International Journal of Social Science And Human Research

ISSN(print): 2644-0679, ISSN(online): 2644-0695

Volume 06 Issue 03 March 2023

DOI: 10.47191/ijsshr/v6-i3-59, Impact factor- 6.686

Page No: 1837-1848

Modelling the Gross Domestic Product and the Per Capita Income of Türkiye using Autoregressive Deep Learning Networks

Dr. Cagatay Tuncsiper

PhD., Centrade Fulfillment Services co-founder, 35580, Karsiyaka, Izmir, Türkiye. ORCID: 0000-0002-0445-3686

ABSTRACT: The gross domestic product and the per capita income are leading indicators regarding the income and the wealth of nations. The gross domestic product and the per capita income can be modelled dependent on various econometric data such as the export revenue, tourism revenue, trade deficit and the industrial revenue. In this work, an alternative and novel method is presented for the modelling of the gross domestic product and the per capita income. In this study, the gross domestic product and the per capita income are modelled autoregressively employing deep learning networks namely autoregressive deep learning networks. The input data of the developed deep learning networks are taken as the past values of the modelled variable making the deep learning networks effectively autoregressive models. As application examples of the autoregressive deep learning models, the gross domestic product and the per capita income data of Türkiye for the period of 1960-2021 are separately modelled. The autoregressive deep learning networks are developed in Python programming language. The coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE) and the root mean square error (RMSE) of the developed models are also computed. The plots of the results of the developed autoregressive deep learning models and the performance metrics of the models show that the developed autoregressive deep learning models can be utilized to accurately model the gross domestic product and the per capita income.

KEYWORDS: Gross domestic product, per capita income, deep learning networks, autoregressive modelling, Python.

I. INTRODUCTION

The gross domestic product and the per capita income are considered to be the leading indicators of the economic development status of a country or region. The gross domestic product can be defined as the sum of all income originated from goods and services in a country or region for a specific period. On the other hand, per capita income is obtained by the gross domestic product divided by the population. Therefore, the gross domestic product and the per capita income are interrelated but separate concepts.

The accurate modelling and forecasting of the gross domestic product and the per capita income is crucial since these data are guiding indicators for the determination and assessment of the economic development objectives. Moreover, the forecasts of the gross domestic product and the per capita income are also used to predict economic contraction or economic expansion in advance. The forecasting of the macroeconomic variables such as the gross domestic product and the per capita income are complex processes since their forecasting computations require the selection of the appropriate independent variables and methods. On the other hand, several economic and financial decisions are made considering the expectations of the gross domestic product and the per capita income therefore their forecasting require a high level of accuracy. The modelling and the forecasting of econometric variables such as the gross domestic product and the per capita income can be performed in two ways namely with or without exogenous variables. In conventional modelling techniques such as the autoregressive moving average (ARMA) method, the previous values of the dependent variable is used in the model and the computation and optimization of the coefficients of the model regarding previous values is the main interest in the model development. On the other hand, some econometric models describe the dependent variable as a function of other data called independent variables. These types of models can be linear or nonlinear and the main point of the model development is the finding and optimization of the coefficients of these linear or nonlinear equations. In addition, there exist new generation of nonlinear models belonging to the machine learning class.

Machine learning is a set of artificial intelligence where the adjustment or optimization of model parameters are performed dependent on the data fed into the system. This adjustment or optimization of the model coefficients is called as the training phase in which the machine learning blackbox “learns” from the data. The main application areas of machine learning is classification and regression. Classification can be defined as the assignment of the input data into distinctive classes such as automobile plate recognition or feature recognition in photographs or moving pictures. Therefore, classification is obviously the practical application area of the machine learning methods in daily life. On the other hand, the second application area of the machine learning methods is the regression in which the relationship of input and output data of an unknown system can be modelled employing the data fed into the system. Regression using machine learning methods is utilized in a wide array of application areas in science and technology such as the modelling of the relationship of various economic variables. Artificial neural networks and deep learning networks are subsets of the machine learning realm which employ neural-synaptic structures for the modelling of unknown relationship among variables. Deep learning networks express the inclusion of multiple hidden layers in the network providing better modelling performance for problems with relatively low number of samples.

A new approach consisting of the combination of autoregressive methodology and deep learning networks is utilized for the modelling of the gross domestic product and the per capita income in this study. The modelling of the gross domestic product and the per capita income of Türkiye for the 1960-2021 period is used as an example problem. In the standard deep learning networks, a dependent output variable is modelled using one or multiple independent input variables however in our approach, the past values of the output variable itself is used as input variables in the deep learning networks hence providing autoregressive deep learning concept. The gross domestic product and the per capita income of Türkiye for the 1960-2022 period are modelled with separate autoregressive deep learning networks developed in Python programming language. The 70% of the available data is utilized as the training data and the remaining 30% of the data is used as the test data as the standard procedure. The plots of the actual gross domestic product and the per capita income and their model results are plotted to visually inspect the performance of the developed autoregressive deep learning models. In addition, standard performance metrics of the models namely the coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE) and the root mean square error (RMSE) are computed in Python which also show the high accuracy of the developed autoregressive deep learning models.

II. LITERATURE ANALYSIS

There are vast amount of studies regarding the modelling of the gross domestic product and the per capita income employing both conventional and machine learning models in the literature considering the importance of the accurate modelling of these macroeconomic data. For example, Barsoum and Stankiewicz studied the modelling of the gross domestic product of the United States employing mixed data sampling approach and have shown that the mixed data sampling approach has better performance compared to the restricted lag polynomials method [1]. In another study, Kouzikas has analysed and modelled the gross domestic product of the United States utilizing new weighted support vector machines method and concluded that their approach provides better performance than the conventional artificial neural network and support vector machine based models [2]. Similarly, Xu et al. have used a modified back propagation algorithm in an improved artificial neural network model for the modelling and forecasting the gross domestic product and have concluded that their method provides better accuracy compared to standard artificial neural networks [3]. Lehmann and Wohlrabe have used large set of indicators for the linear modelling of the gross domestic product for two German states namely Free State of Saxony and Baden-Württemberg and have shown that the forecasting of the gross domestic product can be more accurately performed using their method [4]. Gogas et al. have performed gross domestic product modelling for the United States for the period of 1967-2007 utilizing support vector machine approach and have concluded that modelling with divisia monetary aggregate provides better forecast evaluation [5]. Tkacz has studied the comparison of the artificial neural network models and the standard linear univariate models for the modelling of the gross domestic product of Canada for the period of 1968-1999 and has shown that the artificial neural network models provide higher accuracy compared to the standard models [6]. In another study, Kordanuli et al. have employed artificial neural network models with extreme learning machine and back propagation methods for the prediction of the gross domestic product where they have shown that artificial neural networks with extreme learning method is advantageous compared to the artificial neural networks with back propagation algorithm [7]. Autoregressive integrated moving average (ARIMA), vector autoregressive and autoregressive methods are used in another work where the gross domestic product of Sweden in the period of 1993-2009 is modelled and it is shown that the autoregressive method gives the best results [8]. In another study, the gross domestic product of Japan for the period of 2001-2008 is modelled employing machine learning methods namely the gradient boosting model and the random forest model, the performances of these models are evaluated with the coefficient of determination and the mean absolute error criteria in which it is observed that the gradient boosting model performs better than the random forest model [9]. In another work, the gross domestic product of China is modelled employing a new grey forecasting model with time power term for a higher accuracy and the gross domestic product of China is forecasted for the 2020-2029 period [10].

The quarterly gross domestic product data of France is modelled in another study where bridge models are used with selected explanatory variables to increase the accuracy of the developed model [11]. The gross domestic product data of Egypt for the 1965-2016 period is modelled employing the Box-Jenkins approach leading to autoregressive integrated moving average model where it is shown that the ARIMA(1,2,1) model accurately describes the gross domestic product of Egypt [12]. In a recent study, quantum computing with deep learning namely deep neural decision trees are utilized for the modelling of the gross domestic product data of 70 selected countries where it is concluded that the deep neural decision trees can provide high performance forecasting results thanks to its large-scale processing with mini-batch-based learning phase [13]. In a recent work, big data methods namely the usefulness of dimension reduction, machine learning and shrinkage methods are employed for the nowcasting and forecasting the gross domestic products of emerging market economies of Brazil, Mexico, South Africa and Türkiye where it is shown that the utilization of multiple big data methods in conjunction with local and global diffusion indices can be used for the modelling and forecasting the gross domestic product [14]. In another study, the gross domestic product of Malaysia for the period of 1970-2015 is modelled employing artificial neural network methods where eight variables are utilized as inputs which are the export revenue, the import expenses, the total private consumption, the total government expenditure, the total consumer price index, the inflation rate, the foreign direct investments and the money supply and it is shown that the artificial neural network model describes the gross domestic product of Malaysia accurately with these input variables [15]. In another work, the gross domestic product of Jordanian economy is modelled for the period of 1976-2019 utilizing the Box-Jenkins methodology and it is exposed that the autoregressive integrated moving average model ARIMA(1,1,0) describes the gross domestic product of the Jordanian economy with high accuracy [16]. Similarly, the gross domestic product of Kenya is modelled with the Box-Jenkins method in another study for the 1960-2012 period where it is shown that autoregressive integrated moving average model ARIMA(2,2,2) provides the best accuracy for the modelling of the economy of Kenya [17]. In another work, the quarterly gross domestic product of Canada is modelled using a short-term indicator-based model utilizing all of the available monthly data which is gathered from the official data sources automatically to increase the accuracy of the developed model and it is observed that the developed model provides accurate real-time forecasting performance [18]. There are several studies in the literature for the modelling and forecasting the gross domestic product of Türkiye. For example, Soyler and Kizilkaya employed three different machine learning methods namely multilayer perceptron, radial basis function network and recurring Elman networks for the modelling and forecasting of the gross domestic product of Türkiye for the period of 1988-2010 and they have concluded that radial basis function networks provide the best modelling accuracy [19]. In another study, Simsek and Kadilar have used the autoregressive distributed lag approach with the error correction model to model the gross domestic product of Türkiye for the 1960-2004 period dependent on the real export revenue and labour force [20].

Duzgun has studied the modelling and forecasting of the gross domestic product of Türkiye for the 1987-2007 period using autoregressive integrated moving average and artificial neural network models and compared their performances with the mean absolute error, mean square error and root mean square error criteria and concluded that the artificial neural networks provide better performance compared to the autoregressive integrated moving average model [21]. In another study, Demir and Sever worked on the impact of the tax load for 11 OECD countries including Türkiye for the period of 1980-2014 employing panel data analysis and have shown that the 1% increment of the tax load corresponds to the reducement of the gross domestic product by 0.13% [22]. Similarly, Karayilmazlar and Gode studied the impact of the tax load on the gross domestic product of Türkiye for the 1965-2015 period employing vector error correction model and have shown that the increment of the tax load causes a reduction in the gross domestic product [23]. Celikay has modelled the gross domestic product of Türkiye for the 2005-2014 period dependent on the tax burden of provinces using autoregressive distributed lag approach and have concluded that the 1% increment of the tax burden decreases the gross domestic product by 0.6% in the short-run but increases the gross domestic product by 0.9% in the long-run [24]. Furceri and Karras studied the modelling of the gross domestic product dependent on the tax burden for 26 selected countries for the period of 1965-2007 using panel data analysis and have shown that the 1% increment in the tax burden has around 0.5% negative effect on the gross domestic product [25]. In a similar study, Reed has studied the economies of the 48 states of the United States for the 1970-1999 period and have modelled the per capita income where they have shown that the tax burden has negative impacts on the per capita income [26]. In another work, the economic growth of the United States for the period of 1996-2016 is modelled dependent on the tax income and it is observed that the increment of the tax revenue has an important effect on the growth of the gross domestic product [27]. The fixed effect model is utilized in another study for the modelling of the gross domestic products of 35 OECD countries for the period of 1996-2016 where the tax revenue growth, personal income tax, corporate income tax, social security contributions, tax on goods and services and tax on property are taken as the independent variables and the gross domestic product is the dependent variable and it is shown that 1% increment in the tax revenue causes a 0.29% long-run increment of the gross domestic product [28]. The dependence of the gross domestic product on the tax burden for Türkiye for the period of 1980-2015 is studied by Organ and Ergen employing the bounds test and they have exposed that the gross domestic product and the tax revenue data are cointegrated and that there exists a long-run negative relationship between the gross domestic product and the tax burden [29]. In a similar study, the relationship between the tax burden and the gross domestic product of Türkiye is studied for the 1988-2011 period using bound test and autoregressive distributed lag approach and it is concluded that there is a cointegrated relationship between the tax burden and the gross domestic product and that there exists a negative statistical relationship between the tax burden and the gross domestic product [30].

Umutlu, Alizadeh and Erkilic investigated the modelling of the gross domestic product of Türkiye for the period of 1990-2008 using the conventional least squares analysis and have shown that foreign debt affects the gross domestic product positively while domestic debt impacts the gross domestic product negatively and that the tax burden does not affect the gross domestic product [31]. In another study, the gross domestic product of Türkiye for the 1924-2009 period is modelled using direct and indirect tax revenues employing the cointegration analysis and it is shown that there exists a meaningful and positive relationship between the tax revenues and the gross domestic product [32]. Similarly, the effects of the direct and indirect tax revenues on the modelling of the gross domestic product are studied by Mucuk and Alptekin for Türkiye in the 1975-2006 period using Granger causality and the cointegration tests and it is concluded that direct tax revenues impact the gross domestic product in a positive way [33]. In another study, the relationship of the gross domestic product and the tax revenues of Türkiye for the 1980-2004 period is investigated employing the Engle-Granger test for the long-run relationship and the error correction model in conjunction with the Granger causality analysis for the assessment of the short-run relationship where it is shown that there exists a bidirectional causality relationship between the direct tax revenues and the gross domestic product [34]. In another study, Myles has studied the theoretical and empirical evidence regarding the impact of the taxation on the growth of the gross domestic product and they have argued that the effects of the tax revenues on the gross domestic product is very weak [35]. In a similar study, Gale et al. have also argued that the effects of the direct and indirect tax revenues on the growth of the gross domestic product is limited [36]. Erdogdu has investigated the effects of the monthly tax revenues on the growth of the gross domestic product of Türkiye for the period of 2006-2018 utilizing the mixed data sampling approach and they have concluded that the mixed data sampling approach can be used to model the gross domestic product with better performance compared to the classical regression modelling [37].

On the other hand, Cicek et al. have studied the modelling of the gross domestic product dependent on the domestic and external borrowing of Türkiye for the 1990-2009 period employing unit root tests and cointegration analysis and they have shown that the domestic debt and the external debt have positive and negative effects, respectively, on the gross domestic product [38]. In another study, Diler has investigated the impact of the public expenditure on the gross domestic product of Türkiye for the 1998-2010 period utilizing the autoregressive distributed lag approach and they have shown that there exists long-run cointegration relationship between the public expenditure and the growth of the gross domestic product [39]. Ozgur has studied the impact of the export revenues and import expenditures on the gross domestic product of Türkiye for the 1980-2014 period using autoregressive distributed lag approach and they have shown that the import expenditures affect the growth of the gross domestic product [40].

Genc and Eser have investigated the impact of the tax composition on the growth of the gross domestic product for 37 OECD countries for the period of 1995-2018 using panel data analysis and they have shown that direct tax revenues have positive effect on the growth of the gross domestic product [41]. In another study, the modelling and forecasting of the gross domestic product of Türkiye is performed for the 2003-2020 period employing the adaptive network-based fuzzy logic inference system method and they have shown that the growth of the gross domestic product can accurately be modelled as a function of exports, imports, government expenditures, consumer price index and the inflation rate [42]. The growth of the gross domestic product of Malaysia for the 1995-2000 period is performed in another study using both econometric approaches and the artificial neural network method and it is concluded that the prediction performance of the artificial neural network model is higher compared to the econometric models [43]. Liliana and Napitupulu have studied the data of the Indonesian economy to model the gross domestic product for the 1980-2009 period employing the population growth rate, inflation, exchange rate and political stability and they have shown that the artificial neural network approach provides better modelling of the gross domestic product compared to the conventional methods [44]. In another study, the growth of the gross domestic product of Iran for the 2002-2006 period is modelled using fuzzy logic and neural fuzzy methods and it is concluded that neural fuzzy method models the growth of the gross domestic product with better accuracy compared to the fuzzy logic method [45]. The modelling performance of the neural network and the conventional linear modelling are compared regarding the growth of the gross domestic product of Canada in another study and it is shown that the root mean square errors of the neural network models are %15 to 19% lower than the root mean square errors of the conventional linear methods [46]. The utilization of the artificial neural networks for the modelling of the gross domestic product of the United States is investigated in another study and it is concluded that the artificial neural networks can be used to model the gross domestic product with lower errors compared to conventional methods [47]. The gross domestic product of the United States is modelled also in another study using artificial neural networks and the conventional linear models and their results show that the artificial neural networks significantly outperform the conventional linear models due to the inherent nonlinearity of the economic data and that the artificial neural networks enable to find the best correlation between the inputs and outputs [48]. The impact of the stock market prices on the growth of the gross domestic product of Nigeria is investigated in another study for the 1990-2009 period using artificial neural networks as the method where the input data are the market capitalization, number of deals, all-share value index, total value of shares traded and the inflation rate and it is shown that the artificial neural network model of the growth of the gross domestic product reaches R^2=0.85 [49]. In another study, the gross domestic product of Romania is modelled employing artificial neural networks where the input data are exports revenue, fiscal policy, agriculture revenue and the construction sector revenue and it is shown that the artificial neural network model achieves the coefficient of determination value of R^2=0.95 [50].

Vrbka has investigated the performance of the artificial intelligence based gross domestic product modelling and forecasting methods for the Eurozone countries and they have concluded that radial basis function based functions has the best performance for the modelling of the gross domestic products [51]. In another study, Chuku et al. have studied the comparison of the gross domestic product growth modelling performance of artificial neural networks and the Box-Jenkins approach for African economies and they have shown that artificial neural networks have better performance than autoregressive integrated moving average methods when the input variables are the relevant commodity prices, trade, inflation and interest rate [52]. In a similar study, the economic data of 15 industrialized countries in the 1996-2016 period is investigated employing artificial neural networks and linear models and it is observed that artificial neural networks provide better performance for the modelling of the gross domestic product growth rates compared to the linear models [53]. The economic data of Türkiye is studied in another work where the gross domestic product in the period of 1998-2017 is modelled employing artificial neural networks with the input variables of household consumption import-export, fixed capital investment, total domestic savings, gross foreign debt and exchange rates and it is demonstrated that the coefficient of determination of the artificial neural network is R^2=0.996 indicating the high accuracy of the developed model [54]. In another extensive study, the gross domestic products of eight countries namely the United States, Mexico, Germany, Italy, Spain, France, India, and Japan are modelled using a multilayer artificial neural network structure and it is shown that the prediction error of the artificial neural network is below 2% demonstrating the high accuracy of the model [55]. In another work, the gross domestic product of the European Union countries is modelled dependent on the CO_2 emissions employing extreme machine learning, artificial neural networks and genetic programming techniques and it is concluded that the extreme machine learning model provides the best accuracy compared to the artificial neural network and genetic programming methods [56]. In a similar study, the gross domestic product growth rate of the European Union countries are modelled dependent on the combination of trade, imports and exports using extreme machine learning and the artificial neural networks with back propagation algorithms and it is shown that the extreme machine learning method provides better accuracy than the artificial neural networks with the back propagation algorithms [57]. In another work, the extreme machine learning model and the artificial neural network with back propagation algorithm are utilized to model the gross domestic product of the European Union countries dependent on the electricity usage where it is concluded that the extreme learning algorithm provides better modelling compared to the artificial neural network with back propagation method [58]. The gross domestic product of the United States is forecasted employing artificial neural networks in another study where it is shown that the artificial neural network model has higher accuracy compared to the dynamic factor model [59]. The per capita incomes of thirteen countries in the 1996-2015 period are modelled employing artificial neural network with back propagation algorithm in another work where the independent variables are taken as the education level, number of published academic paper per capita, number of researchers per employed, percentage of research and development expenditure in the gross domestic product and the number of patents per capita and it is shown that the developed model represents the income per capita with a coefficient of determination value of R^2=0.996 indicating high accuracy [60]. In another study, the per capita income of Türkiye for the period of 1960-2015 is modelled employing feedforward artificial neural networks where it is shown that the artificial neural network model accurately represents the per capita income data [61]. As it can be observed from the literature analysis, there are vast amount of studies regarding the modelling and forecasting of the gross domestic product and the per capita income using both conventional linear or artificial neural network models in the literature.

In this work, autoregressive deep learning network models are used for the modelling of the gross domestic product and the per capita income of Türkiye for the 1960-2021 period. In our approach, the past values of the output variable itself is used as input variables in the deep learning networks to realize the autoregressive deep learning concept. The autoregressive deep learning models are developed in Python programming language. In the next section namely the Materials and Method section, the utilized data and the developed autoregressive deep learning networks are described in detail. Then, the actual gross domestic product and per capita income data and the results of the autoregressive deep learning networks are compared together with the computation of the performance metrics in the Results and Discussion section. The possible utilization of the autoregressive deep learning methods for other economic data are then given in the Conclusions section.

III. MATERIALS AND METHODS

The gross domestic product and the per capita income of Türkiye is taken from the Worldbank website [62, 63]. All of the available data, which is the yearly data in the period of 1960-2021 are taken. The raw gross domestic product and the per capita income data are plotted in Figure 1 and Figure 2, respectively.

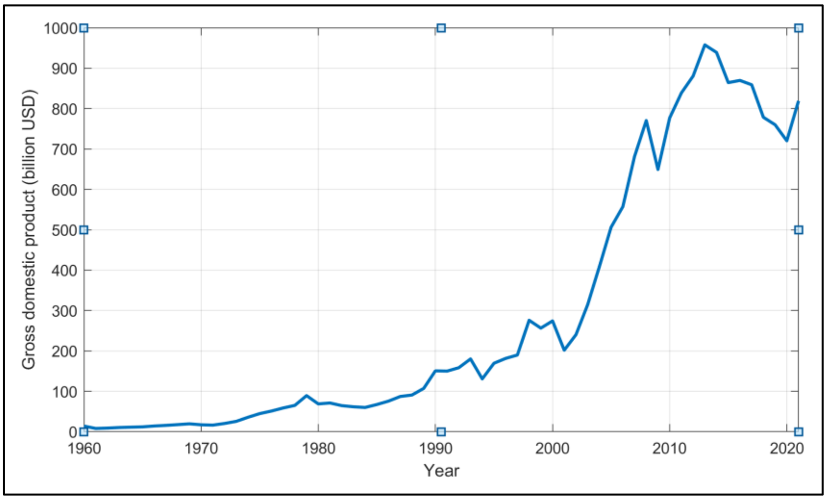

Figure 1. Gross domestic product of Türkiye for the 1960-2021 period

The seasonal components of the gross domestic product and the per capita income are firstly decomposed in Eviews software [64] using the seasonal-trend decomposition with Loess (STL) algorithm [65] to inspect the seasonal components. And then, a deep learning model consisting of three hidden layers is developed in Python programming language employing the MLPRegressor class of the SciKit-Learn (SKLearn) library [66]. The aim of this study is to model the gross domestic product and the per capita income using autoregressive deep learning networks therefore the past values of the modelled data should be used as inputs. Hence, the gross domestic data and the per capita income data has to be splitted as shown in Figure 3.

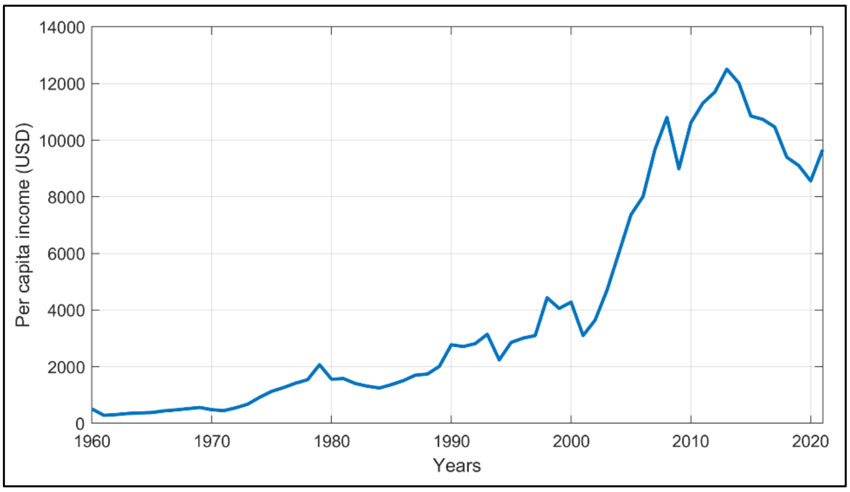

Figure 2. Per capita income of Türkiye for the 1960-2021 period

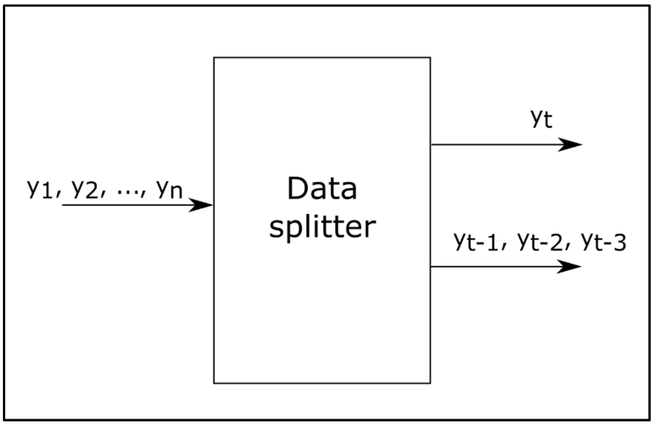

Figure 3. The operation principle of the data splitter algorithm

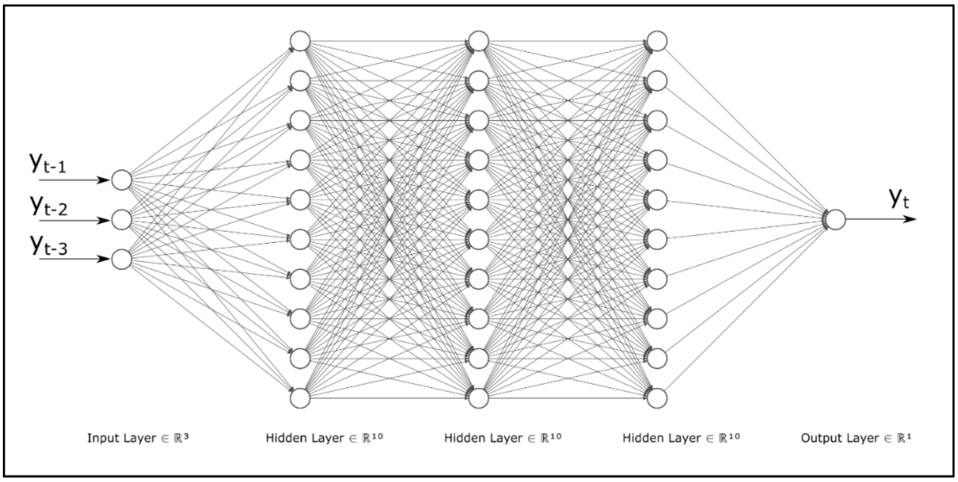

Figure 4. The structure of the developed deep learning network

The data splitter algorithm is coded as a single-input dual-output function in Python programming language. It is worth noting that there exists a trade-off between the number of lags of the input data, which is three in Figure 3, and the amount of the training data which would be available for use in the training phase of the deep learning network. The number of lags, therefore the number of inputs of the deep learning network can be optimized for different types of problems. The number of lags is selected as three in this study considering that the data length is only 62 for the deep learning model as the gross domestic product and the per capita income are yearly data in the period of 1960-2021. After the data splitting operation, the obtained lagged data are fed into the deep learning network developed in Python programming language as shown in Figure 4.

As it can be seen from Figure 4, the developed deep learning network has three hidden layers and each layer consists of ten neurons. The number of hidden layers and the number of neurons can be optimized for different applications. The developed deep learning network accepts three inputs which are in fact the three previous values of the modelled variable thus making the system an autoregressive deep learning network. It is worth noting that the data separation algorithm shown in Figure 3 has to be used in conjunction with the developed autoregressive network because the autoregressive network needs the previous values of the modelled variable as shown in Figure 4.

In the developed deep learning network, the rectified linear unit (relu) function is used as the activation functions of the neurons while the solver is the limited memory Broyden-Fletcher-Goldfarb-Shanno (lmbfgs). The 70% of the available data is used as the training data and the remaining 30% is used as the test data. It is worth noting that the train_test_split function of the SKLearn library is used for the splitting of the available data as the training and the test data which performs this selection randomly. The results of the developed deep learning model and the performance metrics are given in the following Results and Discussion section.

IV. RESULTS AND DISCUSSION

First of all, the seasonal decomposition of the gross domestic product and the per capita income data are performed in Eviews software using the STL decomposition method. The obtained seasonal and trend components of the gross domestic product and the per capita income data are given in Figure 5 and Figure 6, respectively.

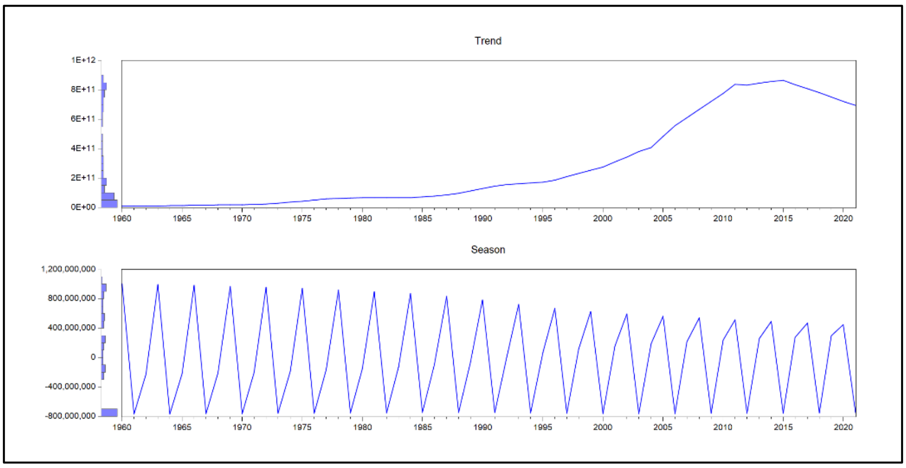

Figure 5. Trend and seasonal components of the gross domestic product

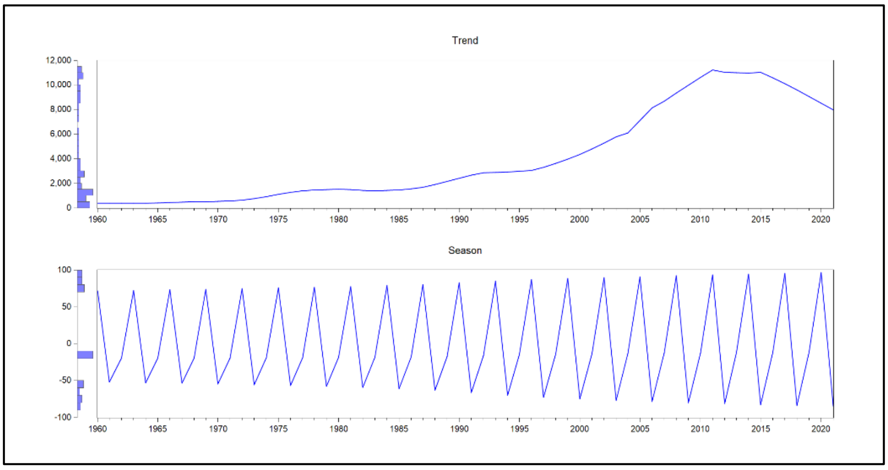

Figure 6. Trend and seasonal components of the per capita income

As it can be seen from Figure 5 and Figure 6, both the gross domestic product and the per capita income have strong seasonal components as expected. As the next step, the gross domestic product and the per capita data are splitted according to the splitting algorithm explained in the previous section. The number of past values is taken as three as shown in Figure 3. Then, the developed deep learning model is trained by the 70% of the data and the loss curves of the training phase of the deep learning network for the gross domestic product and the per capita income are given in Figure 7 and Figure 8, respectively.

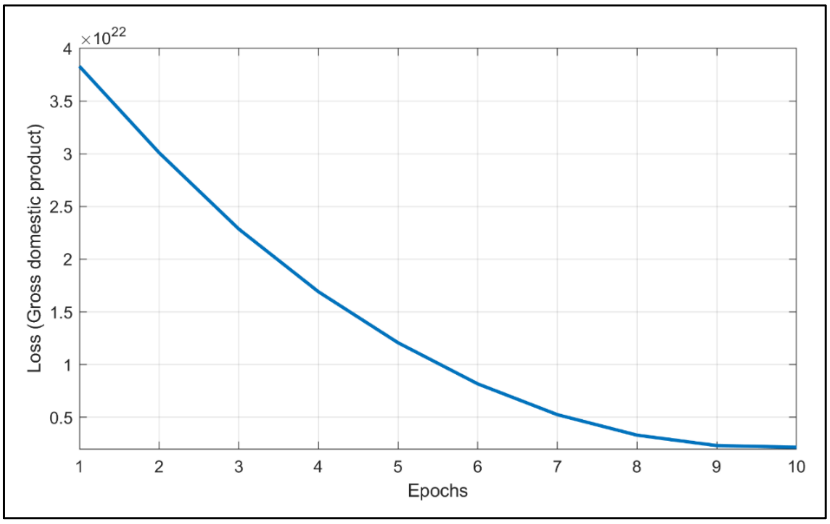

Figure 7. Training performance of the deep learning network for the gross domestic product data

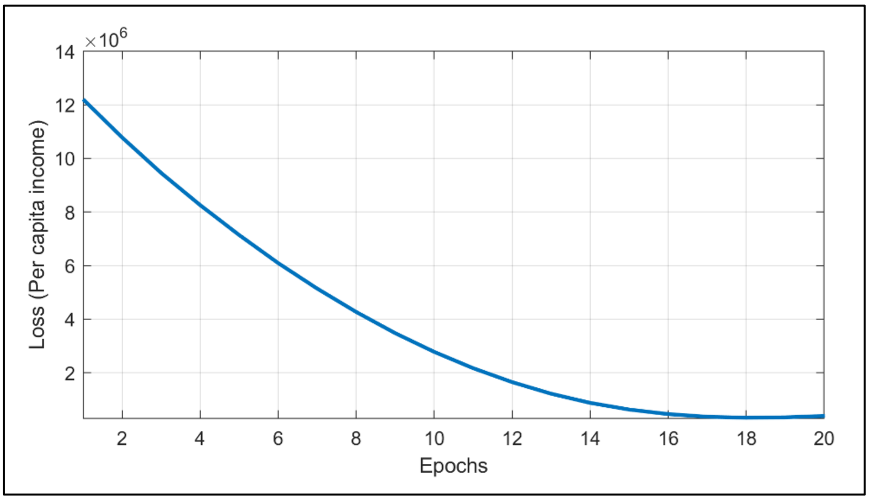

Figure 8. Training performance of the deep learning network for the per capita income data

As it can be observed from Figure 7 and Figure 8, the developed deep learning network converges rapidly for both the gross domestic product and the per capita income data. The actual gross domestic product and the per capita income data and the results of the deep learning modelling are shown in Figure 9 and Figure 10 for the gross domestic product and the per capita income, respectively.

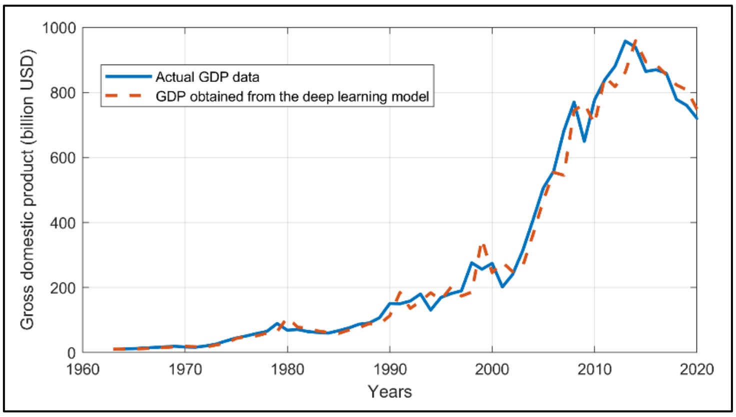

Figure 9. The actual gross domestic product data and the result of the autoregressive deep learning network

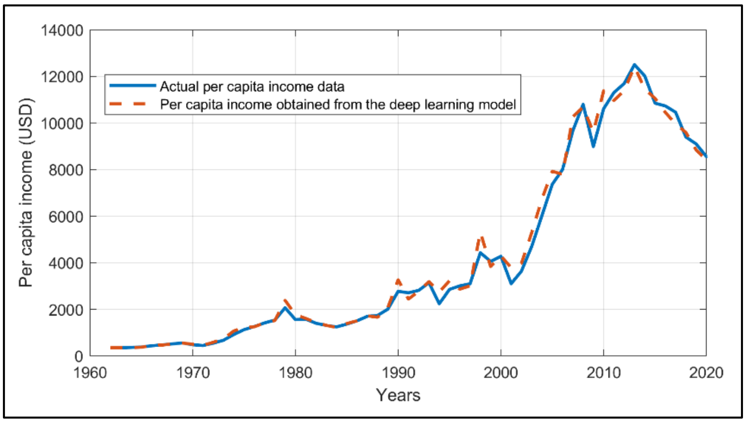

Figure 10. The actual per capita income data and the result of the autoregressive deep learning network

The developed autoregressive deep learning model accurately models both the gross domestic product and the per capita income of Türkiye as it can be seen from Figure 9 and Figure 10. Furthermore, the performance metrics of the models namely coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE) and the root mean square error (RMSE) are also computed in Python for the quantitative assessment of the model performances. The equations used for the computation of these parameters are given in Equations (1) to (4), respectively

$$R^2 = \frac{\sum_1^d (O - avg(O))^2 - \sum_1^d (O-M)^2}{\sum_1^d (O - avg(O))^2} \tag{1}$$

$$MAE = \frac{\sum_1^d |O-M|}{d} \tag{2}$$

$$MAPE = \frac{100}{d} \sum_1^d \left| \frac{O-M}{M} \right| \tag{3}$$

$$RMSE = \sqrt{\frac{\sum_1^d (O-M)^2}{d}} \tag{4}$$

In Equations (1) to (4), O is the actual data, M is the model result and d is the data length. The calculated R^2, MAE, MAPE and the RMSE values for the gross domestic product model and the per capita income model are given in Table 1. As it can be seen from Table 1, the coefficient of determination values are higher than 0.95 indicating the high accuracy of the developed autoregressive deep learning models.

Table 1. The performance metrics of the developed autoregressive deep learning models

Model	R^2	MAE	MAPE	RMSE
Gross domestic product model	0.982	27.665 billion USD	0.124	42.661 billion USD
Per capita income model	0.975	423.566 USD	0.121	617.409 USD

V. CONCLUSIONS

In this work, the gross domestic product and the per capita income of Türkiye for the 1960-2021 period are modelled using autoregressive deep learning networks. The gross domestic product and the per capita income data are taken from the website of Worldbank and then the seasonal-trend decomposition is performed in Eviews software on these data to inspect their seasonal behaviour. Then, the gross domestic product and the per capita income data are splitted into chunks of data such that the previous three values of these data could be fed into the inputs of the deep learning model. The data separation algorithm is coded as a single-input dual-output function in Python programming language. A deep learning network is then developed also in Python programming language suitable for use in the modelling of both the gross domestic product and the per capita income data. The MLPRegressor class of the SciKit-Learn library is used for the development of the deep learning network. The deep learning network has three hidden layers where these layers include ten neurons each. The rectified linear unit functions are utilized as the activation functions of the neurons. The limited memory Broyden-Fletcher-Goldfarb-Shanno algorithm is used for the training phase. As the next step, the developed deep learning network is trained for the gross domestic product and the per capita income separately. The loss curves of the training phases are given which shows the effective convergence of the training phase. Then, the actual values of the gross domestic product and the per capita income are plotted together with the results of the deep learning network and these plots indicate a high performance modelling. Furthermore, the coefficient of determination (R^2), mean absolute error (MAE), mean absolute percentage error (MAPE) and the root mean square error (RMSE) values of the models are computed in Python programming language for the quantitative assessment of the performances of the autoregressive deep learning models. The performance metrics also verify the high accuracy of the developed deep learning models with the coefficient of determination values of R^2=0.982 and R^2=0.975 for the gross domestic product and the per capita income models, respectively. It is worth noting that the developed data separation algorithm and the autoregressive deep learning model presented in this study can also be used for the accurate modelling of other econometric parameters for various countries.

REFERENCES

1) Barsoum, F., and Stankiewicz, S. 2015. Forecasting GDP growth using mixed frequency models with switching regimes. International Journal of Forecasting. 1, 33-50.
2) Kouziokas, G. N. 2020. A new W-SVM kernel combining PSO-neural network transformed vector and bayesian optimized SVM in GDP forecasting. Engineering Applications of Artificial Intelligence. 92, 1-11.
3) Xu, Z., Wang, X., and Jin, Y. 2014. Regional GDP prediction based on improved BP neural network model. International Journal of Multimedia and Ubiquitous Engineering. 9, 51–62.
4) Lehmann, R., and Wohlrabe, K. 2015. Forecasting GDP at the regional level with many predictors. German Economic Review. 16, 226-254.
5) Gogas, P., Papadimitriou, T., and Takli, E. 2013. Comparison of simple sum and divisia monetary aggregates in GDP forecasting: a support vector machines approach. Economics Bulletin. 33, 1101–1115.
6) Tkacz, G., 2001. Neural network forecasting of Canadian GDP growth. International Journal of Forecasting. 17, 57–69.
7) Kordanuli, B., Barjaktarović, L., Jeremić, L., and Alizamir, M. 2017. Appraisal of artificial neural network for forecasting of economic parameters. Physica A: Statistical Mechanics and its Applications, 465, 515-519.
8) Zhang, H., and Rudholm, N. 2013. Modeling and forecasting regional GDP in Sweden using autoregressive models. Working Paper, Hogskolan Dalama University, Sweden.
9) Yoon, J. 2021. Forecasting of real GDP growth using machine learning models: Gradient boosting and random forest approach. Computational Economics. 57, 247-265.
10) Liu, C., Xie, W., Lao, T., Yao, Y. T., and Zhang, J. 2020. Application of a novel grey forecasting model with time power term to predict China's GDP. Grey Systems: Theory and Application, 24, 2043–9377.
11) Barhoumi, K., Darné, O., Ferrara, L., and Pluyaud, B. 2012. Monthly GDP forecasting using bridge models: Application for the French economy. Bulletin of Economic Research. 64, 53-70.
12) Abonazel, M. R., and Abd-Elftah, A. I. 2019. Forecasting Egyptian GDP using ARIMA models. Reports on Economics and Finance. 5, 35-47.
13) Alaminos, D., Salas, M. B., and Fernández-Gámez, M. A. 2022. Quantum computing and deep learning methods for GDP growth forecasting. Computational Economics. 59, 803-829.
14) Cepni, O., Guney, I. E., and Swanson, N. R. 2019. Nowcasting and forecasting GDP in emerging markets using global financial and macroeconomic diffusion indexes. International Journal of Forecasting. 35, 555-572.
15) Sanusi, N. A., Moosin, A. F., and Kusairi, S. 2020. Neural network analysis in forecasting the Malaysian GDP. The Journal of Asian Finance, Economics, and Business. 7, 109-114.
16) Ghazo, A. 2021. Applying the ARIMA model to the process of forecasting GDP and CPI in the Jordanian economy. International Journal of Financial Research. 12, 70.

17) Wabomba, M. S., Mutwiri, M., and Fredrick, M. 2016. Modeling and forecasting Kenyan GDP using autoregressive integrated moving average (ARIMA) models. Science Journal of Applied Mathematics and Statistics. 4, 64-73.
18) Mourougane, A. 2006. Forecasting monthly GDP for Canada. OECD Economics Department Working Papers No. 515.
19) Soyler, H., and Kizilkaya, O. 2015. Artificial neural networks models performance comparisons for Turkey's GDP forecasting. Cumhuriyet University Journal of Economics and Administrative Sciences, 16, 45-58.
20) Simsek, M., and Kadilar, C. 2010. A causality analysis of relationship among human capital, export and economic growth for Turkey. Cumhuriyet University Journal of Economics and Administrative Sciences. 11, 115-140.
21) Duzgun, R. 2008. A Comparison of artificial neural networks and ARIMA models success in GDP forecast. Marmara University Journal of Economics and Administrative Sciences. 15, 165-176.
22) Demir, M., and Sever, E. 2017. The relationship between tax revenues and economic growth: A panel data analysis on the OECD countries. Journal of Aksaray University Faculty of Economics and Administrative Sciences. 9, 51-66.
23) Karayilmazlar, E., and Gode, B. 2017. The effect of tax burden on economic growth. Academic Review of Economics and Administrative Sciences. 10, 131-142.
24) Celikay F. 2018. The effects of tax burden on economic growth: An empirical analysis of provinces in Turkey (2005-2014). Journal of Economics Business and Political Researches. 3, 37-55.
25) Furceri, D., and Karras, G. 2007. Tax changes and economic growth: Empirical evidence for a panel of OECD countries. ECB Public Finance Workshop, 1, 27-44.
26) Reed, R. 2008. The robust relationship between taxes and U.S. state income growth. National Tax Journal. 61, 57-80.
27) Kalas, B., Mirovic, V., and Andrasic, J. 2017. Estimating the impact of taxes on the economic growth in the United States. Economic Themes. 55, 481-499.
28) Andracic, J., Kalac, B., Mirovic, V., Milenkovic, N., and Miloš, P. 2018. econometric modelling of tax impact on economic growth: Panel evidence from OECD countries. Econom ic Computation and Economic Cybernetics Studies and Research. 52, 211-226.
29) Organ, I., and Ergen, E. 2017. A study on the effects of economic growth on tax burden in Turkey. Pamukkale University Journal of Social Sciences Institute. 27, 197-207.
30) Mangir, F., and Ertugrul, H. M. 2012. Tax burden and economic growth: 1989-2011 Turkey experience. Journal of Treasury. 162, 256-165.
31) Umutlu, G., Alizadeh, N., and Erkilic, A. Y. 2011. The effects of fiscal policy tools debt and taxes on economic growth. Uludag Journal of Economy and Society. 30, 75-93.
32) Gocer, I., Mercan, M., Bulut, S., and Dam M. M. 2010. The relationship between economic growth and tax revenues: limit test approach. Dumlupinar University Journal of Social Sciences. 28, 97-110.
33) Mucuk, M, and Alptekin, V. 2008. The relationship of tax and economic growth in Turkey: VAR analysis (1975-2006). Journal of Treasury. 155, 159-174.
34) Durkaya, M, and Ceylan, S. 2006. Tax revenues and economic growth. Journal of Treasury. 150, 79-89.
35) Myles, G. 2000. Taxation and economic growth. Fiscal Studies, 21, 141-168.
36) Gale, W., Krupkin, A., and Rueben, K. 2015. The relationship between taxes and growth: New evidence. National Tax Journal, 68, 919-942.
37) Erdogdu, H. 2020. Forecasting Turkey's GDP growth with mixed data sampling (MIDAS) method. Igdir University Journal of Social Sciences. 22, 519-541.
38) Cicek, H., Gozegir, S., and Cevik, E. 2010. As a tool of public financial polities, connection with public debt and economic growth: Turkey example (1990–2009). Cumhuriyet University Journal of Economics and Administrative Sciences. 11, 141-156.
39) Diler, H. 2016. Public expenditure - economic growth: an application on Turkey. Journal of Economic Policy Researches. 3, 21-36.
40) Ozgur, M. I. 2015. Causality relationships among export, import and economic growth: Turkish case. International Journal of Alanya Faculty of Business. 7, 187-194.
41) Genc, M. C., and Eser, L. Y. 2021. The relationship between economic growth and tax composition: Panel data analysis for OECD countries. Journal of Treasury. 180, 191-207.
42) Sencan, D., and Sahin, A. S. 2022. Forecasting GDP in Türkiye using ANFIS method. Kafkas University Journal of Economics and Administrative Sciences Faculty. 13, 953-971.
43) Junoh, M. Z. H. M. 2004. Predicting GDP growth in malaysia using knowledge-based economy indicators: A comparison between neural network and econometric approaches. Sunway College Journal. 1, 39-50.
44) Liliana, L., and Napitupulu T. A. 2012. Artificial neural network application in gross domestic product forecasting an Indonesia case. Journal of Theoretical and Applied Information Technology. 45, 410-415.

45) Mirbagheri, M. 2010. Fuzzy Logic and neural network fuzzy forecasting of Iran GDP growth. African Journal of Business Management. 6, 925-929.
46) Tkacz, G., and Hu, S. 1999. Forecasting GDP growth using artificial neural networks. Working Paper 99-3 of the Department of Monetary and Financial Analysis Bank of Canada. 2, 1-24.
47) Aiken, M. 2000. Forecasting the United States gross domestic product with a neural network. Journal of International Information Management. 9, 67-75.
48) Aminian, F., Suarez, D., Aminian, M., and Walz, D. T. 2006, Forecasting economic data with neural networks. Computational Economics. 28, 71-88.
49) Maliki, O. S., Emmanuel, I., and Obinwanne, E. E. 2014, Neural network applications in the forecasting of GDP of Nigeria as a function of key stock market indicators. Advances in Applied Science Research. 5, 204-212.
50) Pasarica, A. E., and Popescu, M. 2015. Prediction of the GDP of Romania using neural networks. Interdisciplinary Approaches Between Traditional and Modern Methods Nord 1 International Conference. 1, 47-60.
51) Vrbka, J. 2016. Predicting future GDP development by means of artificial intelligence. Littera Scripta. 9, 154-167.
52) Chuku, C., Oduor, J., and Simpasa, A. 2017. Intelligent forecasting of economic growth for African economies: Artificial neural networks versus time series and structural econometric models. Washington Research Program on Forecasting. 1, 1-28.
53) Jahn, M. 2018. Artificial neural network regression models: Predicting GDP growth. Hamburg İnstitute of İnternational Economics. 185, 1-15.
54) Gecgil, G., and Akgul, Y. 2020. A study on the prediction of neural network value of Turkey's GDP. Journal of Quantitative Sciences. 2, 61-77.
55) Jena, P. R., Majhi, R., Kalli, R., Managi, S., and Majhi, B. 2021. Impact of COVID-19 on GDP of major economies: Application of the artificial neural network forecaster. Economic Analysis and Policy. 69, 324-339.
56) Marjanovic, V., Milovancevic, M., and Mladenovic, I. 2016. Prediction of GDP growth rate based on carbon dioxide (CO_2) emissions. Journal of CO_2 Utilization. 16, 212-217.
57) Sokolov-Mladenovic, S., Milovancevic, M., Mladenovic, I., and Alizamir, M. 2016. Economic growth forecasting by artificial neural network with extreme learning machine based on trade, import and export parameters. Computers in Human Behavior. 65, 43-45.
58) Stevanovic, M., Vujicic, S., and Gajic, A. M., 2018. Gross domestic product estimation based on electricity utilization by artificial neural network. Physica A. 489, 28-31.
59) Loermann, J., and Maas, B., 2019. Nowcasting US GDP with artificial neural networks. MPRA Paper No. 95459, University Library of Munich, Germany.
60) Tumer, A. E., and Akkus, A. 2018. Forecasting gross domestic product per capita using artificial neural networks with non-economical parameters. Physica A: Statistical Mechanics and its Applications. 512, 468-473.
61) Dasbasi, B., Boztosun, D., and Baraz, E. H. 2017. The estimates of population by mathematical modeling and per capita income by artificial neural network: Example of Turkey. Journal of Social and Humanities Sciences Research. 4, 841-850.
62) "GDP (current US$) - Turkiye" taken from the Worldbank website. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?locations=TR. Accessed on 01 March 2023.
63) "GDP per capita (current US$) - Turkiye" taken from the Worldbank website. https://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=TR. Accessed on 01 March 2023.
64) Griffiths, W. E., Hill, R. C., and Lim G. C. 2011. Using EViews for Principles of Econometrics 4th Edition. John Wiley & Sons.
65) Cleveland, R. B., Cleveland, W. S., McRae, J. E., and Terpenning, I. 1990. STL: A seasonal-trend decomposition procedure based on Loess. Journal of Official Statistics. 6. 3-73.
66) Hao, J., Ho, T. K. 2019. Machine Learning Made Easy: A Review of Scikit-learn Package in Python Programming Language. Journal of Educational and Behavioral Statistics. 44, 348-361.

There is an Open Access article, distributed under the term of the Creative Commons Attribution–Non Commercial 4.0 International (CC BY-NC 4.0) (https://creativecommons.org/licenses/by-nc/4.0/), which permits remixing, adapting and building upon the work for non-commercial use, provided the original work is properly cited.