DOI: 10.22625/2072-6732-2025-17-2-96-99

FORECASTING INFECTION FATALITY RATE OF MPOX IN AFRICA USING A HYBRID APPROACH

Djillali Seba
University of Bejaia, Bejaia, Algeria

Прогнозирование уровня смертности от инфекции Mpox в Африке с использованием гибридного подхода

Djillali Seba
Университет Беджайя, Беджайа, Алжир

Abstract

Objective: The main objective of our work is to forecast the daily Infection Fatality Rate (IFR) index for Mpox, a disease that has posed significant challenges, particularly in African countries. Mpox has become a major public health concern due to its rapid spread and the strain it places on healthcare systems

Methods: In this paper, we use a hybrid approach to enhance the performance of traditional models. First, we apply the ARIMA model, which is more suitable for the task, and then we implement a noise reduction technique to further improve the results.

Results and discussions: We utilize four performance measures RMSE, MSE, MAE, and MAPE to evaluate the efficiency of our approach. By combining a denoising technique with ARIMA and integrating Singular Spectrum Analysis (SSA) with the ARIMA model, the SSA-ARIMA model demonstrates the best performance.

Conclusion: Forecasting the Infection Fatality Rate with an appropriate model provides a deeper understanding of this phenomenon, enabling authorities to effectively control and manage the risks associated with Mpox.

Key words: *IFR, Forecasting, ARIMA, noise reduction, Mpox.*

Резюме

Цель: прогнозирование индекса ежедневной смертности (IFR) от инфекции Mpox — заболевания, которое создало значительные проблемы, особенно в африканских странах. Mpox стал серьезной проблемой общественного здравоохранения из-за его быстрого распространения и нагрузки, которую он оказывает на системы здравоохранения.

Методы: гибридный подход для повышения эффективности традиционных моделей. Сначала мы применяем модель ARIMA, которая больше подходит для этой задачи, а затем реализуем метод шумоподавления для дальнейшего улучшения результатов.

Результаты: мы используем 4 показателя эффективности (RMSE, MSE, MAE и MAPE) для оценки эффективности нашего подхода. Объединив метод шумоподавления с ARIMA и интегрировав анализ сингулярного спектра (SSA) с моделью ARIMA, модель SSA-ARIMA демонстрирует наилучшую производительность.

Выводы: прогнозирование уровня смертности от инфекции с помощью соответствующей модели обеспечивает более глубокое понимание этого явления, позволяя властям эффективно контролировать и управлять рисками, связанными с Mpox.

Ключевые слова: *IFR, прогнозирование, ARIMA, снижение шума, Mpox.*

Introduction

Mpox is a viral illness caused by the monkeypox virus, a member of the Orthopoxvirus genus. It is characterized by a painful rash, swollen lymph nodes, fever, headaches, muscle aches, back pain, and fatigue. While most individuals recover completely, some may experience severe illness.

Mpox can spread from person to person through direct contact with infectious skin lesions, it can also be transmitted via respiratory tract and sexual contact. thorn et al. [20] discussed in details Transmission, risk factors, clinical presentation, and outcomes of infection.

Animal-to-human transmission of Mpox occurs when an infected animal transmits the virus to humans through bites, scratches, or activities like hunting, skinning, cooking. Long et al. [12] provides a focused overview of the epidemiology, presentation, evaluation, and management of monkeypox for emergency clinicians to ensure appropriate diagnosis and treatment of this emerging disease.

On August 13, 2024, the Africa CDC declared Mpox a public health emergency of continental security (PHECS) to address the escalating outbreak. Since 2022, 40,874 cases and 1,512 deaths have been reported across 15 AU member states, with the DRC accounting for 96% of cases and 97% of deaths in 2024. Cases surged by 160% and deaths by 19% in 2024 compared to 2023, highlighting a worsening trend.

For successful prevention and management, Mpox forecasting in Africa is essential. Early forecasting can assist in identifying high-risk regions, allowing for the prompt distribution of resources, including medical personnel, vaccines, and therapies. It makes it possible to implement focused public health initiatives, like increasing awareness, improving surveillance, and preventing transmission via early detection.

Over the past three years, Mpox forecasting has been a widely studied topic among researchers, who have explored various methods and techniques.

Frank et al. [7], describe the Mpox describing using four models SIR-SIR, SEIR-SIR, SIR-SEIR, and SEIR-SEIR models, Jena et al. [10] implemented a time series modeling in Africa's most affected countries, Priyanka et al. [14] used deep learning approach to forecast Mpox epidemiological situation in the most affected regions Africa, Americas, and Europe, Langat et al. [11] used a Bayesian hierarchical model, Munir et al. [13] Time series analysis and short-term forecasting of monkeypox outbreak trends in the 10 major affected countries outside Africa, a statistical and regression analysis is implemented by Yasmin et al. We can mention also many other research such as the works of Singh et al. [18], Bleichordt et al. [2], Priyadarshini et al. [15], Cuba et al. [5], Chadaga et al. [4],Elshabrawy et al. [6], Rohrer et al. [16], Shishkin et al. [19].

In the present work, we implement a modeling and forecasting time series approach on infection fatality rate (IFR) of Mpox disease, IFR was discussed in infection disease modeling, we note the works of Grewelle et al. [9], Seba et al. [17] and Basu et al. [1] predict and estimate IFR of COVID-19.

We utilize a hybrid approach to forecast the IFR of mpox, employing an enhanced ARIMA model. A denoising technique is applied to minimize the impact of fluctuations on the data before implementing the ARIMA model. This method enhances the accuracy of the forecasting results. The methods section outlines the data, methodology, and forecasting models. In the third section, we present the results both numerically and graphically, accompanied by their interpretation. Finally, we discuss our findings and provide recommendations for managing the risks associated with the disease.

Methods

Descriptive data

Infection fatality rate (IFR) is a measure used to assess the proportion of infected individuals with fatal outcomes. Here is the formula used to calculate IFR for cumulative Mpox

$$\frac{Number\ of\ daily\ new\ confirmed\ deaths}{Number\ of\ daily\ new\ confirmed\ cases} \times 100 \quad (1)$$

We have dealt with new cases and new deaths in Africa from May, 1st 2022 to November 11th 2024

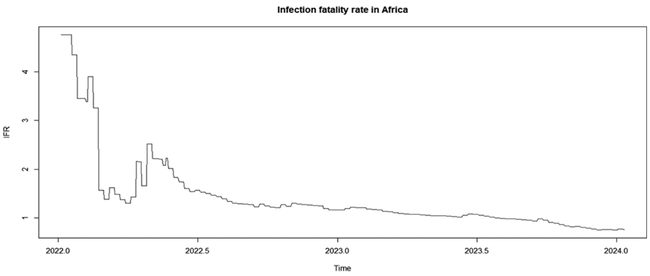

Fig. 1. Daily IFR of Mpox from May, 1st 2022 to November 11th 2024

In 2022, the IFR index exceeded 4 due to a significant Mpox outbreak worldwide, largely driven by the lack of local diagnostic infrastructure, which often left suspected cases unconfirmed. However, IFR values dropped significantly from 2023 onward, thanks to the availability of vaccines and efforts by affected communities, which reduced global infections. Between 2023 and 2024, the IFR remained stable as authorities effectively managed the spread of the disease, followed by a continued decline starting in early 2024 till nowdays. We provide a descriptive statistics in Table 1.

Methodology

Prior to applying any time series forecasting models, we conduct several essential tests to help determine the most appropriate model. adf.test for stationarity test Shapiro wilik test to test normality of data. Teravista's Test for nonlinearity of data.

Tsay's test, Perform the Tsay's test for quadratic nonlinearity in a time series. TAR's test, Perform the Likelihood ratio test for threshold nonlinearity.

The results of tests are presented in Table 2.

Table 2

Test performance results

Tests	Results	Comments
adf.test	0.01	Stationary
Shapiro-Wilk test	2.2e-16	Normally distributed
Teravista's test	0.07748	Linear

After conducting these tests, we have a clear understanding of the model to use. The adf.test confirms the stationarity of the data, indicating that its statistical properties are not influenced by time, as the p-value (0.01) is less than 0.05.

Table 1

Desciptive Statistics

min	1st Qu	Median	Mean	3rd Qu	max	NA's
0.7536	1.0304	1.1965	1.4068	1.4286	4.7619	0

Teravista's test indicates that the data is linear, while the Shapiro-Wilk test confirms that the data follows a normal distribution.

Therefore, we employ the Autoregressive Integrated Moving Average (ARIMA(p,d,q)) model, which is well-suited due to the normal distribution of the residuals and the data's linearity. Although this model is non-stationary, ARMA(p,q), a special case of ARIMA, could be used. However, considering the p-value (0.01) is less than 0.05, in practical applications, ARIMA(p,1,q) can be applied as it closely aligns with the properties of ARMA(p,q).

To enhance the results, we first reduce the noise in the data before applying the ARIMA(p,d,q) model, We utilize singular spectrum analysis to decompose the data into a linear component, where the ARIMA model is applied, and residuals. we use also another technique, denoising is performed by averaging each vector with its neighboring values.

Forecasting models

ARIMA model

Autoregressive integrated moving average (ARIMA) models predict future values based on past values, it gauges the strength of one dependent variable relative to other changing variables.

A stochastic process $(X_t)_{t\geq 0}$ is said to be an ARIMA(p, d, q) an integrated mixture autoregressive moving average model if it satisfies the following equation

$$\varphi(L)(1-L)^d X_t = \theta(L)\varepsilon_t \ \forall t \geq 0 \qquad (2)$$

Where $d \in$ N, L is lag operator, $\varepsilon_t \sim$ N $(0, \sigma^2)$ i.i.d. errors, with $\sigma^2 < \infty$.

$$\varphi(L) = (1 - \varphi_1 L - \ldots - \varphi_p L^p) \text{ with } \varphi_p /= 0$$
$$\theta(L) = (1 - \theta_1 L - \ldots - \theta_q L^q) \text{ with } \theta_q /= 0$$

In the case of $d = 0$, we obtain ARMA(p, q) process For more details see ([3])

Singular spectrum analysis

A nonparametric spectral estimating technique is singular spectrum analysis (SSA) [8]. It combines aspects of traditional time series analysis. The name "singular spectrum analysis" relates to the spectrum of eigenvalues in a singular value decomposition of a covariance matrix.

The fundamental goal of statistical component analysis (SSA) is to break down time series into their sum of identifiable elements, such as trend, periodic components, and noise, with no a-priori assumptions about the parametric form of these components.

Denoising

This function takes a given time series and denoises it. The denoising is achieved by averaging each Takens' vector with his neighbours (time lag = 1).

Results

We split the data into 80% for training and 20% for testing. The training data is used to fit the appropriate model, which is then improved using noise reduction techniques. The test data length is used as the forecasting horizon, and performance metrics are calculated to numerically evaluate the efficiency of the models employed in our approach.

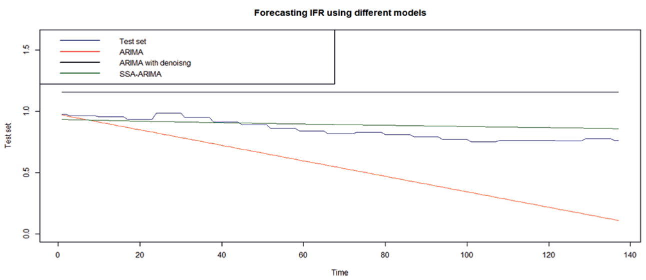

Fig. 2. Forecasting daily IFR using hybrid technique

Table 3

Performance measures

	RMSE	MSE	MAE	MAPE
ARIMA	0.3558	0.1266	0.3092	38.45%
ARIMA with denoising	0.3195	0.1021	0.3095	37.61%
SSA-ARIMA	0.0740	0.0055	0.0651	8.04%

Now, we use RMSE, MSE, MAE, MAPE to measure the performance of our models. As mentioned in the previous section, the improved ARIMA model (SSA-ARIMA) demonstrates the best performance due to its ability to separate the data into linear patterns and non-linear fluctuations. Since the data is predominantly linear, the denoising technique based on averaging is relatively simple and does not significantly enhance the results.

Discussion

In this section, we present the forecasting results for the period from November 11^{th}, 2024, to December 11^{th}, 2024, to observe the future behavior of the daily IFR of Mpox. We observe that the decline is gradual, with a projected decrease of 1.39%. Therefore, authorities must implement strategies to effectively control and manage this epidemic. Strengthening Surveillance and Diagnostics: Establish and expand diagnostic infrastructure for timely case identification. Promote hand hygiene, use of protective equipment, and safe handling of animals. Strengthen infection prevention protocols in healthcare facilities.

Promoting Public Awareness and Education: Educate communities about Mpox symptoms, transmission modes, and prevention measures.

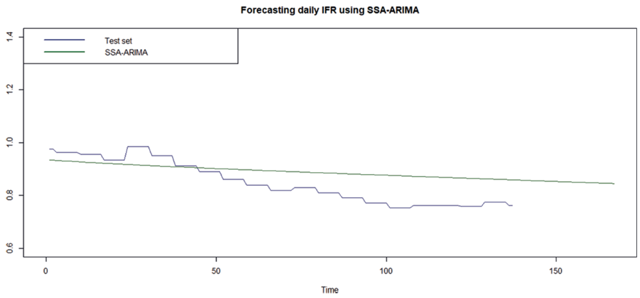

Fig. 3. Forecasting daily IFR using SSA-ARIMA from November, 11^{th} 2024 to december, 11^{th} 2024

Enhancing Vaccination Campaigns: Prioritize high-risk populations for vaccination, including healthcare workers and exposed individuals.

Fostering Regional and Global Collaboration: Coordinate efforts with the Africa CDC, WHO, and other partners to pool resources and expertise.

Conclusion

In summary, this paper examines an important infectious disease over the past three years. We applied a forecasting approach to the Infection Fatality Rate (IFR) of Mpox to gain a better understanding of its behavior. We adopted a hybrid approach, combining ARIMA with a noise reduction technique, and found that SSA yielded the best results in our test case. Finally, we offered recommendations for managing the risks associated with the spread of Mpox.

Acknowledgement

We acknowledge the support of "Direction G´en´erale de la Recherche Scientifique et du D´eveloppement Technologique DGRSDT".MESRS ALGERIA.

References

1. Basu, A. (2020). Estimating The Infection Fatality Rate Among Symptomatic COVID-19 Cases In The United States: Study estimates the COVID-19 infection fa- tality rate at the US county level. Health Affairs, 39(7), 1229-1236.

2. Bleichrodt, A., Dahal, S., Maloney, K., Casanova, L., Luo, R., Chowell, G. (2023). Real-time forecasting the trajectory of monkeypox outbreaks at the national and global levels, July-October 2022. BMC medicine, 21(1), 19.

3. Box, G. E., Jenkins, G. M., Reinsel, G. C., Ljung, G. M. (2015). Time series analysis: forecasting and control. John Wiley and Sons.

4. Chadaga, K., Prabhu, S., Sampathila, N., Nireshwalya, S., Katta, S. S., Tan, R. S., Acharya, U. R. (2023). Application of artificial intelligence techniques for monkeypox: a systematic review. Diagnostics, 13(5), 824.

5. Cuba, W. M., Huaman Alfaro, J. C., Iftikhar, H., Lopez-Gonzales, J. L. (2024). Mod- eling and analysis of monkeypox outbreak using a new time series ensemble technique. Axioms, 13(8), 554.

6. Elshabrawy, M., Eid, M. M., Abdelhamid, A. A., El-Kenawy, E. S. M., Ibrahim, A. (2023, October). Forecasting of Monkeypox Cases Using Optimized SARIMAX Based Model. In 2023 3rd International Conference on Electronic Engineering (ICEEM) (pp. 1-6). IEEE.

7. Frank, T. D. (2024). Mathematical Analysis of Four Fundamental Epidemiological Models for Monkeypox Disease Outbreaks: On the Pivotal Role of Human-Animal Order Parameters-In Memory of Hermann Haken. Mathematics, 12(20), 3215.

8. Golyandina, N., Nekrutkin, V., Zhigljavsky, A. A. (2001). Analysis of time series structure: SSA and related techniques. CRC press.

9. Grewelle, R. E., De Leo, G. A. (2020). Estimating the global infection fatality rate of COVID-19. MedRxiv, 2020-05.

10. Jena, D., Sridhar, S. B., Shareef, J., Talath, S., Ballal, S., Kumar, S., ... Sah, R. (2024). Time series modelling and forecasting of Monkeypox outbreak trends Africa's in most affected countries. New Microbes and New Infections, 62, 101526.

11. Langat, A. K., Mwalili, S. M., Kazembe, L. N., Chepkonga, D., Kamwele, J. M. (2024). Modeling the spread of Mpox viral disease in African countries using a Bayesian hierarchical model. Commun. Math. Biol. Neurosci., 2024, Article-ID.

12. Long, B., Koyfman, A., Gottlieb, M., Liang, S. Y., Carius, B. M., Chavez, S., Brady, W. J. (2022). Monkeypox: A focused narrative review for emergency medicine clinicians. The American Journal of Emergency Medicine, 61, 34-43.

13. Munir, T., Khan, M., Cheema, S. A., Khan, F., Usmani, A., Nazir, M. (2024). Time series analysis and short-term forecasting of monkeypox outbreak trends in the 10 major affected countries. BMC Infectious Diseases, 24(1), 16.

14. Priyanka, T. M. C., Gowrisankar, A., Banerjee, S. (2024). Mpox outbreak: Time series analysis with multifractal and deep learning network. Chaos: An Interdisciplinary Journal of Nonlinear Science, 34(10).

15. Priyadarshini, I., Mohanty, P., Kumar, R., Taniar, D. (2023). Monkeypox outbreak analysis: an extensive study using machine learning models and time series analysis. Computers, 12(2), 36.

16. Rohrer, R., Wilson, A., Baumgartner, J., Burton, N., Ortiz, R. R., Dorsinville, A., ... Greene, S. K. (2025). Nowcasting to Monitor Real-Time Mpox Trends During the 2022 Outbreak in New York City: Evaluation Using Reportable Disease Data Stratified by Race or Ethnicity. Online Journal of Public Health Informatics, 17(1), e56495.

17. Seba, D., Belaide, K. (2024). Forecasting infection fatality rate of COVID-19, measuring the efficiency of several hybrid models. Russian Journal of Infection and Immunity.

18. Singh, V., Khan, S. A., Yadav, S. K., Akhter, Y. (2024). Modeling global monkey- pox infection spread data: a comparative study of time series regression and machine learning models. Current Microbiology, 81(1), 15.

19. Shishkin, A., Bleichrodt, A., Luo, R., Skums, P., Chowell, G., Kirpich, A. (2024). Short-Term Predictions of the Trajectory of Mpox in East Asian Countries, 2022-2023: A Comparative Study of Forecasting Approaches. Mathematics, 12(23), 3669.

20. Thornhill, J. P., Barkati, S., Walmsley, S., Rockstroh, J., Antinori, A., Harrison, L. B., ... Orkin, C. M. (2022). Monkeypox virus infection in humans across 16 countries- April-June 2022. New England Journal of Medicine, 387(8), 679-691.

21. Yasmin, F., Hassan, M. M., Zaman, S., Aung, S. T., Karim, A., Azam, S. (2022). A forecasting prognosis of the monkeypox outbreak based on a comprehensive statistical and regression analysis. Computation , 10(10), 177

Author

Djillali Seba — University of Bejaia, Faculty of exact sciences, Applied Mathematics Laboratory, Associate Professor, Algeria. E-mail: d.seba@esi-sba.dz