TEKSTİL VE MÜHENDİS

(Journal of Textiles and Engineer)

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PREDICTION OF TURKEY'S COTTON SOCK EXPORTS TO GERMANY USING DEEP LEARNING APPROACH

TÜRKİYE'NİN ALMANYA'YA PAMUKLU ÇORAP İHRACATININ DERİN ÖĞRENME YAKLAŞIMI İLE TAHMİNİ

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Online Erişime Açıldığı Tarih (Available online):30 Eylül 2024 (30 September 2024)

Bu makaleye atıf yapmak için (To cite this article):

Ahmet ÖZBEK, Çağatay TEKE (2024): PREDICTION OF TURKEY'S COTTON SOCK EXPORTS TO GERMANY USING DEEP LEARNING APPROACH, Tekstil ve Mühendis, 31: 135, 174- 181.

For online version of the article: https://doi.org/10.7216/teksmuh.1486577

TMMOB Tekstil Mühendisleri Odası
UCTEA Chamber of Textile Engineers
Tekstil ve Mühendis
Journal of Textiles and Engineer

Yıl (Year) : 2024/3
Cilt (Vol) : 31
Sayı (No) : 135

Araştırma Makalesi / Research Article

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Gönderilme Tarihi / Received: 19.05.2024
Kabul Tarihi / Accepted: 07.09.2024

ABSTRACT: Cotton socks are a strategic export product for Turkey. Therefore, the aim of this study is to forecast Turkey's exports to Germany, the world's largest cotton socks market. In order to achieve this objective, the determinants of exports were identified by analysing the literature. Then, expert opinion was sought to determine the importance of these factors for Turkey's cotton socks exports to Germany. Using the deep learning model created from the factors determined as a result of the expert opinion, the prediction of the export of Turkish socks to Germany was realised. A success rate of 96% was achieved with the prediction.

Keywords: Deep learning, MLP neural network, cotton sock, export prediction.

TÜRKİYE'NİN ALMANYA'YA PAMUKLU ÇORAP İHRACATININ DERİN ÖĞRENME YAKLAŞIMI İLE TAHMİNİ

ÖZ: Pamuklu çoraplar Türkiye için stratejik bir ihraç ürünüdür. Bu nedenle, bu çalışmanın amacı Türkiye'nin dünyanın en büyük pamuklu çorap pazarı olan Almanya'ya ihracatını tahmin etmektir. Bu amaca ulaşmak için, literatür analiz edilerek ihracatın belirleyicileri tespit edilmiştir. Daha sonra, bu faktörlerin Türkiye'nin Almanya'ya pamuklu çorap ihracatı açısından önemini belirlemek için uzman görüşüne başvurulmuştur. Uzman görüşü sonucunda belirlenen faktörlerden oluşturulan derin öğrenme modeli kullanılarak Türkiye'nin Almanya'ya çorap ihracatının tahmini gerçekleştirilmiştir. Tahmin ile %96' lık bir başarı oranı elde edildi.

Anahtar Kelimeler: Derin Öğrenme, MLP yapay sinir ağı, pamuklu çorap, ihracat tahmini

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DOI: *https://doi.org/10.7216/teksmuh.1486577* *www.tekstilvemuhendis.org.tr*

1. INTRODUCTION

According to the theory of comparative advantages, the one who has the raw material of a product will have a competitive advantage in the advanced state. From this point of view, cotton production has been carried out in Anatolia since primitive times and cotton clothing sector has been formed depending on this production. Since denim trousers and socks contain a large proportion (more than 90%) of cotton among cotton garments, it is predicted that these products will continue to be produced in Anatolia in the future [1]. These products are also categorised as strategic export products for Turkey due to their characteristics. This is best evidenced by the fact that Turkey is the world's second largest exporter of cotton socks after China with a share of 11.76%, as shown in Table 1.

Sock exports are a complex and dynamic process influenced by factors such as consumer demand, economic conditions, fashion trends, seasonality, exchange rates, logistics, customs duties and trade agreements. The complex interaction of these factors can lead to significant fluctuations in sock export volumes and values across different markets and time periods. Producers and exporters must manage these variables carefully in order to meet the changing needs of global consumers and remain competitive. Moreover, technological advances in production methods and materials can affect the export environment of the sock industry and potentially alter the balance of trade between countries. These factors determine the variation in the amount of sock exports. While some of these factors are measurable and predictable, some of them are not measurable and unpredictable. Therefore, forecasting sock exports is a difficult issue for both producers and exporters. However, forecasting sock exports is of strategic importance in areas such as pricing policies, production planning, inventory management, risk analysis and decision making. The complexity of this situation extends beyond these factors to include technological advances in production, raw material availability and changing global supply chains. Furthermore, sustainability initiatives are increasingly influencing consumer preferences and regulatory frameworks, further complicating the export environment for sock producers. Despite these challenges, accurate forecasts are crucial for businesses to remain competitive and adapt to rapidly changing market conditions in the global sock industry.

Various methods are used for export forecasting. Some of these methods are traditional statistical methods, while others are modern methods such as artificial intelligence, machine learning and deep learning [2-10, 22]. Traditional statistical methods are based on modelling export amounts as time series. Time series analysis is a statistical technique that aims to predict future values using past data. Examples of methods used in this analysis include moving average, regression analysis, Box-Jenkins and ARIMA. These methods are based on the assumption that exports are linear and stationary. On the other hand, exports are a non-linear and complex process in which different parameters affect each other. For this reason, traditional statistical methods are insufficient in export forecasting. Artificial intelligence-based methods, on the other hand, can develop models that can capture the non-linear characteristics of exports and learn complex relationships. This capability offers an alternative approach to export predicting.

Following is the paper's outline: Chapter 1 explains sock export, its difficulties and its forecasting. Chapter 2 gives literature review and emphasize the importance of the study. Chapter 3 describes the methodology. Chapter 4 examines the results and discussion while Chapter 5 includes the conclusion of the research.

Table 1. Countries Exporting the Most Cotton Socks (US Dollar thousand)

	Exporters	**2018**	**2019**	**2020**	**2021**	**2022**
	World	5.502.986	5.662.185	4.960.383	6.361.706	6.991.433
1	China	2.411.323	2.496.333	1.988.130	2.571.529	2.822.713
2	Türkiye	667.991	667.055	627.187	797.644	822.124
3	Netherlands	354.970	360.548	374.835	475.258	446.465
4	Germany	271.804	281.823	285.973	355.925	363.119
5	Pakistan	216.110	220.516	142.096	195.064	336.497
6	Belgium	177.425	177.184	179.204	226.608	251.052
7	Viet Nam	50.802	79.811	87.077	110.447	195.986
8	Italy	125.386	132.775	114.736	149.878	154.711
9	Poland	76.069	89.517	109.772	151.283	154.336
10	Honduras	10.136	23	1	5	129.174
https://www.trademap.org/						

2. LITERATURE REVIEW

When some of the studies in the literature are mentioned within the framework of the subject of the article; Gür and Eşidir (2024) used ARIMA and Multilayer Perceptron (MLP) methods to forecast Turkey's monthly trout exports. The aim of the study is to contribute to trade planning and marketing strategies by accurately forecasting trout exports. Artificial neural networks and ARIMA model were used to forecast future export trends based on historical data. The data set used is obtained from the 18-year period between 2005 and 2023. The MLP model has a multilayer structure and hyperbolic tangent is used as the activation function. According to the results of the study, trout exports, which were estimated to be approximately 22.7 million USD in February 2023, will increase to 33.9 million USD in December 2023. The results show that both models are effective in trout export forecasts. The study suggests that these models can be improved with larger data sets and different modelling techniques in future research [23].

Gür and Eşidir (2024) used Artificial Neural Network (ANN) models to forecast the imports of Turkey's paper and paper products sector. The aim of the study is to support strategic planning and resource management by forecasting paper imports for the period April 2023 - March 2024. In the study, future import values were predicted using MLP and Radial Basis Function (RBF) models. The data set includes 219 months of data between 2005 and 2023. The findings show that the MLP model predicts monthly imports between 270-300 million USD and the RBF model predicts monthly imports between 268-321 million USD. The results show that ANNs provide high accuracy in import forecasting and can improve the decisions of companies in the industry such as inventory management, production planning and marketing strategies [24].

In the study conducted by Özbek and Akalın (2011), ANN models were used to forecast Turkey's denim trousers exports to Germany. Within the scope of the study, ANN models were constructed with variables such as denim pants imports, minimum wage, cotton prices, electricity and water costs, the value of TRY against the dollar, credit utilization in the garment sector, export credits, real effective exchange rate, number of brands, Germany's denim trousers imports, Germany's quota applications to Turkey, per capita income in Germany, Germany's population, unemployment and inflation. The results of the study revealed that the Elman network model showed the best forecasting performance. The study highlights the effectiveness of ANN models for forecasting Turkey's denim trousers exports to Germany [25].

The aim of this study is to forecast Turkey's cotton sock exports to Germany. In order to achieve this objective, firstly, the determinants of cotton sock exports are determined according to expert opinion. To start with, experts in the field are consulted on what these factors might be. This approach helps to identify the key factors that could affect cotton sock exports before conducting further analysis. Then, using these determinants, Turkey's cotton sock exports to Germany are forecasted using a deep learning approach.

Deep learning approach is used in many different fields such as finance, medicine and manufacturing [11-16]. When the studies in the field of finance are analysed, it is seen that there are limited number of studies on export prediction with deep learning [4, 9, 17]. However, there is no study using deep learning techniques for cotton sock export prediction. Therefore, it can be said that this study is the first research attempt on this specific topic. This emphasizes the importance of the study in terms of literature.

3. METHODOLOGY

Within the scope of this study, Turkey's cotton sock exports to Germany were estimated. The methodology of the study is explained in the subheadings below.

3.1. Determination of the Parameters

Within the scope of this study, expert opinion was consulted to determine which of the economic factors determining exports according to the literature are important for Turkey's exports of cotton socks to Germany and to what extent.

In order to determine the experts within the scope of the research, the data of the enterprises exporting socks in 2023 were obtained from the Turkish Exporters Assembly (TIM). These enterprises were reached via e-mail. Among the enterprises reached, 16 experts exporting cotton socks to Germany were reached. 14 of these experts are male and 2 of them are female. The youngest expert is 41, the oldest is 59 and the average age is 47,6. Three of the experts are company owners, four are general managers, four are export managers, two are marketing managers and three are managers. The export experience of the experts is 5 years for the least, 31 years for the most and 19,6 years for the average.

Within the scope of the research, experts were asked to evaluate the level of importance of the export determinants determined from the literature and given in Table 2 for Turkey's exports of socks to Germany according to a value scale of 1 (Not at all important) to 10 (Very Important). The data obtained as a result of the evaluations of the experts are given in Table 2.

According to Table 2, the most important determinants of Turkey's cotton sock exports to Germany are Minimum Wage in Turkey, Currency Rate and Cotton Price. Again according to the table, the least important determinants of Turkey's cotton sock exports to Germany are Total Imports for Germany, Total Sock Exports for Germany and Turkey's Sock Exports to Germany.

3.2. Data Collection and Preparation

The properties of the data of the determined parameters are given in Table 3.

All data pertaining to the parameters are organised on a monthly basis covering the years 2014-2023. While determining the monthly minimum wage, the monthly average dollar exchange rate was taken into consideration. Moreover, while calculating the currency rate, the average of the lowest and highest currency rate values on the days of the relevant month was taken. The currency rate data for the month was calculated by taking the average of these values determined for each day. Also, the monthly cotton price is based on the average value of the lowest and highest prices realised during the month. A sample part of the data set is given in Table 4.

Table 2. Determinants of Turkey's exports of cotton socks to Germany according to expert opinions

Export Determinants	**Expert Reviews**																
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	Ave
Minimum Wage in Turkey	10	10	10	4	10	10	9	7	10	10	8	10	10	9	10	1	8,63
Currency Rate	8	9	8	8	10	10	9	7	10	5	9	10	8	8	1	5	7,81
Cotton Price	10	10	3	3	8	10	7	7	10	10	9	5	9	8	10	5	7,75
Population in Germany	8	9	2	6	7	10	6	5	8	5	8	10	7	8	10	10	7,44
Per Capita Income for Germany	8	8	5	7	10	7	8	7	9	1	8	9	9	7	4	7	7,13
Inflation Rate in Germany	8	9	1	5	10	4	5	9	6	5	7	6	5	3	4	10	6,06
Total Imports for Germany	8	2	5	2	8	2	7	5	9	2	9	7	7	7	3	2	5,31
Total Sock Exports for Germany	8	5	4	2	4	3	6	1	3	8	6	1	5	8	1	10	4,69
Turkey’s Sock Exports to Germany	9	7	1	5	4	3	5	4	1	1	7	4	2	6	1	4	4,00

Table 3. Data properties of the parameters

Parameter	**Type**	**Time Period**	**Unit**	**Source**
Minimum Wage in Turkey	Input	Monthly	USD	Turkish ministry of labor and social security
Currency Rate	Input	Monthly	TRY/EUR	https://www.investing.com/
Cotton Price	Input	Monthly	cent/lb	https://www.investing.com/
Population in Germany	Input	Monthly	Million	Federal Statistical Office of Germany
Per Capita Income for Germany	Input	Monthly	USD	Federal Statistical Office of Germany
Inflation Rate in Germany	Input	Monthly	%	Federal Statistical Office of Germany
Total Imports for Germany	Input	Monthly	Billion USD	Federal Statistical Office of Germany
Total Sock Exports for Germany	Input	Monthly	Million USD	Federal Statistical Office of Germany
Turkey’s Sock Exports to Germany	Output	Monthly	Million USD	Federal Statistical Office of Germany

Table 4. A small data set

Date	Minimum Wage in Turkey	Currency Rate	Cotton Price	Population in Germany	Per Capita Income for Germany	Inflation Rate in Germany	Total Imports for Germany	Total Sock Exports for Germany	Turkey’s Sock Exports to Germany
01.01.2014	373.0652	3.1058	85.41	81198000	46299.23	1.30	102.0738	22.396	16.149
01.02.2014	379.9771	3.0279	86.98	81279500	46443.93	1.30	102.8493	22.765	15.388
01.03.2014	385.2810	3.0354	92	81361000	46588.63	1.10	108.2254	18.477	17.186
01.11.2015	351.5910	3.1127	61.785	82464330	42261.95	0.20	88.2277	17.354	13.189
01.12.2015	341.1319	3.175	62.635	82493163	41684.55	0.30	79.6813	17.087	13.385
01.01.2016	435.4122	3.2595	62.11	82522000	41107.1	0.50	81.7385	19.859	15.296
01.12.2018	302.7268	6.03	76.4	83154663	47684.16	1.70	93.0658	18.78	9.076
01.01.2019	367.7105	6.2312	72.75	83167000	47961.18	1.30	107.5453	26.655	15.573
01.02.2019	384.7391	5.9948	72.13	83166000	47865.27	1.40	103.3931	22.687	10.453
01.11.2021	243.6793	13.2816	116.585	84172000	50669.48	4.80	130.8519	35.08	17.063
01.12.2021	198.7873	16.1233	109.8	84265500	51065.23	4.90	125.1476	31.073	17.608
01.01.2022	321.2659	15.158	120.235	84359000	51460.99	4.20	121.3835	29.868	23.199
…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
01.10.2023	409.1516	29.4524	84.26	84569882	51806.77	3.80	119.2026	26.022	21.263
01.11.2023	399.0872	30.8346	80.69	84579924	52145.71	3.20	126.2682	30.781	18.15
01.12.2023	389.9969	32.1857	79.565	84600000	52823.58	3.70	122.7354	28.401	19.706

3.3. Developed Multi-Layer Perceptron (MLP) Model

In this study, a MLP neural network, which is one of the deep learning techniques, is used in the prediction of sock exports. MLP neural network is one of the most widely used types of artificial neural networks [18]. MLP neural network consists of three layers: input layer, hidden layer and output layer. The input layer is the first layer that transmits data to the network. The hidden layer is the layer where the learning process takes place and represents the properties of the data. The number of hidden layers varies according to the problem, at least one, and is adjusted according to the need. The output layer produces the predictions of the network. MLP neural network is trained using back propagation algorithm. The back propagation algorithm calculates the error between the output of the network and the actual output and updates the weights by propagating this error back to the weights of the network. In this way, the network is learnt. When the targeted learning level is reached, this process is completed. The topology of the developed MLP model is presented in Figure 1.

3.4. Application

The MLP model has 8 input parameters and one output parameter. Different MLP models are designed with 3, 4, 5, 6, 10, 15, 20, 25, 30, 31, 32, 33, 34, 35, 40, 45, 50, 60, 70, 70, 80, 90, 100 neurons in the hidden layer respectively. This is because the number of neurons in the hidden layer affects the prediction performance of the model. When there are not enough neurons in the hidden layer, it becomes difficult for the network to learn. On the other hand, when there are too many neurons, the network may enter the memorization process. For all these reasons, we tried to determine the number of neurons in the hidden layer to maximize the prediction performance.

In order to be used in the training and testing process of MLP models, a total of 120 monthly data covering the years 2014 - 2023 are available, 80% of which are used in the training phase and 20% in the testing phase. These two datasets, referred to as training set and test set, were randomly selected from the total data. These data sets were normalized before use. In this way, the disadvantages that numbers of different sizes may cause in the learning process of the network are avoided. The formula used in the normalization process is given below:

$$X = \frac{(X_i - X_{min})}{(X_{max} - X_{min})} \quad (1)$$

A sample of the normalised training and test sets are shown in Table 5. and Table 6. respectively.

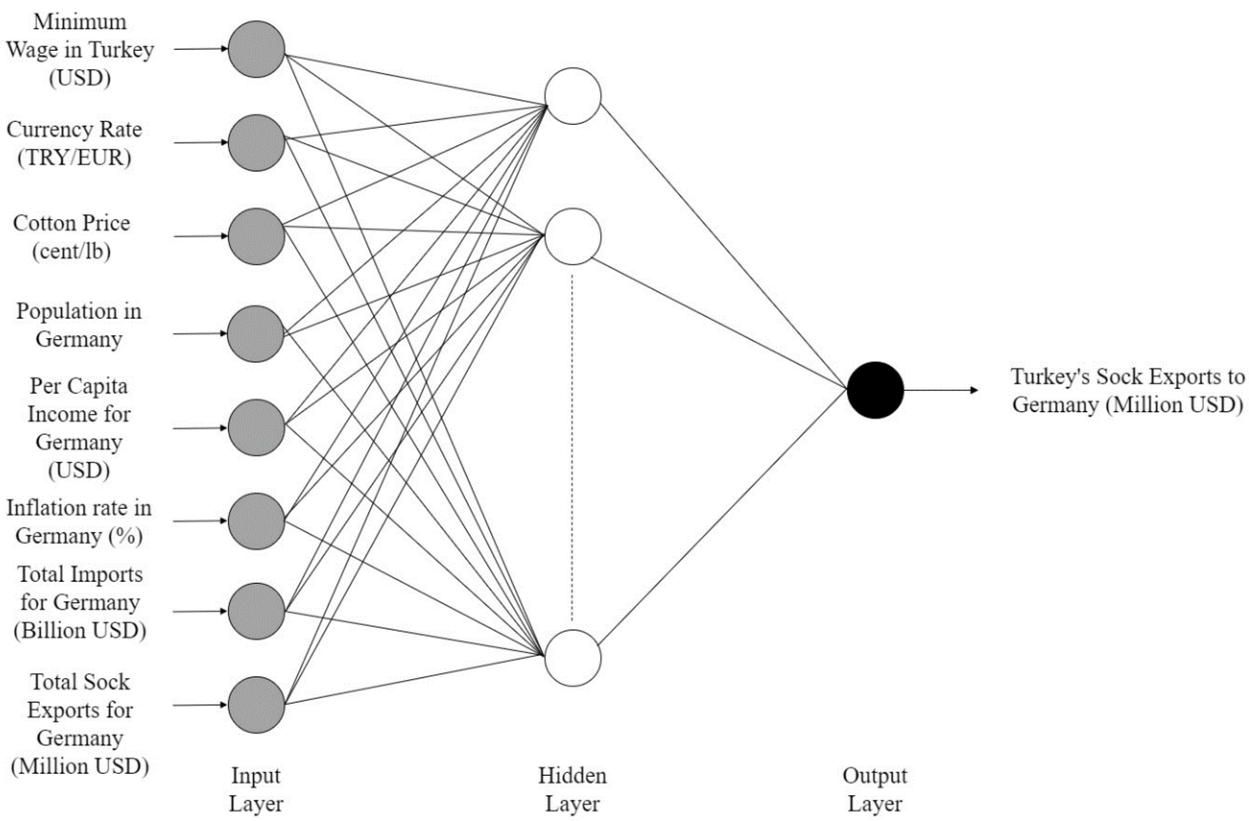

Figure 1. Topology of the developed MLP model

Table 5. A small normalised training set

Data no.	Minimum Wage in Turkey	Currency Rate	Cotton Price	Population in Germany	Per Capita Income for Germany	Inflation Rate in Germany	Total Imports for Germany	Total Sock Exports for Germany	Turkey's Sock Exports to Germany
1	0.667919	0.012980	0.3413937	0	0.4431476	0.202127	0.3561373	0.3877729	0.506395
2	0.694409	0.010335	0.358008	0.0239564	0.4554977	0.202127	0.3678432	0.4024788	0.4722434
19	0.539479	0.019594	0.1024392	0.3637557	0.1478473	0.1595744	0.241479	0.2715606	0.3790333
20	0.585619	0.013213	0.0913804	0.3722310	0.0985662	0.0851063	0.1471271	0.1868324	0.3735583
35	0.768552	0.042479	0.2232393	0.4963506	0.1761663	0.2127659	0.2532689	0.2398373	0.4207691
36	0.741992	0.046374	0.1873644	0.5019112	0.1940378	0.223404	0.2765884	0.2953929	0.4105371
57	0.588820	0.120786	0.0767765	0.5764256	0.5195075	0.1914893	0.3596514	0.518611	0.1592245
58	0.588679	0.122995	0.1084184	0.5758377	0.5031357	0.1702127	0.395289	0.4462776	0.3603644
77	0.398449	0.275757	0.6015133	0.8467078	0.7823706	0.5319148	0.7225230	0.918021	0.6074586
78	0.172048	0.358364	0.671305	0.8741916	0.8161478	0.5744680	0.7905467	0.8932727	0.5474128
…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…
95	0.767648	0.954139	0.2914439	0.9940987	0.9421438	0.4042553	0.7213550	0.7219432	0.5961944
96	0.732810	1	0.27953	1	1	0.4574468	0.6680273	0.6270923	0.6660234

Table 6. A small normalised test set

Data no.	Minimum Wage in Turkey	Currency Rate	Cotton Price	Population in Germany	Per Capita Income for Germany	Inflation Rate in Germany	Total Imports for Germany	Total Sock Exports for Germany	Turkey's Sock Exports to Germany
1	0.767207	0.007460	0.4070585	0.0718694	0.4801979	0.2127659	0.3898348	0.1298820	0.2795404
2	0.85182	0.004736	0.1791100	0.1437389	0.5172483	0.1595744	0.3872479	0.2533875	0.6289548
12	0.712659	0.111038	0.2008571	0.5784832	0.5768089	0.2127659	0.3760519	0.3993703	0.2507741
13	0.575099	0.123866	0.1079422	0.5761316	0.511321	0.1808510	0.4577895	0.5720149	0.3866176
…	…	…	…	…	…	…	…	….	…
…	…	…	…	…	…	…	…	…	…
23	0.864396	0.644544	0.3238266	0.9763880	0.7685729	0.7127659	0.748845	0.5987167	0.4243145
24	0.852111	0.88638	0.3643579	0.9881951	0.8842869	0.5425531	0.5910998	0.7074764	0.8018220

Despite there are many different training algorithms, the LM training algorithm stands out in terms of speed and reliability compared to other algorithms [19]. For this reason, LM training algorithm is preferred in this study. In addition, Log-Sigmoid function is used as the transfer function. The general representation of this function is as follows:

$$a = logsig(n) = \frac{1}{1+e^{-n}} \tag{2}$$

4. RESULTS AND DISCUSSIONS

In this study, MLP neural network is used to predict Turkey's exports of cotton socks to Germany. MLP is one of the most common types of deep learning models and was chosen because it is particularly effective in modeling complex and nonlinear relationships. In addition, its advantages such as flexibility, adaptability, fast computation and ease of implementation have also played a role in its preference. MLP models were created using MATLAB software. In addition, the training and testing phases of each model were carried out by means of this software. After the training and testing phases were completed, the performance of each model was measured. At this stage, Mean Absolute Percentage Error (MAPE) and coefficient of determination (R^2) statistical measures were used. MAPE is one of the most widely used measures of prediction performance and has the best performance measurement, especially when there are no extreme outliers in the data set [20]. It is also a useful measure for comparing the prediction performance of data with different units. The smaller the MAPE value, the better the prediction performance. R^2 is a measure of a statistical model and how well it fits the data. In other words, it is a measure of the agreement between the estimated value and the actual data [21]. R^2 value varies between 0 and 1. A high value indicates that the prediction performance is good. The formulae for MAPE and R^2 are given below respectively:

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{At-Ft}{At}\right| \quad (3)$$

$$R^2 = \left(\frac{n(\sum xy)-(\sum x)(\sum y)}{\sqrt{[n\sum x^2-(\sum x)^2][n\sum y^2-(\sum y)^2]}}\right)^2 \quad (4)$$

where:

- A_t is the actual data
- Ft is the estimated value at time t
- n is the is the number of samples
- x and y are the values of the independent and dependent variables, respectively

Firstly, MAPE values were calculated to determine the prediction performance of MLP models with different number of hidden layer neurons. The results obtained are shown in Figure 2.

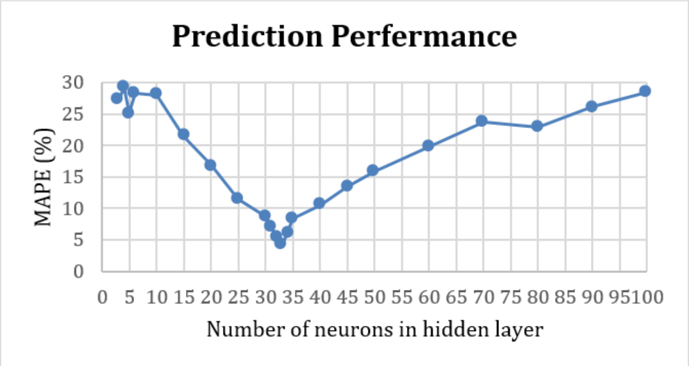

Figure 2. MAPE values of the MLP models

When Figure 2 is analysed, it is seen that MAPE values vary between approximately 4% and 30%. In the case where this value is minimum (4.04%), the number of neurons in the hidden layer is 33. In other words, the MLP model with 33 neurons in the hidden layer has the highest performance among the developed models with a prediction performance of 95.96%.

Afterwards, Regression analysis was performed for the model with the highest prediction performance and R^2 value was calculated. The obtained results are shown in Figure 3.

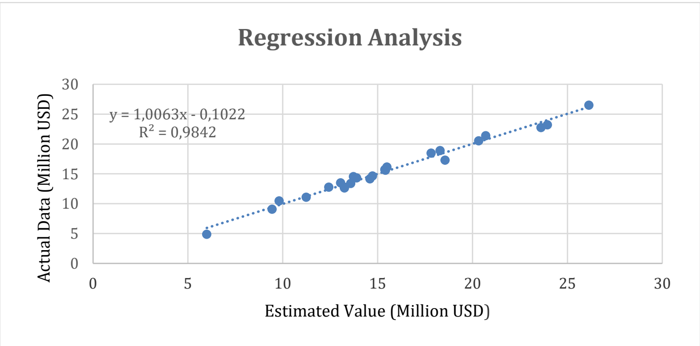

Figure 3. Correlation between estimated value and actual data

As shown in Figure 3, the R^2 value is quite high. These results show that the developed MLP model can successfully understand the behavioural mechanism of Turkey's sock exports to Germany and can predict with high accuracy.

The prediction performance of the model is higher when compared with similar studies in the literature. For example, Bin and Tianli (2020) used artificial neural networks and fuzzy system theory to predict foreign trade exports [4]. In this study, the MAPE value of the best performing model was reported as 4.0899%. Gür and Eşidir developed an MLP model to predict Turkey's monthly plastic imports [18]. In their study, the MAPE value of the model was found to be 7.6% and the R^2 value was found to be 0.971. As can be seen from these comparisons, the MLP neural network model developed in this study outperformed other models in the literature in predicting Turkey's monthly exports of cotton socks to Germany. This shows that the MLP model is better able to learn the factors affecting sock exports and better able to capture the complexity in the data.

5. CONCLUSION

In this study, MLP neural network, one of the deep learning techniques, is used to predict Turkey's cotton sock exports to Germany. Sock exports are an important component of the textile industry and are affected by many factors. Therefore, predicting the future values of sock exports is of strategic importance for both manufacturers and exporters. In this study, a prediction model is developed with MLP neural network using a monthly data set covering the period between 2014 and 2023. The performance of the model is evaluated using statistical measures such as MAPE and R^2. The results show that the MLP neural network is able to predict sock exports with high accuracy.

The contributions of this study are as follows:

- MLP neural network, one of the deep learning techniques, is used to predict Turkey's sock exports to Germany. This is the first study on this subject in the literature.
- The tophology, transfer function and training algorithm of the MLP neural network were determined in accordance with the data set. This improved the performance of the model.
- Developed model showed a high performance in both training and test data sets. The model successfully captured the non-linear and non-stationary characteristics of sock exports as well as learnt and reflected seasonal fluctuations and trends.

Limitations of this study and future work are as follows:

- In this study, only Turkey's sock export data were used. Comparing the performance of the model with sock export data of other countries may be useful to test the generalisability of the model.
- This study uses only MLP neural network. As a future study, comparing the performance of the current model with other deep learning techniques on a similar problem may be useful for further improvement of the model.

REFERENCES

1. Yildiz, A. & Özbek, A., (2020). *Selection of socks export markets for Turkey using multi-criteria decision making methods*. Sigma Journal of Engineering and Natural Sciences, 38(2), 795-815.
2. Avşar, İ. İ., & Ecemiş, O., (2023). *Forecast of turkey's import and export by data mining methods*. Osmaniye Korkut Ata University Journal of The Institute of Science and Technology, 6(3), 1890–1907. https://doi.org/10.47495/okufbed.1220874
3. Awasthi, S., SenGupta, I., Wilson, W., & Lakkakula, P., (2022). *Machine learning and neural network based model predictions of soybean export shares from US Gulf to China*. Statistical Analysis and Data Mining, 15(6), 707–721. https://doi.org/10.1002/sam.11595
4. Bin, J., & Tianli, X., (2020). *Forecast of export demand based on artificial neural network and fuzzy system theory*. Journal of Intelligent & Fuzzy Systems, 39(2), 1701–1709. https://doi.org/10.3233/ jifs-179944
5. Çakan, V. A., (2020). *Forecasts for Turkey Fresh Fig Production and Dried Fig Export: ARIMA Model Approach*. Journal of Tekirdag Agricultural Faculty, 17(3), 357–368. https://doi.org/10.33462/jotaf.684893
6. Han, Z., Zhu, Z., Zhao, S., & Dai, W., (2022). *Research on nonlinear forecast and influencing factors of foreign trade export based on support vector neural network*. Neural Computing & Applications, 34(4), 2611–2622. https://doi.org/10.1007/s00521-021-05900-3
7. Ishaq, M., Ping, Q., Haq, Z., Li, C., & Tong, C., (2016). *Maximum residue limits and agrifood exports of China: choosing the best estimation technique*. Agricultural Economics, 62(2), 78–92. https://doi.org/10.17221/17/2015-agricecon
8. Islam, T., (2016). *An empirical estimation of export and import demand functions using bilateral trade data: The case of Bangladesh*. Journal of Commerce and Management Thought, 7(3), 526. https://doi.org/10.5958/0976-478x.2016.00030.6
9. Nooraeni, R., Nickelson, J., Rahmadian, E., & Yudho, N. P., (2022). *New recommendation to predict export value using big data and machine learning technique*. Statistical Journal of the IAOS, 38(1), 277–290. https://doi.org/10.3233/sji-210855
10. Sun, M., & Yang, H., (2023). Forecasting model of fishery import and export trade data using deep learning method. 2023 International Conference on Blockchain Technology and Applications (ICBTA).
11. Ahmadpour Kasgari, A., Divsalar, M., Javid, M. R., & Ebrahimian, S. J., (2013). *Prediction of bankruptcy Iranian corporations through artificial neural network and Probit-based analyses*. Neural Computing & Applications, 23 (3–4), 927–936. https://doi.org/10.1007/s00521-012-1017-z
12. Ko, P., & Lin, P., (2008). *Resource allocation neural network in portfolio selection*. Expert Systems with Applications, 35(1–2), 330–337. https://doi.org/10.1016/j.eswa.2007.07.031
13. Chang, R.-I., Chiu, Y.-H., & Lin, J.-W., (2020). *Two-stage classification of tuberculosis culture diagnosis using convolutional neural network with transfer learning*. The Journal of Supercomputing, 76(11), 8641–8656. https://doi.org/10.1007/s11227-020-03152-x
14. Etebari, F., & Najafi, A. A., (2016). *Intelligent choice-based network revenue management*. Scientia Iranica, 23(2), 747–756. https://doi.org/10.24200/sci.2016.3860
15. Tsai, C., & Wu, J., (2008). *Using neural network ensembles for bankruptcy prediction and credit scoring*. Expert Systems with Applications, 34(4), 2639–2649. https://doi.org/10.1016/j.eswa.2007.05.019
16. Wang, N., Chen, J., Xiao, H., Wu, L., Jiang, H., & Zhou, Y., (2019). *Application of artificial neural network model in diagnosis of Alzheimer's disease*. BMC Neurology, 19(1). https://doi.org/10.1186/s12883-019-1377-4
17. Alam, T., (2019). *Forecasting exports and imports through artificial neural network and autoregressive integrated moving average*. Decision Science Letters, 249–260. https://doi.org/10.5267/j.dsl.2019.2.001
18. Eşidir, K. A., & Gür, Y. E., (2023). *Turkish plastics industry import forecast with artificial neural networks: April-December 2023*. The Academic Elegance, 10(23), 91–114. https://doi.org/10.58884/akademik-hassasiyetler.1307536
19. Okkan, U., (2011). *Application of Levenberg-Marquardt optimization algorithm based Multilayer Neural Networks for hydrological time series modeling*. An International Journal of Optimization and Control Theories & Applications (IJOCTA), 1(1), 53–63. https://doi.org/10.11121/ijocta.01.2011.0038
20. Prasad, V. K., Bhattacharya, P., Bhavsar, M., Verma, A., Tanwar, S., Sharma, G., Bokoro, P. N., & Sharma, R., (2022). *ABV-CoViD: An ensemble forecasting model to predict availability of beds and ventilators for COVID-19 like pandemics*. IEEE Access: Practical Innovations, Open Solutions, 10, 74131–74151. https://doi.org/10.1109/access.2022.3190497
21. Ratnasih, C., & Sulbahri, R. A., (2022). *Full Costing Method model and Variable Costing Method against cement price determination (case in Indonesia)*. European Journal of Business and Management Research, 7(2), 284–288. https://doi.org/10.24018/ejbmr.2022.7.2.1378
22. Ersen, N., Akyüz, İ., & Bayram, B. Ç., (2019). *The forecasting of the exports and imports of paper and paper products of Turkey using Box-Jenkins method*. Eurasian Journal of Forest Science, 7(1), 54–65. https://doi.org/10.31195/ejejfs.502397
23. Gür, Y. E., & Eşidir, K. A, (2024). *Estimation of turkish trout export with arima and multilayer perceptron models*. Turkish Studies-Economy, 19(1), 187–206. https://doi.org/10.7827/turkishstudies.70444
24. Gür, Y. E., & Eşidir, K. A., (2024). *Forecasting Türkiye's paper and paper products sector import using artificial neural networks*. Hitit Journal of Social Sciences, 17(2), 206-224. https://doi.org/10.17218/hititsbd.1327799
25. Özbek, A., & Akalın, M., (2011). *The prediction of Turkey's denim trousers export to Germany with ANN models*. Textile and Apparel, 21(4), 313-322.