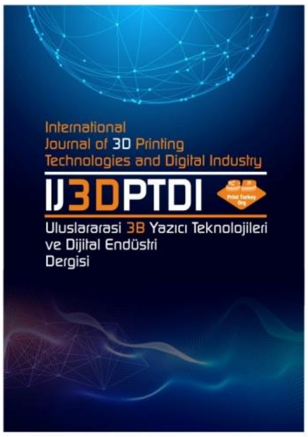

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COMPARATIVE PERFORMANCE ANALYSIS OF ARIMA, PROPHET AND HOLT-WINTERS FORECASTING METHODS ON EUROPEAN COVID-19 DATA

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ABSTRACT

COVID-19 is the most common infectious disease of the last few years and has caused an outbreak all around the world. The mortality rate, which was earlier in the hundreds, increased to thousands and then to millions. Since January 2020, several scientists have attempted to understand and predict the spread of COVID-19 so that governments may make sufficient arrangements in hospitals and reduce the number of deaths. This research article presents a comparative performance analysis of ARIMA, Prophet and HoltWinters Exponential Smoothing forecasting methods to make predictions for the COVID-19 disease epidemiology in Europe. The dataset has been collected from the World Health Organization (WHO) and includes the COVID-19 case data of European countries, which is categorized by WHO between the years of 2020 and 2022. The results indicate that Holt-Winters Exponential Smoothing method (RMSE: 0.2080, MAE: 0.1747) outperforms ARIMA and Prophet forecasting methods.

Keywords: COVID-19, Time Series Forecasting, ARIMA, Prophet, Holt-Winters Exponential Smoothing.

1. INTRODUCTION

Throughout history, there have been various epidemics and pandemics that have affected the lives of thousands to millions of people. Despite improvements in medicine and research, human beings are still being threatened by novel infections that endanger human lives and the healthcare system. In the past two decades, coronaviruses have caused two large-scale pandemics. Coronavirus disease 2019 (COVID-19) pandemics is caused by the severe acute respiratory syndrome coronavirus 2 (SARSCoV-2), which is the seventh coronavirus that has infected humans to date [1]. COVID-19 began in Wuhan, China at the end of 2019, and quickly spread throughout the world [2]. The European countries including Spain, England, Italy, Germany, etc. are seriously affected by COVID-19. More than 200 million cases of infection and more than 2 million deaths are recorded in Europe so far [3].

Several learning models have been used to make predictions in COVID-19 pandemic. In [4], an adaptive boost algorithm with a decision tree estimator was used on the COVID-19 dataset. Beside that, effective feature selection methods with multi-threaded implementations have been investigated to predict the severity of the COVID-19 patients [5]. Time series models facilitate the estimation of the significant trends, seasonality, cyclicity as well as abnormality. In clinical applications, time series models have indeed been successfully applied to predict disease progression, predict mortality, and analyze time-dependent threat. Therefore, these models hold a critical value for making an impact in society. Among the time series models, ARIMA, Prophet and Holt-Winters Exponential Smoothing forecasting methods are well known and popular methods in different areas such as commerce, education and finance [6-8]. Since these methods have a good capability of making effective predictions in different areas, they have been widely used in the medical research field. More specifically, in the literature, ARIMA, Prophet, Holt-Winter time series forecasting methods have been well studied to make predictions of epidemiology and mortality of several diseases including infectious diseases, cancer and cardiovascular diseases. Acquired immunodeficiency syndrome (AIDS) is one of the severe infectious diseases and it is an important public health problem. For estimating the prediction and control of AIDS, ARIMA model was utilized in China [9]. Hepatitis B virus (HBV) infection is one other critical public health problem, and it should be kept under control. ARIMA method is reported as a potential forecasting method to make proper estimations to control the spread of HBV in China [10]. Similarly, prostate cancer is a big concern for the healthcare systems since it is the second most common cause of cancer-related death in Australia. ARIMA models have been used to provide a proper estimation of prostate cancer in Australia [11]. ARIMA models are also used in other health related problems such as hyperglycemia and hypoglycemia correlated with blood glucose concentration [12]. Precise forecasts can help countries to regulate their financial system and economy according to the total health expenditure, social health expenditure and government health expenditure. Zheng *et. al.* provided a total health expenditure estimation for health policy by using the ARIMA model [8]. Not only ARIMA models, but also ARIMA hybrid models have been used to improve the power of prediction and to better fit the model. ARIMAGNN model is one of the hybrid models. When this model is applied on the tuberculosis data, it shows superiority upon the single ARIMA model [14]. In another study, it is shown that the ARIMA model and its combined model with neural networks are suitable for predicting the epidemic situation of brucellosis in China [15,16]. On the other hand, Holt-Winters Exponential Smoothing and ARIMA forecasts have been compared with GMDH-type artificial neural networks for predicting under-five child mortality rate in Nigeria [17]. Prophet, which is another common forecasting method, is used to predict future trends of Schizophrenia in Korea [18].

Recently, for analyzing, modeling and forecasting the COVID-19 pandemic, researchers have proposed a number of mathematical and statistical models. Some researchers attempted to predict the COVID-19 pandemic trend using the above-mentioned methods. More specifically, these forecasting models have been utilized to predict COVID-19 epidemic situations, expenditures, medicine requirements. Ceylan *et al.* attempted to analyze a COVID-19 dataset that is obtained from Italy, France and Spain, by using different ARIMA models, and showed that the generated model can predict the epidemiology of the COVID-19 pandemic [19]. Russia is one of the most affected countries from the COVID-19 pandemic, and it is shown that ARIMA models have a good fitting effect to predict COVID-19 in Russia [20]. Different ARIMA models such as single ARIMA model and ARIMA-NAR models were applied on the COVID-19 data to improve the effectiveness of the model in different countries, including India [21]. ARIMA was also used to evaluate the effect of temporarily suspending national cancer screening programs due to the COVID-19 outbreak on breast and colorectal cancer diagnosis in the Netherlands [22]. Additionally, ARIMA model was used to estimate COVID-19 cases in six worst hit countries; US, India, Brazil, France, Russia, UK, and six high incidence states in India to plan and manage the healthcare system of countries [23,24]. ARIMA model have been used not only for the prediction of COVID-19 pandemic, but also for analysis of the effects of the COVID-19 epidemic in different areas such as the transport sector [25]. In another study, Prophet machine learning forecasting was carried out to analyze the most hitted countries such as the USA, Brazil, India and Russia [26]. Holt-Winters Exponential Smoothing was used for several time-series data analysis problems including Russia COVID-19 cases to predict morbidity of the disease [27]. In another study, different forecasting models including Holt-Winter, Prophet, ARIMA were compared to find the best model for forecasting the number of deaths caused by COVID-19 in

Iran [28]. Another study created a COVID-19 prediction model by applying Holt-Winters Exponential Smoothing forecasting model on COVID-19 pandemic data obtained from the area of Gorontalo, Indonesia [29].

The aim of this study is to forecast COVID-19 pandemic using the time series dataset of Europe, which is categorized by the World Health Organization (WHO) based on the existing data recorded from January 2020 to January 2022. In order to understand the characteristics of COVID-19 and its rapid spread, three different forecasting approaches, i.e., ARIMA, Prophet and Holt-Winters models are applied on the COVID-19 European dataset. Also, along this paper, comparative evaluation of ARIMA, Prophet and Holt-Winters Exponential Smoothing forecasting methods on the COVID-19 European dataset is presented. Even though there are some forecasting studies in the literature, we did not find much study that compares ARIMA, Prophet and Holt-Winters Exponential Smoothing time series models at the same time to make a comparison and an analysis of the COVID-19 European dataset. To the best of our knowledge, in all of the abovementioned studies, the analyzed dataset was limited to specific countries or regions. Unlike other studies in which only specific countries, or a few countries were examined, this study includes several European countries as categorized by WHO. Another novelty of this study lies in the fact that previous studies investigated the datasets which were limited to certain periods of time belonging to the days that pandemic broke out and restricted to only a few forecasting methods. In contrast to other studies where time span is restricted, in this study, the dataset for the whole pandemic period is taken into account. Moreover, the most popular forecasting methods have been employed for completeness.

The rest of this paper is organized as follows: In Section I, the use of forecasting methods in the trend analysis is given in detail. In this section, the existing research on the trend forecasting of COVID-19 has been summarized as well. In section 2, the dataset and methods used in this paper are presented. In section 3, the outcomes of the applied methods are presented and the results of different methods are compared. In section 4, the results are discussed and the paper is concluded.

2. MATERIAL AND METHOD

In this section, the dataset which is utilized in this paper and the methods that are used for analyzing the outbreak of the COVID-19 pandemic in Europe is examined. While Figure 1 summarizes the workflow of our methodology, the following four subsections, namely i) Dataset, ii) ARIMA method, iii) Prophet algorithm, and iv) Holt-Winters Exponential Smoothing algorithm; presents the details of each step.

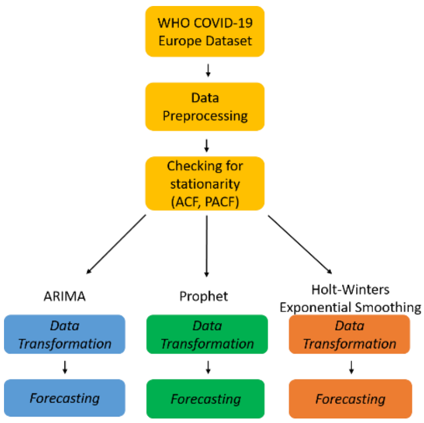


Figure 1. Flowchart of our methodology.

2.1. Dataset

The daily number of COVID-19 cases in Europe was collected by the World Health Organization (WHO) [30]. The dataset includes information on patients having COVID-19, dated from January 3, 2020 to January 13, 2022. The dataset consists of 840 daily records and 6 features. The features of the dataset are: "Date", "Region", "Country", "New_cases", "Cumulative_cases", "New_deaths" and "Cumulative_deaths". Data cleaning was performed in order to extract the appropriate information for forecasting. The European COVID-19 dataset was then created by only including the "New_cases" which has the "Region" field as "Europe". In the European COVID-19 data, each row represents daily records. The characteristics of the dataset are presented in Table 1. The number of new cases are visualized in Figure 2.

Table 1. Description of the dataset.

Features	Data Type	Minimum Value	Maximum Value	Mean	Std. Deviation
Date	Datetime	-	-	-	-
Region	Categorical	-	-	-	-
Country	Categorical	-	-	-	-
New_cases	Numeric	0	358006	2510.7	9162.5
Cumulative_cases	Numeric	0	14862142	540027.1	1350576
New_deaths	Numeric	0	2291	37.1	116.6
Cumulative_deaths	Numeric	0	319172	11205.2	28005.85

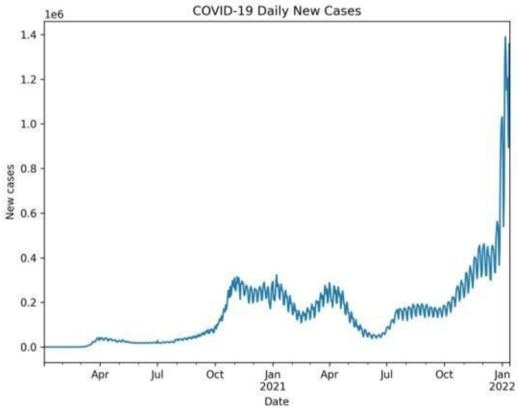


Figure 2. New cases of COVID-19 in Europe.

2.2. AutoRegressive Integrated Moving Average (ARIMA) Method

The AutoRegressive Integrated Moving Average (ARIMA) explains a particular time arrangement based on its own constraints and prediction errors, with the purpose of using that condition to make forecasts [5]. Three parameters define a non-seasonal ARIMA model: the order for the autoregressive expression p, the degree of differencing d, and the order of the moving average expression q. p refers to the number of y occurrences that will be used as indicators. Moreover, q refers to the number of uninteresting prediction errors that should be included in the ARIMA model. The differences required to fix the difference. If the time difference is now fixed, d = 0 at that point. In terms of the series of differences, the general equation is:

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \ldots - \theta q e t\text{-}q \quad (1)$$

where ϕi are the coefficients, y_{t-p} and e_{t-q} are the model's lagging predictors.

Choosing acceptable values for parameters p and q necessitates optimization and testing. In order to choose the values, graphs of the AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) must be examined. For this purpose, the following rules need to be followed. In forecasting, a limited number of univariate time series, relying solely on subjective visual examination, and adhering to these rules may be effective. However, if large numbers must be forecasted, these rules become useless. One solution to this challenge is to select ARIMA's parameters automatically using software packages. Another solution is to search the solution space for possible parameters, and try to suggest the best ones with the lowest error [31].

2.3. Prophet Algorithm

Prophet is a time-series analysis forecasting algorithm developed by Facebook [32]. This model incorporates parameters for holidays, trends, and seasonality, which will help to shape the prediction results and to provide a better performance with time-series data with seasonal effects. The following equation combines these elements:

$$y(t)=g(t)+s(t)+h(t)+\varepsilon t \quad (2)$$

where g(t) represents the trend, which is nonperiodic changes in terms of growth, s(t) represents the seasonal changes and h(t) defines the effects of holidays. The trend is defined by the following equation:

$$g(t) = \frac{C(t)}{1+exp\,(-(k+\alpha(t)^T\delta)(t-(m+\alpha(t)^T\gamma)))} \quad (3)$$

where C(t) is the carrying capability, k is the growth rate and m represents an offset parameter.

Prophet is well-known for its accuracy, speed and robustness to outliers and trend changes. It is totally automated, which aids in producing a reasonable forecast from a disorganized set of data without the need for personal intervention.

It is an additive regression model and includes components such as a piecewise linear or logistic growth curve trend. It discovers changes in patterns instantly by choosing change points from the data [33].

2.4. Holt-Winters Exponential Smoothing Algorithm

The Holt-Winters forecasting algorithm is used for time series forecasting, which involves smoothing time series data before forecasting. Exponential smoothing is an approach of smoothing a time series in which it assigns exponentially decreasing values and weights in contrast to previous data in order to reduce the value of the weights for the past data [34].The Holt-Winters Exponential Smoothing (ES) forecasting method employs exponential smoothing to encode a huge number of past values and then uses them to forecast typical values for the present and future [35]. Forecasting requires components such as level, trend, and season in this model. These components have values ranging from 0 to 1.
The general form of the model is:

$$\hat{y}_{T+1|T} = \alpha y_T + \alpha(1-\alpha)y_{T-1} + \alpha(1-\alpha)^2 y_{T-2} + \cdots \quad (4)$$

where, α is the response of the model. The Holt–Winters model is categorized as an additive model or a multiplicative model based on the seasonal pattern. When the changes in the season are stable throughout the periods, the additive approach is used, but when the variations in the season fluctuate relative to the level of the periods, the multiplicative method is used. The Holt–Winters additive model is employed when the seasonal effect is independent of the time series' prevailing mean level. The Holt–Winters multiplicative model is employed when the seasonal effect is dependent on the mean level of the time series [36].

3. RESULTS

In this section, the use of the three forecasting models is presented. In order to evaluate the forecasting methods, RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) rates are employed as the performance metrics. RMSE and MAE can be defined as follows:

Root Mean Square Error (RMSE)

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

Mean Absolute Error (MAE)

$$MAE = \frac{1}{N}\sqrt{\sum_{i=1}^{N} \|y(i)-\hat{y}(i)\|} \quad (6)$$

where N denotes the number of data points, $y(i)$ is the actual value of ith data point and $\hat{y}(i)$ is the predicted value for the ith data point.

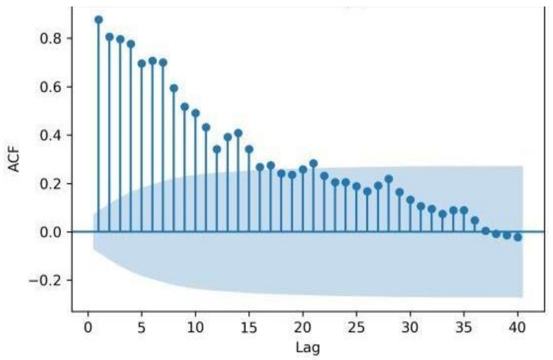
3.1. ARIMA Model Results

Steps given in Figure 1 are followed for the ARIMA analysis.

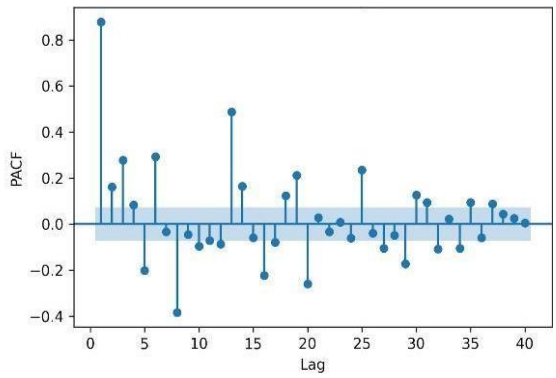
Checking for stationarity: The first step in time series forecasting is to check whether or not the time series data is stationary. Stationarity requires that the data has a consistent pattern across time, which means that the data must maintain a constant variance and mean. If data has a trend information, it may be necessary to transform it. Augmented Dickey Fuller (ADF) Test is the de facto method in statistics to check the stationarity of the data. ADF gives information on the degree of stationarity. ADF results of the data used in this paper yielded test statistic: 1.7763, and p-value: 0.9983, indicating that the data is not stationary. Confidence intervals of 1%, 5% and 10% are 3.4394, -2.8655, -2.5689 respectively.

Data Transformation: This operation is carried out to transform the data into stationary form and to remove the trend and seasonality components from the data. There are numerous approaches for transforming data into stationary data [37]. In this study, log-scale transformation and time-shifting transformation techniques have been employed. Log-scale transformation is carried out by replacing each variable x with $\log(x)$. This process is useful for balancing series that have non-constant variance in order to achieve a more regular distribution in the series [38]. Time shifting is a process of shifting values back and forward in time. The outcomes of the transformation were effective. ADF results of the data after performing transformation (Test Statistic: -3.8252 and p-value: 0.0026) prove the stationarity of the data.

Forecasting: In the ARIMA model, to identify the parameters q and p, the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are inspected. Previous studies also evaluated ACF and PACF plots for evaluating the quality of forecasting for COVID-19 [10,13,16,21,25,37]. Since the data used in this study has become stationary after the data transformation, it can be stated that the degree of differencing (d) in our ARIMA model is 1. ACF gives the degree of correlation between the time series and its lagged values. PACF, on the other hand, indicates the correlation between the time series and lag after removing the linear effects of the lags in between. ACF and PACF plots of COVID-19 European data are illustrated in Figure 3 (a) and in Figure 3(b), respectively.



(a)



(b)

Figure 3. ACF (a) and PACF (b) plots of the transformed COVID-19 European data.

Blue shadows in the correlation plots are the confidence intervals. If the bar heights outside of the confidence interval region, it indicates statistical significance. According to the ACF plot, we have some zero correlations and also non zero correlations. The first 16 lags have statistical significance for autocorrelation. Therefore, q will be 16. For partial autocorrelation, the first 3 lags have statistically significant correlations that will yield p as 3. Here, the solution space for possible (p, d, q) pairs are also searched, and it is aimed to find the best (p, d, q) pair with the lowest RMSE. Based on the results, for ARIMA, the best (p,d,q) pair is chosen as (9,12,18), which results in the RMSE of 0.2426.

Using ARIMA, the new cases of COVID-19 in Europe are forecasted. As presented in Figure 4, although ARIMA can successfully predict the first three months, it may not succeed in prediction in case of sudden fluctuations in the data.

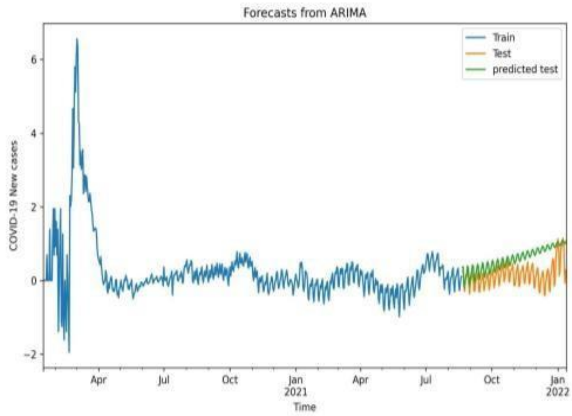


Figure 4. Forecasting COVID-19 cases in Europe using ARIMA model.

3.2. Prophet Model Results

In order to create a Prophet model, the fbprophet package in Python (by Facebook) is used, and the same data transformation protocol that is applied for the ARIMA method (Section 3.1) is followed. The dataset is prepared by generating a new data frame with two columns: 'ds' (date stamp), and 'y' (forecasting measurement). The forecasting period is chosen as 30, and applied in forecasting. The default parameters of the Prophet, which are tuned automatically, are used. Using Prophet, the new cases of COVID-19 in Europe are forecasted, as visualized in Figure 5.

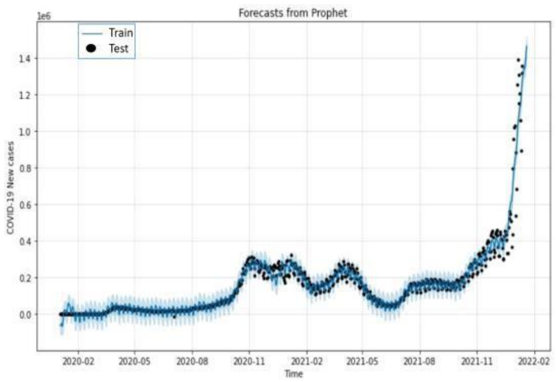


Figure 5. Forecasting COVID-19 cases in Europe using Prophet model.

3.3. Holt-Winters Exponential Smoothing Model Results

For Holt-Winters Exponential Smoothing (ES) model, the standard statsmodel package in Python is used. The same data transformation protocol, which is applied for ARIMA and Prophet algorithms, has been carried out for the Holt-Winter model as well. Using the developed Holt-Winters model, the new cases of COVID-19 in Europe are forecasted. The predictions of Holt-Winters model are illustrated in Figure 6.

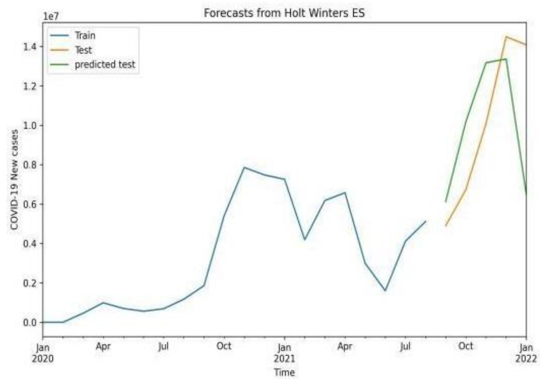


Figure 6. Forecasting COVID-19 cases in Europe using Holt-Winters ES model

Table 2 presents the RMSE (root mean square error) and MAE (mean absolute error) values of ARIMA, Facebook's Prophet and Holt-Winters forecasting methods, in terms of predicting the COVID-19 disease in Europe. As it can be seen on Table 2, Holt-Winters method generates better performance than Prophet and ARIMA methods in forecasting the new cases of COVID-19 in Europe.

Table 2. RMSE and MAE values for ARIMA, Prophet and Holt-Winters forecasting methods.

Forecasting Method	RMSE (Root Mean Square Error)	MAE (Mean Absolute Error)
ARIMA	0.2426	0.4304
Prophet	0.4820	0.3573
Holt-Winter	**0.2080**	**0.1747**

4. DISCUSSION

COVID-19 has been announced as a pandemic by the World Health Organization (WHO) as it infected the majority of countries, and posed a serious threat to humanity. Predicting the future trends for this disease has become an important interest for researchers, so that the governments can develop effective strategies to prevent and control the spread of epidemics. As a consequence, it is crucial to create a trustworthy, convenient and proper forecasting model which will help governments to develop emergency macroeconomic strategies, and to take action on medical resource allocation. In this study, i) the pandemic conditions of the COVID-19 in Europe between January 2020 and January 2022 was presented, ii) the ongoing trend of pandemic (the prevalence of COVID-19 in Europe) was predicted by using the ARIMA, Prophet and Holt-Winters Exponential Smoothing forecasting models, and iii) the developed models were compared in terms of their performances. It has been shown that with COVID-19 European dataset, Holt-Winters Exponential Smoothing model performed as the best model with the lowest RMSE (0.2080) value, as compared with Prophet (RMSE 0.4820) and ARIMA (RMSE 0.2426) forecasting models (as shown in Table 2).

In literature, different models including Holt-Winter, Prophet and ARIMA were utilized to find the best model for forecasting the COVID-19 pandemic. It is shown that different methods work well in different studies [19-21, 23, 24, 26-29,39]. It is shown that the generated ARIMA model can predict the epidemiology of the COVID-19 pandemic using data from Italy, France and Spain [19]. Similarly, different ARIMA models are shown to have a good fitting effect in terms of predicting COVID-19 in Russia, US, UK Brazil, France, India, Turkey [20-24,39]. Another study showed that in comparison to Holt-Winters exponential smoothing method, ARIMA is more accurate for forecasting COVID-19 cases in India [34]. Yet in another study, Prophet machine learning forecasting was carried out to analyze the COVID-19 cases in USA, Brazil, India and Russia [26]. In order to predict morbidity of the COVID-19, Holt-Winters Exponential Smoothing was used for several time-series data analysis problems including Russia, Iran and Indonesia [27-29]. Another scalable pipeline to forecast COVID-19 cases in Germany, Czechia, and Poland employs ARIMA and Holt's linear trend models [40]. There are only a few studies that attempt to forecast COVID-19 in Europe using similar methods that we have used here. Most of the existing studies use a single method, mostly ARIMA method. To the best of our knowledge, only in a study considers all three methods to forecast COVID-19 pandemic in Iran [28]. They reported that Holt-Winters Exponential Smoothing model can be used to forecast death cases because it has a lower error rate.

We would like to note that the methods that are used in this study impose certain limitations on the results. Although ARIMA is a powerful method, its processing is really slow, especially for large datasets like the one used here. Holt-Winters and ARIMA models perform well for long-view forecasting, otherwise, they have similar performances. One of the disadvantages of the Facebook Prophet is that its performance varies by dataset. It also worths to point out that the travel restrictions, quarantine policies, and school closures were applied in almost all countries in Europe at different times, and hence curfews varied from country to country during the pandemic. These are the significant parameters that caused fluctuations in the number of infected people and progression of pandemia. Therefore, there are inherent variations in the dataset.

In this study, ARIMA, Prophet and HoltWinters Exponential Smoothing forecasting models were applied to the overall prevalence of COVID-19 in European countries. COVID-19 European dataset, which is categorized by WHO between January 2020 and January 2022 is collected. Our results show that Holt-Winters method has performed better than ARIMA and Prophet methods on the scale of RMSE and MAE error metrics. As presented here, forecasting methods can facilitate the prediction of future trends for many diseases and they can be beneficial for public health. We hope that for future pandemics, the results of this study will be beneficial to governments and health authorities in terms of effectively planning the medical support, and supplying necessary resources such as medical staff and intensive care facilities. These approaches can be used in future studies to analyze other pandemics or diseases.

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