Using machine learning to predict the next COVID-19 wave using ARIMA, LSTM and FBProphet models

Viraj Sonavane
Computer Science
California State University
Chico California, USA
vdsonavane@mail.csuchico.edu

ABSTRACT

The Coronavirus Disease-2019 (COVID-19) pandemic continues to have a devastating sway on the wellbeing and prosperity of the worldwide populace. Even after vaccinations in several parts of the world, we can still see a rise in new COVID cases. The second COVID-19 wave was deadlier than the first wave, and countries struggled to keep up with it. Even after imposing the Lockdown and following the COVID-19 safety protocol, the country's public health system collapsed, further increasing the new cases and deaths globally. Hence, there is a need for a global predictor that accurately predicts the development of the next COVID-19 wave. This paper discusses three different machine learning models used to predict the next COVID-19 wave. The models are LSTM (Long-Short-Term-Memory) model, FBProphet (Facebook Prophet) model and, ARIMA (Autoregressive Integrated Moving Average) model. We have used live data for training the model to get a real-time forecast and predict the prognosis for the upcoming days. The paper also describes the process of tuning up the hyperparameters of the models to achieve lower RMSE (Root Mean Squared Error) values which help achieve higher accuracy in forecasting the next wave. The paper concludes that the LSTM model provided the lowest RMSE value, followed by FBProphet and ARIMA. Hence, to predict the next covid wave accurately, we can use the LSTM model.

KEYWORDS

COVID-19, ARIMA, LSTM, FBProphet, RMSE.

1 Introduction

It has been two years since we heard about the first COVID-19 case in the world. The World Health Organization (WHO) declared COVID-19 a global pandemic by March 2020 [17]. Many countries suffered from the first COVID-19 peak wave between March 2020 and July 2020 [15]. The introduction of vaccines did help the world to fight back. In the latter half of 2020, numerous vaccine administrations helped the nations control the rising COVID-19 cases and deaths.

Along with COVID-19 vaccines, countries also followed the Lockdown protocol and the COVID-19 safety protocol to limit the new cases further. Due to this, COVID-19 patients started reducing throughout the world, and eventually, countries started easing the Lockdown imposed during COVID-19 peak time. The ease of Lockdown helped the general populous to relax and provided the freedom to roam around. Everything was going well till late 2020, and at the start of 2021 world came to know about a DELTA version COVID-19, which had more infection rate than the primary one [13]. Again COVID-19 cases started rising worldwide; even after vaccinations, the patient count remained prominent. Vaccinations and COVID-19 protocol did not help to keep a lower count of new patients and, this gave rise to the second wave described as the DELTA wave throughout the world. This wave was uglier than the first one because the countries public health systems had just gone through the first wave, and now they were facing the second wave [14]. The public health systems could not handle the new cases, and eventually, the system collapsed, and the general population suffered enormously. Now a new variant of COVID-19 named OMNICRON is spreading in the world. This variant spreads twice as quickly as the DELTA variant and four times as fast as the primary COVID-19 variant. From Figure 4, we can see that countries have eased up the restriction protocol. From Figure 1 and Figure 2, we can see countries in which new cases are rising, which may be due to the OMNICRON variant or ease of restriction. These countries may see a third covid wave unless they take the necessary precautions. Figure 3 shows the Covid restriction's effect on new cases and positive rate. As we can see, the tighter Covid regulation did help to reduce the count of new patients in the past, but only after the case count had gone up, which shows that countries were unprepared and were not informed about the upcoming COVID-19 wave. Hence, there is a need for a COVID-19 peak wave detector to help countries ready their public health system for impeding waves and tackle the upcoming wave effectively using restrictions and Lockdown.

The purpose of this paper is to study and design three machine learning models, namely LSTM (Long-Short-Term-Memory), ARIMA (Autoregressive Integrated Moving Average) and, FBProphet (Facebook). Compare the findings of these models using RMSE (Root Mean Square Error) and narrow down one model with high accuracy to forecast the next COVID-19 wave for all the countries. The paper also discusses how to improve and tune up these models using hyper-parameters to increase the accuracy of forecasts.

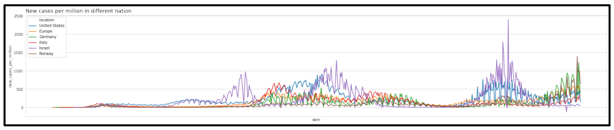


Figure 1: New cases per million for countries

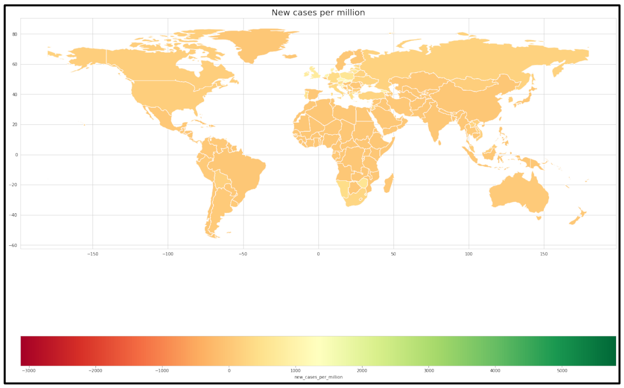


Figure 2: New cases per million in world

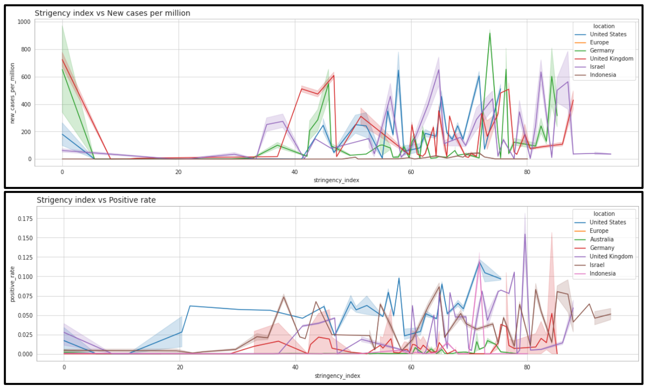


Figure 3: Positive rate vs Stringency index and new cases per million vs Stringency index

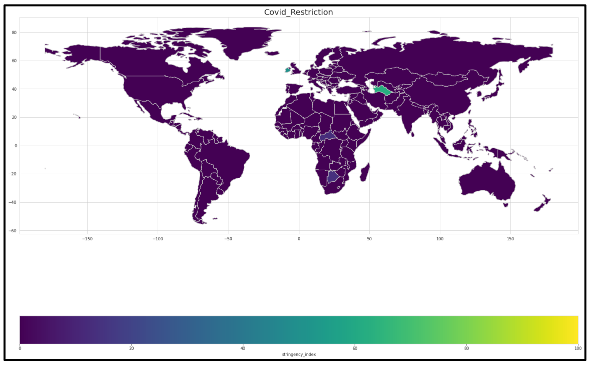


Figure 4: Covid Restriction in different countries

2 Literature Review

The need for a COVID-19 peak detector is very high right now to help countries protect themselves from the upcoming COVID-19 wave. Several studies have been conducted to predict the occurrence of COVID-19 peak waves.

O. Istaiteh et al. [1] worked on the Johns Hopkins University dataset to predict COVID-19 confirmed cases for the next seven days in different countries using machine learning models like ARIMA, ANN, LSTM, and CNN. The paper provides information on the fine-tuning process for every model. The paper compares every model on numerical analysis by calculating mean absolute error (MAPE), root means squared logarithmic error (RMSLE), and mean squared logarithmic error (MSLE). The paper concluded that CNN outperformed other models. ANN and LSTM provide better accuracy than the ARIMA model.

N. Darapaneni et al. [2] analyzed the spread of COVID—19 in India and the three highly affected states of India and created a prediction model using the SIR and FBProphet to forecast the further progression of COVID-19 in the upcoming months. The dataset used in this paper is gathered from the government of India website. The paper provides a comparative analysis between the SIR model and FBProphet on the susceptible rate of population, mean absolute error (MAPE), and root means squared error (RMSE). The paper concluded that both models provide a similar forecast for specific susceptible rates, but in the case of different susceptible rates, SIR provides a better forecast than FBProphet.

G. Battineni et al. [3] have used FBProphet to predict the COVID-19 effect on four widely affected nations USA, Brazil, India, and Russia, for the next 60 days. The dataset used is Johns Hopkins University dataset which is updated daily. The paper achieved an accuracy of 99% using the FBProphet ML model. The paper concluded that we could use FBProphet COVID-19 analysis when we have non-linear trends in datasets.

I. Saleh et al. [4] have used ARMA, AR, MA, and ARIMA to predict the confirmed number of COVID-19 cases in Saudi Arabia for the next four weeks or one month. The dataset used is acquired from the website of Saudi Arabia. The paper has compared the different models using RMSE, MAPE and, RMSRE values. The paper concluded that the ARIMA model performs better than other models with the lowest RMSE value followed by ARMA, AR, and MA.

To develop an outbreak, A. Khakharia et al. [5] have proposed to use nine different ML models, namely ARIMA, ARMA, BRR, HW, LRP, LR, RFR, SVR, and XGB prediction system that predicts COVID-19 patients in ten densely populated countries for the next five days. The dataset used is gathered from the respective country's website. The paper compared the prediction of all models. Furthermore, the paper achieved more than 80% accuracy for all models where ARIMA provides the overall best accuracy. The paper concluded that no single model could predict the upcoming rise in COVID-19 cases in all countries.

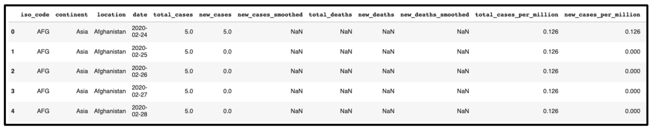
B. Punam et al. [7] worked on the modified SEIRD model and the LSTM model to predict the accurate trend of COVID-19 cases in India and its four worst-affected states for the next 30 days. The data is taken from the Indian government website. The paper has considered the confirmed COVID-19 cases and the Lockdown effect while analyzing the spread of COVID-19 in India. Both the models are compared over the null hypothesis t-test and MAPE value. The paper concluded that modified SEIRD predicts a forecast similar to the forecast obtained by the LSTM model. The LSTM model can be used for short-term forecasts, while SEIRD can be used for the long-term forecast.

In this paper, unlike other papers, we have used three models, first the ARIMA model, which provides high accuracy for forecasting data over a month [4, 5], secondly, FBProphet, which is a good model for forecasting Covid-19 cases for non-linear dataset [3] and, lastly the LSTM model which is a good model for forecasting short term COVID-19 cases [7]. The ARIMA model is used for short-term forecasting of 60-90 days, the FBProphet is used for long-term forecasting of 365 days, and the LSTM is used for short-term forecasting of 250 days. We have compared these models over RMSE values and tuned them up for better accuracy. Comparison over RMSE gives us the perfect model that predicts the COVID-19 wave for all the countries.

3 Methodology

3.1 Data Sources

We are using the COVID-19 dataset provided by the Our World in Data (OWID) team [1]. The OWID dataset is live data, and it gets updated daily by the OWID team. The OWID team provides a dashboard that demonstrates global vaccinations, new cases, and deaths. The dataset has 138941 rows and 67 columns. Figure 5 shows the dataset sample where the first column is the iso_code for every country. The dataset covers a period from as early as 01/01/2020 till the current date for different countries. The OWID dataset collects data from a reliable source like Johns Hopkins University, which provides daily confirmed cases and deaths globally [2]. The dataset does have missing values, and early preprocessing of the raw data is needed.

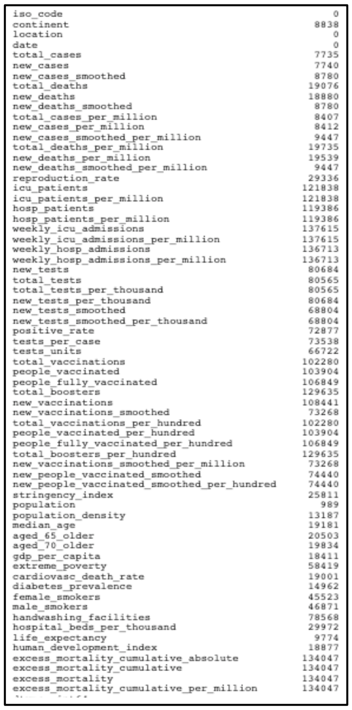


	iso_code	continent	location	date	total_cases	new_cases	new_cases_smoothed	total_deaths	new_deaths	new_deaths_smoothed	total_cases_per_million	new_cases_per_million
0	AFG	Asia	Afghanistan	2020-02-24	5.0	5.0	NaN	NaN	NaN	NaN	0.126	0.126
1	AFG	Asia	Afghanistan	2020-02-25	5.0	0.0	NaN	NaN	NaN	NaN	0.126	0.000
2	AFG	Asia	Afghanistan	2020-02-26	5.0	0.0	NaN	NaN	NaN	NaN	0.126	0.000
3	AFG	Asia	Afghanistan	2020-02-27	5.0	0.0	NaN	NaN	NaN	NaN	0.126	0.000
4	AFG	Asia	Afghanistan	2020-02-28	5.0	0.0	NaN	NaN	NaN	NaN	0.126	0.000

Figure 5: Sample dataset

3.2 Data Preprocessing

The OWID dataset has many missing values, and Figure 6 demonstrates the missing values, so preprocessing is required. So, to clean the data, we have dropped the unrequired columns for this paper. Then we have checked the columns where 80% of the dataset is NULL dataset and then dropped these columns. For the remaining column with less than 80% of the NULL dataset, as shown in Figure 7, we have replaced the NULL values with zeroes. Finally, we have a clean dataset with no NULL values, as shown in Figures 8 and 9.



```
iso_code                                          0
continent                                      8838
location                                          0
date                                              0
total_cases                                    7735
new_cases                                      7740
new_cases_smoothed                             8780
total_deaths                                  19076
new_deaths                                    18880
new_deaths_smoothed                            8780
total_cases_per_million                        8407
new_cases_per_million                          8412
new_cases_smoothed_per_million                 9447
total_deaths_per_million                      19735
new_deaths_per_million                        19539
new_deaths_smoothed_per_million                9447
reproduction_rate                             29336
icu_patients                                 121838
icu_patients_per_million                     121838
hosp_patients                                119386
hosp_patients_per_million                    119386
weekly_icu_admissions                        137615
weekly_icu_admissions_per_million            137615
weekly_hosp_admissions                       136713
weekly_hosp_admissions_per_million           136713
new_tests                                     80684
total_tests                                   80565
total_tests_per_thousand                      80565
new_tests_per_thousand                        80684
new_tests_smoothed                            68804
new_tests_smoothed_per_thousand               68804
positive_rate                                 72877
tests_per_case                                73538
tests_units                                   66722
total_vaccinations                           102280
people_vaccinated                            103904
people_fully_vaccinated                      106849
total_boosters                               129635
new_vaccinations                             108441
new_vaccinations_smoothed                     73268
total_vaccinations_per_hundred               102280
people_vaccinated_per_hundred                103904
people_fully_vaccinated_per_hundred          106849
total_boosters_per_hundred                   129635
new_vaccinations_smoothed_per_million         73268
new_people_vaccinated_smoothed                74440
new_people_vaccinated_smoothed_per_hundred    74440
stringency_index                              25811
population                                      989
population_density                            13187
median_age                                    19181
aged_65_older                                 20503
aged_70_older                                 19834
gdp_per_capita                                18411
extreme_poverty                               58419
cardiovasc_death_rate                         19001
diabetes_prevalence                           14962
female_smokers                                45523
male_smokers                                  46871
handwashing_facilities                        78568
hospital_beds_per_thousand                    29972
life_expectancy                                9774
human_development_index                       18877
excess_mortality_cumulative_absolute         134047
excess_mortality_cumulative                  134047
excess_mortality                             134047
excess_mortality_cumulative_per_million      134047
```

Figure 6: Null values in dataset

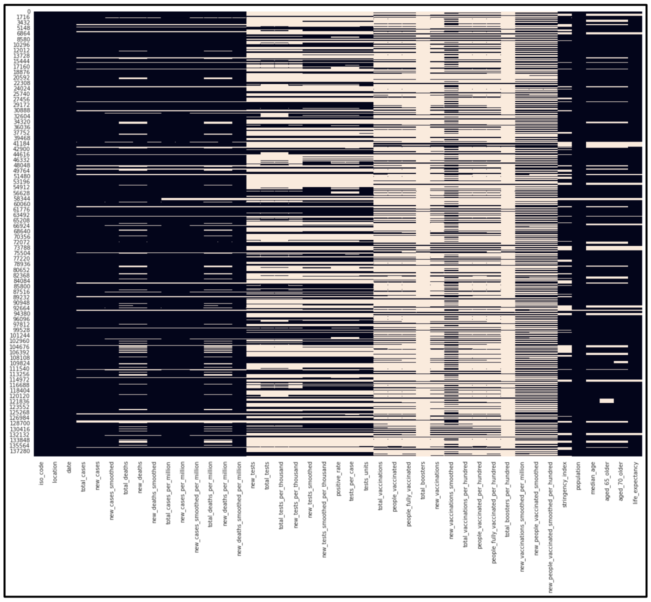
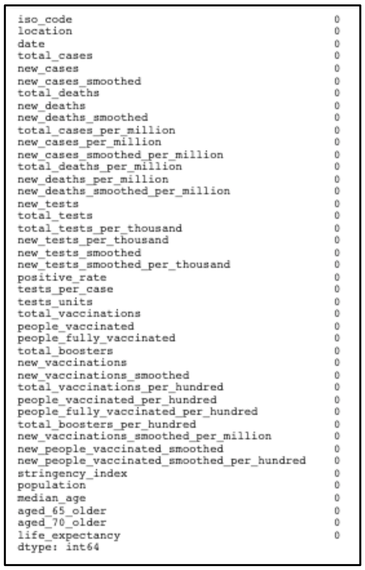


Figure 7: Missing values in dataset



```
iso_code                                        0
location                                        0
date                                            0
total_cases                                     0
new_cases                                       0
new_cases_smoothed                              0
total_deaths                                    0
new_deaths                                      0
new_deaths_smoothed                             0
total_cases_per_million                         0
new_cases_per_million                           0
new_cases_smoothed_per_million                  0
total_deaths_per_million                        0
new_deaths_per_million                          0
new_deaths_smoothed_per_million                 0
new_tests                                       0
total_tests                                     0
total_tests_per_thousand                        0
new_tests_per_thousand                          0
new_tests_smoothed                              0
new_tests_smoothed_per_thousand                 0
positive_rate                                   0
tests_per_case                                  0
tests_units                                     0
total_vaccinations                              0
people_vaccinated                               0
people_fully_vaccinated                         0
total_boosters                                  0
new_vaccinations                                0
new_vaccinations_smoothed                       0
total_vaccinations_per_hundred                  0
people_vaccinated_per_hundred                   0
people_fully_vaccinated_per_hundred             0
total_boosters_per_hundred                      0
new_vaccinations_smoothed_per_million           0
new_people_vaccinated_smoothed                  0
new_people_vaccinated_smoothed_per_hundred      0
stringency_index                                0
population                                      0
median_age                                      0
aged_65_older                                   0
aged_70_older                                   0
life_expectancy                                 0
dtype: int64
```

Figure 8: Zero NULL values in dataset

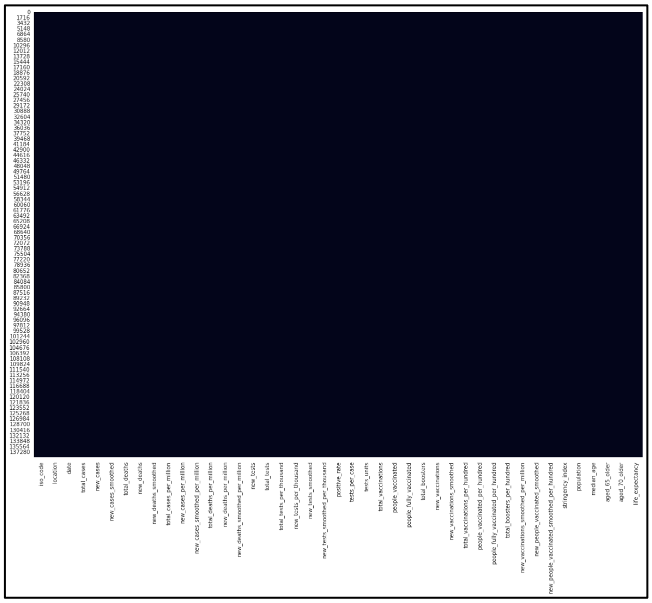


Figure 9: Clean dataset

3.3 Environmental Setup

We are using python as a programming language and a Google Colab environment to train and run the machine learning models. As said earlier, we are using the COVID-19 dataset provided by the OWID team. For this paper, we use only the date and new cases per million columns from the OWID dataset to train the models. For exploratory data analysis, we used the columns, people fully vaccinated, stringency index, and positive rate.

3.4 Proposed Approach

This section emphasizes the working and experimental setup of the models. We have used three different models, LSTM, ARIMA and, FBProphet.

A. Long-Short-Term-Memory (LSTM):

There are different types of deep learning (DL) techniques like convolution neural network (CNN), recurrent neural network (RNN), which is an upgrade over the deep neural network (DNN). The disadvantage of DNN is that it is a feed-forward neural network (FFNN) that permits data to travel forward from one input layer to the following output layer without ever going backward or touching the node from the previous layer. The DL techniques were designed by observing the working of the human brain, and the DNN does not seem to follow the human brain protocol [8]. To overcome this drawback RNN technique was introduced. The RNN solves this issue by using the previous layer to compute the next layer. Hence, it allows data to flow in the backward direction. As RNN uses the nodes of the last layer to calculate the next layer, it can use information effectively as each node in the previous layer gets a chance to analyze the data once again and use that analysis to determine the next layer. This effectively increases the efficiency of the RNN technique. Hence, RNN is used in speech recognition and handwriting recognition [9]. However, RNN also suffers from drawbacks like vanishing/ exploding gradient [10] or long-term dependency. When input data is fed to an RNN network, it breaks the incoming input and assigns different weights to these inputs. The problem is that when RNN receives the last information, it forgets the first input that it has acquired previously because the previously allotted weights have been reduced to zero or irrelevant. LSTM networks are used over RNN to solve such problems. This is a different type of RNN network that has the capacity to learn and understand the long-term dependencies of the input data. The efficiency of LSTM is better than RNN because it incorporates math functions which helps LSTM to have a better memory than RNN. LSTM has three gates Input Gate, Forget Gate, and Output Gate, as shown in Figure 17. The LSTM has the following equations in its cells.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(z_i - \tilde{z}_i)^2}$$

Figure 10: Equation 1 [4]

$$i_t = \sigma\left(W_i \cdot \left[u_{t-1}, x_t\right] + b_i\right),$$

Figure 11: Equation 1 [7]

$$\boxed{\tilde{C}_t = \tanh\left(W_C \cdot [u_{t-1}, x_t] + b_C\right),}$$

Figure 12: Equation 2 [7]

$$\boxed{f_t = \sigma\left(W_f \cdot [u_{t-1}, x_t] + b_f\right),}$$

Figure 13: Equation 3 [7]

$$\boxed{o_t = \sigma\left(W_o \cdot [u_{t-1}, x_t] + b_o\right),}$$

Figure 14: Equation 8 [7]

$$\boxed{C_t = f_t C_{t-1} + i_t \tilde{C}_t,}$$

Figure 15: Equation 9 [7]

$$\boxed{u_t = \tanh C_t \times o_t.}$$

Figure 16: Equation 10 [7]

Where the weights are W_i, W_c, W_f, W_o, and the biases are b_i, b_c, b_f, $b_{o.}$ As we can see from the equations, tanh activation functions are used in all cells of LSTM, which helps distribute the gradients in the LSTM network while training it. We use LSTM because it works better on time-series data, and covid data is time-series data [9].

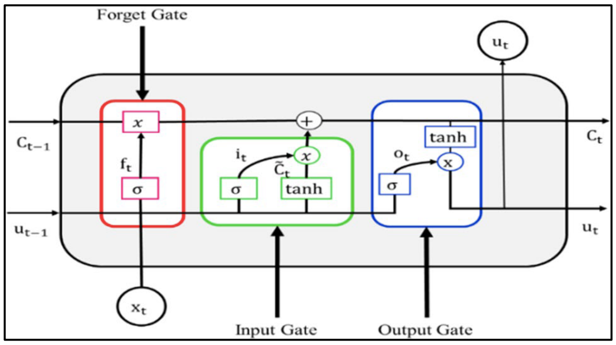
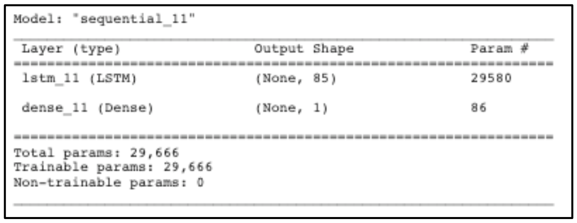


Figure 17: LSTM cell [7]

Experimental Setup:

The LSTM model was imported using Keras API. The dataset was split into 70:30 ratio as training data and testing data. For this paper, we use a time-series generator provided by the Keras module. The neural network requires formatted time series data for forecasting future values. The time-series generator inserts the time series of the dataset into a time-series generator object, and that object is used by the neural network to generate the forecast. We are feeding training and testing data to the time-series generator with a batch size of 64 and a length of 18. The length is the number of months on which the model is trained. So, the last 18-month of data is used to train the LSTM model. For this paper, we are using a univariate sequential LSTM model. The LSTM model has a single hidden layer and one output layer. The hidden layer has 85 neurons, ReLu or rectifier activation function and, input shape (18,1). The output layer is a dense layer that connects the previous neurons to the subsequent neurons.

The LSTM model uses Adam optimizer and mean squared error loss (MSE) with 500 epochs. Figure 18 shows the summary of layers in the LSTM model. Then, we fit the model and can see the loss per epoch. The loss per epoch for the country Norway is shown in Figure 19. The RMSE value for Norway is 11.12, which is not precisely zero but still better, while the MAPE value for Norway is 85.08. Figure 20 shows the actual data and the predicted data for Norway. Finally, we use the trained LSTM model to forecast the upcoming wave over 250 days ahead. Figure 21 shows the future forecast for Norway, where we can see that Norway will get a Covid-19 peak wave by January 2022. The Result section shows the future forecast for different countries using the LSTM model.



```
Model: "sequential_11"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_11 (LSTM)              (None, 85)                29580

 dense_11 (Dense)            (None, 1)                 86

=================================================================
Total params: 29,666
Trainable params: 29,666
Non-trainable params: 0
_________________________________________________________________
```

Figure 18: LSTM layers with 85 neurons

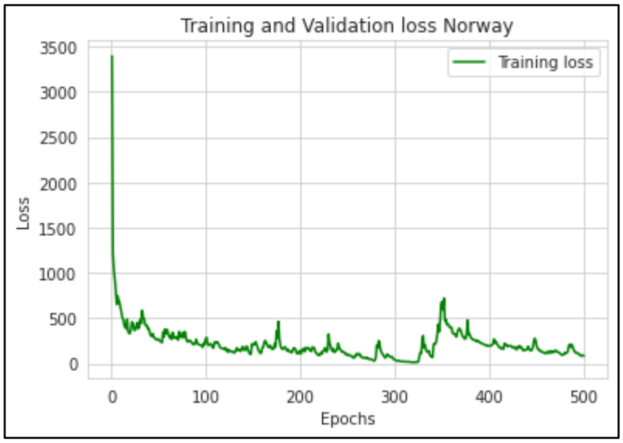


Figure 19: Loss per epochs for Norway

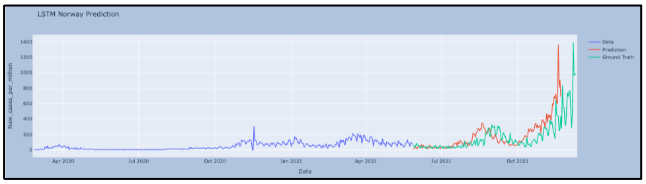


Figure 20: Norway Actual data vs Predicted data

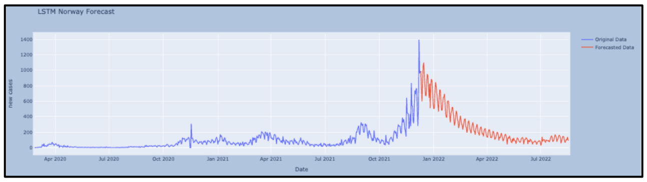


Figure 21: Norway Future Forecast

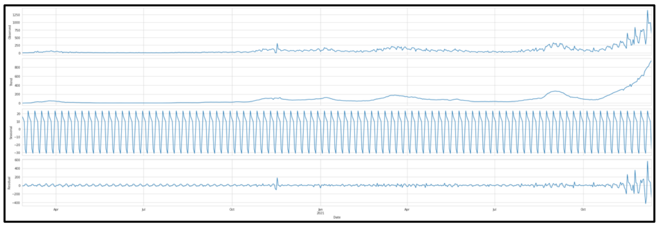
B. Autoregressive Integrated Moving Average (ARIMA)

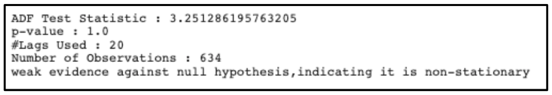
ARIMA is a particular type of statistical model which supports time series forecasting. ARIMA uses past values to predict the future time series. ARIMA is a combination of AR, I and, MA. The AR (Autoregression) is a model that uses the relationship between observation and lags observation. The I (Integrated) work to make the time series stationary by using the technique of differencing the observation. The MA. (Moving Average) is a model that uses the dependency of observation and residual error of the applied model over lagged observation [11]. ARIMA model has three different hyper-parameters p, q, and d, where p is called lag order, represents the autoregression, q is called the moving average and, d is called degree of difference, which shows the required differences [5]. The ARIMA model requires stationary time series data. For this, we have used ADF (Augmented Dicky Fuller) test. If the time series data is not stationary, the model accuracy will vary at different time points. The time series is made stationery using differencing. Then autocorrelation is used to check for trend and seasonality in the supplied dataset. Then we fine-tune p, q and, d values to train the ARIMA model on the obtained non-stationary data.

Experimental Setup:

To check the seasonality and trend in the dataset, we have used seasonal decompose with additive model and extrapolate trend as frequency. Figure 22 shows the seasonal decompose for Norway country. Then we have to use the ADF test on the dataset to see if the data is stationary. Figure 22 also shows the ADF test summary of Norway. The dataset is then passed through the autocorrelation function to see the seasonal trend in the dataset. Figure 24 shows autocorrelation output for Norway. We are using auto-arima provided by the pmdarima API module for this paper. This robust process identifies the best and optimal hyper-parameter for the ARIMA model based on the AIC (Akaike Information Criterion) values and delivers a good ARIMA model.

The working of auto-arima is such that it has inbuilt tests like ADF to find out perfect d, the range for p and q, stepwise algorithms, seasonal tests, and trends. In this paper, we have used auto-arima with ADF test, set the range of p, q as minimum one and maximum 3, set the seasonal as true to fit the computed ARIMA model, set the trace as true to print the summary of the fitted model and set the stepwise algorithm as true to find out optimal parameters and avoid overfitting. First, we have trained the auto-arima model on partial data and used that trained model to predict the next 2-month prediction. Figure 24 shows the auto-arima summary when we supply partial data of new cases per million for Norway. From Figure 24, we can see that auto-arima tried and tested different p, q and, d parameters to find out one optimal p, q and, d over the smaller AIC value. Figure 25 shows the actual data and the predicted data for new cases per million for Norway. We can validate that the model can predict future data correctly. After validating the model, we have trained the model for the whole dataset and used that trained model to predict a two-month future forecast. Figure 26 shows the auto-arima summary for the entire dataset of new cases per million for Norway, and Figure 27 shows the future precisions for Norway. We can see that Norway will have a COVID-19 Peak wave by January 2022. The RMSE value for Norway using the ARIMA model is 58.21. The Result section shows the future forecast for different countries using ARIMA.





```
ADF Test Statistic : 3.251286195763205
p-value : 1.0
#Lags Used : 20
Number of Observations : 634
weak evidence against null hypothesis,indicating it is non-stationary
```

Figure 22: Seasonal decompose and ADF test for Norway

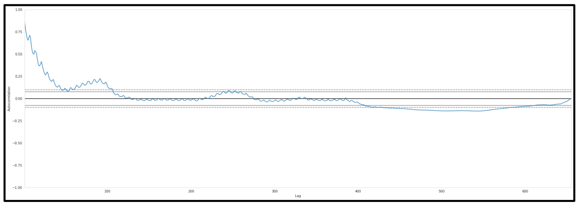
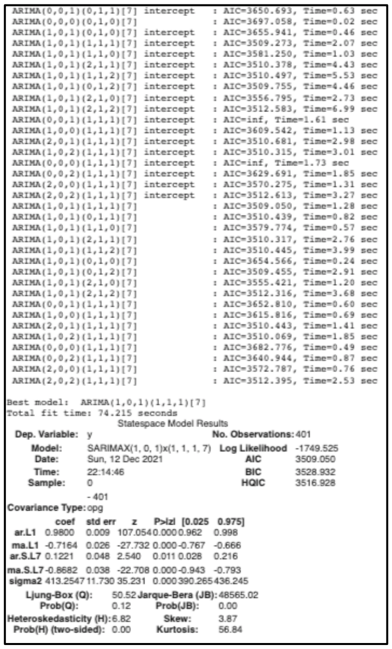


Figure 23: Norway Future Forecast



```
ARIMA(0,0,1)(0,1,1)[7] intercept   : AIC=3650.693, Time=0.63 sec
ARIMA(0,0,0)(0,1,0)[7]             : AIC=3697.058, Time=0.02 sec
ARIMA(1,0,1)(0,1,0)[7] intercept   : AIC=3655.941, Time=0.46 sec
ARIMA(1,0,1)(1,1,1)[7] intercept   : AIC=3509.273, Time=2.07 sec
ARIMA(1,0,1)(1,1,0)[7] intercept   : AIC=3581.250, Time=1.03 sec
ARIMA(1,0,1)(2,1,1)[7] intercept   : AIC=3510.378, Time=4.43 sec
ARIMA(1,0,1)(1,1,2)[7] intercept   : AIC=3510.497, Time=5.53 sec
ARIMA(1,0,1)(0,1,2)[7] intercept   : AIC=3509.755, Time=4.46 sec
ARIMA(1,0,1)(2,1,0)[7] intercept   : AIC=3556.795, Time=2.73 sec
ARIMA(1,0,1)(2,1,2)[7] intercept   : AIC=3512.583, Time=6.99 sec
ARIMA(0,0,1)(1,1,1)[7] intercept   : AIC=inf, Time=1.61 sec
ARIMA(1,0,0)(1,1,1)[7] intercept   : AIC=3609.542, Time=1.13 sec
ARIMA(2,0,1)(1,1,1)[7] intercept   : AIC=3510.681, Time=2.98 sec
ARIMA(1,0,2)(1,1,1)[7] intercept   : AIC=3510.315, Time=3.01 sec
ARIMA(0,0,0)(1,1,1)[7] intercept   : AIC=inf, Time=1.73 sec
ARIMA(0,0,2)(1,1,1)[7] intercept   : AIC=3629.691, Time=1.85 sec
ARIMA(2,0,0)(1,1,1)[7] intercept   : AIC=3570.275, Time=1.31 sec
ARIMA(2,0,2)(1,1,1)[7] intercept   : AIC=3512.613, Time=3.27 sec
ARIMA(1,0,1)(1,1,1)[7]             : AIC=3509.050, Time=1.28 sec
ARIMA(1,0,1)(0,1,1)[7]             : AIC=3510.439, Time=0.82 sec
ARIMA(1,0,1)(1,1,0)[7]             : AIC=3579.774, Time=0.57 sec
ARIMA(1,0,1)(2,1,1)[7]             : AIC=3510.317, Time=2.76 sec
ARIMA(1,0,1)(1,1,2)[7]             : AIC=3510.445, Time=3.99 sec
ARIMA(1,0,1)(0,1,0)[7]             : AIC=3654.566, Time=0.24 sec
ARIMA(1,0,1)(0,1,2)[7]             : AIC=3509.455, Time=2.91 sec
ARIMA(1,0,1)(2,1,0)[7]             : AIC=3555.421, Time=1.20 sec
ARIMA(1,0,1)(2,1,2)[7]             : AIC=3512.316, Time=3.68 sec
ARIMA(0,0,1)(1,1,1)[7]             : AIC=3652.810, Time=0.60 sec
ARIMA(1,0,0)(1,1,1)[7]             : AIC=3615.816, Time=0.69 sec
ARIMA(2,0,1)(1,1,1)[7]             : AIC=3510.443, Time=1.41 sec
ARIMA(1,0,2)(1,1,1)[7]             : AIC=3510.069, Time=1.85 sec
ARIMA(0,0,0)(1,1,1)[7]             : AIC=3682.776, Time=0.49 sec
ARIMA(0,0,2)(1,1,1)[7]             : AIC=3640.944, Time=0.87 sec
ARIMA(2,0,0)(1,1,1)[7]             : AIC=3572.787, Time=0.76 sec
ARIMA(2,0,2)(1,1,1)[7]             : AIC=3512.395, Time=2.53 sec

Best model:  ARIMA(1,0,1)(1,1,1)[7]
Total fit time: 74.215 seconds
                    Statespace Model Results
 Dep. Variable:  y                            No. Observations: 401
    Model:       SARIMAX(1, 0, 1)x(1, 1, 1, 7) Log Likelihood   -1749.525
    Date:        Sun, 12 Dec 2021                   AIC         3509.050
    Time:        22:14:46                           BIC         3528.932
   Sample:       0                                  HQIC        3516.928
                 - 401
Covariance Type: opg
          coef     std err  z       P>|z| [0.025   0.975]
  ar.L1   0.9800   0.009    107.054 0.000 0.962    0.998
  ma.L1   -0.7164  0.026    -27.732 0.000 -0.767   -0.666
 ar.S.L7  0.1221   0.048    2.540   0.011 0.028    0.216
ma.S.L7   -0.8682  0.038    -22.708 0.000 -0.943   -0.793
 sigma2   413.2547 11.730   35.231  0.000 390.265  436.245
    Ljung-Box (Q):          50.52 Jarque-Bera (JB): 48565.02
       Prob(Q):             0.12     Prob(JB):      0.00
Heteroskedasticity (H):     6.82       Skew:        3.87
  Prob(H) (two-sided):      0.00     Kurtosis:      56.84
```

Figure 24: Auto-Arima summary for partial data for Norway

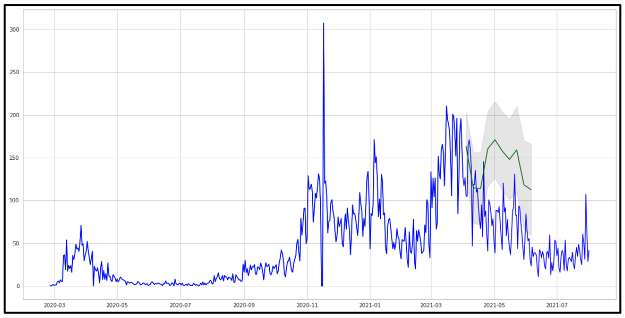
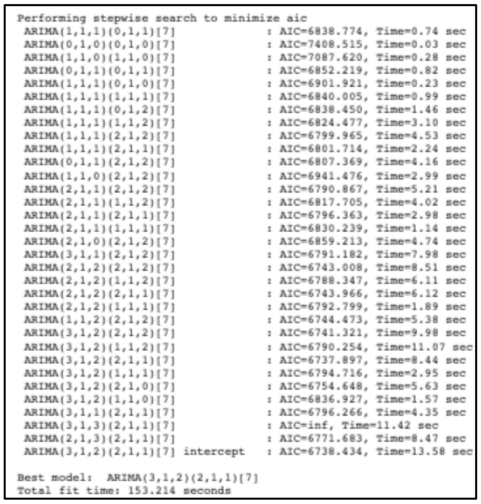


Figure 25: Actual data vs Predicted data by Arima model for Norway



```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,1,1)[7]             : AIC=6838.774, Time=0.74 sec
 ARIMA(0,1,0)(0,1,0)[7]             : AIC=7408.515, Time=0.03 sec
 ARIMA(1,1,0)(1,1,0)[7]             : AIC=7087.620, Time=0.28 sec
 ARIMA(0,1,1)(0,1,1)[7]             : AIC=6852.219, Time=0.82 sec
 ARIMA(1,1,1)(0,1,0)[7]             : AIC=6901.921, Time=0.23 sec
 ARIMA(1,1,1)(1,1,1)[7]             : AIC=6840.005, Time=0.99 sec
 ARIMA(1,1,1)(0,1,2)[7]             : AIC=6838.450, Time=1.46 sec
 ARIMA(1,1,1)(1,1,2)[7]             : AIC=6824.477, Time=3.10 sec
 ARIMA(1,1,1)(2,1,2)[7]             : AIC=6799.965, Time=4.53 sec
 ARIMA(1,1,1)(2,1,1)[7]             : AIC=6801.714, Time=2.24 sec
 ARIMA(0,1,1)(2,1,2)[7]             : AIC=6807.369, Time=4.16 sec
 ARIMA(1,1,0)(2,1,2)[7]             : AIC=6941.476, Time=2.99 sec
 ARIMA(2,1,1)(2,1,2)[7]             : AIC=6790.867, Time=5.21 sec
 ARIMA(2,1,1)(1,1,2)[7]             : AIC=6817.705, Time=4.02 sec
 ARIMA(2,1,1)(2,1,1)[7]             : AIC=6796.363, Time=2.98 sec
 ARIMA(2,1,1)(1,1,1)[7]             : AIC=6830.239, Time=1.14 sec
 ARIMA(2,1,0)(2,1,2)[7]             : AIC=6859.213, Time=4.74 sec
 ARIMA(3,1,1)(2,1,2)[7]             : AIC=6791.182, Time=7.98 sec
 ARIMA(2,1,2)(2,1,2)[7]             : AIC=6743.008, Time=8.51 sec
 ARIMA(2,1,2)(1,1,2)[7]             : AIC=6788.347, Time=6.11 sec
 ARIMA(2,1,2)(2,1,1)[7]             : AIC=6743.966, Time=6.12 sec
 ARIMA(2,1,2)(1,1,1)[7]             : AIC=6792.799, Time=1.89 sec
 ARIMA(1,1,2)(2,1,2)[7]             : AIC=6744.473, Time=5.38 sec
 ARIMA(3,1,2)(2,1,2)[7]             : AIC=6741.321, Time=9.98 sec
 ARIMA(3,1,2)(1,1,2)[7]             : AIC=6790.254, Time=11.07 sec
 ARIMA(3,1,2)(2,1,1)[7]             : AIC=6737.897, Time=8.44 sec
 ARIMA(3,1,2)(1,1,1)[7]             : AIC=6794.716, Time=2.95 sec
 ARIMA(3,1,2)(2,1,0)[7]             : AIC=6754.648, Time=5.63 sec
 ARIMA(3,1,2)(1,1,0)[7]             : AIC=6836.927, Time=1.57 sec
 ARIMA(3,1,1)(2,1,1)[7]             : AIC=6796.266, Time=4.35 sec
 ARIMA(3,1,3)(2,1,1)[7]             : AIC=inf, Time=11.42 sec
 ARIMA(2,1,3)(2,1,1)[7]             : AIC=6771.683, Time=8.47 sec
 ARIMA(3,1,2)(2,1,1)[7] intercept   : AIC=6738.434, Time=13.58 sec

Best model:  ARIMA(3,1,2)(2,1,1)[7]
Total fit time: 153.214 seconds
```

Figure 26: Auto-Arima summary for full dataset for Norway

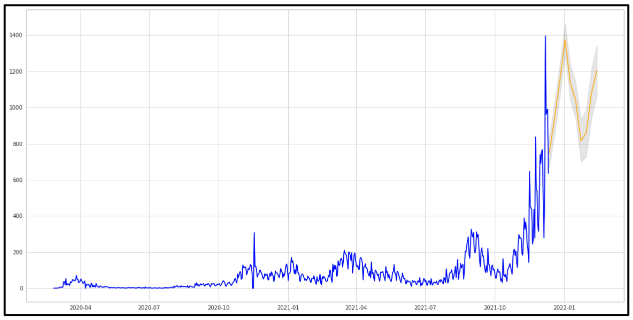


Figure 27: Future Forecast for Norway by Arima model

C. FBProphet

FBProphet is an open-source machine learning algorithm introduced in 2017 by Facebook's Core Data Science team. The Prophet predicts the time series forecast using an additive model. The Prophet is a robust machine learning algorithm that takes care of outlier data from the dataset and detects changes in the trend of the dataset. Hence, it does not require that much preprocessing of data to get an excellent future forecast. The Prophet fits the non-linear trend with daily, weekly, yearly seasonality, and holiday effects. This model requires minimal tweaking as compared to other models. When the provided dataset has good seasonal effects and variation of seasons over the historical data, the models work perfectly. The Prophet comprises three models holiday, seasonality, and trend, represented in Figure 28.

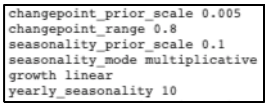
$$\boxed{y(t) = g(t) + s(t) + h(t) + e(t)}$$

Figure 28: FBProphet Equation [3]

Here g(t) represents a trend that can be linear or logistic for modeling the non-periodic changes in the time series, s(t) represents weekly, daily, and yearly changes. The model uses the Fourier series for adjusting the yearly changes. The h(t) means irregular holiday effects, and e(t) is to handle any errors [3]. The Prophet instance class is created then fit and predict methods are called. The input to the model is in the form of two columns: ds, and y, where ds require date columns of the dataset and y requires the numeric dataset on which we want the future forecast [12].

Experimental Setup:

We have imported Prophet from the Prophet API, which follows the sklearn model API. As discussed in the above section, the FBProphet requires columns in two forms that are ds and y. So, we have renamed our columns as ds and y, where ds consist of dates from the COVID-19 dataset and y consists of new cases per million for different countries. FBProphet model has lots of hyperparameters that require refinement to optimize the model. For this paper, we have used changepoint prior scale, changepoint range, seasonality mode, growth, and yearly seasonality parameters to refine the model. To figure out optimal values of the above parameters, we have used cross-validation with full dataset, initial as 400 days, period as 90 and, the horizon as 180 days. The cross-validation uses MAPE to determine the optimal value of changepoint prior scale, changepoint range, seasonality mode, growth, and yearly seasonality parameters. Figure 29 shows optimal values that cross-validation found out for new cases per million in Norway. After we have obtained the optimal values for the hyper-parameters, we have fed these values to the model with one additional feature, seasonality with the period of 30.5, Fourier order as five and, named monthly. This model is then fitted over the COVID-19 dataset and used to make future predictions. We have used the future data frame for 365 days and frequency as 'D'. We have first trained the mode on partial data to see if the trained model can correctly predict the future values. Figure 30 shows actual values versus precited values of new cases per million for Norway. As we can see, the model can forecast the future correctly, and we now train the same model over the entire dataset and use the trained model to forecast future values over 365 days. Figure 31 shows the future forecast of new cases per million for Norway. We can see that Norway will have a COVID-19 peak wave by the end of December 2021 and another wave by April 2022. The RMSE plot for Norway using FBProphet is shown in Figure 32. The future forecast for different countries is shown in the Result section.



```
changepoint_prior_scale 0.005
changepoint_range 0.8
seasonality_prior_scale 0.1
seasonality_mode multiplicative
growth linear
yearly_seasonality 10
```

Figure 29: Optimal values for hyper-parameters

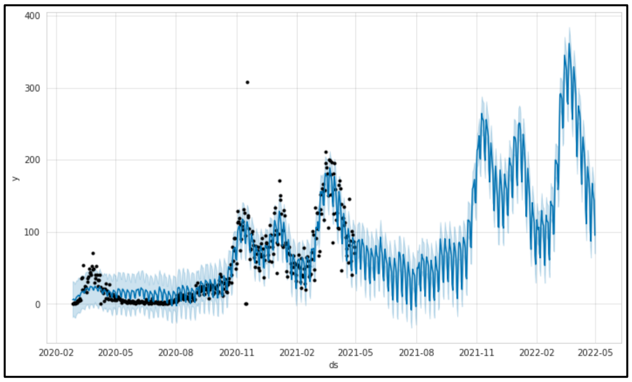


Figure 30: Actual values vs Predicted Values for Norway

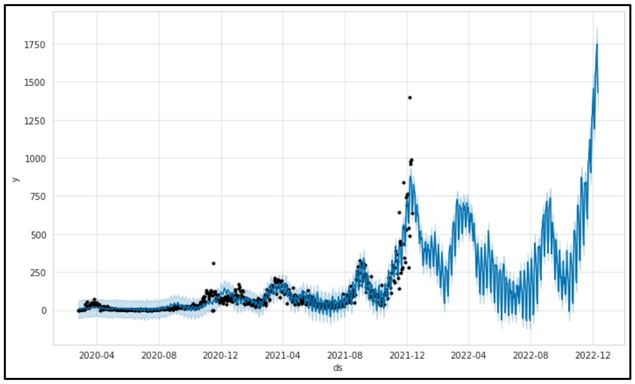


Figure 31: Future forecast for Norway

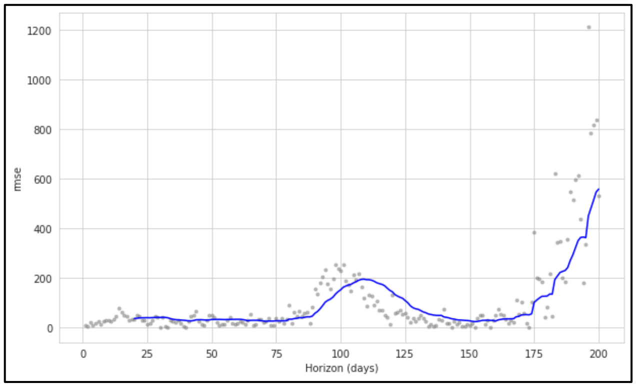


Figure 32: RMSE values for Norway

4. Results

Here we can see the forecast of different countries using LSTM, ARIMA, and FBProphet. The forecasts of all the three models for some countries are very similar. The countries that are used here for forecasting are the ones that currently have high new cases per million overall. The only exception is Indonesia which presently has low new cases per million.

Figures 33, 34, and 35 represent the forecast for the United Kingdom by LSTM, ARIMA, and FBProphet. The LSTM model predicts that the United Kingdom will have a peak wave by December 2021 and the start of January 2022, with new cases per million close to 1200. The ARIMA model predicts that the United Kingdom will have a peak wave by the second week of January 2022, with new cases per million close to 850. The FBProphet model predicts that the United Kingdom will have a peak wave by the last week of January 2022, with new cases per million close to 1300.

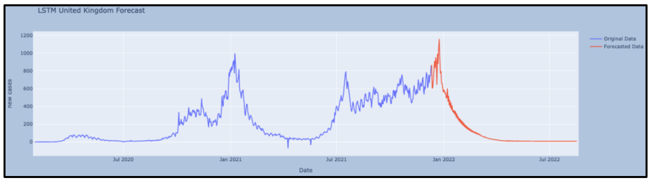


Figure 33: United Kingdom Future Forecast using LSTM

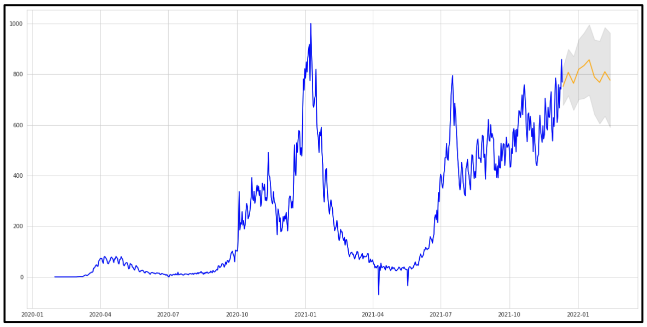


Figure 34: United Kingdom Future Forecast using ARIMA

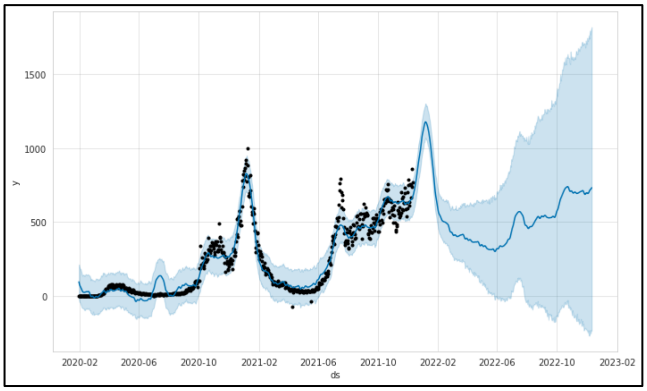


Figure 35: United Kingdom Future Forecast using FBProphet

Figures 36, 37, and 38 represent the forecast for Germany by LSTM, ARIMA, and FBProphet. The LSTM model predicts Germany will have a peak wave between May 2022 and June 2022, with new cases per million close to 1300. The ARIMA model predicts that Germany will have two peak waves by the end of December 2021 and a second wave by January 2022, with new cases per million close to 1000 and 1150. The FBProphet model predicts Germany will have a peak wave between April 2022 and May 2022, with new cases per million close to 700.

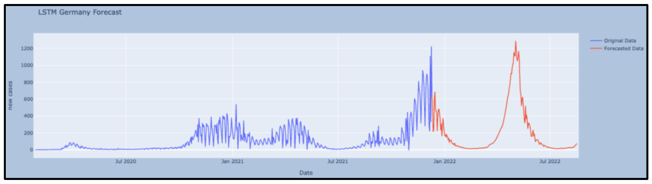


Figure 36: Germany Future Forecast using LSTM

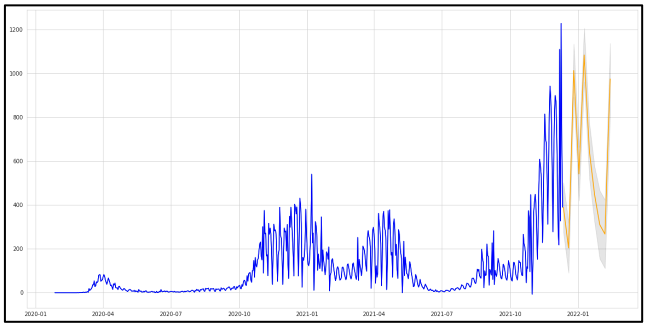


Figure 37: Germany Future Forecast using ARIMA

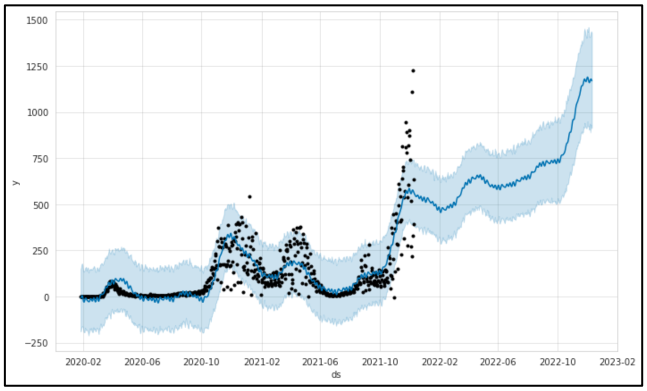


Figure 38: Germany Future Forecast using FBProphet

Figures 39, 40, and 41 represent the forecast for Europe by LSTM, ARIMA, and FBProphet. The LSTM model predicts that Europe will have a peak wave between December 2021 and new cases per million close to 600. The ARIMA model predicts Europe will have peak waves by January 2022, with new cases per million close to 550. The FBProphet model predicts Europe will have three peak waves, the first wave by December 2021, the second wave by March 2022 with new cases per million close to 500, and the third wave by the end of 2022 with new cases per million close to 900.

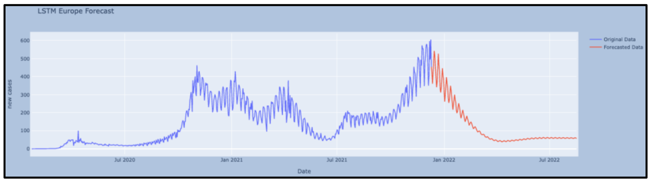


Figure 39: Europe Future Forecast using LSTM

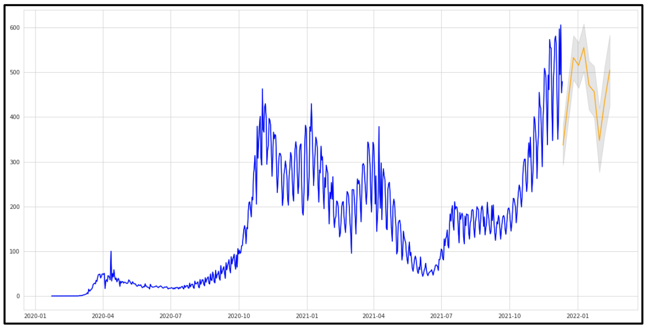


Figure 40: Europe Future Forecast using ARIMA

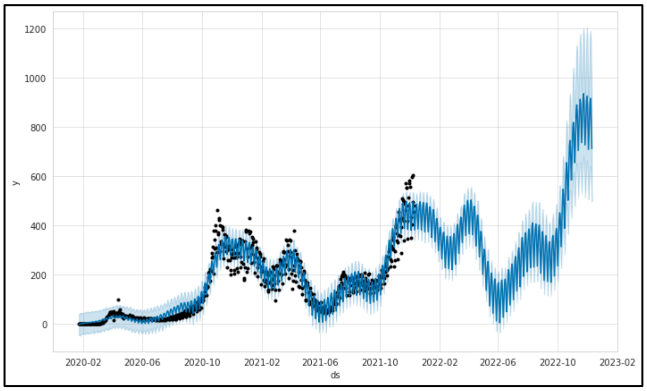


Figure 41: Europe Future Forecast using FBProphet

Figures 42, 43, and 44 represent the forecast for Indonesia by LSTM, ARIMA, and FBProphet. The LSTM model predicts Indonesia will not have an early peak wave, but new cases per million will increase by August 2022, with new cases per million close to 400. The ARIMA model predicts that Indonesia will not have a peak wave by the end of January 2022. The FBProphet model predicts that Indonesia will not have a peak wave by the end of January 2022.

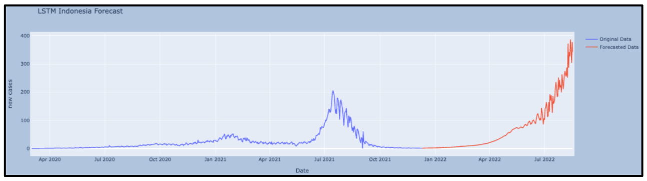


Figure 42: Indonesia Future Forecast using LSTM

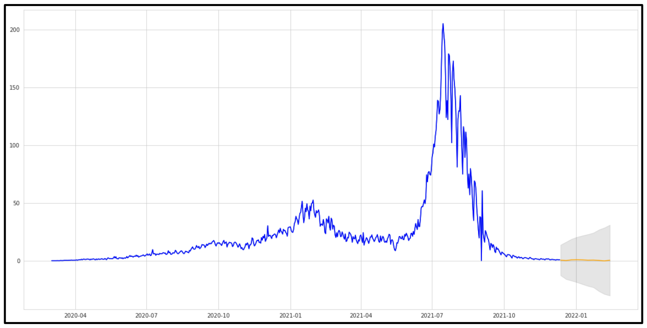


Figure 43: Indonesia Future Forecast using ARIMA

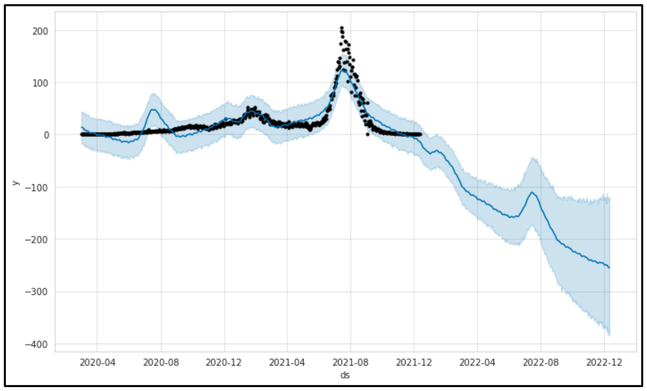


Figure 44: Indonesia Future Forecast using FBProphet

Figures 45, 46, and 47 represent the forecast for the United States by LSTM, ARIMA, and FBProphet. The LSTM model predicts that the United States will not have a peak wave between January 2022 and July 2022, with new cases per million reducing to 150. The ARIMA model predicts that the United States will have a two-peak wave first by the end of December 2021 and a second wave by February 2021 with new cases per million close to 600. The FBProphet model predicts that the United States will have a peak wave by the start of January 2022, with new cases per million close to 650.

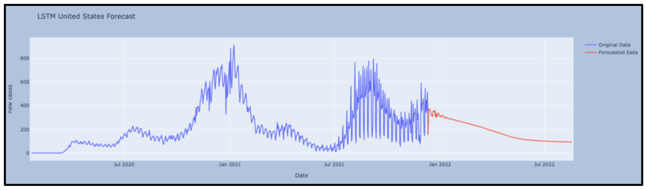


Figure 45: USA Future Forecast using LSTM.

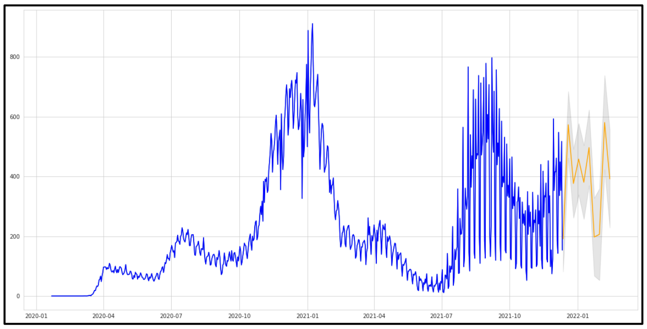


Figure 46: USA Future Forecast using ARIMA.

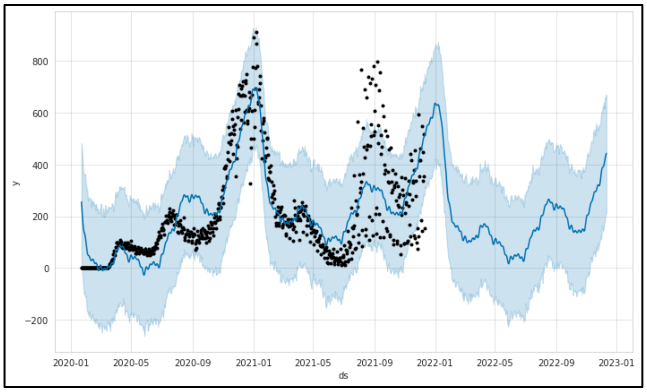


Figure 47: USA Future Forecast using FBProphet.

5 Conclusion and Future work

The increasing COVID-19 cases, even after vaccination, has become an essential matter for all the countries to investigate. This paper uses three machine learning models LSTM, ARIMA, and FBProphet, to predict the next peak wave of COVID-19 in different countries. This paper discussed how the three models could be designed to get an excellent future forecast for other countries. It also focuses on the tuning process of the models, where we figure out the best hyper-parameter combination for the model to improve forecasts accuracy further. Finally, we compare the result obtained from all the models.

Looking at RMSE values of all the three models, LSTM performs better than the other two models, followed by FBProphet and ARIMA. FBProphet could forecast 365 days, while LSTM could forecast 250 days correctly. ARIMA can only predict forecasts for the next 60-90 days. Both LSTM and ARIMA cannot predict 365 days of forecast because the accuracy decreases with increases in forecast days. So, FBProphet should be preferred for long-term forecasting, and for higher accuracy and medium-term forecasting, the LSTM should be used. Currently, we have a limited amount of data, and in the future, the result might change when we have a good amount of data.

Even though the machine learning models that are discussed in this paper provide a reasonable forecast with good accuracy, there are still some problems associated with them. In the LSTM model, even though we are getting an excellent RMSE value, the loss per epoch for some countries is very irregular, decreasing the accuracy of the predicted forecast. Hence, this should be further studied, and a single LSTM model which can provide low loss per epoch with high accuracy of prediction on any country should be developed in the future. The problem with the ARIMA model is that it cannot predict beyond 60-90 days and have a high RMSE value. This problem can be solved by training the model on an extensive dataset in the future. The FBProphet provides an excellent long-term forecast, but the model sometimes cannot catch outlier data, which affects the model's accuracy. This problem can be solved by improving the hyper-parameter like holidays, uncertainty sample, and holiday prior scale that should be done in the future.

While training the models, only new cases per millions column were used. In the future, the model should be trained on data like new COVID-19 variants, booster vaccination, and holidays. A new machine-learning algorithm that can handle multiple datasets should be considered to build a robust model that can predict COVID-19 wave for all countries.

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