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CASE STUDY

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PREDICTING DAILY PATIENT ARRIVALS IN THE EMERGENCY DEPARTMENT BASED ON A DEEP NEURAL NETWORK APPROACH: A CASE STUDY

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ABSTRACT

The goal of this study is to analyze the performance of four forecasting models in predicting daily patient arrivals in the emergency department (ED). Due to the fact that emergency patient flow is highly uncertain and dynamic, this forecasting problem is a challenging task. We evaluated different time series models to forecast ED daily patient arrivals at General Hospital of Cu Chi Area in Ho Chi Minh city, Vietnam. The forecasting models tested in this work are seasonal multiplicative Holt-Winters (HW), seasonal artificial neural network (SANN), the hybrid method which combines Holt-Winters with SANN and the deep neural network model: Long Short Term Memory (LSTM) network. The experimental results show that all the four models bring out acceptable predictive accuracy and LSTM is the best model for forecasting emergency patient arrivals in the selected hospital. The MAPE of LSTM model is 11.31%.

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INTRODUCTION

The Emergency Department (ED) is the busiest department in a hospital and its main purpose is to provide timely emergency care to patients in need. Overcrowded EDs are common in a variety of countries. ED overcrowding results from mismatch between existing capacity and various input, throughput, and output factors. Therefore, forecasting the ED patient arrivals may provide useful inputs for planning available resources (Gul and Celik, 2020). ED demand prediction, expressed in terms of daily patient arrivals, has been evaluated by different time series forecasting methods employed to develop forecast models. For that purpose, the historical data formulated as a time series can be gathered in a regular time frame of hourly, daily, weekly or monthly. ED patient arrival forecasting is regarded as a complicated task. The literature on forecasting of ED patient visits shows no supremacy of any method over others (Calegari *et al*., 2016). Several research works in this application demonstrate that daily patient arrivals for ED is characterized by seasonal and weekly patterns (Calegari *et al*., 2016). Existing forecasting models for ED patient arrivals can be divided into two main groups: linear methods and non-linear methods. The most commonly used linear methods are linear regression (Ekstrom *et al*., 2015), autoregressive integrated moving average (ARIMA) (Kadri *et al*., 2014; Afilal *et al*., 2016; Rosychuk *et al*., 2016; Carvalho-Silva *et al*., 2017; Juang *et al*., 2017), vector ARIMA (Aboagye- Sarfo *et al*., 2015, Kadri *et al*., 2017) and exponential smoothing (Bergs *et al*., 2014; Rema and Sikdar, 2021). In recent years, non-linear methods such as logistic regression (Schonwetter *et al*., 2008),artificial neural networks (ANN) (Menke *et al*., 2014; Pekel *et al*., 2021), support vector regression (Zhang *et al.* in 2018), deep neural networks (Yousefi *et al*., 2019; Harrou *et al*., 2020) have been adopted to model the nonlinear patterns of ED patient arrivals. In this paper, we assess the performance of four selected forecasting models for predicting the ED patient arrivals in General Hospital of Cu Chi Area in Ho Chi Minh City, Vietnam. According to our exploration, this daily ED patient flow dataset is a seasonal time series. This finding is also confirmed by several previous works in the ED daily patient arrival forecasting (Calegari *et al*., 2016; Rosychuk *et al*., 2016; Carvalho-Silva *et al*., 2017). The main contributions of this work can be listed as follows:

i) Long Short Term Memory (LSTM) model is applied in one-day forecast of daily ED patient arrivals. The performance of this deep neural network model is compared with three other forecasting models: Holt-Winters, Seasonal ANN (SANN), the hybrid method which combines Holt-Winters with SANN.
ii) A comparative outline is created by making a standard analysis among the four models in terms of two common forecast accuracy measures: Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE).

iii) A case study on real-world data from a public hospital of Cu Chi Area, in Ho Chi Minh City (Vietnam).

The experimental results show that among the four comparative forecasting models, LSTM approach is the best model for forecasting ED patient arrivals at the selected hospital. The rest of this paper is structured as follows. In section II, we describe the four forecasting models that will be investigated for the emergency patient arrival forecasting. Section III describes the study setting. Our experimental results in comparing the performances of the four forecasting models are reported in Section IV. Finally, Section Vconsists of some conclusions and future works.

Forecasting Methods: In this section, we describe the four forecasting models that will be investigated for the ED patient arrival forecasting problem. They consist of one deep learning model (LSTM network) and three shallow models for seasonal time series prediction.

Holt-Winters Smoothing: The exponential smoothing method is used to forecast time series containing trend patterns, seasonal patterns or containing both simultaneously. Exponential smoothing methods deal with smoothing parameters which are determined according to the past data. In the application of the exponential smoothing model, there are three kinds of models that are widely used in different time series (Goodwin, 2010). Simple exponential smoothing (Type I) is used when the time series has no trend or seasonality. Suppose we have a time series Y_t, observed at $t = 1,.., T$. The simple exponential smoothing model is defined by the following recursive formula:

$$\hat{Y}_{t+1} = \alpha Y_t + (1- \alpha)\hat{Y}_t \qquad \text{.............}(1)$$

where $\hat{Y}_{t+1}$: the predict value for the next time point t+1, α: smoothing constant, Y_t: observed value of series at time point t, $\hat{Y}_t$: thepredict value for time point t.

The initial value for the first forecasted value is defined by equation$\hat{Y}_1 = Y_1$.

When a trend exists in the time series, Holt's method of exponential smoothing (Type II) can be used. Holt's technique requires an estimate of the current *trend* and also an estimate of the current *level*, therefore it uses two different smoothing constants for each. These smoothing constants are $\alpha(0 < \alpha < 1)$ associated with level and $\beta(0 < \beta < 1)$ associated with trend. The three equations used in Holt's method are:

$$\hat{Y}_{t+p} = L_t + pT_t \qquad \text{.............}(2)$$

$$L_t = \alpha Y_t + (1- \alpha)(L_{t-1} + T_{t-1}) \qquad \text{.............}(3)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)\, T_{t-1} \qquad \text{.............}(4)$$

where $\hat{Y}_{t+p}$: forecast for p time points into the future, L_t: estimate of current level, andT_t: estimate of current trend.

Eq. (2) shows the forecast for p time points into the future. For a forecast made at time point t+p, the current trend estimate (T_t) is multiplied by the number of time points to be forecast (p) and the product is then added to the current level (L_t).

To initialize the level, we set $L_1 = Y_1$; to initialize the trend, we set$T_1 = Y_2 - Y_1$.

Holt-Winters' method is an exponential smoothing approach for predicting time series data which exhibit both trend and seasonality (Type III). This method also contains two approaches: multiplicative Winters' method and additive Winters' method. The four equations in the recursive scheme used in Winters' (multiplicative) method are:

$$\hat{Y}_{t+p} = (L_t + pT_t)S_{t-s+p} \qquad \text{.............}(5)$$

$$L_t = \alpha Y_t/S_{t-s} + (1-\alpha)\,(L_{t-1} + T_{t-1}) \qquad \text{.............}(6)$$

$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)T_{t-1} \qquad \text{.............}(7)$$

$$S_t = \gamma Y_t/L_t + (1-\gamma)S_{t-s} \qquad \text{.............}(8)$$

where $\hat{Y}_{t+p}$: predictvalue for $p$steps in the future, Y_t: the observed value at time point t, L_t: estimate of current level, T_t: estimate of trend, S_t: seasonal estimate, α: smoothing parameter for the level ($0 < \alpha < 1$), β: smoothing parameter for the trend ($0 < \beta < 1$), γ: smoothing parameter for seasonality ($0 < \gamma < 1$) and s: length of season. In the multiplicative version of Holt-Winters method, the seasonality estimate is given as a *seasonal index* and calculated by Eq. (8). Eq. (8) shows that the current seasonal component, S_t, is computed as γ times an estimate of the seasonal index given by Y_t/L_t added to (1- γ) times the previous seasonal component S_{t-s}.

Seasonal ANN (SANN): Artificial neural networks (ANN) are able to find complex input-output relationship without assumption of stationary, linearly and variable independences. In this work, one of the most popular artificial neural network (ANN) architectures is used as a comparative method for time series prediction. The architecture is described by a network which consists of three layers of simple processing units connected by acyclic connections: one input layer, one hidden layer and one output layer. Generally, the network can be trained by the historical data of a time series in order to capture the non-linear features of the specific time series. The network parameters (link weights and node biases) will be updated iteratively by a process of minimizing the prediction errors. Using an ANN for time series prediction implies that the input nodes are connected to a number of past observed values supposed sufficient to identify the process at future time steps. As for determining the number of input nodes, there is no theory yet to tell how many nodes are needed. But in the work by Hamzaçebi (2008), the author recommended that the number of input nodes should be equal to the seasonal lengths *s* for better forecasting seasonal time series, e.g. 12 for monthly time series and 4 for quarterly time series. Hamzaçebi named this special model of ANN as Seasonal ANN (SANN). In the paper (Hamzaçebi, 2008), Hamzaçebi compared the performance of SANN with that of seasonal ARIMA over four benchmark seasonal time series datasets and found out the SANN outperforms seasonal ARIMA in most of the four datasets. One important finding from the work (Hamzaçebi, 2008) is that SANN can handle seasonal time series successfully without removing seasonal effects through a preprocessing step.

The Hybrid model of Holt-Winters and SANN

We use a hybrid method integrating Holt-Winters smoothing and SANN model for forecasting time series with trend and seasonality which was proposed by Bao *et al.* (2013). The hybrid forecasting method is described in Figure 1. From Figure 1, the input is fed simultaneously into a neural network model (SANN) and a Holt-Winters exponential smoothing model. The neural network model generates a forecast result, while the exponential smoothing model also yields a time series forecast result. The two results are entered into the hybrid forecast module and generate a hybrid forecast result as final output. In the hybridization stage, we use the same hybridization strategy as in (Bao *et al.*, 2013), i.e.

$$\hat{Y}_{Hybrid} = \omega\hat{Y}_{NN} + (1- \omega)\hat{Y}_{ES} \qquad (9)$$

where $\hat{Y}_{ES}$ is the forecast result obtained from Winters' exponential smoothing model, $\hat{Y}_{NN}$ is the forecast result of SANN and ω is the weight parameter ($0 \le \omega \le 1$). If ω is equal to 0 or close to 0, that means the forecast generated by Winters' exponential smoothing is dominant. If ω is equal to 1 or close to 1, that means the forecast generated by SANN is dominant.

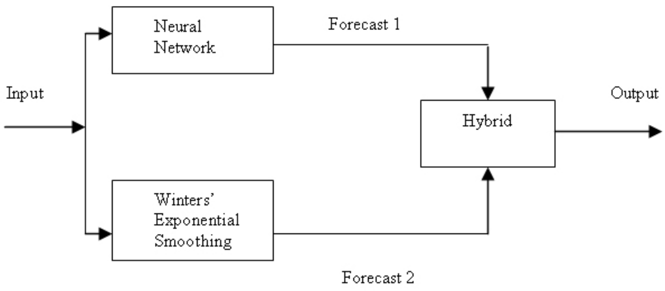

Figure 1. The hybrid forecasting model (Bao *et al*., 2013)

To check the existence of *season* as well as to determine the length of season, we have to pay attention at the locations (lag numbers) of the significant correlation values in the Autocorelation Function (ACF) plot. The main idea is that we compute the distances Δd between successive locations of the high frequency signals. If there are several occurrences of the same distances, the most common distance Δd will be chosen as the season length, according to majority rule. The above mentioned method for estimating the season length based on ACF diagram was propoposed by Ngoc Tran in 2002.

LSTMModel: Recurrent Neural Networks (RNN) were developed as a variant of ANN for time-dependent data. For training RNNs, the backpropagation algorithm is modified, resulting in the Backpropagation Through Time (BPTT) algorithm. However, the application of BPTT incurs two main problems: the weights may start to oscillate (exploding gradient problem), or an excessive computational time to learn long-term patterns (vanishing gradient problem). Long Short Term Memory (LSTM) is an improved version of RNN, proposed by Hochreiter and Schmidhuber (1997) to solve the weakness of RNN in dealing with long-term dependencies, i.e. exploding gradient problem and vanishinggradient problem. Each LSTM unit is a generalization of RNN unit, such that part of information about previous time series data points is stored into the network.

Each LSTM unit (also called LSTM cell) has three gates:

- Forget gate, which is responsible for deciding which part of information from the previous state should be saved or thrown away.
- Output gate, which is responsible for selecting how much information should be output.
- Input gate, which is responsible for obtaining new information.

The deep LSTM neural network contains more than one hidden layer. It consists of many layers of LSTM cells in which the outputs of the previous layer become the inputs of the next layer. Figure 2 describes the structure of a stacked LSTM network which can be utilized in time series prediction.

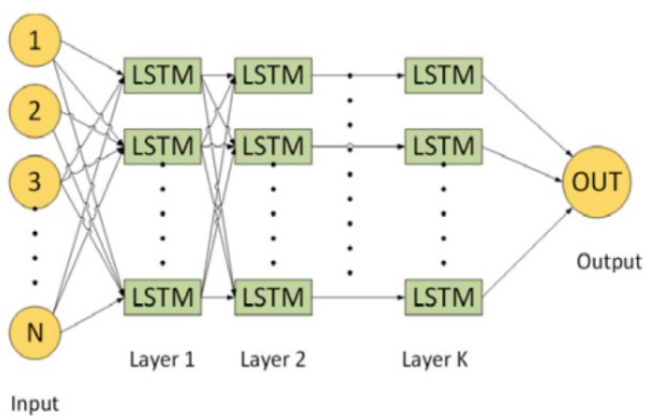

Figure 2. A stacked LSTM network

Consider a time series input sequence denoted by$y = <y_1, y_2, \ldots, y_T>$ as the input to the LSTM network. The output of the LSTM network automatically computes the predicted output in the next time step using the historical information supplied.

Study Setting: The data for our study come from the Emergency Department at General Hospital of Cu Chi Area in Ho Chi Minh City during the period from January 1th 2018 to 31th December 2020, with a total of 75511 patient arrivals. Thus, the data set contains 1095 observations in time series. The mean value of ED patient arrivals is about 68 per day, the minimum value is 7 per day and the maximum value is 122 per day. In this study, the sum of all types of patients is considered. Figure 3 provides the curve of the daily emergency patient arrivals during the three years from 2018 to 2020. From Figure 3 we can intuitively see the nonstationary behavior of the time series. General Hospital of Cu Chi Area is a level 2 hospital located in Cu Chi district which belongs to Ho Chi Minh City. This public hospital is located in the boundary areas with Tay Ninh, Binh Duong and Long An province. Near the hospital, there exist several large-scale industrial parks with a high population of workers.

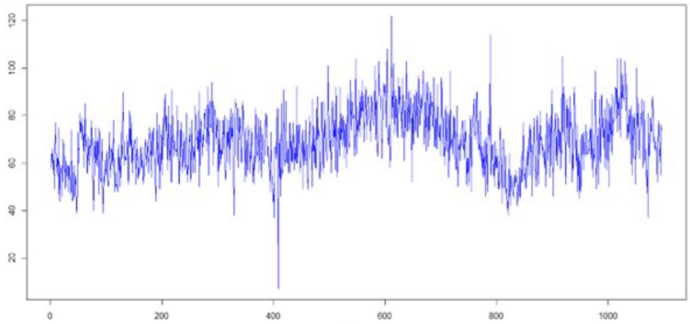

Figure 3. The daily emergency patient arrivals from January 1st , 2018 to December 31th 2020.

Figure 4 provides the curve of the daily emergency patient arrivals in one month from January 1st, 2018 to January 30th, 2018. Based on the time series behavior graphically presented inFigure 3 and Figure 4, the daily ED patient arrivals fluctuate greatly, especially on weekends and holidays. Moreover, a seasonal variation pattern is found over the period of a week.

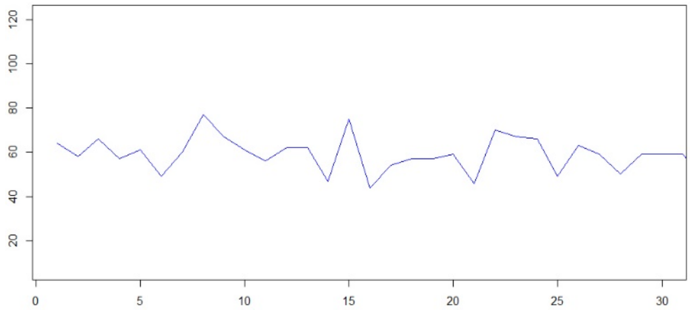

Figure 4. The daily ED patient arrivals in one month from January 1st , 2018 to January 30th , 2018

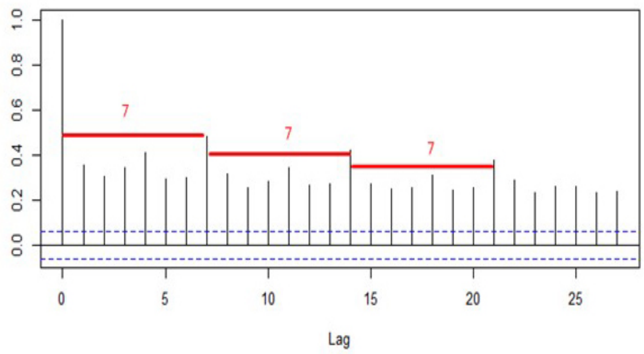

Figure 5. The seasonal length of the time series and the corresponding ACF plot

To detect the seasonal length of this time series dataset, we applied the method described in Subsection II.3 and found out that this time series is seasonal with the seasonal length 7. The ACF plot in which we estimated the seasonal length is shown in Figure 5. We created the ACF plot with the support of R software.

Evaluation Experiments: As mentioned in Section II, Holt-Winters, SANN, the hybrid method between Holt-Winters and SANN (denoted as HW+SANN), and LSTM are implemented and evaluated in this study. The three shallow models are realized using R language (version 4.2). R is a language and environment for statistical computing and graphics, provides several tools for time series analysis (refer the web site http://www.r-project.org/). We implemented LSTM forecaster in Python with open-source framework Keras 2.10.0 (Chollet, 2023). The CPU model of the computer used for testing is theIntel(R) Core(TM) i5-10400F CPU @ 2.90GHz 2.90 GHz; RAM: 16GB.

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

Prediction Evaluation Measures: This work uses the mean squared error (MSE) and the mean absolute percentage error (MAPE) as evaluation measures. The formula for MSE and MAPE are given as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2$$

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|\hat{y}_t - y_t|}{y_t} \times 100\% \qquad (11)$$

where n is the number of data points, y_t is the number ofdaily ED arrivals at time point t, and $\hat{y}_t$ is the forecast value at time point t.

These two measures represents different angles to evaluate forecasting models. The first is an absolute performance measure while the second (MAPE) is a relative measure. The MAPE is a scale-invariant statistic that expresses error as a percentage. The model has higher predictive accuracy when MAPE is much closer to 0%.

Model Parameter Setting: With the help of R software, we can find the best values for the three parameters α, β and γ for Holt-Winters model. For all the four models, the season length of the time series is set to 7 using the method described in Subsection II.3. The number of nodes in the input layer of SANN is set to 7. The number of nodes in the hidden layer of SANN is determined through experiments. The *early-stopping* mechanism is used in the training process of SANN. As for the weight parameter ω of the hybrid method (HW+SANN), we use grid search to find the suitable value. As for the hyper-parametes of the LSTM model (e.g. the number of hidden layers, the number of units in each hidden layer, the number of epoches, etc..), we apply grid search to find the suitable values. The number of nodes in the input layer of LSTM is also set to 7. The LSTM network consists of two hidden layers with 167 units in each. To train the LSTM, we select Adam optimizer. Table 1 reports the best fit parameter values for all the four forecasting models. In this study, we followed the recommendation of some previous research workks, the daily time series data are split into the training sample and the testing sample as follows. The first part (70% of data points) in the time series is used for training and the rest is used for testing. The forecasting models are tested on the testing sample and the performance criteria are computed.

EXPERIMENTAL RESULTS

Forecasting errors of the four investigated methods when applied to daily ED patient arrivals are reported in Table 2. The prediction errors MSE (withEq. (10)) and MAPE (with Eq. (11)) of the four methods are given in column 2 and column 3, respectively.

Table 1. Parameters for the four forecasting models

Model	Parameter Setting
LSTM	Input layer {7}, Hidden layer 1:{167} Hidden Layer 2: {167}, Dense Layer: {1}, epochs = 100
Holt-Winters	α: 0.123768, β: 0.00694, γ: 0.064371 Seasonal length: 7
SANN	7-100-1 Seasonal length: 7
HW+SANN	ω = 0.7455

From the experimental results, we can see that the performances of all the four forecasting models are acceptable for this particular forecasting problem and the prediction errors of LSTM are the lowest (in bold). This model achieves the highest forecasting accuracy with an MAPE of 11.31 %. That means LSTM is the best among the four comparative models in predicting ED daily patient arrivals. The main reason is that LSTM, as a deep learning model suitable for sequential data, can extract complicatedfeatures from this special time series data and perform good forecasting on them. This finding highlights the promising performance of LSTM in forecasting ED patient arrivals.

Table 2. Forecasting errors of each model on the daily ED patient arrivals

Model	MSE	MAPE
HW+SANN	12718.640	13.088%
Holt-Winters	18553.904	17.044%
SANN	13429.730	13.524%
LSTM	**10694.120**	**11.310%**

The performances of the four forecasting models can be ranked decreasingly as follows: LSTM, HW+SANN, SANN and Holt-Winters. Notice that the hybrid model HW+SANN yields better performance than the single Holt-Winters or SANN model. As for execution time which combines the time of building the forecasting model and the time of testing the model, the experimental results (in seconds) are listed in Table 3. From Table 3, we can see thatHolt-Winters is the fastest forecaster.

Table 3. Execution times (in seconds) of each model

Model	Execution time
HW+SANN	2.9
Holt-Winters	**0.0007**
SANN	2.953
LSTM	2.494

CONCLUSION

This work confirms that daily patient arrivals at the Emergency Department is characterized by seasonal and weekly patterns. Therefore forecasting models which can handle seasonal time series can be used to bring out accurate forecasts of high complicated ED patient arrivals. Forecasting accuracy depends on the employed model. This work focus onexploring the use of the LSTM model in this particular forecasting problem. The work also compares the performance of LSTM models with three other forecasting models: SANN, Holt-Winters, the hybrid method which combines Holt-Winters with SANNin predicting daily ED patient arrivals. Among the compared methods, LSTM model yields the best predictive performance. The MAPE of LSTM is 11.31%. This result shows the superiority of the proposed deep neural network model: LSTM. However, this research only considers one day ahead forecasting, thus other prediction horizons are needed to verify the predictive accuracy of the four forecasting models over different horizons. Moreover, we intend to compare the four forecasting models in this study with some other deep neural network models, such as Gated Recurrent Unit (GRU), Stacked-Autoencoder (SAE), and Convolutional Neural Network (CNN).

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