Journal of Engineering Sciences and Information Technology
Volume (6), Issue (3) : 30 Jun 2022
P: 70 - 95
ISSN: 2522- 3321

مجلة العلوم الهندسية وتكنولوجيا المعلومات
المجلد (6)، العدد (3) : 30 يونيو 2022م
ص: 70 - 95

Predicting Economic Activities Trends for Saudi and Non- Saudi Establishments in Saudi Arabia by Using Time Series Forecasting and Deep Learning Models

Bodour Khoja
Ministry of Human Resource and Social Development || KSA
Mohamed Batouche
College of Computer & Information Sciences || Princess Nourah Bint Abdulrahman University || KSA

Abstract: Data related to economic and stock market information are widely used for representing non- stationary time series. The economy goes through different phases, from recession to growth. This project focused on models predicting total added establishments in each economic activity. It aimed to predict the number of establishments after the impact of covid- 19 and estimate the accuracy of the prediction models. Prediction models used for inexpensive, quick evaluation of the added number of existing establishments leading to business risk mitigation. The research was conducted on data extracted from ministry of human resource and social development database. Therefore, the carried- out analysis highlights four activities under examination to capture the significance changes. These activities are construction, health, accommodation and information technology. In this study, five time series models are selected and applied to the business data describing expansion and recession. After model performance evaluation, deep learning models with respect to sliding window approach to predict short term values are recommended and perform better than traditional models. LSTM outperforms the other models in health with 18.22 RMSE and 90.65 RMSE for the information technology. DNN with two hidden layers got the best RMSE for accommodation and construction activities which is equal to 183.98 and 1387.78 respectively. Such work indicates that predicting overall added establishments may assist investors and companies in making economic choices, such as when to invest, increase, or reduce production.

Keywords: Time series forecasting, Establishments, Economic, Covid- 19, ARIMA, Deep learning.

التنبؤ باتجاهات الأنشطة الاقتصادية باستخدام السلاسل الزمنية والتعلم العميق

بدور خالد خوجه
وزارة الموارد البشرية والتنمية الاجتماعية || المملكة العربية السعودية
محمد بعطوش
كلية الحاسب وعلوم المعلومات || جامعة الأميرة نورة بنت عبد الرحمن || المملكة العربية السعودية

المستخلص: تُستخدم البيانات المتعلقة بالاقتصاد ومعلومات سوق الأوراق المالية، على نطاق واسع لتمثيل السلاسل الزمنية غير الثابتة. يمر الاقتصاد بمراحل مختلفة، من الركود إلى النمو. يركز هذا المشروع على نماذج تتنبأ بإجمالي المنشآت المضافة في كل نشاط اقتصادي، بحيث يهدف إلى التنبؤ بعدد المنشآت بعد تأثير كوفيد- 19 وتقدير دقة نماذج التنبؤ. تم استخدام نماذج التنبؤ لإجراء تقييم سريع وغير مكلف للعدد الإضافي من المؤسسات الموجودة مما أدى إلى التخفيف من مخاطر الأعمال. تم إجراء البحث على بيانات

مستخرجة من قاعدة بيانات وزارة الموارد البشرية والتنمية الاجتماعية. لذلك، سلط التحليل الذي تم إجراؤه الضوء على أربعة أنشطة قيد الدراسة لتحديد التغييرات المهمة، هذه الأنشطة هي البناء والصحة والإقامة وتكنولوجيا المعلومات. في هذه الدراسة، تم اختيار خمسة نماذج سلاسل زمنية وتطبيقها على بيانات الأعمال التي تصف التوسع والركود. بعد تقييم أداء النماذج، يوصى باستخدام نماذج التعلم العميق فيما يتعلق بنهج النافذة المنزلقة للتنبؤ بالقيم قصيرة المدى حيث إنها تؤدي أداءً أفضل من النماذج التقليدية. يتفوق LSTM على النماذج الأخرى لنشاط الصحة بما يساوي RMSE 18.22 وبما يساوي 90.65 لتكنولوجيا المعلومات. حصلت DNN مع طبقتين مخفيتين على أفضل RMSE لأنشطة الإقامة والبناء بما يساوي183.98 و1387.78 على التوالي. يعطي هذا العمل مؤشرًا على أن التنبؤ بالمؤسسات المضافة بشكل عام قد يساعد المستثمرين والشركات في اتخاذ الخيارات الاقتصادية، مثل وقت الاستثمار أو زيادة الإنتاج أو تقليله.

الكلمات المفتاحية: التنبؤ بالسلاسل الزمنية، المؤسسات، الاقتصاد، التعلم العميق، كوفيد- 19.

1- Introduction.

Economic time series forecasting is a challenging task due to the noise of the market situations(Qi-Qiao, HePatrick Cheong-Iao Pang,Yain-Whar Si, 2019). Forecasting the total added establishments is a critical task for risk management. The current economic environment shaped by turbulent economic changes imposes challenging conditions for businesses and their prosperity. In the long run, many companies do not survive, and they have to withdraw from the market. Nevertheless, Corporate failures have enormous impacts on whole economic structures. The consequences can be understood not only at the macroeconomic level, but also at the microeconomic level (D. Camska and J. Klecka, 2020). There are some challenges since the project needs high- performance hardware as well as the long training time while implementing deep learning models. Another main challenge is to produce a model that achieves good accuracy to help the ministry in their discussions.

The values of economic indicators could be projected to deteriorate during the contraction period, compared to the expansion phase (D. Camska and J. Klecka, 2020). The purpose of the study is to examine the most activity affected by covid- 19 where the number of opened establishments in economic activity will shrink. On the other hand, assuming that the number of closed establishments will increase. The question is whether the impact mentioned in economic indicators is important and measurable.

In terms of falling local productivity and labor demand, economic response is the most consistent to disasters (J. H. Stock and M. W. Watson, 1993). The Kingdom is using its enormous investment power to build more diversified and sustainable economy. Economic growth is the increase of an economy over time in terms of services produced (M. Alawin and A. Abu-Aisheh, 2020). Economic activities or services provided by the establishment return a specific revenue. While establishment is an economic entity that carries out a certain economic activity. Where economic forecasting is the process of attempting to predict the future of the economy using a combination of significant followed indicators (J. H. Stock and M. W. Watson, 1993). This research considers the number of establishments in economic activity over the time as a main indicator. Hence, it has been proven that the number of establishments have a positive effects on the Gross Domestic Product(M. Alawin and A. Abu-Aisheh, 2020). Therefore, prediction would assist in defining the value added to the private sector in Saudi Arabia. Besides, it could determine the contributions of the economic activity to the Gross Domestic Product based on the number of establishments.

1-1 The problem statement and justification:

To empirically develop a model for forecasting and how such models can best fit for the annual total number of establishments are exposed by practical experiments which give the ministry a clear and accurate vision about near future economic growth. Since covid- 19 is most certainly spreading worldwide economic misery. Global GDP growth for 2020 decreased by 1.5 percent(R. Baldwin and B. W. Di Mauro, 2020). Challenges also lie ahead; the economic situation has created risks for the corporate sector(D. Susskind and D. Vines, 2020).

1-2 The research questions:

1. How the economic activity trend be predicted based on the number of opened establishments for each activity from historical data?
2. Will the time series prediction model be able to assist in growing economic activity?

1-3 The Objectives:

1. To describe and clean the data.
2. To predict the economic activity trend for Saudi and Non- Saudi Establishments in Saudi Arabia by using time series forecasting on Human Resource and Social Development data.

1-4 The significance and the important of the study:

1. Economic forecasts can be used by government managers to define policies and schedule future operations. Many governments base their decisions with respect to investments, recruiting, spending, and other significant policies that impact aggregate economic activity.
2. By monitoring the total added establishments for each economic activity over the time as a primary economic indicator which help to discover future growth rate for several domestic activities. For, instance: (Accommodation, Information Technology, Health, Construction).
3. This project would add value to the future researches and studies in prediction technology by studying and analyzing suitable deep learning models along with other classical methods on data from Ministry of Human recourse and Social development.

1-5 The hypothesis:

1. To identify the character of the phenomenon represented by the sequence of observations, forecasting the future values of the time series variable.

2. To propose an optimal model which will help in empowering the individual, society, and institutions together with promoting social responsibility, upgrading the labor market by developing policies and legislation and enabling the Ministry of Human Resource and Social Development to supply a particular experience to the beneficiaries.

2- Study methodology.

A. Analytical methodology :

1. Descriptive analysis: data visualization to extract insights from the data such as patterns, distributions, cycles and relationships to learn more about past events.
2. Predictive analysis: To build models such as exponential smoothing, ARIMA and deep learning models in order to forecast future events from historical patterns.
3. To evaluate the forecasting models, determine the results and the main findings of the data analysis and forecasting by using appropriate measures, For instance: RMSE, MSE, MAE or MAPE.
4. Along with numerical analyses, the experiment environment will be on Python's Keras Library for deep learning, R program for classical models with required packages such as "timeSeries", "expsmooth" "forecast" are used for modelling and forecasting time series data.

B. Data source:

Companies under investigation have been assigned to relevant industry sectors. Data were extracted from the Human resource and social development database. It consists of 42000 observations of added establishments. More than 1 million exist and not exist aggregated establishments from 1950 to 2021 for 20 main economic activities. The data includes a list of attributes named: Activity name, year, status, total add establishments. Only exist establishments for four activities are under consideration in this research.

C. The scope:

1. Analyze the time series to understand the structures of the observed data using methods in order to extract meaningful statistics to discover the characteristics of the data (stationary, pre- processing and decomposition).
2. Implement mathematical models after describing the mechanisms of time series (fitted function, forecasting and accuracy estimation).

2-1 Study structure:

This report has a standard structure and consists of parts. First reviews of the current researches in this respective field. Second, focus on the materials and methods, explaining the data sample and models predicting applied. Finally, it presents the results of the analysis along with their interpretation and recommendations.

3- Previous studies and literature review.

3-1 Related work:

3-1-1 Forecasting with Exponential Smoothing and Auto- Regressive Integrated Moving Average models ARIMA:

Traditional machine learning and statistical methods are used for forecasting time series(Qi-Qiao, HePatrick Cheong-Iao Pang,Yain-Whar Si, 2019). Good results have not always been obtained by using deep neural networks (J. Zhao, D. Zeng, S. Liang, H. Kang, and Q. Liu, 2020). While exponential smoothing models supported an outline for the seasonality and the trend, ARIMA models aim to describe the autocorrelations within data.

Based on 2020 Bangladesh Gross Domestic Product forecasting using time series analysis. After using the autocorrelation function to test for stationary as statistical analysis. It has been found that ARIMA models got the best fit model for forecasting the Gross Domestic Product (A. Ahmed and M. S. A. Salan, 2019). By contrast, based on statistical comparison between the models, Holt- Winters method presented the best forecasting model and fit performance for incorporating the growth rate significantly in Brazilian gross domestic product 2020 (K. V. S. da Costa, F. L. C. da Silva, and J. d. S. C. Coelho, 2020). For Saudi Arabian and Egyptian economies, annual time series data is used to forecast GDP per capita using ARIMA model. Performance evaluation shows that the provided models are accurate(Eissa, 2020). (A. Fathalla, A. Salah, K. Li, K. Li, and P. Francesco) using ARIMA model to forecast the product prices as an advantage of time series analysis where the prices change over time. (T. J. Mbah, H. Ye, J. Zhang, and M. Long, 2021) indicates that ARIMA model outperforms RNN model for price prediction. ARIMA model has 95.7 percent accuracy, while the RNN has 91.8 percent accuracy.

3-1-2 ANN Artificial Neural Network:

Statistical models may not perform satisfaction when the data frequency is high because they are generally linear forecasting techniques (A. Fathalla, A. Salah, K. Li, K. Li, and P. Francesco).

(N. Budhani, C. Jha, and S. K. Budhani, 2014) an artificial neural network model was proposed to forecast stock price and indicated that the nonlinear model works better than the linear model. Along with the feed forward network, they used an activation function called sigmoid function to multiply input values to neuron weights and sum up before submitting them to the output layer as well as a back propagation algorithm to calculate the error in the predicted value.

3-1-3 DNN Deep Neural Network:

Deep learning is part of a larger group of machine learning approaches focused on learning data representations. Models in deep learning use a multi- layered non- linear processing unit called neurons that can extract features. An Artificial Neural Network is concerned with the network of those neurons.

Gross Domestic Product measures the market value over a period of time of all final products and services provided. Deep learning system at the country level for the GDP estimate of the Contiguous United States (CONUS) time series suggest a strong predictive capacity of the proposed model (J. Sun, L. Di, Z. Sun, J. Wang, and Y. Wu, 2020).

3-1-4 RNN Neural Network principle and characteristics of LSTM model:

Recurrent Neural Network is a type of ANN wherein associations between the Neurons structure, having a self- loop in the hidden layers. This encourages RNN to use the previous condition of the hidden neurons to learn current state. Along with the current input, RNN takes the information they have learnt previously in time. To learn sequential knowledge, they use internal state or memory. This helps them to learn diversity of tasks, such as speech and handwriting recognition (Tipirisetty, 2018).

Depends on the results of the output layer, updates to the weights of hidden layers are propagated back. But in deep neural networks, this adjustment would be vanishingly tiny for the beginning layers, preventing the weights from changing its value and preventing the network from learning. That is known as vanishing gradient problem. In order to deal with forgetfulness, LSTM has been created (Y. Qu and X. Zhao, 2019).

RNN and LSTM models in deep learning are used to forecast the price of foreign exchange financial time series. By comparing the evaluation of the two deep learning models, the experimental results proved that LSTM model has smaller RMSE and MAE than RNN, and the predicted price is more accurate (Y. Qu and X. Zhao, 2019).

3- 1- 5 Ensemble learning:

(I. K. Nti, A. F. Adekoya, and B. A. Weyori, 2020)shows after stock market prediction evaluation, ensemble learning offered higher accuracy. Since in machine learning and statistics, ensemble technique is widely used. Ensemble learning uses methods to combine several single predictors into a committee in order to produce significant and reliable outcomes than any single predictor.

3- 2 Theoretical framework.

3- 2- 1 Establishments and time series analyses:

The effect on the economy can be summarized as: economy can be introduced as a complex web of connected parties: firms, suppliers, consumers, employees and finance. Pandemics are expected to have a negative impact on economic activities. According to (A. Brodeur, D. M. Gray, A. Islam, and S. Bhuiyan, 2020). The impact ranges from: individuals might avoid purchases and consumption of certain goods and services, loss of labor and production. The direct impact is related to the reduced consumption of services and products. Long term social distancing during the pandemic may decrease consumer confidence by keeping consumers at home, wary of spending and pessimistic about the long period economic prospects. Second, the indirect impact through financial market shocks affects the real economy. Savings would increase and household wealth would fall further. The third consists of supply side fluctuation, as covid-19 keeps production halted, it would negatively impact supply chains, leading a rising unemployment rate.

While entrepreneurship leads to create a new firm (D. Neumark, J. Zhang, and B. Wall, 2005). Entrepreneurship also helps to stimulate economic development (Z. J. Acs, D. B. Audretsch, P. Braunerhjelm, and B. Carlsson, 2012). Deaths and births of business enterprises are the main contributors to job growth and loss, and births of new businesses are particularly significant in gross and job creation (D. Neumark, J. Zhang, and B. Wall, 2005).

The economic impact of shocks such as pandemics are usually measured by aggregate time series data. For instance: GDP growth and industrial production(A. Brodeur, D. M. Gray, A. Islam, and S. Bhuiyan, 2020). (J. Zhao, D. Zeng, S. Liang, H. Kang, and Q. Liu, 2020)developed a weekly economic index (WEI) to analyse and track the economic impact of covid- 19 in the United States using different economic variables.

Time series is a set of data points that are listed in time order. Therefore, time series is a sequence taken at consecutive equally spaced points in time. Time series analysis can help to determine how certain economic variables change over time. However, time series forecasting is the use of model to predict the future based on past values. Thus, the majority of time series are considered stochastic, where the data are represented by the past values and the future values need to be described with probability distribution (Chatfield, 2000).

3- 2- 2 Time series components:

1. Level: The long- term average where the data fluctuate around a constant mean.

2. Trend: The general direction over long- term periods where series is increasing or decreasing (upward and downward movements) regularly over time. Linear trends can be found with moving averages or regression analysis.
3. Seasonal effects: Short- term regular predictable fluctuations. Often influenced by months or quarters. Seasonal effects repeat itself over time. Where observations stay high, then drop off (peaks and troughs). Most likely seasonal patterns have constant length.
4. Cyclical effects: Long- term regular fluctuations of the series, it rises and falls of no fixed periodicity (longer than 2 years). Hence, the magnitude of a cycle is more variable than the magnitude of a seasonal pattern.
5. Residual: Any remainder (unexplained random variation) spikes and troughs at random intervals (Chatfield, 2000).

4- Data analysis and proposed solution.

4- 1 Traditional forecasting models:

Since the data does not contain seasonality HOLT's linear trend method and ARIMA model without seasonality will be chosen to predict near future.

Equation (1) is used for a non- seasonal ARIMA model is a combination of differencing, autoregression and moving average model. ARIMA main components:

AR: Autoregression refers to a model that shows a changing variable that regresses on its own lagged values.

I: Integrated represents the differencing which allow the time series to be stationary. In contrast, the data are replaced by the difference between original values and previous observations.

MA: Represents moving average applied to lagged values which incorporates dependency between observation and error(Tipirisetty, 2018).

$$y`_t = c + \emptyset_1 y`_{t-1} + \cdots + \emptyset_p y`_{t-p} + \emptyset_1 \mathcal{E}_{t-1} + \cdots + \emptyset_q \mathcal{E}_{t-q} + \mathcal{E}_t \qquad (1)$$

Specifically, the three types of parameters within the model: the autoregressive parameters (p), the number of differencing passes (d) and moving average parameters (q).

ARIMA model includes autoregressive further as moving average parameters and includes differencing in the formulation of the model. Model is described as ARIMA (p, d, q). The best ARIMA model found for the four activities is ARIMA (0, 1, 0). This implies that it contains zero autoregressive (p) parameters and zero moving average (q) parameters which were computed for the series after it was differenced once.

4- 1- 1 Holt liner model prediction capture the trend:

1. Health forecasting is shown in **Figure 1**

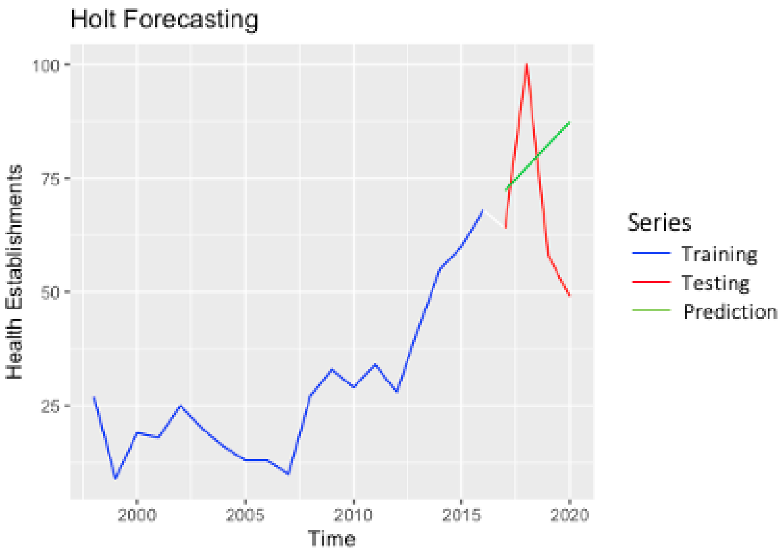

Figure (1) Holt Forecasting for Health Activity *Source: Researchers analyzed data using R program

2. Information Technology forecasting is shown in **Figure 2**

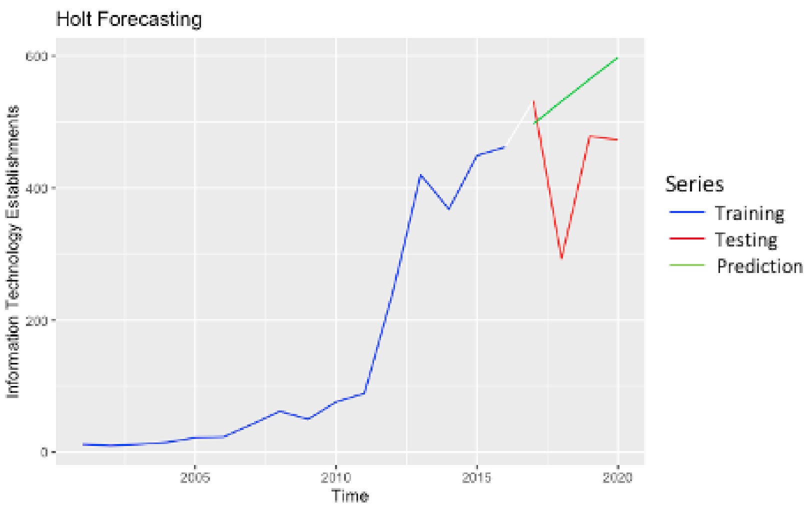

Figure (2) Holt Forecasting for Information Technology Activity *Source: Researchers analyzed data using R program

3. Accommodation forecasting is shown in **Figure 3** .

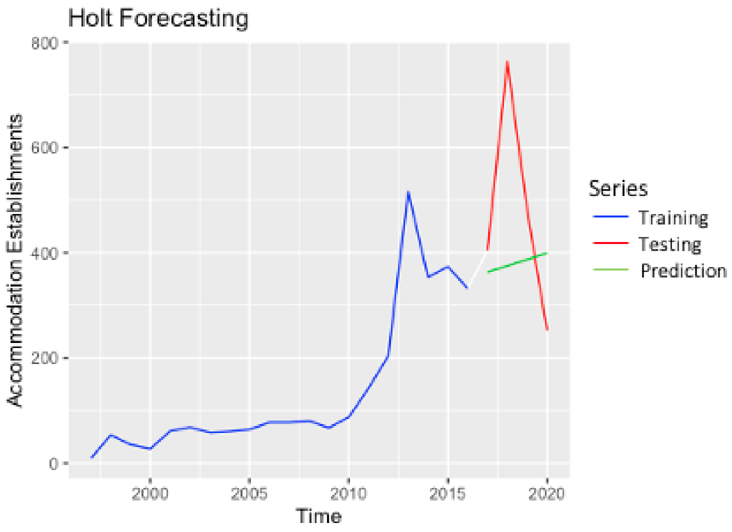

Figure (3) Holt Forecasting for Accommodation Activity *Source: Researchers analyzed data using R program

4. Construction forecasting is shown in Figure **4**.

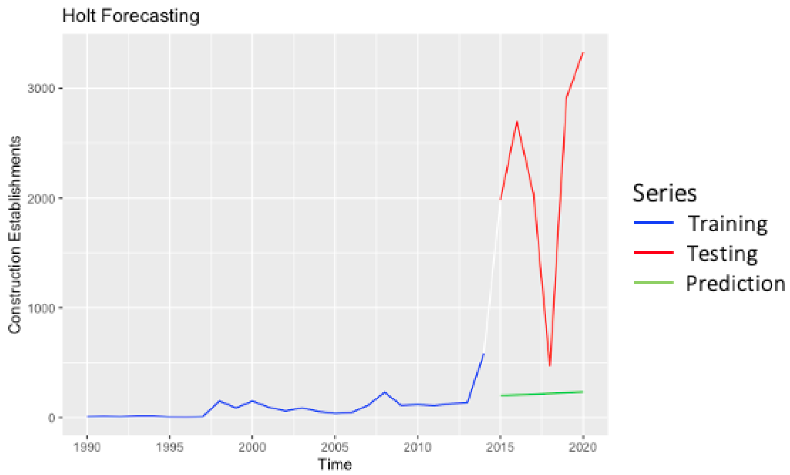

Figure (4) Holt Forecasting for Construction Activity *Source: Researchers analyzed data using R program

4- 1- 2 ARIMA model shows the prediction on average:

1. Health forecasting as shown in Figure 5.

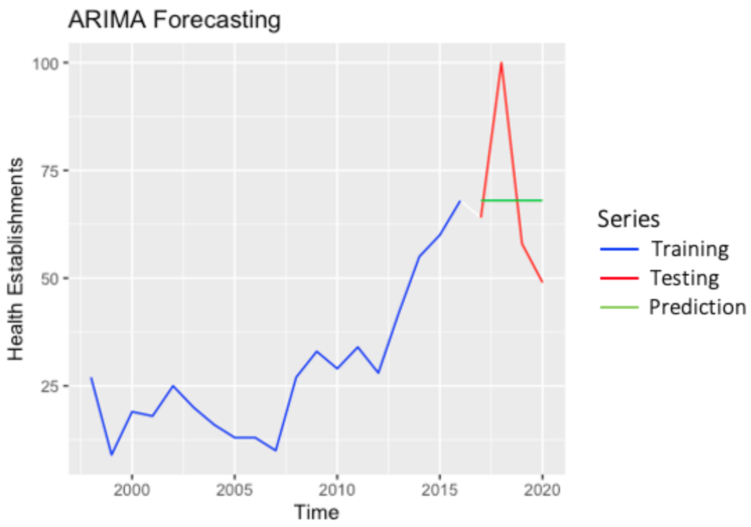

Figure (5) ARIMA Forecasting for Health Activity *Source: Researchers analyzed data using R program

2. Information Technology forecasting as shown in Figure 6.

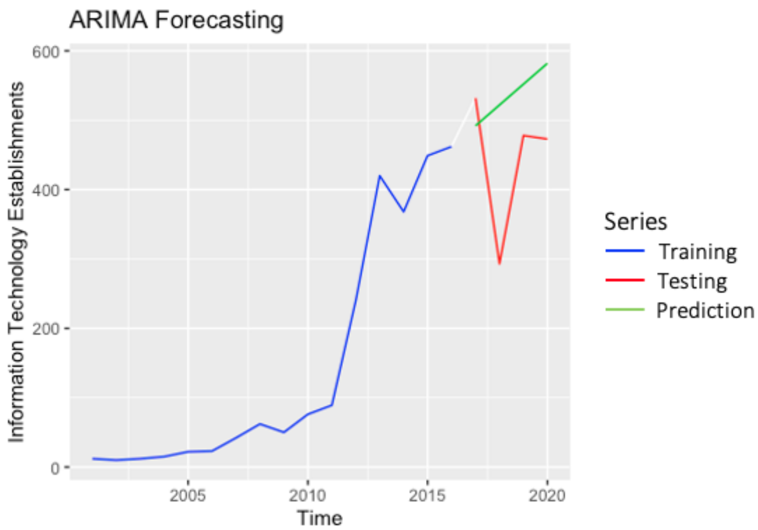

Figure (6) ARIMA Forecasting for Information Technology Activity *Source: Researchers analyzed data using R program

3. Accommodation forecasting as shown in Figure 7.

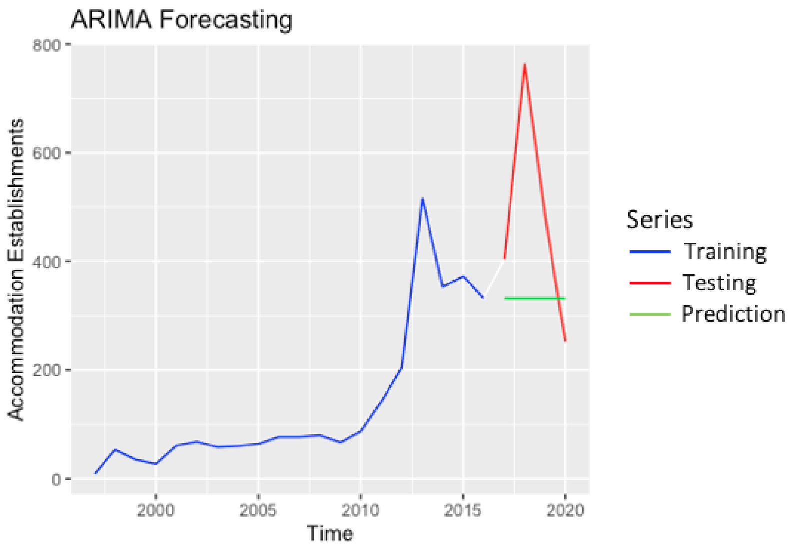

Figure (7) ARIMA Forecasting for Accommodation Activity*Source: Researchers analyzed data using R program

4. Construction forecasting as shown in Figure 8.

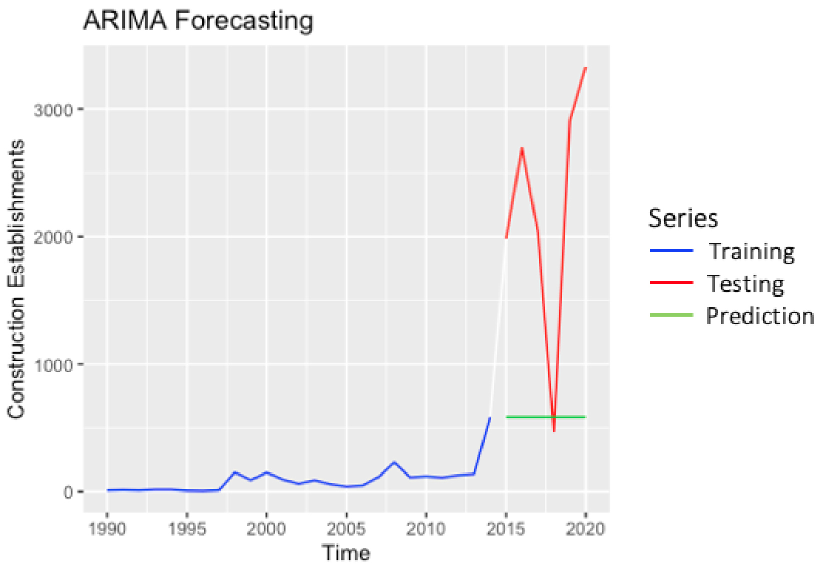

Figure (8) ARIMA Forecasting for Construction Activity *Source: Researchers analyzed data using R program

4- 2 Sliding window technique:

Regression is a type of supervised machine learning algorithms that are used to predict continuous label (L. Fahrmeir, T. Kneib, S. Lang, and B. Marx, 2007). Sliding window technique in deep learning is a partial estimate of the time series data. The window size increases until we hit the least estimate of error (H. Hota, R. Handa, and A. Shrivas, 2017) Move the timeline backward by a year to keep constructing the next set of training and testing. Until we have covered the whole sample, this process will be repeated (Y. Qu and X. Zhao, 2019).

Figure illustrates that the data has been split into 80% training set and 20% testing set which is the best split while training the models(E. Alajrami et al, 2020). Labelling the data is essential since activities data does not contain labels (J. Shen and M. O. Shafiq, 2020). In this research, sliding window technique is applied to generate samples (input window, prediction window) for training and testing the DNN and LSTM models.

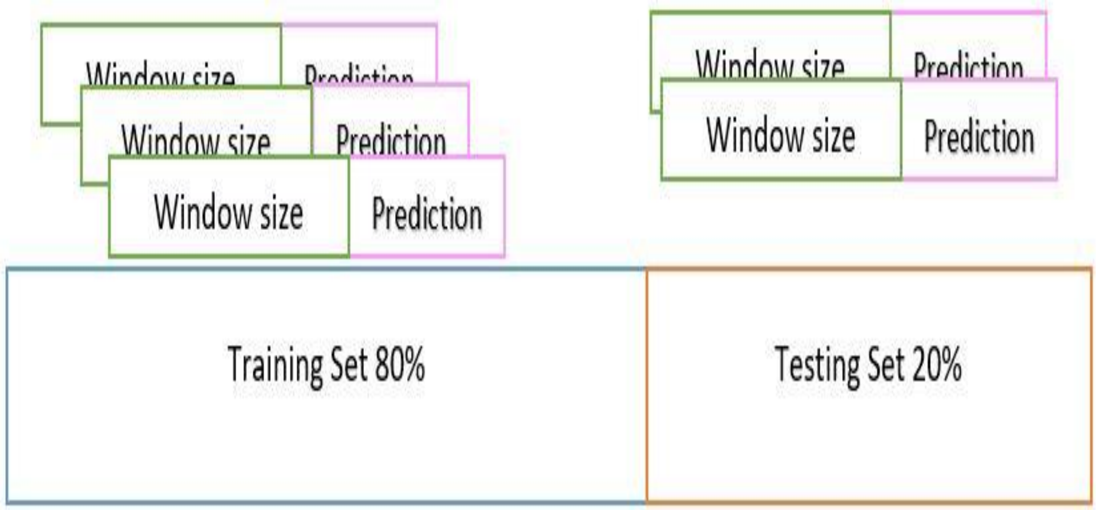

Figure (9) Sliding window Technique*Source: (H. Hota, R. Handa, and A. Shrivas, 2017)

4- 2- 1 Proposed fully connected feed forward Deep Neural Networks architecture:

1. The input layer: The training observations are fed through this layer with respect to sliding window technique.
2. The hidden layers: Between the input and output layers are the Hidden layers. DNN learns about the relationships in the data through these layers. For the proposed DNN model, two hidden layers are used and the number of neurons in each layer is equal to 200. While activation function is a mathematical gate used in the hidden layers, if the aggregated input crosses a threshold value the signal will fire to the next layer. Besides, as activation function in this project, ReLU- Rectified Linear Unit has been chosen because it gives better training performance for multi- layer neural networks. ReLU is the most commonly used activation function due to it is advantages of being nonlinear,

efficient computationally which allows the network to gather quickly and allow for backpropagation (A. Gupta, R. Gupta, and N. Garg, 2021).

3. The output layer: from what happens in the previous layers, the final output is extracted. The output layer contains the number of prediction unit. In our DNN proposed model, a liner activation function is used to the output layer. It takes the inputs and multiplies them by the weights allocated to each neuron to produce an output signal proportional to the input. Allowing multiple outputs, not just yes and no(Y. Qu and X. Zhao, 2019). The proposed DNN model is in Figure 10 .

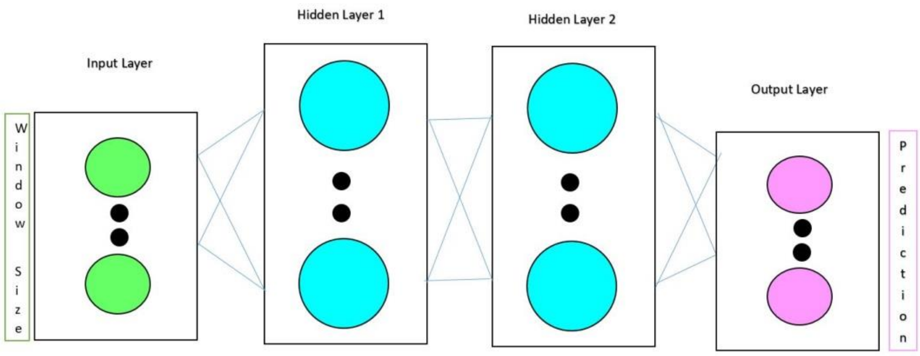

Figure (10) DNN with two hidden layers *Source: (Tipirisetty, 2018)

4- 2- 2 Proposed LSTM model parameters tuning:

Three main parameters are set for LSTM cell: activation function, recurrent activation function and the number of units. For the candidate hidden state and the output hidden state, the activation function would be applied. Whereas the inputs gate, forget gate and the output gates, recurrent activation would be applied. The default value is sigmoid function for recurrent activation function. The default value is hyperbolic tangent for activation function.

The LSTM model used in our approach consists of 150 units with sigmoid as recurrent activation function, Tanh as activation function for the model. LSTM layer has a one- dimensional state vector. Sliding window approach was utilized, for instance, a window of past 2 years was considered as a fixed input size. Due to the final output is numeric, a fully connected layer is added after the LSTM layer. The output layer has a linear activation function. The output layer contains a number of neurons which is equal to the predicted units. Where it will get the output generated from the LSTM cell. LSTM solves the vanishing problem of RNN and the gradient explosion. As a time series prediction, this approach treats the problem as previously mentioned that LSTM has been successful for many time series prediction problems(Qi-Qiao, HePatrick Cheong-Iao Pang,Yain-Whar Si, 2019)(K. Khare, O. Darekar, P. Gupta, and V. Attar, 2017).

4- 2- 3 Common steps which are followed while implementing regression deep learning Models:

First, Build the regression model. Then, compile with optimizer and loss measure for training. In this research project Mean Square Error is used to measure the loss with "Adam" optimizer as a minimizer algorithm. In order to reduce the losses, optimizers methods are used to change the attributes such as weights and learning rate of the neural network. Adam optimizer main advantage is that we did not need to specify the learning rate as in gradient descent. It is saving the optimizing task of the learning rate for the model and it is well suited for problems that are large in parameters and data. The method is suitable as well for non- stationary objectives and problems with sparse gradient and noisy. This method is fast and converges rapidly, corrects high variance and vanishing learning rate(D. P. Kingma and J. Ba, 2014).

Mean Square Error MSE as a loss function for regression is used to compute the quantity that a model should seek to minimize during training. By computing the distance between the predicted value and the real output. Furthermore, large errors cost more than smaller errors due to the differences are squared and larger errors produce much larger squares than smaller errors. However, using MSE would open the machine learning model to outliers, which would disturb training to introduce large errors (Atienza, 2020).

After that, the model is fitted by using number of epochs which is the number of passes through the training data. Where the number of epochs are increasing, loss will decrease (P. Golik, P. Doetsch, and H. Ney, 2013). The proposed DNN set the number of epochs is equal to 10000 While LSTM epochs are equal to 5000.

4- 3 Performance evaluation metrics:

Accuracy metric evaluates the model on a different unseen data which is the testing data to compare the accuracy between the models, where the best model would have lowest value of error (K. V. S. da Costa, F. L. C. da Silva, and J. d. S. C. Coelho, 2020). To evaluate the forecasting model, evaluate the accuracy between the testing set and the fitted model by calculating Root Mean Square Error RMSE as in equation(2) or Mean Square error MSE in equation(3). RMSE is a commonly used metric for regression problems that is used to judge the performance of the model. RMSE which measures the average magnitude of the residuals. It is computed as a square root of the average of squared differences between predicted and observed values. Due to the square term that gives a high weight to the large errors or outliers. Hence, the large error would be reduced if the model optimized to reduce RMSE(D. Entekhabi, R. H. Reichle, R. D. Koster, and W. T. Crow, 2010). Mean Absolute Error and Mean Absolute Percentage error are shown in equations (4)(5) respectively. It is better to use MSE rather than MAE if the average error is small, since MAE shows the forecast error on average. MAPE tells how the error is bad in terms of a percentage. MAPE fails if some of the actual values are equal to zero(Atienza, 2020)(H. Niu, K. Xu, and W. Wang, 2020).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Predictied - Observed)^2} \quad (2)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\mathrm{Predictied} - \mathrm{Observed})^2 \quad (3)$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\mathrm{Predictied} - \mathrm{Observed}|}{|\mathrm{Predictied}|} \quad (4)$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|\mathrm{Predictied} - \mathrm{Observed}|}{|\mathrm{Predictied}|} \times 100 \quad (5)$$

4- 3- 1 DNN with two layers RMSE for different window sizes:

Table (1) RMSE for DNN with different window sizes

	Health	Construction	Information Technology	Accommodation
Window2 Prediction1	25.18553	3338.15	221.2402	233.848
Window 3 Prediction1	20.39767	1387.789	2124.06	254.9339
Window 7 Prediction 1	35.22712	2066.616	1895.333	183.9886

*Source: Researchers analyzed data using R program

Table 1 shows that health, construction and information technology reach small RMSE with small window size rather than the large window size. While in accommodation activity window of size 7 get the lowest RMSE. Along with this:

1. For health activity, the best window size is 3, prediction 1 with RMSE 20.39. As shown in Figure 11, health activity predictions have followed the trend.

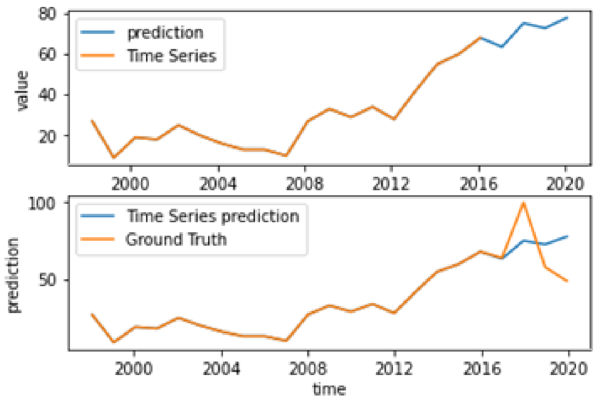

Figure (11) Comparison between DNN prediction and Ground truth for Health activity *Source: Researchers analyzed data using Python

2. For information technology activity,the best window size is 2, prediction 1 with RMSE 221.24. Figure 12 shows the difference between the prediction and the ground truth.

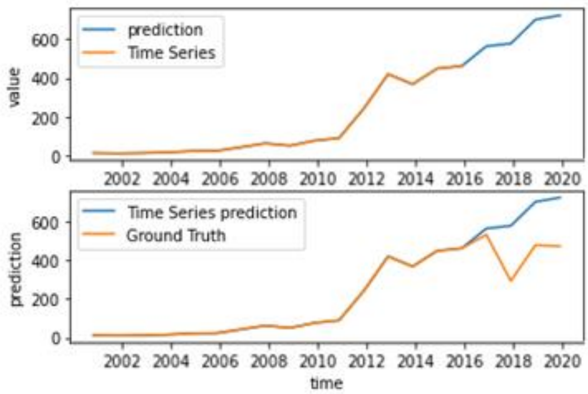

Figure (12) Comparison between DNN prediction and Ground truth for Information Technology activity *Source: Researchers analyzed data using Python

3. For construction activity, the best window size is 3, prediction 1 with RMSE 1387.78. Figure 13 shows the difference between the prediction and the ground truth.

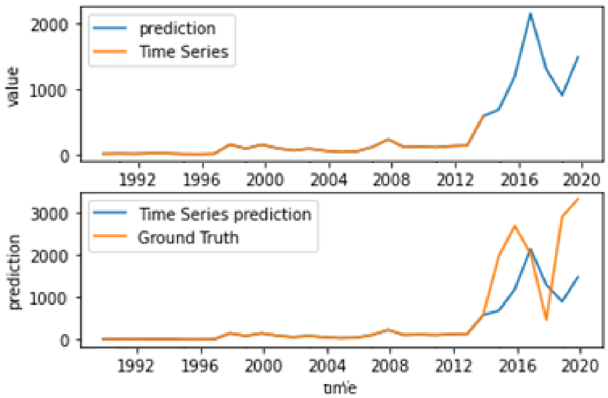

Figure (13) Comparison between DNN prediction and Ground truth for Construction activity*Source: Researchers analyzed data using Python

4. For accommodation activity, the best window size is 7, prediction 1 with RMSE 183.98. As shown in Figure 14 , accommodation activity results are coherent where DNN produce better predictions except 2018.

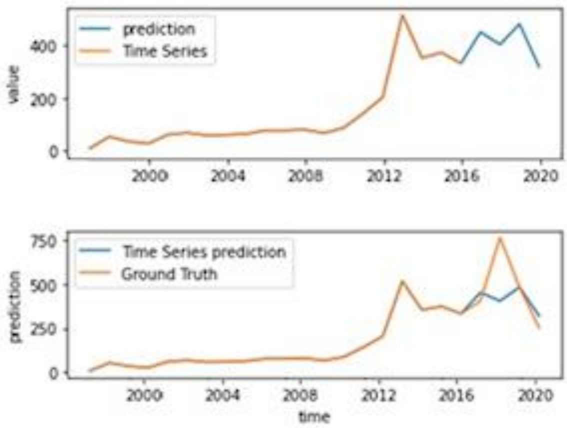

Figure (14) Comparison between DNN prediction and Ground truth for Accommodation activity*Source: Researchers analyzed data using Python

4- 3- 2 LSTM Using Tanh activation function RMSE for different window sizes:

Table (2) RMSE for LSTM Using Tanh and different window sizes

	Health	Construction	Information Technology	Accommodation
Window 3 Prediction 1	19.18323	2135.123	93.56688	204.8575
Window 5 Prediction 1	19.40838	2163.14	90.65822	206.8146
Window 7 Prediction 2	18.22697	2197.135	105.8891	225.759

*Source: Researchers analyzed data using R program

LSTM with Tanh function has a low RMSE with a small window size for the majority of the overall activities except health has 18.58 RMSE with window size 7 as shown in Table 2.

1. For health activity, the best window size is 7, prediction 2 with RMSE 18.22. Figure 15 shows the difference between the prediction and the ground truth.

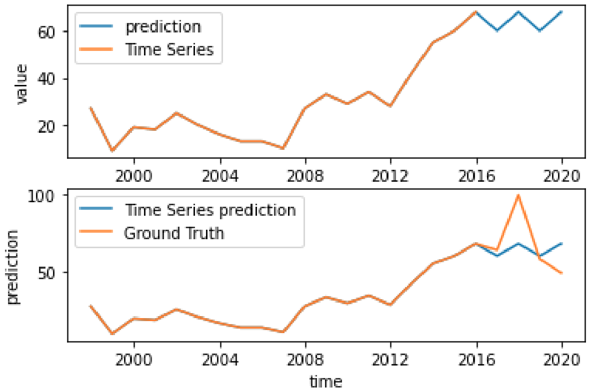

Figure (15) Comparison between LSTM with Tanh prediction and Ground truth for Health activity

***Source: Researchers analyzed data using Python**

2. For information technology activity, the best window size is 5, prediction 1 with RMSE 90.65. It is clear from Figure 16 that most of the predicted and actual values are almost the same. It seems that the prediction is accurate.

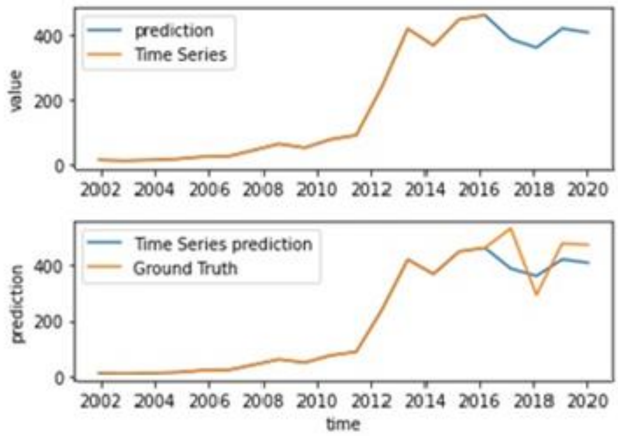

Figure (16) Comparison between LSTM with Tanh prediction and Ground truth for Information Technology activity *Source: Researchers analyzed data using Python

3. For accommodation activity, the best window size is 3, prediction 1 with RMSE 204.85. Figure 17 shows the difference between the prediction and the ground truth.

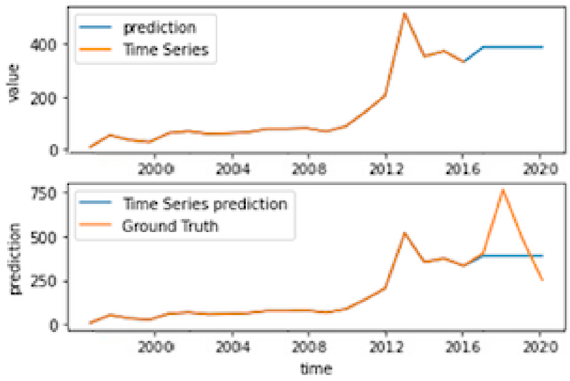

Figure (17) Comparison between LSTM with Tanh prediction and Ground truth for Accommodation activity *Source: Researchers analyzed data using Python

4. For construction activity, the best window size is 3, prediction 1 with RMSE 2135.12. Figure 18 shows the difference between the prediction and the ground truth.

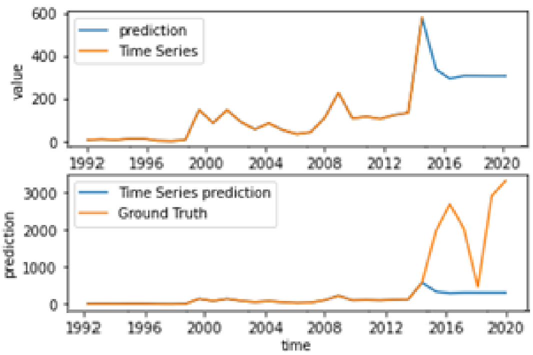

Figure (18) Comparison between LSTM with Tanh prediction and Ground truth for Construction activity *Source: Researchers analyzed data using Python

4- 4 Ensemble learning technique – Averaging

For regression and classification tasks, the averaging technique can be used. The prediction of each year will be the final output represents the average of the outputs of all the models. For Models from M1 to Mn trained and tested with the same dataset, where from Y`1 to Y`n are the predicted output of individual models regarding year j, the final prediction for each year will be the average of the individual models' output as in equation (6)(I. K. Nti, A. F. Adekoya, and B. A. Weyori, 2020).

$$FinalPrediction \mid Year_j = \sum_{i=1}^{n}\left(\frac{\mathcal{Y}`1+\mathcal{Y}`2+..+\mathcal{Y}`\mathrm{n}}{n}\right) \tag{6}$$

4- 5 RMSE between traditional and modern time series forecasting models:

1. Health:

Table (3) RMSE comparison for Health activity forecasting Models

Holt	ARIMA	DNN Window 3 Prediction1	LSTM with Tanh Window 7 Prediction 2	Ensemble learning
25.731185	19.371371	20.39767	18.22697	440.8129

*Source: Researchers analyzed data using R program

Table 3 presents that RMSE for LSTM with Tanh- hyperbolic function is approximately 18, which is the lowest value compared to the other models. Thisindicates that LSTM with Tanh function performs better than the other models for health activity.

2. Information Technology:

Table (4) RMSE comparison for Information Technology activity forecasting Models

Holt	ARIMA	DNN Window2 Prediction1	LSTM with Tanh Window 5 Prediction 1	Ensemble learning
142.22391	133.60202	221.2402	90.65822	220.749

*Source: Researchers analyzed data using R program

Table 4 shows that for information technology, LSTM with Tanh gained the significant value as well with RMSE around 90.

3. Accommodation:

Table (5) RMSE comparison for Accommodation activity forecasting Models

Holt	ARIMA	DNN Window7 Prediction1	LSTM with Tanh Window 3 Prediction 1	Ensemble learning
213.72606	234.27868	183.9886	204.8575	209.6263

*Source: Researchers analyzed data using R program

On the other hand, Table 5 shows that the DNN model for accommodation achieves a good result with RMSE equal to 183.98, which is less than the other models.

Construction.

Table (6) RMSE comparison for Construction activity forecasting Models

Holt	ARIMA	DNN Window 3 Prediction1	LST Mwith Tanh Window 3 Prediction 1	Ensemble learning
2219.37365	1894.228	1387.789	2135.123	1690.609

*Source: Researchers analyzed data using R program

Obviously, from Table 6 , the minimum RMSE for construction activity is 1387.78 which belong to the DNN model. Where RMSE of the other models exceeds DNN.

Results discussion:

1. Health forecasting with LSTM in Figure 19 .

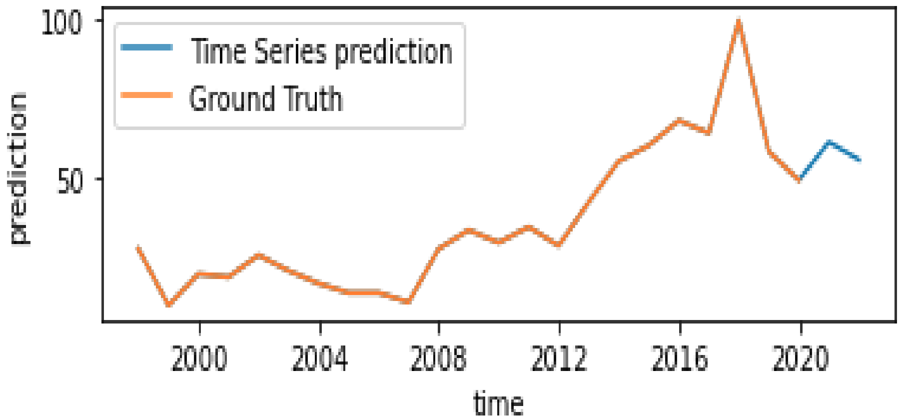

Figure (19) LSTM model for Health forecasting *Source: Researchers analyzed data using Python

2. Information technology forecasting with LSTM in Figure 20 .

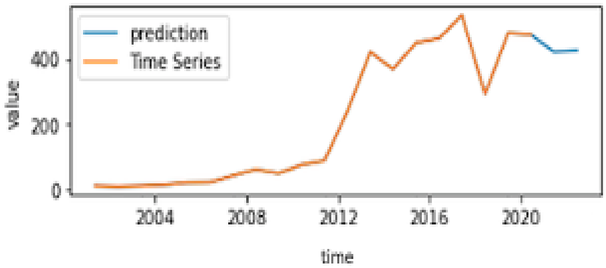

Figure (20) LSTM model for Information Technology forecasting *Source: Researchers analyzed data using Python

3. Accommodation forecasting with DNN in Figure .

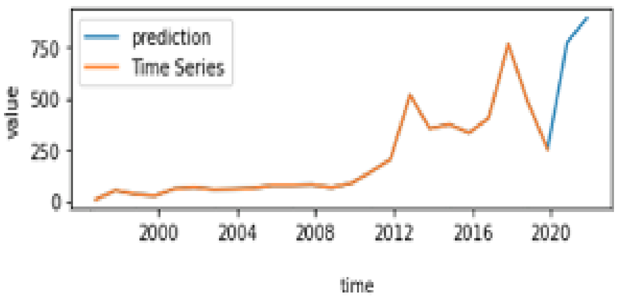

Figure (21) DNN model for Accommodation forecasting *Source: Researchers analyzed data using Python

4. Construction forecasting with DNN in Figure 22 .

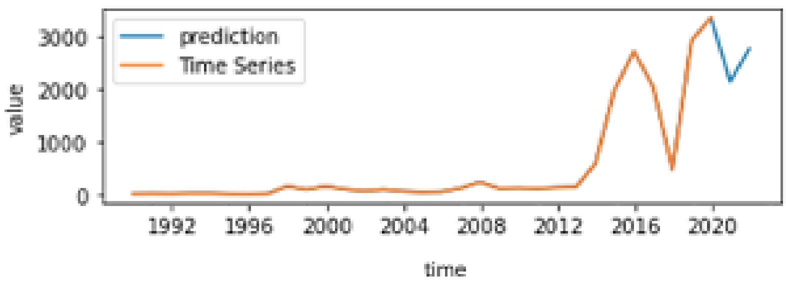

Figure (22) DNN model for Construction forecasting *Source: Researchers analyzed data using Python

Table (7) Short Term Prediction

Activity/Year	2021	2022
Health- LSTM with Tanh	60.507683 Establishments	50.51144 Establishments
Information technology – LSTM with Tanh	772.581 Establishments	888.6364 Establishments
Accommodation- DNN	594.7079 Establishments	1292.4536 Establishments
Construction – DNN	2133.6304 Establishments	2750.5303 Establishments

*Source: Researchers analyzed data using R program

Results of Studies:

1. To answer the research questions, construction activity would have the maximum number of establishments for the next two years as shown in Table 7. The majority of the economic activities have a dramatic infection by covid- 19 after a rapid increase in the vision time. The prediction shows that the trend will start to heal until it hits the general behavior.
2. After the comparison between the models, the results show that deep learning forecasting models are recommended and outperform traditional models in predicting the number of establishments based on RMSE. LSTM was superior and reached the lowest RMSE for health which is equal to 18.22 and 90.65 for the information Technology. DNN with two hidden layers shows the best results for accommodation and construction activity which is equal to 183.98 and 1387.78 respectively.

We conclude that DNN and LSTM have the best fit in forecasting and they provide technological choices for the ministry. The research proved that modern models for time series got the best fit for forecasting activity. For short- term prediction, experiments show that the DNN model with two layers gains the highest performance with two out of four economic activities.

Recommendations.

1. After studying the economic activity behavior, the prediction indicates that the health activity will get the minimum number of establishments. Based on this observation, the ministry needs to define policies that facilitate investments in the health sector.
2. This research project proposed models to predict several economic activities trends for Saudi and Non- Saudi establishments in Saudi Arabia by using time series forecasting on human resource and social development data. For future studies, fine- tuning hyperparameters and more elaborated deep learning models will be considered. The research can be extended to include not exist establishments.
3. For Future work, we expect analysing public sentiment from online sources or mining tweets about economic activities for the same period to compare it with added establishments time series to investigate whether the general opinion can assist in better predicting the economic trend. By utilizing both information, a hybrid model may predict the trend more accurately.

References.

- A. Ahmed and M. S. A. Salan. (2019). Forecasting GDP Of Bangladesh Using Time Series Analysis. International Journal of Mathematics and Statistics Invention (IJMSI), Issue 1, pp. PP- 07- 15.
- A. Brodeur, D. M. Gray, A. Islam, and S. Bhuiyan. (2020). A Literature Review of the Economics of COVID- 19. Issue4.
- A. Brodeur, D. M. Gray, A. Islam, and S. Bhuiyan. (2020). A Literature Review of the Economics of COVID- 19. Journal of economic surveys, Issue4, pp. Pages 1007- 1044.
- A. Fathalla, A. Salah, K. Li, K. Li, and P. Francesco. (n.d.). Deep end- to- end learning for price prediction of second- hand items.
- A. Gupta, R. Gupta, and N. Garg. (2021). An efficient approach for classifying chest X- ray images using different embedder with different activation functions in CNN. Journal of Interdisciplinary Mathematics, Issue 2, pp. pp. 1- 13.
- Atienza, R. (2020)., Advanced Deep Learning with TensorFlow 2 and Keras: Apply DL, GANs, VAEs, deep RL, unsupervised learning, object detection and segmentation, and more. Packt Publishing Ltd.
- Chatfield, C. (2000). Time- series forecasting. CRC press.
- D. Camska and J. Klecka. (2020). Comparison of prediction models applied in economic recession and expansion. Journal of Risk and Financial Management, no. 3, p. p. 52.
- D. Entekhabi, R. H. Reichle, R. D. Koster, and W. T. Crow. (2010). Performance metrics for soil moisture retrievals and application requirements. Journal of Hydrometeorology, no. 3, pp. pp. 832- 840.
- D. Neumark, J. Zhang, and B. Wall. (2005). Business establishment dynamics and employment growth. Hudson Institute Research Paper, no. 05- 02.

- D. P. Kingma and J. Ba. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.
- D. Susskind and D. Vines. (2020). The economics of the COVID- 19 pandemic: an assessment. no. Supplement_1, pp. pp. S1- S13.
- E. Alajrami et al. (2020). Handwritten Signature Verification using Deep Learning.
- Eissa, N. (2020). Forecasting the GDP per Capita for Egypt and Saudi Arabia Using ARIMA Models.
- H. Hota, R. Handa, and A. Shrivas. (2017). Time series data prediction using sliding window based RBF neural network. International Journal of Computational Intelligence Research, no. 5, pp. pp. 1145- 1156.
- H. Niu, K. Xu, and W. Wang. (2020). A hybrid stock price index forecasting model based on variational mode decomposition and LSTM network. Applied Intelligence, no. 12, pp. pp. 4296- 4309.
- I. K. Nti, A. F. Adekoya, and B. A. Weyori. (2020). A comprehensive evaluation of ensemble learning for stock- market prediction. Journal of Big Data, no. 1, pp. pp. 1- 40.
- J. H. Stock and M. W. Watson. (1993). A procedure for predicting recessions with leading indicators: Econometric issues and recent experience, in Business cycles, indicators, and forecasting. University of Chicago Press.
- J. Shen and M. O. Shafiq. (2020). Short- term stock market price trend prediction using a comprehensive deep learning system. Journal of big Data, no. 1, pp. pp. 1- 33.
- J. Sun, L. Di, Z. Sun, J. Wang, and Y. Wu. (2020). Estimation of GDP Using Deep Learning With NPP-VIIRS Imagery and Land Cover Data at the County Level in CONUS. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, p. pp. 1400.
- J. Zhao, D. Zeng, S. Liang, H. Kang, and Q. Liu. (2020). Prediction model for stock price trend based on recurrent neural network. Journal of Ambient Intelligence and Humanized Computing, pp. pp. 1- 9.
- K. Khare, O. Darekar, P. Gupta, and V. Attar. (2017). Short term stock price prediction using deep learning. in 2017 2nd IEEE international conference on recent trends in electronics, information & communication technology (RTEICT), pp. pp. 482- 486.
- K. V. S. da Costa, F. L. C. da Silva, and J. d. S. C. Coelho. (2020). Forecasting Quarterly Brazilian GDP: Univariate Models Approach. arXiv preprint arXiv:2010.13259.
- L. Fahrmeir, T. Kneib, S. Lang, and B. Marx. (2007). Regression. Springer.
- M. Alawin and A. Abu- Aisheh. (2020). Number Of Establishments And Economic Growth: Case Of Kuwait, 2001- 2014. Applied Econometrics and International Development, no. 2, pp. pp. 145- 160.
- N. Budhani, C. Jha, and S. K. Budhani. (2014). Prediction of stock market using artificial neural network. International Conference of Soft Computing Techniques for Engineering and Technology (ICSCTET), pp. pp. 1- 8.

- P. Golik, P. Doetsch, and H. Ney. (2013). Cross- entropy vs. squared error training: a theoretical and experimental comparison. in Interspeech, pp. pp. 1756- 1760.
- Qi- Qiao, HePatrick Cheong- Iao Pang,Yain- Whar Si. (2019). Transfer Learning for Financial Time Series Forecasting. Pacific Rim International Conference on Artificial Intelligence, pp. pp 24- 36.
- R. Baldwin and B. W. Di Mauro. (2020). Economics in the time of COVID- 19: A new eBook. VOX CEPR Policy Portal.
- T. J. Mbah, H. Ye, J. Zhang, and M. Long. (2021). Using LSTM and ARIMA to Simulate and Predict Limestone Price Variations. Mining, Metallurgy & Exploration, pp. pp. 1- 14.
- Tipirisetty, A. (2018). Stock price prediction using deep learning. IEEE.
- Y. Qu and X. Zhao. (2019). Application of LSTM neural network in forecasting foreign exchange price. Journal of Physics: Conference Series, no. 4.
- Z. J. Acs, D. B. Audretsch, P. Braunerhjelm, and B. Carlsson. (2012). Growth and entrepreneurship. Small Business Economics, no. 2, pp. pp. 289- 300.