A PREDICTION MODEL FOR AUTOMOBILE SALES IN TURKEY USING DEEP NEURAL NETWORKS

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Keywords
Deep neural networks, Automobile sales, Demand forecast

Abstract

Demand prediction in the supply chain process, which is the driving force in all decisions, is one of the most essential components of the supply chain process. Prediction of future goods and services is the starting point of all other predictions and provides the primary entry to all other functions. In this study, an 8-layer Deep Neural Network (DNN) model was recommended for automobile sales prediction. The inputs of the model consist of features, such as the exchange rate, the gross domestic product, consumer confidence index, and the consumer price index. The automobile sales prediction was made according to the output of the model. We analyzed a total of 90 data on a monthly basis between the years of 2011 and 2018 was collected. Obtained results show that this approach can be used on various sales prediction problems.

DERİN SİNİR AĞLARI KULLANARAK TÜRKİYE'DEKİ OTOMOBİL SATIŞLARININ TAHMİNİ İÇİN BİR MODEL

Anahtar Kelimeler
Derin sinir ağı, Otomobil satışları, Talep tahmini

Öz

Tüm kararlarda itici güç olan tedarik zinciri sürecinde talep tahmini, tedarik zinciri sürecinin en önemli bileşenlerinden birisidir. Gelecekteki ürün ve hizmetlerin tahmin edilmesi, diğer tüm tahminlerin başlangıç noktası olup diğer tüm süreçlerin temel girdisini oluşturmaktadır. Bu çalışmada, otomobil satış tahmini için 8 katmanlı Derin Sinir Ağ (DSA) modeli önerilmiştir. Modelin girdileri, döviz kuru, gayrisafi yurt içi hasıla, tüketici güven endeksi ve tüketici fiyat endeksi gibi çeşitli ekonomik göstergelerden oluşmaktadır. Modelin çıkışına göre araç satış tahmini yapılmıştır. 2011 ve 2018 yılları arasında aylık bazda toplam 90 veri toplanılarak analizler yapılmıştır. Elde edilen sonuçlar, bu yaklaşımın çeşitli satış tahmin problemlerinde kullanılabileceğini göstermektedir.

Araştırma Makalesi		Research Article	
Başvuru Tarihi	: 07.01.2020	Submission Date	: 07.01.2020
Kabul Tarihi	: 03.04.2020	Accepted Date	: 03.04.2020

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1. Introduction

Demand forecasting is regarded as an essential component of Supply Chain Management (SCM). It is the leading player for almost all decisions made throughout the supply chain process. The fact that demand forecasting is done correctly provides many advantages in the short and long-term plans of the enterprise. These advantages are: (1) increasing customer satisfaction, (2) reducing inventory stock-out, (3) scheduling production more effectively, (4) lowering safety stock requirement, (5) managing transportation better, (7) improving pricing and promotion management, (8) negotiating superior terms with suppliers, and (9) arrangement of sales strategies. By providing customers with the products they want, demand forecasting can help to achieve customer satisfaction. When the demand forecasts are made correctly, customer requirements can be met in a timely manner. Demand forecasting along with inventory optimization methods, assures the order to be made just in the needed quantity to fulfill customer demand without an unnecessary and excessive quantity. Customer demand plan based on forecasting, it can also help the schedule of production resources to be designed more wisely for specific products.

Demand forecasting includes the estimation of products and services that will be bought by the customers in the near future. The anticipation of demand with a narrow margin of error facilitates the activities of critical operation in the supply chain process, such as budgeting, financial planning, sales and marketing plans, the supply of raw materials, production planning, and risk assessment plans. With an effective demand forecasting, "supplier relationships and the improvement of the purchase conditions," "correct and timely resource allocation," "optimization of stock levels," "advanced deployment planning and improvement of the logistics network," "effective management of product lifecycle, "increase in customer satisfaction," and "performance improvement in supply processes" are possible. Demand forecasting can also improve the buying process of raw materials supplied from the suppliers and the relations between the supplier and the customer. By arranging raw materials and product inventory levels with a broad vision, businesses can develop a production plan based on customer orders. As for medium and large-sized businesses with a wide distribution network, they are improving demand prediction enables the stabilization of stocks in the logistics network and the improvement of transport services. Real-time and correct demand prediction allows for the supply of the stocks in the right place and time by accurately designing the measurements of customer services, such as optimized inventory levels and improvement of the distribution network, on-time delivery (OTD), on time in full (OTIF), fill rate, etc. Medium and long-term demand prediction helps new products to come out and the old ones to appear better. Supply chain managers can effectively and efficiently perform various functions, such as sales, finance, purchase, production.

The automotive industry is one of the most important branches of the manufacturing industry. This industry is in close relation with primary industry branches, such as the iron and steel and petrochemical industry, and is the driving force of technological developments in other sectors. This paper provides some useful information about forecasting automobile sales according to the economic indicators. For this purpose, deep neural networks were employed to predict the number of automobile sales. New DNN models were designed to produce efficient predictions. A new dataset that includes some economic indicators and the number of automobile sales in Turkey between 2011 and 2018 years was constructed. As the author's best of knowledge, this is the first study to use the DNN model for prediction automobile sales. In this study, the effect of the economic indicators on the prediction process was investigated separately. According to the obtained results, it can be said that the proposed DNN models can make predictions with high performance compared to the Artificial Neural Network model.

2. Literature Review

The prediction is predicting the future by applying specific methods on historical data. Demand forecasting is the process that is used to progress a prediction of an expected forecast of customer demand. Many forecasting methods have been developed to handle the increasing variety and complexity of managerial forecasting problems in recent years. The forecasting methods can be divided into three main groups: "qualitative," "quantitative," and "artificial intelligence" based prediction methods. While qualitative methods rely more on personal opinions, quantitative methods are based on mathematical formulation. Artificial intelligence-based methods can be used to enable more complex data structures to be analyzed.

Qualitative methods are preferred when the decision is vague and little data exist. Qualitative methods are mainly based on tools, such as survey, interview, Delphi method, market analysis Hand observation analysis, while quantitative methods are based on statistical techniques, such as time series analysis, regression analysis and trend analysis, Holt's and Winter's models, etc. Artificial Intelligence methods (AI) are based on the utilization of sophisticated algorithms that are capable of learning by trial and (Makridakis, Spiliotis, and Assimakopoulos, 2018). This advanced technique utilizes Machine Learning methods, especially Neural Networks Analysis (NNA), which can be employed to develop time-series predictions.

The literature review and methods of Supply Chain Forecasting (SCF) have been increasingly pointed out by researchers. Statistical models, which can help reduce forecast errors to manageable levels, have been widely used by researchers (Gavcar, Şen, and Aytekin, 1999) established a regression and correlation analysis by considering total goods price, import and export quantities, gross national product (GDP) and population variables that affect paper consumption.

Most prior studies have been applied to predict the supply chain context, which is primarily based on time-series models. Time series are able to recognize historical trends and patterns and extrapolate supply chain context, such as demand forecasting, supply forecast, price forecasting, etc. into the future. Time-series forecasting models are divided into different categories, including especially the Naïve method, moving average methods, exponential smoothing models (ESM), ARIMA models, and composite forecasting (CF), in which different previous defined models are combined. ARIMA is considered to be a statistical forecasting method and widely used to forecast supply chain literature. Among studies and literature reviews of ARIMA in a supply-chain context, Wang, Huang, Wang and Chen (2010) proposed an inventory demand forecasting analysis that integrated Taguchi experiments and the ARIMA method. Disney, Farasyn, Lambrecht, Towill, and de Velde (2006) investigated inventory variance and customer service levels by using the ARIMA method. Hsiao and Shieh (2006) proposed the ARIMA model that analyzes the bullwhip effect of information sharing in the supply chain. Anggraeni, Vinarti and Kurniawati (2015) constructed ARIMA and Autoregressive Integrated Moving Average with external variables (ARIMAX) models to predict the demand for children's outfits. Gahirwal (2013) analyzed the amount of sales data trend and seasonally determined sections and made the estimates of these sections separately by using Holt-Winter and ARIMA methods. There are other statistical methods employed in the literature. Chen, Drezner, Ryan and Simchi-Levi (2000) proposed the forecasting technique for predicting inventory levels in the supply chain and used a simple moving average method. Fildes, Goodwin, Lawrence, and Nikolopoulos (2009) investigated the effectiveness of a computerized forecasting system of four supply chain companies. In addition, they used regression analysis, which consisted of more than 60000 forecasts and outputs of four companies. Matsumoto and Ikeda (2015) investigated the efficiency of the forecasting model in auto parts, which are supplied for second-hand markets by using time series models.

An artificial neural network (ANN) is another method that can be widely used to estimate demand in the supply chain. This method has been generally preferred by researchers in recent years. Chawla, Singh, Lamba, Gangwani, and Soni (2019) developed the ANN model to predict the demand of Walmart retail corporations in the US. In the supply chain, artificial neural networks have been used in the estimation of many different product types. For example, drink water demand (Nouiri, Ammar, Belhsen, Jridi, Derbala and Neffati, 2019); daily demand of product (Ferreira, Martiniano, Ferreira, Ferreira and Sassi (2016); demand of a customer product in the supermarket (Slimani, Farissi and Achchab, 2015); oil demand forecasting in India (Jebaraj and Iniyan, 2015); automobile demand forecasting (Wang, Chang and Tzeng, 2011; Arslankaya and Öz, 2018) and fuel filter product (Kochak and Sharma, 2015), etc.

In the literature, they are available in hybrid methods created by integrating different methods. Chang and Wang (2006) studied the fuzzy logic and ANN model that was integrated into the fuzzy back-propagation network (FBPN) to predict the sales for the Printed Circuit Board (PCB) company. Aburto and Weber (2007) introduced a hybrid intelligent model combining ARIMA models and ANN for demand forecasting in Chilean supermarket. Jaipuria and Mahapatra (2014) integrated two approaches: Discrete Wavelet Transforms analysis (DWT) and ANN. They analyzed ARIMA model to test the efficiency of the proposed model. Sultan and Jasim (2016) developed hybrid methods based on ANN and Artificial Bee Colony (ABC) algorithm. Merkuryeva, Valberga and Smirnov (2018) developed three baseline models to estimate pharmaceutical product demand by using the simple moving average method, multiple linear regression, and symbolic regression with genetic programming. Their results indicated that symbolic regression with the genetic programming model had been selected as the most suitable method that has the lowest absolute error and means deviation value.

Wang et al. (2011) constructed a model to predict the sales of three different car types (small, sedan and commercial) in Taiwan by using the Adaptive Network-Based Fuzzy Interface System Model (ANFIS) and regression analysis. Their model consisted of 22 different variables that affect the buying behaviors for cars. Their results showed that the ANFIS model gave better results compared to other methods. Šubelj, Furlan and Bajec (2011) proposed the automobile fraud detection system by using the ANN method. Karaatlı, Helvacıoğlu, Ömürbek, and Tokgöz (2012) used artificial neural network design to predict the number of future automobile sales. Their study indicated that the MAPE score was 16.82 %, and it was seen that the estimated and realized values were close to each other. Chen, Yao and Zhang (2018) investigated the sales forecasts of R brand automobiles by integrating the date of the historic sale of the automobile company. Arslankaya and Öz (2018) developed time series analysis and ANN model to estimate future automobile sales of the leading company in Turkey. Their results showed that the ANN method gives better results than time series analysis. Vahabi, Seyyedi and Alborzi (2016) developed conceptual forecasting models by integrating an Adaptive Neuro-Fuzzy Interface System (ANFIS) with the Genetic Algorithm (GA) to predict automobile sales demand in Iran. Their findings indicated that the integrated models reduced RMSE error and provided better results than other models, such as ANFIS and ANN. Shahabuddin (2009) established two different regression models to understand the variables that affect the sales of automobiles. As reported by their results, there was a considerable relationship between the economic variables and foreign automobiles sales. Hülsmann, Borscheid, Friedricha and Reith (2011) evaluated the sales prediction of German and US-American automobiles by using time series analysis and classical data mining algorithm. Fantazzini and Toktamysova (2015) proposed a multi-dimension model to predict the monthly sales of ten car brands in Germany. Their results demonstrated that Google search data performed better than the case of seasonally-adjusted data. Wang et al. (2011) proposed a sales forecasting method that consisted of 7 variables, which are automobile sales quantity, coincident indicator, a leading indicator, wholesale price index, and income. Then, they predicted the amount of three types of automobile sales by using ANFIS and ANN models. Their paper concluded that economic variables were good indicators to predict Taiwan's automobile sales. Pai and Liu (2018) proposed a multivariate regression model and time series analysis to predict the monthly vehicle sales demand from February 2008 to August 2017 in the US. They collected data from Twitter by three keywords, including "buy a car," "buy track," and "buy a vehicle," and analyzed by SentiStrength. Their study proved that the developed hybrid model which contain both sentiment scores of tweets revealed more accurate result than four-time series models. Fleurke (2017) developed an ensemble forecasting method to aggregate the finding of forecasting, such as the ARIMA model, Holt-Winters model, etc. Their results presented that outcomes of the performance scores for all individual models and their integration, the Ensemble model outperformed all the other models. Literature review related to auto automobiles sales predictions given in Table 1.

Table 1

Sales Forecasting Study in an Automotive Industry

Authors	**Methodology**	**Data**	**Indicators**	**Result**
Chen et al. (2018)	Time serial analysis and sentimental analysis	2016-2018	Sales data of three brand car (R, G, H)	MAPE: 51.6 %
Vahabi et al. (2016)	ANFIS and Genetic Algorithm	1991-1996	Current rate against USD, inflation rate, per capita income, loan interest rate, important tariff, importations value, housing starts value, total sales	RSME : 27092.76
Shed Shahabuddin, (2009)	regression analysis	1959-2006	Industrial demand, personal consumption, discount rate, non-durable goods demand, durable personal consumption, population,	R^2= 91 %
Hülsmann et al.(2011)	times series analysis, data mining	2007-1010	New car registration, GDP, personal income, unemployment rate, interest rate, consumer prices, gasoline prices, private consumption, deviation rates	< %10
Fantazzini and Toktamysova (2015)	Google data, nonlinear model	2011-2014	Building construction, consumer confidence indicators, consumer price index, euro interbank offered rate, gross domestic product, production index, unemployment rate, petrol price	< %10
Karaatlı et al. (2012)	ANN	2007-2011	GDP, Reel sector confidence index, investment expenditure, consumption expenditure, customer confidence index, dollar, time	0,1682
Akyurt (2015)	ANN	2011-2015	Monthly sales of available domestic cars	7,25%
Wang et al., (2011)	ARIMA, ANN model		Automobile sales quantity, coincident indicator, leading indicator, wholesale price index and income	MSE: 9292.66, 8730.31
Pai and Liu (2018)	multivariate regression models, time series models	2008-2017	Sentiment score of tweets, two stock market	< 10 %
Fleurke (2017)	"Time series forecasting, ANN, Generalized Linear Model, Theta, Random Forest, Vector Auto Regression"	2012-2017	The unemployment rate, GDP, the consumer price index	10,30%
Aslankaya and Oz (2018)	Time series analysis, ANN	2011-2016	The registered vehicle, GDP, consumer price index, dollar exchange rate, real sector confidence index, consumer confidence index, monthly working hours, number of models produced	ANN result: 7.44 %

3. Materials and Methods

3.1 Dataset

In this study, while predicting automobile sales, - the experts determined the indicators as the number of automobile sales (ASA), time (month), dollar exchange rate (DER), gross domestic product (GDP), consumer confidence index (CCI), and consumer price index (CPI). Figure 1 presents the economic indicators and the amount of automobile sales. Among these specified indicators, data for the independent variables were obtained from the website of The Central Bank of the Republic of Turkey (TCMB, 2019), and the data for the dependent variable were obtained from the production data of Turkey's leading automotive companies.

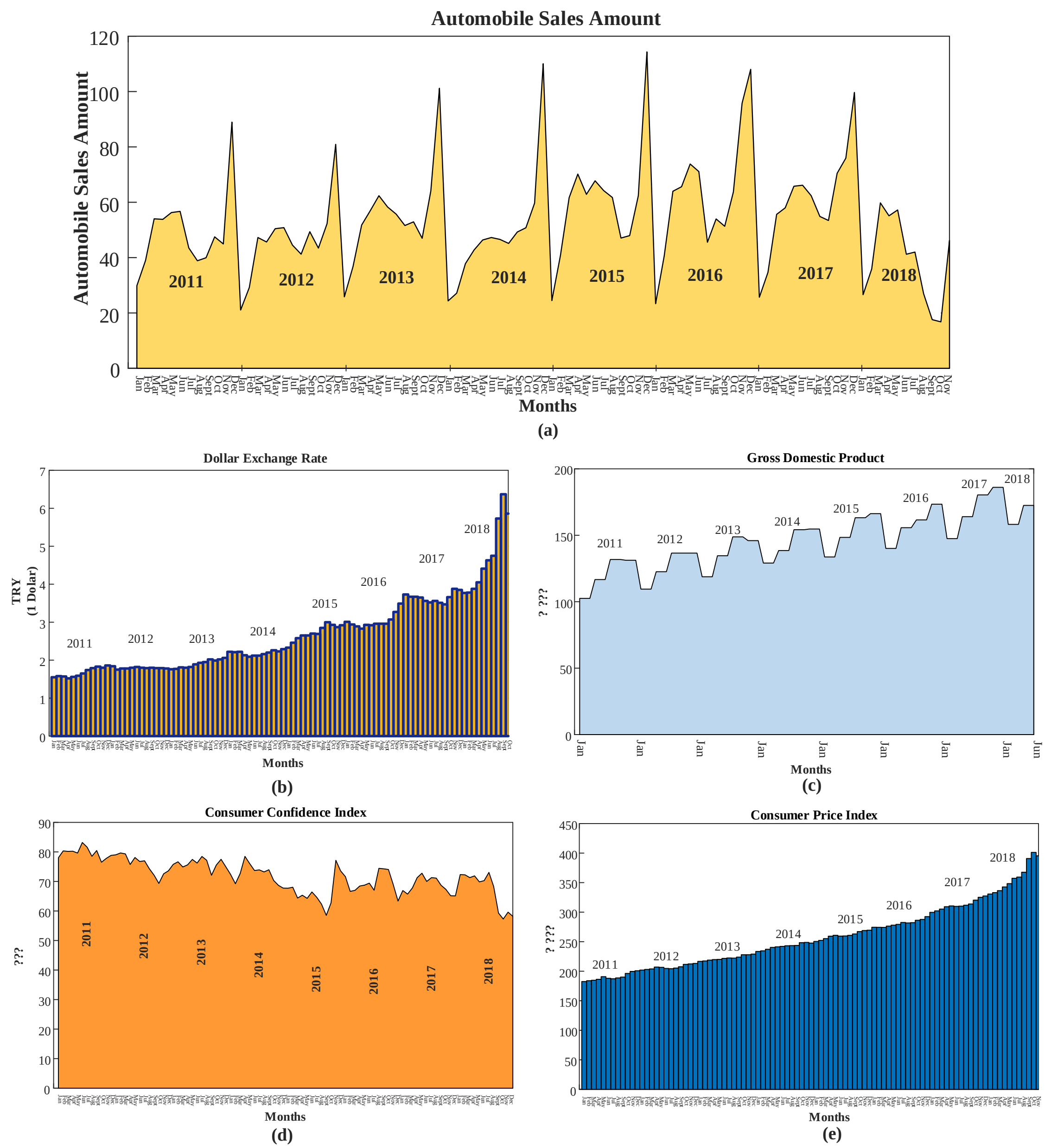

Figure 1. Obtained Economic Indicators for Turkey Between 2011 And 2018: a) Automobile sales amount, b) Dollar exchange rate (DER), c) Gross domestic product (GDP), d) Consumer confidence index (CCI) and e) Consumer price index (CPI).

These factors are as follows:

1. The number of Automobile sales: It shows the monthly variation in the number of automobile sales in Turkey between 2011 and 2018.

2. Gross Domestic Product (GDP): GDP is an economic indicator that presents the total monetary value of final goods and services produced within Turkey during a period of 2011 and 2018.

3. Consumer Price Index (CPI) This is the index that measures variations in prices of goods and services purchased by consumers between 2011 and 2018.

4. Dollar Exchange Rate (DER): It shows the monthly variation in the exchange rate between Dollar and Turkish lira between 2011 and 2018.

5. Consumer Confidence Index (CCI): Index shows the monthly variation in household consumption and saving between 2011 and 2018.

Figures (1a, 1b, 1c, 1d and 1e) show the variations in the amount of the automobile sales, dollar exchange rate, gross domestic product, consumer price index, consumer confidence index, respectively.

3.2 The Proposed Prediction Model

Deep learning is similar to artificial neural networks in terms of structure. Deep learning has multi-layered perceptions that make calculations of machine learning in multiple layers and learn required parameters themselves. Recently, deep learning has become a popular research topic as a sub-branch of machine learning (LeCun, Bengio and Hinton, 2015).

Deep Neural Networks (DNN) is a classical neural network structure with multiple layers between the input and output layers. With the deepening of the network, the ability of generalization is claimed to be better when compared to shallow structures (Kingma and Ba, 2017; Goodfellow, Bengio and Courville, 2016). DNN, which employs deep architectures in standard neural networks (NNs), is one of the most time-consuming methods among the machine learning methods of this decade. DNNs can easily reduce the requirements of feature engineering and solve more complicated problems with multiple layers (Bianchini and Scarselli, 2014).

DNN has become very popular by researchers and experts (Faust, Hagiwara, Hong, Lih and Acharya, 2018). Several successful applications of deep learning have been introduced in several areas, such as image processing (Krizhevsky, Sutskever and Hinton, 2012; LeCun, Boser, Denker, Henderson, Howard, Hubbard and Jackel, 1989), natural language processing (Sarikaya, Hinton and Deoras, 2014), biomedical signal processing (Yildirim, 2018; Faust et al. 2018), forecasting in healthcare (Jiang, Chin, Wang, Qu and Tsui, 2017). Particularly, DNN has achieved good performance to predict future events based on analysis of past and present data due to its deep learning architecture (Gashler and Ashmore, 2016; Hossain, Rekabdar, Louis and Dascalu, 2015; Hu, Zhang and Zhou, 2016).

In this study, a deep learning model was developed to predict automobile sales. Due to their classification and prediction capability, the DNN model was preferred to employ for this study. Keras library for Phyton was used to implementation deep models (Chollet, 2015). A Deep Neural Networks (DNN) based 8-layer network was designed. In this network, a dropout layer was placed after 128, 256, 512-unit hidden layers in order to prevent overfitting. These hidden layers pass 32- and 64-unit hidden layers respectively and with the sigmoid activation in the dropout layer, the prediction was made. Figure 2 presents a block representation of the proposed DNN model. Table 2 provides information on detailed layers and parameters of the proposed DNN model.

While developing the DNN model, a selection based on the brute-force technique was made by considering minimum 16 and maximum 512 as the multiples of two for the numbers of hidden layer units. As for the numbers of hidden layers to be placed into the network, the best version was obtained by starting from the only hidden layer and in the traditional neural network and increasing. The processes of the selection of activation functions and determining hyperparameters were also carried out with the same techniques and by benefitting from previous experiences of deep learning.

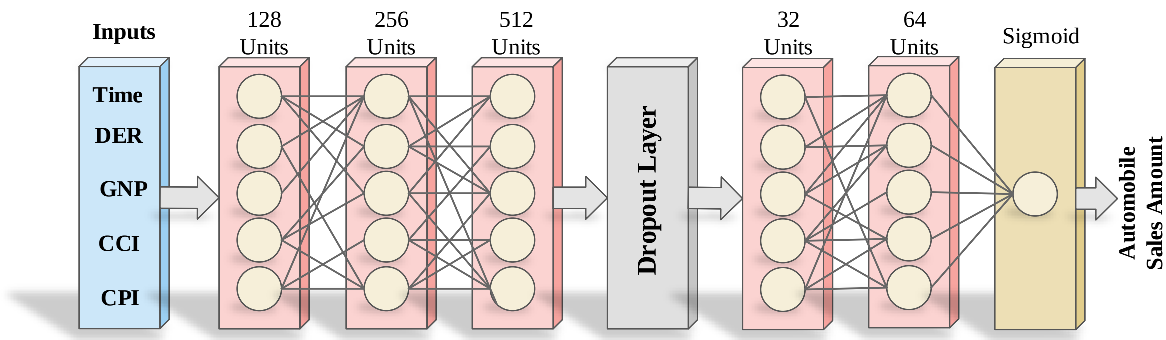

Figure 2. A block representation of the designed DNN model for automobile sales prediction

Table 2

Information on Detailed Layers and Parameters of the proposed DNN Model

Layer Number	Layer Name	Parameter	Activation Function
1	Input	Input_dim=5	
2	Dense	128 Units	Sigmoid
3	Dense	256 Units	Relu
4	Dense	512 Units	Relu
5	Dropout	Rate=0.3	-
6	Dense	32 Units	Relu
7	Dense	64 Units	Relu
8	Dense	1 Unit	Sigmoid

In this study, research and publication ethics were followed. It is stated in this article that no legal/special permission is required. All data sets used in this study are shown in the references.

4. Experimental Results

For experimental studies, a data set of 6×90 dimensions related to economic indicators obtained for Turkey between 2011 and 2018 was employed. The number of automobile sales in the dataset was used for the input of the network, while other economic indicators were used for the output. Thus, in line with the economic indicators used as the input of the model, automobile sales prediction could be made. In order to carry out detailed performance assessments on the limited number of datasets in the DNN model, a 5-fold cross-validation technique was used in the study. Data were split into equal pieces for each fold and each fold is used for both training and test stages. In the study, appropriate weights were obtained in the training process by training the model for the 250 epoch period. Adam optimizer (Kingma and Ba, 2017) was selected for the lost function optimizer in the prediction and mean square error (MSE) as the lost function. Data on input functions were scaled as 0-1 for the pretreatment. Loss graphs obtained for 5-fold cross-validation training made by using all input functions are presented in Figure 3.

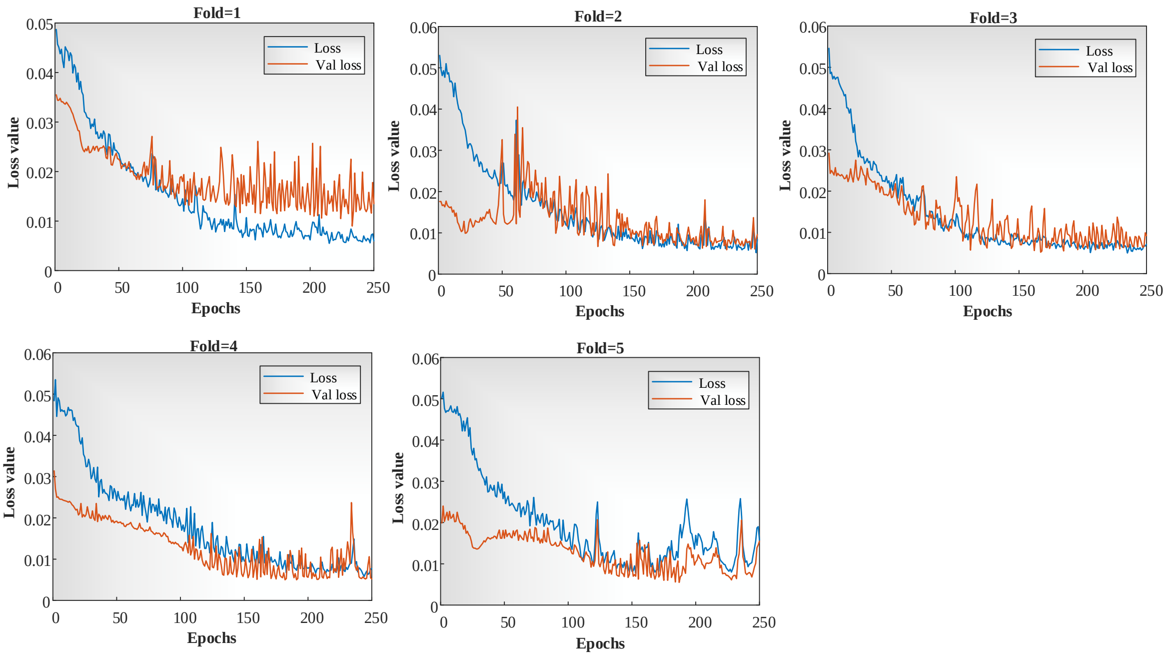

Figure 3. Loss Values Obtained by DNN Model for Each Fold During 250 Epoch Procedure for All Input Functions

As seen in the graphs, training loss value starting at the level of 0.05 declined to 0.001 at the end of 250 epoch. Similarly, validation loss values remained at 0.01 level. When the loss values for the fold were examined, an overfitting problem to be considered in the model did not occur. When all economic indicators for 5-fold and time (months) information were used as input, the average loss value of the DNN model was measured as 0.0106 and standard deviation as 0.0036. In accordance with the test data gathered from the training procedure of the model has been completed, and the model generates prediction values regarding the amount of automobiles sales. The prediction performance of the model was observed by comparing these prediction values with the actual values. Figure 4 shows prediction values on some folds obtained by the trained model and actual values with graphs.

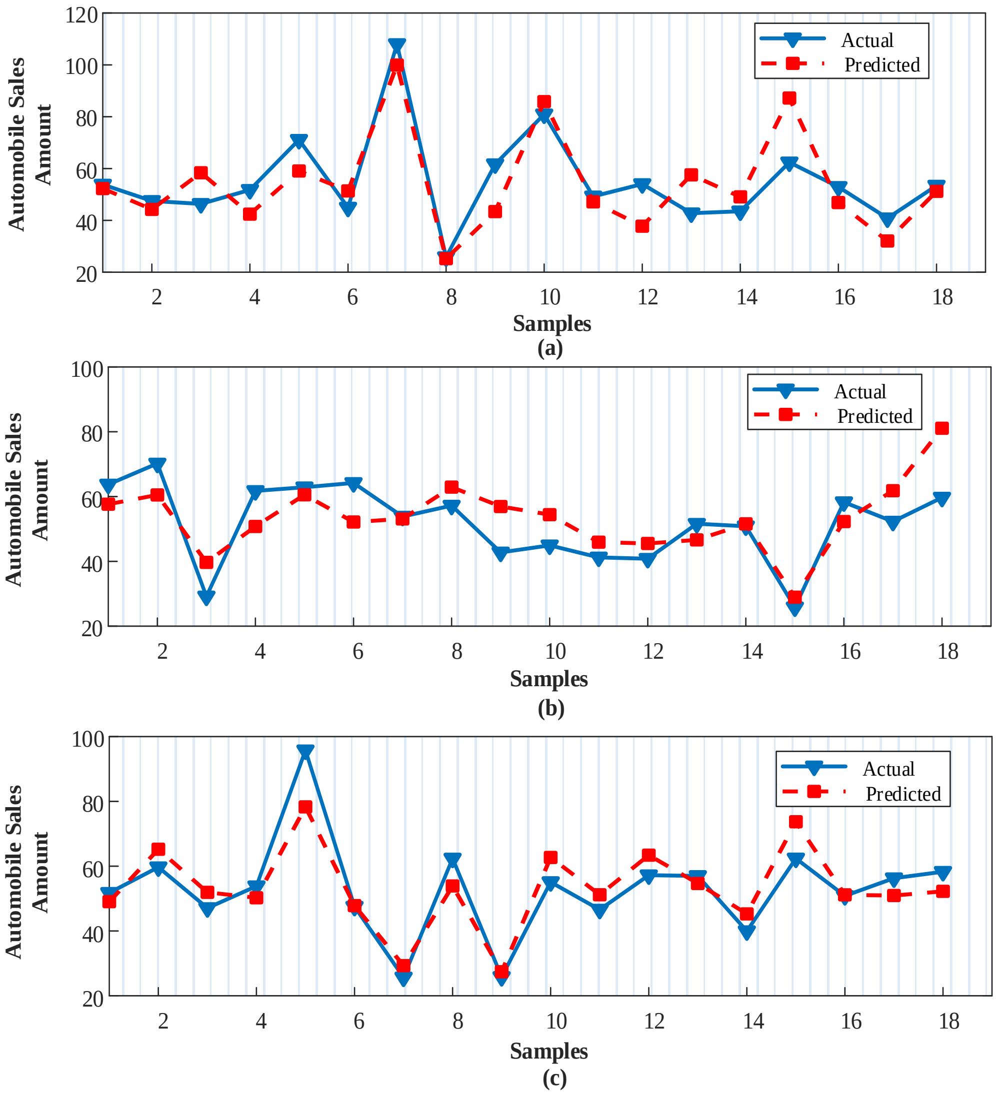

Figure 4. Prediction Results Obtained by DNN Model on Test Data of Some Folds. Continuous Lines and Dashed Lines Represent Actual and Predicted Automobile Sales Amounts, Respectively.

When prediction graphs are analyzed, it can be seen that the prediction values of the DNN model and actual values are close. Especially between automobile sales predicted for test data of Fold-3 and the actual amount of sales, there are very small differences. In this regard, it can be said that the proposed model can make predictions with high performance.

To determine the effectiveness of DNN in the automobile sales prediction problem, a simple 4-layer deep network model, which is closer to classical neural networks, was designed in this study. Figure 5 presents the block representation of DNN consisting of an input layer and two hidden layers. Hidden layers of 128 and 256 units were placed into this 4-layer DNN. Hyperparameters of the network were tuned as the same with 8-layer DNN in order to have a valid comparison.

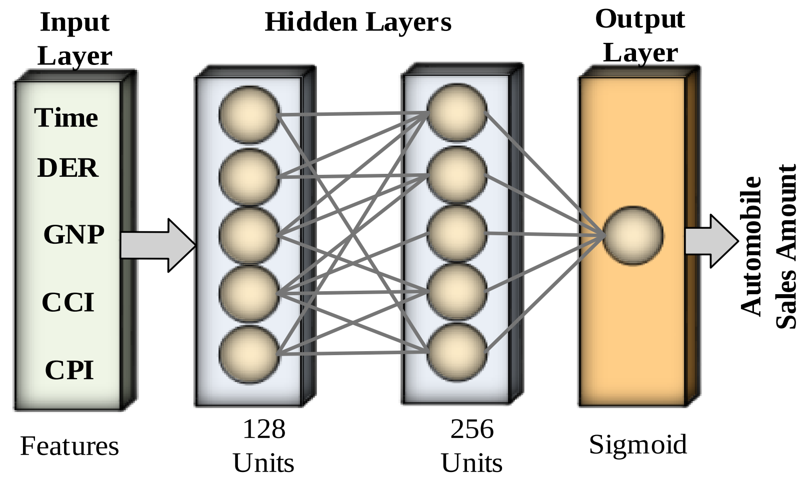

Figure 5. The Block Representation of 4-Layer DNN Developed for Performance Assessment

The 4-layer DNN was assessed on the data set contains all input functions (i.e., economic indicators and time). Fold data, which is the same as the previously used 8-layer network, was employed as input for this network. For the performance comparison, loss graphs of both 4-layer and 8-layer models on Fold-3 data are given in Figure 6.

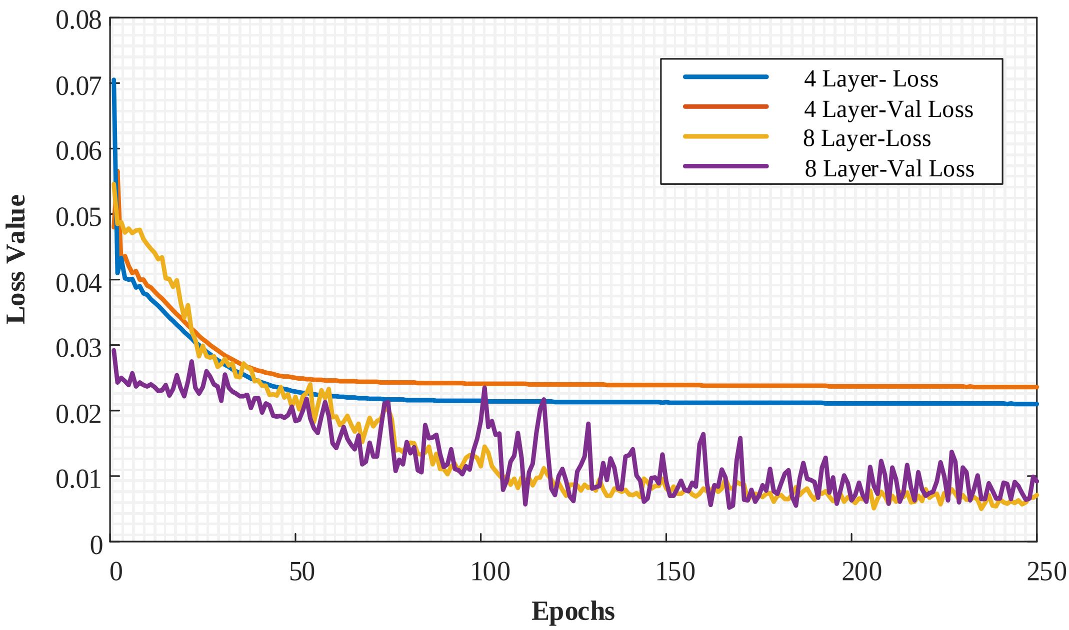

Figure 6. Loss Graphs of DNNs on Fold-3 Input Data During Training Stages

When loss graphs are analyzed, it is seen that the average loss value for the 4-layer network is 0.025 and 0.014 for an 8-layer network. As it is clearly seen in the graphs, the 8-layer DNN model generates prediction results with less error rate. Besides, when the relationship between training loss values and validation loss is concerned, the 4-layer network does not show the same success on validation data in the training stage. Therefore, it is obvious that the increase in the number of layers accelerates the performance.

The graph showing the comparison of the predictions made by both 4-layer and 8-layer networks on automobile sales amount, and the actual amounts are given in Figure 7.

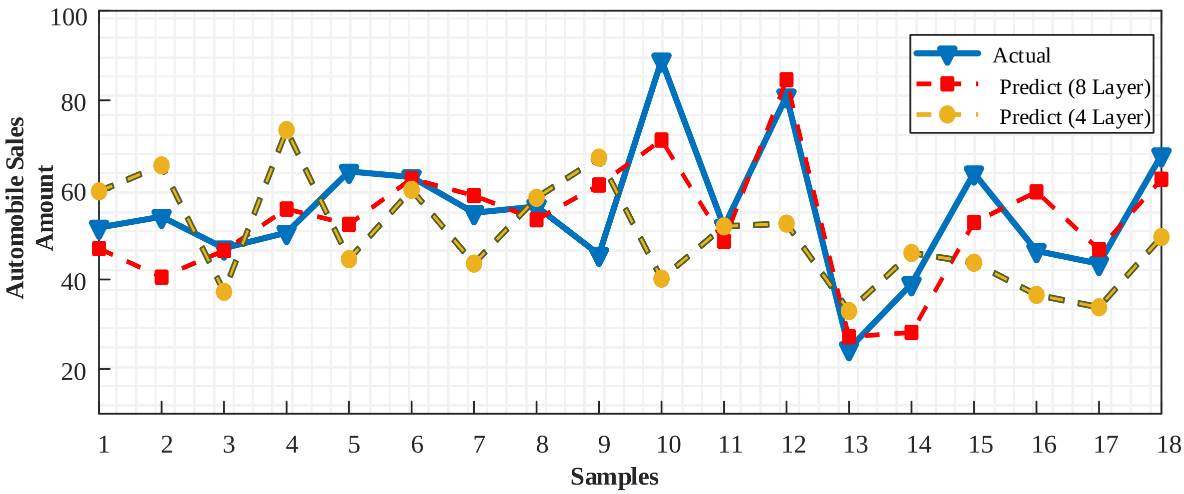

Figure 7. The Graph on The Comparison of Automobile Sales Prediction of DNN Models (4 and 8- layer)

When the prediction and actual values are compared, 8-layer DNN is observed to produce closer prediction results. When MSE values in Table 3 for the prediction values produced by the models are examined, 335.73 value was obtained for the 4-layer model and only 79.83 for the 8-layer model. Prediction values of auto sales are given in Table 3.

Table 3

Prediction Values for Automobile Sales Produced by DNN Models for Fold-3 Dataset

Samples From Fold-3 Dataset	**Actual Automobile Sales Amounts**	**Predicted Automobile Sales Amounts**	
		4- Layer DNN	**8-Layer DNN**
Sample 1	51.6110	59.6828	46.9022
Sample 2	54.0230	65.4708	40.5110
Sample 3	46.9850	37.2489	46.4531
Sample 4	50.4600	73.3664	55.7307
Sample 5	64.1170	44.5401	52.3196
Sample 6	62.8780	60.0292	62.4908
Sample 7	54.8900	43.5320	58.7325
Sample 8	56.3020	58.2327	53.3492
Sample 9	45.5660	67.2141	61.0836
Sample 10	88.9570	40.1646	71.1358
Sample 11	51.7850	51.8599	48.5389
Sample 12	80.9260	52.4810	84.5912
Sample 13	24.4980	32.9492	27.2077
Sample 14	39.0040	45.9225	28.1633
Sample 15	63.7460	43.7447	52.7351
Sample 16	46.3790	36.5534	59.5607
Sample 17	43.5180	33.7977	46.6971
Sample 18	67.7660	49.4727	62.3767
	MSE Values=	335.73	79.83

5. Sensitivity Analysis

In order to analyze the effects of economic indicators and time parameters on the prediction performance of the DNN model, datasets were prepared to include different features. For instance, the effect of time parameter was tried to be detected by assessing the performance of the model with a data set which only used economic indicators without the time parameter with month information. To that end, 4 different datasets were prepared. In the first dataset, all economic indicators (DER + GDP + CCI + CPI) were included, except for the time parameter. In the second dataset, consumer indices (CCI and CPI) and time input were included. In the third dataset, consumer indices were removed and dollar exchange rate (DER), gross domestic product (GDP) and time input were included. The last data set only included time data and the dollar exchange rate (Time + DER). Various prediction graphs obtained by the models trained with these datasets for different folds are given in Figure 8.

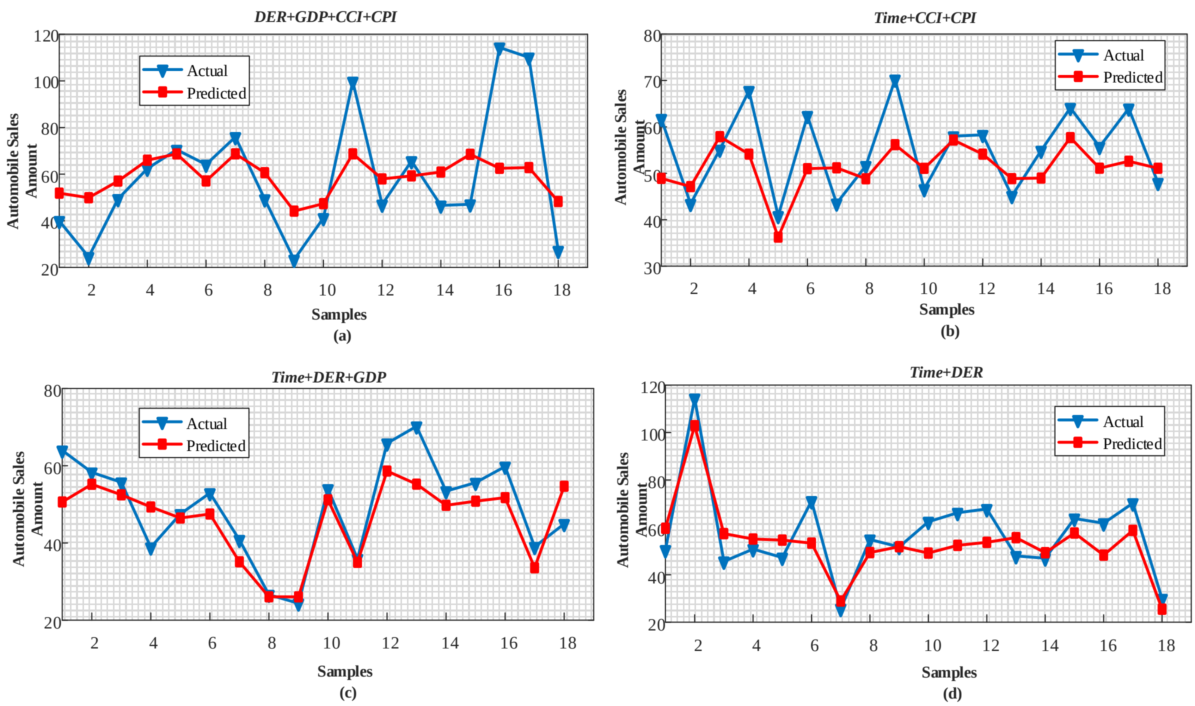

Figure 8. Prediction Graphs Obtained By 8-Layer DNN Model for The Datasets Prepared with Different Attributes, a) DER, GDP, CCI and CPI features, b) Time, CCI and CPI features, c) Time, DER and GDP features and d) Time and DER features.

The most remarkable factor in these graphs is that time information has an active role in prediction. When Figure 8 is analyzed, it is seen that predictions made with only economic indicators by excluding time parameters represent underachievement. In addition, it is also noteworthy that consumer indices do not overly change the success of prediction. The best result for the prediction of automobile sales was seen to be obtained with time, dollar exchange rate and gross domestic product attributes (see Figure 8 (c) and Table 4). Table 4 shows the prediction performance comparison of DNN models and the attributes of the dataset. The best results were obtained from 8-layered DNN that fed with Time, DER and GDP features. The 4-layered DNN has a lower prediction performance than the 8-layered DNN. Therefore, the number of layer increments has a positive effect on performance. Due to more resource consuming the number of the layer was not incremented than 8 layers. In this study, an 8-layer DNN model was determined an optimal model for prediction.

Table 4

Performances of DNN Models and Attributes on Automobile Sales.

Models	**Used Attributes**	**Loss Values (Mean Loss ± Stdv)**
4 Layer DNN	All Attributes	0.0279 ±0.008
8 Layer DNN	All Attributes	0.0106 ±0.003
8 Layer DNN	DER+GDP+CCI+CPI	0.0327 ±0.011
8 Layer DNN	Time+CCI+CPI	0.0112 ±0.003
8 Layer DNN	Time+DER+GDP	0.0086 ±0.002
8 Layer DNN	Time+DER	0.0107 ±0.002

The main limitation of this study is the less amount of data used. Further studies should be conducted with increased data. Besides, comprehensive studies on performance assessment can be carried out by using different economic indicators. Future studies may extend experimental studies by employing different deep learning methods, such as long short-term memory networks (LSTM).

5. Conclusions

In this study, an 8-layer DNN model was recommended for automobile sales amount prediction. The inputs of the model consist of features, such as the dollar exchange rate, the gross domestic product, consumer confidence index, and the consumer price index. Automobile sales prediction was made according to the output of the model. In the study, a total of 90 data on a monthly basis between the years of 2011 and 2018 was collected. In experimental studies, an 8-layer DNN model was observed to realize the prediction of automobile sales with 0.0086 ±0.002 loss value by employing time, DER, and GDP attributes. This study involves significant results regarding the use of deep learning methods for demand prediction problem and this provides valuable information for future studies to be conducted in this field.

This study has made two important contributions to the literature. First, we have experimentally demonstrated that some economic indicators such as the growth rate of national income per capita and tax, dollar exchange rate have become the most significant indicators in the growth of the automotive sector in Turkey. Second, the results of the experiment demonstrated that the 8- layer DNN model makes better prediction compared to the traditional neural network with 4- layers.

A future study could examine a different type of DNNs model to estimate automobile sales by using different numbers and types of indicators.

Contribution of Researchers

In this study, Sema KAYAPINAR KAYA completed literature review, data collection, wrote the manuscript and prepared manuscript formatting and editing while Özal YILDIRIM proposed the prediction model, developed application software, wrote the manuscript, prepared data for visualization and discussed the results.

Conflict of Interest

No conflict of interest was declared by authors.

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