

# Time-Series prediction for the epidemic trends of COVID-19 using Conditional Generative adversarial Networks Regression on country-wise case studies

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## Research Article

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## Time-Series prediction for the epidemic trends of COVID-19 using Conditional Generative adversarial Networks Regression on country-wise case studies

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**Abstract** Probabilistic Regression is a statistical technique and a crucial problem in the machine learning domain which employs a set of machine learning methods to forecast a continuous target variable based on the value of one or multiple predictor variables. COVID-19 is a virulent virus that has brought the whole world to a standstill. The potential of the virus to cause inter human transmission makes the world a dangerous place. This thesis predicts the upcoming circumstances of the Corona virus to subside its action. We have performed Conditional GAN regression to anticipate the subsequent Covid-19 cases of 5 countries. The GAN variant CGAN is used to design the model and predict the Covid-19 cases for three months ahead with least error for the dataset provided. Each country is examined individually, due to their variation in population size, tradition, medical management, preventive measures. The analysis is based on confirmed data, as provided by the World Health Organization. This paper investigates how conditional Generative Adversarial Networks (GANs) can be used to accurately exhibit intricate conditional distributions. GANs have got spectacular achievement in producing convoluted high-dimensional data, but work done on their use for regression problems is minimal. This paper exhibits how conditional GANs can be employed in probabilistic regression. It is shown that conditional GANs can be used to evaluate a wide range of various distributions and be competitive with existing probabilistic regression models.

**Keywords** Conditional Generative Adversarial Networks(CGAN), Covid- 19,Time series, Forecasting, Deep Learning

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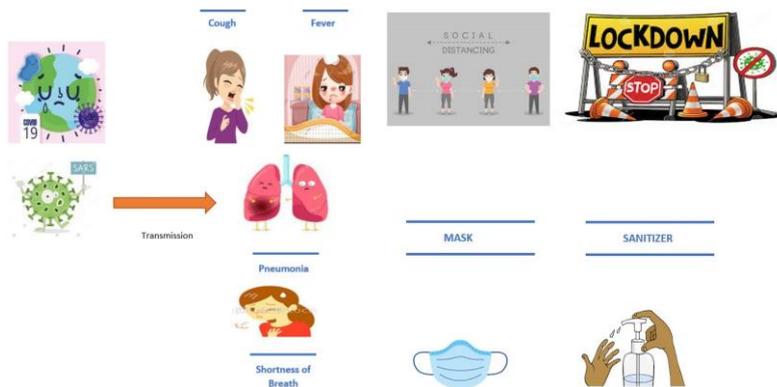
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## 1 Introduction

Since genesis of 2020, COVID-19 has brought entire world to a standstill, infecting greater than 135 million civilians and 2.92M deaths. [1]

This paper gives forecasts for escalation of the COVID19 virus for the widely infected countries like India, USA, Germany, Italy and Spain. Each country is individually inspected, because of their variations in population, habits, customs, health facilities, precautionary measures, etc. The analysis is dependent on actual data, as given by World Health Organization. The deployed deep learning model provides forecasts for new cases and death cases of the population for each country. COVID-19 has a high  $R_0$  value (denoting viral infectivity)[2] [3] of 3.25–3.4, represented by wide inter-human spread through the air, which means the flareup is uncontrollable. The main route of COVID-19 transmission is air-borne, thus curbing the source of infection, breaking off the infection route and prevention of endangered masses are the primary ways to discontinue the transmission of COVID-19. Because of this, many countries have taken measures like social distancing, night curfews, shutting down educational institutions, ceasing travel systems to prohibit more transmission of the epidemic [4][5]. Due to collected effort of authorities, the public, steps have given rise decreased spread in multiple countries, also the epidemic is decreasing to a large extent. Taking into account the seriousness of the pandemic depicting when the epidemic will terminate is extremely essential for the smooth running of systems of affected countries. Since COVID-19 is basically data on time series so forecasting of future data is extremely needed. Machine Learning and Deep Learning techniques are really beneficial and commonly used in time series prediction. Figure 1 shows transmission and mitigation of Covid19.



**Fig. 1** Transmission and mitigation of COVID 19

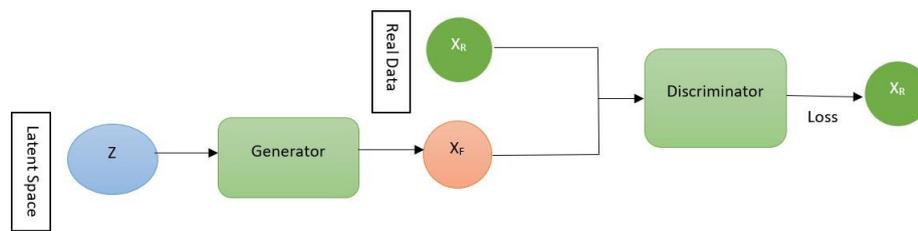


Fig. 2 GAN Architecture

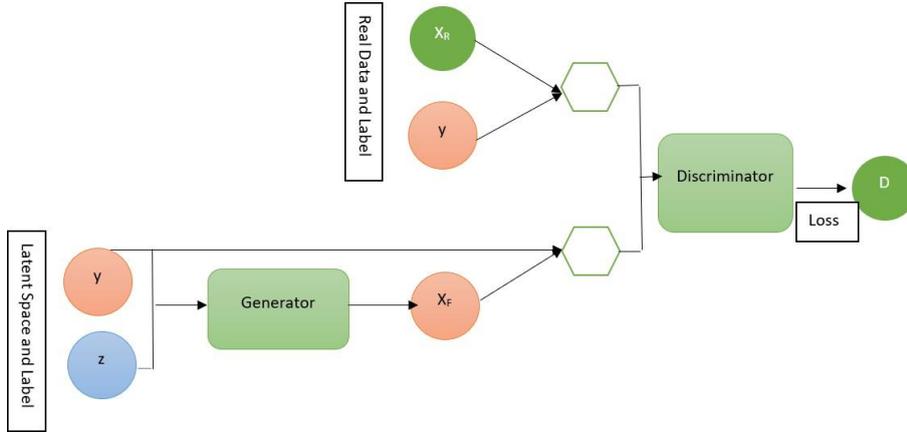
## 2 Related Work

From early centuries the pandemics were prevalent before happening in year 2020. The pace of the entire globe has been stopped due to it. The SARS-COVID-19 virus is originated from Wuhan city, China in the year 2019 [6]. The first death was seen in the month of January that convinced that the virus spread through inter human transmission or very near contact with the person who is suffering from the disease [7]. The United States, Turkey, Russia, the UK and Germany — were the countries mostly affected in December. 46 different countries also saw extreme cases in December. Among them maximum deaths were seen by 31 countries. After fighting long vaccines are available in most countries. Arora et.al. [8] shown the prediction of Covid-19 using LSTM for all states of India with error of 3%. An ensemble model was designed by Abdulmajeed et al. [9] that took realistic COVID-19 data from Nigeria Center of disease control. Clément Massonnaud et. al [10] Studied the epidemic in France, and also evaluated the effect on healthcare resources for each area of France metropolitan. They produced a SEIR model based on attractive area of the hospitals. Cleo Anastassopoulou et. al. [11] provide estimates of the main epidemiological parameters.

Current Machine learning research is based on deploying models that produces distributions similar to underlying data. Most generative models presume a particular variant. CGAN [13] have exhibited a higher capability to produce authentic samples. Kernel methods, deep neural networks form the non-linear function. Intricate noise forms such as heteroscedastic noise have to be produced using specialized models [12]. Nowadays, research is with image data with a huge organized output space. The categories of various issues like regression is given minimal attention. This paper gives a distribution. Conditional Generative adversarial networks [13] regression is used here.

## 3 Methodology

GAN is a model which produces actual data and has two neural networks, generator and discriminator. Generator produces fake samples. The discriminator has to distinguish whether the input it is getting is G versus real data set. The discriminator will output a logic 1 if it finds that its input is more realistic. [14]. GANs



**Fig. 3** CGAN Architecture

are continuously evolving domain that provides generative models which produces real like data across different areas of problems for example in image translation tasks like translating pictures of young face to aging face etc. The generator produces a group of samples. These samples alongwith real like data are given to the discriminator and categorized as fake or real. The discriminator thus gets better at distinguishing original and duplicate samples in the subsequent round. After that, the generator will get updated depending upon how perfectly the generator model fooled the discriminator.

Conditional GAN (CGAN) [13] differs from original GAN in the way that it puts an extra condition to manage the production method of the data by concatenation of an vector  $y$  to both the generator as well as the discriminator. The latent vector  $z$  and vector  $y$  is input to generator. The samples and the information are fed to the discriminator. Figures 2 and 3 show GAN and CGAN architectures respectively. The CGAN objective function is shown in Figure 4

$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x}|\mathbf{y})] + \mathbb{E}_{\mathbf{z} \sim p_z(\mathbf{z})} [\log(1 - D(G(\mathbf{z}|\mathbf{y})))]$$

**Fig. 4** CGAN objective function

#### 4 Experimental Setup and Implementation

In this paper we employ the CGAN [13] where conditioning is performed on the generator and discriminator at the time of training by adding some extra infor-

mation. This information could be anything for example, class labels. Wasserstein GAN [15], can be used also for minimizing loss function[12]. They optimize another loss function, that could affect the performance. We report Root Mean Square Error (RMSE) metric with the experiment. It is one of the important metrics, inspecting importance of the guess of unpredictability is of huge concern.

#### 4.1 RMSE

Given a test dataset,  $(x_i, y_i) \ i=1..N$ , to find the root mean squared error, we first need to evaluate the residuals. Residuals are the subtracted value between the actual values and the predicted values. I denoted them by  $y_i - \hat{y}_i$  where  $y_i$  is the observed value for the  $i$ th observation and  $\hat{y}_i$  is the predicted value. RMSE can have any values both positive as well as non positive as the depicted value lesser or higher rates the actual value. After performing the residuals square, the squares are averaged, and the square root is taken giving us the RMSE. After that the RMSE is deployed as a quantity of the spread of the  $y$  values around the depicted  $y$  value.

#### 4.2 Dataset

We have used the real world WHO - COVID19 dataset taken from <https://covid19.who.int/table>. The dataset consists of new and cumulative cases, new and cumulative deaths which are to be forecasted. The data used for training the model is from 1st January 2020 to 6th April 2021. We have tested the model from 7th April 2021 to 31st July 2021.

#### 4.3 Preprocessing

On real world COVID 19 data, training set was preprocessed using minmax scaler preprocessing.

#### 4.4 Dataset statistics

After dividing our dataset to training, test groups, we find 80% of dataset to be training and 20% of the dataset as test data.

#### 4.5 Model Architecture

We have used DNN for CGAN. A six layered network is used for the generator part. The three-layered multi-layer Perceptron gets as input  $x$  and noise  $z$ . On the other hand the output illustrations are chained to a three-layered network. Linear activation is used for last layer while Rectified linear unit (RELU) [16] as activation function for remaining layers. RELU performed much better activations such as Leaky-RELU or selu. A four-layered network is used for discriminator. The single

non-linear layer takes as input  $x$  and  $y$ . After that, a three layered multi layered perceptron that employs sigmoid activation function in the final layer takes the concatenated output. The optimizer used is Adam and learning rates used are of values  $10^{-2}$ ,  $10^{-3}$ ,  $10^{-4}$ . The number of epochs used was 500. The discriminator and generator training steps ratio was set to 1. Our model used a batch size of 100. Noise  $z$  dimension was taken as 1. the input dimension was 3. Test was performed on a computer having 16GB RAM. CGAN captures very intricate conditional distributions, while different regression methods require various changes.

#### 4.6 Heteroscedastic noise

Covid19 real world dataset shows more complex noise. This dataset employs heteroscedastic noise. CGAN generates more realistic samples and captures the heteroscedastic noise structure very well. CGAN can learn to model any type of noise very easily.

#### 4.7 Increasing the dimensionality of noise

Employing a larger dimensional noise can assist get enhanced behaviour for problems with complex noise.

The proposed framework of the model is shown in Figure 5. The generator network structure and discriminator network structure are shown in Figure 6 and 7 respectively.

#### 4.8 Mechanism of Rolling Update

In COVID-19 cases for achieving extended forecasts, a rolling update process is employed. It is used to upgrade the training example sequence depending on the present forecast values instantaneously for the purpose of training the model. It is actually done to enhance the rolling control of feedback evaluation in a bounded amount of time.

There are different parameters in the model. The input time step is taken as 3, which implies that new cases count of the next day is dependent on the cases of the last three days. The count of hidden neurons is 40, This is the input which is fed to hidden layer. The model used Adam optimizer, training of 500 epochs.

### 5 Results and Discussions

Results of COVID cases and deaths of five countries India, Italy, Spain, USA, Germany are visualised graphically and RMSE classification metric calculation. Covid-19 new cases and death cases predicted values of the five countries are visualised from figures 8-17 The blue curve represents the training portion. The green curve represents true data from 7th April 2021 to 31st July, 2021. And the yellow curve shows the predicted values.

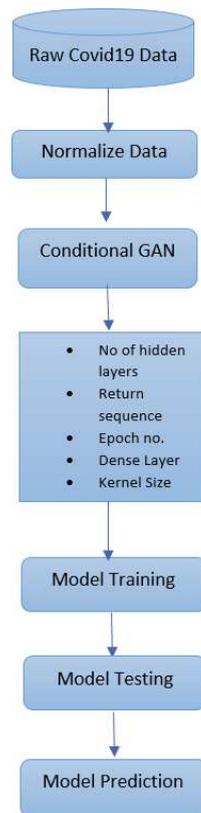


Fig. 5 Proposed Methodology Framework

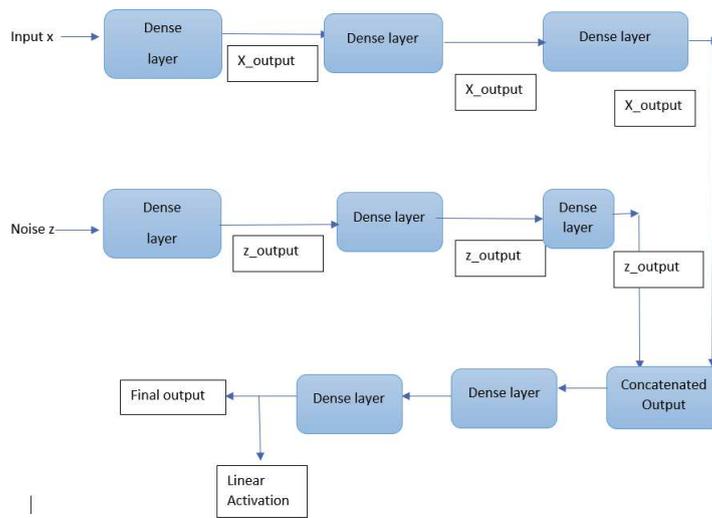
## 6 Covid-19 Forecasting of daily new cases

The COVID19 true and predicted data of the countries India,USA, Spain, Italy, Germany are visualised graphically in the figures 8,10,12,14,16. The blue coloured curve depicts actual values and red coloured curve depicts forecasted values.

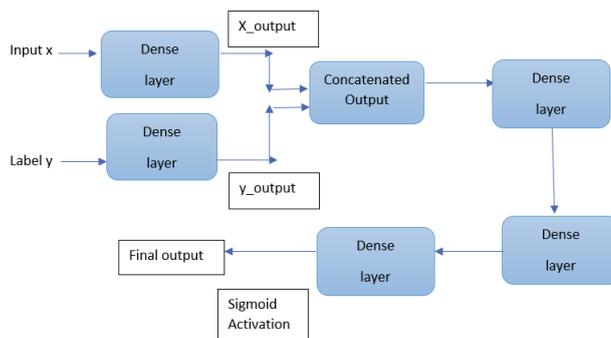
## 7 Covid-19 Forecasting of daily new death cases

The COVID19 true and predicted data of the countries India,USA, Spain, Italy, Germany are visualised graphically in the figures 9, 11, 13, 15, 17 . The blue coloured curve depicts actual values and red coloured curve depicts forecasted values.

The analysis of the graphs and classification metric implies that graphs and CGAN results are very close to the real cases of the five countries. The alpha value



**Fig. 6** Generator network structure



**Fig. 7** Discriminator network structure

or significance level is considered to be 0.05 or 5% . When P-value is smaller than alpha value, the results are statistically significant.

Alpha value is actually a threshold p-value, that is actually decided by a team who conducted the test. It is decided before performing significance test.(Z Test)

To find the reported and forecasted value difference, Root Mean Square Error is

$$\text{RMSE} = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}$$

to be found , by the equation: RMSE =

**Mean absolute percentage error (MAPE)** It evaluates how good a prediction model is. It calculates this accuracy in terms of percentage.

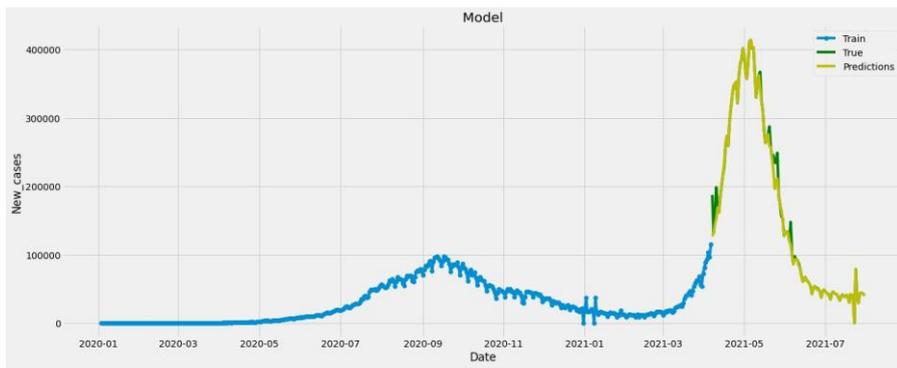


Fig. 8 India New Cases

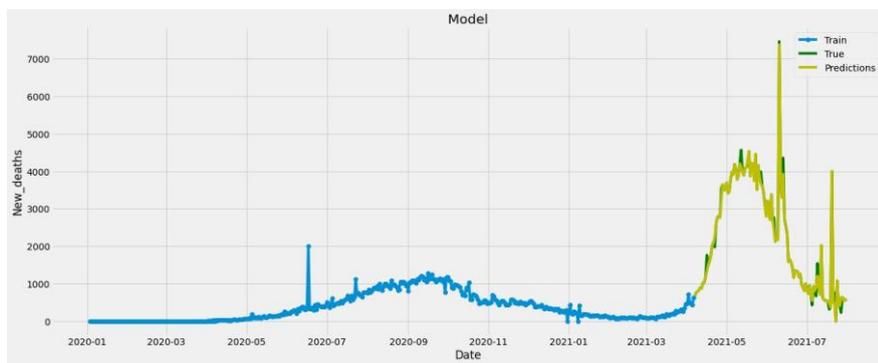


Fig. 9 India New Deaths

MAPE output is non-negative floating point. The best value is 0.0. But note the fact that bad predictions can lead to arbitrarily large MAPE values, especially if some  $y_{true}$  values are very close to zero. Note that we return a large value instead of inf when  $y_{true}$  is zero. MAPE is calculated by the equation  $MAPE =$

$$100\% \sum \frac{|y - \hat{y}|}{y}$$

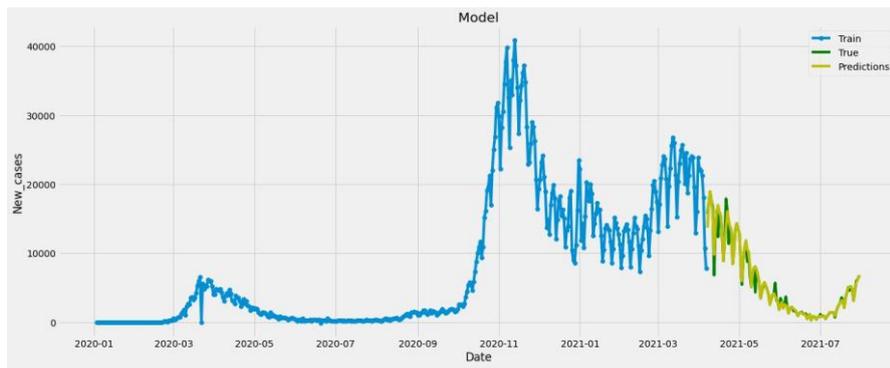
Mean absolute percentage error (MAPE) is shown in Table 4 It gives minimum errors in our predicted data.

**R2 Score** R-squared (R2) or Coefficient of Determination is a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model. It is also

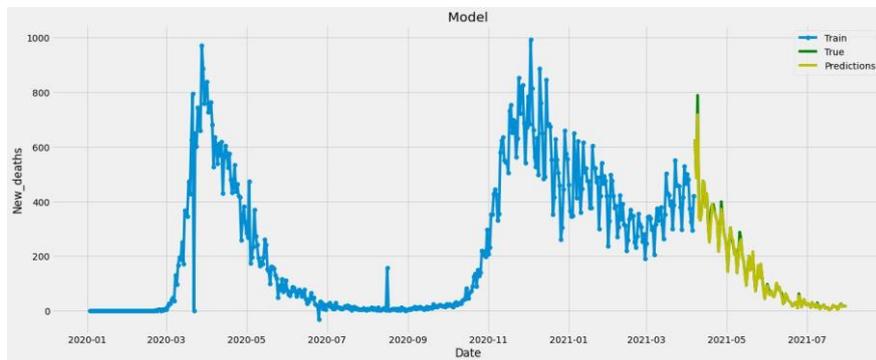
called the coefficient of determination.  $R^2$  Score =  $1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$

Coefficient of Determination is shown in table 5

**Explained variance score** It is used to measure the discrepancy between a model and actual data. In other words, it's the part of the model's total variance that is explained by factors that are actually present and isn't due to error variance. The great score is 1.0 and lesser values are bad.



**Fig. 10** Italy New Cases



**Fig. 11** Italy New Deaths

Explained variance is shown in figure 6.

Table 7 shows predicted and reported data of the new COVID cases of India, Italy, Germany, Spain, USA from 6th June 2021 to 10th June, 2021. The values show that reported and predicted data are very close to each other.

**Table 1** Choosing Data used for experiment

Country	Confirmed cases	Death cases
India	1.1.2020-06.04.2021	1.1.2020-06.04.2021
Germany	1.1.2020-06.04.2021	1.1.2020-06.04.2021
USA	1.1.2020-06.04.2021	1.1.2020-06.04.2021
Italy	1.1.2020-06.04.2021	1.1.2020-06.04.2021
Spain	1.1.2020-06.04.2021	1.1.2020-06.04.2021

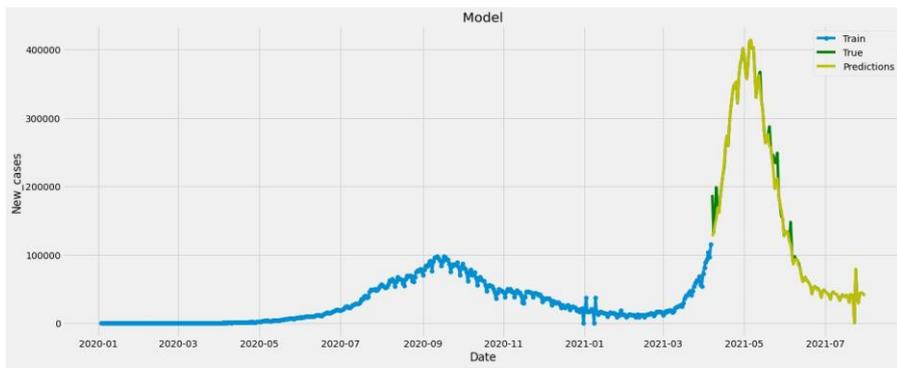


Fig. 12 Germany New Cases

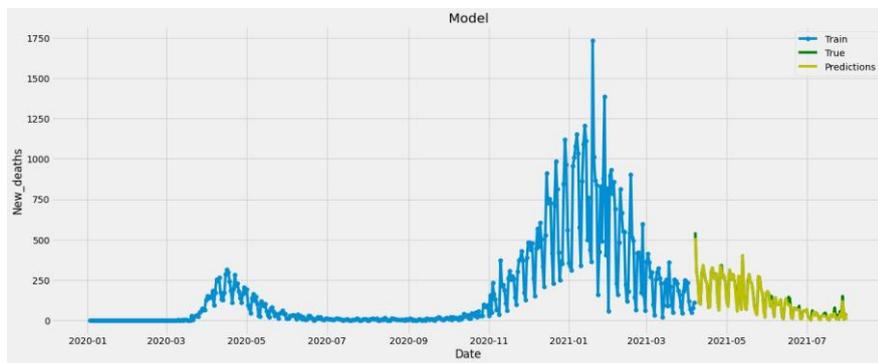


Fig. 13 Germany New Deaths

Table 2 RMSE Values

Country	New Cases	Cumulative Cases	New Deaths	Cumulative deaths
India	557.4	448.49	163.35	503.44
Germany	665.65	231.3	412.6	242.06
USA	709.35	542.8	587.54	142.43
Italy	734.7	681.7	308.5	221.4
Spain	603.56	126.3	253.8	203.4

## 8 Discussions and Suggestions

### 8.1 Development of Vaccine and its side effects

Presently, there are 115 candidate vaccines for [17] COVID-19. In total there are 33 candidate vaccines in stage 3 clinical trials. So far, 15 vaccines have been authorized across several countries. After a thorough evaluation of phase 3 clinical trial data major side effects after getting the Sputnik V vaccine were flu-like illness, headache, fatigue, and reactions at the injection site. It is based on surveys from 12,296

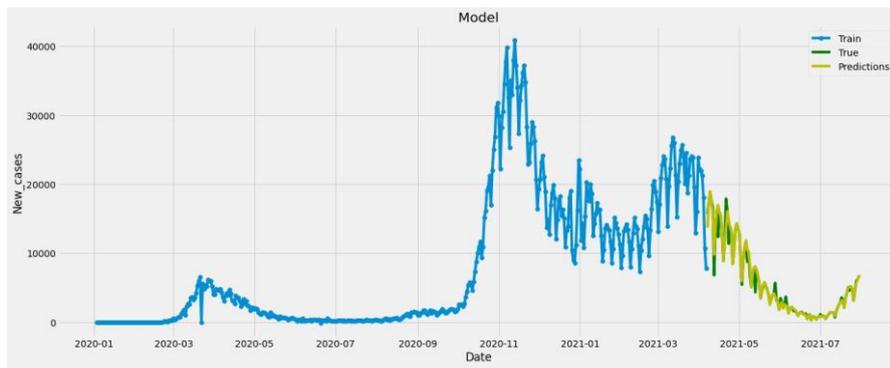


Fig. 14 USA New Cases

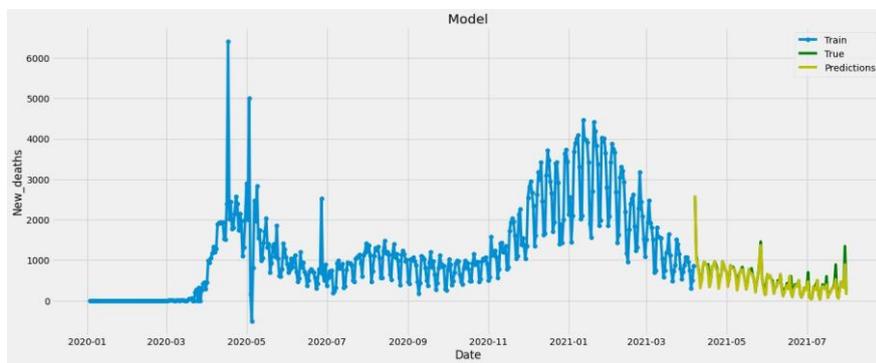


Fig. 15 USA New Deaths

Table 3 P values

Country	New Cases	Cumulative Cases	New Deaths	Cumulative deaths
India	0.02	0.007	$0.008e^{-2}$	$2.15e^{-1}$
Germany	0.003	$2.43e^{-1}$	0.0016	$3.3e^{-2}$
USA	$3.6e^{-2}$	$2.6e^{-1}$	$2.87e^{-1}$	$3.05e^{-2}$
Italy	$2.18e^{-2}$	$1.28e^{-1}$	$3.41e^{-1}$	$2.11e^{-2}$
Spain	0.014	$2.6e^{-2}$	$3.2e^{-1}$	$2.5e^{-2}$

participants who had received two doses of either the vaccine or the placebo. There is quite a lot of turmoil regarding the vaccine, with some scientists unsure of the data and remaining are scared of side effects that the shot employs[18] However, 64 countries have been using the vaccine, in addition to Russia.

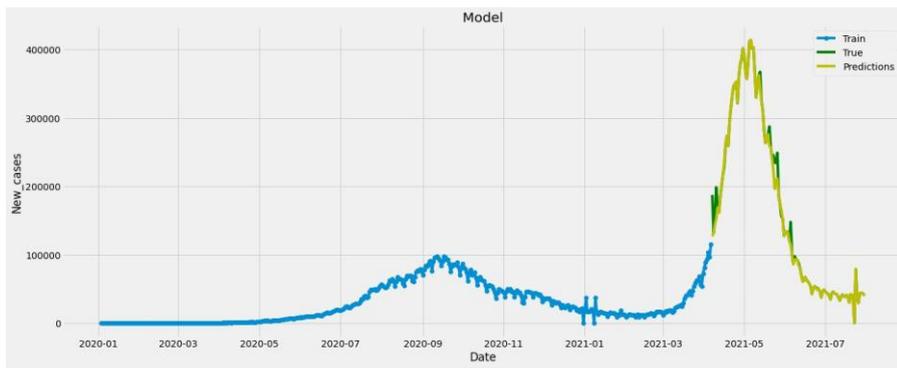


Fig. 16 Spain New Cases

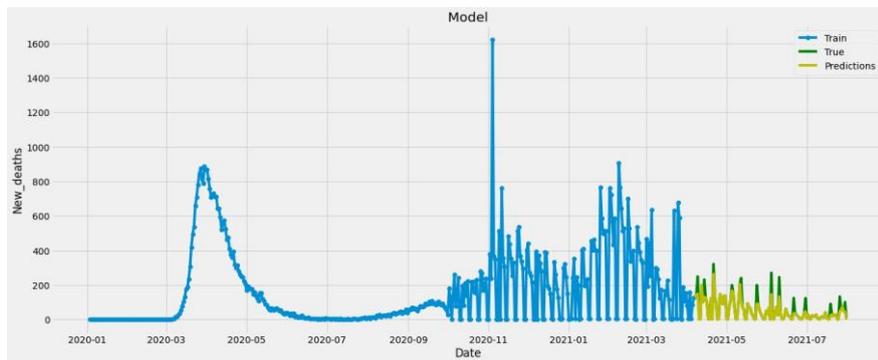


Fig. 17 Spain New Deaths

Table 4 mean absolute percentage error

Country	New Cases	Cumulative Cases	New Deaths	Cumulative deaths
India	2.38	2.49	1.26	0.66
Germany	0.54	2.40	0.84	3.42
USA	0.84	2.64	0.40	3.52
Italy	0.59	2.18	3.33	2.38
Spain	1.94	3.87	3.04	1.91

### 8.2 Transmission of Covid19 through air

Covid-19 is a disease that spreads through air and is a danger to the world, according to various researchers. Aerosol transmission is another mode of transmission of Covid-19. Not going outside house, frequent cleaning of hands and maintaining social distance are compulsory measures for avoiding airborne transferral of COVID-19 according to WHO with various other international authorities. Wearing face masks is extremely essential to stop inhaling aerosol. Social gathering must be avoided. aerosol transmission is not universally accepted till now but some re-

**Table 5**  $R^2$  score, the coefficient of determination

Country	New Cases	Cumulative Cases	New Deaths	Cumulative deaths
India	0.87	0.77	0.89	0.84
Germany	0.768	0.8	0.9	0.96
USA	0.75	0.86	0.78	0.98
Italy	0.83	0.75	0.93	0.88
Spain	0.89	0.94	0.84	0.95

**Table 6** explained variance score

Country	New Cases	Cumulative Cases	New Deaths	Cumulative deaths
India	0.54	0.60	0.61	0.62
Germany	0.68	0.84	0.56	0.64
USA	0.51	0.90	0.76	0.50
Italy	0.73	0.51	0.633	0.60
Spain	0.63	0.85	0.71	0.85

searchers found evidences of it [19]. So, precautionary measures must be taken to be prevented from the dangerous effects of the pandemic.

## 9 Conclusion

Covid-19 has [20] brought the world to a standstill due to its rampant spread. World has to cope with the with the pandemic as it is not known how long the pandemic will be there. We used deep learning model to predict new cases and new death cases for India, USA, Spain, Italy and Germany of COVID19 in this paper. Collecting the data of Covid-19 really hard because of its limited availability for forecasting time series data. Conditional Generative adversarial network is used to model the predictions. The Root mean squared error is evaluated here. The predictions of this paper's CGAN model which provides current situation's results is close to actual Covid-19 data. This paper is the first evaluation of India, USA, Spain, Italy, Germany Covid-19 new cases and deaths. Our study will be essential for the five countries to take proper steps before being dominated by Covid-19 pandemic. We can inspect the losses incurred by the economies of the countries at the end of Covid-19 and take precautionary steps to overcome it, which can help the countries to come back into normal conditions. The Covid-19 new cases and death cases of several other countries can be predicted later on.

## 10 Declaration of Competing Interest

The authors declare that they have no familiar monetary motives that could have portrayed to impact the task presented in this paper.

**Table 7** True and depicted daily new cases comparison

Country	Date	Reported data	Predicted data
India	06.6.2021	100636	100321
	07.6.2021	86498	86212
	08.6.2021	92596	92321
	09.6.2021	93463	93112
	10.6.2021	92291	92345
Germany	06.6.2021	1964	1912
	07.6.2021	1444	1421
	08.6.2021	2253	2289
	09.6.2021	3275	3264
	10.6.2021	2747	2732
USA	06.6.2021	5395	5356
	07.6.2021	15496	15400
	08.6.2021	13013	13000
	09.6.2021	18647	18670
	10.6.2021	14545	14500
Italy	06.6.2021	2275	2289
	07.6.2021	1270	1265
	08.6.2021	1894	1800
	09.6.2021	2198	2450
	10.6.2021	2078	2043
Spain	06.6.2021	3	10
	07.6.2021	9542	9456
	08.6.2021	3504	3605
	09.6.2021	4427	4489
	10.6.2021	14004	14390

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