



Forecasting of Monkeypox Cases in the World Using the ARIMA Model

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Abstract

While the Covid-19 epidemic was not over in the world, the monkeypox epidemic started. The monkeypox virus has spread to more than 100 countries. Computer-aided forecasting models are needed to effectively control this spread. It has been seen in previous outbreaks that time series models are effective in estimating the impact of the epidemic and taking the necessary precautions. In this study, different Automatic Regressive Integrated Moving Average (ARIMA) models were developed to successfully estimate the number of monkeypox cases in the world. Data on daily confirmed cases of monkeypox between 07 May-10 November 2022 were used in the study. 07 May-31 October 2022 data were used in the training of ARIMA models. The prediction performances of the models were tested with data from 01 November-10 November 2022. According to the test results, the ARIMA (5,2,3) model with the lowest RMSE=57, MAE=41, and MAPE=0.05 was determined as the most successful model. It has been determined that the determined ARIMA model is in good agreement with the real values with an error value of less than 1%. The number of monkeypox cases for the next 7 days was estimated using the ARIMA (5,2,3) model. While this model estimates the number of monkeypox cases as 80435 for 17 November 2022, the actual number of cases is 80223, which proves the success of the ARIMA model.

Keywords: Monkeypox, Time-series, ARIMA, Forecasting.

ARIMA Modeli Kullanılarak Dünyadaki Maymun Çiçeği Vakalarının Tahmini

Öz

Dünyada Covid-19 salgını henüz bitmemişken maymun çiçeği salgını başladı. Maymun çiçeği virüsü 100'den fazla ülkeye yayıldı. Bu yayılmayı etkin bir şekilde kontrol etmek için bilgisayar destekli tahmin modellerine ihtiyaç vardır. Zaman serisi modellerinin salgının etkisinin tahmin edilmesinde ve gerekli önlemlerin alınmasında etkili olduğu daha önceki salgınlarda görülmüştür. Bu çalışmada, dünyadaki maymun çiçeği vaka sayısını başarılı bir şekilde tahmin etmek için farklı Otomatik Regresif Entegre Hareketli Ortalama (ARIMA) modelleri geliştirilmiştir. Çalışmada 07 Mayıs-10 Kasım 2022 tarihleri arasında teyit edilen günlük maymun çiçeği vakaları verileri kullanılmıştır. ARIMA modellerinin eğitiminde 07 Mayıs-31 Ekim 2022 verileri kullanılmıştır. Modellerin tahmin performansları 01 Kasım-10 Kasım 2022 verileri ile test edilmiştir. Test sonuçlarına göre en düşük RMSE=57, MAE=41 ve MAPE=0.05 değerine sahip ARIMA (5,2,3) modeli en başarılı model olarak belirlenmiştir. Belirlenen ARIMA modelinin %1'den düşük hata değeri ile gerçek değerlerle iyi bir uyum içinde olduğu tespit edilmiştir. İleriki 7 gün için maymun çiçeği vakalarının sayısı ARIMA (5,2,3) modeli kullanılarak tahmin edilmiştir. Bu model, 17 Kasım 2022 için maymun çiçeği vakalarının sayısını 80435 olarak tahmin ederken, gerçek vaka sayısının 80223 olması ARIMA modelinin başarısını kanıtlamaktadır.

Anahtar Kelimeler: Maymun çiçeği, Zaman serisi, ARIMA, Tahmin.

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1. Introduction

The Covid-19 pandemic has shown the world that countries are unprepared for epidemics. Nearly 500 million people have been infected with the coronavirus since March 2020. While the Covid-19 pandemic is not over yet and new variants are still threatening, the world has faced a new epidemic. Monkeypox virus (MPV) originating from Africa (Marennikova et al., 1972), outside monkeypox-endemic Africa zones began to be seen (Petersen et al., 2019; Zumla et al., 2022). Since the first case detection, the virus has been seen in 110 countries, with a total of 71276 confirmed monkeypox cases reported worldwide (10 November 2022). The countries where the virus was seen and the number of confirmed monkeypox cases in these countries (10 Nov 2022) are given in Figure 1. When the world map in Figure 1 is examined, the countries with the highest case density are the United States, Brazil, Spain, France, and the UK. The spread of the virus in many countries indicates human-to-human transmission (Angelo et al., 2019). Epidemiological studies have reported that the cases are an important travel link to monkeypox regions in Africa and that the virus will continue to spread, with new cases emerging in countries where no cases have yet been reported (Zumla et al., 2022; Heymann et al., 1998; Bunge et al., 2022). Symptoms of the disease include skin lesions, lymphadenopathy, fever, chills, and body aches. The MPV is known to be transmitted from animals to humans. Animals harboring the virus include rodents (rats, dormice, and squirrels) and various species of monkeys (Okay et al., 2022).

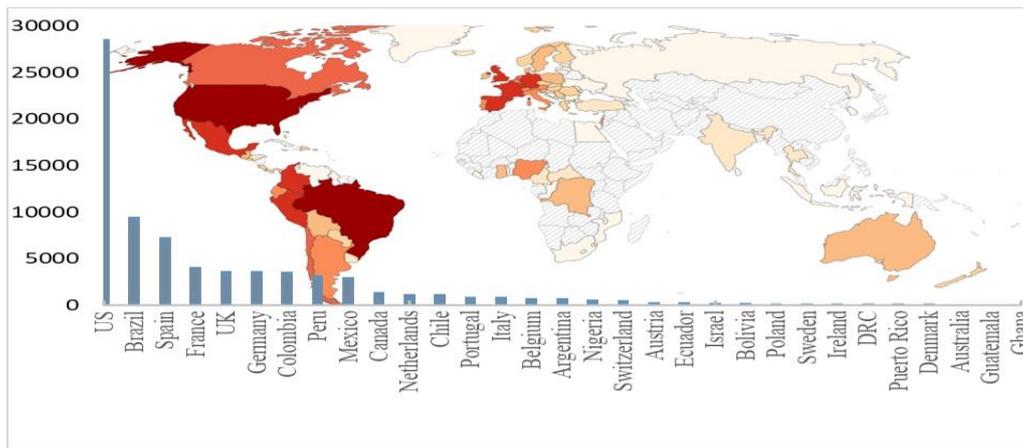


Figure 1. Cumulative confirmed monkeypox cases and case density by country

Currently, there is no vaccine or treatment for MPV infections. JYNNEOS and Smallpox vaccines protect against the MPV, but many young people are not vaccinated against smallpox since smallpox was eradicated in 1980 (Gao & Gao et al., 2022). It is stated that MPV may become an important public health problem worldwide (Arita et al., 1985). While the Covid-19 pandemic is not over yet, it is necessary to control the outspread of the monkeypox virus and to plan the health infrastructure and services effectively. The addition of monkeypox cases to the increase in the number of Covid-19 cases, especially in winter, may cause the health system to collapse. Successful forecasting of monkeypox cases is critical to managing health systems, planning for additional medical supplies and resources, and tackling the epidemic. Mathematical and statistical modeling tools are needed to make short-term and long-term forecasts.

In epidemics, different statistical methods have been used to predict the number of infected patients. Methods such as simulation models, backpropagation neural networks, multivariate linear regression, and gray forecasting models are deficient to analyze the randomness of outbreaks. ARIMA is one of the most used time-series models. It has been frequently used especially in the Covid-19 pandemic due to its abilities such as making successful predictions, fast applicability, simple structure, and explaining the dataset. In Figure 2, the intensity of use of frequently used artificial intelligence methods (blue circles) in different diseases is visualized. Web of Science database was used for this. Studies in which 7 different methods (ARIMA, LSTM, Holt-Winters, ANN, MLP, SVM, GRNN) were used in 15 different diseases were questioned in the WOS database. The resulting study numbers are visualized as edge densities in Figure 2. As the number of studies increases, the line color goes black. In the WOS database, the number of studies using the ARIMA method for Covid-19 disease was determined as 352. It was seen that the most used method was ARIMA and the most studied disease was Covid-19. After the ARIMA method, the most used method is LSTM. The frequent use of both time series methods in Covid-19 disease shows that studies with prospective estimates are more intense.

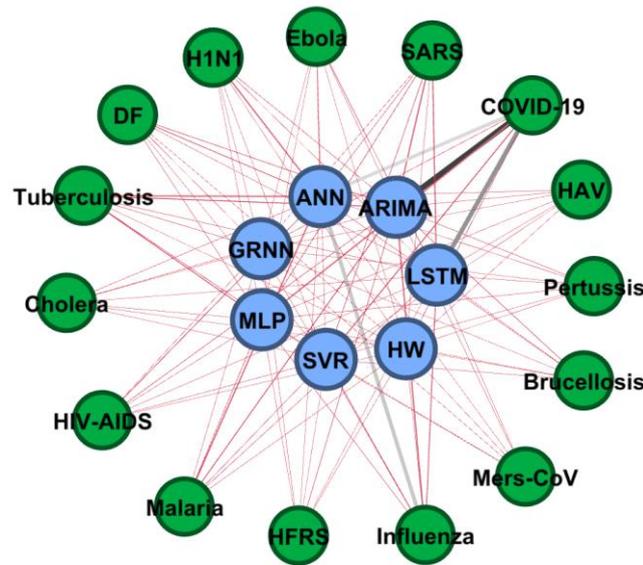


Figure 2. The intensity of the use of artificial intelligence methods in diseases

In the graphic presented in Figure 2, when the Covid-19 pandemic is compared with previous pandemics, it is seen that computer-assisted prediction and diagnosis studies have increased with the development of technology. During the Covid-19 epidemic, many studies have been carried out using artificial intelligence methods. The main ones are estimating the number of Covid-19 deaths and cases (Cihan, 2021; Gökler, 2022; Cihan, 2022) estimating the vaccination rate (Cihan, 2021b), estimating Covid-19 from lung tomography (Carvalho et al., 2021), determining the epitopes that can be used in vaccine development (Cihan & Ozger, 2022; Ozger & Cihan, 2022). Briefly, a lot of studies have been done and continue to be done to prevent the outspread of Covid-19. Especially in winter, if the number of Covid-19 cases increases again and the monkeypox virus continues to spread, health systems will be overloaded. It is therefore important to analyze the status of the monkeypox outbreak and to estimate the prevalence trend.

This study, it was aimed to forecast the number of confirmed monkeypox cases in the world for the next 7-days. This is the first study to date to forecast the number of monkeypox cases in the World. The dataset used in this study includes the number of cumulative confirmed monkeypox cases between 07 May 2022 and 10 Nov 2022. ARIMA models will be developed for the data set created within the scope of the study and the most successful ARIMA model will be determined in estimating the number of monkeypox cases.

2. Material and Method

The daily cumulative confirmed monkeypox cases data were retrieved from the Our World in Data website (Mathieu et al., 2022). In this study, the number of monkeypox cases for the future days will be estimated using the cumulative number of monkeypox cases in the World. Confirmed case data from 07 May to 10 Nov 2022 were used in the study. Box et al. (Box et al., 2015) reported that at least 30 days of data should be used to create a stable and effective ARIMA model. The ARIMA model was trained with the first 178 days of the 188-day time-series dataset used in the study, and the most successful model was selected by evaluating the model prediction performance with the remaining 10 days. With the determined ARIMA model, the number of monkeypox cases was forecasted for the next 7 days. In Figure 3, it is seen that the number of cumulative confirmed monkeypox cases is increasing exponentially day by day.

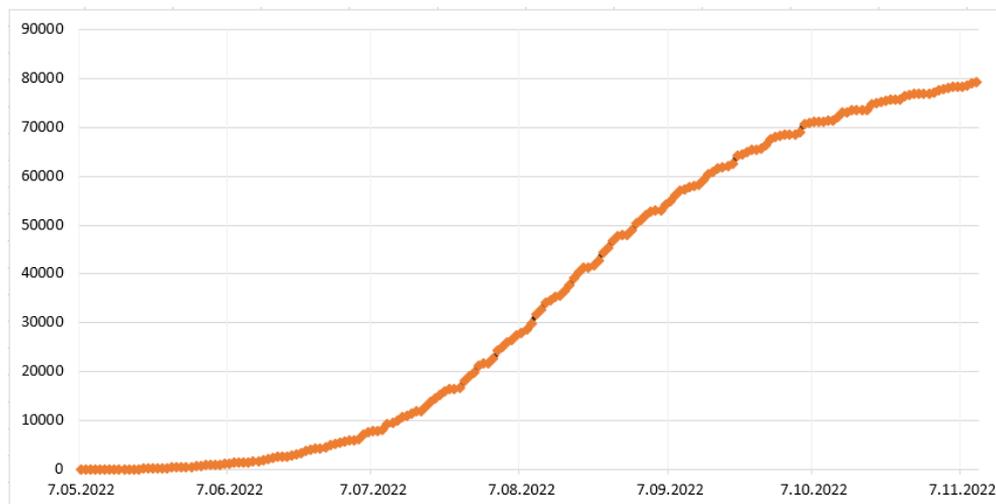


Figure 3. Cumulative confirmed monkeypox cases in the World

2.1. Box-Jenkins ARIMA Model

Box-Jenkins's method, also known as ARIMA models, is a very common method in the analysis of time-series. The main reasons for its widespread use can be listed as making successful predictions and being fast and easy to understand (Ceylan, 2020). The ARIMA method is used in the forward estimation of univariate time series. It is an important assumption for the ARIMA method that the observation data obtained at equal time intervals are discrete and stationary. The ARIMA method includes an experimental process with suitable parameters and suitable model options. This process consists of i) model identification, ii) model parameter estimation, iii) diagnostic checking, and iv) forecasting (Cihan, 2021b). Examining each stage of the ARIMA model and choosing the appropriate parameters to provide more accurate estimations.

The ARIMA model has three components: Autoregression (AR), Integration (I), and Moving Average (MA). AR derives the regression relationship between a variable that changes based on its previous values. Integration (I), refer to modeling the differences between observations so that the time series can be considered stationary. The MA, the moving average component in the Model, contains the relationship between an observation and a residual error from the moving average model applied to previous (or lagging) observations (Tanışman et al., 2021; Karcioğlu et al., 2021). Generally, the series is not stationary in the epidemic time series. The main reason for this is the trend effect. This trend factor disrupts the stationarity of the series. Modeling non-stationary time series primarily depends on making the series stationary. If the observed values in the time series do not add up around the mean of the series, the series is rendered stationary by differencing. Differentiation is symbolized by 'd'. In practice, the series is made stationary by taking the difference of 1 or 2 times. The models applied to the series are made stationary by the difference-taking process, the integrated model or the non-stationary stochastic models are called ARIMA models. The autoregression parameter of these models is expressed as p, the moving average parameter is q, the difference coefficient is d, and the model is written as ARIMA (p, d, q) (Brockwell & Davis, 2002). The general expression of the ARIMA model can be expressed representing as follows.

$$W_t = \phi_1 w_{t-1} + \phi_2 w_{t-2} + \dots + \phi_p w_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \dots - \theta_q a_{t-q}$$

w_t : differenced series

If the first-order difference (d=1) makes the series stationary:

$$\nabla x_t = w_t = x_t - x_{t-1}$$

∇ : It is the difference operator.

2.2. Model Performance Evaluation

The predictive accuracy of a ARIMA model can be measured by how close the predicted and the real/actual value are to each other. RMSE, MAE, and MAPE statistical criteria were used to test the prediction error of ARIMA models. Smaller values of these metrics indicate better model performance. RMSE, MAE, and MAPE can be calculated by using Equations (1), (2), (3), respectively (Hyndman & Koehler, 2006; Cihan, 2022b).

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^N e_t^2} \quad (1)$$

$$MAE = \frac{1}{N} \sum_{t=1}^N |e_t| \quad (2)$$

$$MAPE = \frac{100\%}{N} \sum_{t=1}^N \frac{e_t}{y_t} \quad (3)$$

In the equations the number of time points is indicated by N, the actual value at time t is indicated by y_t , and the difference between the predicted and actual value is e_t .

3. Results and Discussion

There are four steps to follow to create an ARIMA model and make future predictions. In the first step, the stationarity and seasonality of the series are checked. As with many time series techniques, ARIMA assumes that the data is stationary. Stationarity is important and makes it easy to get accurate estimates (Elevli et al., 2016). Time-series, ACF, and PACF graphs were created to check for stationarity and seasonality. ACF plot determines whether the previous value in the series is related to the next value, and the PACF plot determines partial correlations between the series and their own delays. By looking at these three graphs, it can be understood that a series is non-stationary or stationary. However, Augmented Dickey-Fuller (ADF) test can be used to confirm the stationarity statistically. The null hypothesis of the ADF test is the existence of a unit root, that is, the series is not stationary Cheung & Lai, 1995. When the ADF statistical value is lower than the critical value, the null hypothesis is rejected, and it is concluded that the series is stationary.

To determine the ARIMA model that best predicts the number of monkeypox cases in the world, the stationarity of the series was checked first. The original time series, ACF, and PACF plots are given in Figure 4.

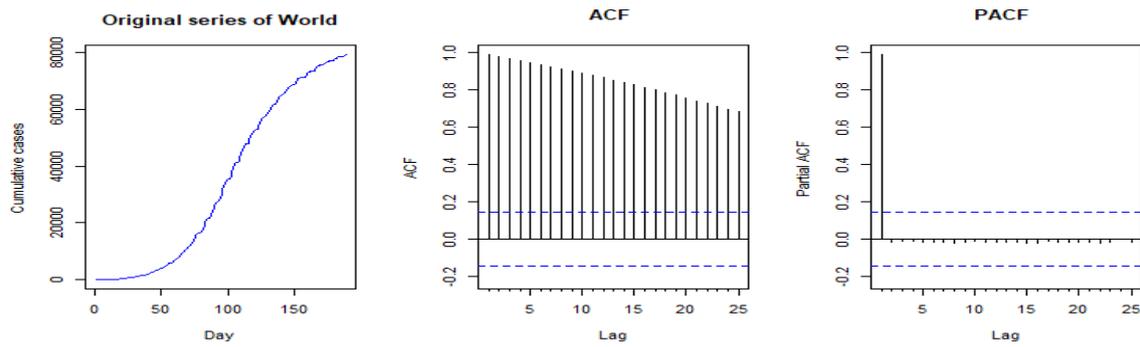


Figure 4. Time series, ACF and PACF graphs of the original data

When the original time series graph is examined, it is seen that the series is not stationary as it shows an upward trend throughout the period. This means that it can be concluded that the mean of the number of cases varies over time and thus the variance of the number of cases is not constant over time. The correlogram graph confirms the analysis that we obtained from the case number time series observation, that is, the series is not stationary. Autocorrelation coefficients are very high, especially for the first 5 lags. ADF unit test was used to check the stationarity of the original series and the results are dedicated in Table 1.

Tablo 1. Xxxxx (Table 1. ADF results of the original series)

Data	ADF Statistic	Significance	Critical Values		Conclusion
Original series	-2.8067	0.0573	-3.47	1%	Not Stationary
			-2.88	5%	Not Stationary
			-2.57	10%	Not Stationary

When the ADF test result is examined, the p-value obtained is greater than the significance level of 0.05. Also, the ADF statistic is higher than any critical value. This shows that the original series is not-stationary. For this reason, the stationarity of the series was checked by taking the first difference, and the Correlogram at the first difference is presented in Figure 5.

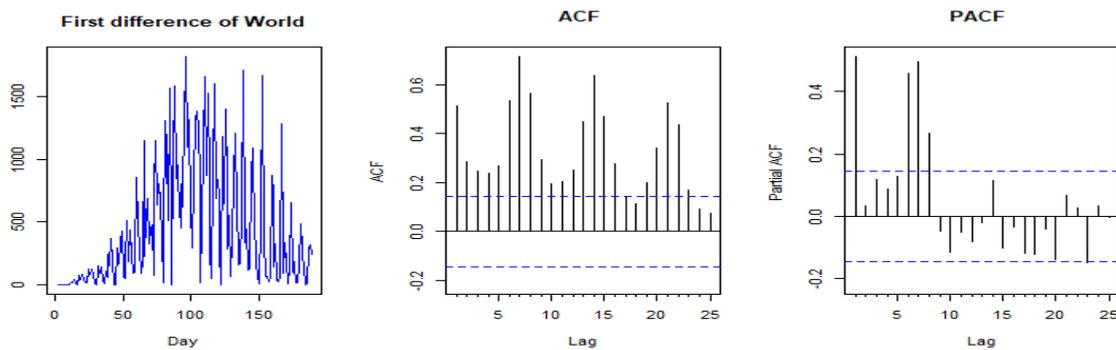


Figure 5. Time series, ACF and PACF graphs of the first differenced data

Table 2. ADF results of the first differenced series

Data	ADF Statistic	Significance	Critical Values		Conclusion
First difference	-1.2213	0.6643	-3.47	1%	Not Stationary
			-2.88	5%	Not Stationary
			-2.57	10%	Not Stationary

When the ADF test results in Table 2 are examined, it can be said that the series is not stationary since the p-value is greater than the significance level of 0.05 and the ADF statistic is higher than the critical value. For this reason, the second difference of the series was taken, and its stationarity was tested. ACF and PACF plots of the second differenced series are presented in Figure 6.

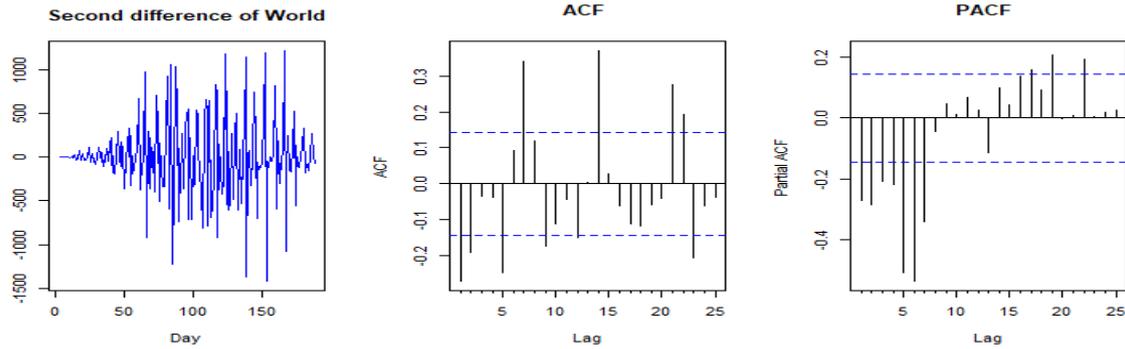


Figure 6. Time series, ACF, and PACF graphs of the second differenced series

When the time-series graph in Figure 6 is examined, it is seen that there is no upward trend, and the data is concentrated around zero. In the ACF and PACF plots, it is seen that the delays are between the levels of significance. ADF test was applied to verify the stationarity of the time series. The results obtained are given in Table 3.

Table 3. ADF unit test results of the second difference series

Data	ADF Statistic	Significance	Critical Values		Conclusion
Second difference	-15.092	0.0000	-3.47	1%	Stationary
			-2.88	5%	Stationary
			-2.57	10%	Stationary

When the ADF test results in Table 3 were examined, the series became stationary because the p-value was less than the significance level of 0.05 and the ADF statistic was lower than the critical values. The modeling phase can be started for the stationary series. Different models were created to determine the ARIMA model, which estimates the number of monkeypox cases in the world closest to the truth, and model performances were compared with various statistical metrics. The actual numbers of monkeypox test cases and the values estimated by the models are given in Table 4.

Table 4. Actual test values and predicted values with different ARIMA models

Date	Test	ARIMA (0,2,0)	ARIMA (0,2,1)	ARIMA (1,2,0)	ARIMA (1,2,2)	ARIMA (2,2,1)	ARIMA (3,2,1)	ARIMA (4,2,2)	ARIMA (5,2,1)	ARIMA (5,2,3)
01.11.2022	77119	76988	77077	76988	77155	77184	77200	77214	77353	77254
02.11.2022	77603	77088	77386	77008	77383	77443	77489	77503	77670	77614
03.11.2022	77909	77028	77595	77028	77604	77665	77741	77759	77936	77904
04.11.2022	78144	77048	77804	77048	77826	77870	77934	77957	78162	78110
05.11.2022	78297	77068	78013	77069	78047	78079	78115	78055	78311	78235
06.11.2022	78297	77088	78222	77089	78269	78294	78313	78118	78356	78280
07.11.2022	78307	77108	78431	77109	78491	78508	78529	78224	78528	78367
08.11.2022	78592	77128	78640	77129	78713	78722	78745	78398	78789	78598
09.11.2022	78902	77148	78849	77149	78935	78935	78955	78626	79064	78921
10.11.2022	79151	77168	79058	77170	79157	79148	79160	78859	79323	79222

ARIMA models were trained with the monkeypox case between 07 May-31 Oct 2022, and the case between 01 Nov-10 Nov 2022 was tested with the learned models. The prediction performances of different ARIMA models were compared according to different statistical metrics and the results are given in Table 5.

Table 5. Statistical comparison of prediction results of models

ARIMA Model	RMSE	MAE	MAPE
ARIMA(0,2,0)	1262	1154	1.47
ARIMA(0,2,1)	194	161	0.20
ARIMA(1,2,0)	1260	1153	1.46
ARIMA(1,2,2)	188	149	0.19
ARIMA(2,2,1)	164	132	0.16
ARIMA(3,2,1)	141	120	0.15
ARIMA(4,2,2)	193	179	0.22
ARIMA(5,2,1)	143	116	0.14
ARIMA(5,2,3)	57	41	0.05

When the estimation performances of the ARIMA models were compared, the ARIMA (5,2,3) model with a minimum value of RMSE=57, MAE=41, and MAPE=0.05 was chosen as the most successful model. It is seen that the determined model makes very close estimations to the real values (Table 4 and Table 5). With this most successful ARIMA (5,2,3) model identified, the number of monkeypox cases for the next 7 days was estimated with an 80% - 95% confidence interval (CI) and the results are given in Table 6 and Figure 7.

Table 6. Estimation of total monkeypox cases for the next 7 days with 80% and 95% CI according to the ARIMA (5,2,3) model

Date	Forecast	80% CI		95% CI		Actual
		Lower	Upper	Lower	Upper	
11.11.2022	79413	79062	79763	78877	79948	79332
12.11.2022	79559	79072	80046	78814	80304	79355
13.11.2022	79576	79001	80151	78696	80455	79429
14.11.2022	79640	78971	80308	78617	80662	79429
15.11.2022	79857	79088	80626	78681	81033	79642
16.11.2022	80149	79302	80996	78853	81444	80014
17.11.2022	80435	79479	81391	78972	81898	80223

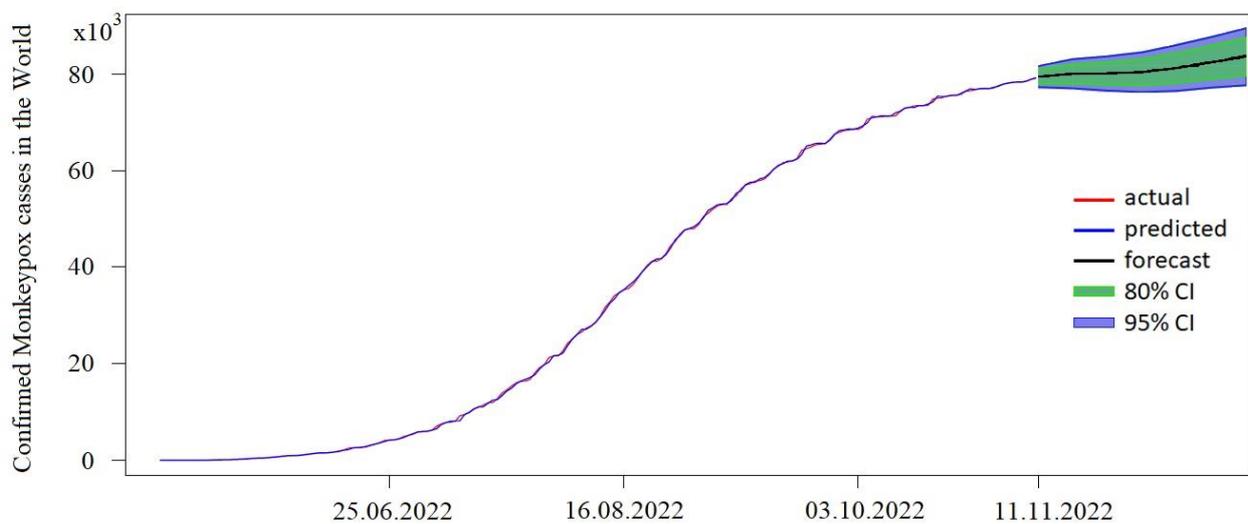


Figure 7. Time-series plots for the ARIMA (5,2,3) model

4. Conclusion

The monkeypox virus spread to more than 100 countries and infected more than 70M patients. Countries are implementing various strategies to control and prevent the spread of epidemics. One of these strategies is to predict the trend of the epidemic using computer-assisted forecasting methods. Thus, the allocation of medical resources, the regulation of health systems, and production activities can be ensured. Predicting the number of cases with computer-aided forecasting models will also positively affect the economic development of countries. For this reason, it is important to establish a successful, reliable, and suitable estimation method that can be a reference in supporting the strategies of the countries.

ARIMA model has been one of the most widely used time-series methods, especially in the Covid-19 pandemic, with its simplicity, acceptable estimation performance, and systematic structure. In this study, the prevalence of the monkeypox epidemic in the world was presented and a short-term prediction was made with the ARIMA model. This study is the first study to forecast the number of monkeypox cases with the ARIMA model. While the model predicts the number of monkeypox cases to be 80223 on 17 November 2022, the actual number of monkeypox cases is 80435 proving the model's success.

5. Acknowledge

All raw data collected within this study are available on <https://ourworldindata.org/monkeypox>.

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