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Modelling the Tourism Revenue of Türkiye Using Deep Learning Networks

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ABSTRACT

The gross domestic product of countries plays a key role in the development and wealth of nations. There are several components of the gross domestic product, such as industrial revenue, revenue from services, and tourism revenue. Türkiye is located in Anatolia, which is very rich from a historical viewpoint. Therefore, Türkiye attracts tourists from all over the world, making its tourism revenue an important contributor to its gross domestic product. This study aimed to model the tourism revenue of Türkiye using machine learning methods. In this study, the tourism revenue of Türkiye, dependent on the number of tourists, oil prices, and the exchange rate, are modelled for the period of 2008-2022. The data of these variables were taken from official sources, and then the causality analyses were carried out. As the next step, the tourism revenue is modelled as a function of the number of tourists, oil prices, and the exchange rate. A deep learning network is developed using the Python programming language for modelling the tourism revenue. The developed deep learning network is then trained using a portion of the data. The performance of the developed deep learning network is then evaluated using the performance metrics such as the coefficient of determination, mean absolute error, root means square error, and the mean absolute percentage error. These metrics show that the developed deep learning network successfully models the tourism revenue dependent on the number of tourists, oil prices, and the exchange rate.

1. Introduction

The development and wealth of nations are strongly dependent on the gross domestic product (GDP) of the countries. GDP has several components, such as industrial revenue, revenue from services, income from international trade, and tourism revenue. The share of these components obviously differs for each country. The tourism revenue of Türkiye has a significant share in its GDP due to the fact that Türkiye is located in Anatolia, which accommodated several civilizations in history, making it rich from the historical perspective (Bahar, 2006; Bal et al., 2016). This historical importance, combined with the modern summer holiday facilities, contributes to the tourism revenue of Türkiye. Modelling and forecasting tourism revenue require the utilization of various econometric variables, as demonstrated in the literature. The modelling of the tourism revenue is important for the planning of the manpower for services and for the consideration of its effects on economic growth. This study aimed to model the tourism revenue of Türkiye using machine learning methods.

2. Literature Review

Modelling the tourism revenue for Türkiye has taken great attention for a long time as international tourism soars due to the advancements in transportation and tourism facilities. For example, in a recent study, the tourism demand data of the 2012-2016 period is considered and autoregressively modelled using artificial neural network (ANN) methods for the prediction of the future trends of tourism demand and revenue (Sercek, 2017). In another study, the effects of the tourism revenue on the current account balance is investigated for the period of 2013-2020 employing ANN methods where the lagged values of the past tourism data are used as inputs for the ANN structure (Cinel et al, 2021). In a similar study, the inbound tourism demand for the period of 1987-2012 was modelled using several neural network types, such as the multilayer perceptron, radial-based function, and time delay neural networks (Cuhadar, 2013). The effects of the tourism demand on economic growth is also an active research area and has been modelled for Türkiye using the Engle-Granger cointegration method for the period of 2003-2018 (Demir et al., 2021). Another study has also demonstrated that the tourism revenue strongly supports economic growth for Türkiye, which was concluded utilizing the Granger causality analysis (Gündüz et al., 2005). The vector autoregressive method has also been used for analysing the effects of tourism revenue on economic growth (Bahar, 2006). Kizilgol et al. have also investigated the relationship between tourism revenue on economic growth using Toda-Yamamoto causality analysis (Kizilgol et al., 2008). This relationship was also analysed using the Johansen cointegration test for Türkiye (Bal et al., 2016) for the period of 1972-2014. Another study employed both Granger causality and Johansen cointegration methods for the analysis of the relationship of tourism revenue and the economic growth of Türkiye for the period of 1980-2014 (Hüseyni et al., 2017). This relationship is also investigated for other countries in the literature. For example, Govdeli et al. used panel cointegration methods for analysing the relationship between tourism revenue and other economic parameters for 34 OECD countries in the period of 1997-2012 (Govdeli et al., 2017). The tourism revenue of Spain and Italy was studied using panel data analysis for the period of 1990-2004 in (Cortes-Jimenez 2008). They have concluded that tourism revenue has a positive effect on economic growth.

Panel data analysis is also employed for the analysis of the effects of the tourism revenue for 42 African countries, and it is found that tourism revenue has positive effects on both the economic growth and the per capita revenue (Fayissa et al, 2008). In another study, the positive effects of the tourism revenue on the economic development in Greece for the period of 1960-2000 were exposed using the Johansen cointegration and Granger causality analysis (Dritsakis, 2004). Cointegration and causality analyses have also been used for the investigation of the effects of tourism revenue on the economic growth of Latin America for the period of 1985-1998 (Eugenio-Martin et al. 2004). In another study, it is shown that long-term economic growth depends on the international tourism revenue for Spain for the period of 1975-1997 (Balaguer et al., 2002).

On the other hand, there are various factors affecting tourism revenue. One of these factors is the exchange rate. In a study regarding the tourism revenue of Türkiye, the effect of the exchange rate on the tourism revenue is investigated using a breakpoint vector autoregressive approach for the 2012-2019 period (Akar et al., 2021). Another factor affecting the tourism revenue is the number of visitors therefore, in another study, the number of tourists from Germany visiting Türkiye has been modelled employing neural network methods for the period of 1998-2019 (Erdogan et al., 2021). The effects of the tourism revenue on the economic growth of seven Mediterranean countries, namely Türkiye, Spain, Italy, France, Germany, Portugal, and Crotia have been analysed utilizing a panel data regression model, and it is concluded that 1% increment of the tourism revenue increases the economic growth by 0.07% (Saridogan, 2019). The relationship between the number of visitors and the tourism revenue for Türkiye in the 2012-2019 period is investigated using grey model GM (1,1), and it is found that the tourism revenue can be estimated from the number of tourists (Simsek et al., 2021). In another study, the effects of the tourism revenue on the foreign trade balance for Türkiye in the period of 2013-2020 were analysed employing forward and back propagation artificial neural networks, and it was found that tourism revenue has a strong effect on the foreign trade balance (Cinel et al., 2021). The relationship between the number of tourists and the tourism revenue has been investigated using vector autoregressive and Granger causality methods for Türkiye for the period of 2005-2012, and it is shown that there is a bidirectional relationship between these variables (Erkan et al., 2013). The vector autoregressive approach has also been used in another study for the analysis of the relationship between the tourism revenue and the economic growth of Türkiye in the 2003-2018 period, and it is shown that there is a single directional causality from the tourism revenue to the economic growth (Yenisu 2018).

There are also comparative studies regarding the modelling of the tourism revenue of Türkiye. For example, the study of Cuhadar employs both autoregressive moving averages and artificial neural network methods for the autoregressive modelling of the tourism revenue of Türkiye for the 2003-2019 period (Cuhadar, 2020). The modelling of the economic variables requires some properties, such as stationarity. This is also valid for tourism revenue. Therefore, the tourism revenue data of Türkiye is examined whether it is stationary or not for the period of 2012-2019, and it is shown that the tourism revenue data is stationary therefore, linear models can be used for modelling (Fendoglu et al., 2019). Tourism revenue is a key variable in various analyses therefore, the relationship of tourism revenue with economic growth, current account balance, and the exchange rate are studied in three different models in another study where they have shown that there are various causality relationships between the tourism revenue and these variables (Kara et al. 2012). The artificial neural networks have also been utilized for the modelling of the tourism revenue with data mining tools, and it is shown that the tourism revenue of Türkiye can be estimated using artificial neural networks on a monthly basis. In summary, these studies show that the tourism revenue of Türkiye is an important economic variable whose relationship with other variables is extensively studied in the literature using several different approaches, including artificial neural networks, data mining, autoregressive moving average methods, and vector autoregressive models. In this study, we have employed a newer approach called deep learning networks for the modelling of the tourism revenue of Türkiye dependent on the number of tourists, Brent oil prices, and the exchange rate using Python programming language, as explained in the following sections.

3. Methods

The tourism revenue, number of tourists, and exchange rate (USD/TRY) have been gathered from the Turkish Statistical Institute (Turkstat) as the official data source for Türkiye. The Brent oil prices are taken from international data sources of oil commodity prices. The monthly data between the period of 2008M1-2022M09 are considered for modelling in this work. The data for the period of 2008-2022 are included since the monthly tourism data is available from the beginning of the year 2008.

The data taken from the Turkish Statistical Institute for the tourism revenue, number of tourists, and the exchange rate and the Brent oil price data taken from international sources are firstly seasonally adjusted using the seasonal and trend decomposition loess method (STL). Then, the pairwise Granger causality analyses were carried out on the data to determine the causality relationships among the data and to verify that the tourism revenue can be modelled dependent on the number of tourists, exchange rate, and oil prices. The tourism revenue is then modelled using the deep learning network developed in Python programming language, whose results are given in the next section.

4. Results and Discussion

First of all, in order to perform Granger causality tests, the data have been seasonally adjusted in Eviews software (Aljandali et al., 2018). Seasonal and trend decomposition employing the loess method (STL) have been used for the seasonal adjustment, where the periodicity has been set as 12 since monthly data is modelled in this study. The seasonal and trend decomposition of the tourism revenue, number of tourists, Brent oil prices and the exchange rate are shown in Figures 1, 2, 3, and 4, respectively.

The Granger causality relationships among the tourism revenue data, number of tourists data, exchange rate data, and the Brent oil price data are also investigated by employing the Eviews software. The group statistics menu is utilized for performing the Granger causality test, where automatic lag selection is used for the pairwise causality tests. The Granger causality test result statistics and the corresponding probability values are shown in Table 1.

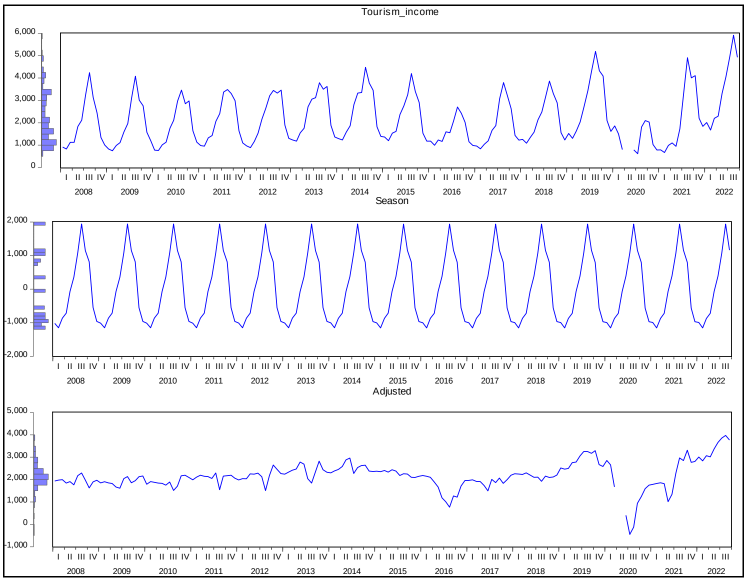

Figure 1. Seasonal adjustment of the tourism revenue data.

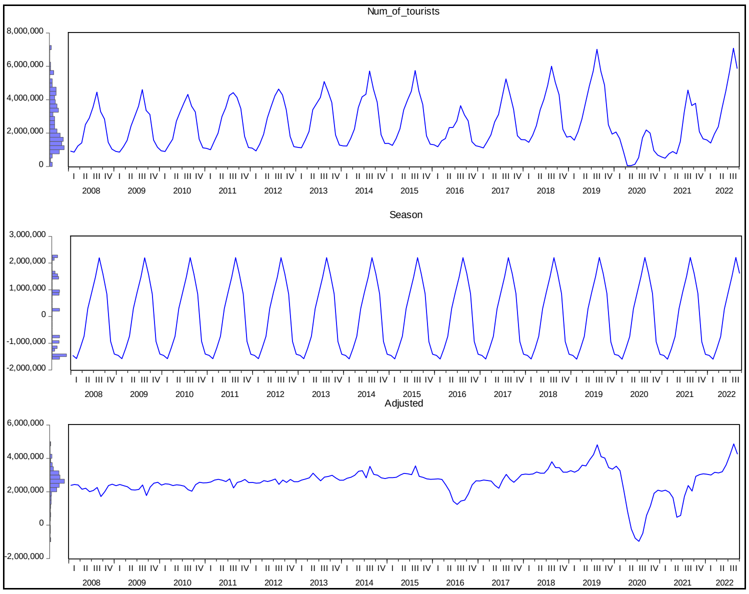

Figure 2. Seasonal adjustment of the number of tourists data.

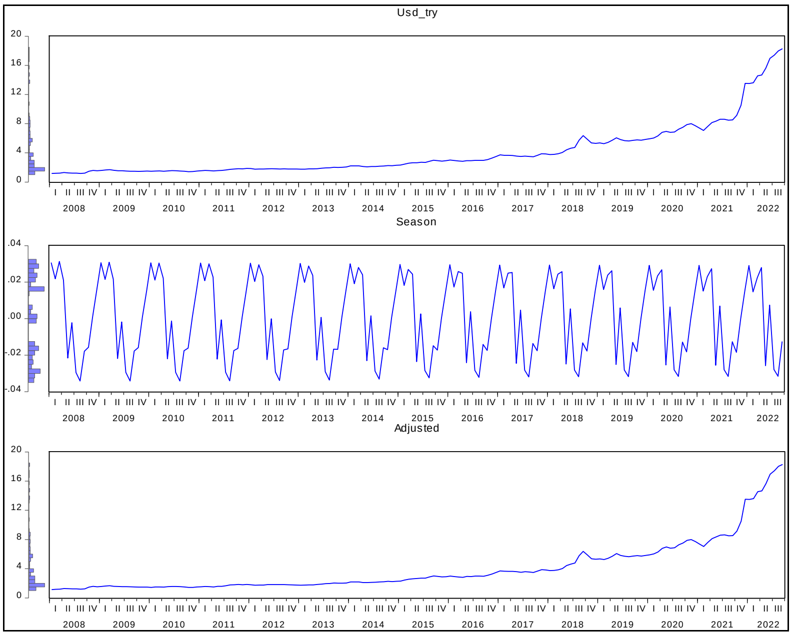

Figure 3. Seasonal adjustment of the exchange rate data.

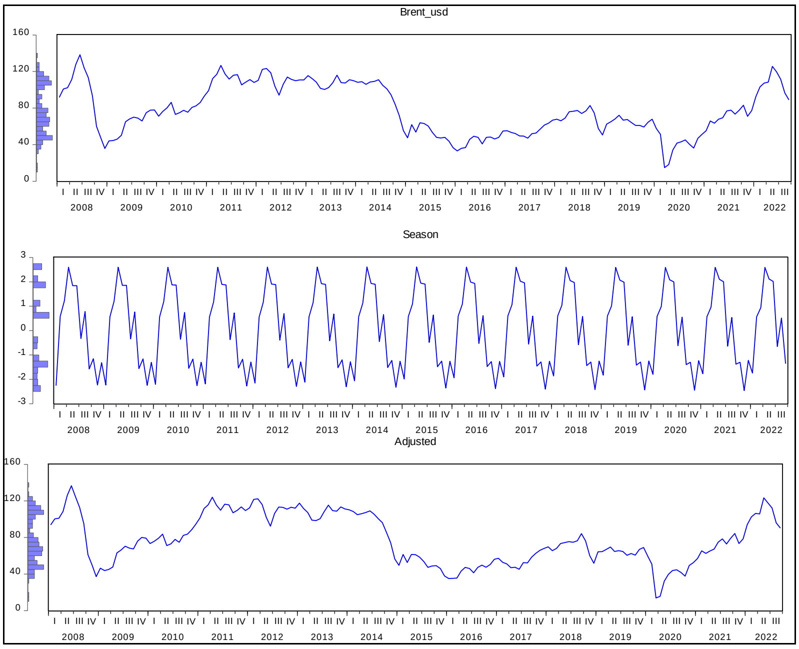

Figure 4. Seasonal adjustment of the Brent oil price data.

The Granger causality relationships among the considered variables are shown in a diagram in Figure 5 as the results of the probability values of Table 1. The causality pairs shown in bold face are the items where the null hypothesis, which is the absence of the Granger causality, is not valid. In other words, the pairs with the bold face indicate where the Granger causality is confirmed. The causality relationships among the considered variables are shown in Figure 5.

Table 1. Pairwise Granger causality test results.

Pairwise Granger causality tests			
Date: 02/07/23 Time: 04:14			
Sample: 2008M01 2022M09			
Null Hypothesis:	Obs	F-statistic	Prob.
NUM_OF_TOURISTS_SA does not Granger Cause BRENT_USD_SA	176	0.49871	0.6082
BRENT_USD_SA does not Granger Cause NUM_OF_TOURISTS_SA	**176**	**2.71520**	**0.0391**
TOURISM_REVENUE_SA does not Granger Cause BRENT_USD_SA	176	2.15844	0.1436
BRENT_USD_SA does not Granger Cause TOURISM_REVENUE_SA	**176**	**3.57854**	**0.0402**
USD_TRY_SA does not Granger Cause BRENT_USD_SA	176	0.09111	0.7631
BRENT_USD_SA does not Granger Cause USD_TRY_SA	176	1.33959	0.2487
TOURISM_REVENUE_SA does not Granger Cause NUM_OF_TOURISTS_SA	176	2.24298	0.1361
NUM_OF_TOURISTS_SA does not Granger Cause TOURISM_REVENUE_SA	**176**	**3.19608**	**0.0435**
USD_TRY_SA does not Granger Cause NUM_OF_TOURISTS_SA	176	2.19911	0.1399
NUM_OF_TOURISTS_SA does not Granger Cause USD_TRY_SA	176	0.03065	0.8612
USD_TRY_SA does not Granger Cause TOURISM_REVENUE_SA	**176**	**8.85430**	**0.0034**
TOURISM_REVENUE_SA does not Granger Cause USD_TRY_SA	**176**	**3.46479**	**0.0336**

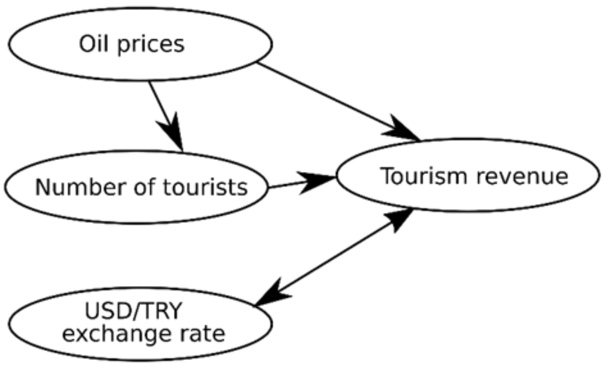

Figure 5. Granger causality relationships among the considered variables.

As can be observed from Figure 5, there is a bidirectional causality relationship between the exchange rate and tourism revenue. In addition, the number of tourists also has a single directional causality relationship to tourism revenue. Furthermore, oil prices have a single-directional causality response to the number of tourists and tourism revenue. In summary, oil prices, the number of tourists, and the exchange rate affect tourism revenue according to the Granger causality analysis results. Therefore, it is shown that the tourism revenue can be modelled dependent on the oil prices, the number of tourists, and the exchange rate.

It is shown that the tourism revenue can be modelled dependent on the oil prices, the number of tourists, and the exchange rate. A deep learning network is developed in Python programming language for the modelling of the tourism revenue dependent on the given independent variables. A deep learning network consisting of an input layer, three hidden layers, and an output layer is constructed in Python programming language, as shown in Figure 6.

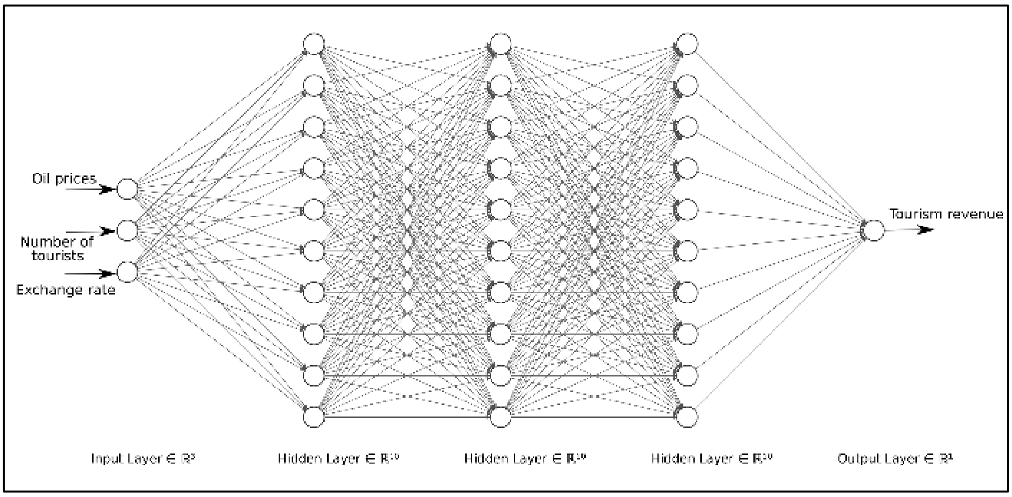

Figure 6. The structure of the developed deep learning network for the modelling of the tourism revenue.

The developed deep learning network has ten neurons in each of the hidden layers, which have hyperbolic tangent functions as the nonlinear activation functions. The available data is automatically separated as the training and test data using the test_train_split class of the SKLearn library of the Python programming language (Rasckha et al., 2019). 30% of the data is used as training data, while the remaining 70% is utilized as test data. The training phase of the deep learning network is successfully completed using the stochastic gradient-based optimizer, as shown in Figure 7.

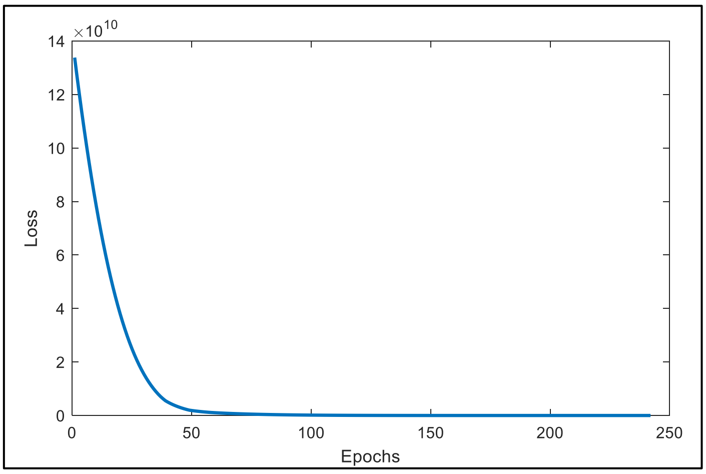

Figure 7. Loss curve of the training phase of the deep learning network.

The loss curve of the training phase is shown in Figure 7 where it can be observed that the training phase is completed under 250 epochs. The tourism revenue data obtained from the trained deep learning network and the actual tourism revenue data are plotted on the same axis pair in Figure 8. It can be seen from Figure 8 that the developed deep learning network successfully models the tourism revenue.

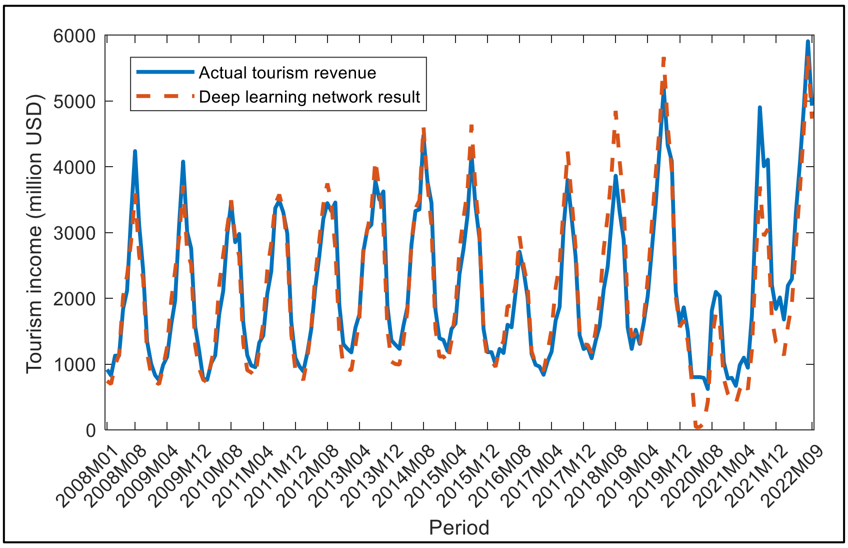

Figure 8. Actual tourism revenue and the tourism revenue obtained from the developed deep learning network.

The developed deep learning model accurately models the tourism revenue data, as can be observed from Figure 8. In order to quantitatively assess the performance of the developed model, the coefficient of determination (R^2), mean absolute error (MAE), root mean square error (RMSE), and the mean absolute percentage error (MAPE) values are calculated in Python employing the sklearn metrics library. The obtained values are given in Table 2.

Table 2. Performance metrics of the developed deep learning model.

Parameter	R^2	MAE	RMSE	MAPE
Value	0.91	247.73	326.17	0.13

Note: MAE, RMSE, and MAPE have units of million USD.

The coefficient of determination has the value of R^2=0.91, demonstrating that the developed deep learning network successfully models the actual tourism revenue data on a monthly basis. It is worth noting that these results show that deep learning networks can accurately be used to model economic variations, and similar machine learning networks can be used to model economic variables of other countries.

5. Conclusion

The tourism revenue of Türkiye for the period of 2008-2022 has been modelled in this study. A deep learning network is developed in Python programming language for the modelling of the monthly tourism revenue data. The pairwise Granger causality tests are firstly performed on the considered economic variables, and it is shown that the Brent oil prices, the number of tourists, and the exchange rate affect the tourism revenue. Therefore, the tourism revenue data is modelled dependent on the Brent oil prices, the number of tourists, and the exchange rate. The developed deep learning network has one input layer, three hidden layers, and one output layer. Each hidden layer of the developed deep learning network consists of ten neurons enabling a fast training phase. 30% of the data is used as the training data, and 70% of the data is utilized as the test data, which is a standard ratio for deep learning network topologies. The loss curve of the training phase shows that the training phase is completed under 250 epochs. After the training phase, the actual tourism revenue data and the data obtained from the developed deep learning model are plotted on the same axis pair, which shows that the developed deep learning network successfully models the tourism data. Furthermore, performance metrics of the developed deep learning network, namely coefficient of determination, mean absolute error, root mean square error, and the mean absolute percentage error, are calculated. The values of these performance metrics also demonstrate the accurate modelling performance of the developed deep learning network, and the coefficient of determination is found to have a value of R^2=0.91. Therefore it can be concluded that deep learning networks can be used to model tourism revenue data effectively. It is worth noting that similar deep-learning networks can be used to model the economic variables of other countries.

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