The Fallacies of Forecasting Models for Coronavirus (COVID-19) Pandemic in India during Country-wise Lockdowns

Ravi Kumar Arya [1], Abhinav Gola[2], Animesh[3], Ravi Dugh[4]

[1] Assistant Professor, Electronic and Communication Engineering, National Institute of Technology, Delhi, India
[2] Student, Electrical and Electronics Engineering, National Institute of Technology, Delhi, India
[3] Student, Electrical and Electronics Engineering, National Institute of Technology, Delhi, India
[4] Student, Goergen Institute for Data Science, The University of Rochester, New York, USA

ABSTRACT

Background: *COVID-19 is widely spreading across the globe right now. While some countries have flattened the curve, others are struggling to control the spread of the infection. Precise risk prediction modelling is key to accurate prevention and containment of COVID-19 infection, as well as for the preparation of resources needed to deal with the pandemic in different regions.*
Methods: *Given the vast differences in approaches and scenarios used by these models to predict future infection rates, in this study, we compare the accuracy among different models such as regression models, ARIMA model, multilayer perceptron, vector autoregression, susceptible exposed infected recovered (SEIR), susceptible infected recovered (SIR), recurrent neural networks (RNNs), long short term memory networks (LSTM) and exponential growth model in prediction of the total COVID-19 confirmed cases. We did so by comparing the predicted rates of these models with actual rates of COVID-19 in India during the nationwide lockdowns.*
Results: *Few of these models accurately predicted COVID-19 incidence and mortality rates in six weeks, though some provided close results. While advanced warning can help mitigate and prepare for an impending or ongoing epidemic, using poorly fitting models for prediction could lead to substantial adverse outcomes.*
Implications: *As the COVID-19 pandemic continues, accurate risk prediction is key to effective public health interventions. Caution should be taken when choosing different risk prediction models based on specific scenarios and needs. To improve risk prediction of infectious diseases such as COVID-19 for policy guidance and recommendations on best practices, both internal (e.g., specific virus characteristics in transmission and mutation) and external factors (e.g., large-scale human behaviours such as school opening, parties, and breaks) should be considered and appropriately weighed.*

Keyword: *COVID-19 SARS-CoV-2, forecasting models epidemics, pandemics computational epidemiology, machine learning method prediction, COVID-19 prediction linear regression (LR), multilayer perceptron (MLP), vector autoregression (VAR), ARIMA , India*

1 Introduction

COVID-19 pandemic, also known as the coronavirus pandemic, is currently wreaking havoc in more than 200 countries [1] worldwide. It is caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2). As of late July 2020, at least 17 million people are diagnosed with this virus. This infectious disease has left more than 668 thousand people dead. The infection numbers are increasing every day, and without a vaccine, it will be difficult to eradicate this virus.

The virus spreads through contact, mainly through coughing, sneezing, or just being close to an infected person. The droplets released by the coughing or sneezing person can travel several feet and can infect the nearby people. If these droplets fall on nearby surfaces, they can contaminate such surfaces and lead to infecting others coming in contact with such surfaces. Currently, there are no medications to prevent or treat this epidemic [2], but many biotech companies have stepped in the race of developing vaccines with millions of dollars at stake.

On January 30, 2020, the first COVID-19 occurrence was registered in India. According to the Ministry of Health and Family Welfare (MoHFW) [3], more than 1.6 million people have been infected by this deadly disease. Coronavirus is also responsible for more than 36,000 deaths until now. India has the highest confirmed case in Asia since June 16, 2020 [1].

Different nations imposed different methods to combat the spread of this disease. These varied for quarantine, mask use, closing of markets/malls, restricting social gatherings, travel restrictions, frequently washing hands, sanitizing frequently used areas, etc.. Some countries imposed lockdowns in different states to restrict the outbreak of the disease further. In India, to counter the spread of this deadly disease, several lockdowns were imposed country-wise. The first nationwide lockdown was imposed on March 24, 2020 , for 21 days. The lockdown was further extended on April 14, 2020, till May 3, 2020. Further extensions were imposed on May 3 and May 17, 2020. With a few exceptions, the nation began unlocking on June 1, 2020 [3]. We use the prediction models during these lockdown times. During this time, as the lockdown was at the national level, there were fewer variables in the supposed model. After these lockdowns, India went into partial lockdowns where some states of India were under lockdowns while others were not.

Several prediction models have been used over the past several months to predict the COVID-19 infection rate. These models forecast the rate of infection, recovery, death, or some combination of these three parameters for the COVID-19 patients. The primary evaluation variables can be split into two groups in order to test a forecast model - virus intrinsic: time of incubation, the element of virulence, etc. and outside: size, quarantine, and so on of the infected population. While no model can accurately forecast the rates of infection and mortality, attempts have been made to consider and analyze the strengths and shortcomings of many studies and models presented regarding the coronavirus. Whereas the forecast models used by the health department or Government of India were not disclosed, we can definitely continue with existing models in separate research publications. Each of these models took different approaches and techniques to predict future outbreak rates. In this study, we review major forecasting models that were used in the context of India and compare them with real/actual data. In this way, the difference of confirmed cases of COVID-19 between forecasted and actual cases gives us the error by which these models made bad/good predictions. For our study, we take published models before the national unlocking period (i.e., June 1, 2020). All the prediction models were chosen so that they could predict the cases during lockdowns. The future deaths are hard to predict as with a path of hurricane [5]. In the US, the CDC (Centre for Disease Control) is relying on a mash-up of 32 models [5]. Often models are used for projections up to 6 weeks as they rely on a variety of untested assumptions (e.g., social distancing) [5].

This study is organized into five main sections. The paper starts with general information about the history and information of the disease, including the underlying mechanism of the outbreak in India, and the effect of measures adopted to prevent the spread of COVID-19. Section 2 provides a survey of the multiple forecasting techniques employed to predict the confirmed cases in the Indian context. Sections 3 and 4 discuss our findings and results. We conclude this research work in section 5 with the best performing forecasting models along with some interesting observations.

1.1 Underlying mechanism of the outbreak in India

COVID-19 is assumed to disperse across two phases (see Fig. 1). The first phase is distinguished on the basis of living animals who contain the virus in their bodies, which is communicated through touch to humans. Phase II is characterized by the swift human-to-human transmission of the virus [20].

All other countries became alert after the viral outbreak in China and immediately took preventive steps, which included strict quarantine measures

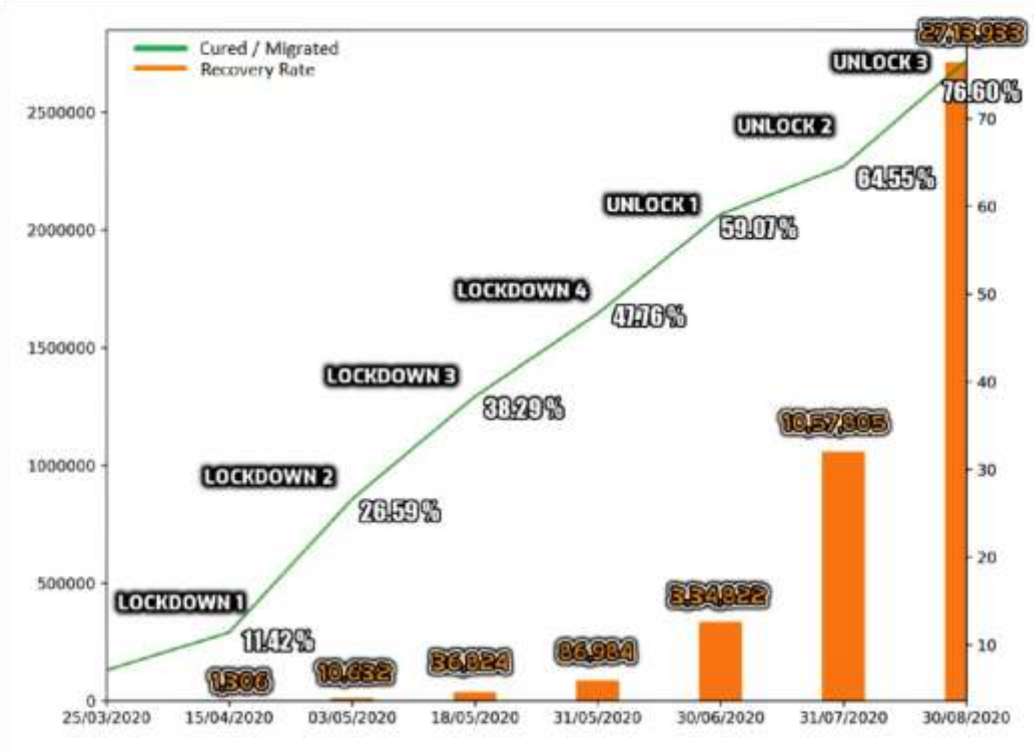


Figure 1: Lockdown effects

at airports. India is the world's second-largest economy. It is also a close neighbor of China and, therefore, more likely to transmit infectious disease (the US and Global Population Clock, 2020).

On January 30, 2020, India registered the first confirmed case from Kerala, which was closely related to the COVID-19 outbreak epicenter, Wuhan. The very first demise in India by COVID-19, recorded from Kalaburagi, Karnataka, was a 76-year-old man who tested positive SARS-CoV-2 [10]. So, in India, on March 11, 2020, Karnataka was the first State to announce COVID19's first death. There has been a significant rise in records of reported cases from other Indian states. The government of India has announced 21 shutdown days, which are effective on March 25, 2020, with approved guidance on vital resources management [11].

1.2 Effect of measures adopted to prevent the spread of COVID-19

To forestall the spread of COVID-19, the Indian government has carried out various preventive measures. The two major policies that have been effective are social detachment and lockdown. While the first refers to an absolute absence of contact between an individual and society, the second is an exigency protocol that normally prevents citizens from leaving a zone. These two measures have been critical in restricting COVID-19 in a country with a 1.3 billion population.

In this study, we will be using the effective reproduction factor (*R*) to evaluate the cogency of these measures. The *R* factor denotes the average number of people to which an infected person will transmit the virus. In basic terms, it measures an infectious disease's capacity to proliferate in a region. This parameter is based on a range of factors, including how virulent the virus is, its development rate, the response of the populace, and possession of any insusceptibility like a vaccination.

Due to the novelty of the SARS-CoV-2, initially, the *R*0, or "R nought" factor was being calculated which signifies the virus's transmission among a region without any immunity. Early research for China indicated its value to be between 2 and 2.5 [17] but more recent estimates have placed it as high as 6.6 [18]. An *R* value of greater than 1 leads to an exponential growth in infection rate while less than 1 gradually leads towards the end of the epidemic. To limit this parameter below the threshold of 1, governments all around the world imposed various lockdown measures, which came along with an unprecedented series of adjustments bringing people's lives and economies to a shuddering halt.

On March 24, 2020, India's prime minister ordered a nationwide lockdown for 21 days, which was extended till May 3 and then accompanied by twoweek extensions starting May 3, 2020 and May 17, 2020 with considerable relaxations. From June 1, the government started "unlocking" the country in three different phases. Sitabhra Sinha, a researcher at the Institute of Mathematical Sciences in Chennai, had projected that without lockdown measures, the basic reproduction number (R0) of Covid-19 in India would have been 1.83, which would have translated to 1 lakh active cases by April 27 [19]. Instead, an R of 1.29 was seen during the first lockdown period and then between May 29 and June 4, the R value further reduced to 1.22 and has been either holding steady or becoming less in different states in India.

To gain a better understanding of the efficacy of the lockdown, in our research, we estimated total positive cases and then compared them with the actual number of cases using different values of reproduction rate. The resulting plots are shown in Fig 2. It can be observed from the figure that if India's curve would have followed China's infection curve, they'd have surpassed 4 lakh cases by June 1 with an R value of 2.5 as opposed to around 2 lakh cases with R being 1.22. Similarly, keeping the R value to 2 or even

1.83 (as predicted by Sitabhra Sinha), we would have an excess of 1.3 lakhs and 0.99 lakhs infected people by June 1, 2020 respectively, if the nationwide lockdown had not been implemented.

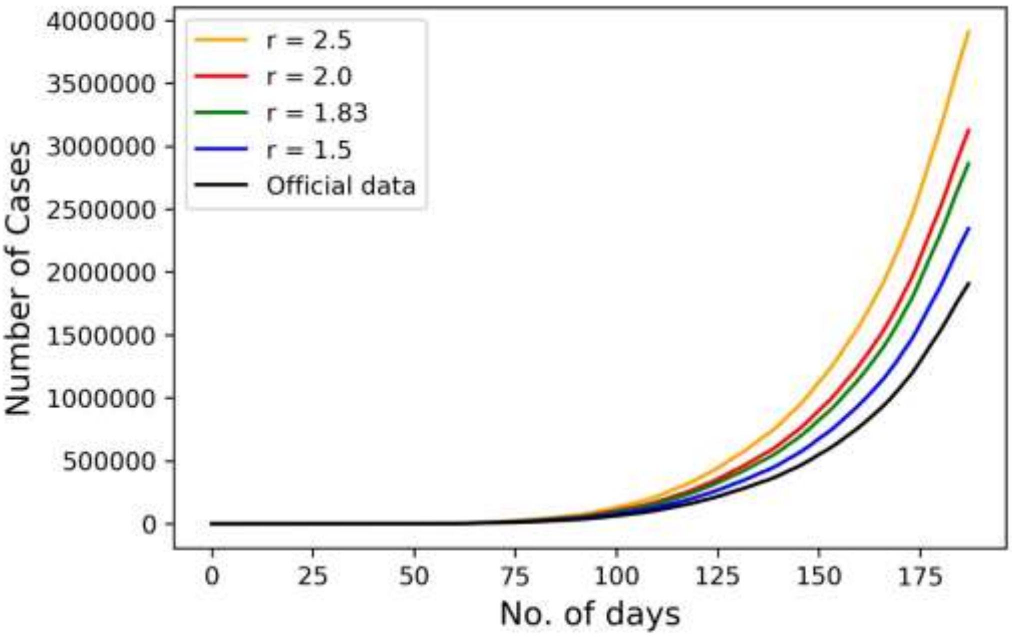


Figure 2: R variations

Thus, it would be fair to conclude that preventive measures, i.e., social isolation and lockdown, have been integral in containing this pandemic. As governments tentatively ease lockdown restrictions around the world, they will be monitoring *R* very carefully for signs of a sudden jump, which can trigger a damaging second wave of the virus. Once *R* is consistently low, and the number of cases is manageable, governments can implement more precise measures to restrict *R*, such as contact-tracing and location-tracking apps approaches that paid dividends when introduced early on in nations such as South Korea and Singapore.

2 Technical Background

Forecasting techniques can be inculcated, thereby assisting the government in designing better strategies and in making effective decisions. These techniques assess the situations of the past, enabling better predictions about the situation to occur in the future. Such predictions will help governments all over the world to prepare for the forthcoming situations. These types of forecasting techniques can play a vital role in yielding nearly accurate predictions.

We provide here a basic introduction to some of these techniques and concepts that were used in the research studies surveyed by us. For further details about different techniques, readers are advised to read research works pertaining to a particular used technique.

2.1 Regression Model

Regression analysis is a form of predictive modeling technique that investigates the relationship between dependent and independent variables. In statistics, linear regression is a linear approach to modeling the relationship between a scalar response (or dependent variable) and one or more explanatory variables (or independent variables).

Given a data set of *n* statistical units, a linear regression model [4] assumes that the relationship between the dependent variable *y* and the *p*-vector of regressors *x* is linear. This relationship is modeled through a disturbance term or error variable - an unobserved random variable that adds "noise" to the linear relationship between the dependent variable and regressors. Thus, the model takes the general form as shown by Eq. 1.

$$y_i = \beta_0 + \beta_1 x_{i1} + \cdots \beta_p x_{ip} + \varepsilon_i = \mathbf{x}_i^\top \boldsymbol{\beta} + \varepsilon_i, \quad i = 1, \ldots, n \qquad (1)$$

where ^{T} denotes the transpose, so that $\mathbf{x}^{>}{}_i\beta$ is the inner product between

vectors x_i and β.

Whereas, polynomial regression is a form of regression analysis in which the relationship between the independent variable *x* and the dependent variable *y* is modeled as an *n*th degree polynomial in *x*. Research work [7] used the polynomial regression for COVIE-19 predictions.

2.2 Auto-Regressive Integrated Moving Average (ARIMA) Model

ARIMA, short for 'Auto-Regressive Integrated Moving Average,' is a family of equations that describe a certain time series dependent upon their prior values, i.e. its own lags and lagged prediction errors, such that the equation can be used to estimate future values. The ARIMA process is also known as the Box-Jenkins method. The Box-Jenkins approach is for a merged ARIMA configuration to be fitted to a particular data set [8].

2.3 A Multilayer Perceptron

A multilayer perceptron (MLP) represents any type of feed-forward neural network composed of multiple hidden layers. MLPs [9] are being increasingly used in complex predicting tasks that can't be solved using traditional machine learning methods. An MLP with a single hidden layer can be graphically represented, as shown in Fig. 3.

A one hidden-layered MLP can be represented in matrix notation by the following equation:

$$f(x) = G \;\; b^{(2)} + W^{(2)} \;\; s \;\; b^{(1)} + W^{(1)}x))) \qquad (2)$$

where $b^{(1)}$,$b^{(2)}$ are bias vectors, $W^{(1)}$,$W^{(2)}$ are weight matrices and *G* and *s* are activation functions. The vector $h(x) = \Phi(x) = s \;\; b^{(1)} + W^{(1)}x)$ constitutes the hidden layer.

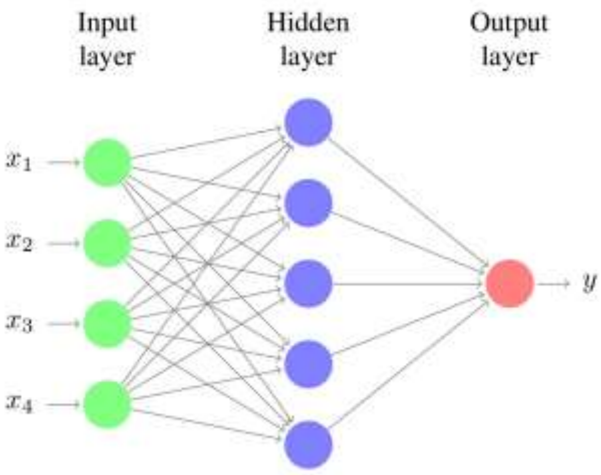


Figure 3: Multilayer perceptron with one hidden layer

2.4 Vector Autoregression

Vector Autoregression (VAR) [16] is a regression technique capturing the relationship of 2 time series which interact with each other. It is employed where the interdependence between the time dispositions included is bi-directional. The general equation for VAR model is:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + \epsilon_t \qquad (3)$$

where α is the intercept, β_1,β_2,...β_p are the coefficients of the lags of Y and $_t$ is the error considered as white noise.

2.5 Susceptible Exposed Infected Recovered (SEIR) Model

The SEIR model is constituted of four major factors which are - Susceptible (S) depicting the individuals which can get the disease, Exposed (E) referring to those people which have been already exposed to the disease, Infected (I) depicting the number of people which have been infected and can infect others and Recovered (R) which refers to those people who have became immune to the disease after contracting it once. Fig. 4 gives a pictorial representation of the SEIR Model [7].

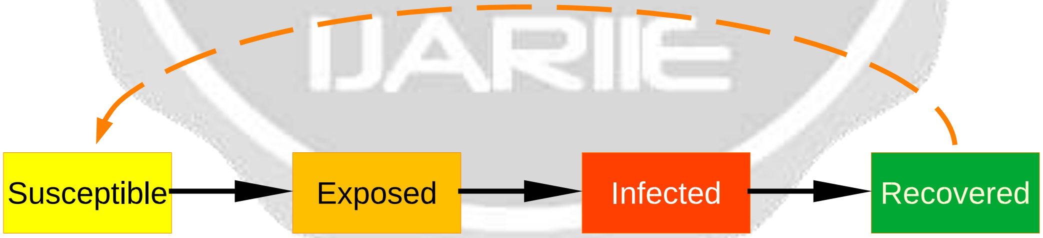


Figure 4: Graphical representation of SEIR model

2.6 Time Series Forecasting using Waikato Environment for Knowledge Analysis (Weka) Software

Time series analysis is the method of analyzing and describing a time-based sequence of data points using statistical techniques. Its forecasting involves the use of a formula to produce future event forecasts based on established events from the past. Time series data have a normal sequential orderdifferent from traditional data mining and computer analysis applications where each data point offers an individual indication of the principle to be studied. Its topics include capacity preparation, inventory refilling, demand projections, and projected staffing ratios [21].

Weka was used to develop the forecasting model [21]. It is a series of data mining machine learning algorithms that can be implemented or named from the own Java code directly into a dataset. It provides resources to pre-process, identify, rectify, cluster, associate rules, and visualize results.

2.7 Recurrent Neural Networks (RNNs)

Recurrent neural networks (RNNs) fall in the domain of deep learning methods where the output from the previous step is fed as input to the current step. In traditional neural networks, its inputs and output data are independent of each other. But for tasks requiring the use of sequential information, we would require the information from previous computations done by the neural network [22].

Thus, RNNs came into existence, which possessed a memory like a feature to remember the information from previously computed calculations. Theoretically, they can make use of this information in randomly long sequences, but in practical cases, they run into the vanishing gradient problem, which inspired researchers to develop Long Short Term Memory Networks.

2.8 Long Short Term Memory Networks (LSTMs)

Long Short Term Memory (LSTM) was developed to deal with the vanishing gradient problem that can be encountered when training traditional RNNs. A common LSTM unit is composed of a cell, an input gate, an output gate and a forget gate. The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. LSTM networks are well-suited to classifying, processing and making predictions based on time series data, since there can be lags of unknown duration between important events in a time series. The equations for the gates in a LSTM [22] are as follows:

$$ft = \sigma g\ (Wfxt + Ufht-1 + bf) \qquad (a)$$

$$it = \sigma g\ (Wixt + ih\ t-1\ bi) \qquad (b)$$

$$ot = \sigma g\ (Woxt + Uoht-1 + bo) \qquad (c)$$

$$c\tilde{}t = \sigma h\ (Wcxt + Ucht-1 + bc) \qquad (d)$$

$$ct = ft \circ ct-1 + it \circ c\tilde{}t\ (e)\ h_t = o_t \circ \sigma_h (c_t) \qquad (f)$$

$$(4)$$

where i_t represents input gate, f_t represents forget gate, o_t represents output gate, h_{t-1} is the output of the previous lstm block (at timestamp t-1), x_t is the input at current timestamp, b_x represents biases for the respective gates (x), w_s refers to the weight for the respective gate (x) neurons and σ represents sigmoid function. Equation 4(a) is for the input gate, which tells us what new information we are going to store in the cell state (that we will see below). The second equation 4(b) is for the forget gate which tells the information to throw away from the cell state. The third one 4(c) is for the output gate which is used to provide the activation to the final output of the LSTM block at timestamp ‘t’. A block of LSTM at any point *t* is shown in Fig. 5.

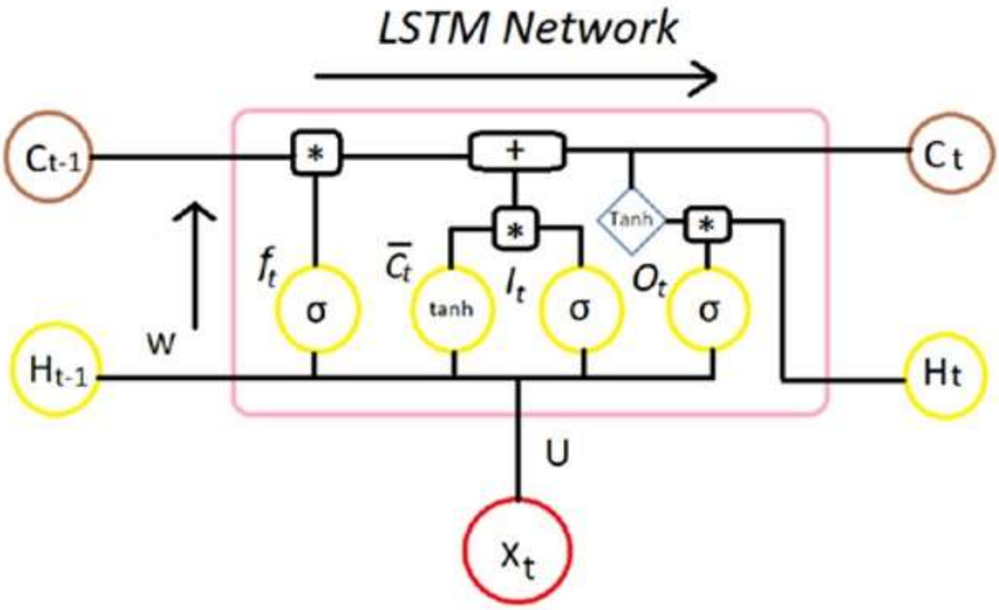


Figure 5: Block of LSTM network at some point of time ‘t’

2.9 Susceptible Infected Recovered (SIR) Model

SIR model is a disease modeling system like SEIR which segregates the whole community into 3 sections - Susceptible, Infected, and Recovered. The definitions of S, I, and R sections are the same as those of the SEIR model. The three categories are interrelated with each other and with parameters according to the following equations [23]: Rate of change of Susceptible Population is given by:

$$\frac{dS}{dt} = -\beta * I * S \tag{5}$$

Rate of change of Infected Population is given by:

$$\frac{dt}{dt} = \beta * I * S - \gamma * I \tag{6}$$

Rate of change of Recovered Population is given by:

$$\frac{dR}{dt} = \gamma * I \tag{7}$$

2.10 Curve Fitting

In this technique, we fit a curve or mathematical function that fits best to a sequence of input data values, conditioned upon some constraints. It can entail the use of interpolation, where an accurate fit to the data is a necessity. Otherwise, a smoothing function is adopted where only an approximate fit to the points is required [24]. Previous research [25] fitted the following polynomial function to their input data with least squares as their loss function:

$$y = -1E-06x^6+0.318x^5-34942x^4+2E+09x^5-7E+13x^2+1E+18x-9E+21 \tag{8}$$

One [26] of the other researchers used an exponential fitting to predict the values. The equation employed is:

$$N(t) = \exp(12.52372 + 0.040t) \tag{9}$$

3 Analysis of Past Forecasting Models

3.1 Methodology Used

The analysis of each study is conducted by comparing their forecasted values for a certain duration with the actual (also called true) number of cases for that duration. This was implemented by extracting values from tables and graphs presented in these research works and then juxtaposing them with the values obtained from the Ministry of Health and Family Welfare website of the Government of India [3]. We have used the Mean Absolute Percentage Error (MAPE) metric for contrasting between predicted and true values. MAPE was chosen because of its scale-independence property, which would remove the size of test data bias from the models. MAPE is a measure of how accurate a forecasting model is and gives its output as a percentage value. It is calculated by normalizing the average error at each point. This is done by dividing the errors by actual values and then averaging their sum using the total size of data using the following mathematical equation:

$$\mathrm{M} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{10}$$

where A_t is the actual value, and F_t is the forecast value.

3.2 Reviewed Past Research Works

For exhaustive research, we considered 10 research studies that focused on forecasting the number of COVID-19 confirmed cases in India. These research works were chosen to analyze a variety of forecasting techniques that are being used. These studies are shown in Table 1 along with some other information such as the models used, the source of the data for respective model, the duration of the forecasting, and the MAPE score the different models achieved. We also found that there were some typos in the data that was published in such research works and we cleaned that data before use in the current research.

4 Results

In this section, we demonstrate how well these models fared against the actual number of cases in India. Two different plots show this information for each study. The first plot represents both the predicted and true curve against the predicted number of days, while the second plot represents the relationship between the forecasted and actual data. Ideally, the second plot should tend to achieve linearity.

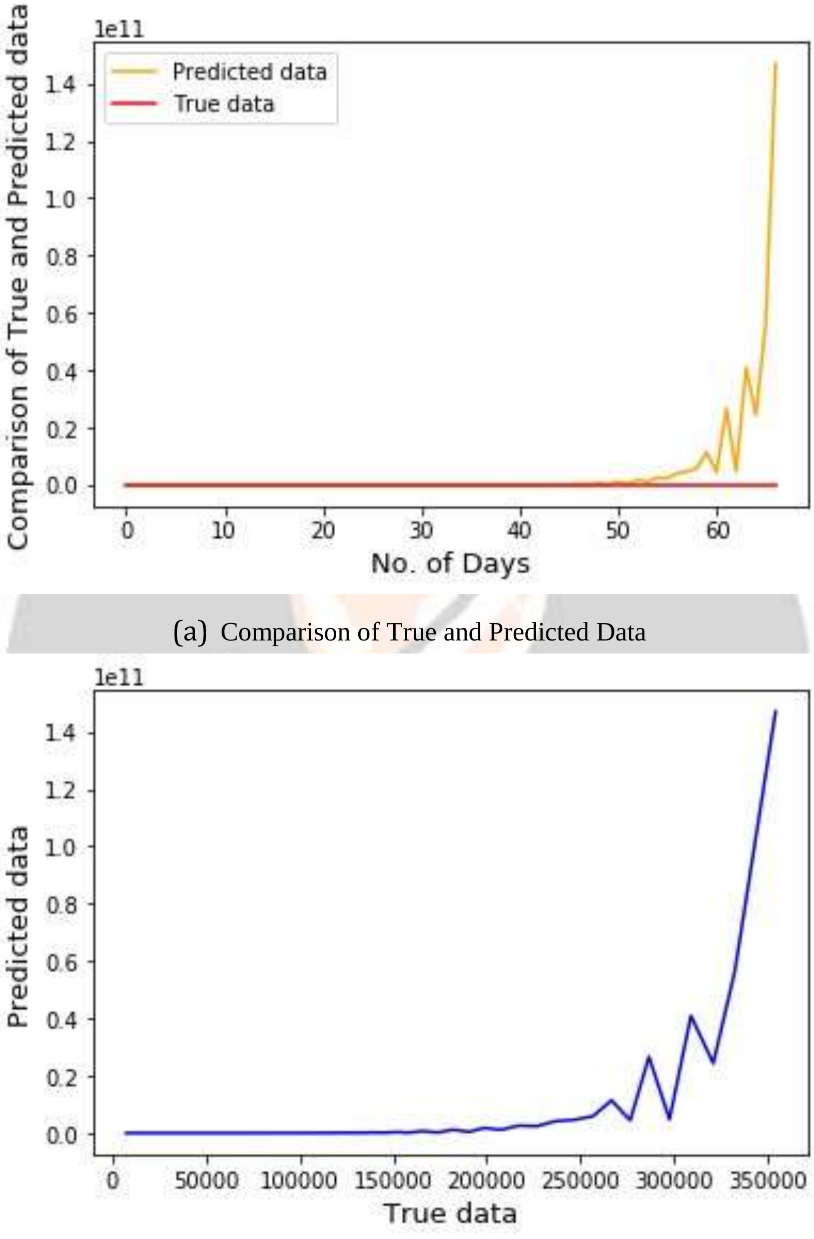
Fig. 6 represents the results of Linear Regression technique proposed by the researchers of [9].There was an outlier value which was causing the graph to plunge towards 0 at the end. The Fig. 6 is drawn after discarding that outlier. This research used the official number of cases from January 22, 2020 , to April 10, 2020, as their input data and predicted values for a duration of 69 days starting from April 11, 2020, to June 18, 2020. This model scores low on our metric with a MAPE score of 1745454.432. The error for some points reaches up to the magnitude of 10^{11}. It means that this research was very far off from the true value of confirmed cases that took place.

Fig. 7 represents the results of the ARIMA model used by the researchers [8]. This research predicted the number of cases for a duration of 50 days starting from March 5, 2020, to April 23, 2020, using the data from January 31, 2020, to March 4, 2020. This model performs moderately with a MAPE score of 66.819.

Fig. 8 represents the results of Multilayer Perceptron model proposed by the researchers [9]. The duration of both the training and testing data are the same as that of the Linear Regression model. This model performed much better than the LR technique with a MAPE of 80.057.

Fig. 9 shows the results of Vector Autoregression technique proposed by the researchers [9] on the same input data as the previous two techniques. Again, there was an outlier value which was causing the graph to go below the x-axis. The fig. 9 is drawn after discarding that outlier. This model again gives a poor performance with MAPE of 43289.29.

Fig. 10 displays the results of time series forecasting conducted by the researchers [21]. Researchers used the official number of cases from January 22, 2020, to April 3, 2020, to train their model. The predicted duration was of 24 days starting from April 4, 2020, to April 27, 2020. This study scores a MAPE score of 55.48984343.

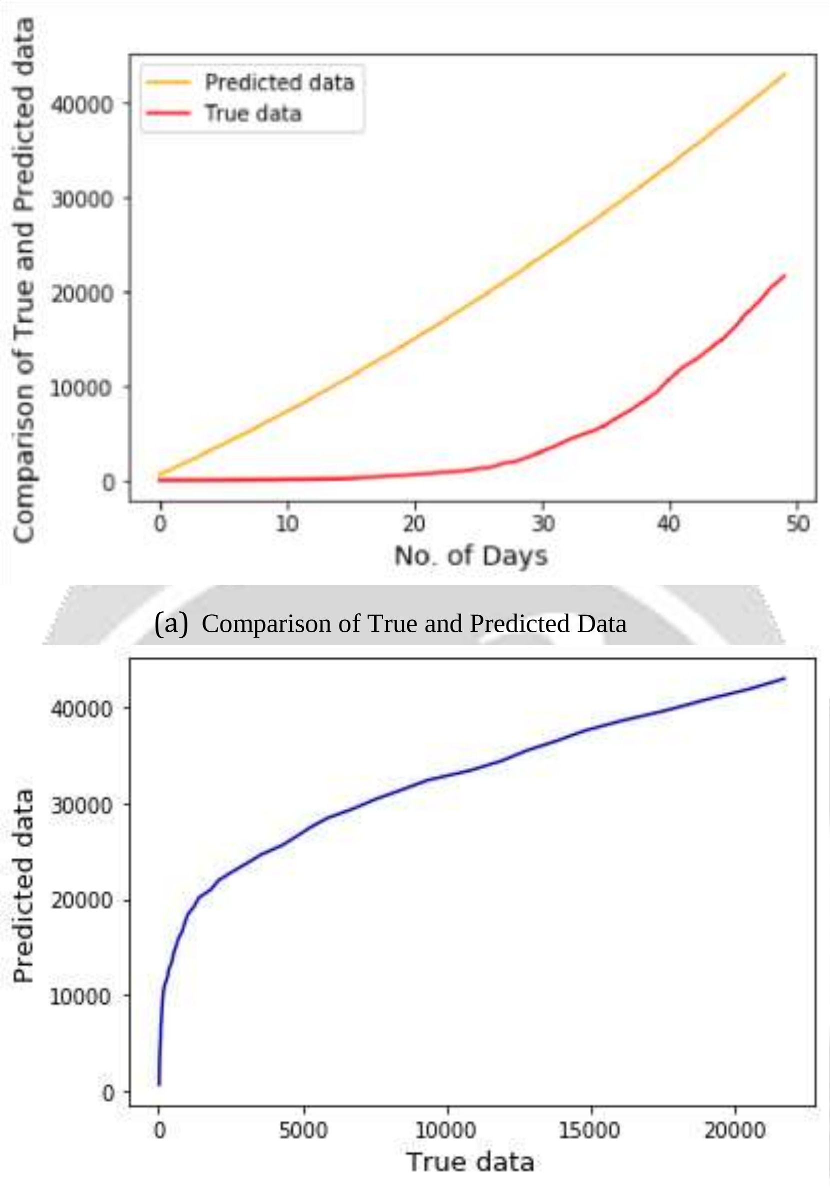


(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 6: Confirmed COVID-19 cases comparison derived from research [9]

Fig. 11 represents the results of the LSTM model used by the researchers [22] to predict for a duration of 25 days from April 5, 2020 to April 29, 2020. The researchers took the data starting from January 30, 2020, to April 4 , 2020, for their model. This study scored well on MAPE metric with a value of 63.357.

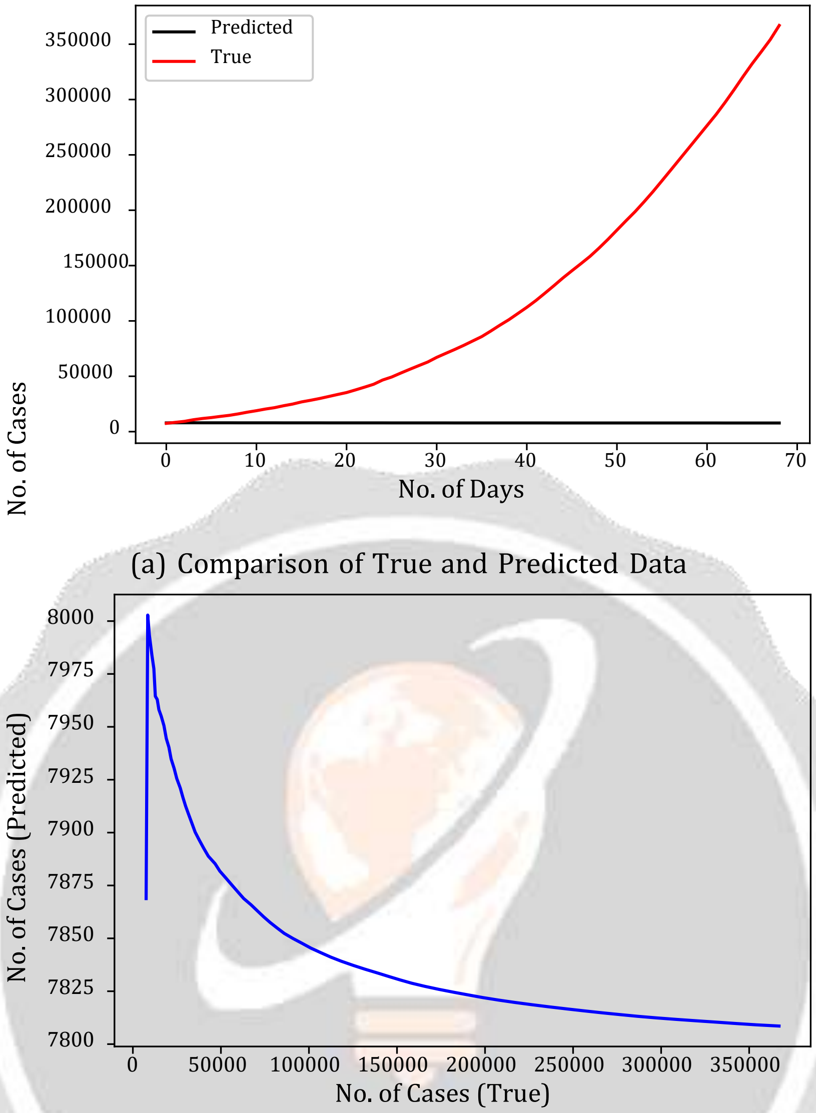


(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 7: Confirmed COVID-19 cases comparison derived from research [8]

Fig. 12 represents the results of GEP model proposed by the researchers [27]. The said research predicted the number of infected cases from May 14 , 2020, to May 23, 2020, for 10 days. Input for that research model was the number of official cases from March 24, 2020, to May 13, 2020. This model got an excellent MAPE score of 7.827.

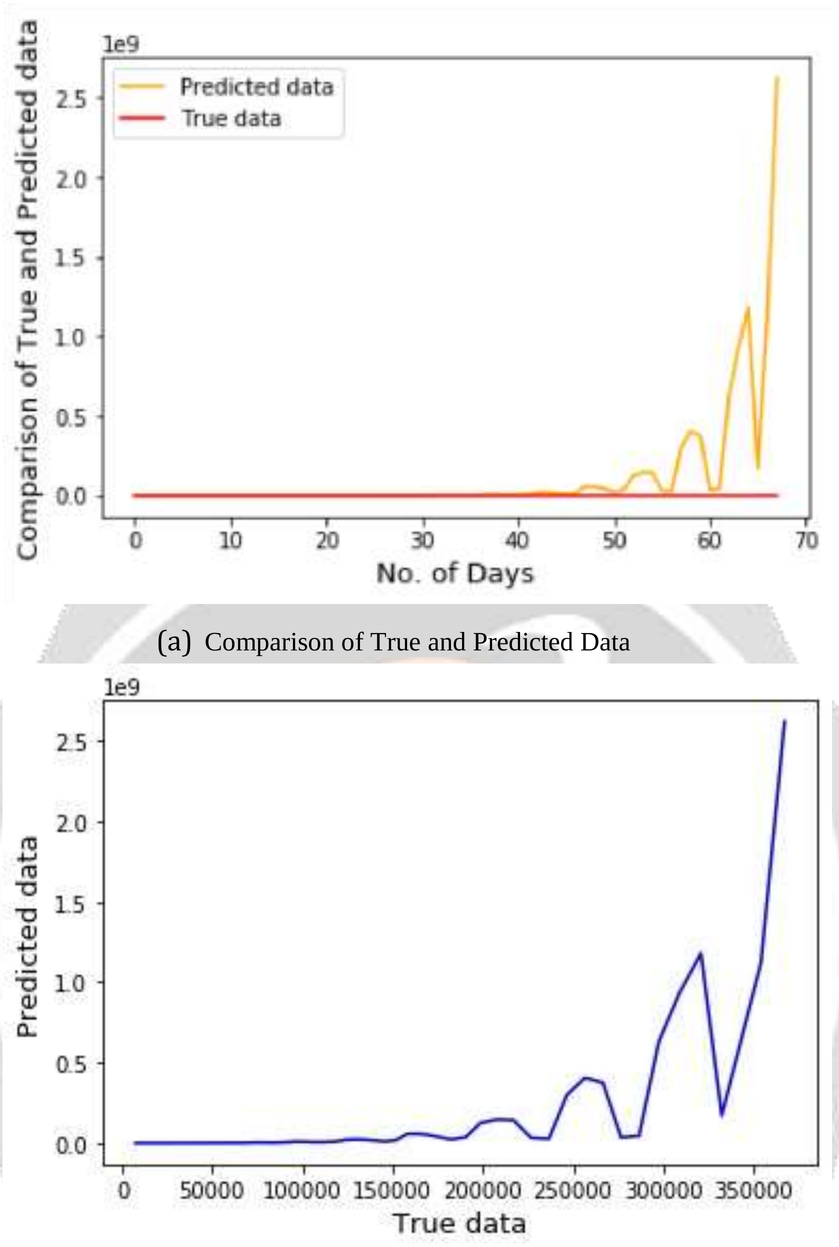


(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 8: Confirmed COVID-19 cases comparison derived from research [9]

Fig. 13 demonstrates the results of the Linear Regression technique proposed by the researchers [7] and the research used the official number of cases from February 11, 2020, to May 11, 2020, as the input data to train the model. The predicted duration was of 33 days, starting from May 12 , 2020, to June 30, 2020. This model scores relatively low on our metric with a score of 662.441.



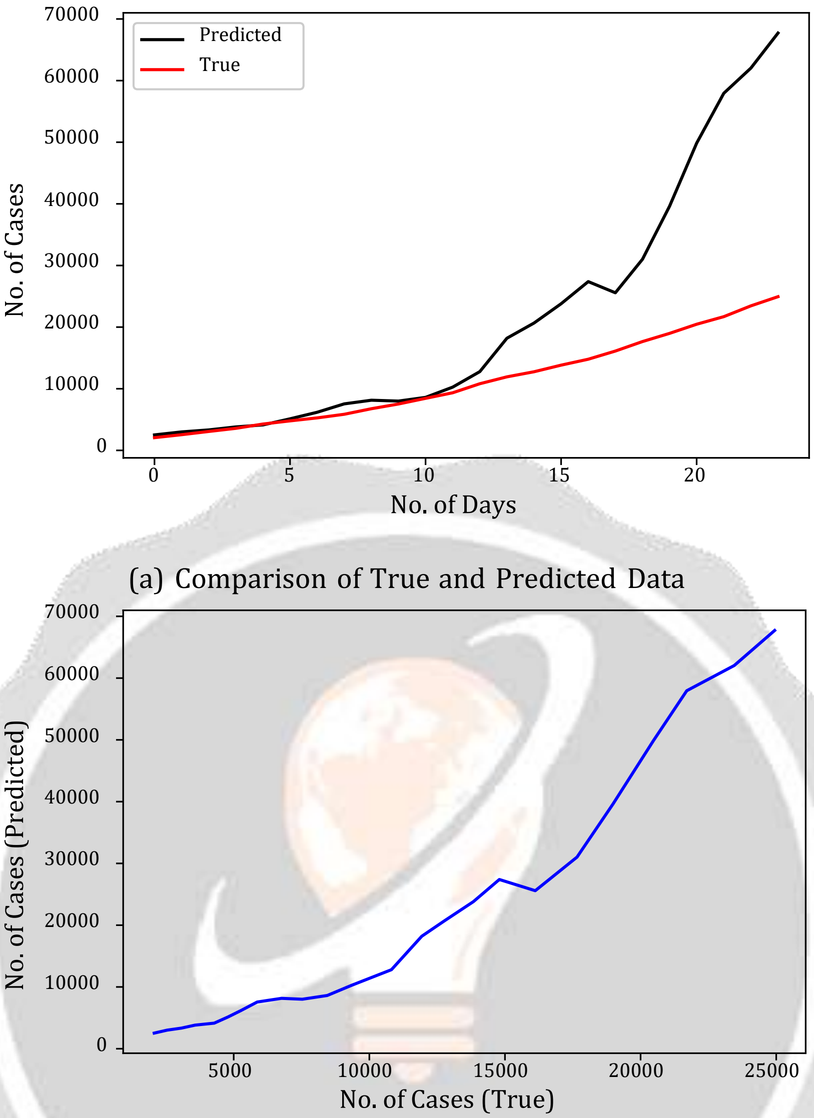
(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 9: Confirmed COVID-19 cases comparison derived from research [9]

Fig. 14 displays the results of the exponential model used by the researchers [28]. The size of both training and test data remains analogous to the linear regression technique. This model gives the MAPE metric result of 2096.000.

Fig. 15 demonstrates the results of SEIR model proposed by the researchers [7] who used the official number of cases from January 30, 2020 to March 30, 2020 as input data to train the model. The predicted duration was of 20 days staring from March 31, 2020 to April 13, 2020. This model scores good on the MAPE metric with a score of 25.533.

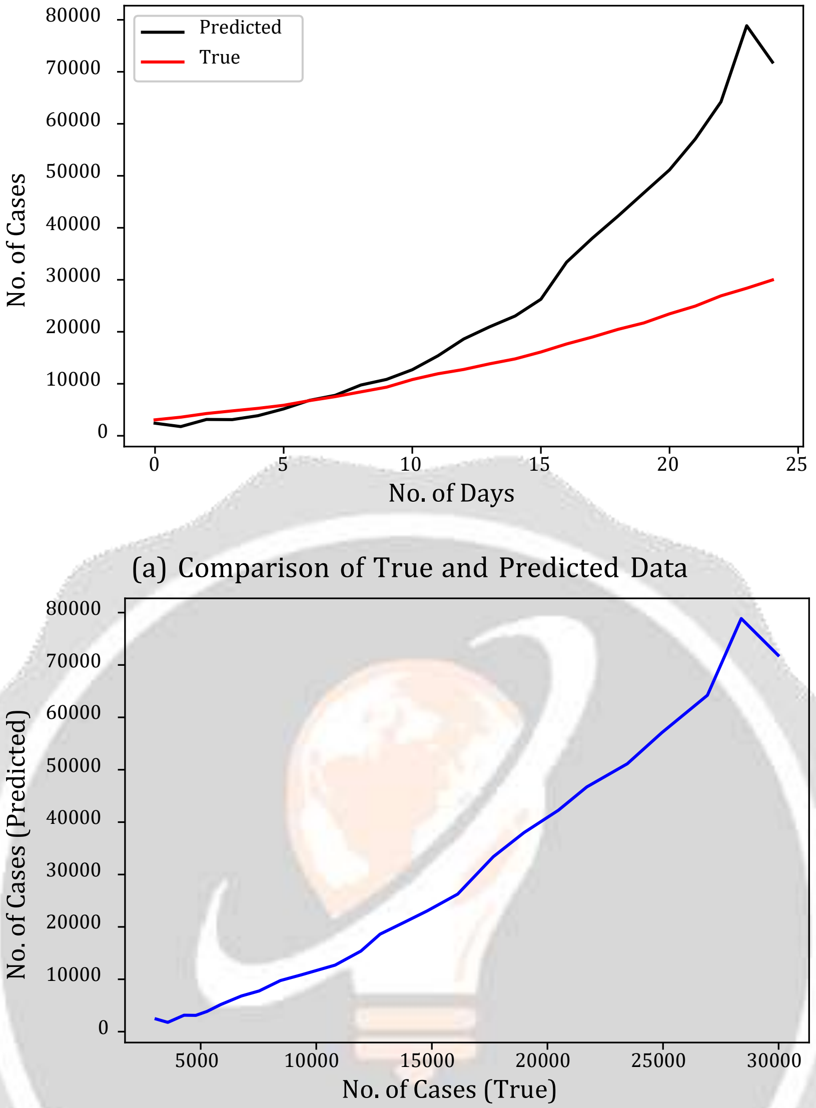


(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 10: Confirmed COVID-19 cases comparison derived from research [21]

Fig. 16 represents the results of Regression model proposed by the researchers [7]. The duration of both the training and testing data are the same as that of the SEIR model. Also, this model performed better than the SEIR technique with a MAPE of 21.889.

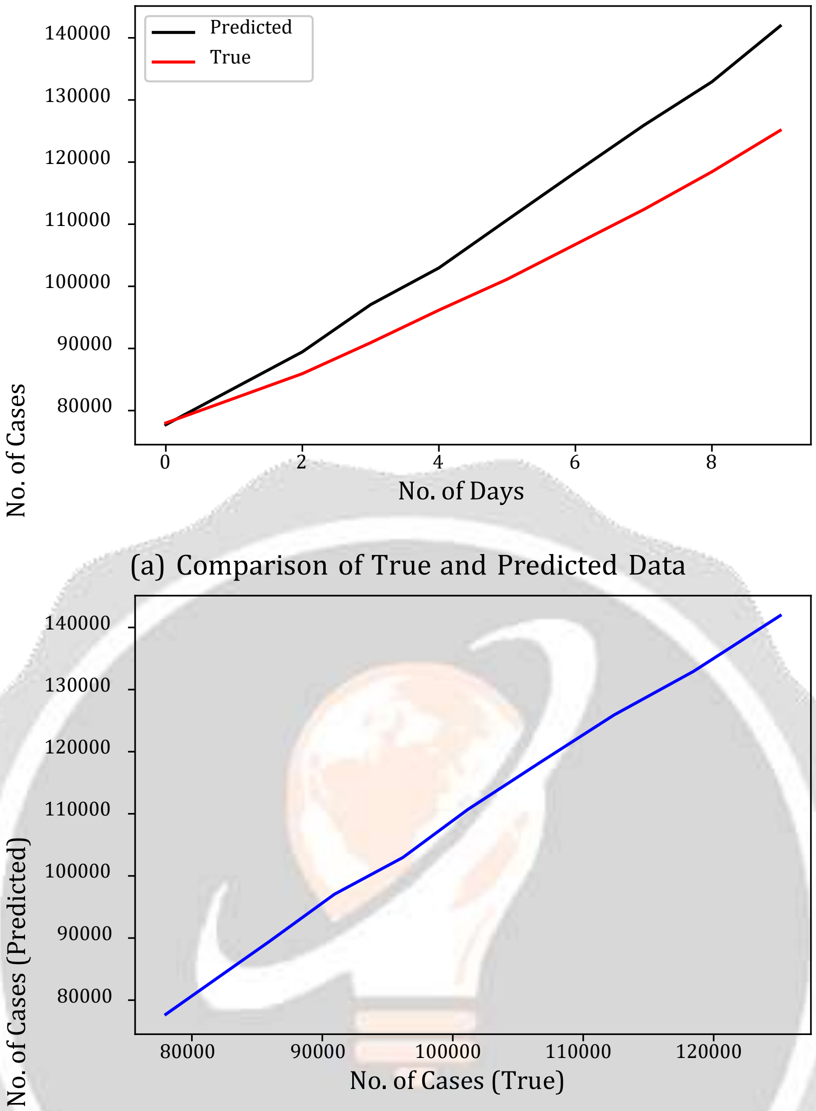


(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 11: Confirmed COVID-19 cases comparison derived from research [22]

Figure 17 represents the results of the SIR model used by the researchers [23] and predicted the number of cases for a duration of 36 days starting from March 23, 2020, to April 27, 2020, using the data from March 3, 2020 , to March 22, 2020. This model scores a modicum MAPE score of 66.819.

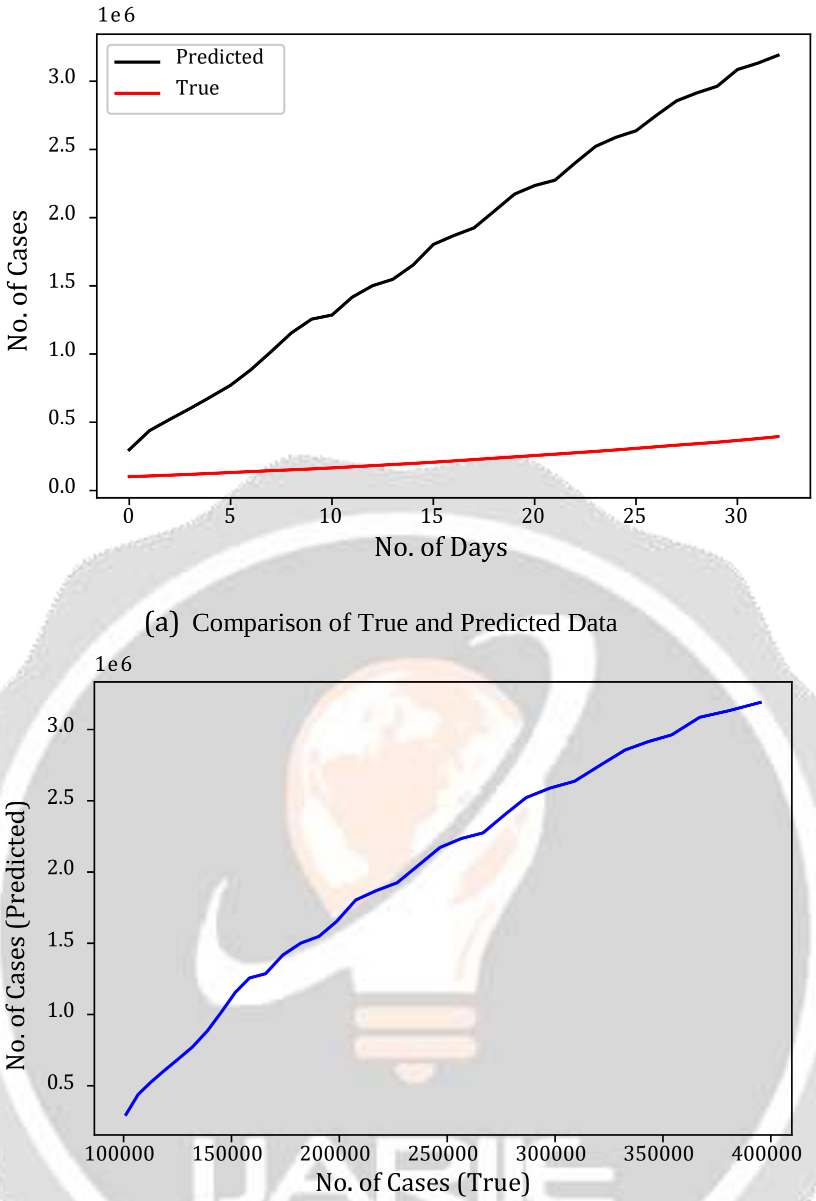


(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 12: Confirmed COVID-19 cases comparison derived from research [27]

Fig. 18 represents the results of Least Square Fitted model proposed by the researchers [25] and this research used the official number of cases from January 30, 2020 to April 26, 2020 as the input data to train the model. The (LR) [28] predicted duration was of 35 days starting from April 27, 2020 to May 31 , 2020. This model gives a MAPE score of 39.816.

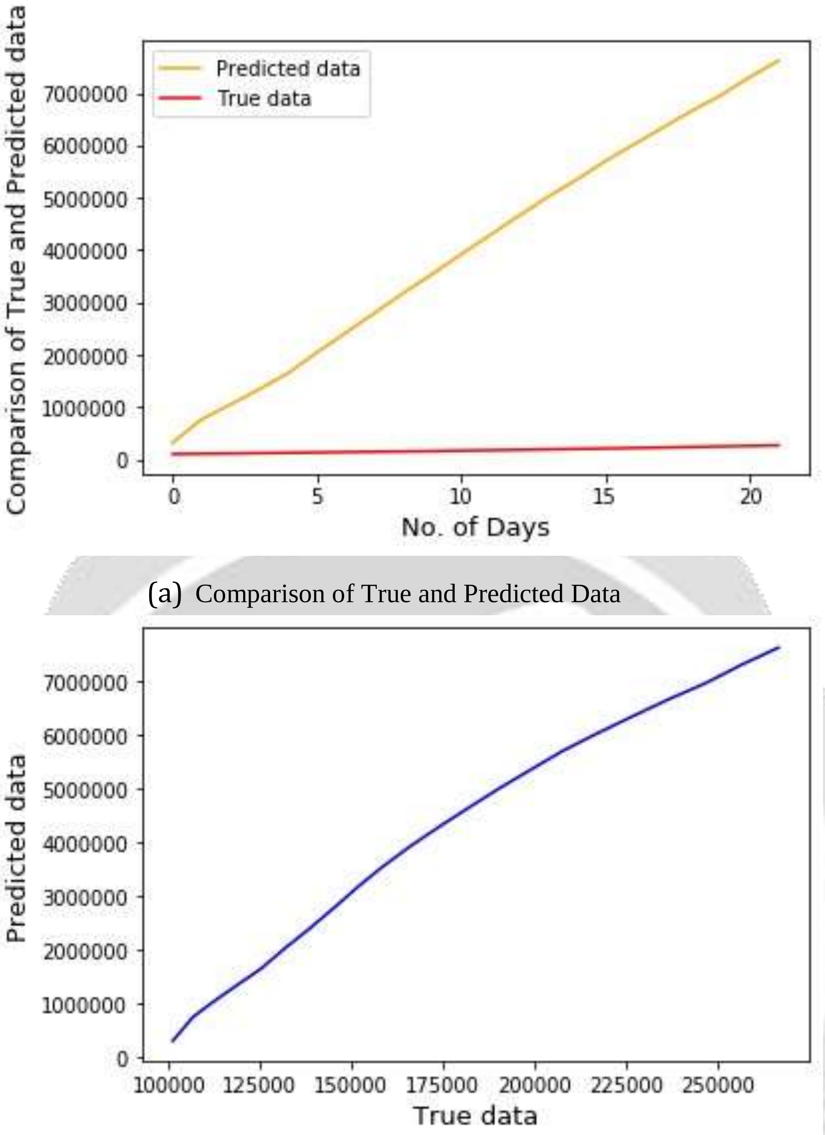


(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 13: Confirmed COVID-19 cases comparison derived from research

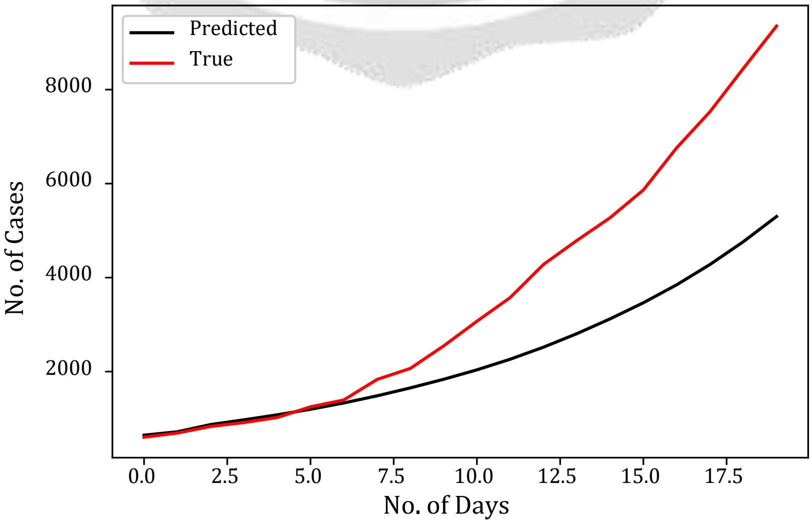
Figure 19 represents the results of Linear Regression technique proposed (exponential model) [28] by the researchers [26] who used the official number of cases from June 1 , 2020, to June 10, 2020, as the input data to train the model. The predicted duration was of 15 days starting from June 10, 2020, to June 24, 2020. This model scores best on the MAPE metric with a score of 6.4807. While the models did not perform well, we investigated further to unearth the causes of a widespread outbreak.

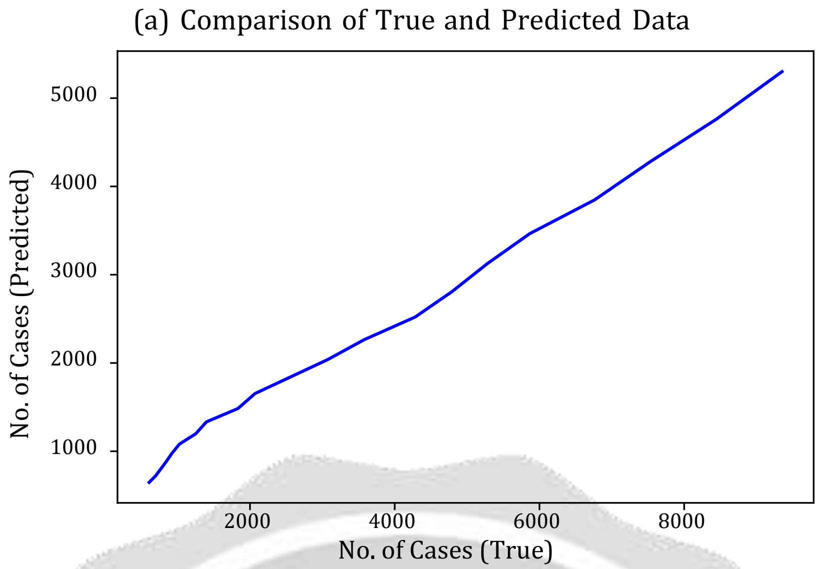


(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

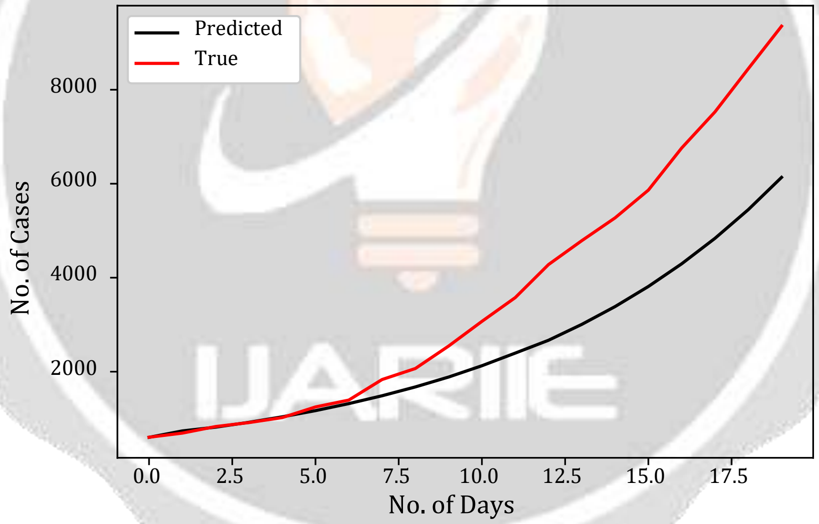
Figure 14: Confirmed COVID-19 cases comparison derived from research

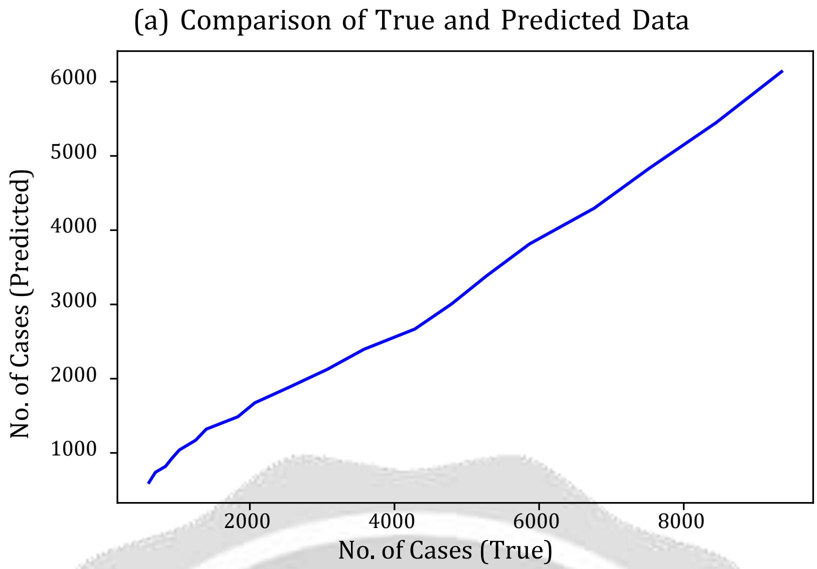




(b) Forecasted vs True data

Figure 15: Confirmed COVID-19 cases comparison derived from research (SEIR model) [7]



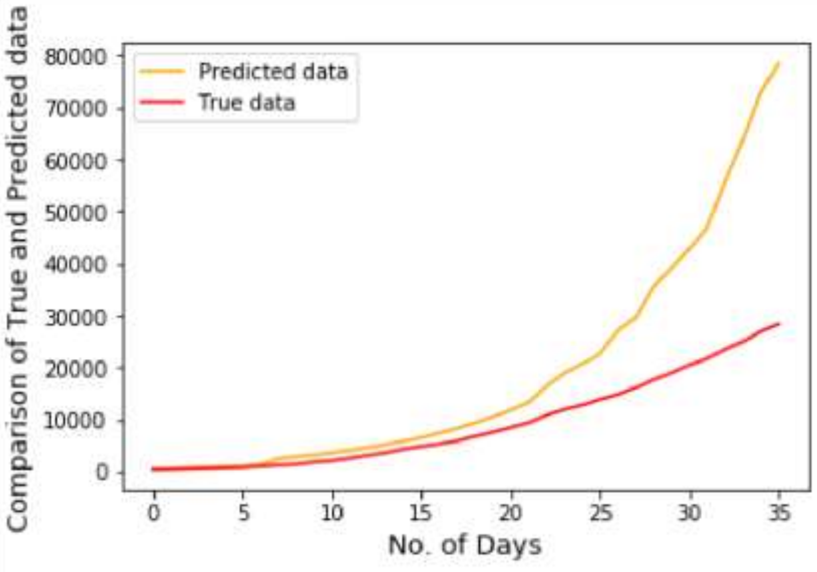


(b) Forecasted vs True data

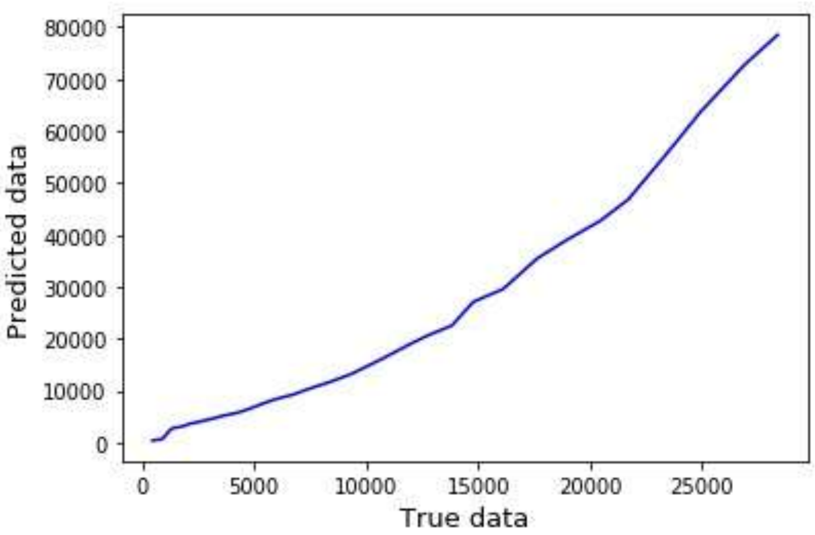
Figure 16: Confirmed COVID-19 cases comparison derived from research (regression model) [7]

4.1 Two key events that led to a big increase in the number of cases

Two significant events recorded in India during the lockdown period led to a surge in coronaviruscases. One linked to the workers' migration to their states in India [12] and another to religious activities at a mass level in New Delhi [13]. It is estimated that about 11 Million workers returned to their homes in various states [14]. The agriculture sector employs about 42% of the workforce but produces just 18% of the GDP. Therefore, there are massive inefficiencies.

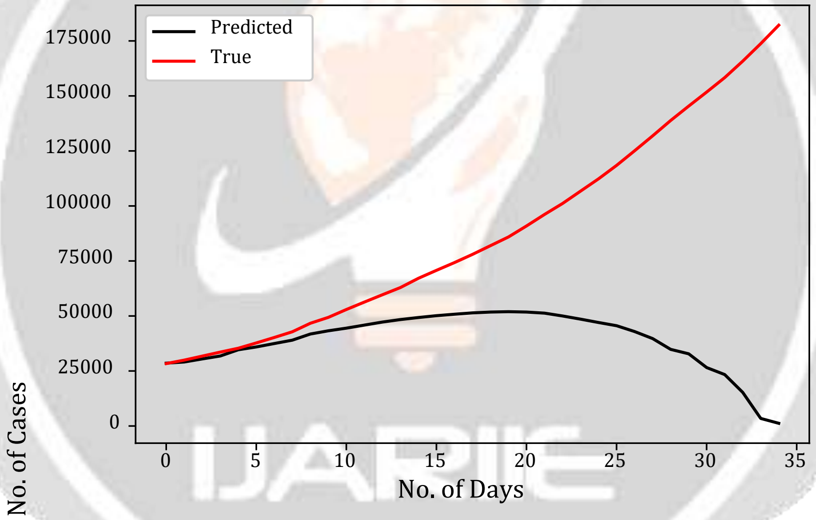


(a) Comparison of True and Predicted Data

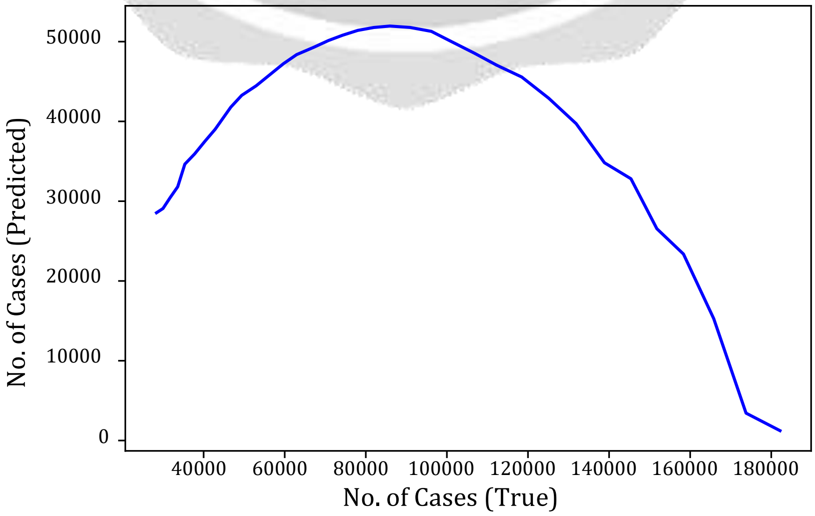


(b) Forecasted vs True data

Figure 17: Confirmed COVID-19 cases comparison derived from research (SIR model) [23]



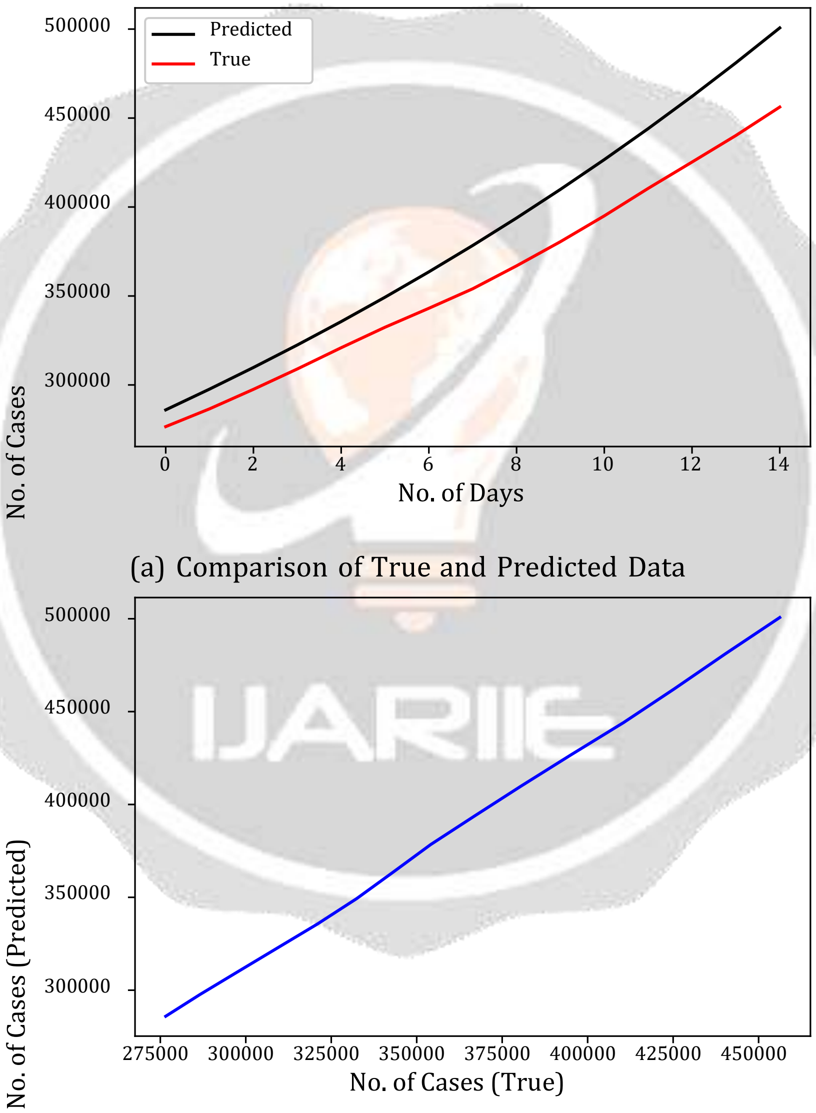
(a) Comparison of True and Predicted Data



(b) Forecasted vs True data

Figure 18: Confirmed COVID-19 cases comparison derived from research [25]

The agricultural sector doesn't have a buffer to absorb an additional workforce. Around 25% of people live below the poverty line and must depend on everyday income in order to feed their families. The fate of these 1.3 billion people was revealed after the lockdown was declared, so even India's government put together a plan amounting to more than $22 billion to assist these workers. Many reports have indicated that India and adjacent Indian countries may be short of food [15] in terms of food security, while others have recorded a loss of millions of jobs during the lockdown of the country due to this massive migration. However, this massive mobilization had no effect on the number of infectious patients since most of the workers had little illness after the move from employers to their homes.



(a) Comparison of True and Predicted Data

(b) Forecasted vs True data

Figure 19: Confirmed COVID-19 cases comparison derived from research [26]

The religious event held in Delhi resulted in the creation of clusters across the world as individuals who participated in this event toured numerous parts of the world without any quarantine laws. Some also came from

India to participate in the case, and they did not obey rules concerning the security of COVID-19. After March 31, 2020, the number of untreated cases rose significantly.

5 Conclusion

This research work considered data related to daily confirmed cases of COVID19 in India during lockdowns on the national level. From the results shown in the previous section, we observe that even after using a size-independent metric, models which predicted for lesser durations (less than 20 days) [27], [26] scored best on our MAPE metric. Overall, the exponential curve fitting [26] on recent data produced the lowest value score of 6.4807. But its use should be limited to only short-term forecasting as predicting values for a longer duration will lead to the fitted curve moving away from the true values.

Discarding these outlier models which conducted forecasting for smaller durations, we conclude that the least square fitted model [25] outperforms all the other techniques and, thus, should be used for future purposes of predicting the infection rate under similar conditions. Also, disease modeling systems such as SEIR and SIR [7], [23] fared much better than other regression models, and we believe that if applied with more precision, they can achieve good results.

While we compared the prediction performance among selected models, we could not recommend one particular model over another, for two reasons. First, in most cases, the models were mostly far from accurate. Second, in addition to the algorithm used for prediction, assumptions of the algorithms and baseline conditions should also be considered. This is particularly important when such risk prediction is to be used to revise health policies and recommend practices for the public, such as lockdown, safety distance, and reopening. National lockdowns, for example, are often associated with substantial economic and societal costs. According to the International Monetary Fund [6], many countries have spent roughly 20 percent of their GDP to support emergency responses during the COVID-19 pandemic. As the daily infection rate of the coronavirus continues to increase in many countries such as India, Brazil, and the US, it is likely due to a combination of factors, such as delayed public response and inaccurate projections. Findings from this study can inform future development of risk prediction models of infectious disease, mainly by considering both virus-intrinsic characteristics and external variables, such as mass testing, social distancing, and decision on lockdown or reopening of institutions.

References

[1] https://covid19.who.int accessed on July 31, 2020

[2] https://www.who.int/emergencies/diseases/ novel-coronavirus-2019/question-and-answers-hub/q-a-detail/ q-a-coronaviruses accessed on July 31, 2020

[3] Ministry of Health and Family Welfare,, https://www.mohfw.gov.in accessed on July 31, 2020

[4] Montgomery, Douglas C., Elizabeth A. Peck, and G. Geoffrey Vining. “Introduction to linear regression analysis,” Vol. 821. John Wiley & Sons, 2012.

[5] https://www.washingtonpost.com/politics/2020/08/05/ health-202-why-individual-models-coronavirus-deaths-are-often-wrong/ accessed on August 8, 2020

[6] https://www.bbc.com/news/business-52450958 accessed August 8 , 2020

[7] Gaurav Pandey, Poonam Chaudhary, Rajan Gupta, Saibal Pal, “SEIR and Regression Model based COVID-19 outbreak predictions in India”, doi: 10.1101/2020.04.01.20049825

[8] Farhan Mohammad Khan, Rajiv Gupta, “ARIMA and NAR based prediction model for time series analysis of COVID-19 cases in India,” Journal of Safety Science and Resilience, Volume 1, Issue 1, Pages 12-18, 2020

[9] R. Sujath, Jyotir Moy Chatterjee & Aboul Ella Hassanien, “A machine learning forecasting model for COVID-19 pandemic in India” *Stochastic Environmental Research and Risk Assessment*, volume 34, pages 959–972(2020), doi: 10.1007/s00477-020-01827-8

[10] Dwarakanath, N. (2020). First coronavirus death in India: 76yearold who died in Karnataka had Covid-19, says state govt. (2020). https://www.indiatoday.in/ india/story/first-coronavirus-death-in-indiakarnatak a-man-1654953-2020-03-12.

[11] M. David, Lokeshkumar P. and Suraj S. Dabire, “COVID-19 (CORONAVIRUS): A GLOBAL EMERGENCY OUTBREAK AND ITS IMPLICATIONS IN INDIA,” International Journal of Zoology and Applied Biosciences, Volume 5, Issue 2, pp: 89-98, 2020

[12] [3]. AlJazeera (2020). India: Coronavirus lockdown sees exodus from cities, Aljazzera News Channel. Accessed from https://www.aljazeera.com/programmes/newsfeed/2020/04/indiacoronavirus-lockdown-sees-exodus-cities-200406104405477.html on April 6 2020

[13] Coronavirus: Search for hundreds of people after Delhi prayer meeting, BBC News. Accessed from https://www.bbc.com/news/world-asia-india52104753on April 2 2020

[14] The impact of COVID-19 and the policy response in India from https://www.brookings.edu/blog/future-development/2020/07/13/theimpact-of-covid-19-and-the-policy-response-in-india/ on September 25 , 2020

[15] Biswas, S. (2020). Will coronavirus lockdown cause food shortages in India? BBC News. Accessed from https://www.bbc.com/news/world-asiaindia-52176564 on April 7 2020

[16] https://www.machinelearningplus.com/time-series/ vector-autoregression-examples-python/

[17] https://www.who.int/docs/default-source/coronaviruse/who-chinajoint-mission-on-covid-19-final-report.pdf

[18] Steven Sanche, Yen Ting Lin, Chonggang Xu, Ethan RomeroSeverson, Nick Hengartner, Ruian Ke, “The Novel Coronavirus, 2019-nCoV, is Highly Contagious and More Infectious Than Initially Estimated”, medRxiv 2020.02.07.20021154, doi: https://doi.org/10.1101/2020.02.07.20021154

[19] https://theprint.in/india/r0-at-1-27-but-experts-say-india-yet-to-hitcovid-peak-lockdown-alone-cant-end-pandemic/416595/

[20] Dhama K, Sharun K, Tiwari R, Sircar S, Bhat S, Malik YS, Singh KP, Chaicumpa W, Bonilla-Aldana DK, Rodriguez-Morales AJ., “Coronavirus

Disease 2019 – COVID-19,” Clin Microbiol Rev 2020 Oct; 33(4):e00028-20

[21] Sunita Tiwari, Sushil Kumar, Kalpna Guleria, “Outbreak trends of CoronaVirus (COVID-19) in India: A Prediction” Disaster Med Public Health Prep. 2020 Apr 22: 1–6., doi: 10.1017 /dmp. 2020.115

[22] Anuradha Tomar, Neeraj Gupta. “Prediction for the spread of COVID-19 in India and effectiveness of preventive measures” Science of The Total Environment Volume 728, 1 August 2020, 138762, doi:

10.1016 /j.scitotenv. 2020.138762

[23] Jay Naresh Dhanwant, V. Ramanathan, “Forecasting COVID 19 growth in India using Susceptible-Infected-Recovered (S.I.R) model”, arXiv:2004.00696 [q-bio.PE]

[24] Arlinghaus, Sandra. Practical handbook of curve fitting. CRC press, 1994.

[25] Mr. Sudip Ghosh, “An Overview: Situation Assessment and Prediction of Corona Virus in India” Mukt Shabd Journal Volume IX Issue V, MAY/2020 Issn No: 2347-3150

[26] Hemanta Kumar Baruah, “Nearly Perfect Forecasting of the Total COVID-19 Cases in India: A Numerical Approach”, doi:

10.1101/2020.06.13.20130096

[27] Rohit Salgotra, Mostafa Gandomi, Amir H Gandomi, “Time Series Analysis and Forecast of the COVID-19 Pandemic in India using Genetic Programming” Chaos, Solitons & Fractals Volume 138, September 2020 , 109945, doi: 10.1016 /j.chaos. 2020.109945

[28] Ajit Kumar Pasayat, Satya Narayan Pati, Aashirbad Maharana, “Predicting the COVID-19 positive cases in India with concern to Lockdown by using Mathematical and Machine Learning based Models” doi: 10.1101/2020.05.16.20104133

[29] Shinde, G.R., Kalamkar, A.B., Mahalle, P.N. et al. Forecasting Models for Coronavirus Disease (COVID-19): A Survey of the State-of-the-Art. SN COMPUT. SCI. 1, 197 (2020). https://doi.org/10.1007/s42979-02000209-9

[30] https://www.kaggle.com/imdevskp/corona-virus-report/data

[31] https://coronavirus.jhu.edu/

WHO. Situation report–1. Novel coronavirus (2019-nCoV). https://www.who.int/emergencies/diseases/novel-coronavirus-2019/ situation-reports

[32] Kaggle. Novel corona virus 2019 dataset, https://www.kaggle.com/ sudalairajkumar/novel-corona-virus-2019-dataset

[33] https://www.mygov.in/covid-19/?cbps=1

[34] https://www.worldometers.info/ accessed on July 31, 2020

[35] https://www.who.int accessed on July 31, 2020

[36] https://data.mendeley.com/datasets/tmrs92j7pv/1

[37] http://covid19india.org/ accessed on July 31, 2020

Table 1: Reviewed Research Works

S. No.	Reference	Forecasting Techniques	Duration of Forecasting	Data Source	MAPE Score
1	[7]	SEIR and Regression models	20 Days	JHU[31]	SEIR:25.533, Regression:21.889
2	[8]	ARIMA and NAR	50 Days	[3] and [38]	ARIMA:362.1761
3	[9]	LR, MLP and VAR	69 Days	Kaggle [30]	LR:1745454.432, MLP:80.057, VAR:43289.290
4	[21]	Time Series Forecasting using Weka	24 Days	Kaggle [33]	55.489
5	[22]	LSTM	25 Days	Govt. Of India [34]	63.357
6	[27]	Genetic programming based model (GP) [GEP model]	10 Days	Mendley Time series datasets [37]	7.827
7	[28]	Exponential Growth Model and ML based LR model	33 Days	Humanitarian website for COVID data	LR:662.441, Exponential:2096.000
8	[26]	Short term forecasting using	15 Days	[35]	6.4807