An Effective Prediction on COVID-19 Prevalence for India and Japan using Fbprophet Model

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ABSTRACT
Coronavirus has become a significant concern for the whole world. It has had a substantial influence on our social and economic life. The infection rate is rapidly increasing at every moment throughout the world. At present, predicting coronavirus has become one of the challenging issues for us. As the pace of COVID-19 detection increases, so does the death rate. This research predicts the number of coronavirus detection and deaths using Fbprophet, a tool designed to assist in performing time series forecasting at a large scale. Two major affected countries, India and Japan, have been taken into consideration in our approach. Using the prophet model, a prediction is performed on the number of total cases, new cases, total deaths and new deaths. This model works considerably well, and it has given a satisfactory result that may help the authority in taking early and appropriate decisions depending on the predicted COVID situation.
INTRODUCTION

Coronavirus is a respiratory virus triggered by a plain intense respiratory disease that causes infections to humans and animals. The novel coronavirus disease (COVID-19) is a new virus discovered throughout the whole world. None of us is ready to fight against this. The deadly pandemic has caused millions of deaths worldwide by establishing itself as the world's worst incubus. However, the first Covid-19 case was identified in Wuhan, China, in December 2019 [1]. COVID-19 spread from individual to individual over the respiratory stretch after coughing, sneezing, or breathing of an infected person. A new infection occurs when inhaled droplets or aerosols from an infected person enter the mouth, nose, or eyes in close contact with an infected person [2]. By the end of May 2021, the number of COVID-19 patients identified globally has reached about 160 million, and more than 3.5 million people have already died [3].

In an attempt to monitor the expanse of the virus, governments worldwide have taken several close observations, such as social distances and clothing masks, surgical masks, respirators, or other facial coatings to control stem infections.

Predictive analysis of COVID-19 has already become a popular research area. Besides, modelling and predicting the day-to-day expanse of the virus can help frontline healthcare professionals prepare for the compromise of an impending number of patients. Accurately predicting the disease is a matter of concern because it can affect government policies and control rules, health systems, and social life. In this circumstance, we introduce the predictive capabilities using the Fbprophet forecasting model. This paper proposes a predictive model that uses the Fbprophet framework and probability to forecast outcomes, and Time-series analysis is also performed here. This model has been used to predict new cases, total cases, new deaths, and total deaths of people in India and Japan. The main objective of our proposed model is to help the authority in making decisions by predicting the upcoming affected and death number due to COVID-19.

This model will play an essential role in handling the COVID-19 pandemic in India and Japan in the upcoming waves. The author also thought that it might be possible to determine coronavirus outbreaks in future events with this model.

LITERATURE REVIEW

Various research work is underway to assess and capture the global catastrophe of COVID-19 on the human race. The research studies include predictions about future cases and an analysis of moving liable for the Covid tract. Chintalapudi et al. [4] adopted a seasonal Arima model to predict data from 19 cases in Covid-Italy, until March 2020. They analyzed the impact of the two-month lockdown in Italy and observed a decrease in the number of cases recovered due to the lockdown and a reduction in confirmed cases. Alibi et al. [5] have used the Fbprophet model to predict the spread of COVID-19, where they represented the number of confirmed and predicted deaths, and their model was accurate near 79.6%. Ribeiro et al. [6] studied predictive assessments of models using COVID-19 day-level cases from ten states in Brazil. Conferring to the authors, the piling ensemble and SVR achieved better than the Arima, Cubist, Ridge, and RF models for the accepted standards. Fanelli et al. [7] established and studied the Arima (P, D, Q) model of the COVID-19 epidemic trend in three countries; Spain, Italy, and France. They suggested that the Arima models are suitable for forecasting the spread of COVID-19 for the coming days. Parikshit et al. [8] predicted using COVID-19's treatment perspective by Fbprophet model because of the open-source algorithm, accuracy, and fast data fitting. Using the prophet model, they forecast 1.6 million infected patients worldwide by May 2020 and 2.3 million by June 2020. Aditya et al. [9] used a humble hitherto active mathematical model to forecast the futurity of India using standing data. They also valued the result of social separation through time-dependent coefficients of the model. The model study with the correct odds indicates that the epidemic will be at its peak in late June or the first week of July. About 108k Indians are likely to be infected when the lockdown will be relaxed after three months. Wynants et al. [10] focused on studies involving the diagnosis of COVID-19 and the number of predictions that may be transmitted in the future. The authors recommended that investigation based COVID-19 data have to be made publicly available to inspire more precisely designed recognition and prediction models. Pandey et al. [11] operated two arithmetic algorithms to

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estimate and forecast the spreading of COVID-19 in India. They applied a dataset reclaimed from the John Hopkins University source. Kumar et al. [12] forecast the COVID-19 blowout in the 15 most transited countries with the model of ARIMA. The product of their prediction shows that circumstances would deteriorate in Iran and Europe, mainly in Italy, Spain, and France. Likewise, their prediction showed that more constant cases were found in mainland China and South Korea.

3. METHODOLOGY

Numerous outbreak prediction models for COVID-19 are castoff by officials around the world to make resolutions and implement relevant control measures. Among the standard models for the COVID-19 global pandemic forecast, we used the Fbprophet model to predict the covid cases.

3.1 Predictive Model

Predictive analyzes are branches of advanced analysis that are used to make predictions toward incognito future events. It uses many methods of data mining, statistics, modelling, machine learning and artificial intelligence to investigate current data to predict the future. This is an effective way to add intelligence to our application for predicting consequences alongside new data. In our approach, we used the Fbprophet model with Python language for making a predictive model for COVID-19 case prediction.

3.2 Fbprophet Model

Fbprophet is an uncluttered source framework for Facebook to predict the time series [13]. This is a prediction process applied to Python that offers quick and fully automated predictions that data scientists and analysts can manually tune in and use to predict the results for future observations. It provides spontaneous parameters that are tranquil to tune. Even somebody who deficiencies the skills of time series forecasting models can use it to produce expressive predictions.

3.3 Time Series Forecasting

A time series is an instruction at data points that are recorded at reserved time points most of the time at fixed intermissions (seconds, hours, days, months, etc.). Each corporation produces a large quantity of data every day for its auctions statistics, pays, circulation, or operating expenditures. Time series can create valued evidence for data mining, long-term business choices, yet they work in most companies. Below is a list of possible ways to take advantage of time series datasets: Trend Analysis: Only plotted data against time can generate a lot of strong insight. Very early use of data only understands the temporal pattern/trend measuring [14]. It can even give an initial indication of the overall direction of a general business hoop in business. Predictions: Predicting future values using historical data is a general method for data extrapolation. Predictive Analysis like advanced statistical analyzes, such as panel data models heavily rely on multi-variant longitudinal datasets [15]. This type of analysis helps predict business, identify explanatory variables, or understand connections between the properties of a dataset. In our case, the predictive analysis is performed to predict the future situation of COVID-19 epidemic and show the gap that affects the whole world.

3.4 Data Source and Research Material

The large dataset of COVID-19 was collected from a publicly available repository of Kaggle. The dataset link is provided here: https://www.kaggle.com/bolkonsky/covid19. The primary use that we have used for implementation is GoogleColab, where the scripting language is Python3. Matplotlib is used for data visualization.

3.5 Research Design

Here in Fig. 1, the research design is represented in the form of a flowchart.

At first, we collect the dataset from Kaggle that reports new COVID-19 cases and total cases, new death, and total deaths for India and Japan. Then we import the dataset in GoogleColab and create a date frame for convert the given series object to date frame. Then data is split for training and testing, 80% data is for training and 20% for testing. Next, we create our model and fit the model with train data. We used this model because fully automated forecasting techniques can be fragile [16], and they are often not too complicated to include proper guesses or heuristics. After that it makes a future date and made the prediction with that. Afterwards, we show a visualization of the comparison between predicted data and original data. The effect of COVID-19 is shown on a weekly, yearly basis through visualization.
4. PREDICTIVE MODELING

4.1 Forecasting of COVID-19 Cases for India with Prophet based model

Table 1 displays COVID-19 new cases of India that forecast Yhat (indicating the accurate prediction), yhat_lower (minimum forecast) and yhat_upper (maximum forecast). Here, the standard prediction value is 46913, minimum and maximum prediction values are 34768 and 59161, respectively.

Fig 2 indicates the relationship between the black dotted line, which marks the predicted value and the solid line as the actual value in the new case of COVID-19 in India. The predictions and key values we see in Fig. 9 run the same way. Here, we see some errors that the effects of the coronavirus were getting worse at the moment.

Table 2 shows the COVID-19 forecast of India, where yhat indicating the accurate prediction, yhat_lower is the minimum forecast, and yhat_upper is the maximum forecast for the next 60 days. So based on the table above, the number of new death till 2021-04-06 is increasing to 108. We imbibe from Table 2 that people are affected day after day, and it increases both the actual value and the predicted value significantly. The predicted values will increase slightly compared to the actual values.
Table 1. Forecasting of new cases

| Date       | yhat      | yhat_lower | yhat_upper  |
|------------|-----------|------------|-------------|
| 426 2021-03-31 | 45988.905232  | 33331.119869  | 58772.268267  |
| 427 2021-04-01  | 45904.084206  | 34317.240120  | 57849.267510  |
| 428 2021-04-02  | 46665.877903  | 34199.683831  | 58524.455565  |
| 429 2021-04-03  | 47917.355130  | 36006.815581  | 60012.879981  |
| 430 2021-04-04  | 46586.293051  | 34466.093271  | 59377.519147  |
| 431 2021-04-05  | 43124.592240  | 31466.280872  | 55356.148018  |
| 432 2021-04-06  | 46913.739800  | 34768.394670  | 59161.419776  |

Fig. 2. Predicted value vs Actual value for new cases

Table 2. Forecasting of new deaths

| Date       | yhat      | yhat_lower | yhat_upper  |
|------------|-----------|------------|-------------|
| 426 2021-03-31 | 101.345369  | -66.955130  | 245.077139  |
| 427 2021-04-01  | 93.844757  | -65.718594  | 238.597509  |
| 428 2021-04-02  | 88.521151  | -58.640266  | 245.467072  |
| 429 2021-04-03  | 84.765906  | -63.921418  | 237.964912  |
| 430 2021-04-04  | 49.006681  | -100.815293 | 208.166026  |
| 431 2021-04-05  | 28.808199  | -126.289107 | 178.316326  |
| 432 2021-04-06  | 107.801444 | -50.314030  | 257.061117  |

Fig. 3. Predicted value vs Actual value for new death
Fig 3 indicates the relationship between the black dotted line, which specify the predicted value and the solid line referred to as the actual values of the confirmed case of COVID-19 in India. Almost predicted, and the original values run the same as we saw in Fig 3. Similarly, graph of total deaths and total cases matches exactly with Fig. 3.

4.2 Forecasting of COVID-19 Cases Japan with Prophet based Model

From Table 3 on the 2020-11-27, the prediction result for Total cases with covid infection in Japan was 115182. Minimum prediction value was 112968 and maximum prediction value was 1151822. so based on the table above, the number of Total cases is increasing.

From this figure, we can see black scattered line specify the prediction outcome, and blue hard line indicated actual value. Both values in an identical track, this model fit well in Fig. 4.

From Table 4 on the 2021-04-06, the prediction result for new cases with covid infection in Japan was 1145. Minimum and maximum prediction value was 131 and 2107.

We can see scattered black outlines signposts prediction outcome, and blue hard-line indicates actual value from this figure. Both values in an identical track, this model fit well in Fig. 5.

The Table 5 overhead displays COVID-19 virus Predicting of new deaths in Japan yhat representative the precise prediction, yhat_lower is the smallest forecast and yhat_upper is the maximum forecast. So founded on the table beyond the amount of total death till 2021-04-07 is cumulative to 44.

From this Fig. 6 we can see black scattered line specify predication outcome and blue hard line indicated actual value. Both values in identical track, here we can see some error that's mainly counting error.

Similarly graph of total deaths matches exactly with Fig. 4.

| Date     | yhat     | yhat_lower | yhat_upper |
|----------|----------|------------|------------|
| 304      | 2020-11-21 | 112066.113963 | 110863.2784382 | 113436.276043 |
| 305      | 2020-11-22 | 112502.313643. | 111173.608387 | 114055.397039 |
| 306      | 2020-11-23 | 112901.793776 | 111298.578982 | 114585.316030 |
| 307      | 2020-11-24 | 113413.835491 | 111713.906782 | 115464.387527 |
| 308      | 2020-11-25 | 112968.037660 | 112208.006383 | 116196.723629 |
| 3093     | 2020-11-26 | 114580.019943 | 112487.260699 | 117046.205274 |
| 310      | 2020-11-27 | 115182.474312 | 1128661.066538 | 117871.951980 |

**Table 3. Forecasting of total cases**

![Fig. 4. Predicted value vs Actual value for total cases](image-url)
Table 4. Forecasting of new cases

| Date       | yhat   | yhat_lower | yhat_upper |
|------------|--------|------------|------------|
| 434 2021-03-31 | 1439.281794 | 428.180817 | 2378.757268 |
| 435 2021-04-01  | 1523.823363 | 535.685250 | 2614.734557 |
| 436 2021-04-02  | 1447.977863 | 491.043398 | 2372.97914 |
| 437 2021-04-03  | 1434.134168 | 486.040438 | 2489.417169 |
| 438 2021-04-04  | 1191.198777 | 226.646797 | 2167.333333 |
| 439 2021-04-05  | 889.915080 | -116.530941 | 1926.768635 |
| 440 2021-04-06  | 1145.511665 | -131.226715 | 2107.182476 |

Fig. 5. Predicted value vs actual value for new cases

Table 5. Forecasting of new deaths

| Date       | yhat   | yhat_lower | yhat_upper |
|------------|--------|------------|------------|
| 435 2021-04-01  | 42.938365  | 23.732355  | 61.748345  |
| 436 2021-04-02  | 47.903292  | 26.855199  | 67.837511  |
| 437 2021-04-03  | 38.385619  | 18.995403  | 58.456150  |
| 438 2021-04-04  | 35.289575  | 16.841006  | 55.066479  |
| 439 2021-04-05  | 39.321817  | 19.438198  | 60.836823  |
| 440 2021-04-06  | 43.854992  | 24.767389  | 64.986767  |
| 441 2021-04-07  | 43.581328  | 21.903581  | 62.781666  |

Fig. 6. Predicted value vs. Actual value for new death
5. RESULTS AND DISCUSSION

5.1 Experimental Result for India

For total cases from these two tables, we can see the prediction result and the actual result are matched 98.01%. This model has given good results. On the 17-12-2020, the total number of cases was 9956557 that we got from Table 6 beside the number of Predicted results 1015798 that we get from Table 7. Observing this result, we can assume that the model fits well.

For new cases from these two tables, we can see the prediction result and the actual result are matched by 89.93%. On 06-04-2021, the new cases were 1788 that we get from Table 9 results of Wikipedia, which is subtracted with the result of 29-11-2020 to 28-11-2020 beside for new cases, predicted result was 1988 that we get from Table 8. The actual result matched with the yhat_lower value that indicated minimum prediction result. Perceiving this consequence, we can expect that the model fits quite well.

Similarly, we can see that for total deaths and new deaths, on 06-01-2021, the total number of deaths was 150114 that we got from Table 11 beside the number of Predicted result 167724 that we get from Table 10. It has achieved an accuracy of 89.50%. Again, for new deaths on 06-04-2021, the new death was 446 from Table 13 results of wikipedia, which is subtracted with the result of 06-04-2021 to 05-04-2021. And for the new cases, the predicted outcome was 257 that we get from Table 9. Here we can see it has reached 57.6%. Here, model performance cannot be considered well.

Live Source: [https://en.wikipedia.org/wiki/COVID-19_pandemic_in_India](https://en.wikipedia.org/wiki/COVID-19_pandemic_in_India)

### Table 6. Prediction result for total cases

| Date     | yhat      | yhat_lower | yhat_upper |
|----------|-----------|------------|------------|
| 313      | 2020-12-08| 1.098752e+07| 1.072042e+07| 1.123218e+07 |
| 314      | 2020-12-09| 1.105772e+07| 1.076820e+07| 1.131163e+07 |
| 315      | 2020-12-10| 1.112728e+07| 1.083712e+07| 1.138160e+07 |
| 316      | 2020-12-11| 1.119691e+07| 1.089775e+07| 1.146167e+07 |
| 317      | 2020-12-12| 1.126702e+07| 1.096384e+07| 1.156753e+07 |
| 318      | 2020-12-13| 1.134405e+07| 1.102900e+07| 1.163638e+07 |
| 319      | 2020-12-14| 1.147722e+07| 1.106616e+07| 1.172711e+07 |

### Table 7. Live covid result from Wikipedia

| Date     | Deaths | Recoveries | Active cases | #of cases      | #of deaths   |
|----------|--------|------------|--------------|----------------|--------------|
| 2020-12-14| 143355 | 9388159    | 352586       | 9,884,100(+0.27%) | 143,355(+0.23%) |
| 2020-12-15| 143709 | 9422636    | 339820       | 9,906,165(+0.22%) | 143,709(+0.25%) |
| 2020-12-16| 144096 | 9456449    | 332002       | 9,932,547(+0.27%) | 144,096(+0.27%) |
| 2020-12-17| 144451 | 9489740    | 322366       | 9,956,557(+0.24%) | 144,451(+0.25%) |

### Table 8. Prediction result for new cases

| Date     | yhat      | yhat_lower | yhat_upper |
|----------|-----------|------------|------------|
| 426      | 2021-03-31| -66.955130 | 245.077139  |
| 427      | 2021-04-01| -65.718594 | 238.597509  |
| 428      | 2021-04-02| -58.640266 | 245.467072  |
| 429      | 2021-04-03| -63.921418 | 237.964912  |
| 430      | 2021-04-04| -100.815293| 208.166026  |
| 431      | 2021-04-05| -126.289107| 178.316326  |
| 432      | 2021-04-06| -50.314030 | 257.061117  |
Table 9. Live covid result from Wikipedia

| Date       | Deaths | Recoveries | Active cases | #of cases | #of deaths |
|------------|--------|------------|--------------|-----------|------------|
| 2021-04-03 | 164110 | 11569241   | 658909       | 12,392,260(+0.72%) | 164,110(+0.44%) |
| 2021-04-04 | 166423 | 11629289   | 691597       | 12,485,509(+0.75%) | 164,623(+0.31%) |
| 2021-04-05 | 165101 | 11682136   | 741830       | 12,589,067(+0.83%) | 165,101(+0.29%) |
| 2021-04-06 | 165547 | 11732279   | 788223       | 12,686,049(+0.77%) | 165,547(+0.27%) |

Table 10. Prediction result for total deaths

| Date       | yhat     | yhat_lower | yhat_upper |
|------------|----------|------------|------------|
| 426        | 2021-03-31 | 101.345369 | -66.955130 | 245.077139 |
| 427        | 2021-04-01 | 93.844757  | -65.718594 | 238.597509 |
| 428        | 2021-04-02 | 88.521151  | -58.640266 | 245.467072 |
| 429        | 2021-04-03 | 84.765906  | -63.921418 | 237.964912 |
| 430        | 2021-04-04 | 49.006681  | -100.815293| 208.166026 |
| 431        | 2021-04-05 | 28.808199  | -126.289107| 178.316326 |
| 432        | 2021-04-06 | 107.801444 | -50.314030 | 257.061117 |

Table 11. Prediction result for new deaths

| Date       | yhat     | yhat_lower | yhat_upper |
|------------|----------|------------|------------|
| 336        | 2020-12-31 | 173930.166187 | 164824.819397 | 183315.666754 |
| 337        | 2021-01-01 | 174746.887996 | 164919.390284 | 184490.837009 |
| 338        | 2021-01-02 | 175539.156068 | 165424.797256 | 185829.658692 |
| 339        | 2021-01-03 | 176422.827846 | 166018.941470 | 186725.574019 |
| 340        | 2021-01-04 | 177185.239846 | 166431.445708 | 187828.747032 |
| 341        | 2021-01-05 | 178050.176531 | 167185.945491 | 188700.068731 |
| 342        | 2021-01-06 | 178888.717514 | 167724.371060 | 190134.882407 |

Table 12. Live covid result from for total deaths Wikipedia

| Date       | Deaths | Recoveries | Active cases | #of cases | #of deaths |
|------------|--------|------------|--------------|-----------|------------|
| 2021-01-02 | 149218 | 9906387    | 250183       | 10,305,788(+0.19%) | 149,218(+0.15%) |
| 2021-01-03 | 149435 | 9927310    | 247220       | 10,323,965(+0.18%) | 149,435(+0.15%) |
| 2021-01-04 | 149649 | 9946867    | 243953       | 10,340,469(+0.16%) | 149,649(+0.14%) |
| 2021-01-05 | 149850 | 9975958    | 231036       | 10,356,844(+0.16%) | 149,850(+0.13%) |

Table 13. Live Covid result for new deaths from Wikipedia

| Date       | Deaths | Recoveries | Active cases | #of cases | #of deaths |
|------------|--------|------------|--------------|-----------|------------|
| 2021-04-03 | 164110 | 11569241   | 658909       | 12,392,260(+0.72%) | 164,110(+0.44%) |
| 2021-04-04 | 164623 | 11629289   | 691597       | 12,485,509(+0.75%) | 164,623(+0.31%) |
| 2021-04-05 | 165101 | 11682136   | 741830       | 12,589,067(+0.83%) | 165,101(+0.29%) |
| 2021-04-06 | 165547 | 11732279   | 788223       | 12,686,049(+0.77%) | 165,547(+0.27%) |

Fig. 7. Comparison between the actual and predicted value of India
Fig. 7 showed the comparison between the actual and predicted value of India by a randomly selected date. This graph indicated that there was no enormous difference between the actual and predicted value. So it can be said that the model that we used was suitable for the prediction of Covid-19.

5.2 Experimental Result for Japan

For total cases from these two tables, we can see the prediction result and the actual result are matched (84.50%). This model has given a very good result. On 27-11-2020, the total number of cases was 139491 that we got from table 15 beside the number of Predicted results 115182 that we obtain from table 14. Observing this result, we can assume that the model fits well.

We can see the predicted result and the actual result match 94.55% for total deaths from these two tables. This model has given good results. On 29-03-2021, the total number of cases was 9061 that we got from Table 17 beside the number of predicted results 9583 that we get from Table 16. Observing this result, we can expect that the model fits too.

For new cases and new deaths, on 06-04-2021, the number of new cases was 2220 that we got from Table 3, which is subtracted with the result of 06-04-2021 to 05-04-2021 beside the number of predicted result 2107 that we get from Table 18.

It achieved 95.99% accuracy beside new deaths on the 07-04-2021 the new Deaths was 30 that we got from Table 20 results of Wikipedia. And for the new deaths, the predicted result was 21 that we get from Table 19. Here we can see it reached 73.33%.

Live result Source: https://en.wikipedia.org/wiki/COVID-19_pandemic_in_Japan#Timeline

Table 14. Prediction result for total cases

| Date   | yhat    | yhat_lower | yhat_upper |
|--------|---------|------------|------------|
| 304    | 2020-11-21 | 112066.113963 | 110863.278482 | 113436.276048 |
| 305    | 2020-11-22 | 112502.313843 | 111173.608387 | 114055.397039 |
| 306    | 2020-11-23 | 112901.793776 | 111298.578982 | 114585.316030 |
| 307    | 2020-11-24 | 113413.835491 | 111713.906782 | 115464.387527 |
| 308    | 2020-11-25 | 113968.037660 | 112208.006383 | 116196.723629 |
| 309    | 2020-11-26 | 114580.019943 | 112487.260699 | 117046.205274 |
| 310    | 2020-11-27 | 115182.474312 | 112861.086538 | 117871.951980 |

Table 15. Live covid result from Wikipedia

| Date       | Deaths | Recoveries | Active cases | #of cases | #of deaths |
|------------|--------|------------|--------------|-----------|------------|
| 2020-11-22 | 1974   | 111163     | 17042        | 130,179(+2,514) | 1,974(+11) |
| 2020-11-23 | 1981   | 112269     | 18108        | 132,358(+2,179) | 1,981(+7) |
| 2020-11-24 | 1989   | 113340     | 18600        | 133,929(+1,571) | 1,989(+8) |
| 2020-11-25 | 2001   | 114725     | 18674        | 135,400(+1,471) | 2,001(+12) |
| 2020-11-26 | 2022   | 116378     | 18861        | 137,261(+1,861) | 2,022(+21) |
| 2020-11-27 | 2051   | 118135     | 19305        | 139,491(+2,230) | 2,051(+29) |

Table 16. Prediction result for total deaths

| Date       | yhat    | yhat_lower | yhat_upper |
|------------|---------|------------|------------|
| 426        | 2021-03-23 | 9303.664653 | 9173.547639 | 9440.588717 |
| 427        | 2021-03-24 | 9375.380776 | 9230.944984 | 9509.816763 |
| 428        | 2021-03-25 | 9445.266719 | 9295.625063 | 9560.347772 |
| 429        | 2021-03-26 | 9519.857558 | 9388.010905 | 9657.078930 |
| 430        | 2021-03-27 | 9565.346158 | 9443.101573 | 9720.663626 |
| 431        | 2021-03-25 | 9658.248266 | 9521.536505 | 9798.694676 |
| 432        | 2021-03-29 | 9725.764538 | 9553.638394 | 9661.648231 |
Table 17. Live COVID result from Wikipedia

| Date      | Deaths | Recoveries | Active cases | #of cases       | #of deaths |
|-----------|--------|------------|--------------|-----------------|------------|
| 2021-03-24 | 8908   | 436463     | 13672        | 459,043(+1,289) | 8,908(+47) |
| 2021-03-25 | 8938   | 437702     | 14257        | 460,897(+1,854) | 8,938(+30) |
| 2021-03-26 | 8967   | 438879     | 14994        | 462,840(+1,943) | 8,967(+29) |
| 2021-03-27 | 8998   | 440200     | 15668        | 464,866(+2,026) | 8,998(+31) |
| 2021-03-28 | 9031   | 441237     | 16581        | 466,849(+1,983) | 9,031(+33) |
| 2021-03-29 | 9061   | 442369     | 17187        | 468,614(+1,765) | 9,061(+30) |

Table 18. Prediction result for new cases

| Date      | yhat   | yhat_lower | yhat_upper |
|-----------|--------|------------|------------|
| 2021-03-31 | 1439.281794 | 428.180817 | 2378.757268 |
| 2021-04-01 | 1523.823363  | 535.685250  | 2614.734557  |
| 2021-04-02 | 1447.977863  | 491.043398  | 2372.297914  |
| 2021-04-03 | 1434.134168  | 486.040438  | 2489.417169  |
| 2021-04-04 | 1191.198777  | 226.646797  | 2167.333333  |
| 2021-04-05 | 889.915080   | -116.530941 | 1926.78635   |
| 2021-04-06 | 1145.511665  | 131.226715  | 2107.182476  |

Table 19. Prediction result for new deaths

| Date      | yhat   | yhat_lower | yhat_upper |
|-----------|--------|------------|------------|
| 2021-04-01 | 42.93635   | 23.732355   | 61.746345  |
| 2021-04-02 | 47.903292  | 26.855199   | 67.837511  |
| 2021-04-03 | 33.386169  | 13.995403   | 58.456150  |
| 2021-04-04 | 35.269575  | 16.841006   | 55.06479   |
| 2021-04-05 | 39.321817  | 19.436193   | 60.383682  |
| 2021-04-06 | 43.854992  | 24.7E7TSEO  | 64986767   |
| 2021-04-07 | 43.581323  | 21.903581   | 62.781666  |

Table 20. Live COVID result from Wikipedia

| Date      | Deaths | Recoveries | Active cases | #of cases       | #of deaths |
|-----------|--------|------------|--------------|-----------------|------------|
| 2021-04-01 | 9162   | 446416     | 19195        | 474,773(+2,661) | 9,162(+49) |
| 2021-04-02 | 9185   | 447515     | 20558        | 477,458(+2,685) | 9,185(+23) |
| 2021-04-03 | 9213   | 449091     | 21861        | 480,165(+2,707) | 9,213(+28) |
| 2021-04-04 | 9221   | 450624     | 23022        | 482,867(+2,702) | 9,221(+8)  |
| 2021-04-05 | 9231   | 452155     | 23939        | 485,325(+2,458) | 9,231(+10) |
| 2021-04-06 | 9249   | 454055     | 24241        | 487,545(+2,220) | 9,249(+18) |
| 2021-04-07 | 9279   | 455382     | 24915        | 489,576(+2,031) | 9,279(+30) |

Fig. 8. Comparison between the actual and predicted value of Japan
Fig. 8 showed the comparison between the actual and predicted value of Japan by a randomly selected date. This graph showed that there was no massive difference between the actual and predicted value. So it can be said that the model that we used was appropriate for the prediction of Covid 19.

6. CONCLUSION
This paper presents the forecasting and analysis of new COVID-19 cases. It shows the number of cases, based on the total number of deaths, total cases and new cases of COVID-19, and the case time series based on current information. Although various studies have been published, it has been noticed that there are still limited applications and contributions to the predictions of the series during this war. These are partly due to the limited availability of data about COVID-19. In the case of time series forecasting methods, it is usually necessary to learn computer models and gain a lot of data. This paper provides satisfactory results about the prevalence of COVID-19 for the last 60 days, where graphical analysis is presented using the time-series analysis in case of death.

COMPETING INTERESTS
Authors have declared that no competing interests exist.

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