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OPTIMIZED FACEBOOK PROPHET FOR MPOX FORECASTING: ENHANCING PREDICTIVE ACCURACY WITH HYPERPARAMETER TUNING

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Abstract— *MPOX (Monkeypox) has become a significant global health concern, requiring accurate forecasting for effective outbreak management. This study improves MPOX case prediction using Facebook Prophet with hyperparameter optimization. The dataset consists of global MPOX case records collected over time. Data preprocessing includes missing value imputation, normalization, and aggregation. Facebook Prophet is applied to forecast case trends, with model performance evaluated using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). A baseline Prophet model is first trained using default parameters. The model is then optimized by fine-tuning seasonality mode, changepoint prior scale, and growth model. The results show that hyperparameter tuning significantly enhances forecasting accuracy. The optimized model reduces MSE from 541,844.77 to 320,953.34 and RMSE from 736.10 to 566.53, demonstrating improved precision. The model also captures trend shifts and seasonal fluctuations more effectively. In conclusion, this study confirms that tuning Facebook Prophet improves epidemic forecasting, making it a reliable tool for MPOX monitoring. Future research should integrate external factors, such as vaccination rates and mobility data, to further refine predictions.*

Keywords*: epidemic modeling, facebook prophet, hyperparameter tuning, MPOX forecasting, time series prediction.*

Intisari— *MPOX (Monkeypox) telah menjadi masalah kesehatan global yang signifikan, sehingga membutuhkan peramalan yang akurat untuk manajemen wabah yang efektif. Penelitian ini meningkatkan prediksi kasus MPOX menggunakan Facebook Prophet dengan optimasi hyperparameter. Dataset terdiri dari catatan kasus MPOX global yang dikumpulkan dari waktu ke waktu. Prapemrosesan data meliputi imputasi nilai yang hilang, normalisasi, dan agregasi. Facebook Prophet diterapkan untuk meramalkan tren kasus, dengan kinerja model yang dievaluasi menggunakan Mean Squared Error (MSE) dan Root Mean Squared Error (RMSE). Model dasar Prophet pertama kali dilatih menggunakan parameter default. Model ini kemudian dioptimalkan dengan menyempurnakan mode musiman, skala titik awal, dan model pertumbuhan. Hasilnya menunjukkan bahwa penyetelan hyperparameter secara signifikan meningkatkan akurasi peramalan. Model yang dioptimalkan mengurangi MSE dari 541.844,77 menjadi 320.953,34 dan RMSE dari 736,10 menjadi 566,53, yang menunjukkan peningkatan presisi. Model ini juga menangkap pergeseran tren dan fluktuasi musiman dengan lebih efektif. Kesimpulannya, penelitian ini mengonfirmasi bahwa menyetel Facebook Prophet meningkatkan prakiraan epidemi, menjadikannya alat yang dapat diandalkan untuk pemantauan MPOX. Penelitian di masa depan harus mengintegrasikan faktor eksternal, seperti tingkat vaksinasi dan data mobilitas, untuk lebih menyempurnakan prediksi.*

Kata Kunci*: facebook prophet, optimasi hyperparameter, pemodelan epidemi, peramalan MPOX, prediksi deret waktu.*

INTRODUCTION

The Monkeypox (MPOX) outbreak has raised global health concerns, necessitating accurate forecasting to support timely intervention and disease mitigation (Jena et al., 2024). MPOX is a viral disease that spreads through close human contact, with transmission patterns influenced by various epidemiological and environmental factors (Mohapatra et al., 2024) (Chaturvedi et al., 2024). The increasing number of cases worldwide highlights the urgent need for predictive modeling to anticipate outbreaks and allocate healthcare resources effectively. Traditional statistical models, such as Autoregressive Integrated Moving Average (ARIMA) and Seasonal ARIMA (SARIMA), have been widely used for time series forecasting in epidemiology. These models have demonstrated reasonable accuracy in forecasting infectious diseases such as influenza (Orang et al., 2024) (An et al., 2024). However, they often struggle to capture complex nonlinear trends, seasonal variations, and external influences in epidemic progression (Haque et al., 2024).

Recent advancements in machine learning-based forecasting have introduced more robust approaches, such as Long Short-Term Memory (LSTM) neural networks and Facebook Prophet, which are specifically designed to handle time series data with seasonal, trend, and external factor components Alamsyah *et al*. (Alamsyah, Yoga, et al., 2024) and Putrada *et al*. (Putrada et al., 2024). Prophet has been successfully applied in predicting infectious diseases, such as COVID-19 (Islam et al., 2024) (Dash et al., 2024) (Singh & Pandey, 2024), influenza(Chen et al., 2024), dengue fever (Syfullah et al., 2024), and Zika virus (Babanejaddehaki et al., 2024), demonstrating its capability in epidemic forecasting. Despite its effectiveness, default Prophet configurations may not always provide optimal results, as hyperparameter settings significantly impact forecasting accuracy. Studies have shown that tuning hyperparameters—such as seasonality mode, changepoint prior scale, and growth parameters—can substantially improve model performance (Maleki et al., 2024) (Muñoz et al., 2024).

Monkeypox (MPOX) is a zoonotic disease caused by the Monkeypox virus (MPXV), first identified in 1958, with human cases emerging in 1970. Initially endemic to Central and West Africa, the 2022 global outbreak spread to non-endemic regions, raising concerns about human-to-human transmission and public health preparedness. While MPOX has a lower mortality rate than smallpox, its severe complications and increasing global spread necessitate robust forecasting models to aid in early intervention and resource allocation. Traditional models like ARIMA and SEIR often fail to capture nonlinear transmission patterns, making machine learning-based approaches, such as Facebook Prophet, more suitable for real-time epidemic prediction. Given MPOX's unpredictable nature, an accurate forecasting model is essential for strengthening public health surveillance and outbreak response strategies.

However, while Prophet has been extensively utilized in COVID-19 forecasting, research on its application for MPOX case prediction remains limited. Most existing studies on MPOX forecasting rely on traditional models (Bleichrodt et al., 2024) (Priyanka et al., 2024), and very few have explored the integration of hyperparameter tuning in machine learning-based approaches. This research aims to fill this gap by implementing a hyperparameter-optimized Facebook Prophet model for MPOX forecasting. The proposed model is compared against the default Prophet settings, evaluating its predictive performance using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE).

The key contribution of this research lies in applying systematic hyperparameter optimization to improve MPOX forecasting precision, enabling better epidemic preparedness. By refining Prophet's configuration, this study contributes to the growing body of research on machine learning-based epidemic forecasting, providing valuable insights for health policymakers and epidemiologists. The findings of this study can aid public health officials in monitoring and predicting MPOX outbreaks, allowing for more effective resource allocation and policy planning.

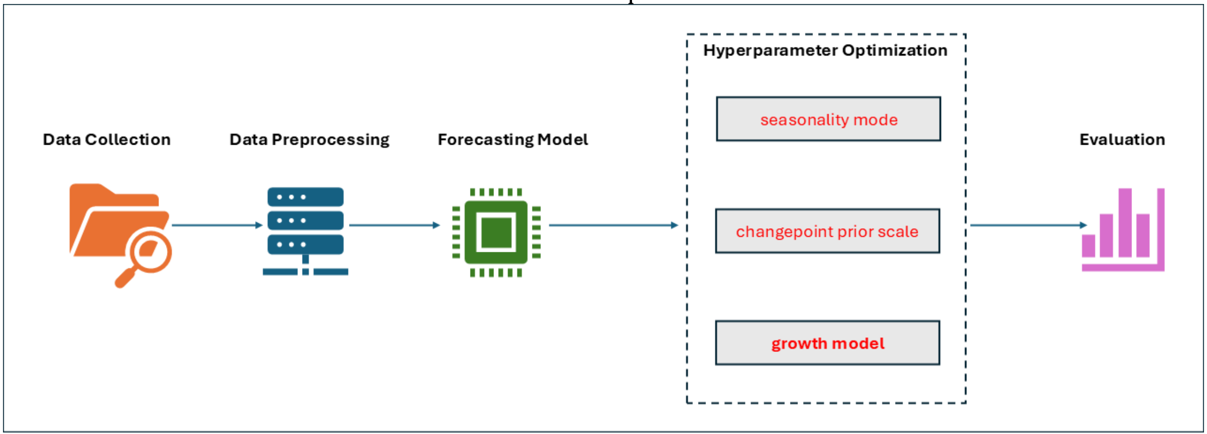
MATERIALS AND METHODS

This study follows a structured methodological approach to forecast MPOX cases using Facebook Prophet with hyperparameter optimization. The methodology consists of five key stages: data collection, data preprocessing, forecasting model implementation, hyperparameter optimization, and model evaluation. The first stage involves gathering global MPOX case records from reliable sources, followed by data preprocessing, which includes handling missing values, formatting timestamps, and aggregating daily case counts. Next, Facebook Prophet is employed as the primary forecasting model due to its capability to capture nonlinear trends and seasonality in time series data. To enhance predictive accuracy, hyperparameter tuning is applied to optimize seasonality mode, changepoint prior scale, and growth model parameters. Finally, model performance is evaluated using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) to compare the default Prophet model with the optimized version.

The proposed methodology aims to improve the accuracy and reliability of MPOX outbreak forecasting, providing insights that can support public health decision-making. The structured workflow ensures that the model effectively captures variations in MPOX case trends while adapting to changes in outbreak patterns. The overall research framework is illustrated in Figure 1, which presents a visual representation of the proposed methodology. The following sections describe each phase in detail.

1. Data Collection

The dataset used in this study was obtained from Kaggle, a well-known open data platform that provides structured datasets for data science and machine learning applications. The dataset contains time-series records of MPOX (Monkeypox) cases across multiple countries, including epidemiological attributes such as total cases, new cases, total deaths, and case rates per million. The data was collected over a specified period, ensuring that it provides sufficient historical information for forecasting purposes. The dataset consists of 33,666 rows and 15 columns, where each row represents a daily record for a specific country, allowing for both country-level and global trend analysis. The dataset comprises the following key features, as summarized in Table 1:



Source : (Research Results, 2025)

Figure 1. Proposed Method

Table 1. Dataset Features And Descriptions

Feature Name	Description
date	The date of the record in YYYY-MM-DD format.
location	The country or region where the cases were reported.
total_cases	Cumulative number of confirmed MPOX cases reported up to that date.
new_cases	The number of new MPOX cases reported on that day.
total_deaths	Cumulative number of deaths attributed to MPOX.
new_deaths	The number of newly reported MPOX-related deaths on that day.
new_cases_smoothed	A 7-day moving average of new cases to smooth fluctuations.
new_deaths_smoothed	A 7-day moving average of new deaths.
total_cases_per_million	The total number of cases per one million people in the country.
new_cases_per_million	The number of new cases per one million people in the country.
total_deaths_per_million	The total number of deaths per one million people in the country.
new_deaths_per_million	The number of new deaths per one million people in the country.
reproduction_rate	The estimated reproduction number (R) of the virus in that country.
stringency_index	A government response index that measures the strictness of public health measures.

Source : (Research Results, 2025)

2. Data Preprocessing

Before training the forecasting model, several preprocessing steps were applied to ensure data quality and consistency (Hikmawati & Alamsyah, 2024). The raw dataset contained 33,666 records across 15 features, requiring data cleaning and transformation to make it suitable for time-series forecasting. One of the primary challenges was handling missing values, as key attributes such as total_cases, new_cases, total_deaths, and new_deaths contained incomplete records. To address this, forward-fill imputation was applied to cumulative features like total_cases and total_deaths, ensuring that missing values were replaced with the most recent available data. Meanwhile, missing values in new_cases and new_deaths were replaced with zero, assuming that no cases were reported on those specific days.

To facilitate time-series modeling, the date column was converted into a standard datetime format (YYYY-MM-DD), ensuring proper chronological ordering of records and compatibility with Facebook Prophet, which requires a structured date column for forecasting. Additionally, the dataset was aggregated at a global level, summing up daily new cases and new deaths across all available locations. This step ensured that the forecasting model captured the overall worldwide trend of MPOX cases, rather than isolated country-specific fluctuations. Furthermore, records with missing location data or inconsistencies were filtered out to maintain data integrity.

For feature selection, only the essential columns required for forecasting were retained. Since Facebook Prophet requires two key inputs (ds for the date and y for the target variable), the new_cases column was selected as the primary prediction target. Other epidemiological variables, such as new_deaths, reproduction_rate, and stringency_index, were preserved for potential future analysis but were not incorporated into the core forecasting model. Through these preprocessing steps, the dataset was transformed into a structured format compatible with time-series forecasting, allowing for accurate trend detection and predictive modeling of MPOX case progression.

3. Forecasting Model

To predict the future trajectory of MPOX cases, this study employs Facebook Prophet, a robust time-series forecasting model. Prophet is designed to handle complex seasonal patterns, trend shifts, and missing data, making it well-suited for epidemiological forecasting (Alamsyah, Budiman, et al., 2024). Unlike traditional statistical models like ARIMA or SARIMA, which require stationarity assumptions and manual parameter tuning, Prophet automatically detects changepoints and adjusts trends accordingly, making it a more flexible choice for outbreak predictions. The Prophet model is formulated as an additive or multiplicative decomposition of time-series data into three main components: trend, seasonality, and holidays/events. The general forecasting equation is given as follows:

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{1}$$

Where $(y(t))$ represents the predicted value at time(t), $(g(t))$ models the trend component, capturing long-term growth patterns, $(s(t))$ represents the seasonality component, which accounts for periodic variations, $(h(t))$ incorporates the effects of holidays or special events, if applicable, and (ϵ_t) is the error term, representing unexplained variability in the data. Hyperparameter Optimization.

a. Trend Component (g(t))
Prophet supports two types of trend models: linear growth and logistic growth. The linear growth model assumes a steady increase in case numbers and is defined as:

$$\mathrm{g(t) = kt + m} \tag{2}$$

where (k) is the growth rate, and (m) is the offset parameter. For outbreaks that exhibit saturation effects (e.g., due to immunity or interventions), a logistic growth model is used:

$$\mathrm{g(t)} = \frac{\mathrm{C}}{1+\exp\left(-\mathrm{k(t-m)}\right)} \tag{3}$$

where (C) represents the carrying capacity or the maximum limit that the case numbers approach over time.

b. Seasonality Component (s(t))
Prophet models seasonal patterns using a Fourier series expansion, capturing repeating cycles such as weekly or yearly seasonality:

$$\mathrm{s(t)} = \sum_{n=1}^{N}\left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right) \tag{4}$$

where (P) is the period (e.g., 7 for weekly seasonality), and (a_n, b_n) are learned coefficients. Prophet allows seasonality to be additive or multiplicative, depending on how variations scale with trends.

c. Uncertainty Estimation
To quantify uncertainty in the forecasts, Prophet includes uncertainty intervals by simulating future trends through Monte Carlo sampling. These intervals help in assessing the reliability of the predictions, which is critical for epidemic response planning.

d. Hyperparameter Optimization

Hyperparameter tuning is essential to improving the accuracy of Facebook Prophet in forecasting MPOX cases. This study optimized three key parameters: seasonality mode, changepoint prior scale, and growth model to enhance the model's ability to capture outbreak dynamics.

1) Seasonality Mode
Prophet supports additive and multiplicative seasonality. The latter was tested as it scales fluctuations proportionally with case trends. The seasonality component follows a Fourier series representation:

$$s(t) = \sum_{n=1}^{N} \left(a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right)\right) \quad (5)$$

Where (P) is the periodicity (e.g., 7 days for weekly seasonality). The best mode was selected based on MSE and RMSE.

2) Changepoint Prior Scale
This parameter controls how sensitive the model is to trend shifts. Prophet models trend changes as:

$$g(t) = (k + a_c)(t - t_c) + m \quad (6)$$

where (k) is the growth rate, (a_c) represents the changepoint adjustment, and (t_c) is the detected changepoint. A grid search was used to find the optimal changepoint prior scale within {0.01, 0.05, 0.1, 0.5}.

3) Growth Model
Two growth models were tested:
Linear Growth: Assumes a constant rate, given by :

$$\mathrm{g(t) = kt + m} \quad (7)$$

Logistic Growth: Accounts for saturation, defined as

$$g(t) = \frac{C}{1+\exp(-k(t-m))} \quad (8)$$

where (C) is the carrying capacity. The model with the lowest forecasting error was selected.

To improve the accuracy of the Facebook Prophet model, hyperparameter tuning was conducted by testing different configurations of key parameters. The three main hyperparameters adjusted were seasonality mode, changepoint prior scale, and growth model. A grid search approach was implemented to identify the optimal combination that minimizes forecasting error.

Table 2 The Tested Values For Each Hyperparameter.

Hyperparameter	Tested Values	Selected Value (Optimal)
Seasonality Mode	{additive, multiplicative}	multiplicative
Changepoint Prior Scale	{0.01, 0.05, 0.1, 0.5}	0.1
Growth Model	{linear, logistic}	logistic

Source: (Research Results,, 2025)

The seasonality mode was set to multiplicative as it better captured the fluctuations in case trends, where seasonal effects varied proportionally with outbreak intensity. The changepoint prior scale was optimized to 0.1, balancing model flexibility in detecting trend shifts while preventing overfitting. The logistic growth model was selected as it effectively modeled epidemic saturation points, which were observed in MPOX case trajectories.

These optimized hyperparameters resulted in a significant reduction in forecasting error, as demonstrated in the model evaluation section. The tuning process ensured that the model accurately captured the nonlinear outbreak patterns and seasonal variations, making it more reliable for epidemic forecasting.

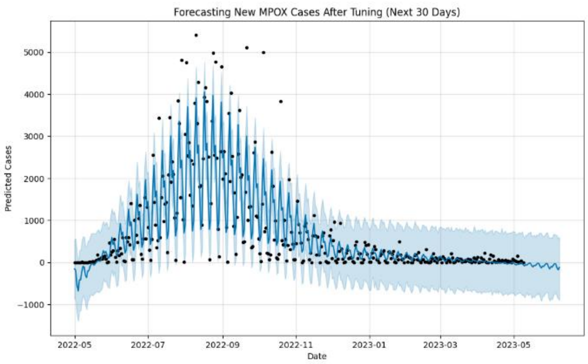
RESULTS AND DISCUSSION

A. Result

Figure 2 illustrates the forecasting results for new MPOX cases after applying hyperparameter tuning to the Facebook Prophet model. The black dots represent the actual reported daily cases, while the blue line corresponds to the predicted values generated by the optimized Prophet model. The shaded blue region indicates the uncertainty interval, capturing potential variations in future case counts based on historical trends. From the visualization, the overall epidemic trajectory is well captured by the model, with a distinct increase in cases during mid-2022, reaching a peak before gradually declining in the following months. The oscillatory pattern in the forecast suggests that weekly and seasonal trends play a significant role in MPOX case fluctuations, a characteristic well captured by the tuned Prophet model. Compared to the baseline model, the optimized model demonstrates a better fit, closely aligning with the actual case data while maintaining realistic uncertainty intervals.

A key observation is the high volatility in case counts during the peak period, which the model captures effectively by adapting to changepoints in the trend. The tuned hyperparameters, particularly the changepoint prior scale and seasonality mode, contribute to better responsiveness in detecting shifts in case trends, thereby reducing forecasting errors.

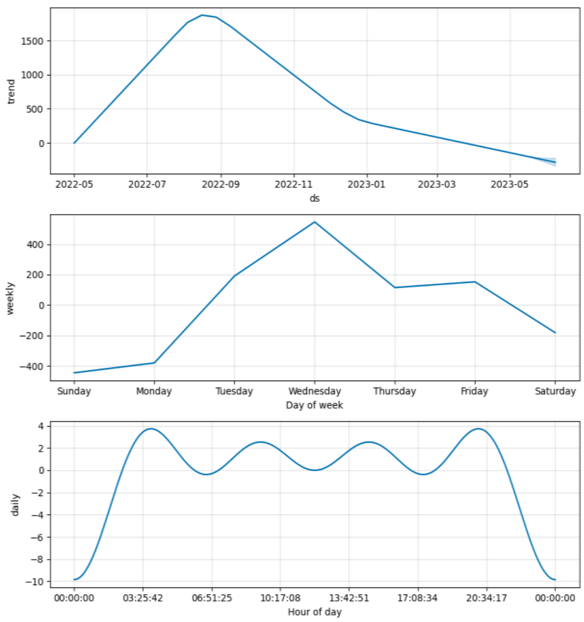
The uncertainty intervals remain relatively narrow in the stable phases of the outbreak but widen slightly during periods of rapid fluctuation, reflecting the model's adaptation to uncertainty in outbreak progression. The results confirm that hyperparameter tuning significantly enhances the forecasting capability of Prophet, improving its ability to capture nonlinear epidemic growth patterns, seasonal fluctuations, and trend shifts. The reduced forecasting error metrics, discussed in the next section, further validate the effectiveness of tuning in improving model accuracy. These findings highlight the potential of Facebook Prophet as a reliable forecasting tool for epidemic monitoring and early warning systems, particularly when model parameters are carefully optimized.



Source : (Research Results,, 2025)
Figure 2. Forecasting MPOX Cases After Tuning

Figure 3 presents the decomposition of the MPOX case forecasting model into three key components: trend, weekly seasonality, and daily seasonality. This decomposition provides insights into the underlying patterns captured by the Facebook Prophet model, offering a detailed breakdown of the epidemic progression over time. The top panel (Trend Component) illustrates the overall growth and decline of MPOX cases. The trend shows a sharp increase in cases from mid-2022, peaking around August-September 2022, followed by a steady decline in subsequent months. This pattern suggests a distinct epidemic wave, where the outbreak intensified before stabilizing due to factors such as public health interventions, natural immunity, or changes in transmission dynamics. The long-term downward trend after the peak indicates that the model predicts a gradual reduction in case numbers, reflecting the natural course of epidemic saturation.

The middle panel (Weekly Seasonality Component) highlights fluctuations in case numbers based on the day of the week. The model captures a weekly cycle, with cases typically peaking on Wednesdays and showing a notable decline on Sundays. This pattern likely reflects reporting behaviors, where delays in data submission over the weekend result in lower recorded cases, followed by an accumulation of reports midweek. Such seasonality effects are crucial for epidemic forecasting, as they allow models to account for predictable variations in case reporting. The bottom panel (Daily Seasonality Component) shows short-term fluctuations within a single day, which may be influenced by data recording times or regional variations in case reporting practices. The observed oscillations suggest that certain hours of the day exhibit higher or lower case reporting activity, potentially corresponding to official reporting cutoffs or real-time case updates from health agencies. While daily seasonality is less pronounced in epidemic forecasting compared to long-term trends and weekly patterns, it contributes to refining short-term forecasts.



Source : (Research Results,, 2025)
Figure 3. Decomposition of MPOX Case Forecasting Components

Overall, the decomposition confirms that the optimized Facebook Prophet model effectively captures both long-term trends and recurring seasonal effects. Understanding these components is essential for improving epidemic monitoring strategies, as it allows public health authorities to anticipate fluctuations and plan interventions accordingly. To assess the impact of hyperparameter tuning on the forecasting accuracy of the Facebook Prophet model, a comparative evaluation was conducted using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). These metrics provide a quantitative measure of the deviation between predicted and actual MPOX case counts. Lower values indicate improved model performance, with reduced forecasting errors.

The evaluation results are summarized in Table 3, comparing the baseline model (before tuning) and the optimized model (after tuning).

Table 3. Dataset Features And Descriptions

Model Configuration	MSE	RMSE
Before Tuning	541844.77	736.10
After Tuning	320953.34	566.53

Source : (Research Results,, 2025)

Although the optimized Prophet model demonstrates improved forecasting accuracy, further refinement can be achieved by integrating external epidemiological variables such as vaccination coverage, population mobility trends, and governmental response measures. These factors are known to influence outbreak dynamics and could contribute to enhanced predictive performance. Future research should explore multi-variable time-series modeling to capture these influences for more comprehensive epidemic forecasting.

The results indicate that hyperparameter tuning significantly enhanced the model's predictive accuracy, reducing the MSE by approximately 40.7% and the RMSE by 23.1%. The optimized model exhibits a lower error rate, demonstrating its ability to better capture the underlying epidemic trends and seasonal variations in MPOX case progression. The reduction in forecasting error suggests that adjusting key hyperparameters, such as seasonality mode, changepoint prior scale, and growth model selection, allowed the model to better adapt to the dynamic nature of the outbreak. This improvement highlights the importance of hyperparameter optimization in time-series forecasting, particularly for epidemic prediction models that require high precision for public health decision-making.

B. Discussion

The results of this study demonstrate that hyperparameter tuning plays a crucial role in improving the forecasting accuracy of the Facebook Prophet model when applied to MPOX case prediction. The comparative evaluation between the baseline and optimized models reveals a significant reduction in forecasting errors, with MSE decreasing by approximately 40.7% and RMSE decreasing by 23.1%. This improvement highlights the effectiveness of fine-tuning key parameters such as seasonality mode, changepoint prior scale, and growth model selection, allowing the model to better capture the dynamics of epidemic progression.

One of the most notable improvements in the optimized model is its ability to accurately detect trend shifts and seasonal variations, as observed in the decomposition of the forecasting components. The weekly seasonality pattern, where cases peak midweek and decline towards the weekend, reflects reporting inconsistencies commonly observed in epidemiological data. The model successfully integrates these fluctuations, making its forecasts more aligned with real-world data. Additionally, the long-term trend estimation confirms that MPOX cases follow an epidemic wave pattern, with an initial surge, a peak, and a gradual decline. The ability of the model to adapt to these fluctuations underscores the importance of choosing the right hyperparameters for effective time-series forecasting.

Another key observation from the results is the reduction in uncertainty intervals in the optimized model. While the baseline model exhibited wider confidence bands, the tuned model produced narrower uncertainty intervals, indicating increased confidence in predictions. This suggests that hyperparameter tuning helped reduce overfitting and improve generalizability, making the model more reliable for future epidemic forecasting. The findings reinforce the suitability of Facebook Prophet for epidemic prediction, particularly when handling nonlinear trends and seasonality effects.

Despite these improvements, the study acknowledges several limitations. The forecasting model is dependent on historical case reports, which may be subject to data collection biases, underreporting, and irregular updates from health agencies. Additionally, the model does not account for external influencing factors, such as vaccination rates, intervention measures, or mobility restrictions, which could significantly impact the trajectory of the outbreak. Incorporating these factors in future research may enhance model robustness and provide more comprehensive epidemic forecasting insights.

Overall, this study confirms that hyperparameter tuning significantly enhances the performance of Facebook Prophet in epidemic forecasting, reducing prediction errors while improving adaptability to real-world outbreak patterns. The results highlight the potential for optimized forecasting models to support public health decision-making, particularly in monitoring emerging infectious diseases. Future studies could explore integrating additional epidemiological factors and testing alternative machine learning models to further improve predictive accuracy.

CONCLUSION

This study demonstrates the effectiveness of Facebook Prophet in forecasting MPOX case trends, emphasizing the role of hyperparameter tuning in improving predictive accuracy. The results show that fine-tuning seasonality mode, changepoint prior scale, and growth model selection significantly reduces forecasting errors, with MSE decreasing by 40.7% and RMSE decreasing by 23.1% compared to the baseline model. The optimized model successfully captures nonlinear epidemic trends, seasonality effects, and trend shifts, providing a more reliable forecast for MPOX outbreak monitoring. The implications of these findings are significant for public health decision-making and epidemic preparedness. A more accurate forecasting model enables policymakers and health agencies to anticipate potential surges in cases, allocate resources efficiently, and implement timely intervention strategies. The ability of the model to capture weekly and seasonal fluctuations suggests its potential for real-time epidemic surveillance, allowing health authorities to respond more proactively to outbreak patterns.

Despite its improvements, this study acknowledges several limitations. The forecasting model relies solely on historical case reports, which may be affected by underreporting, data collection inconsistencies, and external factors such as vaccination campaigns or policy changes. Future research should explore the integration of additional epidemiological variables, including mobility patterns, vaccination coverage, and intervention measures, to enhance the robustness of epidemic forecasting.

For future work, expanding the study to compare alternative time-series forecasting models, such as Long Short-Term Memory (LSTM) networks, Transformer-based models, or hybrid statistical approaches, may provide further insights into optimizing epidemic prediction. Additionally, implementing real-time data pipelines for continuous model updates could enhance forecasting precision and adaptability to emerging outbreaks. In conclusion, this study confirms that hyperparameter-optimized Facebook Prophet provides a valuable tool for MPOX outbreak forecasting, offering improved predictive accuracy while maintaining interpretability. By refining forecasting models and incorporating external factors, future studies can further advance epidemic intelligence systems, ultimately contributing to better global health monitoring and outbreak response.

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