JURNAL ABSIS
Jurnal Pendidikan Matematika dan Matematika
Vol. 9 No. 1, April 2026

FORECASTING PATIENT VISITS IN PRIMARY HEALTHCARE USING ARIMA, HOLT'S EXPONENTIAL SMOOTHING, PROPHET, AND WEIGHTED ENSEMBLE MODELS

Nayla Saadah Fiddaraeni[1], Madona Yunita Wijaya[2], Mahmudi[3]
[1-3] Universitas Islam Negeri Syarif Hidayatullah Jakarta, Indonesia
naylasaadahf22@gmail.com

ABSTRACT The variability of patient visits in primary healthcare facilities requires accurate and interpretable forecasting methods to support service planning, resource allocation, and staff scheduling. This study aims to evaluate the forecasting performance of ARIMA, Holt's exponential smoothing, Prophet, and weighted ensemble models in predicting monthly patient visits at XYZ Primary Clinic in Bogor City. A quantitative time series forecasting approach was applied using monthly patient visit data from January 2020 to December 2023, consisting of 48 observations. The data were divided into 38 training observations and 10 testing observations using an approximately 80:20 split. Model performance was evaluated using Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). The results show that Holt's exponential smoothing provided the best individual forecasting performance, with the lowest MAPE of 9.39%, RMSE of 169.43, and MAE of 141.60. Among the ensemble configurations, the combination of Holt's and Prophet produced the best ensemble performance, with a MAPE of 9.56%, RMSE of 171.01, and MAE of 146.11. However, the weighted ensemble models did not outperform the best individual model. These findings indicate that the patient visit data exhibit a relatively stable trend pattern, making Holt's exponential smoothing more suitable than more complex approaches for this dataset. This study highlights the importance of selecting forecasting models based on data characteristics rather than model complexity alone. The findings provide practical implications for improving patient visit forecasting, resource planning, and service management in primary healthcare settings.

Keywords: time series forecasting, patient visits, Holt's exponential smoothing, Prophet, weighted ensemble, primary healthcare

ABSTRAK Variabilitas kunjungan pasien pada fasilitas layanan kesehatan primer membutuhkan metode peramalan yang akurat dan mudah diinterpretasikan untuk mendukung perencanaan layanan, alokasi sumber daya, dan penjadwalan tenaga kesehatan. Penelitian ini bertujuan untuk mengevaluasi kinerja model ARIMA, Holt's exponential smoothing, Prophet, dan weighted ensemble dalam meramalkan kunjungan pasien bulanan di Klinik Pratama XYZ Kota Bogor. Penelitian ini menggunakan pendekatan kuantitatif berbasis peramalan deret waktu dengan data kunjungan pasien bulanan periode Januari

https://doi.org/10.30606/absis.v9i1.3507

2020 hingga Desember 2023, yang terdiri atas 48 observasi. Data dibagi menjadi 38 observasi pelatihan dan 10 observasi pengujian dengan rasio sekitar 80:20. Kinerja model dievaluasi menggunakan Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), dan Mean Absolute Error (MAE). Hasil penelitian menunjukkan bahwa model Holt's exponential smoothing memberikan kinerja peramalan individu terbaik dengan nilai MAPE terendah sebesar 9,39%, RMSE sebesar 169,43, dan MAE sebesar 141,60. Pada konfigurasi ensemble, kombinasi Holt's dan Prophet menghasilkan kinerja ensemble terbaik dengan MAPE sebesar 9,56%, RMSE sebesar 171,01, dan MAE sebesar 146,11. Namun, model weighted ensemble tidak mampu mengungguli model individu terbaik. Temuan ini menunjukkan bahwa data kunjungan pasien memiliki pola tren yang relatif stabil, sehingga Holt's exponential smoothing lebih sesuai dibandingkan pendekatan yang lebih kompleks untuk dataset ini. Penelitian ini menegaskan pentingnya pemilihan model peramalan berdasarkan karakteristik data, bukan semata-mata kompleksitas model. Temuan ini memberikan implikasi praktis bagi peningkatan peramalan kunjungan pasien, perencanaan sumber daya, dan pengelolaan layanan pada fasilitas kesehatan primer.

Kata-kata kunci: peramalan deret waktu, kunjungan pasien, Holt's exponential smoothing, Prophet, weighted ensemble, layanan kesehatan primer

INTRODUCTION

Primary healthcare facilities, known in Indonesia as *Fasilitas Kesehatan Tingkat Pertama* (FKTP), play a central role in Indonesia's healthcare system as the first point of contact for patients seeking medical services. These facilities are responsible for providing accessible, continuous, and cost-effective care to the population. Due to their strategic position in healthcare delivery, primary healthcare facilities face continuous pressure to manage patient flow efficiently while operating under limited human, financial, and infrastructural resources. This condition requires accurate and data-driven service planning to ensure optimal service quality despite existing resource constraints.

One of the main operational challenges in primary healthcare facilities is the variability of patient visit demand. Patient arrivals often fluctuate due to temporal patterns, such as seasonal changes, demographic factors, and external conditions. This variability complicates healthcare planning, particularly in terms of staffing, resource allocation, and service scheduling. Uncontrolled fluctuations in patient volume may lead to overcrowding, increased waiting time, and reduced quality of service delivery, which ultimately affect healthcare system performance and patient satisfaction (Morley et al., 2018). Inefficient management of demand variability can also decrease the responsiveness of healthcare services (Grot et al., 2023). In addition, patient visit demand is influenced by long-term trend patterns, which further increases forecasting difficulty in primary care settings (Luo et al., 2017).

To address these challenges, time series forecasting methods have been widely applied in healthcare demand prediction. Classical statistical approaches, such as Autoregressive Integrated Moving Average (ARIMA), Holt's exponential smoothing, and Prophet, remain widely used because of their interpretability and relatively low computational requirements. ARIMA is effective in modeling linear relationships and autocorrelation structures in time series data (Juang et al., 2017), although its assumption of linearity may limit its performance in capturing more complex patterns. Holt's method is suitable for capturing level and trend components in non-seasonal data and has demonstrated strong forecasting performance in healthcare applications (Wiyanti, 2023). Meanwhile, the Prophet model is designed to handle trend changes and irregular patterns in time series data, making it applicable for healthcare demand forecasting (McCoy et al., 2018).

In addition to individual forecasting models, ensemble forecasting methods have gained attention for improving prediction accuracy by combining multiple models. Ensemble approaches can reduce individual model bias and improve overall robustness in forecasting tasks (Sukolkit et al., 2024). However, many existing ensemble methods rely on machine learning or deep learning techniques, which often require large datasets and high computational resources. For instance, hybrid models combining ARIMA, Multilayer Perceptron (MLP), and Long Short-Term Memory (LSTM) have shown strong performance in healthcare prediction tasks (Kaushik et al., 2020). Nevertheless, such approaches involve high model complexity and substantial computational requirements, which may limit their applicability in resource-constrained primary healthcare environments. This limitation indicates the need for alternative approaches that can maintain predictive performance while remaining computationally efficient and interpretable.

Despite the growing use of forecasting models in healthcare, relatively few studies have focused on statistical ensemble approaches for patient visit forecasting in primary healthcare settings. Most existing studies either use individual statistical models or hybrid machine learning frameworks (Patrick et al., 2023), which may increase complexity and reduce interpretability. This gap suggests that existing research has not sufficiently explored whether statistical ensemble approaches can achieve a balance between accuracy, interpretability, and computational efficiency in resource-constrained primary healthcare contexts.

To address this gap, this study proposes a weighted ensemble approach based on Mean Absolute Percentage Error (MAPE). MAPE was selected because it provides a scale-independent measure that enables fair comparison across models. Compared to Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), MAPE expresses forecasting error in percentage terms, making it more interpretable for healthcare decision-making. However, MAPE is sensitive to very small actual values and may produce unstable results in such cases. Despite this limitation, MAPE remains appropriate for this study because patient visit data in primary healthcare facilities generally do not contain extreme zero values, and percentage-based errors are useful for operational decision-making.

The objective of this study is to evaluate the forecasting performance of ARIMA, Holt's exponential smoothing, and Prophet models, and to develop a weighted ensemble model for predicting patient visit volumes in primary healthcare settings.

https://doi.org/10.30606/absis.v9i1.3507

This study contributes to the literature by introducing a simple, transparent, and computationally efficient forecasting framework tailored to resource-constrained healthcare systems while maintaining reliable predictive performance. Unlike many existing ensemble approaches that rely on complex machine learning techniques, this study focuses on a statistical weighting scheme that prioritizes interpretability and practical applicability in primary healthcare service planning.

METHODS

This study used a quantitative time series forecasting approach to predict monthly patient visit volumes in primary healthcare settings. Historical monthly patient visit data were obtained from XYZ Primary Clinic in Bogor City, covering the period from January 2020 to December 2023. The dataset consisted of 48 monthly observations. Although the number of observations was relatively limited, the dataset was considered adequate for evaluating simple and interpretable time series models in a primary healthcare context.

The data were divided chronologically into a training set and a testing set. The training set consisted of 38 observations, while the testing set consisted of 10 observations, representing an approximate 80:20 split. The training data were used to estimate model parameters, while the testing data were used to evaluate out-of-sample forecasting performance. Data processing and model estimation were conducted using RStudio and Google Colab. ARIMA and Holt's exponential smoothing models were implemented in RStudio, while Prophet was executed in Google Colab to support model tuning and implementation.

The forecasting methods evaluated in this study consisted of ARIMA, Holt's exponential smoothing, Prophet, and a weighted ensemble model. These methods were selected because they represent interpretable forecasting approaches that can be applied in resource-limited healthcare settings. The weighted ensemble model was developed by combining the forecasting results of the three individual models based on their forecasting accuracy.

ARIMA Model

The Autoregressive Integrated Moving Average (ARIMA) model is an extension of the ARMA model, originally developed for stationary time series data by Box and Jenkins (1976). ARIMA is used to model nonstationary time series data by applying differencing to achieve stationarity. This model is widely used because of its flexibility in various forecasting applications (Kontopoulou et al., 2023). The general form of the ARIMA (p, d, q)model used in this study refers to Dani et al. (2023), as follows:

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)a_t$$

where:

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$$
$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$$

Y_t = observed value at time t
B = backshift operator
$(1-B)^d$ = differencing operator
d = order of differencing
a_t = error term at time t

Holt's Exponential Smoothing Model

Holt's exponential smoothing model was used because it is suitable for time series data with trend patterns. This suitability is supported by Muchayan (2019), who explains that Holt's method can be applied effectively to trend data. This method gives greater weight to recent observations, allowing the model to respond to changes in trend patterns over time (Kamaruddin et al., 2022). The equations for Holt's method are as follows:

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + T_{t-1})$$
$$T_t = \beta(S_t - S_{t-1}) + (1-\beta)T_{t-1}$$
$$F_{t+m} = S_t + mT_t$$

where:

S_t = smoothed level at time t
T_t = smoothed trend at time t
F_{t+m} = forecast value at time $t+m$
X_t = actual observation at time t
α = level smoothing parameter
β = trend smoothing parameter
m = number of periods ahead to be forecast

The values of $\alpha$and $\beta$are smoothing parameters that determine the weight of recent observations in the forecast. The parameter αcontrols the weight placed on the most recent observation when smoothing the level of the time series, while βcontrols the responsiveness to changes in the trend component. Both parameters range from $0 < \alpha, \beta \leq 1$. Values close to 1 make the model more responsive to recent changes, while values close to 0 make the model more stable by reducing the influence of short-term fluctuations.

In this study, grid search was used for parameter optimization. Different combinations of $\alpha$and βvalues ranging from 0.1 to 1.0 were tested. The optimal parameter combination was selected based on the lowest Mean Absolute Percentage Error (MAPE) value. This process aimed to reduce forecasting error and improve the performance of Holt's model for patient visit data with trend patterns (Fadila & Hartono, 2025).

Prophet Model

Prophet is a forecasting model introduced by Taylor and Letham (2018). This model decomposes time series data into trend, seasonality, and holiday effects, making it suitable for data that may contain trend changes and irregular patterns. Hyperparameter tuning was conducted using grid search to obtain the best model configuration. The candidate values of the Prophet hyperparameters are presented in Table 1.

Table 1. Hyperparameters and Candidate Values for the Prophet Model

Hyperparameter	Candidate Values
changepoint_prior_scale	0.001; 0.01; 0.1; 0.5
seasonality_prior_scale	0.01; 0.1; 1.0; 10.0
holidays_prior_scale	0.01; 0.1; 1.0; 10.0
seasonality_mode	Additive; Multiplicative

The changepoint_prior_scale parameter determines the flexibility of the model in detecting trend changes, while seasonality_prior_scale controls the strength of the seasonal component. The holidays_prior_scale parameter controls the influence of holiday effects on the forecast, and seasonality_mode determines whether seasonality is modeled additively or multiplicatively. These parameters have also been applied in hybrid forecasting studies, such as Guruge and Priyadarshana (2025). Each parameter combination was tested on the training data, and the configuration with the lowest MAPE value was selected as the final Prophet model.

Weighted Ensemble Model

The ensemble model was used to combine the forecasting results from ARIMA, Holt's exponential smoothing, and Prophet. Ensemble forecasting is an approach that combines several forecasting methods to improve prediction accuracy by taking advantage of the strengths of each individual model and reducing their weaknesses (Bertsimas, n.d.). In this study, the ensemble model was constructed using a weighted averaging approach.

The weight of each model was determined based on its forecasting accuracy during the validation stage. The MAPE value was used as the basis for determining the weight, where models with lower MAPE values received higher weights. Thus, the model with better forecasting performance contributed more strongly to the final ensemble forecast.

The denominator of the total weight was calculated as follows:

$$Total = \sum_{i=1}^{k} \frac{1}{MAPE_i}$$

Then, the weight of each model was computed using the following formula:

$$w_i = \frac{\frac{1}{MAPE_i}}{\sum_{j=1}^{k} \frac{1}{MAPE_j}}, i = 1,2, \dots, k$$

The total weight of all models equals 1, ensuring that the combined forecast remains consistent with the scale of the actual data. The final forecast from the ensemble model was calculated using the weighted average formula adapted from Patrick et al. (2023):

$$\hat{y} = \sum_{i=1}^{k} w_i \, \hat{y}_i$$

where:

w_i = weight assigned to the i-th model
$\hat{y}_i$ = forecast result produced by the i-th model
$\hat{y}$ = final forecast result from the ensemble model
k = total number of models used

Model Evaluation

Model performance was evaluated using Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). MAPE was used as the primary evaluation metric because it expresses forecasting error in percentage form, making it easier to interpret for healthcare service planning. A model with a lower MAPE value is considered to have better forecasting accuracy (Handrianto & Cipta, 2023).

The MAPE formula is as follows:

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100$$

The RMSE formula is as follows:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

The MAE formula is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

where:

y_i = actual value at the i-th observation
$\hat{y}_i$ = predicted value at the i-th observation
n = total number of observations

The model with the lowest MAPE, RMSE, and MAE values was considered the most suitable model for forecasting monthly patient visits in the primary healthcare setting.

FINDING AND DISCUSSION

The analysis began with exploratory data analysis to understand the pattern of patient visits at XYZ Primary Clinic during the period 2020–2023. This step was important to identify general trends, fluctuations, and possible seasonal tendencies before applying the forecasting models.

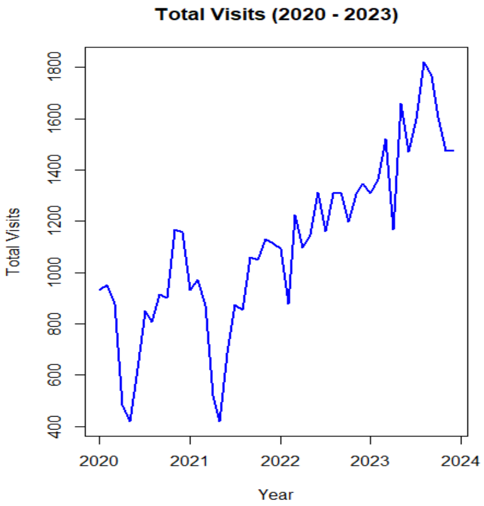


Figure 1. Number of Patient Visits at XYZ Primary Clinic from 2020 to 2023

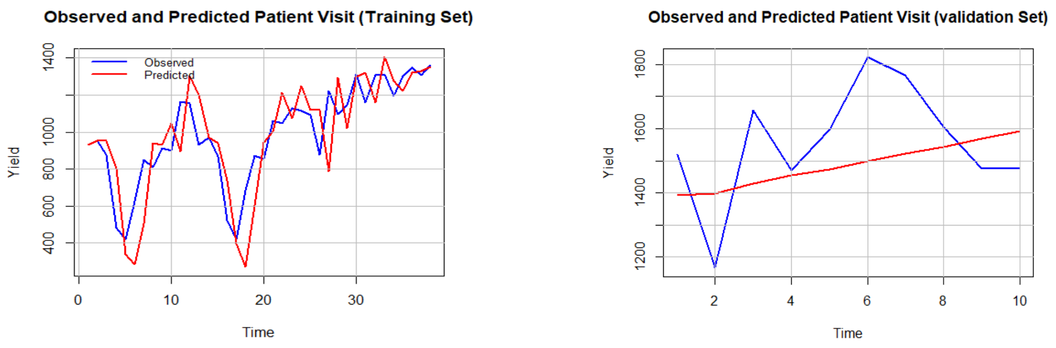
Figure 1 shows that patient visits fluctuated during the observation period. A sharp decline can be observed around the early to middle part of the year, and a similar pattern appeared again in 2021, suggesting the possible influence of seasonal or external factors. After the middle of the year, the number of visits gradually increased and reached relatively high levels in 2023. However, although fluctuations appear repeatedly, the pattern does not show strong and consistent temporal regularity across years. This indicates that the seasonal effect in the data is relatively weak. The variation in patient visits may also be influenced by non-recurring external conditions, such as healthcare policy changes, holiday periods, or unexpected events that affect patient visit behavior.

ARIMA Model

In the ARIMA model, the analysis was conducted through several stages, including model identification, parameter estimation, and diagnostic checking. Based on the initial analysis, the patient visit data showed irregular fluctuations, indicating that the series was not stationary in both mean and variance. To stabilize the variance, a Box-Cox transformation was applied with an optimal lambda (λ)value of 2. After transformation, the Augmented Dickey-Fuller (ADF) test produced a p-value of 0.1507, indicating that the data were still nonstationary in mean. Therefore, second-order differencing was applied. After differencing, the ADF test produced a p-value of 0.0226, confirming that the data had become stationary in mean.

After stationarity was achieved, the next step was to determine the appropriate ARIMA (p, d, q)model. Based on the ACF and PACF plots, two candidate models were identified, namely ARIMA(2,2,1) and ARIMA(2,2,0). Both models were evaluated based on the significance of their parameters. The ARIMA(2,2,1) model contained non-significant coefficients, particularly AR(1) and AR(2), with p-values of 0.8882 and 0.4315, respectively. In contrast, all parameters in the ARIMA(2,2,0) model were statistically significant.

The ARIMA(2,2,0) model also passed the residual diagnostic tests. The Shapiro-Wilk normality test produced a p-value of 0.05295, and the Jarque-Bera test produced a p-value of 0.216, indicating that the residuals were approximately normally distributed. In addition, the Ljung-Box test produced a p-value of 0.7738, suggesting no significant autocorrelation in the residuals. Therefore, the ARIMA(2,2,0) model was considered adequate for forecasting patient visits.


Observed and Predicted Patient Visit (Training Set)

Observed and Predicted Patient Visit (validation Set)

(a) Training Set

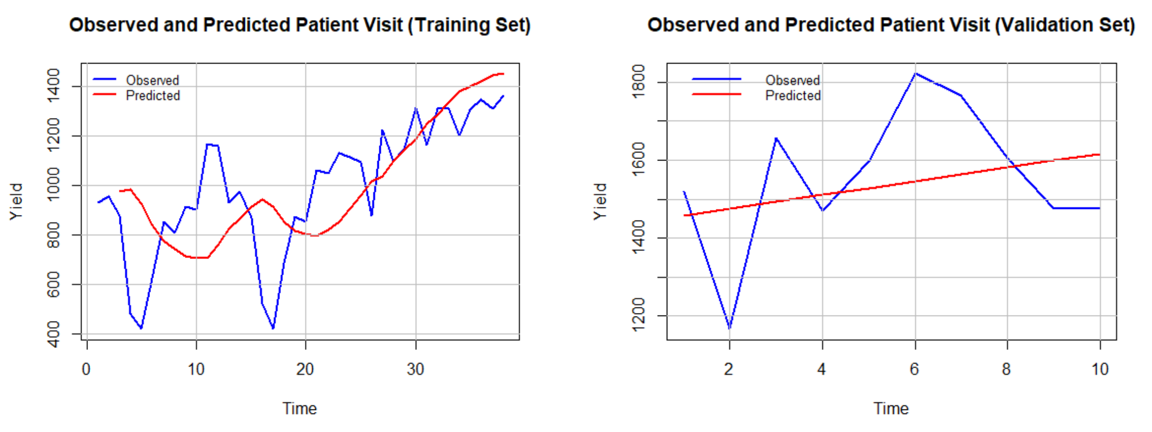
(b) Testing Set

Figure 2. Observed and Predicted Patient Visits Using the ARIMA Model

Figure 2 shows the observed and predicted values generated by the ARIMA(2,2,0) model. In the training set, the model was able to follow the general fluctuations in the data. However, it showed a slight lag in responding to sharp changes, indicating limited responsiveness to sudden variations. In the testing set, the ARIMA model did not fully capture short-term fluctuations in the unseen data. The model produced a MAPE value of 10.03%, which indicates an acceptable forecasting performance, although it was not the best among the models evaluated. This limitation may be related to the irregular pattern and weak seasonal structure of the patient visit data.

Holt's Exponential Smoothing Model

For Holt's exponential smoothing model, parameter optimization was conducted for $\alpha$and βusing a grid search procedure to obtain the minimum forecasting error. The optimal parameter values were $\alpha = 0.1$and $\beta = 0.5$.



(a) Training Set (b) Testing Set

Figure 3. Observed and Predicted Patient Visits Using Holt's Exponential Smoothing Model

Compared to ARIMA, which attempts to follow data fluctuations more closely, Holt's model tends to capture the general direction of the trend. This model is suitable for data with a relatively stable trend because it focuses on level and trend components rather than short-term irregular movements. Although Holt's model is less sensitive to sudden spikes or extreme changes, it demonstrated the best forecasting performance in this study. The model achieved a MAPE value of 9.39%, along with the lowest RMSE and MAE values. This result suggests that the patient visit data were relatively trend-dominated, making Holt's exponential smoothing more appropriate than more complex models for this dataset.

Prophet Model

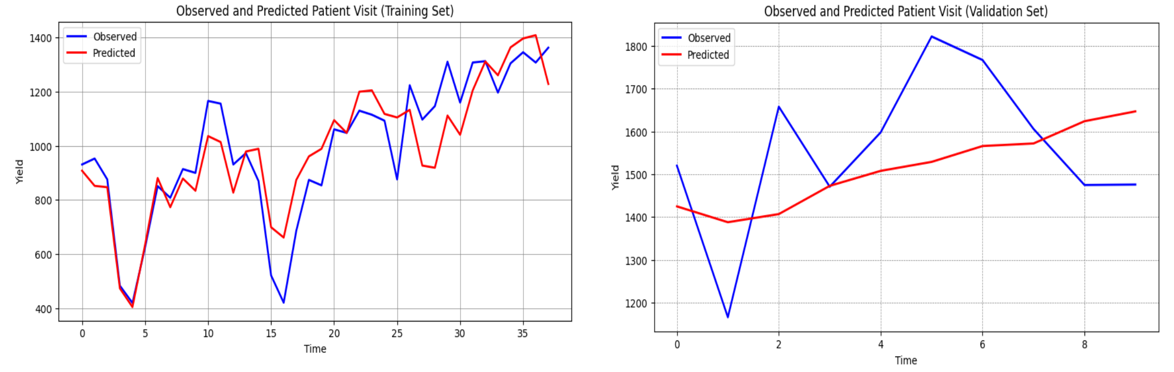
In the Prophet model, grid search was used to optimize the hyperparameters and reduce forecasting error. The five best hyperparameter combinations based on MAPE values are presented in Table 2.

Table 2. Best Hyperparameter Combinations Based on MAPE

Changepoint Prior Scale	Seasonality Prior Scale	Holidays Prior Scale	Seasonality Mode	MAPE
0.5	0.01	0.01	Additive	0.09746
0.5	0.01	0.10	Additive	0.09746

Changepoint Prior Scale	Seasonality Prior Scale	Holidays Prior Scale	Seasonality Mode	MAPE
0.5	0.01	10.00	Additive	0.09746
0.5	0.01	1.00	Additive	0.09746
0.5	0.01	1.00	Multiplicative	0.09799

Based on Table 2, the best hyperparameter combinations produced a MAPE value of approximately 0.09746, or 9.75%. The first combination was selected as the optimal configuration because it produced the lowest MAPE during the grid search process. This configuration was then used to generate forecasts for the training and testing sets.



(a) Training Set (b) Testing Set

Figure 4. Observed and Predicted Patient Visits Using the Prophet Model

Figure 4 shows that the Prophet model was able to follow the general trend in the training data. However, in the testing set, the model was less accurate in capturing short-term fluctuations, although the overall trend was still represented. This limitation is likely related to the weak and inconsistent seasonal patterns in the dataset. Prophet is designed to decompose time series into trend, seasonality, and holiday effects, which can be useful for nonstationary data. However, when seasonal patterns are not strong, this advantage may not substantially improve forecasting accuracy. With a MAPE value of 9.75%, Prophet remains a competitive alternative, but it did not outperform Holt’s exponential smoothing in this study.

Weighted Ensemble Model

Patient visit forecasting was also conducted using a weighted ensemble approach by combining forecasts from ARIMA, Holt’s exponential smoothing, and Prophet. Each model’s weight was calculated inversely proportional to its MAPE value, allowing models with lower prediction errors to contribute more strongly to the final ensemble forecast. The obtained weights were 0.345 for Holt’s model, 0.3228 for ARIMA, and 0.3323 for Prophet.

https://doi.org/10.30606/absis.v9i1.3507

Table 3. Forecasting Results for 2023

Month	ARIMA	Holt's	Prophet	Ensemble
March	1393	1458	1425	1426
April	1397	1476	1388	1421
May	1430	1493	1407	1444
June	1456	1511	1473	1481
July	1473	1528	1508	1504
August	1499	1546	1529	1525
September	1523	1563	1566	1551
October	1544	1581	1572	1566
November	1568	1599	1624	1597
December	1592	1616	1647	1619

After obtaining the forecasted values from each model, the forecasting accuracy was evaluated using three metrics: MAPE, RMSE, and MAE. In addition to the three individual models, several ensemble combinations were also evaluated to examine whether combining models could improve forecasting accuracy. The comparative results are presented in Table 4.

Table 4. Model Comparison Evaluation

Model	MAPE	RMSE	MAE
ARIMA	10.03%	180.87	156.40
Holt's	9.39%	169.43	141.60
Prophet	9.75%	175.57	150.80
Ensemble ARIMA + Holt's	9.60%	173.10	147.30
Ensemble ARIMA + Prophet	9.87%	177.30	153.36
Ensemble Holt's + Prophet	9.56%	171.01	146.11
Ensemble ARIMA + Holt's + Prophet	9.65%	173.30	148.47

Table 4 shows that all models produced relatively good forecasting accuracy, with MAPE values around or below 10%. Among the individual models, Holt's exponential smoothing achieved the best performance, with the lowest MAPE of 9.39%, RMSE of 169.43, and MAE of 141.60. This indicates that Holt's model was the most suitable model for the patient visit data used in this study.

Among the ensemble combinations, the Holt's + Prophet ensemble produced the best ensemble performance, with a MAPE of 9.56%, RMSE of 171.01, and MAE of 146.11. However, this result was still slightly lower than the performance of Holt's model as an individual model. Therefore, although the ensemble approach improved the stability of combined forecasts, it did not outperform the best individual model in this dataset.

This finding suggests that the patient visit data at the primary clinic had a relatively simple and stable trend pattern. As a result, a model that directly captures level and trend components, such as Holt's exponential smoothing, performed more effectively than models with greater complexity. This result is in line with the view that ensemble models can improve prediction accuracy by combining different model strengths (Patrick et al., 2023). However, the present findings also show that ensemble models do not always produce better accuracy than individually optimized models. This is consistent with Hao et al. (2020), who noted that ensemble methods may not always outperform individual models when the data characteristics are better represented by a simpler model. Thus, in resource-limited primary healthcare settings, a simple and interpretable model such as Holt's exponential smoothing may provide reliable forecasting performance while remaining practical for operational decision-making.

CONCLUSIONS AND RECOMMENDATIONS

Based on the forecasting evaluation results, Holt's exponential smoothing model provided the best performance for predicting monthly patient visits at XYZ Primary Clinic. This model achieved the lowest error values, with a MAPE of 9.39%, RMSE of 169.43, and MAE of 141.60, outperforming ARIMA, Prophet, and all ensemble model combinations. These results indicate that the patient visit data have a relatively stable trend pattern, making Holt's model more suitable than more complex forecasting approaches.

The weighted ensemble models showed satisfactory forecasting accuracy, particularly the combination of Holt's and Prophet, which produced the best ensemble performance with a MAPE of 9.56%, RMSE of 171.01, and MAE of 146.11. However, the ensemble approach did not substantially improve forecasting accuracy compared to Holt's model as the best individual model. This finding suggests that combining models does not always lead to better performance, especially when the data pattern can already be captured effectively by a simpler model.

Overall, this study shows that simple and interpretable statistical forecasting methods can provide reliable results in primary healthcare settings with limited data and resources. The findings highlight the importance of selecting forecasting models based on data characteristics rather than model complexity alone. Practically, Holt's exponential smoothing can be considered an appropriate forecasting tool to support patient visit planning, resource allocation, staff scheduling, and service management in primary healthcare facilities. Future studies are recommended to include longer observation periods and additional external variables, such as holiday periods, disease outbreaks, or healthcare policy changes, to improve forecasting accuracy and capture more complex visit patterns.

REFERENCES

Bertsimas, D., & Boussioux, L. (2023). *Ensemble modeling for time series forecasting: An adaptive robust optimization approach*. arXiv. https://doi.org/10.48550/arXiv.2304.04308

Dani, A. T. R., Wahyuningsih, S., Putra, F. B., Fauziyah, M., Wigantono, S., Sandariria, H., A'yun, Q. Q., & Zen, M. A. (2023). Aplikasi model ARIMAX dengan efek variasi kalender untuk peramalan trend pencarian kata kunci "Zalora" pada data Google Trends. *Inferensi, 6*(2), 107. https://doi.org/10.12962/j27213862.v6i2.15793

Fadila, I., & Hartono, B. (2025). Pendekatan hibrid double exponential smoothing dan GRU untuk optimasi prediksi harga cabai rawit merah. *Building of Informatics, Technology and Science (BITS), 6*(4), 2301–2310. https://doi.org/10.47065/bits.v6i4.6815

Grot, M., Kugai, S., Degen, L., Wiemer, I., Werners, B., & Weltermann, B. M. (2023). Small changes in patient arrival and consultation times have large effects on patients' waiting times: Simulation analyses for primary care. *International Journal of Environmental Research and Public Health, 20*(3), Article 1767. https://doi.org/10.3390/ijerph20031767

Guruge, P. B., & Priyadarshana, Y. H. P. P. (2025). Time series forecasting-based Kubernetes autoscaling using Facebook Prophet and long short-term memory. *Frontiers in Computer Science, 7*, Article 1509165. https://doi.org/10.3389/fcomp.2025.1509165

Handrianto, M., & Cipta, H. (2023). Peramalan jumlah produksi minyak kelapa sawit menggunakan metode Holt-Winters exponential smoothing (Studi kasus: PT. Sinar Gunung Sawit Raya). *Jurnal Absis: Jurnal Pendidikan Matematika dan Matematika, 6*(1), 781–793. http://journal.upp.ac.id/index.php/absis/article/view/2165

Hao, T., Elith, J., Lahoz-Monfort, J. J., & Guillera-Arroita, G. (2020). Testing whether ensemble modelling is advantageous for maximising predictive performance of species distribution models. *Ecography, 43*(4), 549–558. https://doi.org/10.1111/ecog.04890

Juang, W. C., Huang, S. J., Huang, F. D., Cheng, P. W., & Wann, S. R. (2017). Application of time series analysis in modelling and forecasting emergency department visits in a medical centre in Southern Taiwan. *BMJ Open, 7*(11), Article e018628. https://doi.org/10.1136/bmjopen-2017-018628

Kamaruddin, Asrul, B. E. W., & Matalangi. (2022). Implementasi metode double exponential smoothing untuk prediksi hasil panen sayuran kentang. *Jurnal Fokus Elektroda, 7*(3), 193–199. https://elektroda.uho.ac.id/

Kaushik, S., Choudhury, A., Sheron, P. K., Dasgupta, N., Natarajan, S., Pickett, L. A., & Dutt, V. (2020). AI in healthcare: Time-series forecasting using statistical, neural, and ensemble architectures. *Frontiers in Big Data, 3*, Article 4. https://doi.org/10.3389/fdata.2020.00004

Kontopoulou, V. I., Panagopoulos, A. D., Kakkos, I., & Matsopoulos, G. K. (2023). A review of ARIMA vs. machine learning approaches for time series forecasting in data driven networks. *Future Internet, 15*(8), Article 255. https://doi.org/10.3390/fi15080255

Luo, L., Luo, L., Zhang, X., & He, X. (2017). Hospital daily outpatient visits forecasting using a combinatorial model based on ARIMA and SES models. *BMC Health Services Research, 17*(1), 1–13. https://doi.org/10.1186/s12913-017-2407-9

McCoy, T. H., Pellegrini, A. M., & Perlis, R. H. (2018). Assessment of time-series machine learning methods for forecasting hospital discharge volume. *JAMA Network Open, 1*(7), Article e184087. https://doi.org/10.1001/jamanetworkopen.2018.4087

Muchayan, A. (2019). Comparison of Holt and Brown's double exponential smoothing methods in the forecast of moving price for mutual funds. *Journal of Applied Science, Engineering, Technology, and Education, 1*(2), 183–192. https://doi.org/10.35877/454ri.asci1167

Patrick, S., Mirau, S., Mbalawata, I., & Leo, J. (2023). Time series and ensemble models to forecast banana crop yield in Tanzania, considering the effects of climate change. *Resources, Environment and Sustainability, 14*, Article 100138. https://doi.org/10.1016/j.resenv.2023.100138

Sukolkit, N., Arunyanart, S., & Apichottanakul, A. (2024). An open innovative inventory management based demand forecasting approach for the steel industry. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(4), Article 100407. https://doi.org/10.1016/j.joitmc.2024.100407

Taylor, S. J., & Letham, B. (2018). Forecasting at scale. *The American Statistician, 72*(1), 37–45. https://doi.org/10.1080/00031305.2017.1380080

Wiyanti, W. (2023). Effectiveness of single and double exponential smoothing: SES, ARRSES and Holt's linear for time series data prediction with trend and non-seasonal characteristic (COVID-19 vaccinate case). *Jurnal Matematika, Statistika dan Komputasi, 20*(1), 52–64. https://doi.org/10.20956/j.v20i1.27193