



COVID-19 Global Prediction: A Mathematical Approach based on Data Trend Lines and Probability

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Abstract

To better understand data and its possible consequences, mathematical models are the must. For COVID-19 outbreak, it helps predict and therefore, policies are guidelines can be designed accordingly. In this study, we define the practical prediction model for COVID 19 by considering the different essentials such as the total number of cases, recovery cases and death cases. The special grading for countries involves the government policies as well as the involvement of the society intended for controlling COVID 19. We investigate trend lines for the data with the help of correlation coefficients and coefficient of determination. The linear and the second-degree equations help to make predictions of active patients of COVID 19 in the future.

The study of existing data patterns is done and is used to predict the spread of COVID in the world. This analysis assists us to decide the futuristic guidelines, requirements, and policies for governing the spread of COVID 19.

Keywords : COVID-19; Correlation coefficient; Grading; Prediction; Data Patterns;

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1. Introduction

Coronavirus disease (COVID-19) is a pandemic that is currently being witnessed by six continents namely Africa, America, Eastern Mediterranean, Europe, Southeast Asia, and Western Pacific making the total infected sum

of countries, areas or territories with cases to 217. Globally 5 451 532 cases are registered. The death count has reached 345 752. COVID-19's first outbreak was observed in Wuhan, China. After a short period of time, this epidemic turned into the pandemic. This pandemic is now turning into an endemic situation. In March



2020, the World Health Organization (WHO) declared COVID-19 as a pandemic first of its kind since the last swine flu pandemic. The common symptoms of COVID-19 are dry cough and fever. The incubation period of COVID-19 is 2- 14 days. Once detected COVID-19 positive, they are advised to go for quarantine.

With WHO, Countries around the world have put in place a range of public health and social measures to suppress or stop community spread of COVID-19. Of all measures, social distancing has been widely practicing across the world [1, 2]. However, we have not observed the COVID-19 spreading rate slowing down.

In mathematical epidemiology is domain, there has been commendable work done in the field. Since, successes of malaria modeling really attract all possible attention, it is common to use mathematical modeling to predict infectious diseases. The reason behind this attention is that these models can provide useful insights, such as prediction of patterns, prediction for the number of infected patients, and fatality rate. As COVID-19 spreading rate is found to be exponential, its data collection needs to be done in a timely and efficient manner as well. The collected data is used for modelling purpose. But however, there are challenges or uncertainties, such as incomplete data, noisy data, and various forms of data, etc. These challenges still pose a great deal of obstacle in a way. Therefore, discrete and/or stochastic models may not predict close-to-actual values. The model that has been widely popular is SEIR/SIR (Susceptible-Exposed-Infectious-Removed)/(Suspected-Infected-Recovered) model [3, 4]. Along with this model, one revolutionary model is also gaining attention called as SEIARD model: susceptible ($S(t)$), exposed ($E(t)$), infected ($I(t)$), asymptomatic ($A(t)$), recovered ($R(t)$) and dead ($D(t)$). All these models use the patient count (those who are infected, recovered and deceased) to predict the growth of the disease [5]. Instead, mathematical models that are typically data-driven could potentially be a better choice(s).

This remainder of the paper is structured as follows. The second section consists of previous

works that are related to COVID-19 prediction models. Third, the section deals with the evaluation of the proposed work. The fourth section represents the proposed prediction model for COVID-19. A novel mathematical formulation for the grading of each country is modelled by dividing periods into subintervals and it also finds the trend lines for the same. The net increase in the cases of COVID -19 is also predicted in this paper. It is mapping of administrator policies and their strict obedience by the population. If the administrator policies and the all the necessary hygiene instructions are followed by the people then the number of infected people can decrease. Also daily recovery rate from the period from 22 January 2020 to 30 April 2020 is studied. Depending on these factors the extensive prediction model is designed. Fifth and sixth sections of the paper deal with the results and discussion of the model, respectively.

2. Related Works

In the literature, various works have been going on about the prediction of the infection rate of COVID-19. These studies are done on various datasets that are retrieved from WHO, national datasets, newspapers and online social media. The predictions are done based on various models i.e. mathematical models that include stochastic theory, probability theory and differential equations and predictions are also done based on machine learning techniques. Cherniha and Davydovych [6] proposed a mathematical model for COVID-19 outbreak based on the SIR model. The analysis is done on the dataset of China. The analysis shows the impact number of contacts, size of the city and population on spread rate of COVID-19. The study recommends that the social distancing can reduce the spread rate of the COVID-19. Bärwolff [7] presents SIR based model for prediction based on the European Centre for Disease Prevention and Control dataset for USA and UK. In this work impact of temporary lockdown, social distancing and the high-risk population is discussed. However, the



mathematical models cannot cover precautions taken by physicians and politicians. The infected people may not be distributed evenly in the locations of the city; these parameters may impact the results of the mathematical model. Christopher E. et al. [8] presented an analysis of a range of statistical models. In this work challenges in mathematical modeling for a pandemic like COVID-19 are discussed. Results show that the bias in parameters like reporting time of infected person (delay), dynamic travel rate, and truncated sample data can impact majorly on the prediction of spread rate.

Viguerie et al. [9] presented the Susceptible-Exposed-Infected-Recovered-Deceased (SEIRD) model with heterogeneous diffusion for predictions. Dataset of Italy is used for analysis and results of analysis recommend that reopening must consider the population in a particular location and infection dynamics; it should not be the same for every location. Santos et al. [10] present the SEIR model for analysis. In this work infection, incubation periods and fatality rate are used and results show that due to lockdown and awareness in people can reduce the infection rate of the COVID-19. Godio et al. [11] proposed an SEIR based model using computational swarm intelligence. In this model impact of mobility rate on COVID-19 infection spread rate is analyzed. The analysis is done on the nationalized dataset of Spain and South Korea. Shaikh et al. [12] presented a mathematical model based on fractional derivative for prediction of COVID-19. The stability of this model is verified by Picard successive approximation technique. Mahmud et al [13] presented a mathematical model based on social awareness for predictions. In this work awareness level of each country is estimated based on parameters like GDP per capita, literacy rate, density of population, stability of economy etc. results show that higher social awareness can reduce the infection rate of COVID-19. Reno et al. [14] presented the SEIR model for forecasting COVID-19. The analysis is done on the dataset for Italy and the results of the model show that forecasting under different

scenarios can help to understand and form new containment policies to reduce the infection rate.

Leon et al. [15] present susceptible, Exposed, Infected, Asymptomatic, Recovered and Dead (SEIARD) model for prediction of death count in Mexico. In this work impact of a number of asymptomatic individuals is considered as these individuals spread infection unknowingly and this spread rate may be very much faster as an individual is unknown about infection. This work recommends the importance of self-quarantine, with its separation of a healthy population and asymptomatic population that can be done easily, which can lower the spread rate of COVID-19 infection. Koltsova et al. [16] presents a prediction model based on a discrete logistic equation. In this infection growth index is based on the parameters like quarantine measures, size of population and density of population. In this work infection rate of Asian, European nations are compared with the infection rate of Moscow and Russia. Chérifet al. presented susceptible, Exposed, Infected, Recovered, Dead and Quarantine (SEIRDQ) model based on the non-linear differential equation [17]. In this work impact of quarantine population is discussed. In this work guidelines of quarantine are proposed based on the results of the model. Chhetri et al. [18] presents the mathematical model for understanding drug interventions in the COVID-19. In this study combination of two categories of drugs are discussed, first drugs that impact on the virus and second, drugs that improve the immune system response. A result of this work recommends that optimal dosage of both drugs can help to recover patient and also helps to reduce side effects of drugs. Goel and Sharma presents mobility based mathematical model for COVID-19 [19]. In this work distribution of the population and connectivity between various locations that are geographically distinct. This work recommends isolation and quarantine as the best solution to reduce the spread rate of COVID-19. Ndairoual. [20] presents SIR based mathematical model for prediction of COVID-19 in Wuhan. In this study parameters like a number of super-



spreader and hospitalized individuals are considered. In the literature apart from SIR and modified SIR various models based on machine learning are also used for forecasting [21-28].

3. Evaluation of Related Works

Although, there has been a lot of efforts to model and predict the feast of COVID-19, there are many issues which are not yet addressed. Most of the models which have been presented in the literature are referring to the data set which is specific to the particular country. We should not the reasons of being modeling of COVID-19 challenging. This section briefs the same and also focuses on the few limitations of the existing predictions. Most of the models rely on the data which is available from prior outbreaks of the same infection and the results are also compared with the existing predictions. However, these methods work better for popular diseases like H1N1, hypertension as there is an ample amount of tested data of different outbreaks since decades and also from varied types of communities. Limited information available about COVID-19 like ways of transfer, the life of virus, incubation period also plays an important role in building a reliable prediction model. In addition to this, different assumptions have been taken into considerations by different models for predictions. Assumptions include anticipation of COVID-19 like H1N1 or SARS-COV which makes different models giving different predictions. The context in which the model is developed is also an important parameter and the way in which predictions have been presented in the literature is also equally important. Fuzzy way of modeling the predictions is relatively better than predicted in a crisp way as most of the time resource owner do not have do not have access to the crisp resources. From the literature, it is also clear all the parameters of COVID-19 are not taken into consideration by researchers for prediction and modeling and in turn the predictions are not complete. Most of the studies are commenting on the peak of the disease but none of the studies is carried out to model when the number of infected people by COVID-19 pandemic will start decreasing.

All models presented in the literature are based on Artificial Intelligence (AI) and Machine Learning (ML). However, there are many reasons which also should be revisited in order to understand why these AI and ML models have limitations and constraints [28]. The key point to note here that the AI-based model needs an ample amount of data on COVID-19 to train. All AI and ML-based models for predictions are based on small and biased data and mostly all these data sets are from China and the majority of the work are not peer-reviewed. As stated in [29], with the increasing spread, the social media traffic accumulation around the original data increases and suitable data cleaning methods are required for filtering before the same data is used for training and testing purpose. Outlier data is also another reason for the failure of predictions. In the sequel, these observations conclude that there is a need of core math-based model for prediction.

In most of the cases the theoretical models are easy to understand but very difficult to apply for solving real life problems. There are so many hidden assumptions or data may be continuous. It is very challenging to write mathematical model by considering all aspects of the data.

The rate of an infected people by COVID 19 depends upon the policies of the governments, people of the concerned country, medical expertise and infrastructure, immunity power of people and many more. Hence, we need to understand the practical approach of the model and make corresponding assumptions for implementation of the model.

4. Proposed Work

As we know that the rate of increase of microbes in a culture is proportional to the number of microbes present in it. Generally, we follow the same approach in simple circumstances. But for the prediction model of the COVID 19, it depends upon the total number of people infected, the number of people recovered and the number of deaths. There are some peoples who are infected by COVID 19 and speculating in the society but



they are not tested. It is very perplexing to identify such types of cases. By considering the above consequences, we define the rates of increase or decrease of any virus according to theoretical as well as practical approach as follows.

Let U be the universal set and $I(t)$ be the set of living beings or people infected by the virus at any time t . The rate of the change of an infected living beings is directly proportional to the number of living beings presented at that instant. Therefore,

- *Prediction Model for any Virus: A General Approach*

$$\frac{dI}{dt} \propto I(t) \Rightarrow \frac{dI}{dt} = kI \Rightarrow dI = kI dt$$

$$\therefore I = A e^{kt}$$

- *Prediction Model for COVID-19: A Theoretical Approach*

Let $I(t)$ be the set of an infected people by COVID19 at time t . Let I_Q be the set of people who are quarantine or susceptible people and I_R be the set of people who are recovered by COVID 19 at that instant. Let I_D be the set of people who died due to COVID19. Therefore,

$$\frac{dI}{dt} \propto I(t), \quad \frac{dI}{dt} \propto I_Q(t), \quad \frac{dI}{dt} \propto I_R(t) \quad \text{and} \quad \frac{dI}{dt} \propto I_D(t)$$

$$\frac{dI}{dt} = g I(t), \quad \frac{dI}{dt} = s I_Q(t), \quad \frac{dI}{dt} = -m I_R(t) \quad \text{and} \quad \frac{dI}{dt} = -n I_D(t)$$

The proportionality constants g and s are positive because generally, as t increases, $I(t)$ increases. But, the negative sign is attached to m and n , as t increases, $I(t)$ decreases.

Thus, the net rate of change of $I(t)$ is given by

$$\frac{dI}{dt} = g I(t) + s I_Q(t) - m I_R(t) - n I_D(t)$$

- *Prediction Model for COVID-19: A Practical Approach*

It is very difficult to track the susceptible people, so merge it into the set $I(t)$. So the proportionality constant will be changed. Therefore, $I(t)$ be the set of an infected or susceptible people.

Thus, the net rate of the change of $I(t)$ is given by

$$\frac{dI}{dt} = \mu I(t) - m I_R(t) - n I_D(t)$$

Where, μ is the proportionality constant.

The proportionality constants in the above three models depend upon administrator policies, integrity of society, medical infrastructures and quality medical staff.

In this context, the prediction of the number of infected patients depends upon the proportionality constant. Depending upon the nature proportionality constant, the types of

the prediction model will be defined as linear or exponential, logarithmic, power functions and so on. Moreover, the proportionality constant of the model of COVID 19 has governed by "How the concerned government design strategies? And how people are following it?" So first we understand applicable assumptions and then calculate the associated values. Additionally, we require delineating the grading



of the government as well as the people of the concerned country. Therefore, we need to care of the total number of cases, recovery cases, number of deaths and the number of active cases. These prediction models are used for the predictions of the number of active and passive cases of the COVID 19. All these interconnected concepts are explained as follows.

- *Proportionality Constants μ :*

An effect of the pandemic in any country is depends upon the administrator policies and the people of the country. Whether an administrator is serious about this pandemic or not? If yes, then up to what grading administrator implement policies? There are the following twenty possibilities of whether the administrator is honestly handling this pandemic or not.

Table No.1: Grading of the Administrator and Society.

Sr. No.	Percentage Range	Letter Grade	Grade Number
1	More than 95 %	GH ₁ or SH ₁	0.975
2	90% to 95%	GH ₂ or SH ₂	0.925
3	85% to 90%	GH ₃ or SH ₃	0.875
4	80% to 85%	GH ₄ or SH ₄	0.825
5	75% to 80%	GM ₁ or SM ₁	0.775
6	70% to 75%	GM ₂ or SM ₂	0.725
7	65% to 70%	GM ₃ or SM ₃	0.675
8	60% to 65%	GM ₄ or SM ₄	0.625
9	55% to 60%	GM ₅ or SM ₅	0.575
10	50% to 55%	GM ₆ or SM ₆	0.525
11	45% to 50%	GL ₁ or SL ₁	0.475
12	40% to 45%	GL ₂ or SL ₂	0.425
13	35% to 40%	GL ₃ or SL ₃	0.375
14	30% to 35%	GL ₄ or SL ₄	0.325
15	25% to 30%	GL ₅ or SL ₅	0.275
16	20% to 25%	GL ₆ or SL ₆	0.225
17	15% to 20%	GL ₇ or SL ₇	0.175
18	10% to 15%	GL ₈ or SL ₈	0.125
19	5% to 10%	GL ₉ or SL ₉	0.075
20	0% to 5%	GL ₁₀ or SL ₁₀	0.025

By applying the Normal distribution curve (Bell shaped curve), it is assumed that if the probability is more than 0.8, then the administrator is very (high) serious about the pandemic. If the probability is between 0.5 and 0.8, then the administrator is medium serious and if the probability is less than 0.5, then the administrator is low serious about handling the

pandemic. These twenty levels are denoted by GH_i, GM_j, and GL_k, respectively. Moreover, the spread of pandemic not only depends upon the administrator policies but also an honesty of the society of the concerned country.

Similarly, there are twenty different levels of honesty of the society as that of the administrator. SH_i, SM_j, and SL_k denote these levels of society, respectively.



An effect of spread any virus or COVID 19 depend upon the combined efforts of the Administrator, Society and the medical facilities of the concerned country. Therefore the combined grading of administrators as well as society is defined as follows.

Let G_i and S_j are different grading of administrator and society respectively. Let $P(G_i)$

and $P(S_j)$ be the probabilities of occurrences of G_i and S_j respectively. Here we assume that G_i and S_j are independent events of the universal set under consideration.

Hence, $P(G_i \text{ and } S_j) = P(G_i) * P(S_j)$,

The following table shows the combined grading of the administrator and society.

Table No.2: Combined Grading of the Administrator and Society.

G/S	0.975	0.925	0.875	0.825	0.775	0.725	0.675	0.625	0.575	0.525
0.975	0.950 63	0.9018 8	0.8531 3	0.8043 8	0.7556 3	0.7068 8	0.6581 3	0.6093 8	0.5606 3	0.5118 8
0.925	0.901 88	0.8556 3	0.8093 8	0.7631 3	0.7168 8	0.6706 3	0.6243 8	0.5781 3	0.5318 8	0.4856 3
0.875	0.853 13	0.8093 8	0.7656 3	0.7218 8	0.6781 3	0.6343 8	0.5906 3	0.5468 8	0.5031 3	0.4593 8
0.825	0.804 38	0.7631 3	0.7218 8	0.6806 3	0.6393 8	0.5981 3	0.5568 8	0.5156 3	0.4743 8	0.4331 3
0.775	0.755 63	0.7168 8	0.6781 3	0.6393 8	0.6006 3	0.5618 8	0.5231 3	0.4843 8	0.4456 3	0.4068 8
0.725	0.706 88	0.6706 3	0.6343 8	0.5981 3	0.5618 8	0.5256 3	0.4893 8	0.4531 3	0.4168 8	0.3806 3
0.675	0.658 13	0.6243 8	0.5906 3	0.5568 8	0.5231 3	0.4893 8	0.4556 3	0.4218 8	0.3881 3	0.3543 8
0.625	0.609 38	0.5781 3	0.5468 8	0.5156 3	0.4843 8	0.4531 3	0.4218 8	0.3906 3	0.3593 8	0.3281 3
0.575	0.560 63	0.5318 8	0.5031 3	0.4743 8	0.4456 3	0.4168 8	0.3881 3	0.3593 8	0.3306 3	0.3018 8
0.525	0.511 88	0.4856 3	0.4593 8	0.4331 3	0.4068 8	0.3806 3	0.3543 8	0.3281 3	0.3018 8	0.2756 3
0.475	0.463 13	0.4393 8	0.4156 3	0.3918 8	0.3681 3	0.3443 8	0.3206 3	0.2968 8	0.2731 3	0.2493 8
0.425	0.414 38	0.3931 3	0.3718 8	0.3506 3	0.3293 8	0.3081 3	0.2868 8	0.2656 3	0.2443 8	0.2231 3
0.375	0.365 63	0.3468 8	0.3281 3	0.3093 8	0.2906 3	0.2718 8	0.2531 3	0.2343 8	0.2156 3	0.1968 8
0.325	0.316 88	0.3006 3	0.2843 8	0.2681 3	0.2518 8	0.2356 3	0.2193 8	0.2031 3	0.1868 8	0.1706 3
0.275	0.268 13	0.2543 8	0.2406 3	0.2268 8	0.2131 3	0.1993 8	0.1856 3	0.1718 8	0.1581 3	0.1443 8
0.225	0.219 38	0.2081 3	0.1968 8	0.1856 3	0.1743 8	0.1631 3	0.1518 8	0.1406 3	0.1293 8	0.1181 3
0.175	0.170 63	0.1618 8	0.1531 3	0.1443 8	0.1356 3	0.1268 8	0.1181 3	0.1093 8	0.1006 3	0.0918 8
0.125	0.121 88	0.1156 3	0.1093 8	0.1031 3	0.0968 8	0.0906 3	0.0843 8	0.0781 3	0.0718 8	0.0656 3
0.075	0.073	0.0693	0.0656	0.0618	0.0581	0.0543	0.0506	0.0468	0.0431	0.0393



	13	8	3	8	3	8	3	8	3	8
0.025	0.024 38	0.0231 3	0.0218 8	0.0206 3	0.0193 8	0.0181 3	0.0168 8	0.0156 3	0.0143 8	0.0131 3
G/S	0.475	0.425	0.375	0.325	0.275	0.225	0.175	0.125	0.075	0.025
0.975	0.463 13	0.4143 8	0.3656 3	0.3168 8	0.2681 3	0.2193 8	0.1706 3	0.1218 8	0.0731 3	0.0243 8
0.925	0.439 38	0.3931 3	0.3468 8	0.3006 3	0.2543 8	0.2081 3	0.1618 8	0.1156 3	0.0693 8	0.0231 3
0.875	0.415 63	0.3718 8	0.3281 3	0.2843 8	0.2406 3	0.1968 8	0.1531 3	0.1093 8	0.0656 3	0.0218 8
0.825	0.391 88	0.3506 3	0.3093 8	0.2681 3	0.2268 8	0.1856 3	0.1443 8	0.1031 3	0.0618 8	0.0206 3
0.775	0.368 13	0.3293 8	0.2906 3	0.2518 8	0.2131 3	0.1743 8	0.1356 3	0.0968 8	0.0581 3	0.0193 8
0.725	0.344 38	0.3081 3	0.2718 8	0.2356 3	0.1993 8	0.1631 3	0.1268 8	0.0906 3	0.0543 8	0.0181 3
0.675	0.320 63	0.2868 8	0.2531 3	0.2193 8	0.1856 3	0.1518 8	0.1181 3	0.0843 8	0.0506 3	0.0168 8
0.625	0.296 88	0.2656 3	0.2343 8	0.2031 3	0.1718 8	0.1406 3	0.1093 8	0.0781 3	0.0468 8	0.0156 3
0.575	0.273 13	0.2443 8	0.2156 3	0.1868 8	0.1581 3	0.1293 8	0.1006 3	0.0718 8	0.0431 3	0.0143 8
0.525	0.249 38	0.2231 3	0.1968 8	0.1706 3	0.1443 8	0.1181 3	0.0918 8	0.0656 3	0.0393 8	0.0131 3
0.475	0.225 63	0.2018 8	0.1781 3	0.1543 8	0.1306 3	0.1068 8	0.0831 3	0.0593 8	0.0356 3	0.0118 8
0.425	0.201 88	0.1806 3	0.1593 8	0.1381 3	0.1168 8	0.0956 3	0.0743 8	0.0531 3	0.0318 8	0.0106 3
0.375	0.178 13	0.1593 8	0.1406 3	0.1218 8	0.1031 3	0.0843 8	0.0656 3	0.0468 8	0.0281 3	0.0093 8
0.325	0.154 38	0.1381 3	0.1218 8	0.1056 3	0.0893 8	0.0731 3	0.0568 8	0.0406 3	0.0243 8	0.0081 3
0.275	0.130 63	0.1168 8	0.1031 3	0.0893 8	0.0756 3	0.0618 8	0.0481 3	0.0343 8	0.0206 3	0.0068 8
0.225	0.106 88	0.0956 3	0.0843 8	0.0731 3	0.0618 8	0.0506 3	0.0393 8	0.0281 3	0.0168 8	0.0056 3
0.175	0.083 13	0.0743 8	0.0656 3	0.0568 8	0.0481 3	0.0393 8	0.0306 3	0.0218 8	0.0131 3	0.0043 8
0.125	0.059 38	0.0531 3	0.0468 8	0.0406 3	0.0343 8	0.0281 3	0.0218 8	0.0156 3	0.0093 8	0.0031 3
0.075	0.035 63	0.0318 8	0.0281 3	0.0243 8	0.0206 3	0.0168 8	0.0131 3	0.0093 8	0.0056 3	0.0018 8
0.025	0.011 88	0.0106 3	0.0093 8	0.0081 3	0.0068 8	0.0056 3	0.0043 8	0.0031 3	0.0018 8	0.0006 3



The grade number 0.95063 represents that the administrator as well as society are very serious about the COVID 19. The administrator policies and an honesty of the society is medium if the grade number is 0.60063. Now, if the grade number is 0.57813, its corresponding numbers are 0.925 and 0.625. Therefore, there are two predictions.

a) For the administrator associated number is 0.925, so the administrator is very serious about their policies. The grade number of the society is 0.625, which means the society is an average serious about following rules of the administrator. Hence, the combined effect is 0.57813.

b) In this case, interchange the grading of the administrator and society. Thus, the administrator policies are medium but an honesty of society is high.

The above representation is symmetry about its diagonal.

By studying different facets of the COVID 19, we have divided data according to the Normal Distribution. The following table bestows the range of the total cases of COVID 19, Number of countries and the corresponding grade numbers according to the available data from 22 January to 30 April 2020.

Table No. 3: Total Number of Cases of COVID 19 and Grading

Total Cases of COVID 19 per Million	No. of Countries	Grade Number
0.1 – 50	63	0.95
50 – 100	24	0.9
100 - 150	14	0.85
150 – 200	8	0.8
200 - 250	13	0.75
250 – 300	7	0.7
300 – 350	3	0.65
350 -400	1	0.6
400 – 450	3	0.55
450 -500	2	0.5
500 – 550	5	0.45
550 – 600	0	0.4
600 – 650	4	0.35
650 – 700	4	0.3
700 – 750	1	0.25
750 – 800	1	0.2
800 – 850	0	0.15
850 – 900	3	0.1
900 – 950	2	0.05
950 onwards	47	0.01

In the table No. 3, if the total number of cases is 210, then the corresponding grade number is 0.75. Therefore, according to the table no 2, grade number 0.75 is closed to 0.75563 and the

corresponding grading are 0.975 and 0.775. Consequently, between administrator and society, one of them is very serious and the



other is medium about the controlling of COVID 19.

• *Grades of Countries:*

The grade number (G_c) of each country is obtained by the following formula.

$$G_c = G_L + [(U - N)/1000]$$

Where, G_c = Grade Number of the country.

L = Interval comprising N

G_L = Grade number of the interval L .

U = Upper limit of interval L

N = Total cases of COVID 19 per million of the country C .

In view of available data, the following table studies the country, total cases per million, Grade number and the rank of the country.

Table No. 4: Grading of Countries

Country /location	Total Cases Per Million	Grade Number	Rank
Yemen	0.201	0.999799	1
Nepal	1.956	0.998044	9
Zimbabwe	2.288	0.997712	11
Kenya	7.141	0.992859	26
Nigeria	8.383	0.991617	29
Bhutan	9.072	0.990928	32
India	23.949	0.976051	47
Sri Lanka	30.308	0.969692	50
Indonesia	35.723	0.964277	54
Bangladesh	43.13	0.95687	59
Iraq	49.798	0.950202	63
Afghanistan	50.066	0.949934	64
Egypt	51.478	0.948522	65
China	58.322	0.941678	69
Pakistan	71.342	0.928658	74
Philippines	74.94	0.92506	75
South Africa	90.206	0.909794	81
Japan	111.388	0.888612	90
Colombia	122.065	0.877935	94
Mexico	138.049	0.861951	99
Malaysia	183.68	0.81632	106
South Korea	209.97	0.79003	114
New Zealand	234.124	0.765876	119
Greece	247.144	0.752856	122
Australia	264.55	0.73545	125
Hungary	287.257	0.712743	129
Poland	333.98	0.66602	132
Brazil	367.718	0.632282	133
Saudi Arabia	614.755	0.385245	145
Russia	681.121	0.318879	149
Iran	1115.058	-0.11506	164
Canada	1366.827	-0.36683	168
Denmark	1555.194	-0.55519	174
Israel	1829.348	-0.82935	179

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Germany	1899.159	-0.89916	180
France	1967.751	-0.96775	181
Sweden	2010.244	-1.01024	182
Netherlands	2264.505	-1.26451	185
United Kingdom	2433.801	-1.4338	188
Singapore	2673.518	-1.67352	189
United States	3141.694	-2.14169	190
Italy	3367.265	-2.36727	191
Switzerland	3388.249	-2.38825	192
Belgium	4129.472	-3.12947	197
Spain	4564.988	-3.56499	200
World	401.717	0.598283	134

As per the record on 30 April 2020, India has 23.949 cases of COVID 19 per million and the corresponding grading is **0.976051**. Therefore it seems that India is controlling COVID 19 very amusingly. Hence, according to the combined grading of the Administrator and society, India has gained 0.95063 grade. Thus, the Indian administrator and society are in the first category, which is both have 0.975 grading. So, administrator and society are working together very honestly and proficient fashion.

Now, New Zealand has 234.124 cases of COVID 19 per million and its grading is 0.79003. Therefore by a table of the combined grading, it is much closed to 0.76313 grade. Its corresponding grades are 0.925 and 0.825. Therefore it seems that administrator and

society are working with grades 0.925 and 0.825 or 0.825 and 0.925 respectively.

By table 4, the number of cases of COVID 19, in ITALY is 3367.265. Hence the grading of Italy is - 2.36727. Thus the performance of Italy administrator and society is very low.

By taking care of all above aspects, we can find the proportionality constant for the number of cases of COVID 19.

- *Daily Recovery from COVID 19*

We study daily recovery (cured) of patients. As the recovery rate is not fixed, we consider the group of 10 days together for a period from 22 January 2020 to 30 April 2020. Fit the data in excel and find two curves for the best fitting of data. Details are explained as follows.

Table No. 5 Table for recovery from COVID 19

Period No. (P)	Limits of Periods	Correlation coefficients (r)	Coefficients of Determination (r ²)	Linear Prediction Equations	Second Degree Prediction Equations
I	22 - 31 Jan	0.65745	0.43224	R = 4.963d - 1.8	R = 1.647d ² - 13.16d + 34.45
II	1 - 10 Feb	0.981996	0.964317	R = 73.69d - 762.3	R = 2.822d ² - 13.78d - 107.6
III	11 - 20 Feb	0.945034	0.89309	R = 140.9d - 2144	R = 1.465d ² + 66.14d - 1203
IV	21 Feb - 1 Mar	0.672369	0.45208	R = 112.3d - 1328.	R = -18.51d ² + 1427.d - 24514
V	2 - 11 Mar	-0.69739	0.48635	R = -102.8d + 6998	R = 13.81d ² - 1360d + 35484
VI	12 - 21 Mar	0.675549	0.456366	R = 163.3d - 6345	R = 28.44d ² - 2993.d + 81032
VII	22 - 31 Mar	0.928835	0.862735	R = 1112.d - 64630	R = -15.28d ² + 3115.d - 13007



VIII	1 – 10 Apr	0.66515	0.442425	$R = 993.7d - 55217$	$R = 23.25d^2 - 2518.d + 77165$
IX	11 – 20 Apr	0.025096	0.00063	$R = 48.24d + 23013$	$R = -441.0d^2 + 75472d - 3E+06$
X	21 – 30 Apr	0.031283	0.000979	$R = 208.2d + 19657$	$R = -42.35d^2 + 8293d - 36586$
	22 Jan to 30 April 2020	0.8232757	0.677782882	$y = 391.7x - 9391.$	$y = 7.897d^2 - 405.9d + 4168.$

In table no 1, it is observed that there is a strong linear relationship between the number of days (d) and the number of patients recovered (R) daily in three periods 1 – 10 February, 11 – 20 February and 22 – 31 March 2020, as their correlation coefficients are respectively 0.981996, 0.945034 and 0.928835. In the periods II, III, and VII, the coefficient of determination (r^2) are respectively 0.964317, 0.89309, and 0.862735. In period II, 96 % of the total variation in the number of patients recovered (R) daily is elucidated by the linear relationship between d and R and 4% of the total variation remains unexplained. In the periods II and VII, 89 % and 86 % of the total variation in R respectively is explicated by the linear relationship but, 11% and 14 % of R residue unexplained by this relationship. Thus, there is a strong linear relationship between d and R in these periods.

The value of r^2 for all remaining periods is less than 0.5. Therefore, there is a weak linear

relationship between d and R and more than 50 % variations of R, are residue by this linear relationship. Hence, for the prediction of this, consider second-degree equations only. To find the predictions in these periods, find the first ordered derivative of the second degree polynomials at different points. If we consider the total period, 0.8232757 is the concerned correlation coefficient and the coefficient of the determination is 0.677782 (approximately 68%). As a result, the linear relationship of this data is medium and 68% observations are studied through this relationship. The remaining relations are studied by second degree polynomial function, power function ($y = 0.567d^{2.319}$) and exponential functions ($y = 71.37e^{0.071x}$). By considering the most appropriate functions, that is linear, second degree and the power function and finding the number of patients cured by COVID19. Then we find the average of these three, which is explained through the following table.

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Table No. 6 Table for Predictions of recovery from COVID 19

Days	$y = 391.7x - 9391.$	$y = 7.897x^2 - 405.9x + 4168$	$y = 0.567x^{2.319}$	Average
110	33696	55073	30731	39833
120	37613	69177	37601	48130
130	41530	84860	45271	57220
140	45447	102123	53759	67110
150	49364	120966	63087	77805
160	53281	141387	73272	89313
170	57198	163388	84332	101640
180	61115	186969	96285	114790
190	65032	212129	109147	128769



200	68949	238868	122934	143584
210	72866	267187	137661	159238
220	76783	297085	153342	175737
230	80700	328562	169993	193085
240	84617	361619	187626	211287
250	88534	396256	206256	230348
260	92451	432471	225895	250272
270	96368	470266	246556	271063
280	100285	509641	268252	292726
290	104202	550595	290994	315264
300	108119	593128	314795	338681
310	112036	637241	339665	362981
320	115953	682933	365617	388167
330	119870	730204	392660	414245
340	123787	779055	420807	441216
350	127704	829486	450067	469085
360	131621	881495	480450	497856
370	135538	935084	511968	527530
380	139455	990253	544630	558112
390	143372	1047001	578445	589606
400	147289	1105328	613423	622013

After June, the number of patients cured will be more than 90,000 per day and that will be more than 175000 per day after August. Thus the rate of recovery will increase as time increases.

We studied all new cases per day and made 10 suitable periods of the total time from 22 January 2020 to 30 April 2020. Details are given in the table no 7.

• *New Cases of COVID19:*

Table No. 7 Table for new cases of COVID 19

Period No. (P)	Limits of Periods	Correlation coefficients (r)	Coefficients of Determination (r ²)	Linear Prediction Equations	Second Degree prediction Equations
I	22 - 31 Jan	0.96501446	0.9312529	$y = 241.3x - 176.4$	$y = -3.227x^2 + 276.8x - 247.4$
II	1 – 10 Feb	-0.1623589	0.0263604	$y = -25.26x + 3506$	$y = -49.14x^2 + 1498.x - 7895$
III	11 – 20 Feb	-0.5378507	0.28928341	$y = -693.3x + 21167$	$y = 45.72x^2 - 3025.x + 50524$
IV	21 Feb – 1 Mar	0.82363184	0.67836941	$y = 134.3x - 3578$	$y = 31.38x^2 - 2093.x + 35712$
V	2 – 11 Mar	0.91009825	0.82827882	$y = 459.5x - 17145$	$y = 40.20x^2 - 3199.x + 65757$
VI	12 – 21 Mar	0.9554915	0.91296401	$y = 2608.x - 12689$	$y = 215.1x^2 - 21272x + 53401$



VII	22 – 31 Mar	0.92962272	0.86419841	$y = 4089.x - 21204$	$y = -389.7x^2 + 55148x - 2E^6$
VIII	1 – 10 Apr	0.29488763	0.08695872	$y = 768.5x + 25124$	$y = 363.6x^2 - 54144x + 2E^6$
IX	11 – 20 Apr	0.18456215	0.03406319	$y = 352.6x + 48456$	$y = -327.7x^2 + 56400x - 2 E^6$
X	21 – 30 Apr	-0.1389449	0.01930568	$y = -446.4x + 12523$	$y = -184.3x^2 + 34772x - 2 E^6$
	22 Jan to 30 April	0.892813	0.797115035	$y = 1108.x - 22942$	$y = 11.78x^2 - 81.87x - 2701.$

From table no 7, the rate of the daily new cases of COVID 19 for the periods I, V, VI and VII is linear. Moreover there is a strong linear relationship between the number of days and the daily new cases. As the coefficient of determination is more than 0.8, therefore more than 80% observations are studied through linear relationship.

In period IV, the coefficient of determination is 0.6783, so there is a medium linear relationship between the corresponding variables. There is no linear relationship for the remaining all periods. Hence, the rate of new cases is irregular.

Furthermore, if we observed total time from 22 January to 30 April, the correlation coefficient is 0.8928 and the coefficient of determination is 0.797115035 (Approximately 80%). Therefore the linear relationship between the number of days and the new cases is strong. Hence, for predicting the daily number of cases, we can make use of the linear relationship, which gives 80% correct predictions.

• *Death Cases:*

The following table gives the correlation coefficients, coefficient of determination and the best suitable curve of the concerned data.

Table No. 8 Table for Death Cases Daily

Period No. (P)	Limits of Periods	Correlation coefficients (r)	Coefficients of Determination (r ²)	Linear Prediction Equations	Second Degree Prediction Equations
I	22 - 31 Jan	0.93695061	0.87787645	$y = 3.945x + 4.2$	$y = 0.390x^2 - 0.346x + 12.78$
II	1 – 10 Feb	0.9850775	0.97037768	$y = 6.212x - 20.38$	$y = 0.132x^2 + 2.102x + 10.37$
III	11 – 20 Feb	-0.0875865	0.0076714	$y = -0.539x + 136.6$	$y = -0.541x^2 + 27.08x - 211.1$
IV	21 Feb – 1 Mar	-0.6491067	0.4213395	$y = -7.533x + 347.7$	$y = 1.439x^2 - 109.7x + 2149.$
V	2 – 11	0.91783905	0.84242852	$y = 28.10x -$	$y = 40.20x^2 - 3199.x +$



	Mar			1121	65757
VI	12 – 21 Mar	0.96697452	0.93503973	$y = 136.9x - 6753$	$y = 12.25x^2 - 1222.x + 30878$
VII	22 – 31 Mar	0.97433507	0.94932883	$y = 310.8x - 17266$	$y = 0.003x^2 + 310.3x - 17250$
VIII	1 – 10 Apr	0.71037141	0.50462754	$y = 237.1x - 11531$	$y = 23.04x^2 - 3242.x + 11962$
IX	11 – 20 Apr	0.00613448	0.00003	$y = 2.351x + 6398$	$y = -100.3x^2 + 17153x - 72595$
X	21 – 30 Apr	0.86605003	0.75004265	$y = -135.0x + 18955$	$y = 73.68x^2 - 14209x + 69037$
	22 Jan to 30 April	0.86605003	0.750042655	$y = 85.13x - 1955.$	$y = 1.087x^2 - 24.72x - 88.28$

It is found that the death rate is strongly linear relationship for the periods I, II, V, VI, and VII, as its coefficient of determinations are more than 83%. For periods VIII and X, r^2 is between 0.5 to 0.79, therefore the linear relationship of these periods is medium. The linear relationship for the remaining periods is weak. Moreover, if we consider the total period, we get, $r^2 = 0.75$,

consequently there is a medium linear relationship between the daily death and the number of days. Thus, the death predictions can be elucidated 75 % correctly.

5. Results and discussion

By analysing above all data and its interpretations, briefly we get the following things.

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Table No. 9 Formula of Net Cases Daily

Sr. No.	Cases Daily	Limits of Periods	Correlation coefficients (r)	Coefficients of Determination (r^2)	Linear Prediction Equations	Second Degree Prediction Equations
1	Total Number of New Cases	22 Jan to 30 April	0.892813	0.797115035	$y = 1108.x - 22942$	$y = 11.78x^2 - 81.87x - 2701.$
2	Total Number of Recovery Cases	22 Jan to 30 April	0.8232757	0.677782882	$y = 391.7x - 9391.$	$y = 7.897d^2 - 405.9d + 4168.$



3	Total Number of Death Cases	22 Jan to 30 April	0.86605003	0.750042655	$y = 85.13x - 1955.$	$y = 1.087x^2 - 24.72x - 88.28$
4	Net change in cases	22 Jan to 30 April	0.8267 (Approx.)	0.6835 (Approx.)	$y = 717.06x - 13552$	$y = 3.8905x^2 + 324.12x - 6871.8$

By considering the formulae for the net cases daily, we find the rate of net increase of daily cases of COVID 19, which is given in the table no 10

Table No. 10 Net Cases of COVID 19 Daily

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Month	Days	$y = 717.06x - 13552$	$y = 3.8905x^2 + 324.12x - 6871.8$	Average
May	110	65325	75856	70591
May	120	72495	88046	80271
May	130	79666	101013	90340
June	140	86836	114759	100798
June	150	94007	129282	111645
June	160	101178	144584	122881
July	170	108348	160664	134506
July	180	115519	177522	146520
July	190	122689	195158	158924
August	200	129860	213572	171716
August	210	137031	232764	184898
August	220	144201	252735	198468
Sept.	230	151372	273483	212428
Sept.	240	158542	295010	226776
Sept.	250	165713	317314	241514
Oct.	260	172884	340397	256640
Oct.	270	180054	364258	272156
Oct.	280	187225	388897	288061
Nov.	290	194395	414314	304355
Nov.	300	201566	440509	321038
Nov.	310	208737	467482	338110
Dec.	320	215907	495234	355571
Dec.	330	223078	523763	373421
Dec.	340	230248	553071	391660
Jan.	350	237419	583156	410288
Jan.	360	244590	614020	429305
Jan.	370	251760	645662	448711
Feb.	380	258931	678082	468506



Feb.	390	266101	711280	488691
Feb.	400	273272	745256	509264

From table no 10, it is predicted that, there will more than 1,00,000 net increase in cases of COVID 19 in June. In the middle of July, the net increase in cases will be 146520 daily. If there will be the same situation in August, then the net increase in cases daily will be 184898. Thus, there is rapid increase in the net cases of COVID 19.

6. Conclusion

In this paper, we have defined the most appropriate practical model to study the prediction of spread of the virus in the world and applied it for the predictions of the spread of COVID 19. We have considered an authentic data and divided it into subintervals for finding trend lines. After getting suitable trend lines, if required we have taken an average of the data for studying as well as predictions of COVID 19.

Using the normal curve approach grading is defined. Moreover, the grading of countries are also given according to how the administrator and the society tackled this pandemic situation by considering the total cases per million. Futuristic predictions are made for the net increase of new cases of COVID-19 daily by assuming the same circumstances. Compared to state-of-the-art models, the proposed mathematical model could be useful to plan short-term/long-term guidelines.

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