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RESEARCH ARTICLE

A MACHINE-LEARNING-BASED MODEL FOR FORECASTING MEDICAL DEVICE FOREIGN TRADE

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ABSTRACT

Forecasting the medical device foreign trade is a very important issue and a challenging problem due to many external artifacts in the medical device market for making an efficient policy. Many reports, including the simple statistical based methods do not provide sufficient forecasting for foreign trade and this problem may be solved using a machine-learning based approach. The purpose of this study is to introduce an efficient model for forecasting medical device foreign trade. In this respect, export and import data obtained with 54 different commodity codes were performed using some machine-learning algorithms. The best prediction performance was achieved with SVM regression model with the average R^2=0.974 and for the last five years. In 2025, total medical device exports and imports are expected to be $1.03 billion and $2.12 billion, respectively. We also performed Market Penetration Index and Product Diversification Index to analyze medical device foreign trade.

Keywords: Medical device, Foreign trade, Regression, Forecasting, Market index

1. INTRODUCTION

Medical device industry, includes different dynamics and many stakeholders, and needs rapid change in multidisciplinary cooperation depending on the developing technology. It is one of the fastest growing sectors with over $400 billion in the world. The countries with higher income have a manufacturer role and they are generally main suppliers in the world. It is a crucial point to present the current state of medical device market and to forecast foreign trade for further analysis to increase the market size and collaborations with better policies. For this purpose, research companies have published many reports including foreign trade and market size forecasts for the following years. However, the approaches presented in these reports are usually based on simple statistical methods such as correlation, and reveal estimates far from the values actually achieved [1, 2]. Exports and imports of all countries are available in the Trade Map database [3] and these statistics play an important role to understand the bilateral relationships between the countries, economic development and globalization [4]. In an analysis based on statistical methods such as only correlation, it is more difficult to take into account the parameters originating from the internal dynamics of the sectors. Therefore, using machine-learning approaches can provide more advantages. Recently, the approaches using learning models has become more popular in international trade and market analysis, but there are a limited number of studies in this framework. Sun et al. has reported that radial basis function based regression model outperforms the other regression models in gross domestic product forecasting [5]. Another study conducted by [6] also proposed an ensemble SVM model, which uses general economic parameters such as the inflation rate and exchange rate to estimate China's total export and import volumes. In our opinion, the weak side of the previous studies is to use the values of the previous and next years together in the model learning phase of these studies while predicting the foreign trade statistics of a year. In fact, it is not possible to use the data of the coming years, which have not been obtained yet, in a model developed to make a future estimation. For this reason, if the data of which year is to be estimated in a proposed model, only the data obtained from previous years should be used. Analyzing each sector by evaluating its dynamics together can

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contribute to policies that are more effective. For this reason, it is very important to conduct a detailed analysis of the medical device industry, which is among the important and strategic sectors. Although determining the commodity codes used in international trade of medical devices is a separate challenge, as far as we know, there is no analysis in this direction in the literature. This requires knowledge and experience in medical device legislation and technical perspective. The medical device industry is regulated all over the world with the specific regulations and it is a sector that requires many parameters to be taken into account. Turkey is among the list of candidate countries for European Union membership and the same directives in [7-9] are applied. In this study, the current state of medical device market is presented, and a machine learning based model was proposed to forecast Turkey's medical device foreign trade.

2. MATERIALS AND METHODS

2.1. Data collection

In this study, Turkey's foreign trade in billion $ between the years 2001-2019 were used. The data are collected from the International Trace Centre TradeMap database [3] using 54 HS6-digit Customs Tariff Statistics Position (CTSP) commodity codes (Supplementary File 1). The number of the observations in the dataset is 19 from 2001 to 2019 for each commodity code. Every commodity code may include multiple medical devices and so it is an another issue to distinguish the medical device associated commodity codes. To our knowledge It is known that there is not a distinct rule to define the commodity codes for target products. Technological content, raw-material used and special customs regime are some of the parameters in assigning a commodity code for a product and this is an international code system. There is not any previous study in which the medical device associated commodity codes have been investigated. All products are classified according to their usage target area such as consumable, optical, therapeutic, diagnostic imaging, dental, orthopaedics-prosthetics, hospital furniture, patient aids, in-vitro diagnostics and other medical devices.

2.2. Market Penetration Index

Market penetration index (MPI) is a measure of what degree total import demand of a product is satisfied by import from a country and MPI of product k for country m is expressed as below;

$$MPI_{mk} = \frac{M_{mk}^{j}}{M_{mk}^{w-j}} \times 100 \tag{1}$$

where M_{mk}^{j} refers to import value of product k from country j while M_{mk}^{w-j} refers to import value of product k from out of country j for country m. A greater MPI index means that tendency mostly prefers to import product k from country j [10]. This parameter was used in many studies conducted for different sectors [11-12].

2.3. Product Diversification Index

Product diversification index (PDI), which is the inverse of the Herfindal Index, is a metric that shows the degree of export concentration of a country for all products. In general, diversification reduces the dependency on the small product number in foreign trade and a country's vulnerability to external artifacts [13]. Demand-side shocks in domestic market affect low and middle-income countries because of their high product concentrated exports [14]. PDI is calculated by the formula as below;

$$PDI_{ds}^{t} = 1 \, / \, HIP_{ds}^{t} \tag{2}$$

where HIP is the Herfindal Index that is calculated as below;

$$HIP_{ds}^{t} = \sum_{p=1}^{np} \left(\frac{X_{dp}^{t}}{X_{ds}^{t}}\right)^{2} \tag{3}$$

where X_{dp}^{t} is the export value of product p by country d, X_{ds}^{t} is the export value of all products in sector s (it is medical device sector in our case) by country d. The range of PDI is between 0 and +∞ [13].

2.4. Learning models

The main task in this study is to estimate the foreign trade value (export or import) of a year using the previous years' foreign trade values. Linear regression aims to introduce the relation between input (the old foreign trade values) and output (the target year's foreign trade values) vectors with a linear map. This linear mapping could be defined with the following equation:

$$y = W^{T}x + c \tag{4}$$

where W is a parameter vector and c is an offset value, x and y are input and output vectors, respectively. In linear regression, the best fitting line is calculated by minimizing differences between this line and each input data [15].

Support Vector Machine Regression (SVR) is another common method used in regression problems. SVR uses multiple hyperplanes to represent the relations between input and output data. In this model, the finest hyplanes are achieved by minimizing the error and maximizing the margins. Linear or non-linear kernel functions could be prefered to build the best model [16].

2.5. Evaluation

We used Root Mean Squared Error (RMSE), Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) as evaluation metrics. RMSE is a measure that calculates the difference between predicted and actual values. It is defined as the root of the MSE and expressed as follows (17):

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \|A_i - E_i\|^2}{n}} \tag{5}$$

where n is the number of genes and A_i and P_i are actual and estimated value, respectively. MAE is the mean of the absolute errors between the actual and the predicted values. It is expressed as follows (18):

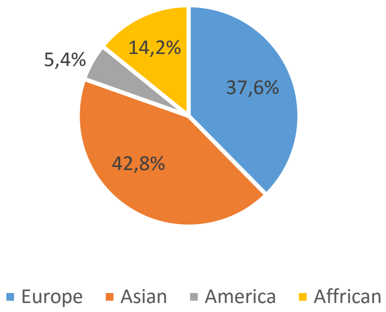
$$MAE = \frac{1}{n}\sum_{i=1}^{n} |e_i| \tag{6}$$

R^2 is a common statistical measure that shows how to fit the regression model. It is calculated by dividing the residual variance by total variance. It takes the value of 1 for the best estimation in which the estimated values are more highly correlated to actual values (19). In this study, we applied ten-fold cross validation procedure in which 9/10 of the dataset is used in the training of the model and the model is performed on the remaining set of the trade value vectors.

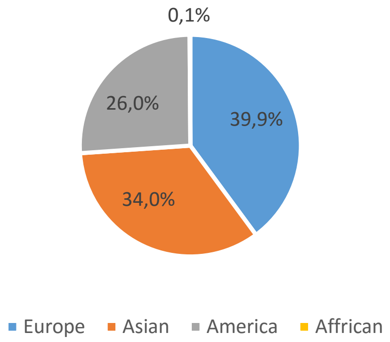
3. RESULTS

3.1. The Current Position in Medical Device Foreign Trade

Figure 1 shows the export and import shares of Turkey by region. Analyzing the foreign trade data, it is observed that the highest exports were made to Asian and European countries with 42.8% and 37.6%, respectively. It is observed that the highest imports were made to European and Asian countries with 39% and 34% respectively. Table 1 and Table 2 shows Turkey's export and import values of the sub-categories of medical devices, respectively. Total medical device exports increased by 170% in the last five years, reaching $ 643.1 million in 2019, while the total import value decreased by 357% to $ 1.99 billion.



a. Export



b. Import

Figure 1. Turkey's medical device export and import shares by region in 2018

Table 1. Turkey's export values by product category (x $1000)

Product category	**2015**	**2016**	**2017**	**2018**	**2019**
Dental	26.984	28.198	31.338	33.544	34.458
Imaging	26.309	21.605	33.616	32.978	36.368
Hospital furniture	29.820	32.151	36.902	43.989	49.840
Patient-aid	8.812	12.472	13.550	19.505	17.458
In Vıtro Diagnostic	29.556	26.540	29.184	38.583	43.773
Optic	10.281	11.558	11.827	11.920	12.746
Orthopaedics	51.710	54.302	51.704	59.222	66.055
Therapeutic	17.678	16.142	20.884	16.727	16.276
Consumable	157.027	151.824	177.492	217.872	233.902
Other	114.338	107.943	127.047	130.919	132.175

Table 2. Turkey's import values by product category (x $1000)

Product category	**2015**	**2016**	**2017**	**2018**	**2019**
Dental	169.127	171.239	183.452	178.214	168.823
Imaging	476.049	454.387	482.813	434.529	332.933
Hospital furniture	29.855	32.656	24.501	22.252	21.437
Patient-aid	96.436	109.654	105.106	97.631	91.744
In Vıtro Diagnostic	238.745	244.166	249.677	246.002	235.714
Optic	112.571	109.214	101.106	85.483	76.495
Orthopaedics	279.613	282.597	252.419	202.387	180.663
Therapeutic	116.702	100.027	98.956	89.421	93.024
Consumable	418.684	446.442	472.679	419.562	425.599
Other	413.316	416.988	394.310	369.860	367.650

Another common parameter (so-called "coverage ratio") in foreign trade is the ratio of exports to imports. This ratio is calculated by dividing the export value by the import value. Table 3 shows the coverage ratios in medical devices for 2015 and 2019. This ratio increased from 20.1% of all medical devices in 2015 to 32.2% in 2019. The highest change in the coverage ratio is 132,6% between 2015 and 2019 in hospital furniture.

Table 3. The coverage ratio for 2015 and 2019

Product category	2015	2019	Change
Dental	16.0%	20.4%	4.4%
Imaging	5.5%	10.9%	5.4%
Hospital furniture	99.9%	232.5%	132.6%
Patient-aid	9.1%	19.0%	9.9%
In Vıtro Diagnostic	12.4%	18.6%	6.2%
Optic	9.1%	16.7%	7.6%
Orthopaedics	18.5%	36.6%	18.1%
Therapeutic	15.1%	17.5%	2.4%
Consumable	37.5%	55.0%	17.5%
Other	27.7%	36.0%	8.3%

Figure 2 shows the MPI results for the main importers of Turkey. Since Turkey's main importers are USA, China and Germany, it is clear that they have a higher penetration index than other countries (see Figure 2). In 2018, the three highest MPI are 24.7, 16.0 and 15.6 for USA, China and Germany, respectively. Germany was the second country with highest MPI among the importers of Turkey before 2017.

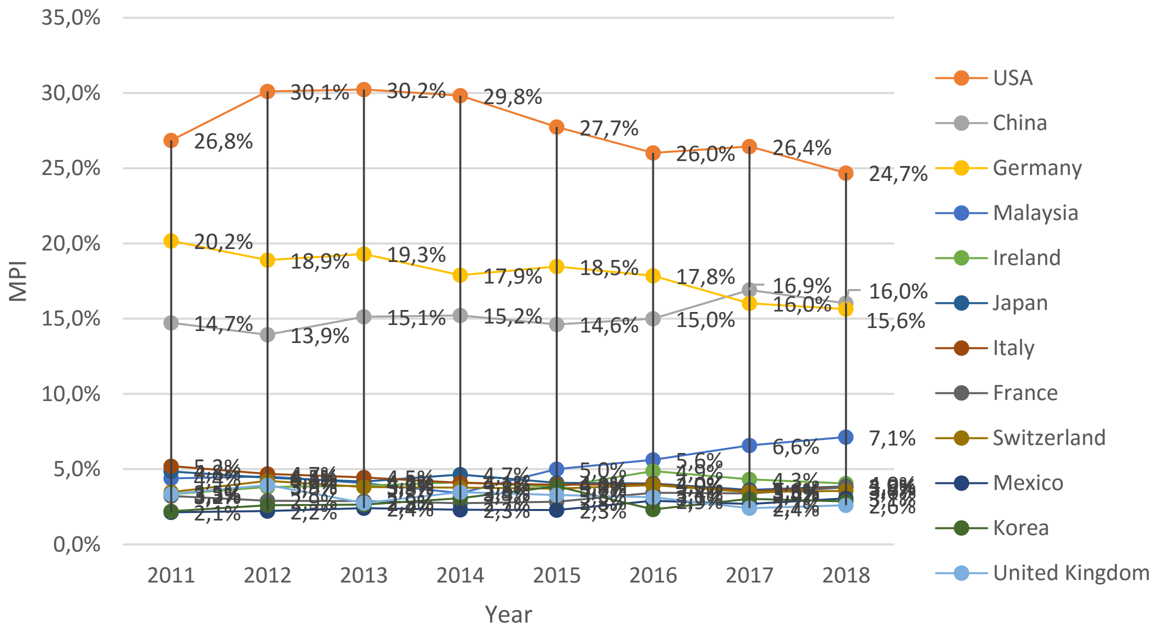


Figure 2. MPI for Turkey's major importers

Product diversification in medical device export is shown in Figure 3. PDI has increased by 39% between 2001 and 2019. There are two different curves with positive slope between 2010 and 2019. The slope of three years between 2011 and 2014 is greater than the slope of two years between 2016 and 2018 in the last ten years.

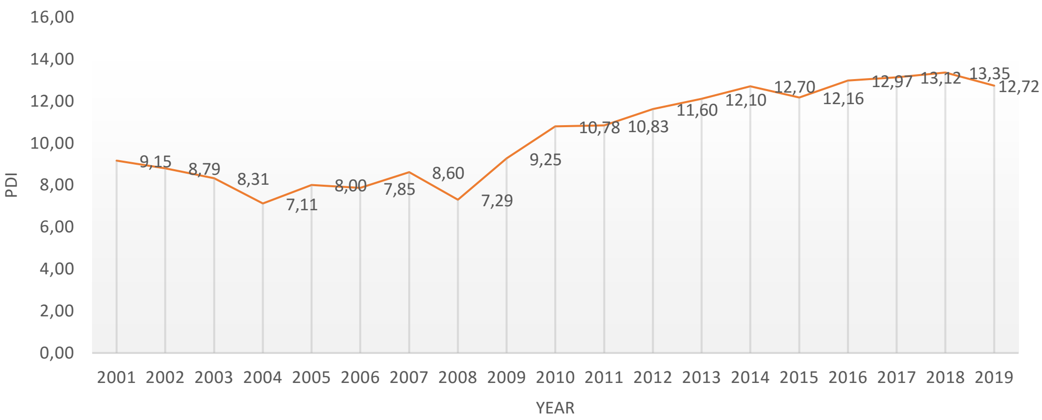


Figure 3. PDI values between 2001 and 2019

3.2. Empricial Results

The prediction results of medical device export for the last five years in Turkey are shown in Table 4. The best performance is achieved by SVM regression model with linear kernel, which yields that the average R^2 is 0.938 for the last five years. It is calculated that the average R^2 is 0.936 and 0.672 for LR and decision tree, respectively. The prediction results of medical device import for the last five years in Turkey are shown in Table 5. Similarly, the best estimation result is achieved by SVM regression model with linear kernel, which yields that the average R^2 is 0.974 for the last five years. It is calculated that the average R^2 is 0.956 and 0.644 for LR and decision tree, respectively.

Table 4. The prediction results for medical device export of the last five years

	LR				DECISION TREE				SVM			
	RMSE	R^2	MSE	MAE	RMSE	R^2	MSE	MAE	RMSE	R^2	MSE	MAE
2015	4931.4	**0.91**	24318705.96	2902.4	11582	**0.5**	134142724	4479.2	5633.6	**0.88**	31737449	2656.3
2016	3388.8	**0.95**	11483965.44	1879.5	7857.3	**0.75**	61737163	3175.7	3807.9	**0.94**	14500102	1860
2017	3208.5	**0.97**	10294472.25	1943.4	9681.2	**0.7**	93725633	3820.9	2935.2	**0.97**	8615399	1717.4
2018	7164.9	**0.87**	51335792.01	3613.5	11035	**0.7**	121771225	5123.5	4553.6	**0.95**	20735273	2607.2
2019	3256.4	**0.98**	10604140.96	2145.8	11672	**0.71**	136235584	5150.2	4676.8	**0.95**	21872458	2465.1

Table 5. The prediction results for medical device import of the last five years

	LR				TREE				SVM			
	RMSE	R^2	MSE	MAE	RMSE	R^2	MSE	MAE	RMSE	R^2	MSE	MAE
2015	18715	0.93	350251225	9367.3	38583	**0.69**	1488647889	15840	13856	**0.96**	191988736	6757
2016	14077	**0.96**	198161929	7177.1	34817	**0.76**	1212223489	13551	9495.6	**0.98**	90166419	5761.1
2017	7715.3	**0.99**	59525854	5165.9	37644	**0.69**	1417070736	16759	9368.9	**0.98**	87776287	5368.8
2018	12506	**0.96**	156400036	7031.6	45377	**0.49**	2059072129	18255	8660.7	**0.98**	75007724	5685.3
2019	15229	**0.94**	231922441	8741	40768	**0.59**	1662029824	15660	10557	**0.97**	111450249	5882.3

Figure 4 shows the forecasting values of medical device export and import for the next five years (the right side of the red line) using SVM regression that is the best estimation model achieved in the previous section. The medical device export and import values are expected to be about \$1.03 billion and \$2.12 billion respectively.

Figure 4. Forecasts of foreign trade for next five years

4. DISCUSSION

Medical device market is multidisciplinary with a large number of internal parameters, and so we can observe only outcomes of these parameters. Figure 1 shows that Turkey's main target markets are African and European countries. We consider that these close relations in medical device trade are depending on the geographical location of Turkey and the same medical device legislation with the European Union (EU) although Turkey is in the candidate list of membership for EU. Table 1 shows that Turkey has a great ability to export of consumable products because the country has an important manufacturing potential in consumable medical devices such as stents, dialysis set, injector, and surgical instruments etc., so the highest export value of the country is in these products. The incentive for domestic product use in the country and the bilateral cooperation with other countries have an important effect on the enormous increase in exports in the last five years. Table 2 shows that the medical device group which is mostly imported is imaging systems with advanced technologies such as magnetic resonance and computer tomography. It is essential to determine strategies for the target fields to increase the manufacturing capacity of high-level technology in medical devices. On the other hand, in Table 3, it is seen that the greatest coverage ratio between the last five years belongs to hospital furniture. One of the reasons for this result is that the technological level of these products is lower than the other products and it is easier to place on the market in accordance with medical device legislation. Although the medical device market size consists of local production, local consumption, export and import, to our knowledge, there is not any public available database that contains local production and consumption volumes in Turkey. Bilateral relations between countries and effective policies implemented in foreign trade can make a significant contribution to the increase in foreign trade volume. Here, in some cases, even the technology level of the product can be considered secondary. The diversification of imported products is more important than the volume of imports. Another product in the international trade with higher MPI can compensate the contraction in the import of one product. Figure 3 shows two local minimum points that can also be considered as a breaking point. We believe that these breaking points of 2004 and 2008 were related to the economic balances in the country in those years. Furthermore, the slope of the interval of 2011-2014 is greater than the slope of the interval of 2016-2018, and there is a rapid decrease in 2015. This shows that it is required to apply a sustainable policy in foreign trade.

2017/745 Medical Device Regulation (MDR) and 2017/746 In-Vitro Medical Device Regulation (IVDR) were published by the EU. There is a transition period for MDR until May 2021. During this period, Turkey is applying an adoption plan to put it in force. These regulations include many new rules for economic operators and all stakeholders from transparency to conformity assessment. Clinical investigation has become more important for manufacturers to place a medical device on the market. Stricter rules in conformity assessment have been identified and this new approach may require more cost for economic operators. We observe that new investments should be considered to take a place in the EU market for local manufacturers.

The training is based on a time-variant system. For example; while foreign trade data between 2002-2020 is used to forecast foreign trade of 2021, this used data for 2020 was forecasted by testing the foreign trade of 2001-2019 in the previous step in the model. This point is unclear in the previous studies. Considering the Table 4 and Table 5, it is seen that there is a decrease in import between 2017 and 2019, while there is an increase in export in the same period. It is thought that the incentives for the use of domestic products have an impact on these results. On the other hand, it is expected a rapid change in import will be observed in the next five years in Figure 4. Turkey is making large investments to build city hospitals across the country. The number of city hospitals that provide healthcare services at the end of 2021 will be 18. The contractors on these projects will import medical devices involving high-level technology. A crucial step of increasing manufacturing potential in medical devices involving advanced technology is to promote clinical trial for manufacturers by setting up the required infrastructure. It is very important to conduct a detailed root-cause analysis in the medical device industry and create an action plan for the solution of the identified problems.

5. CONCLUSION

Machine-learning-based approach may help in forecasting the medical device foreign trade. It is concluded that the incentive policies in place for use of domestic products across the country may increase the venture capital of the manufacturers, which is very effective in producing innovative products. In addition, it can be determined that sector-specific policies that consider compliance with legislation provide more opportunities in international trade of medical devices.

REFERENCES

[1] Espicom Medical device reports. BMI Research Company. 2018.

[2] EvaluateMedTech World Preview 2018 available from https://info.evaluate.com/WPMT2018-CS.html (Accessed 10 October 2019)

[3] ITC Trade Map. Available at: https://www.trademap.org/Index.aspx. Retrieved April 20. 2020.

[4] Charles L, Daudin G. Eighteenth-Century International Trade Statistics. Sources and Methods. Revue de l'OFCE 2015; 4: 7-36.

[5] Sun J, Suo Y, Park S, Xu T, Liu Y, Wang, W. Analysis of bilateral trade flow and machine learning algorithms for GDP forecasting. Engineering. Technology & Applied Science Research 2018; 8(5): 3432-3438.

[6] Yu L, Wang S, Lai K K. Forecasting China's foreign trade volume with a kernel-based hybrid econometric-AI ensemble learning approach. Journal of Systems Science and Complexity 2008; 21(1): 1-19.

[7] Council. E. COUNCIL DIRECTIVE 93/42/EEC concerning medical devices. Official Journal of The European Communities. Luxembourg, 1993.

[8] Council. E. COUNCIL DIRECTIVE 98/79/EC concerning in vitro diagnostic medical devices. Official Journal of The European Communities. Luxembourg, 1998.

[9] Council. E. COUNCIL DIRECTIVE 90/385/EEC concerning active implantable medical devices. Official Journal of The European Communities. Luxembourg, 1990.

[10] Erkan B. Product and market diversification in Turkey's foreign trade. IJAME, 2018.

[11] Lévay PZ, Drossinos Y, Thiel C. The effect of fiscal incentives on market penetration of electric vehicles: A pairwise comparison of total cost of ownership. Energy Policy 2017; 105: 524-533.

[12] Fronczek, M. Import penetration rate in view of a new concept of measuring foreign trade. Argumenta Oeconomica 2017; 38: 285-297.

[13] Brakman S, Van Marrewijk C. A closer look at revealed comparative advantage: Gross- versus value- added trade flows. Papers in Regional Science 2017; 96(1): 61-92.

[14] Gozgor G, Can M. Effects of the product diversification of exports on income at different stages of economic development. Eurasian Business Review 2016; 6(2): 215-235.

[15] Bangdiwala SI. Regression: simple linear. International journal of injury control and safety promotion 2018; 25(1): 113-115.

[16] Malegori C, Marques EJN, de Freitas ST, Pimentel MF, Pasquini C, Casiraghi E. Comparing the analytical performances of Micro-NIR and FT-NIR spectrometers in the evaluation of acerola fruit quality, using PLS and SVM regression algorithms. Talanta 2017; 165: 112-116.

[17] Dong X, Greven MC, Kundaje A, et al. Modeling gene expression using chromatin features in various cellular contexts. Genome biology 2012; 13(9): R53.

[18] Chai T, Draxler RR. Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature. Geoscientific model development. 2014; 7(3): 1247-1250.

[19] Gelman A, Goodrich B, Gabry J, Vehtari A. R-squared for Bayesian regression models. The American Statistician 2019; 73(3): 307-309.