



International Journal of Computer Science and Mobile Computing
A Monthly Journal of Computer Science and Information Technology

Roqaiah Saleh Al-Sanea *et al*, Volume 15, Issue 9, September 2026, pg. 108-118
(An Open Accessible, ISI Indexed, Fully Refereed and Peer Reviewed Journal)

ISSN: 2320-088X
Impact Factor: 7.056

Forecasting the Spread of COVID-19 Pandemic in Yemen using Prophet Machine Learning Model

Roqaiah Saleh Al-Sanea¹; Basheer Mohamad Al-Maqaleh²

¹Department of Computer Science, Faculty of Computers and Informatics, Tamar University, Yemen

²Department of Information Technology, Faculty of Computers and Informatics, Tamar University, Yemen

¹roqaihsaleh844@gmail.com; ²basheer.almaqaleh@tu.edu.ye

DOI: <https://doi.org/10.47760/ijcsmc.2026.v15i09.009>

Abstract: The spread of COVID-19 has caused it to be a pandemic. This has caused massive disruption to our daily lives, both directly and indirectly. In the healthcare industry, there is much evidence that Artificial Intelligence (AI) and machine learning algorithms can provide effective models that solve problems in order to predict confirmed and death cases. Thus, early prediction of the COVID-19 spread can facilitate the planning of necessary actions from the government and people.

In this paper, a forecasting the spread of COVID-19 pandemic in Yemen using prophet machine learning model is proposed. The proposed model is tested and validated to forecast confirmed and death cases at any specific period of time using COVID-19-Yemen dataset in the period of January 2020 till the end of August 2024. The proposed model is trained on 80% of the data and tested on the remaining 20%. The obtained results are evaluated using some common evaluation measures such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of determination (R^2).

The obtained results are promising, as the proposed model achieves high ability in forecasting confirmed and death cases using COVID-19-Yemen dataset. The performance of the proposed model is compared with other related models such as decision tree regression and polynomial regression. The comparative study confirms that the proposed model has less forecasting error with high accuracy, so it outperforms other models as it scores 1.28 in MAE, 4.41 in RMSE and 0.99 in R^2 for confirmed cases. Furthermore, for death cases, the proposed model scores 0.40, 1.59, and 0.95 for MAE, RMSE and R^2 respectively.

The findings have yielded a realistic picture of the disease direction and provide useful insights for decision makers so as to be prepared for the future evolution of the pandemic.

Keywords: COVID-19, Time Series Forecasting, Prophet Model, Machine Learning, Pandemic Prediction



International Journal of Computer Science and Mobile Computing
A Monthly Journal of Computer Science and Information Technology

Roqiaiah Saleh Al-Sanea *et al*, Volume 15, Issue 9, September 2026, pg. 108-118
(An Open Accessible, ISI Indexed, Fully Refereed and Peer Reviewed Journal)

ISSN: 2320-088X
Impact Factor: 7.056

I. INTRODUCTION

The novel coronavirus disease (COVID-19) emerged in Wuhan, China, in December 2019 and rapidly spread across countries, eventually becoming a global pandemic [1]. The pandemic placed substantial pressure on healthcare systems and caused widespread social and economic disruptions, significantly affecting daily life worldwide [2]. As of early 2026, global confirmed cases have reached approximately 704,753,890 with over 7,010,681 deaths, underscoring the persistent threat of the virus even in its post-peak phase [3].

Yemen, already grappling with a protracted humanitarian crisis and weakened health infrastructure, has been particularly vulnerable to the pandemic [4]. According to OWID data, Yemen recorded 11,945 confirmed cases and 2,159 deaths between January 2020 and August 2024 [5]. However, these figures likely represent significant underreporting due to limited testing capacity, surveillance system disruptions, and the stigma associated with infection. The coexistence of other diseases including swine flu, dengue fever, and malnutrition further complicates accurate case identification [6].

Forecasting future outbreaks of epidemics is crucial for understanding the current situation and assessing the severity of the pandemic [7]. Therefore, utilizing available data to predict future epidemic outbreaks is of high importance in understanding the current situation and evaluating the severity of the pandemic [6]. Machine learning techniques have demonstrated considerable potential in epidemiological forecasting by identifying complex patterns in historical data [8]. Among these, Facebook prophet, an open-source forecasting tool introduced in 2017, has gained prominence for its ability to handle time series data with strong seasonal effects, missing values, and outliers through an additive regression model [9].

Therefore, accurate forecasting of epidemic patterns has become crucial for implementing successful intervention aimed of preventing and controlling the spread of disease. Some existing models were suggested to deal with the COVID-19 in Yemen [6,10].

The drawbacks of these models to forecast the spread of COVID-19 include their sensitivity to initial conditions, the number of parameters used, and the overfitting of the data. Furthermore, they can't forecast well in specific period of time as they ignore the variations of data including trends, seasonality and vacations.

The primary objective of this research is to develop and validate a robust forecasting model based on prophet that accurately predicts confirmed and death cases of COVID-19 in Yemen from January of 2020 till the end of August 2024. The model addresses critical gaps in existing approaches by explicitly modelling trend components, multiple seasonality patterns, and holiday effects. The importance of the research lies in the ability to forecast the number of infected cases and deaths during any specific period of time until the necessary and possible solutions are developed to overcome these causes and improve decisions for decision makers.

The remainder of this paper is organized as follows: Section II introduces the related works. Section III presents the COVID-19-Yemen dataset description. Section IV describes the proposed model. Section V discusses computational results and discussion. Section VI concludes the paper with future works.

II. RELATED WORKS

Recently, several research studies have proposed different mathematical and machine-learning based forecasting models to estimate the spread of the COVID-19 disease, and determine its impact [11].

Prediction of COVID-19 cases in India using prophet was developed in [12]. The model forecasted a steady rise in the number of infected cases in the days to come. This implies that the country's existing measures would not be sufficient to control the ongoing epidemic. Based on the forecasting model and assuming the current conditions of the COVID-19 outbreak, a rapid and exponential increase in the number of cases is expected. Bangladesh COVID-19 daily cases time series analysis using prophet model was presented in [13]. They said the cases are dropping day by day, there is some space if the trend which is seen in July continues, then an updated study using this model would predict the lowering of daily cases.



International Journal of Computer Science and Mobile Computing
A Monthly Journal of Computer Science and Information Technology

Roqaiah Saleh Al-Sanea *et al*, Volume 15, Issue 9, September 2026, pg. 108-118
(An Open Accessible, ISI Indexed, Fully Refereed and Peer Reviewed Journal)

ISSN: 2320-088X
Impact Factor: 7.056

Predicting active, death and recovery rates of COVID-19 in Algeria using prophet model was developed in [14]. Results showed that the active rate and the death rate decrease for the next days while the cured rate increases.

COVID-19 forecasting in Morocco using prophet model in Python was presented in [15]. Results show that the proposed model has a low ability to forecast the recovered cases of the COVID-19 dataset. In contrast, the proposed model of death cases has a high ability to forecast the COVID-19 dataset. This confirms that prediction is not an easy journey for researchers and relies on the accuracy of the data sources and the data flow.

Time series prophet model for COVID-19 outbreak prediction in Saudi-Arabia was developed in [16]. They found that the proposed model has a low ability to forecast the recovered cases of the COVID-19 dataset. In contrast, the proposed model of death cases has a high ability to forecast the COVID-19 dataset.

Hybrid ARIMA-LSTM for COVID-19 forecasting: a comparative AI modeling study was developed in [17]. This study evaluates and compares the performance of ARIMA, LSTM, and hybrid ARIMA-LSTM models in predicting pandemic trends, using COVID-19 data from the Malaysian Ministry of Health as a case study. All findings support the adoption of hybrid modelling approaches for pandemic forecasting, contributing to more accurate and reliable predictive analytics in epidemiology. Future research should investigate the generalizability of hybrid models across various infectious diseases and integrate additional real-time external variables to improve forecasting reliability.

Predictive modelling for pandemic forecasting: A COVID-19 study in New Zealand and partner countries was presented in [18]. They findings reveal that LSTM and ARIMA consistently outperform prophet, with LSTM achieving the highest predictive accuracy in most cases, particularly when trained on 20-week datasets. ARIMA, however, demonstrates superior stability and reliability across varying time frames, making it a robust choice for short-term forecasting. The results contribute to the development of adaptive forecasting frameworks that can empower public health authorities to respond proactively to emerging health threats.

Forecasting COVID-19 new cases in Yemen using ANN was presented in [10]. The residuals and forecast evaluation criteria (Forecast Error, MSE and MAE) of the applied model tell us that the model is stable and indeed suitable for forecasting purposes. It is projected that daily COVID-19 cases in Yemen are likely to remain high over the out-of-sample period. The study suggested the continued compliance to control and preventive COVID-19 measures such as social distancing, quarantine, isolation, face-mask wearing and so on, as well as country-wide vaccinations.

AI-driven health analysis for emerging respiratory diseases: A case study of Yemen patients using COVID-19 data was developed in [6]. They developed models to distinguish COVID-19 from other respiratory disease as the have similar symptoms and the prevalence of comorbidities. The work presented in this paper is considered as an attempt to forecast the spread of COVID-19 from the COVID-19-Yemen dataset using prophet model in the period of January 2020 till August 2024. Unlike ANN and other models that require extensive parameters tuning, the proposed model automates most of the process and it provides clear insight into trend components, seasonal and vacations effects. Furthermore, the successful studies which are implemented abroad and mentioned in this survey have motivated this study to tackle the underlying problem that exist in our country related to COVID-19 pandemic forecasting.

III.COVID-19-YEMEN DATASET DESCRIPTION

The main source of the dataset used in this study from OWID [5]. The OWID is one of the most well-known platforms for providing and analysing data on major global issues. The COVID-19 pandemic has spread across Yemen infecting 11,945 people and killing 2,159. This dataset contains the latest COVID-19 world state-wise data in detail from 01/01/2020 to 30/08/2024. The overall number of confirmed cases in the dataset had totalled 11,945, the total number of active cases had totalled 9,786 and the total number of death cases had totalled 2,159 for Yemen as a whole, as shown in Table 1. The dataset was formatted with ds as the date and y as the daily confirmed/death cases.



TABLE 1: NUMBER OF COVID-19-YEMEN CASES.

	Confirmed	Death	Active
Total	11945	2159	9786

The reason for the frequent changes in the number of confirmed cases and deaths, as well as the significant decrease in the number of active cases (currently infected cases) between 04/10/2020 and 30/08/2024 in Yemen could be attributed to several factors such as [6] successive waves and variant surges, improvements in reporting and testing, public health interventions and vaccination, and healthcare system adaptation.

IV. THE PROPOSED MODEL

The proposed model consists of three phases. The first phase is preprocessing phase which makes the dataset is ready for the second phase. In this phase, data filtering features selection and data splitting processes are applied. The second phase is the core phase in the proposed model. In this phase, hyperparameters tuning process is applied, and prophet model is used to train the model using the processed dataset. In this phase, new cases and new deaths of infections during specific period of time would be forecasted. Each season can be daily, weekly, monthly, annuals or customized according to content. The third phase is used to evaluate the time series forecasting results using common metrics such as MAE, RMSE, and R^2 . The workflow of the proposed model is shown in Fig.1.

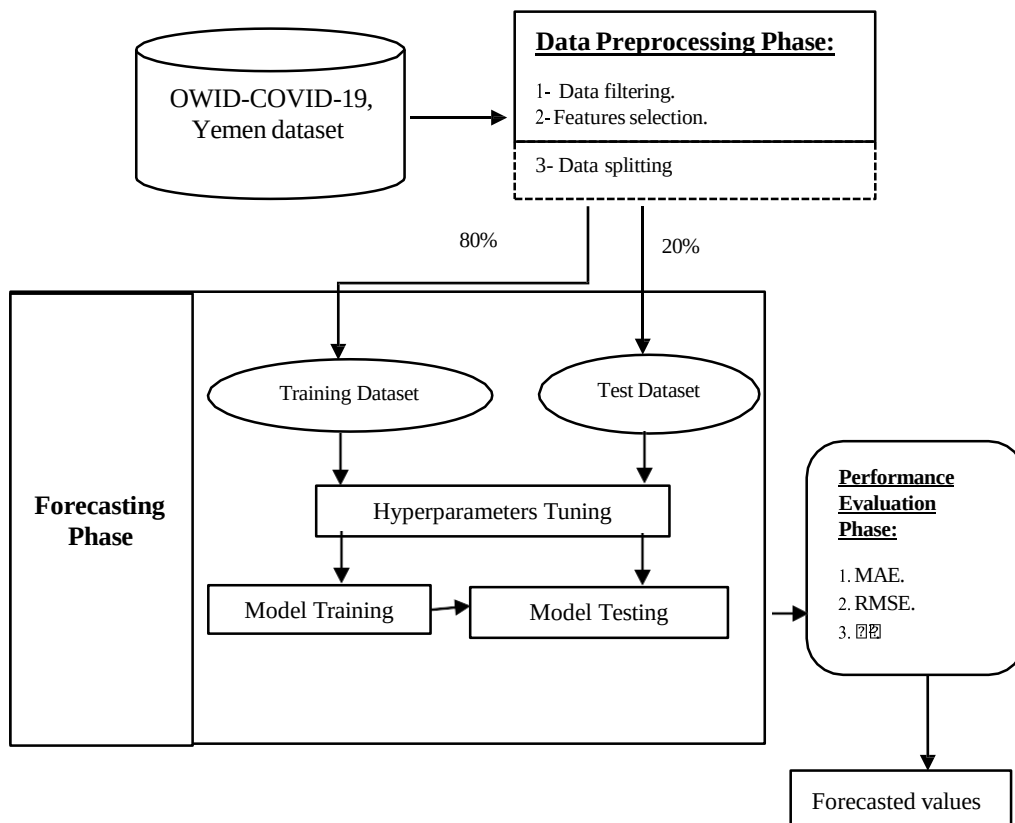


Fig.1: The workflow of the proposed forecasting model



International Journal of Computer Science and Mobile Computing
A Monthly Journal of Computer Science and Information Technology

Roqaiah Saleh Al-Sanea *et al*, Volume 15, Issue 9, September 2026, pg. 108-118
(An Open Accessible, ISI Indexed, Fully Refereed and Peer Reviewed Journal)

ISSN: 2320-088X
Impact Factor: 7.056

The detailed description of these phases are demonstrated below.

A. Data Preprocessing Phase

The preprocessing phase comprises three sequential processes:-

- 1) **Data Filtering:** Records from countries other than Yemen are removed from the global dataset (originally 429,435 rows), retaining only Yemen-specific observations.
- 2) **Features Selection:** Only date, new confirmed cases, and new death cases are retained. The date column is converted to prophet-compatible datetime format using `pandas.to_datetime()` and renamed as 'ds', while target variables are designated as 'y'.
- 3) **Data Splitting:** The time series is partitioned into training (80%, 1,339 observations) and testing (20%, 335 observations) subsets. The training set captures pandemic evolution patterns including multiple waves, while the testing set represents the post-2022 period characterized by minimal reported cases. Prophet's inherent robustness eliminates the need for explicit missing value imputation or outlier removal, as the model automatically excludes missing target values during fitting.

B. Forecasting Phase

In this phase, two processes are applied as follows:-

- 1) **Hyperparameter Tuning:** Hyperparameter tuning is a critical process in machine learning that aims to identify an appropriate combination of hyperparameter values to optimize model performance and generalization. Common approaches include grid search, random search, and Bayesian optimization [19]. In this research, the prophet model is optimized using a grid search approach to identify the best hyperparameters for forecasting COVID-19 cases in Yemen. The following key hyperparameters are tuned for the prophet model.
 - **changepoint_prior_scale:** This parameter controls the flexibility of the trend in the model. A higher value allows the model to be more responsive to abrupt changes, while lower values make the model more conservative in detecting changes in trends.
 - **seasonality_prior_scale:** This parameter regulates the strength of the seasonal components in the model. Larger values make the model more responsive to seasonal variations, while smaller values result in smoother seasonal effects.
 - **n_changepoints:** This parameter defines the number of points at which the model can change its trend. The number of changepoints controls how much flexibility the trend component.
 - **interval_width:** This parameter specifies the width of the uncertainty interval for the forecast. It controls the confidence level of the forecast, with larger values offering a wider range of potential outcomes. The grid search technique is employed to explore different combinations of these hyperparameters to find the optimal configuration as shown in Table 2.

TABLE 2. HYPERPARAMETER SEARCH SPACE.

Parameter	Tested Values	Selected Value
changepoint_prior_scale	[0.01, 0.1, 0.2, 0.3]	0.1
seasonality_prior_scale	[10.0, 15.0, 20.0]	10.0
n_changepoints	[25, 50, 100, 150]	50
interval_width	[0.8, 0.9, 0.95]	0.95

- 2) **Model Training/Testing Process:** In forecasting phase, prophet model is used for forecasting time series data based on an additive model including yearly, weekly, and daily seasonality, as well as holiday effects. It performs well with time series with strong seasonal effects and multiple seasons of historical data, making it an excellent choice for forecasting COVID-19 numbers. The proposed model was trained on 80% of the COVID-19-Yemen dataset and tested on the remaining 20% to assess its forecasting accuracy. During training, the proposed model identified change points corresponding to major pandemic waves. For testing, forecasting was



International Journal of Computer Science and Mobile Computing
A Monthly Journal of Computer Science and Information Technology

Roqaiah Saleh Al-Sanea *et al*, Volume 15, Issue 9, September 2026, pg. 108-118
(An Open Accessible, ISI Indexed, Fully Refereed and Peer Reviewed Journal)

ISSN: 2320-088X
Impact Factor: 7.056

generated for the test set period and compared against actual values using evaluation measures such as MAE, RMSE and R^2 . The train-test split validates that the proposed model can generalize and generate reliable short-term forecasts for COVID-19 in Yemen. The proposed model employs a decomposable time series model formulated as an additive regression[9]:-

$$y(t)=g(t)+s(t)+h(t)+\epsilon t \quad (1)$$

where:

- $g(t)$ represents the trend component modeling non-periodic long-term evolution
- $s(t)$ captures periodic seasonality (daily, weekly, monthly, yearly patterns)
- $h(t)$ accommodates holiday and event effects
- ϵt denotes the irreducible error term

The main components of The proposed model as follows:-

- 1) **Trend Component:** The model implements piecewise linear growth with automatic changepoint detection. The trend function is expressed as
- 2) **Seasonality Component:** prophet employs Fourier series to model periodic effects.
- 3) **Holiday Component:** Custom holiday effects are incorporated using indicator functions for significant dates including Eid al-Fitr and Eid al-Adha.

C. **Performance Evaluation Phase**

The most common time series forecasting evaluation measures to evaluate the performance of the proposed model as follows [20]:-

- 1) **Mean Absolute Error (MAE):** The MAE is a widely used metric for evaluating the accuracy of predictive models, particularly in regression analysis. It measures the average absolute difference between the actual values and the predicted values, providing an indication of how close the predictions are to the true values it is computed as under:-

$$MAE = \frac{1}{n} \sum_{i=1}^n |y^{\wedge} - y|$$

- 2) **Root Mean Square Error (RMSE):** The RMSE is the square root of the difference between the anticipated and observed values. It is defined by the following formula:-

$$RMSE = \sqrt{\sum_{i=1}^N \left(\frac{(y^{\wedge} - y)^2}{N} \right)}$$

- 3) **Coefficient of Determination (R^2):** R^2 is a measure of confidence that is easy to compute. It tells us how good the regression line predicts the real values. As R^2 score of 1 means that the regression predictions fit the



International Journal of Computer Science and Mobile Computing
A Monthly Journal of Computer Science and Information Technology

Roqaiah Saleh Al-Sanea *et al*, Volume 15, Issue 9, September 2026, pg. 108-118
(An Open Accessible, ISI Indexed, Fully Refereed and Peer Reviewed Journal)

ISSN: 2320-088X
Impact Factor: 7.056

data faultlessly about its means. Higher the R^2 measure better the model performance. It is defined as under:-

$$R^2 = 1 - \frac{\sum_{i=1}^N (x_i + y_i)^2}{\sum_{i=1}^N (\hat{y}_i + y_i)^2}$$

V. COMPUTATIONAL RESULTS AND DISCUSSION

A. *Experimental Setup*

The performance of the proposed model is validated on COVID-19-Yemen dataset in the period of 01/01/2020 to 08/04/2024. In all experiments the dataset is divided into a training dataset and a test dataset, using 80% of training dataset and 20% for testing. The performance of the proposed model is evaluated using common evaluation measures such as MAE, RSME and R^2 . The obtained results are compared with other related models such as decision tree and polynomial regression. All experiments are conducted on an Intel Core i5 processor with 8GB RAM running Windows 10 Pro 64-bit. The proposed model is implemented in Python 3.9 using the prophet library (version 1.1.0).

B. *Forecasting Results for Confirmed Cases*

The prophet model demonstrates exceptional performance in forecasting confirmed COVID-19 cases. Table 3 presents training and testing phase results.

TABLE 3 PERFORMANCE METRICS FOR CONFIRMED CASES

Phase	MAE	RMSE	R^2
Training	1.28	6.39	0.98
Testing	1.28	4.41	0.99

The proposed model attained an MEA of 1.28 across training and testing datasets. This result demonstrates the model's strong generalization capability, with no signs of overfitting. The testing phase exhibits improved RMSE and R^2 compared to training, indicating strong generalization capability. The near-perfect R^2 score of 0.99 signifies that the model explains 99% of the variance in confirmed cases. Fig. 2 visualizes the alignment between actual and predicted values during the testing period.

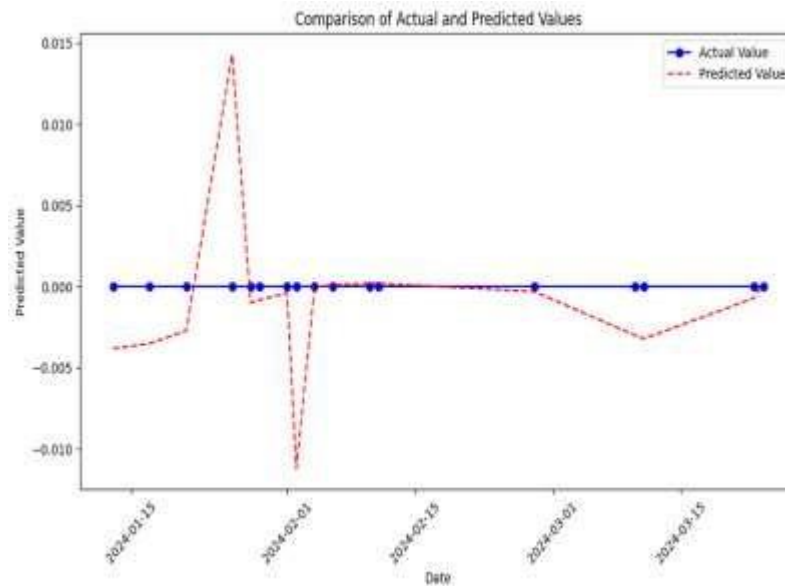


Fig. 2 Actual vs Predicted Confirmed Cases (Testing Period)

C. Forecasting Results for Death Cases

Table 4 summarizes model performance for death cases forecasting.

TABLE 4 PERFORMANCE METRICS FOR DEATH CASES

Phase	MAE	RMSE	R ²
Training	0.48	2.10	0.93
Testing	0.40	1.59	0.95

The model achieves superior accuracy in death case prediction with minimal error margins. The testing phase R² of 0.95 confirms robust predictive capability despite sparse mortality reporting in later periods. Fig. 3 shows the comparison between actual and predicted values during the testing process for death cases.

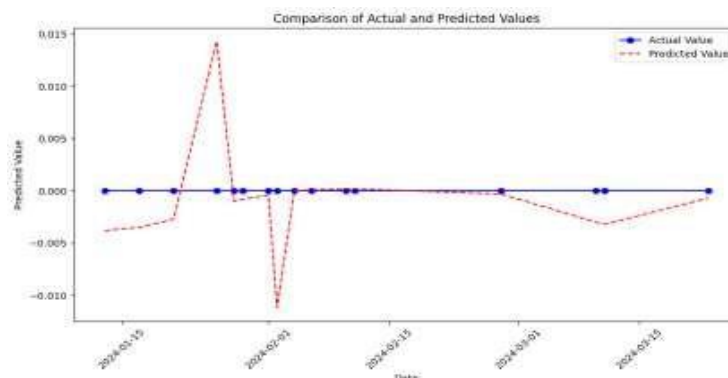


Fig. 3 Actual vs Predicted Death Cases (Testing Period)



International Journal of Computer Science and Mobile Computing
A Monthly Journal of Computer Science and Information Technology

Roqaiyah Saleh Al-Sanea *et al*, Volume 15, Issue 9, September 2026, pg. 108-118
(An Open Accessible, ISI Indexed, Fully Refereed and Peer Reviewed Journal)

ISSN: 2320-088X
Impact Factor: 7.056

D. Comparative Study

The proposed prophet model is benchmarked against decision tree regression and polynomial regression models. Table 5 presents comparative results for confirmed cases in testing phase.

TABLE 5 COMPARATIVE RESULTS FOR CONFIRMED CASES

Model	MAE	RMSE	R^2
The proposed model	1.28	4.41	0.99
Decision tree regression	3.40	24.07	0.67
Polynomial regression	3.97	21.29	0.74

It can be seen from Table 5 that, the values of all two evaluation metrics such as MAE, and RMSE in the proposed model for predicting confirmed cases are lower than those in the decision tree regression and polynomial regression models. But in the R^2 measure the proposed model scores the highest prediction accuracy (0.99) comparing to decision tree (0.67) and polynomial regression (0.74). Therefore, the obtained results show that the proposed model prediction almost matches the actual values whereas the other models did not perform as well especially in MSE and RMSE, and R^2 measures. Furthermore, Table 6 presents comparative results for death cases in testing phase.

TABLE 6 COMPARATIVE RESULTS FOR DEATH CASES

Model	MAE	RMSE	R^2
The proposed model	0.40	1.59	0.95
Decision tree regression	3.97	21.29	0.74
Polynomial regression	3.21	24.07	0.67

The proposed model consistently outperforms both comparative models across all evaluation metrics. For death cases, the proposed model reduces MAE by approximately 89.9% compared to decision tree and 87.54% compared to polynomial regression. Compared to the decision tree regression and polynomial regression models, the proposed model attained RMSE improvement factors of 13.39 and 15.14, respectively. R^2 score of 0.95 was attained by the proposed model, demonstrating that COVID-19 death cases were predicted with high accuracy.

The obtained results demonstrate that the proposed model outperforms the other two related models across all evaluation measures used for comparison, for both confirmed and death cases.

VI. CONCLUSION AND FUTURE WORK

In this paper, prophet machine learning model is used as a forecasting model that forecasts accurately the expected number of confirmed and deaths cases using COVID-19-Yemen dataset in the period of January 2020 to August 2024. The proposed model consists of three phases such as data preprocessing, forecasting and evaluation phases. The performance of the proposed model is evaluated using standard measures such as MAE, RMSE and R^2 . The obtained results are promising as the proposed model achieves low values of MAE and RMSE and high value of R^2 which proves that forecasted values are much closer to the actual values.

The performance of the proposed model is compared with other related models such as decision tree regression and polynomial regression. The comparative study confirms that the proposed model achieves better performance in all evaluation measures compared to other related models. The proposed model would support health policymakers by providing predictive insight that can help at reducing the spread of the virus and increase the medical facilities accordingly.

In future work, deep learning techniques may be integrated with the proposed model to further enhance the prediction of COVID-19 speed. The obtained forecasting results further can be improved by taking various



variables into account like population density, weather, health system, patient history etc. to discover the correlation relationship with COVID-19 disease by using interesting classification based association rules approach [21].

REFERENCES

- [1]. T. Singhal, "A review of coronavirus disease-2019 (COVID-19)," *Indian Journal of Pediatrics*, vol. 87, no. 4, pp. 281–286, 2020, doi: 10.1007/s12098-020-03263-6.
- [2]. W. Olesińska, M. Biernatek, S. Lachowicz-Wiśniewska, and J. Piątek, "Systematic review of the impact of COVID-19 on healthcare systems and society—The role of diagnostics and nutrition in pandemic response," *Journal of Clinical Medicine*, vol. 14, no. 7, p. 2482, 2025, doi: 10.3390/jcm14072482.
- [3]. A. Bansal, "Economic burden of long COVID: macroeconomic, cost-of-illness and microeconomic impacts," *npj Primary Care Respiratory Medicine*, vol. 35, no. 1, p. 53, 2025, doi: 10.1038/s41533-025-00460-8.
- [4]. F. Dureab, S. Al-Awlaqi, and A. Jahn, "COVID-19 in Yemen: preparedness measures in a fragile state," *The Lancet Public Health*, vol. 5, no. 6, p. e311, 2020, doi: 10.1016/S2468-2667(20)30101-8.
- [5]. Our World in Data, "COVID-19 dataset," 2024. [Online]. Available: <https://ourworldindata.org/covid-cases>.
- [6]. S. I. Alzahrani, W. M. S. Yafooz, I. A. Aljamaan, A. Alwaleedi, M. Al-Hariri, and G. Saleh, "AI-driven health analysis for emerging respiratory diseases: A case study of Yemen patients using COVID-19 data," *Mathematical Biosciences and Engineering*, vol. 22, no. 3, pp. 554–584, 2025, doi: 10.3934/mbe.2025021.
- [7]. A. Rodríguez, H. Kamarthi, P. Agarwal, J. Ho, M. Patel, S. Sapre, and B. A. Prakash, "Machine learning for data-centric epidemic forecasting," *Nature Machine Intelligence*, vol. 6, pp. 1122–1131, 2024, doi: 10.1038/s42256-024-00895-7.
- [8]. R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 2nd ed. Melbourne, Australia: OTexts, 2018.
- [9]. S. Su, "Machine learning for COVID-19: A review on forecasting models," *Applied and Computational Engineering*, vol. 4, pp. 717–723, 2023, doi: 10.54254/2755-2721/4/2023404.
- [10]. S. P. Nyoni, T. Nyoni, and T. A. Chihoho, "Forecasting COVID-19 new cases in Yemen," *International Research Journal of Innovations in Engineering and Technology*, vol. 5, no. 6, p. 605, 2021.
- [11]. O. Baker, Z. Ziran, M. Mecella, K. Subramaniam, and S. Palaniappan, "Predictive modelling for pandemic forecasting: A COVID-19 comparative analysis of ARIMA, Prophet, and LSTM models," *International Journal of Environmental Research and Public Health*, vol. 22, no. 4, p. 562, 2025.
- [12]. M. Indhuja and P. P. Sindhuja, "Prediction of COVID-19 cases in India using Prophet," *International Journal of Statistics and Applied Mathematics*, vol. 5, no. 4, pp. 103–106, 2020.
- [13]. S. Mahmud, "Bangladesh COVID-19 daily cases time series analysis using Facebook Prophet model," *SSRN Electronic Journal*, 2020, doi: 10.2139/ssrn.3660368.
- [14]. M. Lounis, "Predicting active, death and recovery rates of COVID-19 in Algeria using Facebook Prophet model," *SSRN Electronic Journal*, 2021, doi: 10.2139/ssrn.3867193.
- [15]. T. Chafiq, M. Ouadoud, and K. Elboukhari, "COVID-19 forecasting in Morocco using FBProphet Facebook's framework in Python," *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 5, 2020, doi: 10.30534/ijatcse/2020/251952020.
- [16]. M. Khayyat, K. Laabidi, N. Almalki, and M. Al-zahrani, "Time series Facebook Prophet model and Python for COVID-19 outbreak prediction," *Computers, Materials & Continua*, vol. 67, no. 3, pp. 3781–3793, 2021, doi: 10.32604/cmc.2021.014918.
- [17]. A. Mahmud, S. H. N. S. H. Noor, K. I. Musa, F. M. Hamzah, Z. M. Yudin, N. Kamaruddin, A. M. Madawana, and M. A. A. Nawi, "Hybrid ARIMA-LSTM for COVID-19 forecasting: A comparative AI modeling study," *PeerJ Computer Science*, vol. 11, e3195, 2025, doi: 10.7717/peerj-cs.3195.
- [18]. O. Baker, Z. Ziran, M. Mecella, K. Subramaniam, & S. Palaniappan. Predictive modeling for pandemic forecasting: A COVID-19 study in New Zealand and partner countries. *International Journal of Environmental Research and Public Health*, 22(4), 562. 2025.
- [19]. J. Won, H.-S. Lee, and J.-W. Lee, "A review on multi-fidelity hyperparameter optimization in machine learning," *ICT Express*, vol. 11, no. 2, pp. 245–257, 2025, doi: 10.1016/j.icte.2025.02.008.



International Journal of Computer Science and Mobile Computing
A Monthly Journal of Computer Science and Information Technology

Roqiaiah Saleh Al-Sanea *et al*, Volume 15, Issue 9, September 2026, pg. 108-118
(An Open Accessible, ISI Indexed, Fully Refereed and Peer Reviewed Journal)

ISSN: 2320-088X
Impact Factor: 7.056

- [20]. D. C. Montgomery and G. C. Runger, *Applied Statistics and Probability for Engineers*, 7th ed. Hoboken, NJ, USA: Wiley, 2020.
- [21]. S. S. Al-Gabli, and B. M. Al-Maqaleh, "Effective mining approach of interesting classification based association rules for heart disease diagnosis", *The 6th International Conferences on Emerging Smart Technologies and Application (eSmarTA-2026)*, Faculty of Computers and Information, Thamar University, Yemen, pp.1-8, 2026, doi:10.1109/eSmarTA70636.2026.11652143.