Modelling the Employment Rate in Türkiye Using Machine Learning Methods

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DOI: https://doi.org/10.52403/ijrr.20230539

ABSTRACT

Employment rate is a crucial economic indicator that measures the percentage of the working-age population that is employed. Considering this importance, the employment rate of Türkiye is modelled in this work. The employment rate, gross domestic product, gross fixed capital formation, government expenditures, export and import data of the 1991-2021 period are taken from the World bank database and then the seasonal-trend decomposition of these data are performed in EViews software. After inspecting the nonlinearity of the data, a nonlinear machine learning model namely a feedforward artificial neural network model is developed in Python programming language for the modelling of the employment rate dependent on the gross domestic product, gross fixed capital formation, government expenditures, export and import data. The 70% of the available data is used as the training data and the developed feedforward artificial neural network is trained with a successful convergence despite the low number of samples thanks to its optimal structure. Then the remaining 30% of the available data are utilized as the test data. The actual employment rate data and the result of the developed feedforward neural network model are plotted on the same axis pair which show continuous overlap in a wide range. Apart from the visual inspection of the results of the developed model, the performance metrics are also calculated in Python programming language such as the mean absolute percentage error, coefficient of determination, root mean square error and the mean absolute error. The performance metrics of the results of the developed model also verify the high accuracy of the model. It is argued that the developed feedforward neural network model can also be used for the situations where low

number of samples need to be modelled thanks to the optimal structure.

Keywords: Employment rate, modelling, machine learning, artificial neural networks, estimation.

INTRODUCTION

The employment rate is a crucial economic metric that gauges the percentage of the population of working age who are employed. It provides valuable insights into the economic strength, health, and capacity of a country to provide income and job opportunities to its populace. A high employment rate is usually considered a positive indicator since it implies a low level of unemployment and a significant part of the population actively participating in the workforce. Conversely, a low employment rate may suggest weak economic growth, limited job prospects, and a possible rise in unemployment. Governments and policymakers rely on employment rates to determine their economic policies and programs, and to assess their effectiveness in generating jobs and lowering unemployment rates. Overall, the employment rate is a critical gauge of a country's economic prosperity and its oscillations may have noteworthy societal and political implications. The employment rate is not only a significant economic indicator but also a key factor that influences personal identity and social norms. Being employed is often regarded as an essential aspect of self-worth, and those who are jobless may experience a range of negative emotions, including shame, frustration, and depression. Unemployment can also lead to social exclusion and disconnection, which can have long-term effects on an individual's mental and physical health. A high employment rate, however, can foster social cohesion by promoting community involvement and a sense of belonging. Thus, the employment rate is a crucial metric that not only reflects the economic condition but also impacts individual well-being and social norms.

The employment rate is influenced by a range of factors in an economy. One essential element is the overall economic situation, where growth tends to create iob opportunities and increase the employment rate. Conversely, recessions or economic downturns can lead to job losses, causing higher levels of unemployment and a lower employment rate. The employment rate is also affected by labour force participation rates, as those who leave the workforce due to retirement or further education are not included in the employment rate. Demographic changes such as population growth or aging can impact the supply and demand of labour. influencing the employment rate. Technological advancements and automation can also alter the employment rate by leading to job displacement and a shift in labour demand towards high-skilled workers. Government policies and regulations, including labour laws and taxation policies, can also influence the employment rate by impacting the cost of and hiring doing business. Thus. understanding the various factors that impact employment rate is critical for the policymakers to develop effective strategies that can promote job creation and reduce unemployment.

Gross domestic product (GDP) affects the employment rate as indicated by various studies in the literature. The correlation between the employment rate and GDP is not a simple one, as both variables can have an impact on each other. Economic growth usually leads to higher demand for goods and services, creating job opportunities and boosting the employment rate. Conversely, a decrease in GDP can result in a decline in demand, leading to fewer jobs and a lower employment rate. However, the relationship between the two is more complex, with other factors affecting it, such as technological advancements that can increase labour productivity and reduce the number of workers needed, potentially leading to lower employment rates despite high GDP. Moreover, the type of industries contributing to GDP can affect employment rates, as labour-intensive industries can create more iobs than capital-intensive ones. Policymakers need to understand the complex relationship between GDP and employment rates to create effective policies economic growth that promote for sustainable and inclusive labour markets. On the other hand, the correlation between the employment rate and import and export rates is complex and multifaceted. While exportoriented industries like manufacturing and agriculture can increase production, create jobs and positively affect employment rates, imports may have a negative effect by reducing demand for domestically produced goods, resulting in job losses. Trade deficits can further worsen the situation, indicating a reduction in domestic production and job creation. However, the relationship between trade and employment rates is not linear, as imports can also create job opportunities in industries that depend on imported goods like retail and transportation. It is vital for policymakers to consider both sides of the equation to support employment rates and economic growth. Striking a balance between imports and exports is crucial to ensuring that domestic industries remain competitive in the global marketplace, while maintaining access to a wide variety of goods and services that contribute to economic development.

The government expenditures also have a significant impact on the employment rate. The link between government expenditures and the employment rate is a critical issue for policymakers. Public sector spending can directly and indirectly affect the employment rate. Directly, government spending on public services and infrastructure can create

jobs. Indirectly, increased demand for goods and services stimulated by government expenditures can lead to job creation in the private sector. Government investments in education and training can also enhance the skills of the workforce and make them more employable. However, policymakers should avoid excessive government spending as it can cause inflation, financial strain on the public sector, and higher taxes, leading to investment. reduced Therefore. policymakers must focus on creating a balance between government spending and revenue generation. They must invest in areas that can drive economic growth and job creation in the long run.

The gross fixed capital formation (GFCF) also has a correlation with the employment rate. This link is significant, as GFCF represents investment in fixed assets such as machinery, equipment, and buildings, which boost business productivity can and efficiency. The increased demand for goods and services can create job opportunities for a larger workforce. However, the impact of GFCF on employment is influenced by various factors, such as government policies, technological competition, and advancements. To avoid potential job loss due to overcapacity, businesses need to invest in fixed assets based on market demand. Therefore, policymakers should aim to create a conducive environment that encourages sustainable investment in fixed assets and a skilled workforce that can adapt to changing market trends.

The employment rate in Türkiye for the 1991-2021 period is modelled in this study considering the importance of the subject. The gross domestic product, government expenditures, gross fixed capital formation, import and export rate data are considered as independent variables the and the employment rate is modelled dependent on these data. All of the required data are gathered from the World bank database. First of all, the seasonality and nonlinearity of the considered data are investigated using EViews software. Then, a nonlinear machine learning model namely a feedforward

artificial neural network model is developed in Python programming language for the modelling of the employment rate. The 70% of the available data are taken as the training data and the developed machine learning model is trained. The test_train_split class of the Scikit Learn library of Python is used for splitting the training and the test data for an objective assessment of the developed model. The remaining 30% of the data is employed as the test data. As the next step, the actual employment rate and the result of the developed model are plotted on the same axis pair which shows an overlap in a wide range. Furthermore, the performance metrics relate to the model namely the mean absolute percentage error. coefficient of determination, mean absolute error and the root mean square error are also computed. The values of these performance metrics further verify the accuracy of the developed model. Finally, it is concluded that the developed feedforward neural network model can be utilized also for other modelling problems with low number of samples.

LITERATURE REVIEW

The modelling and estimation of the employment rate is an important problem therefore there exist vast number of studies in the literature regarding this subject. For example, the economic data of Türkiye is analysed for the period of 1963-1994 in a study and it is shown that the export revenues have impacts on the employment ratio (Erlat, 2000). In an extensive work, the economic data of 92 selected countries for the 1985-2004 period employing the panel data analysis where it is concluded that there is a positive correlation between the openness and the employment rate (Dutt et al., 2009). Similarly, the Vietnamese economic data is analysed for the period of 1999-2004 and it is observed that the there exists a positive and meaningful relationship between the export revenue and the employment rate (Kien and Heo, 2009). In another study, the effects of the import expenditures on the employment rate for the South African economy in the

1970-2008 period are investigated and it is concluded that the increments in the imports have negative impacts on the employment rate of the agricultural, mining and the construction sectors (Chinembiri, 2010). Similarly, the economic data of Argentina is studied for the 1994-1999 period where it is shown that the import volume has negative impact on the employment rate (Gibson, 2010). The factors affecting the employment rate investigated for Türkiye in the period of 2003-2008 and it is observed that production volume affects the employment rate in a positive way (Polat et al., 2011). In another work, the economic data of Türkiye for the 1988-2007 period are investigated and it is found out that export and import volume affects the employment rate in a positive way in the short term (Polat and Uslu, 2010). The economic data of Türkiye for the 2004-2009 are analysed using generalized method of moments and it is concluded that the employment rate depends on the export volume (Gozgor and Piskin, 2011). In an extensive work, the economies of selected developed and developing countries are analysed in the period of 1980-2010 where it is shown that there is a unidirectional causality relationship from the import volume to the employment rate for the developing countries and a unidirectional relationship from the export volume to the employment rate for the developed countries (Gul and Kamaci, 2012). The relationship between the foreign trade volume and the employment rate for Türkiye is studied for the 1983-2009 period and it is shown that there is a positive relationship between the foreign trade volume and the employment rate for the long term (Karacor and Sarac, 2011). Similarly, the economic data of Türkiye for the 1998-2002 period is investigated and it is exposed that the foreign positively volume affects trade the employment rate (Ayas and Cestepe, 2010). The Turkish economy is studied for the 1994-2010 period in another work where it is exposed that import and export volumes affect the employment rate in a positive way (Uslu and Polat, 2012). Similarly, the economic data of Türkiye is investigated for the 2003-2010 period using the panel data analysis method and it is shown that export demand and import competition impacts the employment rate (Akkus, 2014). Similarly, the factors affecting the employment rate in Türkiye for the period of 2000-2015 are analysed employing the impulse-response analysis and the variance decomposition method where it is found out that the exchange rate and the money supply affects the employment rate (Akcan and Ener, 2018). In another study, the economies of selected developing and developed countries are analysed in the period of 1980-1999 and it is shown that openness has a negative effect on the employment rate for the developed countries and the openness has a positive effect for the developing countries (Yanikkaya, 2013). In another work, the economic data of Türkiye for the 1990-2017 period is analysed utilizing multiple regression method and it is exposed that there exists an inverse relationship between the between the inflation and the unemployment rate (Eygu, 2018). The relationship among the import volume, export volume and the employment rate are studied for Türkiye in 2005-2014 period using the the autoregressive distributed lag method and it is demonstrated that the industrial production affects the employment rate in a positive way (Ayhan, 2018). In another work, the economic data of Türkiye for the period of 2005-2014 is analysed using the Johansen cointegration analysis and it is shown that there exists an inverse relationship between the inflation and the unemployment rate (Zengin, 2016). The economy of Türkiye for the period of 1980-2002 is analysed using the Phillips curve and it is observed that there is an inverse relationship between the inflation and the unemployment rate (Uysal and Erdogan, 2004). In another study, Granger causality analysis is applied on the economic growth and the unemployment rate data of Türkiye for the 1978-2004 period where it is concluded that there is a unidirectional relationship causality from the unemployment rate to the economic growth

(Yilmaz, 2005). Similarly, the correlation between the inflation and the unemployment rate of Türkiye for the 2005-2014 period is analysed employing the Spearman correlation test and it is found out that there does not exist statistically meaningful causality relationship between the inflation and the unemployment rate (Ulusoy and Dibo, 2016).

The least squares method is utilized for the analysis of the economic data of Iran for the 1968-2000 period and it is exposed that there is a positive correlation between the inflation and the unemployment rate (Valadkhani, 2003). The Granger causality test is utilized for the analysis of the Turkish economy for the 2000-2001 period where it is observed that there exists short term correlation between the employment rate and the economic growth (Muratoglu, 2011). The Romanian economy is analysed for the 1997-2005 period in another study where it is observed that the employment rate decreases as the economic growth increases (Momete, 2007). In another work, the relationship between the economic growth and the employment rate of Türkiye is studied for the 1990-2003 period and it is shown that the economic growth is a prerequisite for the increment of the employment rate (Duruel and Kara, 2012). The economic data of Türkiye for the 2001-2006 period is studied utilizing the Granger causality tests and it is concluded that the economic growth and the employment rate are positively correlated (Akan et al., 2008). Similarly, the Granger causality test is utilized to analyse the labour market in Türkiye for the 1995-2007 period and it is found out that economic growth and the employment rate are positively related in the long term (Akcoraoglu, 2012). A similar result is concluded in another work where the economic data of Pakistan is investigated for the period of 1972-2006 using the vector error correction model such that the economic growth and the employment rate are correlated in a positive way (Hussain et al., 2010). The Nigerian economy is studied for the 1981-2006 period employing the least squares method in another work where it is concluded that the economic growth and the employment rate are related in a positive way (Sodipe and Ogunrinola, 2011). The technological advances also have impacts on the employment rate. For example, the effects of the technological innovation on the employment rate are studied for the US economy in the 1996-2002 period in another paper and it is observed that the technological innovation affects the employment rate positively (Coad and Rao, 2011). Similarly, the relationship between the research and development expenditures and the employment rate in the UK is analysed for the 1987-1994 period where it is shown that the research and development investments have positive effects on the employment rate (Greenhalgh et al., 2003). The technological innovation and the employment rates of the selected 30 OECD countries are investigated in another study employing canonical correlation analysis and it is observed that there exists strong positive technological correlation between the employment innovation and the rate (Nurdogan, 2021). A similar relationship between the technological innovation and the employment rate in Germany for the 1982-2002 period is studied where it is exposed that the technological innovation positively affects the employment rate (Lachenmainer and Rottman, 2011). The effects of the technological innovation on the employment rate in the United States are investigated in another work and a positive correlation has been determined (Doms et al., 1995). On the contrary, the relationship between the technological innovation and the employment rate of the banking sector in Türkiye is studied employing the grey estimation method where it is concluded that the technological innovation of the banking sector negatively affects its employment rate (Tuzun, 2020). The negative correlation between the technological innovation and the employment rate is concluded also in another previous study (Vivarelli, 1995). In another extensive work, the economic data of 81 selected countries are analysed utilizing extended least squares method and it is

shown that the technological innovation of the end user products have positive effect on the employment rate (Bulut and Yenipazarli, 2020). In another study, the relations of the technological innovation and the employment rate in the UK, Germany, France and Italy are investigated for the 1998-2000 period using the panel data analysis method and it is shown that technological innovation positively affects the employment rate (Harrison et al., 2014). The relationships between the research and development expenditures, technological product exports, number of patent applications and the employment rate in Türkiye for the 1991-2018 period are studied using Johansen cointegration and the vector autoregressive analysis where it is exposed that technological product export volume has negative effect on the employment rate while the research and development expenses and the number of patent applications have positive effects on the employment rate (Bayar and Ozturk, 2021). In another study, it is shown that the renewable energy production plants have positive impact on the employment rate (Yilmaz, 2014). The renewable policies energy and the employment rate of the EU countries are studied for the 1990-2012 period using Granger causality tests and it is found out that there exists a causality relationship between the wind power plants and the employment rate (Jaraitea et al., 2015).

The relationship of the foreign direct investments and the employment rate for Türkiye in the period of 1970-2005 is studied in another work using the Granger causality test and it is shown that there does not exist any causality relationship between the foreign direct investments and the employment rate (Karagoz, 2007). In another work, the relationship between the GDP and the unemployment rate in Türkiye for the 1970-2006 period is analysed utilizing the cointegration and the Granger causality tests where it is concluded that there exists a unidirectional causality relationship from the GDP to the unemployment rate (Ayhan, 2008). The interaction between the economic

growth and the employment rate of Türkiye for the 1988-2011 period is investigated in another study employing the least squares method and it is found out that there exists a positive correlation between the economic growth and the employment rate (Altuntepe and Guner, 2013). The cointegration method and the vector error correction model are utilized to analyse the relationship between the foreign direct investments and the employment rate for Türkiye in the 1970-2009 period and it is exposed that there does not exist any causality relationship between the foreign direct investments and the employment rate (Saray, 2011). The economic data of Türkiye is studied in another work for the period of 2004-2011 in another work using the panel data analysis method where it is observed that the increase the export volume increases in the employment rate (Aktakas et al., 2013). The cointegration test is utilized to analyse the relationship between the export volume, investments foreign direct and the unemployment rate of Türkiye for the 2000-2011 period and it is shown that both the export volume and the foreign direct investments decrease the unemployment rate in the long term (Gocer et al., 2013). In another work, the relationship between the investments and the unemployment rate in Türkiye for the 1980-2013 period is investigated utilizing the cointegration and the Granger causality analysis where it is demonstrated that there exists an inverse correlation between the investments and the unemployment rate (Kanca and Bayrak, 2015). Similarly, the economic data of Türkiye is studied for the 1990-2013 period employing the Granger causality tests and it is exposed that there exists a unidirectional causality relationship from the employment rate to the current expenditures (Kaya et al., 2015). In another work, the relationship between the economic growth rate and the unemployment rate in Türkiye is studied using the cointegration method and the Granger causality test for the 1980-2014 period where it is concluded that there does not exist any causality relationship between the economic growth and the unemployment (Ari, 2016). The autoregressive rate distributed lag boundary test is employed to the relationship between assess the employment rate and the import and export volumes for Türkiye and it is observed that there exists a positive correlation between the export volume and the employment rate while a negative correlation exists between the import volume and the employment rate (Ayhan, 2016).

The economic data of Türkiye is studied for the 2005-2017 period using the cointegration and the Toda-Yamamoto causality analysis in another work and it is concluded that there exists bidirectional causality relationship between the import and export volumes and the unemployment rate (Cutcu and Cenger, The Toda-Yamamoto causality 2017). analysis is utilized also in another study where the economic data of Türkiye is investigated in the 2002-2014 period where it is shown that there exists a unidirectional causality relationship from the real GDP to the unemployment rate (Durkaya and Ceylan, 2016). In another work, the relationship between the public expenditures on the sectoral employment using the panel data analysis method and it is exposed that public the expenditures affect the employment in the production and services sectors in a positive way (Sancar et al., 2016). The effects of the investments shocks on the unemployment rate is analysed in another study using the vector autoregressive method for Türkiye in the 2005-2016 period and it is shown that investment shocks have significant effects on the unemployment rate (Yildirim and Yildirim, 2017). The Turkish economy is studied for the 2003-2016 period using the multivariate adaptive regression spline method and it is concluded that the economic growth affects the unemployment rate negatively (Yuksel and Adali, 2017). The Granger causality test is utilized to investigate the relationship between the employment rate and the direct foreign investments in Türkiye for the 1990-2015 period and it is shown that there does not exist any causality relationship between the employment rate and the direct foreign investments (Koyuncu, 2017). Similarly, the relationship causality between the unemployment rate and the economic growth in Türkiye for the 1990-2015 period is analysed employing the Granger causality analysis and it is concluded that there exists a bidirectional causality relationship between the unemployment rate and the economic growth (Ucan, 2017). On the contrary, cointegration and the Toda-Yamamoto causality analysis are utilized to investigate the relationship between the economic growth and the unemployment rate for Türkiye in the 1980-2016 period and it is argued that there does not exist causality relationship between the economic growth and the unemployment rate (Durmus and Akbulut, 2017). In another work, the economic data of Türkiye is studied for the 1960-2009 period using the Granger and Toda-Yamamoto causality tests and it is observed that the employment rate affects the economic growth in the long term (Aksu, 2017). Similarly, the relationship between the sectoral expenditure and the sectoral employment in Türkiye for the 2000-2016 period is studied utilizing the Toda-Yamamoto method where it is concluded that there exist causality relationships between some of the sectoral expenditures and the corresponding employment rates (Ersin and Ergec, 2018).

As it can be seen from the literature survey above, there are several factors affecting the employment rate and various methods have been utilized in the literature to analyse the effects of these factors on the employment rate. Considering the importance of the subject, the employment rate of Türkiye is modelled dependent on various independent data in this work. The yearly data in the period of 1991-2021 period are taken from the World bank database and then the required seasonal-trend decomposition analyses are performed on these data. As the next step, a machine learning model namely a feedforward artificial neural network is developed for the expression of the employment rate as a nonlinear function of the selected independent variables. The details of the considered data and the developed feedforward artificial neural network are presented in detail in the next section.

MATERIALS & METHODS

First of all, the employment rate, gross domestic product, gross fixed capital formation, government expenditures, imports of goods and services, exports of goods and services data are gathered from the World bank database (World bank, 2023). The data except the employment rate are utilized as the independent variables for the modelling of the employment rate data in this work. As the next step, the seasonal-trend decomposition of these data is performed in EViews software utilizing the seasonal-trend decomposition using loess algorithm (Cleveland et al., 1990; Agung, 2011). The original data, seasonal components and the seasonally-adjusted data as the results of the STL decompositions are given in Figure 1-6 for the employment rate, gross domestic product, gross fixed capital formation, government expenditures, imports and exports, respectively.



Figure 1. The original data, seasonal components and the seasonally-adjusted data regarding the employment rate



Figure 2. The original data, seasonal components and the seasonally-adjusted data regarding the gross domestic product



Figure 3. The original data, seasonal components and the seasonally-adjusted data regarding the gross fixed capital formation



Figure 4. The original data, seasonal components and the seasonally-adjusted data regarding the government expenditures



Figure 5. The original data, seasonal components and the seasonally-adjusted data regarding the imports



Figure 6. The original data, seasonal components and the seasonally-adjusted data regarding the exports

As it can be seen from Figures 1-6, bot the dependent and independent data have strong seasonal and nonlinear behaviour therefore nonlinear models are required to accurately represent the employment rate dependent on the other variables. Moreover, the order of the employment rate and other variables are significantly different therefore it is required to normalize the independent variables having high order values. A feedforward artificial neural network is developed for the expression of the employment rate dependent on the gross domestic product, gross fixed capital formation, government expenditures, imports and exports. The block diagram of the developed feedforward artificial neural network model with the normalization block is shown in Figure 7.



Figure 7. The block diagram of the developed feedforward artificial neural network together with the normalization blocks

The feedforward neural network and the normalization blocks are implemented in Python programming language. The MLPRegressor class of the SciKit Learn library is utilized for the realization of the feedforward neural network (Geron, 2019; Magbool, 2023). The normalization blocks are implemented using custom-coded Python classes. The number of hidden layers is three as shown in Figure 7, which is optimized for accuracy. After the development of the model in Python, the 70% of the available data is used as the training data whereas the remaining 30% of the available data is taken as the test data. The convergence details of the training phase and the results of the feedforward neural network model are presented in the following section.

RESULT

The developed feedforward neural network with normalization blocks have been trained using the training data split by the test_train_split class of the SK-Learn library (Vrigazova and Ivanov, 2020). The test_train_split class is utilized to provide transparency in the training phase and the assessment of the developed feedforward neural network model. The loss curve regarding the training phase of the developed model is presented in Figure 8.



Figure 8. The loss curve of the training phase of the developed feedforward neural network model

International Journal of Research and Review (ijrrjournal.com) Volume 10; Issue: 5; May 2023

The training phase of the developed feedforward neural network model is converged in 3275 epochs. The convergence requires large number of epochs since the number of samples of the training data is very low namely 24 samples. It is worth noting that convergence is achieved even for low number of samples thanks to the optimized

neural network structure having the normalization blocks.

The actual employment rate data and the employment rate obtained from the developed feedforward neural network model are plotted on the same axis pair in Figure 9.



Figure 9. The actual employment rate data and the result of the developed feedforward neural network model

As it can be observed from Figure 9, the developed feedforward neural network model accurately represents the employment rate dependent on the gross domestic product, gross fixed capital formation, government expenditures, imports and exports. The performance metrics related to the developed model are also presented in the next section.

DISCUSSION

The performance of the developed feedforward neural network model is further assessed using the performance metrics namely the coefficient of determination. mean absolute error. mean absolute percentage error and the root mean square error. These performance metrics are calculated in Python using the classes existing in the SKLearn.metrics library (Bisong, 2019). The performance metrics can be expressed in Eqs. (1-4) for the coefficient of determination, mean absolute error, mean absolute percentage error and the root mean square error, respectively.

$$R^{2} = \frac{\sum_{1}^{d} (o - avg(0))^{2} - \sum_{1}^{d} (o - M)^{2}}{\sum_{1}^{d} (o - avg(0))^{2}}$$
(1)

$$MAE = \frac{\sum_{1}^{d} |O-M|}{d}$$

$$MAPE = \frac{100}{d} \sum_{1}^{d} \left| \frac{O - M}{M} \right|$$
(3)

$$RMSE = \sqrt{\frac{\sum_{1}^{d} (O-M)^2}{d}}$$
(4)

In Eqs. (1-4), O is the actual data, M is the model result and d is the length of the data (Mombeini and Chamzini, 2015). The obtained performance metrics are shown in Table 1.

Table 1. The performance metrics of the developed model				
Performance	Coefficient of	Mean absolute	Mean absolute	Root mean
	1.4			
metric	determination	error	percentage error	square error

The performance metrics of the developed model shown in Table 1 verify the accuracy of the model. The mean absolute percentage error is on the order of 0.679% indicating the high accuracy of the model (Cuhadar, 2014; Witt & Witt, 1992; Fretchling, 2001). It can be argued that the developed feedforward neural network model can be adopted for the accurate modelling of other econometric data with low number of samples.

CONCLUSION

This work focuses on modelling the employment rate of Türkiye, which is a significant economic indicator that measures the percentage of employed working-age individuals. Data from the World Bank database, including the employment rate, gross domestic product, gross fixed capital formation, government expenditures, export and import data from 1991-2021, were used purpose. The seasonal-trend for this decomposition of the data was performed using EViews software, and a feedforward artificial neural network model was developed in Python to model the employment rate based on the aforementioned variables. The model was trained using 70% of the available data and tested on the remaining 30%, and its accuracy was assessed using performance metrics such as the mean absolute percentage error, coefficient of determination, root mean square error, and mean absolute error. The developed model exhibited high accuracy and could be used in situations where there is a low number of samples, thanks to its optimal structure. The results were visually inspected and verified by the performance which demonstrated metrics. the effectiveness of the model. The mean absolute percentage error of 0.679% is achieved implying the high accuracy of the developed model. It can be argued that the developed model can be adapted for use in other economic modelling problems having low number of data samples.

Declaration by Authors Acknowledgement: None Source of Funding: None Conflict of Interest: The authors declare no conflict of interest.

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How to cite this article: Cagatay Tuncsiper. Modelling the employment rate in Türkiye using machine learning methods. *International Journal of Research and Review*. 2023; 10(5): 323-337. DOI: *https://doi.org/10.52403/ijrr.20230539*
