An Extensive Analysis of the Effect of Social Distancing in Transmission of COVID-19 in Bangladesh by the Aid of a Modified SEIRD Model

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2020 2nd International Conference on Advanced Information and Communication Technology (ICAICT) | 978-0-7381-2323-3/20/$31.00 ©2020 IEEE | DOI: 10.1109/ICAICT51780.2020.9333517

***Abstract*—The upsurge of Coronavirus has become widespread all around the world. More than 200 countries got affected by Coronavirus. Research works are being conducted to study the pattern of this infectious disease to minimize the transmission of this virus. Epidemiological models are one of the major approaches being used as part of the study. These models help in analyses of different aspects associated with a contagious disease such as death rate, recovery rate, infected rate. Models like SIR, SEIR, SIQR are being promptly used to investigate the patterns of Coronavirus in different countries. In this paper, we proposed a modified SEIRD model to study the trend of this infectious disease concerning Bangladesh. The SEIRD model was developed further by incorporating two new factors isolation and social distancing. We will observe the effect of these factors on the transmission rate of this virus and make predictions about the related factors. Results show that our predicted results well match the real world scenario.**

***Index Terms*—Coronavirus, COVID-19, SEIRD Model, Simulation, Social Distancing, Epidemic.**

I. Introduction

Coronavirus (COVID-19) is a currently discovered infectious disease which is caused by severe acute respiratory syndrome Coronavirus 2 (SARS-CoV-2). Firstly, the outbreak was identified in Wuhan, China, in December 2019. The World Health Organization (WHO) declared the outbreak as a global pandemic on 11th March. Meanwhile, more than 200 countries have been reported with confirmed cases including Bangladesh. This life-threatening virus has been fatal in many cases. The fatality rate started to rise exponentially with time all around the world. In Bangladesh, the first three new cases were reported on the 7th of March, 2020. Though, infections endured low during March we can observe a rise in April 2020. The government has taken many steps to slow down the outspread. Many preventive measures are recommended in which social distancing is a major one.

Epidemiologists has made cubicle models for years to make vital forecasts about epidemics like Measles [1] and Polio [2]. By these mathematical models such as SIS [3], [4], SIR [5], SIRD [6], SEIR [7], MR-SIR [8], SIQR model [9], we can estimate that how many people can get infected or how quickly the infections will outspread through a huge number of inhabitants. Understanding the disease through such data and model helps us to illuminate the best way we can always use to fight the disease.

Researchers all around the world are trying to make a model that can help others to predict the spread of this infectious disease. Moreover, this study will help others to understand many other aspects associated with this disease like death rate, recovery rate, and the rate at which people are being infected. Most importantly this will also show a prediction about the rate at which the disease may decrease if preventive measures like social distancing are taken.

In this paper, we inspected the evolution of COVID-19 in Bangladesh with a modified SEIRD model and also dictated the expansion of this disease in Bangladesh. To the best of our knowledge, This work is the *first* to model social distancing with SEIRD model to analyze situation in Bangladesh.

The fundamental *objective* of this work is to carry out the effects of social distancing. We also provide a comparison between our predicted result with actual result. Our work covers: (i) developing a model for predicting the impact of coronavirus, (ii) Analyzing the impact of social distancing, and (iii) Analyzing the impact of isolation factor.

The remaining part of this paper is outlined as follows: In the Section II we discussed previous methods related to model Coronavirus or other pandemics. Section III gives an explicit explanation on the already established SEIRD model. We propose more effective and practical approach based on SEIRD model in Section IV. Section V reports the results of our proposed model, followed by conclusions in Section VI.

II. Related Work

To estimate a standard epidemiological model of the COVID-19 pandemic, many countries have approached many models such as SIS, SIR, SIRD (expansion of SIR model), SEIR, SIQR, etc. The epidemiological model mainly uses a microscopic description to predict the macroscopic behavior of disease spread through a population. For this paper, we would use a model SEIRD which is an extension of the SIR model. It describes the time estimation of the number of infected individuals during a disease outbreak. The population is classified according to their health state, susceptible (S),

* Equal Contribution

exposed (E), infectious (I), and removed (R) (recovered or deceased). It is very difficult to estimate an accurate parameter as the data is often incomplete due to a lack of reporting. Mathematical models also have capabilities as well as limitations. Sometimes the modeler can find the right combination of available data which can lead us to an answer. Now, there are a lot of works related to this COVID- 19 pandemics referring to epidemiological models. We focused on the recent ones which can lead us to more accurate predictability.

In the SIS model, the infected (I) individuals on recovery return to the susceptible (S) class as the disease confers no impunity from reinfection [3], [4], [10], [11]. Using the same model, many researchers found out the source of infection [12] and also some of them applied this model based on heterogeneous networks [13]. A study analyzes the spread of COVID-19 using the SIR model in South Korea [5] and also other European countries [14]. They [5] referred to the modeling problem as a forward-inverse problem. Using deep learning, they considered (S, I, R) and (β,γ) as variable and parameter accordingly. By using time-dependent parameters, they can successfully approximate the SIR model while the COVID-19 data fits. An entrenched paper regarding COVID-19 where cumulative data was studied to establish a SIR model on Euclidean network [15].

Another well-established work of estimating and simulating a SIRD model of COVID-19 for many countries, States, and Cities was published on May 2, 2020 [6]. They used data on deaths in New York City, various U.S states and various countries around the whole world. Their model fits the death equally well with alternate mortality rates of 0.3 percentage or 1.0. They considered five states in the SIRD model with social distancing where they showed important behavioral changes in response to the pandemic as well as policy changes related to social distancing.

Another work regarding targeted lock-down [8]; they used the Multi risk SIR model (MR-SIR) where infection, hospitalization and fatality rates vary between groups-in particular between the "young", "middle-aged" and "the old". If it is feasible to reduce interactions between high-risk groups and the rest of society with policies similar to those used for lock-down, then fatality rates can be reduced significantly and also optimal targeted policy can allow both a faster economic recovery.

Six endemic models were discussed for infectious diseases in a paper where they used SIQS and SIQR model with three incidence [16]. Here, they found out that the SIQR model with the quarantine-adjusted incidence, the indigenous equilibrium is an unstable spiral for some parameter values.

In another paper, the SIRS epidemic model for infections with non-permanent acquired immunity was introduced where it generalized the non-linear incidence rate and also the disease-related death [17]. Using the regression model and the SEIR model COVID-19 outbreak was predicted in India and another SEIR model was published based on Influenza in Bangladesh [18]. The paper in India which was published on April, 2020 [19] where (S) is the fraction of susceptible individuals, (E) is the fraction of exposed individuals (those who have been infected but are not yet infectious), (I) is the fraction of infected individuals (those capable of transmitting the disease) and R is the fraction of recovered individuals. Another analysis of COVID-19 by the SIQR model was introduced on the 9th of April, 2020 by an author of Bombay, Mumbai, India [20]. It is a variant of the classic SIR model. This model's variables are susceptible (s), infected (I), quarantine (Q), and recovered (R). In this paper, it was dictated that an individual can affect 1.55 other individuals who are less than Brazil and Italy because of the strict lock-down. Analyzing the dynamic compartments and epidemic parameters of COVID-19 the SEIR model determined the spread in a heterogeneous community [21].

A modified SEIR model was proposed in April, 2020 which was based on data in Bangladesh [7]. In this model, five different groups of the population were considered based on isolation. They have modified the SEIR model into the SEII$_s$R model where they have considered the isolation process of the infected patients. They have also shown graphically how lock-down is important to control the COVID-19 situation in Bangladesh. In the UK, another SEIR model was developed where the model was able to assess future epidemic situation considering different intervention strategies [22]. The remodeling of the SEIRD model was presented by introducing a time-dependent transmission rate. They reported the maximum infection spread for the three Italian regions firstly affected by the COVID-19 outbreak [23].

III. Preliminaries

SEIRD model is an epidemiological model and it is an improved version of the SEIR model. In this model there are 5 factors which are- Susceptible (S), Exposed (E), Infected (I), Recovered (R) and Death (D).

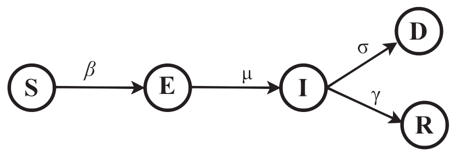

Fig. 1: Diagram of the SEIRD Model

The group of people who have not been infected but are at risk would be the susceptible category (S). Those who are prone to be infected will be in the exposed category (E). These people may not show any symptoms of Coronavirus for approximately 14 days. The people who have been infected and has visible symptoms of the disease fall under the infected category (I). After a brief period of treatment when infected individuals get cured, they are taken into account in the recovered category (R) and those who are not cured are taken in the account of death category (D).

The following Table I, outlines all the symbols which are used in Section III and also for the further remaining sections.

TABLE I: NOTATIONS USED IN THE ANALYSIS

Symbol	Parameter Name
S	Susceptible Population
E	Exposed Population
I	Infected Population
I_s	Isolated Population
R	Recovered Population
D	Death Population
α	Rate of Isolation (I_s)
β	Rate of Exposure (E)
γ	Rate of Recovery/ Mortality (R)
σ	Rate of Fatality/ Death (D)
μ	Rate of Infection/ Spread (I)
ρ	Social distancing factor

IV. Modelling Approach

A. Modified SEIRD Model

In our proposed SEIRD model, we have introduced two new elements which are the Isolation(I_s) state and the Social Distancing(ρ) factor. Firstly, we discuss the influence of isolation state, which we are adding to an already established SEIRD model. After that, we analyze the impact of social distancing.

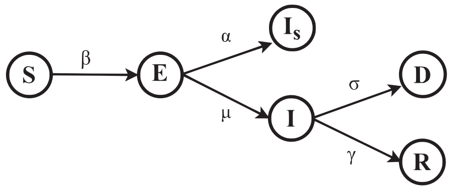

Fig. 2: Our Proposed SEII$_s$RD Model

Among the exposed individuals (E), those who have high chance of being infected would be kept segregated from rest of the population.This group of individuals will be considered for Isolation (I_s) category to prevent transmission of the virus. The confirmed cases of COVID-19 will be considered in the Infected (I) category.

B. Modified SEIRD Model using Social Distancing

One of the key factor that can play major role in reducing the spread of Coronavirus in Bangladesh is social distancing. The susceptible individuals can prevent themselves from being exposed to or infected by Coronavirus if they do social distancing by avoiding public gathering.

Since social distancing can reduce the transmission of Coronavirus, many countries are taking the matter very seriously. In our proposed model, we want to include the social distancing factor to see its impact on the rate of transmission of the virus. We introduced rho (ρ) as the social distancing factor. We observed the change in rates by changing the value of ρ. In our model, we tried to regulate the rate of exposure (β) by multiplying different values of the social distancing factor (ρ).

$$\beta_{\text{With Social Distancing}} = \rho * \beta_{\text{Without Social Distancing}}$$

With lower value of ρ we can decrease the rate of exposure hence resulting in lower cases of COVID-19. Similarly, increasing the value of ρ can result in higher rate of exposure meaning more number of COVID-19 cases. The effect is more prominent in the long run which is shown in Fig. (5), which will be discussed later.

C. Equations

eqs. (1) to (6) are differential equations of our proposed model [fig 2].

$$\frac{\partial S}{\partial t} = -\beta\frac{(S \times I)}{N} \tag{1}$$

$$\frac{\partial E}{\partial t} = \beta\frac{(S \times I)}{N} - \mu E - \alpha E \tag{2}$$

$$\frac{\partial I}{\partial t} = \mu E - \gamma I - \delta I \tag{3}$$

$$\frac{\partial I_s}{\partial t} = \alpha E \tag{4}$$

$$\frac{\partial R}{\partial t} = \gamma I \tag{5}$$

$$\frac{\partial D}{\partial t} = \delta I \tag{6}$$

By solving eqs. (1) to (6), we derived the equation of α, β, γ, δ, μ, shown in eqs. (7) to (11).

$$\alpha(t) = \frac{\Delta I_s}{E(t)} \tag{7}$$

$$\beta(t) = \frac{(\Delta_E + \Delta_I + \Delta_R + \Delta_D + \Delta_{Is}) \times_N}{S(t) \times I(t)} \tag{8}$$

$$\gamma(t) = \frac{\Delta_R}{I(t)} \tag{9}$$

$$\delta(t) = \frac{\Delta_D}{I(t)} \tag{10}$$

$$\mu(t) = \frac{\Delta_I \times \Delta_R \times \Delta_D}{E(t)} \tag{11}$$

V. Results and Analysis

In section IV we discussed the new factors that we incorporated in our Proposed SEI$_s$IRD Model. Our model showed satisfactory results. The prediction made by our model was really close to the real-time data that can be obtained from different reliable sources. A comparison between the real-data and the predicted data can be seen in Fig.3. The accuracy of our model was calculated and given in table II. In our model, we have taken ρ as the social distancing factor. By altering the value of ρ, we observed the rate of exposure, infection, isolation, death and recovery. If the value of ρ is equal to 1 it indicates current situation. If the value is greater than 1, it indicates people will maintain less social distancing then their current situation (relaxing the lock-down).

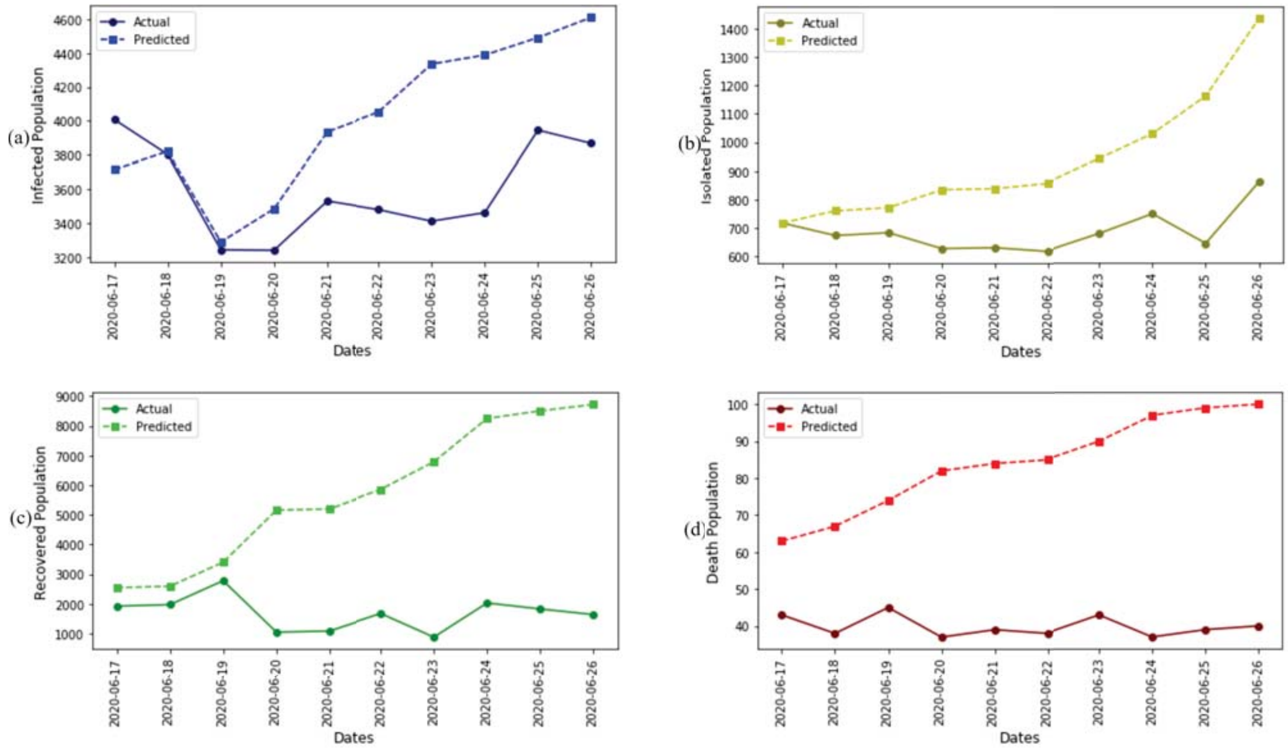

Fig. 3: Comparison of predicted data with the real time data (a) Infection (b) Isolation (c) Recovered and (d) Death.

A. Dataset

In this paper, our main focus is to study the effects of Coronavirus pandemic in Bangladesh. In order to do so we need some real-time information of the current situation. Hence, we started collecting the data from various reliable websites which provides the real-time data, like WHO[1], IEDCR[2] and another reliable source[3]. The dataset [4]includes daily number of deaths, recovered cases, tested cases, confirmed cases and number of people going into isolation. Data for 57 days were collected dating from 1st May till 26th June.

B. Prediction by Our Model

In our model, we used real time data to find the accurate value of infected, exposed, recovery and death. From Fig. 3 we can perceive that, in case of Infected (a), Isolation (b), Recovery (c) and Death (d) graphs respectively; their lines of prediction and real time are intersecting partially. In this regard, we can contend that our $SEII_sRD$ model is predicting the rate of Infection (I), Recovery (R), Isolation (I_s) and Death (D) quite satisfactorily. Training parameter of our model was basically based on the data of May (1st-31st), 2020, by which we trained data of 1st June to 15th June. Afterwards, we used those trained data to anticipate data of more 10 days. In this instance, our model learns the data of any one day and then it predicts the result of the immediate upcoming day. For example, based on 15th June data we are predicting the values of 16th June ; then again, based on 16th June we are forecasting the data of 17th June and so on.

Furthermore, using data of 16th June, 2020, we calculated our accuracy using the real time data and predicted data (II). On the basis of 16th June's data, we were somehow obtaining similar results which is why we started collecting data of 3rd day to compute accuracy which is shown in Table II. As we mentioned earlier V-A that we used data of 57 days consecutively, so based on 16th June we referred 19th June as 3rd day, 21st June as 5th day and 25th June as 10th day in the evaluation table. In most cases, our model has predicted with approximately 80-90% accuracy.

TABLE II: Accuracy Evaluation

Variables	Accuracy		
	3rd day	5th day	10th day
Infected	98.6%	89.7%	87.8%
Recovery	81.7%	20.9%	21.5%
Isolation	86.6%	75.2%	60%
Death	60.8%	46.4%	40%

[1]https://www.who.int/emergencies/diseases/novel-coronavirus-2019

[2]https://iedcr.gov.bd/

[3]https://manzurul-hassan.maps.arcgis.com/apps/opsdashboard/index.html#/09b3ecb62ca74ba1a5fe74671edc5e13

[4]https://github.com/MahirShahriar224/Modified-SEIRD-Model/tree/master/Datasets

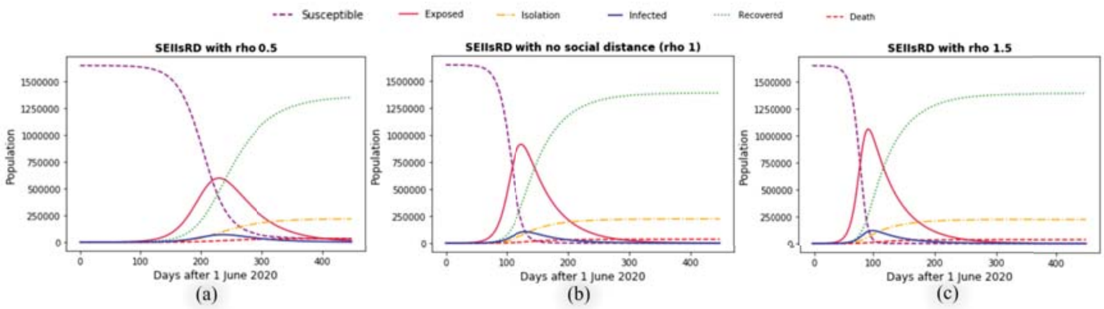

Fig. 4: Overall Pattern of our SEII$_s$RD Model with different value of ρ

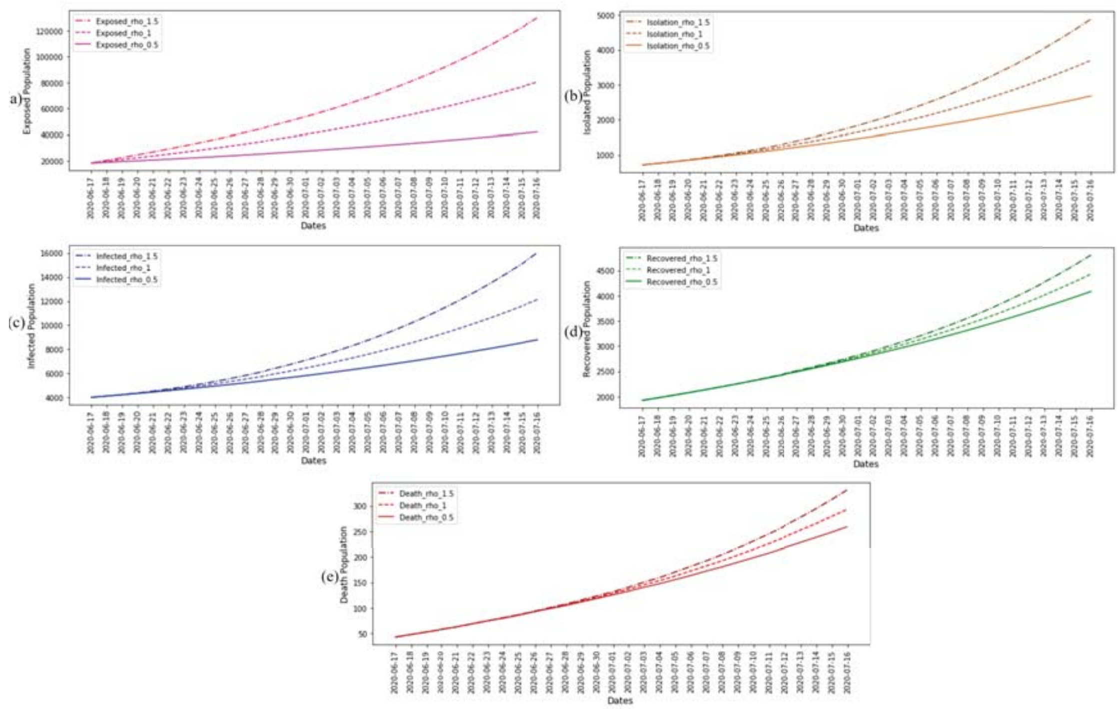

Fig. 5: Graph showing the change of rates with different values of rho (ρ) for (a) Exposed (b) Isolation (c) Infected (d) Recovery (e) Death

In worse case scenario, if the values are somehow much higher than usual values which means if there is any unusual data then it would impact our model's predicted result. However, by the time being, the impact will be lessen and the model would learn and start predicting accordingly. There are also some other factors which can affect our model's result. If people starts taking appropriate precautions as well as follows the advice provided by local public health agency and also if in the meantime, Bangladesh government improves their health care system in a significant way then our model's result can vary in respect to the real time.

C. Consequences of changing value of ρ

The rate of exposure, infection, isolation, death and recovery was studied individually. The graphs in Fig. 5 shows the results of altering the value of ρ. We can see that without social distancing and lock-down lifted, the infection rate is really high but if we maintain social distancing to some extent, the infection rate drops with respect to time. The more we consider perpetuating social distance the less we get the infection rate. In Fig. 4 an overall trend of our SEII$_s$RD model can be seen which gives a summary of all six factors of the model. It shows the impact of the value of ρ on different curves. We can observe the results of social distancing in contrast with no social distancing.

Social distancing will slow down the rate of infection of Coronavirus. This is a prime element which will help in flattening the curve. The curves in Fig. 4 depicts that maintaining strict social distancing can have a drastic change in rate of infection and consequently lead to flattening of the curve.

1) Impact of No Social Distancing: It is very tough to maintain social distancing in an over-populated country like Bangladesh. Moreover, it is a country where majority part of the population live on daily wage or very minimal income. If no social distancing is maintained, the rate of transmission will be considerably high as it can be seen in Fig. 4 (b). Here the the value of ρ is 1.

2) Impact of lockdown lifted: Lifting up the lock-down will have adverse effect in Bangladesh.The rate of transmission will rapidly increase. In Fig. 4 (c), we can see the trend when when the value of ρ is taken as 1.5.This indicates there is no social distancing and the lock-down has been lifted.

3) Impact of Social Distancing: Notable changes can be observed on the rates due to the effect of social distancing. In Fig. 4 (a) it can be observed that the change of ρ values has significant impact on the rates. Here, the value of ρ is considered as 0.5. There is fall in the rate of exposure and infection. Due to this reason,less number of people will go to isolation and the rate of isolation decreases as well. So, we can say that social distance has a positive effect in combating the Coronavirus.

VI. Conclusion

In this study, we have designed a modified SEIRD model which has a different architecture than classic SEIRD model including two new aspects: Social distancing and Isolation. We attained a satisfactory outcome using this model. The results which we acquired are very close to the real time data. We also estimated the consequences by considering the value of our one of the dominant factors which is ρ (social distancing).

As we can see from our study, the more we consider perpetuating social distance the less we get the infection rate. In these circumstances, appraising social distancing strictly can be an adequate resolve to overcome this distressing situation of Bangladesh more swiftly. There are also some elements which we didn't consider to estimate our result. For instance, if there are drastic constructive changes in our health care providing system or if the vaccine is invented of COVID-19, then it would definitely affect the out-turn of our model. This is one of our model's limitations which we would like to work with afterwards.

In the future, we intent to analyse the second wave of this contagious disease and examine how the age difference can affect the other variables in our model. To improve the efficiency performance further and to get a more promising result we would like to work with machine learning algorithms in particular.

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