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The Implementation of Long-Short Term Memory for Tourism Industry in Malaysia

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ABSTRACT

Across the world, tourism is known as the largest contributor towards economy and the fastest developing industry. It has the capability of generating income, creating job opportunities and help people to understand the culture diversity of other countries. Therefore, tourism demand forecasting is really needed to help the practitioners involved as well as government in pricing setting, in assessing future requirements of capacity to fulfil the customers' demand or in making wise decisions on whether to explore new market or not. This study focuses on tourism demand forecasting based on the number of tourist arrival using recurrent neural network (RNN), which is long-short term memory (LSTM) model. The data used in this study is historical data of number of tourist arrivals in Malaysia before the onset of Movement Control Order (MCO) starting from January 2000 to February 2020 due to the COVID-19 outbreak. The data set was divided into two subsets, training and testing data sets based on ratio 80:20. The objective of this study is to determine an accurate forecasting model especially in tourism industry in Malaysia. The forecast evaluation implemented to predict the error of each model are Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) and the analyses for this model was performed by using Python software. Based on the results obtained, the LSTM model was considered as one of the accurate prediction methods for tourism demand in Malaysia due to the least error produced. It is hoped that these results can help the government as well as practitioners in tourism industry to make a right judgement and formulate better tourism plans in order to minimize any consequences in the future.

1. Introduction

Tourism is defined as leaving home for a while to relax, spend time with family, friends and relatives, recreation and etc., while using the services provided by hospitality practitioners [1]. In Malaysia, the tourism industry is known as one of the most important and strategic industries and can be classified as Malaysia's second largest revenue contributor, right after manufacturing sector.

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This sector has highest potential to boost the Gross Domestic Income (GDI) so that Malaysia can be a developed nation in the future.

In early 2020, the tourism industry in Malaysia has been greatly affected by COVID-19 pandemic and cause big impact towards economies, public services and opportunities on all aspects. Based on the Tourism Satellite Account 2020 released by Department of Statistics Malaysia, the record showed that in 2020, the percentage of tourist arrivals in Malaysia decreased by 83.4% compared to year 2019, and its contributing 14.1% only towards the total Gross Domestic Product (GDP) [2]. Nowadays, we can see that the Ministry of Tourism, Art and Culture (MOTAC) of Malaysia is committed to redevelop this tourism industry after COVID-19 outbreak. Therefore, in order to accelerate the recovery process of this industry, a lot of aids and incentives have been provided, especially to the private sectors. Based on the observations after the country's borders reopened on 01 April 2022, the government are confident that the tourism industry was on the right path to recovery.

Figure 1 shows the trend of the number of tourist arrivals in Malaysia before Movement Control Order (MCO). Overall, there was up and down trends over the time. But, unfortunately, after the COVID-19 outbreak starting from February 2020, the number of tourist arrivals in Malaysia decreased dramatically.

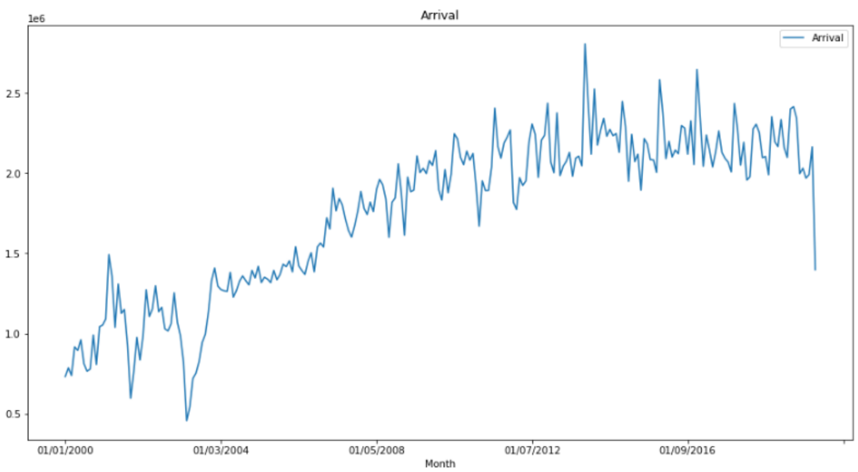

Fig. 1. The number of tourist arrivals in Malaysia before MCO from January 2000 to February 2020

Accurate forecasting will give a big impact on the future decision-making process [3]. Based on the valuable information generated from accurate demand forecasting, a lot of organizations are able to make right decision regarding pricing, strategies for business development and the needs to fulfil the customer expectations in the future [4].

Recently, RNN has been widely implemented especially in time series forecasting. Based on Mikolov *et al.*, [5], RNN also called as multilayer perceptron (MLP) architecture improved version, which consisting of three important layers such that input layer, hidden layer and output layer. RNN was designed to link the inputs, as a whole to each output in the presence of previous computations, whereas the existing feed-forward artificial neural network is limited to one-to-one mapping only [6]. RNN have the ability to store the output of a specific layer and returning this back to the input to forecast the outcome of the layer.

LSTM model is a special kind of RNN and broadly used in time series prediction due to its capability of handling non-linear features of time series data. This architecture introduced by Hochreiter and Schmidhuber in 1997 and comprises of iterative learning unit in the model and several gates, namely input gate, input modulation gate, forget gate and output gate [7,8]. According to Sepp Hochreiter and Jurgen Schmidhuber [9], each gate in LSTM has its own special role. Input gate will handle the new input from outside and process newly arrived data; memory cell input gate takes input from the output of the LSTM cell in the last iteration; forget gate decides when to forget the output results and selects the optimal time lag for the input sequence; and output gate takes all results computed and generate output for the LSTM cell. With the existing of these features, LSTM has great potential in handling problems related to forecasting, especially in tourism demand forecasting.

In 2020, Zhang *et al.*, [10] implemented LSTM and other four benchmark models to predict the daily tourist flow with Jiuzhaigou consumer search data. Based on the experimental results, LSTM is well performed in tourism demand forecasting based on the accuracy level. J. Saivijayalakshmi and N. Ayyanathan [11] designed LSTM forecasting model to predict the trend of foreign tourists' arrival to India. LSTM, ARIMA models and Holt-Winter Exponential Smoothing were compared and they concluded that LSTM outperformed others with the least error. On the other hand, Shun-Chieh Hsieh [12] used LSTM, Bidirectional LSTM (Bi-LSTM) and Gated Recurrent Unit networks (GRU) to improve the accuracy level of tourism demand forecasting in Taiwan. From the observations, the researcher found that the best forecasting model was LSTM with its variants with lowest percentage error. Meanwhile Anisa *et al.*, [13] implemented three models of Long Short-Term Memory (LSTM) to predict the demand factors of tourist arrivals in Indonesia. They claimed that all predictive models are performed well with highest accuracy percentage.

Apart from tourism demand forecasting, LSTM is also widely used in non-tourism-related industry. Weng *et al.*, [14] formulated an integration between LSTM and light-GBM for supply chain sales forecasting. The results shows that this combination did an excellent job in predicting supply chain sales. Furthermore, in 2020, Shankar *et al.*, [15] applied LSTM for container throughput of Port of Singapore Authority (PSA) prediction. The researcher found that the LSTM has slightly higher accuracy compared to other baseline models. Pranolo *et al.*, [16] also used LSTM for rainfall forecasting. Based on the experimental analysis, the LSTM displayed better performance compared to Back Propagation Neural Network (BPNN) with the least error. In 2023, Gopalakrishnan Ramasubramanian and Singaravelu Rajaprakash [17] proposed A^2VO-RNN-LSTM model to improve 5G-IoT networks security level. The researchers found that this proposed model outperformed the other benchmark models with highest accuracy. Furthermore, Sivalingam *et al.*, [18] implemented RNN classification method, which is LSTM method to identify the plant leaf disease. According to the results obtained, LSTM method was considered as the best classifier with accuracy of 98%. Meanwhile, Maheshwari *et al.*, [19] proposed a hybrid method, comprising of RNN-LSTM and attention mechanism for credit card fraud detection. The findings of this study showed that the proposed hybrid method work effectively in detecting credit card frauds or scams by producing a high level of accuracy.

From the point of view, an accurate and effective tourism demand forecasting model is required to speed up the recovery process of this tourism sector after the outbreak. Commonly, data of tourism demand consisting of linear and nonlinear features. The existing forecasting models are not able to analyse the nonlinear part of the time series data and may contribute inaccurate forecasting results. Therefore, in this study, Long-Short Term Memory (LSTM) model, one of the Recurrent Neural Network (RNN) architecture is proposed to enhance the tourism demand forecasting accuracy in Malaysia.

2. Methodology

2.1 Data Collection

The historical data that will be considered in this study is the number of tourist arrivals in Malaysia, starting from January 2000 until February 2020 (242 data) before the onset of MCO. The data were taken from Ministry of Tourism, Arts and Culture Malaysia (MOTAC) database.

2.2 Long-Short Term Memory (LSTM) Model

Recently, LSTM which is one of the deep learning approaches is more convenient and able to produce more accurate forecasting results, especially in tourism and hospitality industry. According to Law *et al.*, [8], the general equation of LSTM is given as follows:

$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + b_i\right) \tag{1}$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + b_f\right) \tag{2}$$

$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + b_o\right) \tag{3}$$

$$c_t = f_t \times c_{t-1} + i_t \times \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right) \tag{4}$$

$$h_t = o_t \times \tanh\left(c_t\right) \tag{5}$$

where i_t is the input gate, f_t is the forget gate, o_t is the output gate, c_t is the memory cell, x_t is the input vector, h_t is the output, σ and $\tanh$ are recurrent activation functions and W and b are the LSTM learning parameters during model training process.

2.3 Procedures of LSTM Model

There are several stages need to be considered to yield an accurate tourism demand forecasting model by using LSTM. All analyses will be performed by using Python software.

2.3.1 Stage 1: Data preparation

The raw historical data obtained from relevant resources will be undergo this process to ensure that the data are clean and compatible for LSTM model.

2.3.2 Stage 2: Data normalization

This process will re-scales the data within the range [0,1] by using MinMaxScaler. This process is required to enhance the learning acceleration rate and at the same time to improve the forecasts accuracy level.

2.3.3 Stage 3: Data splitting

The data will be partitioned into two parts; in-sample data set (training data set) and out-sample data set (testing data set) based on ratio 80:20 respectively. The training data set will be inserted into training algorithm to identify the output of our prediction model, meanwhile the testing data set will perform a reasonable check on the algorithm.

2.3.4 Stage 4: Network training

Throughout this process, the hyper-parameters or known as relevant parameters that control the learning process will be adjusted to enhance the accuracy level and at the same time to avoid over-fitting or under-fitting. The hyper-parameters are listed as follows: number of nodes or hidden layers; number of units in dense layer; activation function; number of training epochs; size of batch; learning and decay rate; dropout layer; weight initialization; learning rate and momentum. Generally, there are no rules or guidelines on how to identify the value of hyper-parameters. But we can use trial and error approach to figure out the value of hyper-parameters, depending on the complexity of the data.

2.3.5 Stage 5: Forecasting

Finally, the testing data will be inserted into trained model for forecasting. The denormalization procedures will be performed on the obtained prediction data afterward. The summary of LSTM procedures in demand forecasting is illustrated in Figure 2.

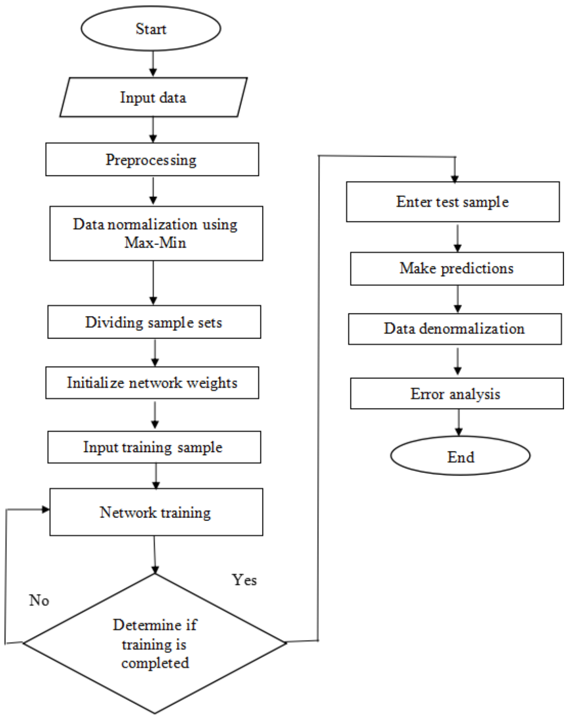

Fig. 2. The procedures of LSTM model

3. Results and Discussion

All the experiments in LSTM were built using Tensorflow 2.9.1 and Keras 2.9.0 for Python. A LSTM model was formulated with specific hyper-parameters required to control its performance. In this

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study, the LSTM model consisting of a single hidden layer with 1 input and 4 LSTM blocks or neurons and single output layer that produces a single value for forecasting was implemented. For the LSTM blocks, the sigmoid function was chosen as activation function. This model was compiled with Adam optimization algorithm, batch size of 1 and mean squared error as its loss function. Throughout the network training process, the number of epochs were set up for 50 epochs.

Based on the observations, the training network stopped at 46th epoch with loss value 0.5%, which means that starting from 47th epoch onwards, the model will start over-fitting. Therefore, the optimal epochs number to train this model is at 46. Furthermore, since the loss value is relatively small, we can conclude that all the parameters assigned are good enough to control this model and in line with the training sample. Before we proceed to the next stage, all the predictions must be denormalized to its original state so that they align with the original data set.

Figure 3 shows the results of our LSTM model, where the actual data set in blue, the predictions for the training data set in red and the predictions on the unseen testing data set in green. Based on Figure 3, we can see that this LSTM displayed a better performance in fitting both the training and testing data set since the pattern of predicted data set mimic the actual data set pattern.

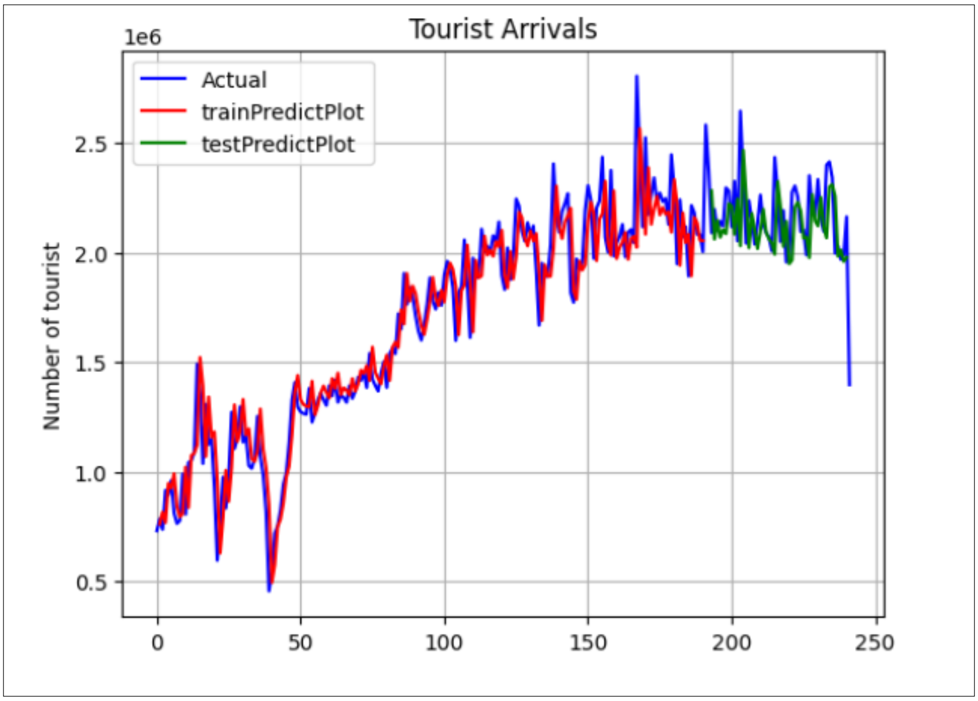

Fig. 3. The performance of the LSTM model towards training and testing data sets

The performance of LSTM model was measured by two metrics, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). Based on the results obtained, this LSTM model is appropriate for tourism demand forecasting and considered as highly accurate prediction model due to its least MAPE value [20]. The results were presented in the Table 1.

Table 1
Analysis of MAPE and RMSE for LSTM model

Forecast evaluation	MAPE	RMSE
LSTM	6.8123	182382.0

4. Conclusions

Tourism has been known as a powerful booster of economic development, generating employment, income and tax revenue in Malaysia. In addition, Malaysia also has been categorized as unique and fascinating country in Southern Asia due to the features such as cultures diversity, marvellous dishes, tropical climates, affordable prices for living expenses, halal destinations and etc. The aim of this study is to identify whether LSTM has the capability to be a forecasting model in tourism demand or not. Overall, LSTM is one of the most significant models to forecast the outcome of tourism demand in the future. Based on results obtained, the LSTM is a highly accurate forecasting model with smaller value of percentage errors.

Nowadays, the government is committed to developing the tourism industry after was hit by COVID-19 pandemic in year 2020. Therefore, it is hoped that the findings of this study can help the government as well as practitioners in tourism industry to make a right judgement and formulate better tourism plans in order to minimize any consequences in the future. Providing services that exceed the number of target tourists can result in huge losses to the tourism industry if the forecast for the next year goes down. Otherwise, predictive analytic will help optimize services for tourists such as accommodations, plane tickets, transportation, food and beverages and others if the forecast goes up. Besides, the study will contribute as a reference for the future studies. As a direction for future study, the algorithms proposed in this study will be extended by considering hybridization of SARIMA and LSTM models to improve the accuracy level of tourism demand forecasting in Malaysia.

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