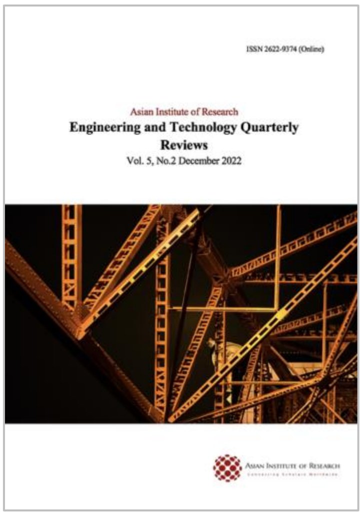

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Forecasting Tourist Arrivals with Partial Time Series Data Using Long-Short Term Memory (LSTM)

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Abstract
Tourism is a source of foreign exchange income, especially in the economic field. Increasing foreign tourist arrivals is essential in supporting the economy of Indonesia. The development of the tourism industry can be seen from the increase in tourist visits every year. Based on data obtained by the Indonesian Central Statistics Agency (BPS), there was an increase and decrease in the number of tourist visits during 2006-2019. Along with these conditions, the provision of various tourism products and services needed to support the industry must be adjusted to prevent financial losses. Unfortunately, tourism products are generally easily damaged, so it is necessary to forecast tourist arrivals. This study aims to predict the arrival of foreign tourists to Indonesia using the Long Short Term Memory (LSTM) method. This method is suitable for sequential data such as tourist arrival data. This shows the results of the evaluation using the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) of 591897.46 for RMSE and 636.2 for MAPE. Based on this research, it can be concluded that LSTM is suitable to be used as a model to predict the arrival of foreign tourists in Indonesia.

Keywords: Tourism, Forecast, LSTM, Neural Network, Time Series

1. Introduction

Tourism is one of the mainstay sectors for the country's foreign exchange earnings. Tourist arrivals are one of the determining factors for tourism development. Increasing foreign tourist arrivals is more important in supporting the economy than local tourists, especially in Indonesia (Mariyono, 2017). The increase in foreign tourist arrivals will increase people's income (Yang & Wong, 2012). Indicators of Tourism Development can be seen from the increase in tourist arrivals to Indonesia every year (Fattah et al., 2018). The number of tourist arrivals to Indonesia has increased and decreased from 2006 - 2019. This data was obtained from the Indonesian Central Statistics Agency (BPS). An unexpected increase or decrease in tourist arrivals will cause difficulties in providing services (Hsieh, 2021). Along with the condition, to prevent financial losses caused by the fluctuations of number of tourists, the supply of various kinds of tourism products and service which are needed to support the industry, got to be adjusted. Therefore, it is essential to know the pattern of tourist visits one year ahead for stakeholders in the tourism sector, this is to anticipate unexpected numbers of tourists. Good management of tourist attractions is one of the keys to attracting foreign and local tourists.

This study aimed to evaluate the performance of the LSTM introduced by Hochreite et al. (Hochreiter & Schmidhuber, 1997). On tourist visits from each country to Indonesia. Previous studies that discussed tourist visits to Indonesia were conducted using ARIMA and RBFNN (Haviluddin & Jawahir, 2015), which were conducted from all countries per year, not from each country. Meanwhile, other research on tourist visits was carried out using LSTM with search index data and historical tourism arrival data, but not for tourist visits to Indonesia (Peng et al., 2021). Forecasting tourist arrivals to Indonesia based on nationality in the following month. the tourism industry players can achieve the goal of providing comfort for tourists and making decisions to improve service quality. Because of the importance of forecasting, various studies on forecasting have been carried out. There are several studies related to forecasting that researchers including Forecasting demand for medical services have carried out (Huang et al., 2020), Forecasting in US national parks for campground demand (Rice et al., 2019), Forecasting cases of COVID-19 (Mukhtar et al., 2022), (Santoso et al., 2021). Forecasting the use of electrical loads (Bouktif et al., 2018), and other forecasting.

2. Related Works

In research done by (Haviluddin & Jawahir, 2015), forecasting of tourist arrivals to Indonesia was carried out using ARIMA and RBFNN. Where the data used is the accumulation of tourist arrivals from each country every year starting from 1974 to 2013. This study concludes that RBFNN is more efficient than ARIMA for modeling time-series datasets. Whereas the study of Peng *et al* (Peng et al., 2021), Used LSTM to model the non-linear relationship between tourist arrivals and index search query data. Forecast accuracy was verified using two compared samples, Beijing City and Jiuzhaigou Valley. The results obtained from this study indicate that RF-DE-LSTM outperforms several other machine learning methods. The branch of computer science that has progressed very fast is Artificial Intelligence (AI) (Mazlan et al., 2021). This artificial intelligence inspires Artificial Neural Networks (ANN) to be developed. ANN imitates the understanding of the human brain (Weytjens et al., 2019). The development of this ANN eventually gave rise to machine learning. Machine learning is suitable for forecasting (Abidin et al., 2020), so that forecasting is more accurate and reliable. Profound learning results from a combination of Machine learning and recurrent neural networks (RNNs). Deep learning differs from machine learning in that its algorithm comes with a set of rules, and is able to evaluate examples and improve accuracy based on a set of instructions by modifying the model slightly (Bulchand-gidumal, 2020).

RNN is able to process time-series data, but the inability to accommodate long memory causes RNN to experience a situation where the value for updating the weights will be lost (Ouhame & Hadi, 2019). Time series data modeling can use artificial neural networks that have been developed, such as LSTM (Kang et al., 2020). LSTM inputs are capable of dealing with long-term dependencies (Ren et al., 2021). This method is suitable for sequential data such as tourist arrival data (Hsieh, 2021). LSTM is a development of RNN which has fundamental block functions to complete many tasks sequentially. These tasks include machine translators, language modeling and answering questions. The advantage of LSTM is that it is suitable for time series forecasting because LSTM contains a special unit called a memory block in a hidden layer that repeats itself (Goyal A., Kumar R., Kulkarni S., 2016). Memory blocks contain memory cells with links that store temporary network states in addition to special copying units called information flow control gates (Quy et al., 2020). LSTM is able to overcome long-term dependencies on its input (Bandara et al., 2019). This method is suitable for sequence data (Masri et al., 2020). This method tries to provide forecasts using step by step sequence data (Kilimci et al., 2019).

Our rationale in this study is to provide recommendations to decision-makers regarding tourist arrival policies. Forecasting tourist arrivals needs to be done to anticipate surges in tourist arrivals such as basic needs while in Indonesia. Considering that the arrival of foreign tourists also sometimes experiences a decline, forecasting is also needed considering that tourism products are easily damaged. The policymakers here are the government of the Republic of Indonesia, specifically the Ministry of Tourism of the Republic of Indonesia. The Ministry of Tourism can regulate tourism activities in all parts of the Republic of Indonesia. Forecasting tourist arrivals is needed to prepare the state and tourism actors, the hotel industry, amusement/recreation parks, culinary, and others. Careful preparation will facilitate decision-making and policy on handling tourists. The purpose of the forecasting of tourist arrivals is to reduce state losses due to unnecessary preparations as a measure of state/regional budget efficiency. With the forecasting of tourist visits, decision-makers can prepare needs that are in accordance with the country of origin of tourists, no less and no more.

3. Methodology

At this stage, the steps used in the research is explained. This research consists several stages, starting from the research planning stage, Data Processing, Testing, and evaluation stage. Fig 1 shows the stages of the study discussed. The data processing step for estimating tourist arrivals to Indonesia begins with inputting the dataset, analyzing the dataset, then processing the data by changing the actual value in the dataset to deal with a zero to one scale using normalized min-max scale. then divide the normalized dataset totaling 770 data lines into training data and test data with a composition of 660 training data and 110 testing data (Román-Portabales et al., 2021).

Forecasting with this LSTM uses 660 training data and 110 test data. Forecasting results are obtained from testing the training data and test data. After obtaining forecasting results for training and test data, denormalization is carried out to return the output value of the actual forecasting results. The final forecasting process evaluates the performance of LSTM by comparing the difference between actual and forecast values using RMSE and MAPE and measuring the quality.

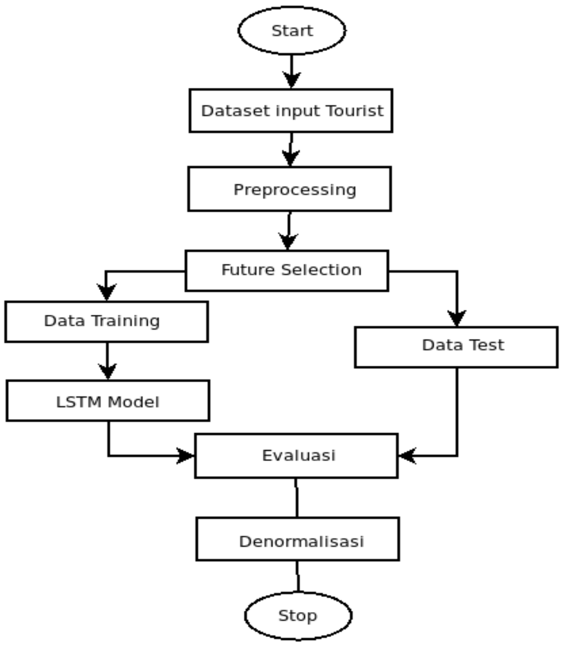

Figure 1: Research Workflow (Sehovac et al., 2019)

3.1. Data Set

The dataset used is data from the Indonesian Central Statistics Agency which was taken directly from the official website. The data is an excel file from 2006 to 2019. The BPS URL address is https://www.bps.go.id. The data used in this case study of tourist arrivals to Indonesia consists of 55 countries. The dataset used is time-series data from 2006 to 2019. We divided the dataset into 2 groups of data, which are training data and test data. The training data consists of 714 rows, and the Test data consists of 55 rows.

3.2. Data Normalization

The stages of dataset normalization using a min-max scaler are carried out for data pre-processing (Hsu & Chen, 2020). That is by changing the real value in the dataset into a range interval.

$$x' = \frac{(x - x_{min})}{(x_{max} - x_{min})} \quad (1)$$

where X is the actual data, X_{max} is the maximum value of the input data, x_{min} is the minimum value of the input data (Bahi et al., 2018).

At this stage, the existing dataset preparation process is also carried out by dividing the dataset into two parts: training and test data. Training data is used to train the model and test data is used to obtain forecasting results. So that during the production process, the dataset is in a constant state and does not change. The dataset modeling process is carried out by dividing the dataset into 660 training data and 110 test data.

3.2.1. Proposed Long Short-Term Memory Forecasting Architecture

The Keras Python module is used to create an LSTM-based forecasting architecture (Kang et al., 2020). Then the LSTM layer and dense layer import the model sequentially. (Hsieh, 2021). A model with one input layer is called a sequential model (Quy et al., 2020). LSTM has one output layer and several hidden layers (Lee et al., 2018). One hidden layer with 50 neural units composes an architecture built by creating new variables that function to process data, and this layer is also an input layer with shape parameters. Relu is used for its activation. information that has been processed from the hidden layer is made output by the Dense layer. Configure the training process by calling the compile() function by optimizing adam and calculating the percentage loss with mean squared error.

Figure 2 shows the tanh layer which is the only iterative RNN Model layer (Goyal A., Kumar R., Kulkarni S., 2016). The tanh layer aims to make the input into a number with a range of -1 to 1. Xt-1 is the previous input, ht-1 is the previous output which is entered as input along with the new input. Ht+1 is output after order t and Xt+1 is input after order t (Pal et al., 2021).

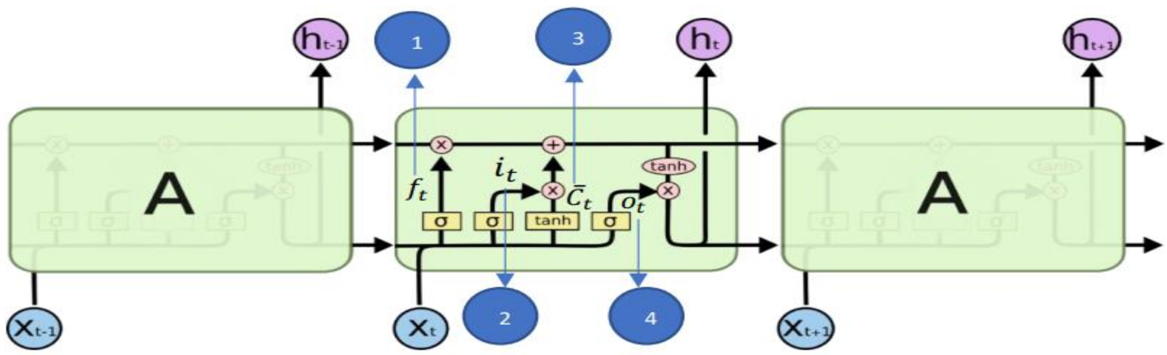

Figure 2. Recurrent Neural Network Architecture (Goyal A., Kumar R., Kulkarni S., 2016).

After the LSTM model is determined, then the training data inputted to process the training model with the fit() function on the training data variables (x_train and y_train). The parameters used for training are validation data or test data (x_test and y_test), the number of epochs with a value of 50, batch_size number with a value of 1, and the display of info in the verbose training process with a value of 2. Based on the resulting output, LSTM forecasting model training got 0.00025123 loss value and 0.000053806 val_loss value for the error rate in the test data or validation process.

3.3. Testing and Denormalization

In testing stage, the model that has been obtained in the training process was being tested using test data and training data that has been obtained from previous data processing. and as a test stage result, the forecast is obtained. After obtaining the forecasting results from the previous process, it is necessary to denormalize the data before calculating the accuracy with RMSE. Denormalization converts data into the original value again after normalizing the min-max scaler at various intervals. Denormalization is done to make the data easy to read and easy to understand.

$$d = d(X_{max}) + X_{min} \qquad (2)$$

where d is the value of normalized data, X_{max} is the maximum value of the actual data, x_{min} is the minimum value of the actual data.

3.4. Calculating Accuracy with Rmse And Mape

This study uses measuring tools RMSE, and MAPE. Measurements are made to find the level of accuracy based on the difference between the original data and the forecasted data. The smaller the difference, the better.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(y_1 - \hat{y}_1)^2}{n}} \qquad (3)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^{n} \frac{|y\iota - y|}{yi} \qquad (4)$$

where n is the number of observed data. $y_1, y_2, y_3, \dots, y_n$ is the observed value, and $\hat{y}_1, \hat{y}_2, \hat{y}_3, \dots, \hat{y}_n$ is the predicted value.

3.5. Prediction of Next Year

From a dataset of 770 lines of data, forecasting of foreign tourist arrivals for the following year, 2020 is carried out using LSTM forecasting. Forecasting results can be combined with the original data, and a comparison graph of the two data is formed continuously.

4. Results and Discussion

The prediction model is built based on the designed method, with the batch_size of 1, and the verbose of 2. At 1000 epochs, the model got the loss value at 0.00025123, which is the error rate at training data. and the val_loss value at 0.0000053806 which is the error rate in the test data for a validation. The prediction correlated with root mean squared error and Mean Absolute Persentage Error has been done with several sets of epoch and produces the following result. Based on the results obtained, it was found that the training data had an RMSE of 591897,46. shows the deviation of the data points from the linear regression line or the difference between the actual data and the forecasted data is in hundred of thousands.Considering the minimum data range is 0 and the maximum data is 2,980,753 then the RMSE obtained is still high.

Table 1: Predicted Correlation With Root Mean Squared Error

No	Country of origin	Actual 2019	Predicted 2019	Abs Error	Square error
1	Brunei Darussalam	19278	107409	88463	7825702369
2	Malaysia	2980753	80272	2899703	8408277488209
	..				

54	South Africa	47657	65471	13877	192571129
55	Other Africa	51262	107416	56245	3163500025
RMSE					591897.46
%MAPE					636.2%

The next process is forecasting for the following years from 2019 to 2021 using the LSTM forecasting model that has gone through the training process, and is implemented to do forecasting by way of LSTM studying the time series data from previous years that already exists and then forecast the data of the next year.

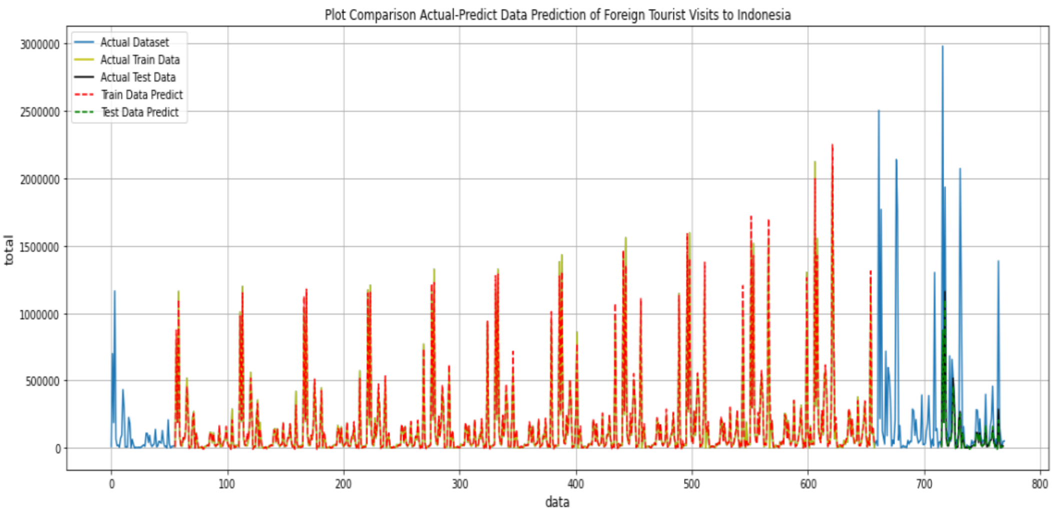

Figure 3: Prediction Results of Test Data and Training Data

Table 2: Forecasting Results 2019-2021

No	Country of origin	2019 (actual)	2020	2021
1	Brunei Darussalam	19278	107409	144180
2	Malaysia	2980753	80272	195046
	...			
54	South Africa	47657	65471	239229
55	Other Africa	51262	107416	156945

Based on the graph above, it shows the forecasting of 2020 foreign tourist arrival which obtained from the original data from 2006 to 2019 actual data. The results of forecasting shows that the number of foreign tourist arrivals increased in some countries and decreased in the others, where the highest increase in number of tourist arrival is from other Asian countries which reached 1234524 tourist addition, and the lowest decrease in number of tourist is 2900481 reduction of tourists from Malaysia.

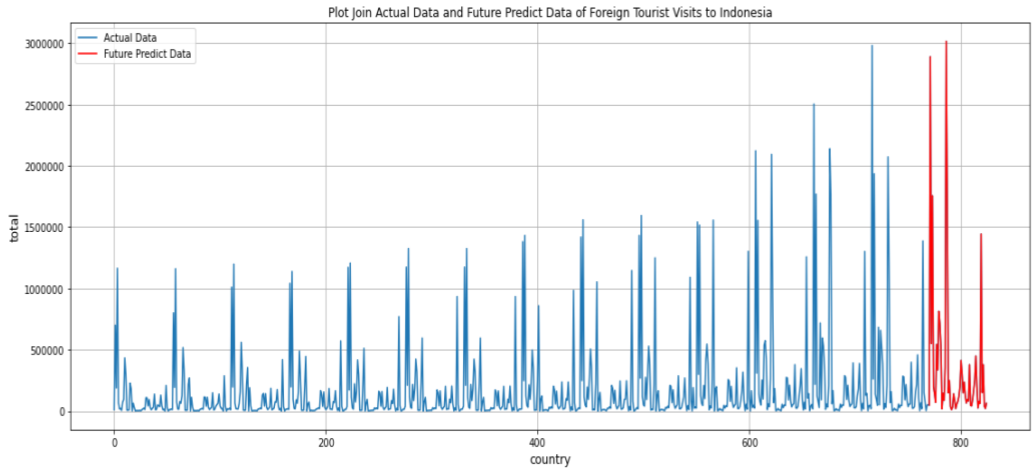

Figure 4: Actual Data and Future Prediction Results in 2020

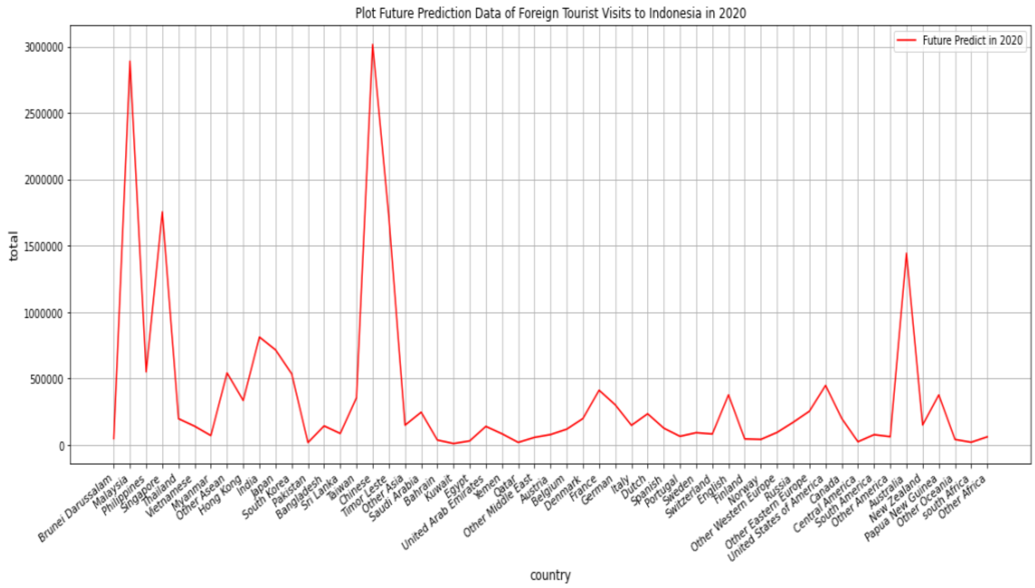

Figure 5: Future forecasting results in 2020

6. Conclusion

Research that discusses tourist arrivals to Indonesia uses LSTM, which can be applied to annual forecasting. Forecasting worked on a dataset of 770 data from 2006 to 2019. And LSTM is able to forecast the future tourist arrival of year 2020. Evaluation of the Long Short Term-Memory algorithm in forecasting foreign tourist arrivals to Indonesia, shows the results of the RMSE evaluation of the model is 591897.46 with a MAPE at 636.2. considering the range of time series datasets used is ranging from 0 to 2,980,753 it can be concluded that the resulting RMSE is high. The number of dataset used is the biggest influence of the obtained number of the result. The purposed algorithm needs lot of parameter and expected to give a good result. But the amount of dataset of each single country which is only 14 data (based on year of measurement) per country is not enough to give a good forecasting result, and potentially generate overfitted model.

References

Abidin, N. H. Z., Remli, M. A., Mohd Ali, N., Eh Phon, D. N., Yusoff, N., Adli, H. K., & Busalim, A. H. (2020). Improving Intelligent Personality Prediction using Myers-Briggs Type Indicator and Random Forest Classifier. *International Journal of Advanced Computer Science and Applications*, *11*(11), 192–199. https://doi.org/10.14569/IJACSA.2020.0111125

Bahi, Y. F. El, Ezzine, L., El Moussami, H., & Aman, Z. (2018). Modeling and Forecasting of Fuel Selling Price Using Time Series Approach: Case Study. *2018 5th International Conference on Control, Decision and Information Technologies, CoDIT 2018*, 283–288. https://doi.org/10.1109/CoDIT.2018.8394835

Bandara, K., Shi, P., Bergmeir, C., Hewamalage, H., Tran, Q., & Seaman, B. (2019). Sales demand forecast in E-commerce using a long short-term memory neural network methodology. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11955 LNCS*, 462–474. https://doi.org/10.1007/978-3-030-36718-3_39

Bouktif, S., Fiaz, A., Ouni, A., & Serhani, M. A. (2018). Optimal deep learning LSTM model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches. *Energies*, *11*(7). https://doi.org/10.3390/en11071636

Bulchand-gidumal, J. (2020). Impact of Artificial Intelligence in Travel, Tourism, and Hospitality. *Handbook of E-Tourism*, *August*. https://doi.org/10.1007/978-3-030-05324-6

Fattah, J., Ezzine, L., Aman, Z., El Moussami, H., & Lachhab, A. (2018). Forecasting of demand using ARIMA model. *International Journal of Engineering Business Management*, *10*, 1–9. https://doi.org/10.1177/1847979018808673

Goyal A., Kumar R., Kulkarni S., K. S. & V. M. (2016). A Solution to Forecast Demand Using Long Short-Term Memory Recurrent Neural Networks for Time Series Forecasting. *Midwest Decision …*, 18. https://mwdsi2018.exordo.com/files/papers/70/final_draft/LSTM_Final_Paper_MWDSI.pdf

Haviluddin, & Jawahir, A. (2015). Comparing of ARIMA and RBFNN for short-term forecasting. *International Journal of Advances in Intelligent Informatics*, *1*(1), 15–22. https://doi.org/10.26555/ijain.v1i1.10

Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, *9*. https://doi.org/10.17582/journal.pjz/2018.50.6.2199.2207

Hsieh, S.-C. (2021). Tourism Demand Forecasting Based on an LSTM Network and Its Variants. *Algorithms*, *14*(8), 243. https://doi.org/10.3390/a14080243

Hsu, C. J., & Chen, H. H. (2020). Taxi demand prediction based on LSTM with residuals and multi-head attention. *VEHITS 2020 - Proceedings of the 6th International Conference on Vehicle Technology and Intelligent Transport Systems*, *Vehits*, 268–275. https://doi.org/10.5220/0009562002680275

Huang, Y., Xu, C., Ji, M., Xiang, W., & He, D. (2020). Medical service demand forecasting using a hybrid model based on ARIMA and self-adaptive filtering method. *BMC Medical Informatics and Decision Making*, *20*(1), 1–14. https://doi.org/10.1186/s12911-020-01256-1

Kang, T., Lim, D. Y., Tayara, H., & Chong, K. T. (2020). Forecasting of Power Demands using Deep Learning. *Applied Sciences (Switzerland)*, *10*(20), 1–11. https://doi.org/10.3390/app10207241

Kilimci, Z. H., Akyuz, A. O., Uysal, M., Akyokus, S., Uysal, M. O., Atak Bulbul, B., Ekmis, M. A., & Silva, T. C. (2019). An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain. *Complexity*, *2019*. https://doi.org/10.1155/2019/9067367

Lee, K., Kang, D. Y., Choi, H. R., Park, B. K., Cho, M. J., & Kim, D. (2018). Intermittent Demand Forecasting with a Recurrent Neural Network Model Using IoT Data. *International Journal of Control and Automation*, *11*(3), 153–168. https://doi.org/10.14257/ijca.2018.11.3.14

Mariyono, J. (2017). Determinants of Demand for Foreign Tourism in Indonesia. *Jurnal Ekonomi Pembangunan*, *18*(1), 82. https://doi.org/10.23917/jep.v18i1.2042

Masri, F., Saepudin, D., & Adytia, D. (2020). Forecasting of Sea Level Time Series using Deep Learning RNN, LSTM, and BiLSTM, Case Study in Jakarta Bay, Indonesia. *E-Proceeding of Engineering*, *7*(2), 8544–8551. https://openlibrarypublications.telkomuniversity.ac.id/index.php/engineering/article/view/12760

Mazlan, A. U., Sahabudin, N. A., Remli, M. A., Ismail, N. S. N., Mohamad, M. S., Nies, H. W., & Abd Warif, N. B. (2021). A Review on Recent Progress in Machine Learning and Deep Learning Methods for Cancer Classification on Gene Expression Data. *Processes*, *9*(8), 1466. https://doi.org/10.3390/pr9081466

Mukhtar, H., Taufiq, R. M., Herwinanda, I., Winarso, D., & Hayami, R. (2022). Forecasting Covid-19 Time Series Data using the Long Short-Term Memory (LSTM). *International Journal of Advanced Computer Science and Applications*, *13*(10), 211–217. https://doi.org/10.14569/IJACSA.2022.0131026

Ouhame, S., & Hadi, Y. (2019). Multivariate workload prediction using Vector Autoregressive and Stacked LSTM models. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3314074.3314084

Pal, S., Ma, L., Zhang, Y., & Coates, M. (2021). RNN with Particle Flow for Probabilistic Spatio-temporal Forecasting. *ArXiv*. http://arxiv.org/abs/2106.06064

Peng, L., Wang, L., Ai, X. Y., & Zeng, Y. R. (2021). Forecasting Tourist Arrivals via Random Forest and Long Short-term Memory. *Cognitive Computation*, *13*(1), 125–138. https://doi.org/10.1007/s12559-020-09747-z

Quy, T. Le, B, W. N., Spiliopoulou, M., & Ntoutsi, E. (2020). A Neighborhood-Augmented LSTM Model for Taxi-Passenger Demand. *Semantic*, *1*, 100–116. https://doi.org/10.1007/978-3-030-38081-6

Ren, X., Li, Y., Zhao, J. J., & Qiang, Y. (2021). Tourism Growth Prediction Based on Deep Learning Approach. *Complexity*, *2021*. https://doi.org/10.1155/2021/5531754

Rice, W. L., Park, S. Y., Pan, B., & Newman, P. (2019). Forecasting campground demand in US national parks. *Annals of Tourism Research*, *75*(March), 424–438. https://doi.org/10.1016/j.annals.2019.01.013

Román-Portabales, A., López-Nores, M., & Pazos-Arias, J. J. (2021). Systematic review of electricity demand forecast using ann-based machine learning algorithms. *Sensors*, *21*(13), 1–23. https://doi.org/10.3390/s21134544

Santoso, A., Pranata, R., Wibowo, A., Al-Farabi, M. J., Huang, I., & Antariksa, B. (2021). Cardiac injury is associated with mortality and critically ill pneumonia in COVID-19: A meta-analysis. *American Journal of Emergency Medicine*, *44*(xxxx), 352–357. https://doi.org/10.1016/j.ajem.2020.04.052

Sehovac, L., Nesen, C., & Grolinger, K. (2019). Forecasting building energy consumption with deep learning: A sequence to sequence approach. *Proceedings - 2019 IEEE International Congress on Internet of Things, ICIOT 2019 - Part of the 2019 IEEE World Congress on Services*, 108–116. https://doi.org/10.1109/ICIOT.2019.00029

Weytjens, H., Lohmann, E., & Kleinsteuber, M. (2019). Cash flow prediction: MLP and LSTM compared to ARIMA and Prophet. *Electronic Commerce Research*, *0123456789*. https://doi.org/10.1007/s10660-019-09362-7

Yang, Y., & Wong, K. K. F. (2012). A Spatial Econometric Approach to Model Spillover Effects in Tourism Flows. *Journal of Travel Research*, *51*(6), 768–778. https://doi.org/10.1177/0047287512437855