Forecasting of COVID-19 Pandemic Using ARIMA and Fb-Prophet Models: UK Case Study

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Abstract: This study aims to provide insights into predicting future cases of COVID-19 infection and rates of virus transmission in the UK by critically analyzing and visualizing historical COVID-19 data, so that healthcare providers can prepare ahead of time. In order to achieve this goal, the study invested in the existing studies and selected ARIMA and Fb-Prophet time series models as the methods to predict confirmed and death cases in the following year. In a comparison of both models using values of their evaluation metrics, root-mean-square error, mean absolute error and mean absolute percentage error show that ARIMA performs better than Fb-Prophet. The study also discusses the reasons for the dramatic spike in mortality and the large drop in deaths shown in the results, contributing to the literature on health analytics and COVID-19 by validating the results of related studies.

1 INTRODUCTION

According to WHO data, the United Kingdom, the United States, Mexico, France, and Brazil are among the countries most affected by the pandemic. On January 30, 2020, the first two verified cases of COVID-19 were discovered in the United Kingdom (Gaur et al., 2020). Since then, COVID-19 has mutated into numerous variants, including "Alpha," which was first found in the UK, "Beta," in South Africa, "Gamma," in Brazil, and "Delta," in India, causing two devastating infection waves in the UK and other areas of the world. Finally, the Omicron variant made its appearance and is now the most common. In recent months, the UK has observed a reduction in infection rates following multiple vaccination campaigns and early adherence to strict regulatory laws such as face masking, social distancing, and prohibitions on religious, cultural, and educational gatherings. Furthermore, those who were considered to be very sensitive to serious sickness were advised to stay home in self-isolation and avoid social interactions. Artificial intelligence technology has also been deployed to help in COVID-19 diagnosis, screening, prediction, and drug repurposing. The UK National Health Service (NHS) test and trace service help people with symptoms that are associated with COVID-19 to get tested and then follow up with those who test positive.

Regardless, the pandemic will persist as a global health issue for at least a few more years. There are expectations that additional waves of the pandemic will occur due to the virus's dynamic nature, which has previously mutated into other variants. As such, it is necessary to study how the virus spreads so we can learn from visualization and prediction of the current situation and be better prepared for the following waves and their impact. To this end, AI predictive modeling can be employed to analyze and forecast COVID-19 based on past and current data.

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AI and Big Data research has been at the forefront of the COVID-19 battle, especially in the detection and forecasting of the disease spread. Time series–based forecasting methods, such as Auto-Regressive Integrated Moving Average (ARIMA), Fb-Prophet, Nonlinear Autoregression Neural Network (NARNN), and Long-Short Term Memory (LSTM) approaches, have recently been popular in AI predictive analysis (Wang et al., 2020). Therefore, this study is focused on time series analysis and forecasting of the COVID-19 cases in the UK using ARIMA and Fb-Prophet predictive models. We have chosen these models as they are most suitable for time-series forecasting. They capture different aspects of underlying patterns, which is the main requirement of COVID-19 data to predict the trend based on data. This will help improve our understanding of how COVID-19 spreads and allow us to plan ahead to mitigate the crisis. Furthermore, a comparison between these models is conducted to determine which performs better.

2 LITERATURE REVIEW

Starting in December 2019, every country has been dealing with COVID-19 outbreaks; as a result, forecasting future instances using different time series forecasting models or algorithms based on historical data is now a focus of recent research.

Gecili et al. (2021) implemented four models on COVID-19 data from USA and Italy: 1) the Holt model, which uses dual exponential smoothing; 2) the ARIMA model; 3) the TBATS model (Trigonometric Exponential smoothing state space model with Box-Cox transformation, ARIMA errors, Trend and Seasonal component), and 4) the Cubic Smoothing Spline model based on a stochastic state space model that permits the use of a possible strategy for predicting the smoothing parameter. The result showed that ARIMA and Cubic Smoothing Spline Models performed better than TBATS and Holt-Winter models, with smaller prediction errors and narrower prediction intervals. Similar results were obtained by (Sharma et al., 2021). by applying ARIMA with a further decomposition of the time series to test for unit roots and validate against data from multiple countries. They employed the root-mean-square error (RMSE) to evaluate the prediction performance; (Benvenuto et al., 2019) further justified ARIMA's prediction properties through descriptive analysis.

Based on the COVID-19 dataset of confirmed cases in China (Ye and Yang, 2021) proposed an uncertain time series detection model. The aim of this model is to analyze the evolution of the confirmed cases. They compared their model with other classical methods to deal with time series datasets and found that the proposed method outperformed other methods in describing the COVID-19 epidemic by reducing the estimated variance of the disturbance term to an acceptable value.

In the work of Rasjid et al. (2021), LSTM and Savitzky-Golay Smoothing methods were employed to create prediction models for predicting the death and infected COVID-19. They applied the prediction models to the dataset from Indonesia and compared their performance. The results showed that the LSTM forecast has a clear upward trend and is consistent with the Time Series data.

In a COVID-19 dataset gathered from the Kaggle website for Indonesia (Satrio et al., 2021) investigate the application of ARIMA and Fb-Prophet models to forecast the confirmed deaths and recovered cases. The performance and accuracy of these models' outputs were compared using R^2, Mean Squared Error (MSE), Mean Absolute Error (MAE), and Mean Forecast Error (MFE). The results of the error measurements indicated that the Prophet model outscored the ARIMA model with minimal differences between the actual data.

Dwivedi et al. (2021) examined the efficacy and suitability of the Fb-Prophet and the ARIMA prediction models to the Indian COVID-19 dataset with confirmed deaths and recovered cases, which was collected from the COVID-19 India site. Comparing these two models showed that ARIMA surpasses Prophet in terms of its prediction accuracy.

In order to forecast future COVID-19 infections and mortalities in Bangladesh, (Sarkar et al., 2020) used ARIMA and machine learning algorithms in their research and evaluated them by RMSE. The Fb-Prophet model delivered the best forecasting result with exceptional precision among other forecasting models, including Holt's Linear Regression, Support Vector Regression, and Holt's Winter Additive Model.

As the COVID-19 pandemic is becoming a prevalent danger for humankind worldwide (Arora et al., 2021) investigated the COVID-19 data from a source at Johns Hopkins University for five months in 2020 and predicted the trend in weeks using ARIMA and regression models. The evaluation results from error measurement by Root Mean Squared Logarithmic Error (RMSLE) showed that ARIMA outperformed regression models.

By examining the most recent literature relating to the prediction of COVID-19 confirmations and mortality, it can be concluded that ARIMA and Fbprophet are the least geographically constrained compared to other methods and demonstrate good predictive power (Battineni et al., 2020). Therefore, ARIMA and Fbprophet were chosen for this study to examine the UK context. In addition, error metrics are also used to evaluate our models by measuring the difference between predicted and actual data.

3 MATERIALS AND METHODOLOGY

Using the Google Colab IDE, effective data analysis techniques and prediction models are implemented in Python 3.8. ARIMA and Fb-Prophet models from the openly available packages “statsmodels” and “Fb-Prophet”, respectively, are used to forecast COVID-19 confirmed cases in the UK for the next 365 days. Finally, the evaluation metrics root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) of both models are compared to find the best forecasting model. The workflow of this study is presented in Figure 1.

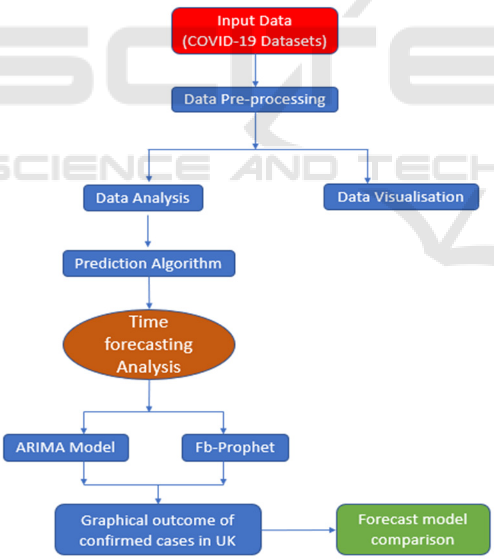

Figure 1: Study Workflow.

3.1 Forecasting Models

3.1.1 Fb-Prophet

Fb-Prophet is a forecasting algorithm developed by Meta. This model is based on the additive regression technique, which recognizes patterns, seasons, and holidays before combining them to improve forecast accuracy (Anandatirtha et al., 2020). This model uses a combination of non-linear and linear algorithms, as well as time as a regressor. It is expressed as follows.

$$(Forecasting = g(t) + s(t) + h(t) + e(t)\,) \quad (1)$$

where g(t) is the trend function; piecewise linear or logical growth to fit non-periodic changes in the value of the time series, s(t) are the periodical variations (e.g., week after week/yearly irregularity), h(t) are the effects of holidays that occur on irregular schedules over a day or more, and e(t) is any unusual change which is not accommodated by the model.

The model's input is always a time series with two components: t is time, and y is the total number of occurrences in a given country.

3.1.2 Arima (Autoregressive Integrated Moving Average Model)

ARIMA is a common time-series model that can be used to detect linear trends in definite time values. ARIMA forecasts future values by examining the differences between values in the time series. ARIMA(p, d, q) models are a fusion of integrated autoregressive (AR) and moving average (MA) models.

$$Y_t = \mathrm{c} + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \dots + \phi_p Y_{t-p} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \dots + \theta_q \epsilon_{t-q} + \epsilon_t \quad (2)$$

Where:

- Y: the value of the time series at time t
- c: the constant or intercept term
- p: the order of the autoregressive (AR) part of the model
- d: the degree of difference needed to make the time series stationary
- q: the order of the moving average (MA) part of the model
- ϕ_i : the coefficient of the ith lagged observation in the AR part of the model
- θ_i: the coefficient of the ith lagged error term in the MA part of the model
- ϵ_t: the error term at time t

Parameter Evaluation By Testing for Stationarity. In time series, stationary is a crucial component. For data to be stationary, it has a mean, variance, and autocorrelation structure that remain constant across time. A model cannot forecast on non-stationary time series data. Hence the first step in ARIMA time series forecasting is to calculate the number of differencing necessary to make the series stationary.

The Augmented Dickey-Fuller (ADF) test was used to determine whether or not the time series data were stationary before calculating the parameters for the ARIMA model (Alzahrani et al., 2020). This approach aims to maintain the reliability of the test based on white noise. Assume that the significance level is 5%, and the null hypothesis is that the series is not stationary. Suppose the critical value of the ADF test is greater than 0.05. the null hypothesis is accepted and the time series is confirmed to be non-stationary. In this case, differences of varying degrees are then used in the series to produce a stationary series (Wanjuki et al., 2021).

3.2 Quantitative Study

3.2.1 Data Source and Description

The datasets for this study were obtained from the GitHub account of the Johns Hopkins University Centre for Systems Science and Engineering's (JHU CSSE) data repository for the 2019 Novel Coronavirus Visual Dashboard (Alzahrani, et al., 2020)

Two different time series datasets were obtained: confirmed cases and deaths, containing information collected daily throughout the globe and is updated in real-time.

3.2.2 Data Preprocessing

Data cleaning was carried out in order to acquire useful data for analysis, visualization, and forecasting. The columns "Province," "Lat," and "Long" were dropped from the dataframe since they were no longer needed. Meanwhile, the data collection dates columns are transposed to a single column and indexed as a timestamp for time series forecasting. Missing values in each of the datasets were also checked and replaced with zeros.

As this study focuses on the COVID-19 cases in the United Kingdom, the data samples from the UK were extracted from the global COVID-19 time series repository. For each dataset, there are 807 data samples, recording the number of confirmed/death from January 22, 2020 to April 7, 2022.

Calculations for the following statistical information were obtained:

UK daily percentage growth rate in the past 30 days = (Active cases of the current day – Active cases 30 days ago / Active cases 30 days ago) *100

UK daily death rate = (Daily deaths / Daily confirmed cases) *100

UK death rate = (Accumulated deaths / Accumulated confirmed cases) *100

3.3 Model Performance Evaluation Metrics

The performance of each of the models mentioned above is evaluated using a widely popular accuracy measurement function. These measures are explained below.

3.3.1 Mean Absolute Percentage Error (MAPE)

MAPE is derived as the mean absolute percent inaccuracy for each time period, excluding actual values divided by real values and assesses the accuracy of the forecast as a percentage—the better the forecast, the lower the MAPE.

$$MAPE = \frac{100}{n}\left|\frac{A_t - F_t}{A_t}\right| \quad (3)$$

3.3.2 Mean Absolute Error (MAE)

MAE calculates the absolute value of an anticipated value. After that, we simply add up all of the absolute values that have been recorded. A better fit is evidenced by a reduced MAE value.

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \quad (4)$$

3.3.3 Root Mean Squared Error (RMSE)

It evaluates the forecast model's absolute fit to the data or how close the model's predicted values are to the observed data points. It's frequently used as an evaluation metric as well as a loss function.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_1 - \hat{y}_1)^2} \quad (5)$$

In equations (3) to (5), n is the number of observations, A_t is the actual value, and F_t is the predicted value.

4 DATA VISUALISATION AND ANALYSIS

4.1 Summary of COVID-19 in the UK

Our analysis is based on the code (COVID-19 data, 2023). From Figure 2, we can observe that confirmed cases are rising rapidly from July 2021 onwards till April 2022, while the death rates are below the 0.5 percentile. Although the number of deaths is significantly lower than the number of confirmed cases, these huge numbers imply how much people's lives and work are affected. Moreover, it remains on an upward trend and has not plateaued, meaning that the impact continues.

Figure 3 indicates the confirmed case growth in the UK from March 13, 2022, to April 11, 2022. It is shown that the few days have the highest count up to 1.0 and other days below 0.6. This can give us an idea of the upcoming few days ahead.

Figure 4 shows there is a peak in the death rate in the UK in May 2020, with a maximum percentile of 15 and then a slow decline begins. Between October and late November 2021, the mortality rate drops sharply to about 3%, and after September 2021, the rate drops to below 2%. This helps us understand that the impact of COVID-19 on death rates is reduced and stabilized in the span of two years.

4.2 Forecasting UK Confirmed Cases by Fb-Prophet

Figure 5 shows Fb-Prophet's prediction of confirmed cases for the coming year (365 days) from March 1, 2022. The black line indicates the original data points in the training set. The shaded area in the light blue color indicates the uncertainty level with an upper and lower boundary, and the dark blue line indicates the prediction. The uncertainty intervals can be used to make more informed decisions. In the case of predicting confirmed cases of COVID-19, healthcare providers can prepare in advance based on the upper limit of the uncertainty interval. In the future, there may be a steady increase in the number of cases. Therefore, the UK government should plan to act accordingly to prevent this as much as possible.

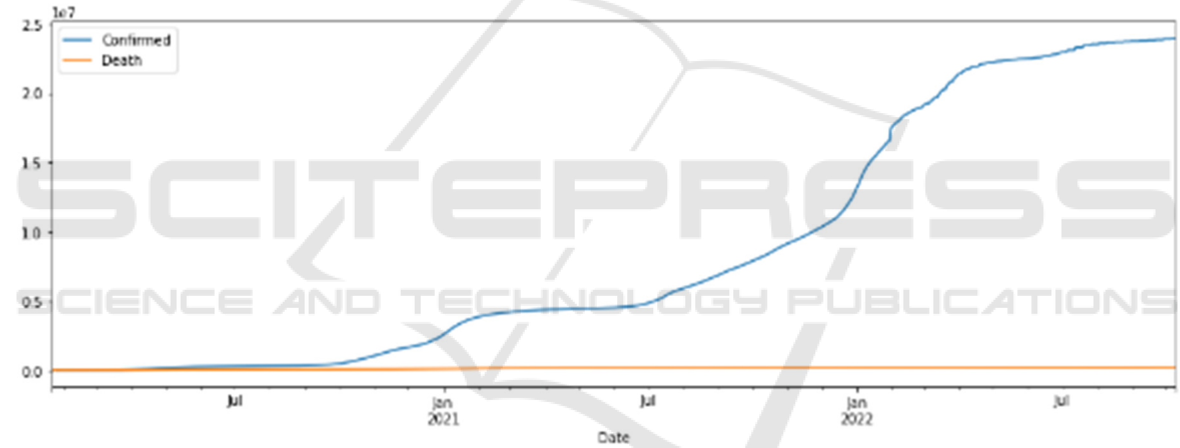

Figure 2: UK Confirmed and Death cases.

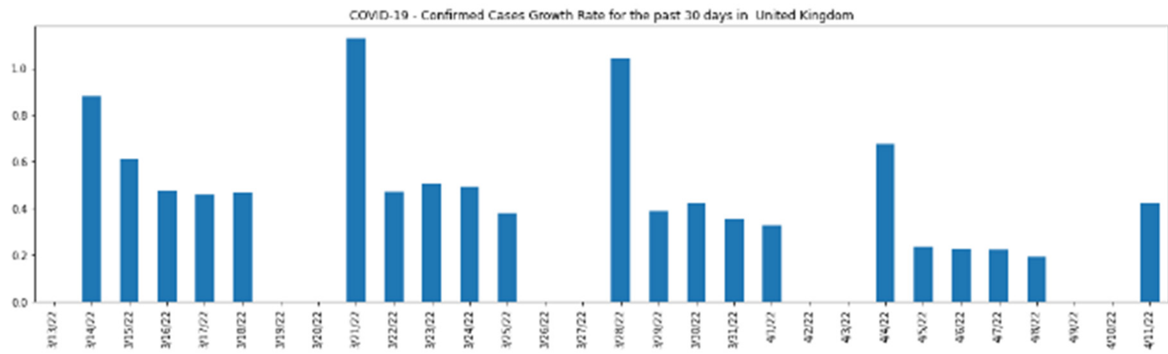

Figure 3: Confirmed cases growth rate from 3/13/2022 to 4/11/2022 in the UK.

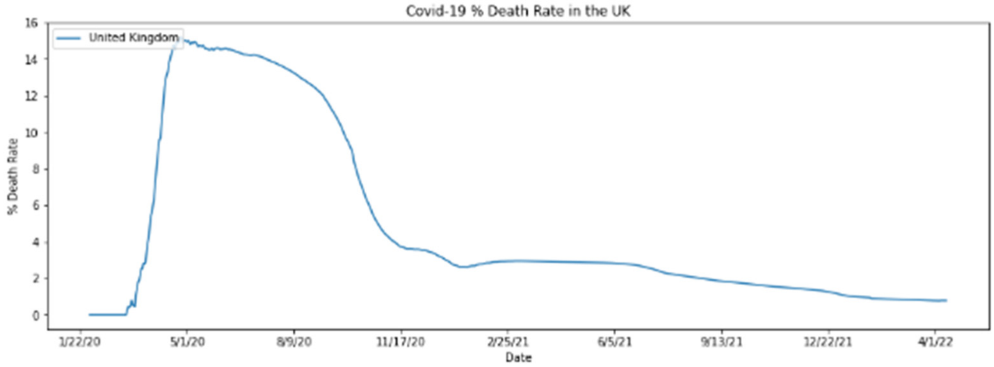

Figure 4: COVID-19 death rate percentage in the UK.

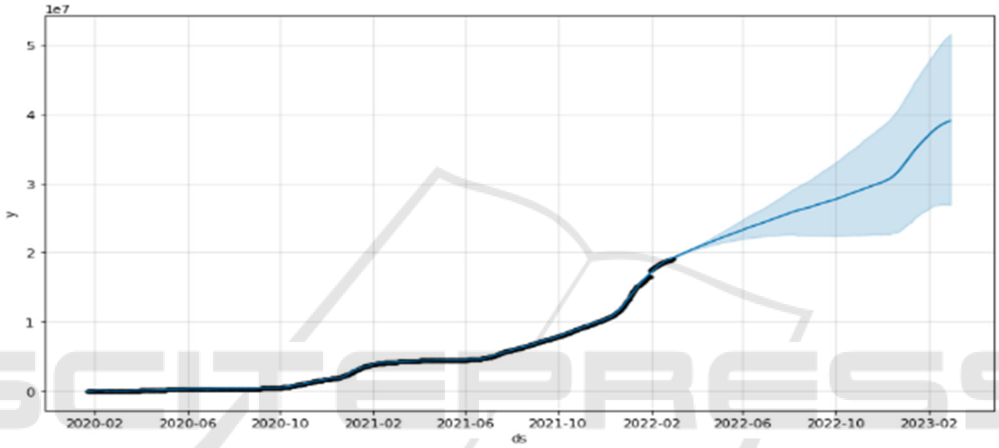

Figure 5: Fb-Prophet 365 days forecast.

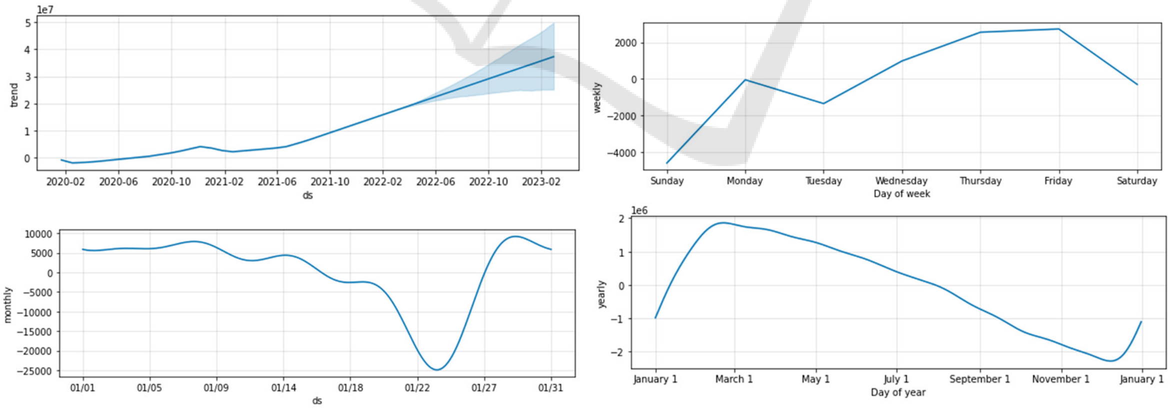

Figure 6: Forecast trend and seasonality.

Figure 6 shows the trend of the COVID-19 confirmed cases and the seasonality (in a week, a month, and a year) of the time series data. The first sub-figure of Figure 6 shows a high increase in cases around June 2022, and there is predicted to be a steady increase leading into 2023. The weekly forecast shows a high increase in cases from Tuesday to Friday and then a steady drop. The monthly forecast shows a steady curve in cases from January 1 to January 18 and then a huge drop until the end of the month before an extreme spike. The yearly forecast shows a high increase in cases from January 1 to March 1 and then a steady drop till the end of the year and a hike on January 1 again.

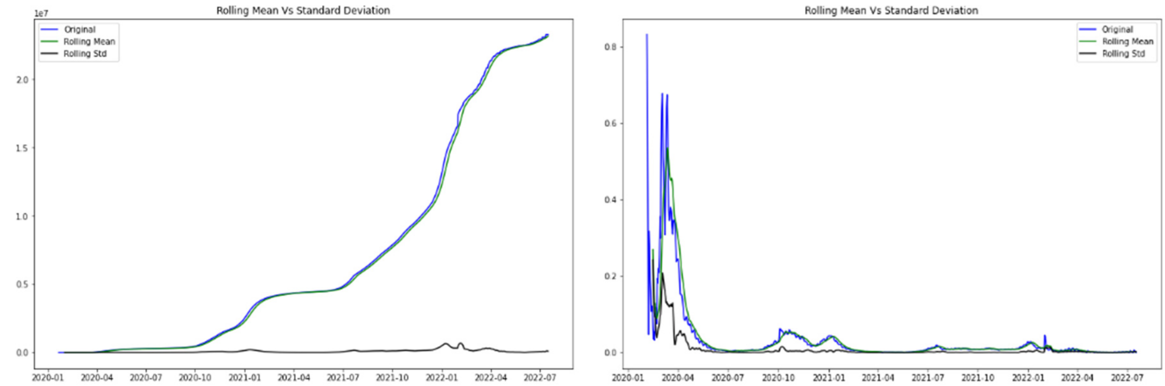

Figure 7: ADF Test for initial data (left) and for logarithmic values (right).

4.3 Forecasting UK Confirmed Cases by ARIMA

The result of the stationary test is shown in Figure 7. As shown in this figure, the rolling mean and original data are trending in the same path while the rolling standard deviation is constant. In addition, the p-value of the test is 0.98 ($p > 0.05$). Therefore, the time-series data appeared to be non-stationary based on the ADF test result, and the variance between the data must be compressed using the log scale of the data.

After transforming the data into the log form, this study conducted the ADF Test again to check the stationary values. The null hypothesis was rejected because, after applying the initial difference, d(0), the p-value produced was less than the significance level (p 0.05), and the statistical ADF was smaller than all the other critical bounds. The results are shown in Figure 7.

After checking the dataset for the stationary, the stepwise search by (Hyndman and Khandaka, et al 2008) was conducted to figure out the order for the best ARIMA model. The results show that the order for the best model is ARIMA(3,2,3)(0,0,0)[0], with the minimum Akaike's Information Criterion (AIC) of 21,376.38 and Bayesian Information Criterion of 21410.04. The parameters obtained were then used to train the Arima model and make predictions on the test set. The results (Figure 8) of the ARIMA model validate the increasing trend forecast by Fb-Prophet.

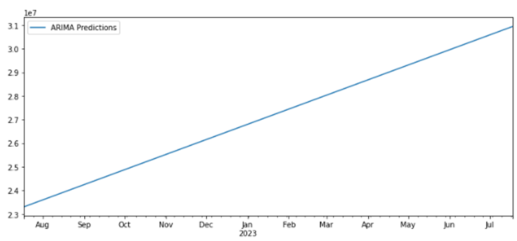

Figure 8: ARIMA Forecast.

The Linear trend is almost perfect, which may happen due to the following reasons.

- The model is overfitting the data, it may fit the trend too close.
- The data exhibits the linear trend, ARIMA is perfectly capturing a trend component of the time series, it also indicates that the model is removing the trend component from the data, so it is not a cause of concern.

5 ANALYSIS AND FINDINGS

A comparison of active cases in the UK and some other countries worst hit by the pandemic is shown in Figure 3. In the graph, the UK was 4th on the list of countries with the most active cases. The percentage growth rate of confirmed cases from March 13, 2022 to April 11, 2022, was calculated and visualized in Figure 3. March 21 and April 8, 2022, recorded the highest and lowest confirmed case growth rates, respectively.

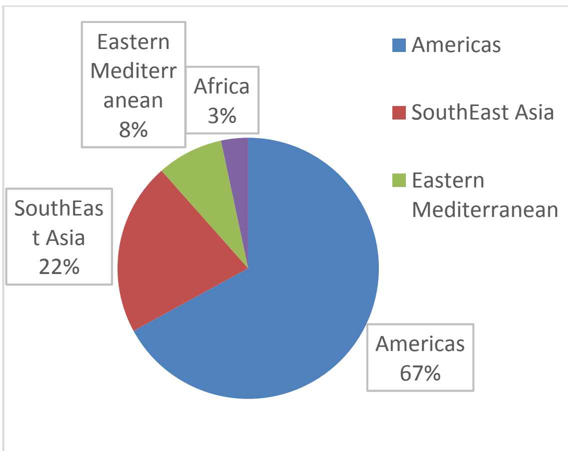

Figure 9: Active Cases from Jan 2020 to Jan 2023.

5.1 Model Evaluation

Figures 5 and Figure 6 show the Fb-Prophet forecast model trend of confirmed cases in the next 365 days. These show the underlying trend in the prediction is a linear trend while also accurately modeling weekly and monthly seasonality. The exponential curves of the forecast from the Fb-Prophet and ARIMA models show there will be more confirmed cases in the next year (365 days).

Table 1: Evaluation Metrics Comparison between Models.

Model	RMSE	MAE	MAPE
ARIMA	473888.97	379160.07	0.02
Fb-Prophet	1539062.30	1504264.94	0.15

In order to evaluate the performance of the Fb-Prophet and ARIMA models, error measurement metrics, RMSE, MAE, and MAPE, were carried out and the results are shown in Table 1. They are commonly used metrics to evaluate the accuracy of time series forecasting models. We have made this comparison to determine which model gives less error and is more accurate in predicting the result. A lower value of the different evaluation metrics indicates a model is well fit and has a higher prediction accuracy. A comparison of RMSE, MAE, and MAPE shows that the ARIMA model performed better than Fb-Prophet. The MAE for ARIMA is 379160 and for Fb-Prophet is 1504264, which is three times higher than the MAE for ARIMA. Similarly, the RMSEs of the two models show a vast difference, with ARIMA being at 473888 and Fb-prophet at 1539062. Finally, we compared the MAPE values of the two models at 0.02 for ARIMA and 0.15 for Fb-Prophet. The significantly lower values of error indicators for ARIMA show that ARIMA is better at capturing the patterns and trends in the time series data and making accurate forecasts than Fb-Prophet.

5.2 Forecasting Discussion

The following can be inferred from the analysis with respect to existing literature:

- Figure 4 shows a considerable decrease in deaths due to the deployment and adherence to pandemic control measures such as lockdowns, social distancing, face masking, sanitization, and vaccination by individuals and the UK authority. Dashtbali and Mirzaie's work in 2021 is therefore justified. They created two models, SEIHRD and SMEIHRDV, that accurately predicted how social distancing and vaccination are used to manage the COVID-19 pandemic (Mohan, et al., 2022).
- There was a drastic spike in the death rate, as seen in Figure 4, during the early months of the outbreak. It is evident in the work of Anderson et al. (2020) that data collection and research to better understand the virus's nature and behavior were ongoing while healthcare systems were overwhelmed due to the hospitalization cases surge (Anderson, et al., 2020).

6 CONCLUSIONS AND IMPLICATIONS

Predictive analysis of COVID-19 infectious disease using a time-series model is a useful application of AI and Big Data in the fight against the virus. The proposed models predicted an exponential slope from confirmed cases, implying that there will most probably be more instances in the next 365 days. Nevertheless, new variants, herd immunity, vaccines, and available resources may all alter mortality case projection curves. This study will enable the government and healthcare providers to understand the current situation better and prepare for the next wave so that less damage is caused in the near future.

In the future study, we can enhance this study by taking the latest data and adding time series algorithms like SEIR(Suspected Exposed Infections Removed) for short-term and long-term forecasting, Hybrid models like combining ARIMA with LSTM to capture trends in data.

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