EAI Endorsed Transactions
on Smart Cities

Research Article EAI.EU

Performance Evaluation of ARIMA and FB-Prophet Forecasting Methods in the Context of Endemic Diseases: A Case Study of Gedaref State in Sudan

Hussein Ali Hussein[1], Mukhtar M. E. Mahmoud[2,*] and Haroun A. Eisa[3]

[1]Department of Information Technology, University of Gedaref, Gedaref, Sudan
[2]Faculty of Computer Science and Information Technology, University of Kassala, Kassala, Sudan
[3]Department of Computer Science, Alsharg Ahlia College, Kassala, Sudan

Abstract

Today, artificial intelligence is a key tool for turning a city into a smart city, and advances in information and communication technology (ICT) have led to the development of smart cities with many different parts. Smart Health is one of these components and is used to improve healthcare by providing services such as disease forecasting, early diagnosis, and others. There are various machine learning algorithms available now that can help with S-Health services, but which is better for disease forecasting? Gedaref State, for example, has some of Sudan's heaviest rains, and malaria and pneumonia are widespread throughout the year. Predicting future trends for these diseases has been a major focus for researchers in order for Gedaref's administration and the state's ministry of health to design effective ways to prevent and control the development of these diseases, as well as to prepare an adequate stock of medicine. As a result, it is necessary to establish a trustworthy and accurate forecasting model to aid Gedaref's government in developing economic and medical strategies for dealing with these diseases, as well as taking action on medical resource allocation. This study uses a time series dataset collected from the state's ministry of health to estimate malaria and pneumonia as common diseases in Gedaref state, Sudan, five months later. To comprehend the overall number of cases of diseases, two forecasting methodologies, namely the ARIMA and Prophet models, are applied to the disease's dataset. The performance of the ARIMA and FB-Prophet forecasting systems in predicting malaria and pneumonia diseases in Gedaref State is compared in this study. The data was collected from the state's ministry of health between January 2017 and December 2021. The results reveal that the ARIMA technique outperforms the FB-Prophet forecasting method in both malaria (RMSE: 182.8, MAE: 141.6, MAPE: 0.0057, and MASE: 0.0537) and pneumonia (RMSE: 1400.3, MAE: 1001.4, MAPE: 0.0513, and MASE: 0.9136).

Keywords: smart city, artificial intelligence, pneumonia and malaria diseases, endemic diseases, Gedaref state.

Received on 07 February 2023, accepted on 08 March 2023, published on 30 March 2023

doi: 10.4108/eetsc.v7i2.3023

*Corresponding author. Email:

1. Introduction

In recent years, smart cities have dominated discussions about shifting economic growth, local geographic development, and accessibility. Despite enormous amounts of global investment in smart cities, such as $608 billion USD, many people are still unclear about what smart cities are. A smart city is defined as a metropolitan area that uses electronic and technological infrastructure, such as information and communication technology (ICT), to collect real-time data and insights, supply key services, and address local issues. Smart cities are also used to improve municipal operations such as public transportation, power and water supply, and sanitation.

Using this information, the city administration may make educated decisions about establishing effective solutions to the city's present problems [1].

The use of machine learning and other cognitive sciences to help doctors make decisions is an important way AI is used in medicine.AI could help specialists and clinical professionals share more accurate findings and treatment plans by using information about the patient and other data. Furthermore, by breaking down massive volumes of data to produce better preventative care suggestions for patients, AI can help make medical services more predictive and proactive. Medical services are likely the most essential area in the bigger picture of huge information because of their critical role in a flourishing society. AI implementation Knowledge can mean the difference between life and death in the healthcare profession. In their regular work, specialists, medical caregivers, and other medical service employees can profit from computer-based intelligence. Simulated intelligence in medical services can increase preventive care and personal happiness, lead to more precise judgments and treatment techniques, and result in improved overall outcomes. By evaluating data from administration, medical services, and other sources, simulated intelligence can also anticipate and track the development of dangerous diseases. As a result, as a tool for preventing illnesses and pandemics, AI has the potential to play a vital role in global well-being [2].

Gedaref State is located in eastern Sudan, bordering Ethiopia; Kassala and Khartoum States in the north; Al-Jazira State in the west; and SENNAR State in the south. The international border crossings in Gedaref State are the Hamdayet border crossing in the north and the Gallabat border crossing in the south. Gedaref is home to many tribes, including Arabs, Beja, Nubians, and others. The state is known for its large-scale rainfed agriculture activities and vast agricultural acreage. Sorghum and sesame are the two main agricultural products. Rainfed agriculture and the production of Arabic gum are the state's main sources of revenue [3].

Malaria and pneumonia are the most common diseases in Gedaref state, with the most cases between 2017 and 2021, according to data from the state's ministry of health.

The WHO says that malaria is a dangerous disease that is found in most tropical countries. Prevention and therapy are both options. However, simple malaria can progress to a severe type of sickness that is commonly fatal without treatment if a prompt diagnosis and appropriate treatment are not delivered. Female Anopheles mosquito bites, which are not contagious and cannot spread the disease from person to person. Plasmodium falciparum and Plasmodium vivax are the two parasite species that cause malaria and do the most harm to people. There are around 400 Anopheles mosquito species, and about 40 of these, known as vector species, are capable of conveying disease. Several factors, such as the kind of local mosquitoes, influence the likelihood of infection, with certain areas being more vulnerable than others. The risk is greatest in tropical settings during the rainy season, although it may vary seasonally [4].

Pneumonia, according to the World Health Organization, is an acute respiratory disorder that mostly affects the lungs. When a healthy person breathes, tiny air sacs called alveoli fill up and form the lungs. When a person gets pneumonia, the alveoli get blocked with pus and fluid, making breathing difficult and oxygen intake limited. Pneumonia is the leading infectious cause of death in children worldwide. Pneumonia killed 740 children under the age of five in 2019, accounting for 14% of all deaths in children under the age of five but 22% of all deaths in children aged one to five. Pneumonia affects children and families all throughout the world, with the highest fatality rates in Southern Asia and Sub-Saharan Africa. Pneumonia in children can be avoided, and it can be managed with low-cost, low-tech treatment and care [5].

Using past and present data, time-series forecasting is a way to predict future values over time or at a single point in time. We may make well-informed decisions about the Ministry of Health's strategy and future trends by looking at data from the past [6].

The autoregressive integrated moving average (ARIMA) method is a one-dimensional technique. The AR component, often known as p, is calculated by correlating current values in a data series with past values in the same series. The MA component, q, is obtained by associating current values of a random error term with prior values. Current and historical data mean and variance values are thought to be steady, or unaffected, over time. A component (symbolized by d) is included if necessary to compensate for a lack of stationarity via differencing. In a non-seasonal ARIMA (p, d, q) model, the number or order of AR terms is denoted by p, the number or order of differences by d, and the number or order of MA terms by q. The parameters p, d, and q are all numbers that are bigger than or equal to 0 [7].

FB-Prophet is a time series data forecasting method based on an additive model that takes into account yearly, monthly and daily seasonality as well as holiday factors. It works best with time series that have strong seasonal influences and data from multiple seasons. Prophet is robust to missing data and trend changes, and it deals effectively with outliers [8].

This study presents estimates of malaria and pneumonia as common diseases in Gedaref state, Sudan, five months later, using a time series method and a dataset collected from the state's ministry of health. To comprehend the overall number of cases of diseases, two forecasting methodologies, namely the ARIMA and Prophet models, are applied to the disease's dataset. The performance of the ARIMA and FB-Prophet forecasting systems in predicting malaria and pneumonia diseases in Gedaref State is compared in this study. The data was collected from the state's ministry of health between January 2017 and December 2021. Although there are several predicting studies in the literature, we could not find much that compares ARIMA and Prophet time series models at the same time to compare and analyze the malaria and pneumonia datasets. To the best of our knowledge, the dataset investigated in all of the studies listed below was limited to certain commodities or places. Unlike prior studies that focused on a specific condition, this one looked at a number of them. Furthermore, the most popular forecasting approaches have been used for completeness.

The rest of the paper is structured as follows: Section 2 presents the related work. Section 3 describes the dataset and methodology used. Section 4 shows the results of the methods employed and investigates the outcomes of various methods. Section 5 discusses the findings. Section 6 concludes the paper.

2. Related Work

This section provides a summary of the most relevant papers on the application of ARIMA and FB-Prophet in epidemiology.

Ersoz et al. [9] compare the accuracy of ARIMA, Prophet, and HoltWinters exponential smoothing forecasting algorithms for COVID-19 disease epidemiology in Europe. The dataset was obtained from the World Health Organization (WHO) and comprises COVID-19 case data from European countries classified by the WHO between 2020 and 2022. The results show that the Holt-Winters exponential smoothing approach (RMSE: 0.2080, MAE: 0.1747) outperforms the ARIMA and Prophet forecasting methods; the study's main weakness is the limited amount of available data.

Ziyuan Ye et al. [10] made a hybrid model to predict how dirty the air will be in Shenzhen, China. For blending time and space relationships, it is based on ARIMA (the auto-regressive integrated moving average model) and Prophet. After training their models with data from 11 sites that measure air quality, the researchers gave their models weights. Experiment results demonstrated that this hybrid technique can improve air pollutant prediction in Shenzhen. In certain ways, ARIMA is more accurate than Prophet, but it takes 10 times as long as B. The majority of ARIMA's computation time is spent seeking for the best sequence of (p, d, q) and (P, D, Q, S).

Kumar et al. [11] suggested that data from supermarkets be used to make an FB Prophet tool that can predict how much food will be sold. In the proposed study, many forecasting models, such as the additive model, the autoregressive integrated moving average (ARIMA) model, and the FB Prophet model, were looked at. According to the proposed research effort, FB Prophet is a better prediction model in terms of low error, better prediction, and better fitting.

The statistical approaches given by Sirisha et al. [12] for this successful inquiry, the autoregressive integrated moving average (ARIMA) and seasonal ARIMA models (SARIMA), as well as the deep learning technique of long short-term memory (LSTM) neural network modeling in time series forecasting, were applied. It was converted into a stationary dataset for ARIMA but not SARIMA or LSTM. Based on test data, fitted models were constructed and utilized to forecast profit. Forecasts for the next five years have been completed with 93.84% (ARIMA), 94.378% (SARIMA), and 97.01% accuracy (LSTM). In terms of developing the optimal model, the results show that LSTM beats both statistical models.

Ning et al. [13] present a machine learning-based time series forecasting system that uses existing data as time series and extracts prominent attributes from historical data to predict future time sequence values. Three methods were explored and evaluated to overcome the restrictions of traditional production forecasting: auto-regressive integrated moving averages (ARIMA), the long-short-term memory (LSTM) network, and Prophet. This study begins with reflective oil supply data from a well in an unconventional reservoir in the Denver-Julesburg (DJ) Basin, and the application of ARIMA, LSTM, and Prophet techniques to 65 wells in the DJ Basin demonstrates that ARIMA and LSTM perform better than Prophet—most likely because not all oil production data includes seasonal changes and ARIMA is strong in forecasting the oil production of wells across the DJ Basin.

3. Material and Method

This section talks about the malaria and pneumonia datasets that were used in this paper and how they were evaluated. While Figure 1 depicts the workflow of our methodology, the three subsections that follow, namely I) dataset, II) ARIMA technique, and III) FB-Prophet technique, provide details on each phase.

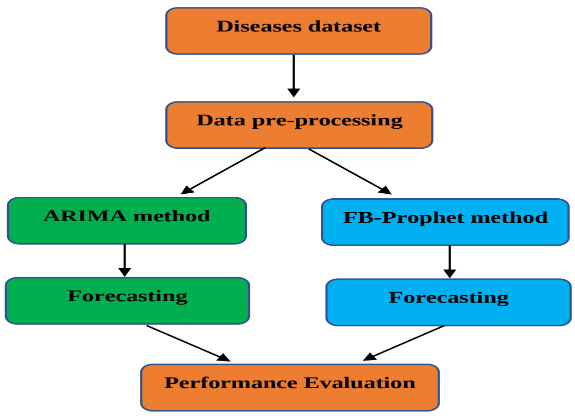

Figure 1. Flowchart of our methodology

The methodology of the work is divided into 5 steps as follows:

Step 1: Disease dataset: This step concerns collecting the disease dataset from the Ministry of Health.

Step 2: Data pre-processing: This step contains three stages to guarantee the accuracy and completeness of the data: I) Data cleaning; II) Feature selection; and III) Feature extraction and transformation.
Step 3: Time series forecasting methods (ARIMA and FB-Prophet): In this step, we prepare the system for predicting diseases five months later.
Step 4: Forecasting: This step concerns conducting the forecasting methods and gives the results for each one.
Step 5: Performance evaluation: In this step, we use the error metrics (RMSE, MAE, MAPE, and MASE) to evaluate the performance of forecasting methods and choose the best one.

3.1. Dataset

The diseases dataset in Gedaref state was collected by the ministry of health's statistics department and the state's information center. The dataset contains data on the total number of disease cases from January 1, 2017 to December 31, 2021. The dataset contains 25062 records from all diseases in the state during this time period, as well as 20 characteristics. The features of the dataset are ("Quarter", "Diseases", "Diseases code", "Male -1", "Female -1"," Male 1-4 years", "Female 1-4 years", "Male 5-14 years", "Female 5-14 years", "Male 15-44 years", "Female 15-44 years", "Male 45-64 years", "Female 45-64 years", "Male 65+ years", "Female 65+ years", "Sum of Males", "Sum of Females", "Total Cases", "Localities", "Years").

Data cleaning was undertaken to ensure the accuracy, completeness, and accuracy of the data, which was obtained in Arabic and then transformed to English.
Feature selection: The purpose of this stage was to pick the suitable features (date and total cases) for use in the forecasting procedure.
Feature extraction and transformation: In this step, the feature that was chosen before is taken out and changed into a form that helps with prediction.

The disease dataset was then made by just adding "Date" as a time series. It has 60 rows, and the common "diseases" in the state are malaria and pneumonia. In the disease dataset, each row showed the total number of disease cases for each month from 2017 to 2021. Tables 1 and 2 show the features of the dataset, and Figure 2 shows the dashboard of full diseases, which shows the most common diseases in the state. Figures 3 and 4 show the overall number of malaria and pneumonia cases over the five-year period.

The data was divided into two sets: one for training the models and one for testing the approaches' performance.

Table 1. Demonstrate the whole dataset before data pre-processing

No	Features	Data Type
1	Quarter	Categorical
2	Diseases	Categorical
3	Diseases code	Categorical
4	Male -1	Numeric
5	Female -1	Numeric
6	Male 1-4 years	Numeric
7	Female 1-4 years	Numeric
8	Male 5-14 years	Numeric
9	Female 5-14 years	Numeric
10	Male 15-44 years	Numeric
11	Female 15-44 years	Numeric
12	Male 45 -64 years	Numeric
13	Female 45-64 years	Numeric
14	Male + 65 years	Numeric
15	Female + 65 years	Numeric
16	Sum of Males	Numeric
17	Sum of Females	Numeric
18	Total Cases	Numeric
19	Localities	Categorical
20	Years	Datetime

Table 2. Demonstrate the dataset after data pre-processing.

Features	Data Type	Min Value	Max Value	Mean	Std. Dev
Date	Datetime	-	-	-	-
Malaria	Numeric	6786	32383	16839	6082
Pneumonia	Numeric	9565	27177	18659	4014

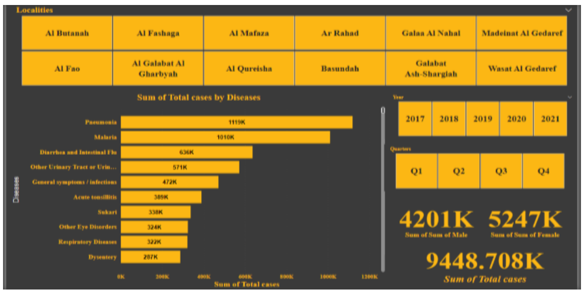

Figure 2. Demonstrate the dashboard of whole diseases.

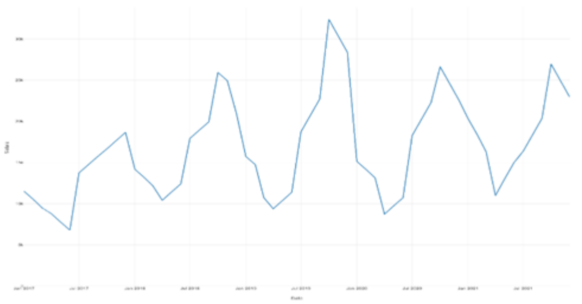

Figure 3. Illustrates the malaria disease over five years in months.

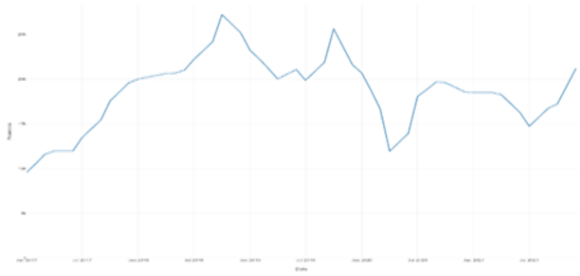

Figure 4. Illustrates the Pneumonia disease over five years in months.

3.2 Auto Regressive Integrated Moving Average (ARIMA) Method

The Auto Regressive Integrated Moving Average (ARIMA) generates forecasts by providing a specific temporal arrangement depending on its limitations and prediction mistakes [14].

The order of the autoregressive expression p, the degree of differencing d, and the order of the moving average expression q define a non-seasonal ARIMA model. The integer p is the number of y occurrences that will be used as indicators. Also, q is the number of prediction errors that are not interesting and should be added to the ARIMA model. The modifications required to solve the problem d = 0 if the temporal difference is constant at that instant. The following is the generic difference series equation:

$$\hat{y}t = \mu + \phi 1\ yt\text{-}1 + \ldots + \phi pyt\text{-}p - \theta 1et\text{-}1 - \ldots - \theta qet\text{-}q \quad (1)$$

Where ϕi are the coefficients, yt-p, and et-q are the model's lagging predictors.

Choosing suitable p and q values necessitates optimization and testing. Graphs of the AutoCorrelation Function (ACF) and Partial AutoCorrelation Function (PACF) must be analyzed to calculate the values. The following prerequisites must be met in order to achieve this goal: A few univariate time series forecasting algorithms that rely purely on subjective eye assessment and follow these guidelines may be beneficial. However, when large sums must be projected, these criteria become ineffective. One option is to use software tools to select ARIMA's parameters automatically. Another approach is to search the solution space for different parameters and propose the ones with the lowest error [15].

3.3 FB-Prophet Method:

Facebook developed the FB-Prophet time-series analysis and forecasting algorithm [16]. This model incorporates parameters for holidays, trends, and seasonality, which will help shape prediction results and provide higher performance with time-series data that has seasonal affects. The following equation is used to combine these ingredients:

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

Where g(t) represents the trend, which is non-periodic growth changes, s(t) reflects seasonal variations, and h(t) describes the effects of holidays. The following equation defines the trend:

$$g(t)=C(t)\ /\ 1+exp\ (-(k+\alpha(t)^T\delta)\ (t-(m+\alpha(t)^T\gamma))) \qquad (3)$$

Where C(t) is the carrying capacity, k is the growth rate, and m is an offset parameter. The precision, speed, and resilience to outliers and trend shifts of FB-Prophet are well-known. It is totally automated, allowing it to produce an accurate forecast from a jumbled set of data without the need for human intervention.

It's an additive regression model with trends like a piecewise linear growth curve or a logistic growth curve. It recognizes changes in patterns in real time by identifying data change points [17].

4. Results

This section describes the application of two forecasting models. As performance measures, RMSE (Root Mean Squared Error), MAE (Mean Absolute Error), mean absolute percentage error (MAPE), and mean absolute scaled error (MASE) rates are used to evaluate forecasting algorithms. The following are the definitions of RMSE, MAE, MAPE, and MASE:

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \bar{x}_i)^2}{N}} \qquad (4)$$

$$\boldsymbol{MAE} = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \qquad (5)$$

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.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{6}$$

Where M denotes mean absolute percentage error, N denotes the number of times the summation iteration happens, A_t denotes the actual value and F_t denotes the forecast value.

$$MASE = mean\left(\frac{|e_j|}{\frac{1}{t-1}\sum_{T=2}^{T}|y_t - y_{t-1}|}\right) \tag{7}$$

Where e_j is the prediction error for a specific time, defined as the actual value (Y_j) minus the predicted value (F_j) for that period: $e_j = Y_j - F_j$, and the denominator is the mean absolute error of the one-step.

4.1 ARIMA Model Results:

To estimate the parameters q and p, the ARIMA model evaluates the autocorrelation function (ACF) and partial autocorrelation function (PACF) graphs. ACF measures the degree of correlation between a time series and its lagged values. After the linear effects of the lags in between are removed, PACF indicates the correlation between the time series and the lag. The ACF and PACF graphs from the disease dataset are given in figures 5 and 6 for malaria disease and 7 and 8 for pneumonia disease, respectively.

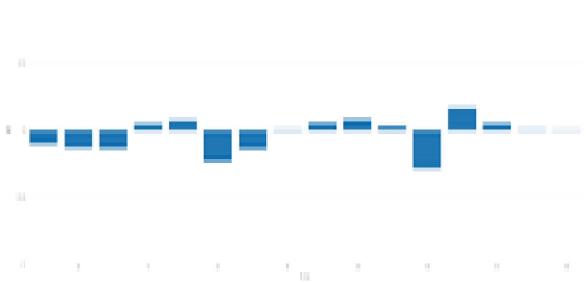

Figure 5. Illustrates ACF in Malaria disease.

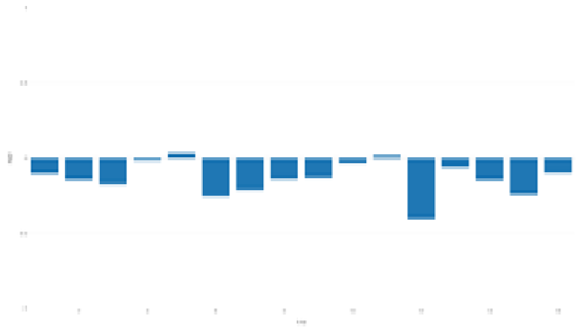

Figure 6. Illustrates PACF in Malaria disease.

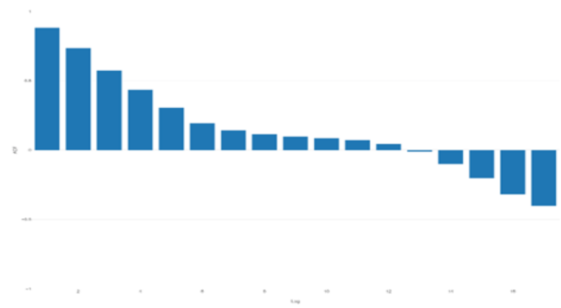

Figure 7. illustrates ACF in Pneumonia disease.

Figure 8. Illustrates PACF in Pneumonia disease.

From the aforementioned figures, we must select the best (p, d, q) pair with the lowest RMSE, MAE, MAPE, and MASE. Based on the results, the ARIMA approach has the lowest RMSE, MAE, MAPE, and MASE from the figures above. Based on the data, the best (p, d, q) combination for malaria disease is chosen as (0, 1, 0), resulting in an RMSE of 182.8, MAE of 141.6, MAPE of 0.0057, and MASE of 0.0537 for the ARIMA approach. As demonstrated in figures (9) and (10) for the effective ARIMA forecasting process for 5 months on malaria and pneumonia disease, the optimal p, d, and q pair is chosen as (0, 0, 2) for pneumonia disease, resulting in an RMSE of 1923.9, MAE of 1578.3, MAPE of 0.0834, and MASE of 1.4399.

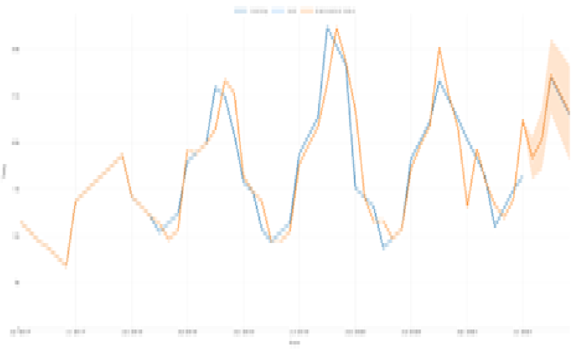

Figure 9. Forecasting malaria disease using the ARIMA model.

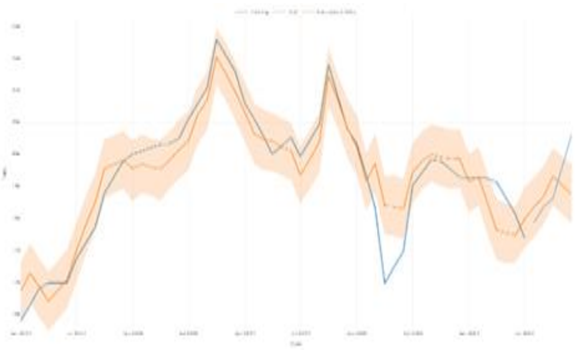

Figure 10. Forecasting Pneumonia disease using the ARIMA model.

4.2 FB-Prophet Model Results

In the application for exploratory data analysis, the parameters of the FB-default Prophet are used to make an FB-prophet model. These parameters are changed automatically. According to the findings, the FB-Prophet model for malaria disease has an RMSE of 2815.9, MAE of 2614.6, MAPE of 0.1237, and MASE of 0.9907, while the FB-Prophet model for pneumonia disease has an RMSE of 1923.9, MAE of 1578.3, MAPE of 0.0834, and MASE of 1.4399.

Figures 11 and 12 show how ARIMA can be used to make accurate predictions about malaria and pneumonia over a period of 5 months, respectively.

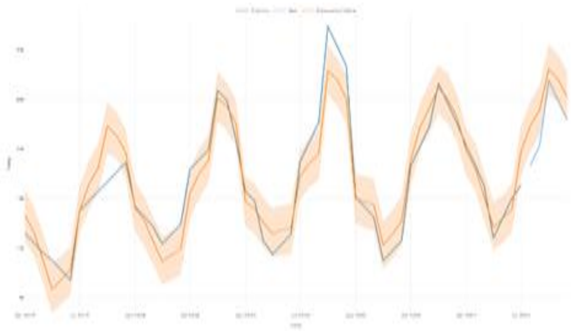

Figure 11. Forecasting malaria disease using the FB-Prophet model.

Figure 12. Forecasting pneumonia disease using the FB-Prophet model.

Table 3 shows the RMSE, MAE, MAPE, and MASE values of ARIMA and Facebook's Prophet for predicting malaria and pneumonia in Gedaref state. As shown in Table 3, the ARIMA approach outperforms the FB-Prophet method in forecasting new cases of both malaria and pneumonia in Gedaref state.

Table 3. Demonstrate RMSE, MAE, MAPE, and MASE values for ARIMA and FB-Prophet Forecasting Methods

Forecasting Method	Diseases	Performance Metrics			
		RMSE	**MAE**	**MAPE**	**MASE**
ARIMA	Malaria	182.8	141.6	0.0057	0.0537
	Pneumonia	1400.3	1001.4	0.0513	0.9136
FB-Prophet	Malaria	2815.9	2614.6	0.1237	0.9907
	Pneumonia	1923.9	1578.3	0.0834	1.4399

5. Discussion

As governments stockpile medicines, it has become important for them to try to figure out how malaria and pneumonia will change in the future. Because of this, it is very important to build a reliable and accurate forecasting model that will help governments come up with economic and medical plans to deal with these endemic diseases and decide how to allocate medical resources. In this study, there were 60 data points that broke down the malaria and pneumonia disease statistics for Gedaref state by month. ARIMA and FB-Prophet models were used to figure out how malaria and pneumonia will change in the future. When the constructed models were compared in terms of performance, the results revealed that the ARIMA technique outperformed and had the lowest error than the FB-Prophet forecasting method in both malaria (RMSE: 182.8, MAE: 141.6, MAPE: 0.0057, and MASE: 0.0537) and pneumonia (RMSE: 1400.3, MAE: 1001.4, MAPE: 0.0513, and MASE: 0.9136).

We notice that, in the small dataset, ARIMA is a powerful method. The FB-prophet method requires holiday effects in the dataset to boost its performance.

6. Conclusion

In this work, the ARIMA and FB-Prophet forecasting models were used to predict how many people in Gedaref State would get malaria and pneumonia. Between January 2017 and December 2021, the data was gathered from the state's ministry of health. In terms of RMSE, MAE, MAPE, and MASE error metrics, our results suggest that the ARIMA model in both malaria (RMSE: 182.8, MAE: 141.6, MAPE: 0.0057, and MASE: 0.0537) and pneumonia (RMSE: 1400.3, MAE: 1001.4, MAPE: 0.0513, and MASE: 0.9136) outperforms the FB-Prophet model. Forecasting methodologies, as demonstrated here, can aid in the prediction of future patterns for a variety of diseases as well as be implemented to reduce the number of diseases in the state, which is beneficial to public health. We anticipate that the study's findings will be valuable to governments and health authorities in terms of correctly planning medical support and providing necessary resources, such as medical staff and care facilities, for future diseases. These methods will be combined with IoT-enabled solution to provide a smart disease management framework in our future work.

Acknowledgments

The authors would like to thank the Ministry of Health in Gedaref State for providing us with this information, particularly Dr. Hussein, Director of the Ministry of Information and Statistics Center.

References

[1] S. Myeong and K. Shahzad, “Integrating Data-Based Strategies and Advanced Technologies with Efficient Air Pollution Management in Smart Cities,” Sustainability, vol. 13, no. 13, p. 7168, Jun. 2021, doi: https://doi.org/10.3390/su13137168.

[2] S. R., S. R. S., H. R., A. S., and R. K. C., “Artificial Intelligence in Smart cities and Healthcare,” EAI Endorsed Transactions on Smart Cities, vol. 6, no. 3, p. e5, Sep. 2022, doi: 10.4108/eetsc.v6i3.2275.

[3] M. A. A. Osman, J. O. Onono, L. A. Olaka, M. M. Elhag, and E. M. Abdel-Rahman, “Climate Variability and Change Affect Crops Yield under Rainfed Conditions: A Case Study in Gedaref State, Sudan,” Agronomy, vol. 11, no. 9, p. 1680, Aug. 2021, doi: https://doi.org/10.3390/agronomy11091680.

[4] L. C. S. PINHEIRO, L. M. FEITOSA, F. F. D. SILVEIRA, and N. BOECHAT, “Current Antimalarial Therapies and Advances in the Development of Semi-Synthetic Artemisinin Derivatives,” Anais da Academia Brasileira de Ciências, vol. 90, no. 1 suppl 2, pp. 1251–1271, 2018, doi: https://doi.org/10.1590/0001-3765201820170830.

[5] Z. Rustam, R. P. Yuda, H. Alatas, and C. Aroef, “Pulmonary rontgen classification to detect pneumonia disease using convolutional neural networks,” TELKOMNIKA (Telecommunication Computing Electronics and Control), vol. 18, no. 3, p. 1522, Jun. 2020, doi: https://doi.org/10.12928/telkomnika.v18i3.14839.

[6] S. Makridakis, R. J. Hyndman, and F. Petropoulos, “Forecasting in social settings: The state of the art,” International Journal of Forecasting, vol. 36, no. 1, pp. 15–28, Jan. 2020, doi: https://doi.org/10.1016/j.ijforecast.2019.05.011.

[7] W. D. Lesmono, S. Mardiyati, D. Lestari, and A. H. A. Zili, “Forecasting tuberculosis morbidity rate in Indonesia using autoregressive integrated moving average (ARIMA) method,” Journal of Physics: Conference Series, vol. 1725, p. 012031, Jan. 2021, doi: https://doi.org/10.1088/1742-6596/1725/1/012031.

[8] P. Kumar, R. Sharma, and S. K. Singh, “Predictive Analysis of Real-Time Strategy using Face book’s Prophet Model on Covid-19 Dataset of India,” Journal of Pharmaceutical Research International, pp. 305–312, Nov. 2021, doi: https://doi.org/10.9734/jpri/2021/v33i51a33496.

[9] ERSÖZ, N. Ş., GÜNER, P., AKBAŞ, A., & BAKİR-GUNGOR, B. (2022). Comparative performance analysis of Arima, Prophet, and holt-winters forecasting methods on European COVID-19 data. International Journal of 3D Printing Technologies and Digital Industry. https://doi.org/10.46519/ij3dptdi.1120718.

[10] Ye, Z. (2019). Air pollutants prediction in Shenzhen based on Arima and Prophet Method. E3S Web of Conferences, 136, 05001. https://doi.org/10.1051/e3sconf/201913605001.

[11] Kumar Jha, B., & Pande, S. (2021). Time Series forecasting model for supermarket sales using FB-prophet. 2021 5th International Conference on Computing Methodologies and Communication (ICCMC). https://doi.org/10.1109/iccmc51019.2021.9418033.

[12] Sirisha, U. M., Belavagi, M. C., & Attigeri, G. (2022). Profit prediction using Arima, Sarima and LSTM models in time series forecasting: A Comparison. IEEE Access, 10, 124715–124727. https://doi.org/10.1109/access.2022.3224938.

[13] Ning, Y., Kazemi, H., & Tahmasebi, P. (2022). A comparative machine learning study for time series oil production forecasting: Arima, LSTM, and prophet. Computers & Geosciences, 164, 105126. https://doi.org/10.1016/j.cageo.2022.105126.

[14] Deniz A., Kiziloz, H.E., Sevinc, E., and Dokeroglu, T., "Predicting the severity of COVID-19 patients using a multi-threaded evolutionary feature selection algorithm," Expert Syst., Vol. 39, Issue. 5, 12949, 2022.

[15] Alabdulrazzaq, H., Alenezi, M. N., Rawajfih, Y., Alghannam, B. A., Al-Hassan, A. A., Al-Anzi, F. S., "On the accuracy of ARIMA based prediction of COVID-19 spread" Results in Pyhsics, Vol. 27, 2021.

[16] Taylor, S. J., Letham, B., "Forecasting at Scale," Am. Stat., Vol. 72, Issue. 1, Pages 37–45, 2018.

[17] Mahanty, M., Swathi, K. Teja, K. S., Bhattacharyya, D., "A Prophet Model to Forecast Spread of Covid-19 Pandemic," Journal of Xidian University, Vol 14, Issue 7, Pages 949-962, 2020.