order 2 and the polynomial of order 3. Polynomial of order 5 fits gives the best solution. Hence, we have used the polynomial of order 5 fit as an approximate solution shown in Fig. 15.

Analysis of the fits of Polynomial of order 2, a polynomial of order 3 and polynomial of order 4 on daily new cases with R-squared value is shown in Fig. 13. The R-squared value of polynomial of order 4 is higher in the polynomial of order 2 and polynomial of order 3.

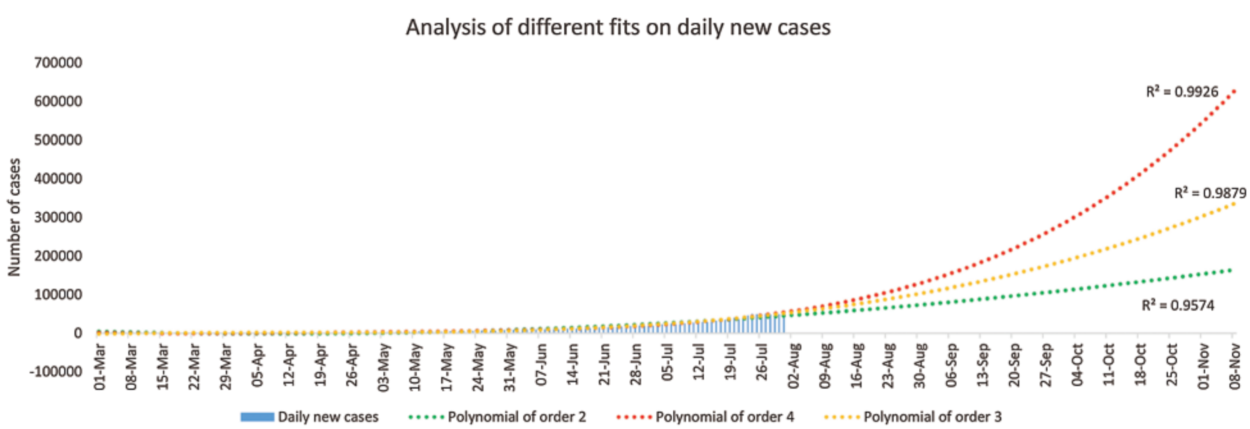


Figure 13: Analysis of polynomial fits of orders 2, 3 and 4 on daily new cases with R-squared value

Analysis of linear fit, logarithmic fit and polynomial of order 2 on daily new cases with R-squared value have been shown in Fig. 14. The R-squared value of polynomial of order 2 is higher in comparison of linear fit and logarithmic fit.

Prediction of total cases for 100 days and approximate solution with the polynomial fit of order 5 is shown in Fig. 15. The Polynomial of order 5 R-squared value is 0.991, which is better than the quartic polynomial, and the fitting curve show that no cases will come by 30 October.

Our basic approach is to predict COVID-19 disease and analyze the spread scenario of COVID-19 disease in India. Our current data listed in Tabs. 1 and 2 are day wise sequential data. We compare our proposed work with deep learning models. LSTM (Long short-term memory) and Sequence-to-Sequence deep learning models are well suited for making predictions based on time series data.

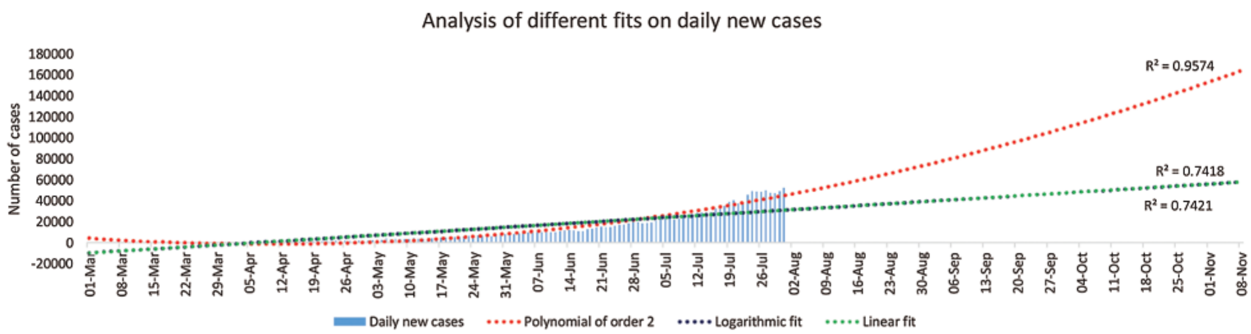


Figure 14: Analysis of polynomial fit of order 2, linear and logarithmic fit on daily new cases with R-squared value

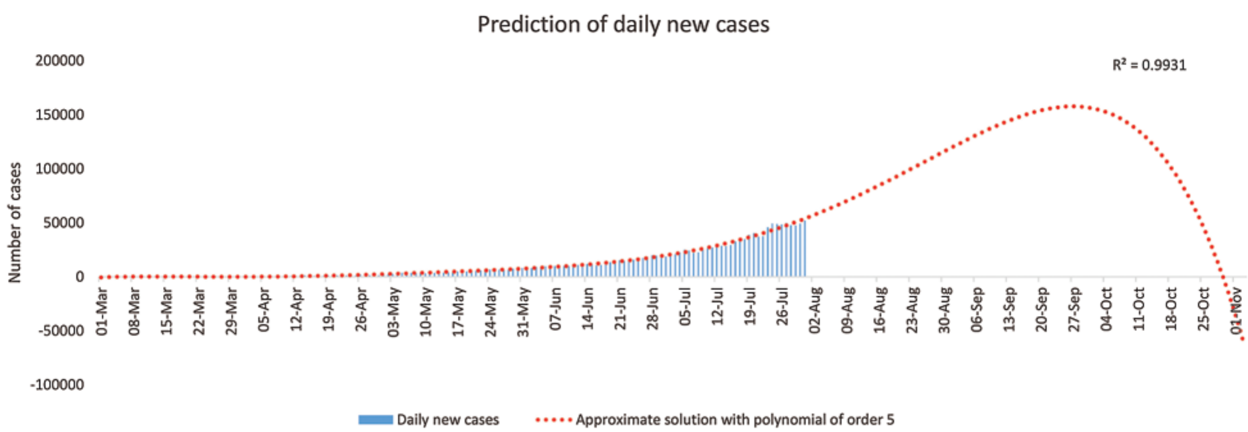


Figure 15: Prediction of daily new cases for 120 days and approximate solution with the polynomial fit of order 5

5.1 Evaluation Criteria

The prediction performance of the proposed system is evaluated using the following metrics:

1. Mean absolute percentage error (MAPE)

Analyze the efficiency of the forecasting model of our method, we use the mean absolute percentage error (MAPE) [31] or Mean Absolute Percentage Deviation (MAPD) as the criteria standard. Its formula is express as the following equation

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{y_i}\right| \times 100 \qquad (5)$$

where y_i denotes the ith actual value, and x_i represents the ith predicted value. If the value of MAPE is low, the accuracy of the method is high.

2. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) [32] or Root-Mean-Square Deviation (RMSD) is a measure of the average magnitude of the errors. Specifically, it is the square root of the average squared differences between the prediction and actual observations. Therefore, the RMSE will be more useful when large errors are particularly undesirable. If the value of RMSE is low, the accuracy of the method is high. RMSE formula is express as the following equation

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^{obs} - y_i^{pred})^2} \tag{6}$$

where y_i^{obs}andy_i^{pred} are the actual and predicted observations, respectively.

Table 5: Proposed method compare with the deep learning prediction models

Prediction models	Root mean square error (RMSE)	Mean absolute percentage error (MAPE)
LSTM[1] [33]	50645.27	0.9804
Seq2Seq[2] [34]	8965.09	0.0974
Proposed[3]	**3089.68**	**0.0278**

LSTM[1]—Long short-term memory model;
Seq2Seq[2]—Sequence-to-Sequence Model;
Proposed[3]—Proposed Method

Table 6: Proposed method compare with the state-of-the-art methods

Prediction models	Root Mean Square Error (RMSE)	Mean Absolute Percentage Error (MAPE)
SIR[1] [35]	26395.96	0.3098
ARIMA[2] [36]	5957.17	0.0702
SARIMAX[3] [37]	39630.88	0.6464
Proposed[4]	**3089.68**	**0.0278**

SIR[1]—Susceptible Infectious Recovered Model;
ARIMA[2]—Autoregressive integrated moving average Model;
SARIMAX[3]—Seasonal ARIMAX Model;
Proposed[4]—Proposed Method

The overall performance of deep learning methods is not better because there is less set of training data. If the training data set increases, the performance of the deep learning method will improve. For model validation, we have used precision measures, MAPE and RMSE. Tab. 5 shows the proposed model outperforms the LSTM model and the Seq2Seq model. The result shows that the RMSE and MAPE accuracy of the proposed model better as compared to the LSTM and Seq2Seq models.

Tab. 6 shows the proposed model outperforms the state-of-the-art methods such as the SIR model, the ARIMA model and the SARIMAX model. The proposed model outperforms the LSTM model and the Seq2Seq model. The result shows that the RMSE and MAPE accuracy of the proposed model better as compared to the SIR, ARIMA and the SARIMAX models.

6 Conclusion

India is in the early stage of the COVID-19 pandemic, with a lower growth rate than other countries studied. In the present manuscript, three mathematical models have been presented to estimate the growth function of COVID-19 disease. It has been found that the numbers of COVID-19 patients will be more without screening the peoples coming from other countries. Since every people suffering from COVID-19 disease are spreaders. The screening and quarantine have been implemented in mathematical Model 2. It has been found that the number of spreaders is less than that of Model 1. However, expected performance is not achieved due to leakage, i.e., peoples not the following quarantine. Mathematical Model 3 has been designed with screening, quarantine with NPIs. It has achieved reasonable performance in reducing the number of spreaders. Hence, it is found that the immediate implementation of Non-Pharmacological Interventions among the general population, including complete lockdowns, can retard the pandemic's progress. It has also been observed that the COVID-19 spread will be recovered till 30-October-2020 approximately in India.

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Conflicts of Interest: The authors have no conflicts of interest to report regarding the present study.

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