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# COMPARATIVE STUDY OF HOLT-WINTERS, LSTM AND PROPHETIN FORECASTING HOSPITAL OUTPATIENT VISITS FLOW

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## ABSTRACT

Effective hospital outpatient visits flow forecasting is an important task for modern hospitals to implement intelligent management of medical resources. Since outpatient visits flow may be nonlinear and dynamic, we investigate a comparative study of three methods: Holt-Winters, LSTM and Prophetto find the most suitable model for forecasting hospital outpatient visits flow. Holt-Winters is a classical statistics model, LSTM is a deep learning model, and Prophet is a new hybrid model. The comparative experiments were conducted on the two datasets: the outpatient visits flow at General Hospital of Cu Chi Area (in Ho Chi Minh City, Viet Nam) and the outpatient visit flow at Ho Chi Minh City Hospital of Dermato-Venereology. The experimental results demonstrate that Holt-Winters is more effective than LSTM and Prophet model in this forecasting problem.



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# INTRODUCTION

Accurate forecasting the healthcare demand and resource availability becomes more important and critical. Outpatient departments which play an important role in hospital service face increasing pressure year by year(Lou *et al*., 2017). Effective hospital outpatient visits forecasting is beneficial for the suitable planning and allocation of healthcare to meet the medical demands. Due to multiple characteristics of daily outpatient visits, such as randomness, cyclicity and trend (Lou *et al*., 2017), in the past, several researchers have studied various methods for this prediction problem such as statistics analysis and machine learning methods. Some typical research works can be listed as follows. Li *et al*. (2014) proposed ARIMA (Auto Regressive Integrated Moving Average) model for forecasting monthly outpatient visits flow at a grade 3 hospital in China. Kim *et al*. (2020) compared the performances of two methods: ARIMA and SARIMA in forecasting outpatient visits flow on the datasets of some hospitals in Gangnam-gu, Seoul and the results show that SARIMA brings out better prediction performance than ARIMA. Sumitra and Basri (2020) compared the performances of three methods: ARIMA, Simple Exponential Smoothing and Holt-Winters in forecasting outpatient visits flow at a Community Health Center in Indonesia and the results show that Holt-Winters brings out the best prediction performance. Abdillah *et al*. in 2023 compared the performances of two methods: Holt-Winters and ARIMA in forecasting outpatient visit flow at a Public Health Center and the results show that Holt-Winters brings out the best prediction performance. Guan and Elgelhardt (2019)compared the performances of four methods: linear regression, ANN, Recurrent Neural Network (RNN) and Long-Short-Term-Memory (LSTM) neural networks in forecasting pediatric outpatient volume. Thapa and Timalsina (2023) proposed Gated Recurrent Unit (GRU), an improved variant of LSTM, in forecasting hospital outpatient volume. There have been several hybrid methods proposed for forecasting outpatient visits flow which are listed as follows. Wang *et al*. (2015) proposed a hybrid method which combines a time series decomposition technique (EEMDAN) with multiple local predictor fusion for forecasting diarrhoea outpatient visits at some hospitals in Shanghai, China. Lou *et al*. (2017) used a combination model based on ARIMA and Simple Exponential Smoothing (SES) for forecasting outpatient visits flow at some large hospitals in China. Huang and Wu (2017) proposed a hybrid method which combined empirical mode decomposition (EMD)technique with multiple artificial neural networks in forecasting hospital outpatient volume. Buengbongkoch and Nupairoj in 2024 proposed a hybrid method which combined ensemble empirical mode decomposition (EEMD) technique with LSTM for forecasting outpatient volume at a private hospital in Thailand. Jiang *et al*. (2019) proposed a combination method which couples deep neural networks and classical regression models for forecasting outpatient volume in Hong Kong. Deng *et al*. (2023) proposed a hybrid model which combines ARIMA with deep neural network LSTM model for forecasting outpatient visits flow at some departments at the First Hospital of Shanxi Medical University in China.

The hybrid model by Deng *et al*. (2023) aims to combine the ability of capturing the linear components of the time series by ARIMA model with the ability of capturing the nonlinear components of the time series by LSTM model. Zhou in 2023 proposed a hybrid model which combines Prophet with deep neural network LSTM model for forecasting outpatient visits flow at a hospital in Xiang yang City, Hubei Province. Anh and Tan in 2025 proposed a hybrid method which combined motif information and k-nearest-neighbors for forecasting outpatient visits flowat a hospital in Ho Chi Minh City.

In this paper, we aim to compare the performances of the three methods: Holt-Winters, LSTM and Prophet in forecasting hospital outpatient visit flow in order to find the best method for this special forecasting problem. The three above-mentioned methods are representatives of the three typical kinds of forecasting models. Holt-Winters is a classical statistics model, LSTM is a deep learning model and Prophet is a new hybrid method. This paper makes the main contributions as follows.

- We compare the performances of the three comparative forecasting methods on two datasets: the outpatient visits flow at General Hospital of Cu Chi Area (in Ho Chi Minh City, Viet Nam) and the outpatient visit flow at Ho Chi Minh City Hospital of Dermato-Venereology.
- Experimental results on the two datasets reveal that Holt-Winters performs better than LSTM and Prophet model in forecasting hospital outpatient visits flow.

# METHODOLOGY

***Holt-Winters:*** The Holt-Winters model is a kind of exponential smoothing prediction method which is suitable for time series with increasing or decreasing trend and seasonal variation. This model can be described by two approaches: multiplicative and additive. The four equations used in Holt-Winters multiplicative method are:

$$\hat{Y}_{t+p} = (L_t + pT_t)S_{t-s+p} \quad (1)$$

$$L_t = \alpha Y_t/S_{t-s} + (1-\alpha)(L_{t-1} + T_{t-1}) \quad (2)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \quad (3)$$

$$S_t = \gamma Y_t/L_t + (1-\gamma)S_{t-s} \quad (4)$$

where $\hat{Y}_{t+p}$ : forecast for $p$ periods into the future, $L_t$: estimate of current level, $T_t$: estimate of trend, $S_t$: seasonal estimate, $\alpha$: smoothing constant for the level ($0 < \alpha < 1$), $\beta$: smoothing constant for the trend ($0 < \beta < 1$), $\gamma$: smoothing constant for seasonality estimate ($0 < \gamma < 1$) and $s$: length of seasonality. If $\gamma$ is equal to 0, that means there is no seasonal component in the time series. If both $\gamma$ and $\beta$ are equal to 0, the model does not have seasonal component and trend component. Thus, Holt Winters method is the most general model in the exponential smoothing methods. In the multiplicative version of Holt-Winters method, the seasonality estimate is given as a *seasonal index* and calculated by Eq. (4). Eq. (4) shows that the current seasonal component, $S_t$, is computed as $\gamma$ times an estimate of the seasonal index given by $Y_t/L_t$ added to (1- $\gamma$) times the previous seasonal component $S_{t-s}$. The additive version of Holt-Winters is not described here due to limit of space. For the equations used in Holt-Winters (additive) method, interested readers can refer to (Hanke and Wichenrn, 2014).

The advantage of Holt-Winters exponential smoothing is that it is capable of predicting trend and seasonal time series with minimal effort in model identification.

***LSTM:*** Long Short-Term Memory (LSTM) is an improvement of Recurrent Neural Networks (RNN). LSTM was proposed by Hochreiter and Schmidhuber (1997) to solve the weakness of RNN in dealing with long-term dependencies. LSTM is able to capture long-term memories and dependencies when reading each time step of the time series. Each LSTM unit (also called cell state) has three operation gates: forget gate, output gate and input gate.

The deep LSTM neural network may have more than one hidden layers. Figure 1 describes the structure of a stacked LSTM network which can be used in time series forecasting. Recently, several research works have applied LSTM successfully in time series predictions for a wide variety of real-world applications (Torres *et al*., 20221).

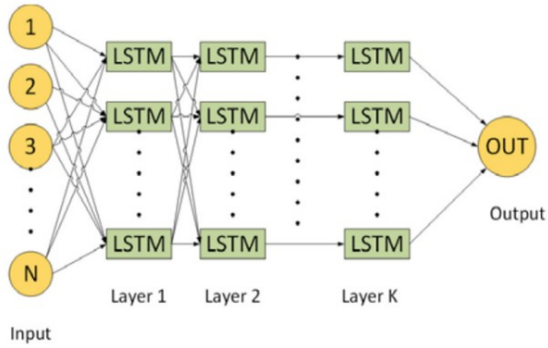


**Figure 1.Architecture of a stacked LSTM network**

***Prophet:*** Prophet is a forecasting model developed by Facebook Core Data Science Team since 2017. The Prophet prediction model is an enhanced traditional decomposition-based time series model that includes three components: a trend, seasonality, and a holiday term. The final assumption is derived from the expression reported by (Taylor and Letham, 2018).

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t \quad (5)$$

where $g(t)$ demonstrates the trend, $s(t)$ demonstrates seasonality, and $h(t)$ demonstrates the holiday impact on the data behavior and attitude. The value of $\varepsilon_t$is a measurement error that the model does not account for.

The Prophet model is covered by two trend models: a nonlinear saturating growth model and a piecewise linear model. The logistic growth model is commonly used to model a nonlinear model. The linear growth model expression is used, which is presented by:
(6)

$$g(t) = (k + a(t)^{T}\delta)t + (m + a(t)^{T}\gamma) \quad (6)$$

where $k$ represents the growth rate, $m$ is an offset variable, $\delta$ is the vector of growth rate modification, $\gamma$ is the vector of correction modifications at change points, and $a(t)$ is the vector of modification parameters. The time series may include various types of seasonal cycles. A Fourier series is chosen to approximate the periodic property, and the seasonal model can be mathematically represented.
(7)

$$s(t) = \sum_{n=1}^{N}(a_n\cos(\frac{2\pi nt}{P}) + b_n\sin(\frac{2\pi nt}{P})) \quad (7)$$

where $P$ is the seasonality period, the value of $P$ for yearly seasonality is 365.25 and $P$ for weekly seasonality is 7, $t$ denotes a date and $a_i$, $b_i$ denote two coefficients. Holidays and events provide a relatively large, and normally predictable changes in time series, frequently do not have a periodic pattern, thus the effects are not well factored by a smooth cycle. Prophet offers an extra variable in the model to feed a custom list of pastand future holidays and events, and also assume they are independent.Prophet assumes that each holiday$i$ in the list $L$will affect with a constant value $\kappa_i$on the forecasting value:

$$h(t) = Z(t)\kappa = \sum_{i=1}^{L}\kappa_i \cdot 1(t \in D_i) \quad (8)$$

The Prophet model is trained and tested on a training dataset. Following hyper parameter tuning, the FB-Prophet model with optimum parameters, including daily and weekly seasonality, is used with four change points.

# RESULTS AND DISCUSSION

We implemented Holt-Winters model by using the Rlibrary (http://www.r-project.org/). As for LSTM, we implemented it by Keras (http://keras.io/) on the platform Tensorflow.

We implement FaceBook Prophet by using Prophet library of Meta (https://facebook.github.io/prophet/). We conducted the experiments on an Intel XeonCPU @ 2.20 GHz RAM52.96 GB, GPU NVIDIA L4 23GB.

**Finally, only one-day ahead forecasting (a form of short-term forecating) is considered in this research.**

***The Datasets: Hospital 1*:** The first dataset for our study comes from the General Hospital of Cu Chi Area (Ho Chi Minh City, Vietnam), collected during the period of 3 years from1 January 2018 to 31 December 2020 with the total number of 75,511 outpatients.

Thus, the dataset contains 1092 observations in the time series. The average of outpatient visits every day is 1843, the minimum value is 4 and the maximum value is 3850. General Hospital of Cu Chi Area is a Level 2 hospital in Ho Chi Minh City.

Figure 2 provides the curve of the daily emergency patient arrivals in3 years from 2018 to 2020. Figure3 provides the curve of the daily outpatient arrivals in one month (January 2018).

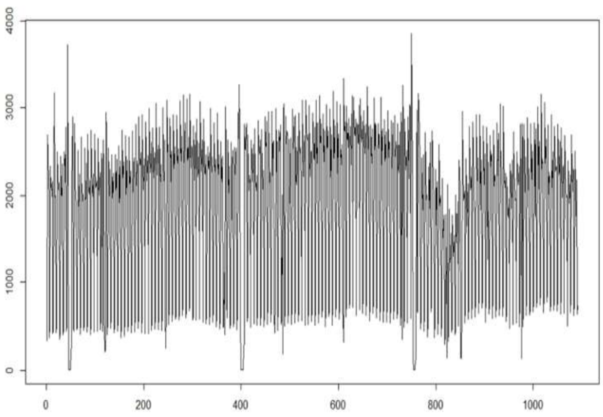


**Figure 2. The daily outpatient visits in three years from 2018 to 2020 (Hospital 1)**

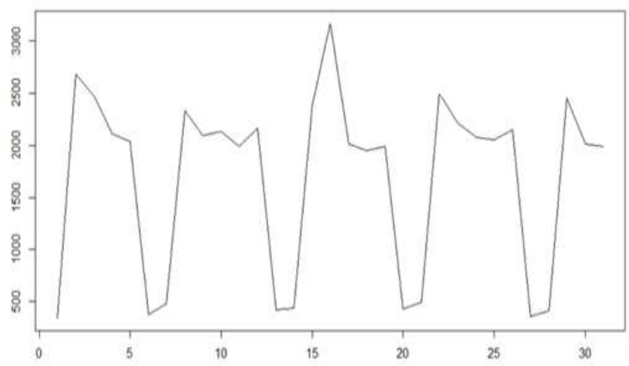


**Figure 3. The daily outpatient visits in one month (January 2018) (Hospital 1)**

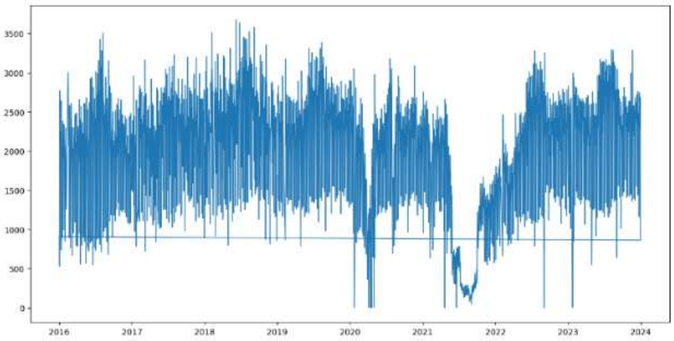


**Figure 4. The daily outpatient visits from January 2016 to December 2023 (Hospital 2)**

*Hospital 2*: The second dataset for our study comes from the Hospital of Dermato-Venereology in Ho Chi Minh City, collected during the period of 8 years from January 2016 to December 2023 with the total number of 5666002 outpatient visits. Thus, the dataset contains 2785 observations in time series. The average of outpatient visits every day is2034, the minimum value is1and the maximum value is 3673.

Figure 4 provides the curve of the daily outpatient arrivals during the eight years from 2016 to 2023. Figure 5 provides the curve of the daily outpatient arrivals in one month from January 1st, 2018 to January 30th, 2018.

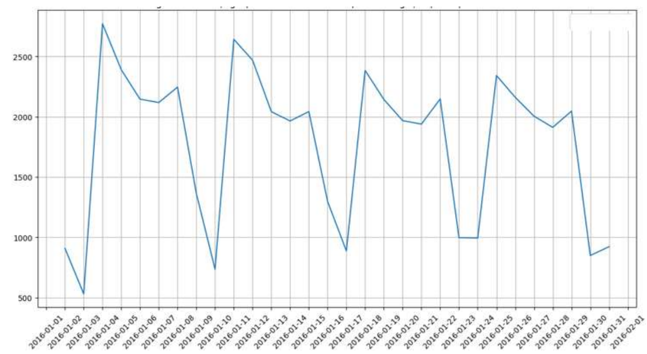


**Figure 5. The daily outpatient visits in one month from January 1st , 2016 to January 31th, 2016 (Hospital 2)**

From Figure 2, Figure 3, Figure 4 and Figure 5, it can be seen that the daily outpatient visits fluctuate greatly, especially on weekends and holidays. Moreover, a seasonal variation pattern is found over the period of one week.

In the experiments, each dataset is divided into two sub-datasets: the training dataset (80%) and the testing dataset (20%).

*Parameter Setting:* For the two datasets, we apply a method proposed by N. Ngoc Tran (2002) to determine the seasonal length for each time series data seat. This method is based on ACF(auto correlation function) plot of the time series. Figure 6 provides the ACF plot of the daily outpatient visit flow (Hospital 1).

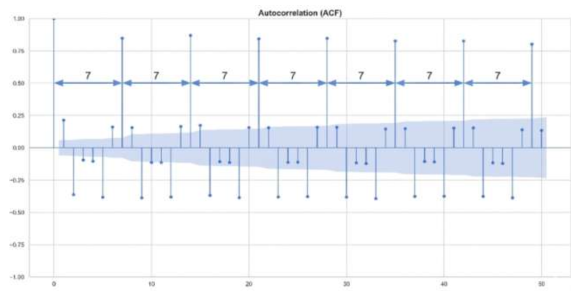


**Figure 6.ACF plot of the outpatient visit flow (Hospital 1)**

As for hyper parameters of LSTM, we apply grid search to determine suitable values. The best fit parameter values of the three forecasting methods for the first dataset are given in Table1.

**Table 1 Parameter estimation results of the three methods**

| Method | Parameter values |
|---|---|
| Holt-Winters | $\alpha = 0.19$, $\beta = 0.01$, $\gamma = 0.15$,<br>seasonal length = 7 |
| LSTM | input size = 7, number of hidden layers = 2<br>number of units in the 1st hidden layer = 128<br>number of units in the 2nd hidden layer = 64 |
| Prophet | Changepoint prior scale = 0.5<br>Seasonality prior scale = 5<br>Seasonality mode: multiplicative<br>Seasonality = 7<br>Holiday prior scale = 5 |

The best fit parameter values of the three forecasting methods for the second dataset are given in Table 2.

**Table 2. Parameter estimation results of the three methods**.

| Method | Parameter values |
|---|---|
| Holt-Winters | $\alpha = 0.04$, $\beta = 0.01$, $\gamma = 0.5$,<br>seasonal length = 7 |
| LSTM | input size = 7, number of hidden layers = 2<br>number of units in the 1st hidden layer = 256<br>number of units in the 2nd hidden layer = 256 |
| Prophet | Changepoint prior scale = 1<br>Seasonality prior scale = 30<br>Seasonality mode: multiplicative<br>Seasonality = 7<br>Holiday prior scale = 1 |

***Prediction Evaluation Measures:*** In this study, the mean absolute error (MAE), the mean squared error (MSE) and the symmetric mean absolute percentage error (sMAPE) are used as evaluation criteria. The formula for MAE, MSE, and sMAPE are given as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (9)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (10)$$

$$sMAPE = \frac{100\%}{n}\sum_{i=1}^{n} \left| \frac{(y_i - \hat{y}_i)}{\frac{|y_i| + |\hat{y}_i|}{2}} \right| \quad (11)$$

where $n$ is the number of observations, $y_t$ is the actual value for time point $t$, and $\hat{y}_t$ is the forecast value for time point $t$. The use of these measures represents different aspects to evaluate forecasting models. The first and the second are absolute performance measures while the last one (sMAPE) is a relative measure. The sMAPE is a scale-invariant statistic that expresses error as a percentage. The model has higher predictive accuracy when MAE, MSE or sMAPE is much closer to 0.

***Experimental Results:*** In the experiment, we compare Holt-Winters with the two other methods: LSTM and Prophet model. The MAE, MSE and sMAPE error results of the three forecasting methods for the first dataset (Hospital 1) are given in Table 3. The MAE, MSE and sMAPE error results of the three forecasting methods for the second dataset (Hospital 2) are given in Table 4.

**Table 3. Forecasting errors of the three methods on the daily hospital outpatient visits dataset (Hospital 1)**

| Method | MAE | MSE | sMAPE (%) |
|---|---|---|---|
| Holt-Winters | 131.006 | 51,703.32 | **7.76** |
| LSTM | 141.808 | 53,457.38 | 9.06 |
| Prophet | 214.409 | 76,072.08 | 14.42 |

**Table 4. Forecasting errors of the three methods on the daily hospital outpatient visits dataset (Hospital 2)**

| Method | MAE | MSE | sMAPE (%) |
|---|---|---|---|
| Holt-Winters | 191.412 | 128,888.10 | **9.80** |
| LSTM | 201.859 | 113,229.94 | 10.22 |
| Prophet | 484.355 | 418,630.27 | 22.96 |

**From the experimental results in Table 3 and Table 4, we can see that:**

- Based on MAE, MSE and sMAPSE indicators, Holt-Winters and LSTM perform better than Prophet approach. Between Holt-Winters and LSTM, Holt-Winters method outperforms LSTM. In terms of predictive accuracy, the order of the three forecasting methods is as Holt-Winters > LSTM > Prophet. This finding indicates that since hospital outpatient visit flow is a trended and seasonal time series, Holt-Winters is the most suitable model for this forecasting problem. That means LSTM and Prophet are suitable for a kind of time series data which is more complex than the dataset of hospital outpatient visit flow. In other words, sophisticated models do not necessarily produce a better forecast.

- The finding in this work seems consistent with two previous works which are listed as follows. Sumitra and Basri in 2020, compared the performance of Holt-Winters, Simple Exponential Smoothing (SES) and ARIMA in forecasting hospital outpatient visit flow and found out that Holt-Winters outperforms ARIMA and SES in this forecasting problem. Tinh in 2022compared the performance of Holt-Winters and artificial neural network (ANN) in forecasting hospital outpatient visit and found out that Holt-Winters outperforms ANN in this forecasting problem.

# CONCLUSIONS

This paper contributes to exploration of prediction methods to forecast outpatient visits flow at the two hospitals: General Hospital of Cu Chi Area and Ho Chi Minh City Hospital of Dermato-Venereology. We compared the performances of the three comparative forecasting methods: Holt-Winters, LSTM and Prophet on the two above-mentioned datasetsin forecasting hospital outpatient visits flow. Experimental results revealed that Holt-Winters performs better than LSTM and Prophet model in forecasting hospital outpatient visits flow. This finding indicates that since hospital outpatient visit flow is a trended and seasonal time series, Holt-Winters is the most suitable model for this forecasting problem. As for future work, we intend to develop a hybrid method which combines a time series decomposition technique (EMD) with an ensemble of local predictors (Huang *et al*., 2017) in hospital outpatient visit flow forecasting. Besides, we plan to enhance hospital outpatient visit flow forecasting to multi-step ahead forecasting (Ben Taieb *et al*., 2012).

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