

AN ANALYSIS OF THE FACTORS AFFECTING THE CONSUMPTION OF GEOGRAPHICALLY INDICATED PRODUCTS USING DECISION TREE AND ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

In the present study, the consumer perception and consumption level of Geographically Indicated Products (hereafter GIP) in the Tokat province of Turkey has been investigated. The data were collected from 382 consumers through a questionnaire. Artificial neural networks and decision tree models were used to determine the factors affecting the consumers' consumption of the specified products. Results indicated that the variables of monthly walnut consumption, whether Niksar walnuts are known to be a GIP, monthly income level, the willingness to pay more for a GIP and whether they read labels on GIP packaged products affected consumption.

Key Words: data mining, machine learning, algorithm, geographical indication, decision tree

Published first online January 06. 2022

Published final July 30. 2022

INTRODUCTION

Geographical indication refers to a local product name that differs from its counterparts. This difference owes to the region from which it originates. Hence, the geographical indication is a kind of sign indicating that a product is identified with the region, area, territory or country where the product originates from in terms of its distinctive quality, reputation and/or other characteristics. There are two main systems used in relation to geographical indications: Protected Designation of Origin and Protected Geographical Indication. The names are used to define products that originate from a region or locality in the country in exceptional cases. They take all of or just their basic characteristics from natural and human elements specific to the geographical region. The production, processing and other processes are all carried out within the boundaries of the geographical region, which are protected designations of origin. The names used to define the products that originate from a region, an area or a country whose geographical boundaries are identified, that are identified with this geographical area in terms of their distinctive quality, reputation or other characteristics, and whose production, processing or at least one of whose production processes are carried out within the boundaries of this geographical area are protected geographical indications (Anonymous, 2019).

Divya and Anoop (2018) examined the benefits of geographical indications under four headings: social benefits, economic benefits, benefits to the producer and benefits to the consumer. The contributions of geographical indications to the business/firm include: They can provide a competitive advantage, create added value for the product, increase the chance of domestic and foreign trade, and make the brand name more recognisable. Geographical indications have become important intellectual assets related to various goods in

recent years. They are a legal and economic tool that is used not only to protect the interests of consumers and to strengthen the trust in high-quality local products, but also to protect rural development and cultural heritage (Zografos, 2008).

A geographical indication provides high economic returns and increases the socio-economic status of the society in question, especially that of low-income individuals because geographical indications are usually agricultural products, handicrafts and craft products. The income level of those engaged in these activities is relatively low (Dhamotharan *et al.*, 2015). De Rosa (2015) emphasises that geographical indications foster food safety. Raimondi *et al.* (2019) states that geographical indications affect export prices positively. Products with geographical indications increase the region's national and international popularity (Sitepu, 2018). It is estimated that there are more than 10,000 geographical indications worldwide and that \$50 billion dollars in income is generated from the trade of these products (Giovannucci *et al.*, 2009). The demand for geographical indications also leads to an increase in employment in the sectors producing the products.

Geographical indications certify the origin and quality of the good. Geographical indications serve as a marketing tool that can add economic value to agricultural products (Babcock and Clemens, 2004). Geographical indications help to increase the value and number of branded products. Geographical indications have many benefits other than the legal protection offered and quality certification function. Geographical indications contribute to the protection of resources through the characteristics of natural and cultural heritage. Another function of geographical indications is product differentiation. Geographical indication turns the agricultural product from a commodity into a product of certain origin (Durand and Fournier, 2017).

Rural tourism is increasingly becoming an important sector in the world. Tourists now want to taste local agricultural products in season in a particular place, buy folkloric products and spend more time in rural areas. When seen from this perspective, geographical indications have an important effect on the development of rural tourism.

The demand for healthy and quality food has been increasing in recent years. This issue is extremely important in today's world where pandemics and epidemics alike have become the most important problem for multiple countries. Consumers are now more conscious, and they want to make sure that they know about the place of production of the goods and their quality. Consumers like products to be produced using traditional methods, and they like them to be sold from the manufacturer to the consumer without any intermediaries (Fernandez-Ferrín *et al.*, 2019). The development of gastronomy tourism can be considered another important factor in relation to the consumers' consumption of local and geographically indicated products. Now, additive-free and natural products are at the top of consumer preferences. Relevant literature indicated that consumers are willing to pay more to consume geographically indicated products. Many researchers determined that consumers look positively at geographical indications and want to pay more for these products (Fotopoulos and Krystallis, 2003; Skuras and Vakrou, 2002). Similarly, Cacic *et al.* (2011) reported that the share of geographically indicated wines in the Croatian wine market is 59%.

The registration process for geographical indications in Turkey is conducted by the Turkish Patent and Trademark Office affiliated with the Ministry of Industry and Technology (Çukur and Çukur, 2017). Turkey is rich in terms of regional products. Apart from agriculture and food products, there are many geographically indicated products in non-agricultural sectors such as handicrafts, carpets and natural resources (Dokuzlu, 2016). In 2020, there are 8 geographically indicated products in the Tokat province of Turkey. The products consist of Erbaa Narince vine leaves, Niksar walnuts, Tokat kebabs, Tokat Narince pickled vine leaves, Turhal yoğurtmacı, Zile churchkhela, Zile molasses and Tokat scarves. Seven of the products are food products and one (Tokat scarf) is a textile product. Turhal yoğurtmacı is a local food product and takes its name from the act of kneading. Flour, yeast, salt, butter, walnuts or poppy seeds are mixed and then cooked on a wood fire.

The purpose of the present study was to determine the factors influencing the consumers' consumption of geographically indicated products in Tokat province. The other purposes of the study were to determine the rate of the consumers' consuming geographically indicated products and the consumers' perception of geographically indicated products.

MATERIALS AND METHODS

According to the data issued by the Turkish Statistical Institute, the population of Tokat province was 612,446 in 2018. In the current study, this number was taken as the population size and it was decided to include a part of the population in the study through the chosen sampling method. To this end, the following proportional sample volume formula was used (Newbold, 1995).

$$n = \frac{Np(1-p)}{(N-1)\sigma_{px}^2 + p(1-p)}$$

In this equation:

n: Sample size

N: Population size

p: Prediction rate (those purchasing geographical indication products. In order to reach the highest sample size, p was taken as 0.50)

σ_{px}^2 : Variance of the proportion

With a 95% confidence interval and 5% error margin, the required sample volume was found to be 384. Because of the missing data, 2 questionnaires were excluded from the study, meaning that a total of 382 questionnaires were included in the analysis. In the development of the questionnaire, the study by Meral and Şahin (2013) was taken as the basis. The questionnaire was carried out in November and December 2019.

In the current study, a 5-point Likert scale was used to determine the consumers' perception of geographically indicated products. The response options to the scale items can be defined as 1. Strongly Disagree, 2. Disagree, 3. Undecided, 4. Agree and 5. Strongly Agree.

Artificial neural networks and decision tree models are among the most widely used data mining methods. In the current study, artificial neural networks and decision tree models were used to determine the factors affecting the consumers' consumption of geographically indicated products. The variables used in the artificial neural network and decision tree models are as shown in Table 1.

Table 1. Variables used in the decision tree and neural network models.

Acronym	Variable description	Type of measure	Data type
AGE	Consumer's age	If the age is $31 \leq$, young If the age is $31 \leq x \leq 50$, middle-aged If the age is ≥ 51 , old	Numerical
SEX	Consumer's gender	Male, female	Nominal
MARITA	Consumer's marital status	Married, single	Nominal

L			
EDU	Consumer's education level	If the education level is ≤ 5 years, elementary. Otherwise, more educated	Numerical 1
INCOME	Consumer's monthly income	If the monthly income is < 4000 TL, low income. Otherwise, high income	Numerical 1
FOODEX P	Consumer's monthly food expenditure	If the expenditure is < 600 TL, low. Otherwise, high	Numerical 1
CONSUM	Consumer's monthly walnut consumption	If the consumption is < 750 gram, low. Otherwise, high	Numerical 1
WILL	Consumer's willingness to pay more for geographically indicated products	Yes or No	Nominal
LABEL	Consumer's reading the label on the package	Yes or No	Nominal
NIKSAR	Consumer's knowledge that he Niksar walnut is geographically indicated	Yes or No	Nominal

Artificial Neural Networks: The general working principle of artificial neural networks can be explained as taking an input set and converting it into an output set. For this, the network needs to be trained to produce the correct outputs for the inputs shown to it. The process of determining the weight values of the process elements in

the artificial neural networks is called "training the network" (Öztemel, 2016).

Artificial neural networks are divided into two perceptrons known as recurrent and multilayer. Recurrent perceptrons consist only of input and output layers (Fig 1). Multilayer perceptrons consist of an input layer, a hidden layer/layer and an output layer (Fig 2).

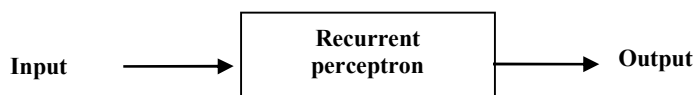


Fig 1: Recurrent perceptron

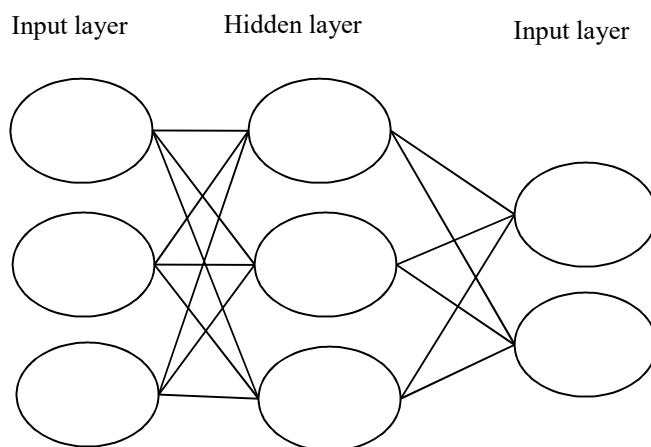


Fig 2: Multilayer perceptron

Considering the structure, artificial neural networks are divided into two sections, specifically feed-forward and feedback. In feed-forward neural networks, the connection is unidirectional. In this structure, the neurons in any layer connect only to the neurons in the next layer. In feedback neural networks, neurons can also be connected to any neurons in the previous layer or its current layer. In the current study, feed-forward multilayer artificial neural networks were used to determine the factors affecting the consumption of geographical indications. Batch size specifies the number of samples that will be used to train the neural network at a time. The epoch value indicates how many times the training process will be repeated. In the current study, the batch size was taken as 100 and the epoch value was 500.

Decision Trees: Creating a decision tree is a machine learning method. It is also called supervised learning (learning by example). In decision tree-based methods, the decision rules are shown graphically (Kirchner *et al.*, 2004). The results are easy to interpret and the model does not take much time to build (Byeon, 2019).

Decision tree analysis is a classification procedure that divides the data set into smaller subsections. The decision tree model predicts the outputs using the given inputs and divides the area of each variable repeatedly, creating rules for the whole area (Kim and Yoon, 2018). The basic concept of a decision tree is to divide a complex decision into simpler

decisions. This can lead to an easier solution to interpret (Zhang *et al.*, 2008).

A simple decision tree is shown in Fig 3. A symbolises the root node, B and C symbolise the inner

nodes, and D, E, F and G symbolise the leaf nodes. The purpose of the decision tree is to classify the data accurately with the least amount of branching.

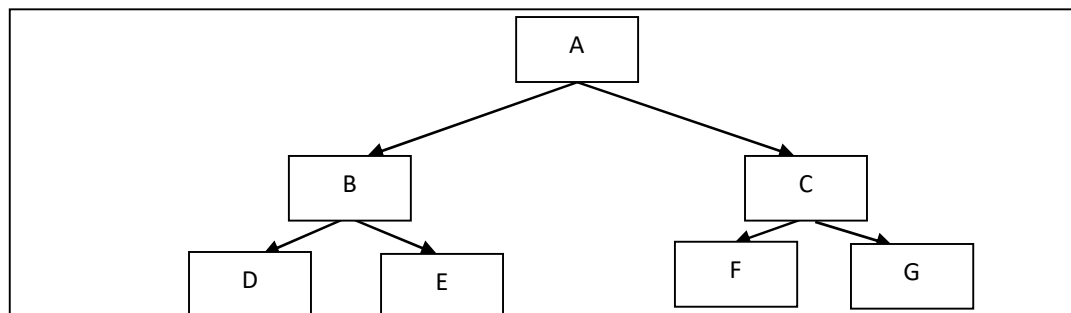


Fig 3. Decision tree

Criteria Used in the Performance Evaluation of the Models:

To determine the classification success of the models used in this study, 2 different methods were used. In the first method, the data set was divided using the percentage split. According to the percentage split method, 66% of the data set was used for training and 34% for testing. In the second method, the 10-fold cross-validation method was used. The accuracy criterion was used to determine classification success. The study also examined the Kappa statistics, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Recall, Precision and F-measure values of the models.

The Kappa statistic was used to measure the harmony between two variables in the tables with an equal number of rows and columns. When calculating the Kappa statistics, two different possibilities were calculated. These were Pr (a) and Pr (e). Pr (a) is the total proportion of compliance observed for the two evaluators, whereas Pr (e) is the probability of this compliance occurring by chance (Aydemir, 2019). The formula used for the Kappa statistics is shown below.

$$K = \frac{\text{Pr}(a) - \text{Pr}(e)}{1 - \text{Pr}(e)} \quad (1)$$

MAE is a criterion used to measure how close the estimates are to the actual results. RMSE is another criterion used to measure the difference between the estimates and actual results. Precision is the ratio of the number of True Positive samples estimated to be class 1 to the number of all samples estimated to be class 1. Recall is the ratio of the number of positive samples correctly classified to the total number of positive samples. When calculating F-Measure, precision and recall values are used. F-Measure is the harmonic mean of precision and recall. The criteria used when evaluating the algorithms used in this study were calculated using the following formulas. Since the numerical data (the consumer's age, education level, monthly income, monthly food expenditure and monthly walnut consumption) was converted to categorical data before the analysis, the normalisation process was not applied.

$$MAE = \frac{1}{n} \sum_{i=1}^n |a_i - p_i| \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (a_i - p_i)^2} \quad (3)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (4)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (5)$$

$$F - \text{Measure} = 2 \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (6)$$

RESULTS AND DISCUSSION

Socio-demographic characteristics of the consumers:

The mean age of the consumers was determined to be 29.16. Of the participants, 65.71% were males and 34.29% were females, and 35.60% of them were married. The mean monthly income of the participants was 4013.87 TL and the mean monthly food expenditure was 629.05 TL. It was determined that 55.50% of the participants reside in their own home and 44.50% rent. When the education levels of the consumers were examined, it was determined that many of the consumers participating in the study were high school graduates (46.60%) (Table 2).

Findings related to the geographically indicated products:

The consumers' knowledge of the geographically indicated products has been detailed in Table 5. The consumers' knowledge of these products was found to range from 53.40% to 93.19%. The most widely known geographical indication was found to be the Tokat kebab. In the study carried out by Teuber (2011), it was determined that the awareness and level of knowledge of consumers about geographical indication is very limited. In the study conducted by Supekova *et al.* (2008), it was determined that 43% of women and 32% of men know about geographical indications and that women are more interested in geographical indications than men. Similarly, Gracia *et al.* (2012) determined that

the women's desire to purchase local food products is higher than that of men. Oh *et al.* (2018) noted that the vast majority of dried palm farmers and consumers are not familiar with geographical indications, therefore it is necessary to promote geographical indications by making a website or developing a smartphone app. In the study conducted by Cacic *et al.* (2011), it was determined that there is a relationship between familiarity with the geographically marked wine and the education level of the consumers.

It was determined that 48.95% of the consumers participating in the current study want to pay more for products with geographical indications. In the study conducted by Brandao *et al.* (2012), it was determined that consumers would pay more for geographical indications. Seetisarn (2012) also found that 65% of consumers want to pay more for geographical indications. In the study conducted by Ahrendsen and Majewski (2017), it was found that 70% of the consumers were willing to pay higher prices for geographical indications and that the price they can pay for these products is 32% more on average.

The consumers' perceptions of geographical indications are shown in Table 6. Almost all of the participants (4.6) think that geographical indications are produced in a particular geographic area. The majority of the participants (3.0) believe that the products with geographical indications are handmade and difficult to produce. Adinolfi *et al.* (2011) reported that the rate of consumers who know what geographical indications mean is 64%. In the study conducted by Dong (2019), the rate of consumers who do not know anything about geographical indications was found to be 13.33% whereas the rate of consumers who were highly informed about them was found to be 10.48%. Zhan *et al.* (2017) determined that the place where the product is produced, its perceived quality and knowing that geographical indications are protected are the variables that have an important effect on the loyalty of consumers specific to geographical indications. In the study by Likoudis *et al.* (2015), it was determined that approximately 50% of consumers want to buy products with geographical indications and that factors such as the origin of the product, health claims and sustainable consumer behaviour are effective in terms of encouraging the consumers to purchase products with geographical indications.

Table 2. Consumers' education level.

Education level	f	%
Elementary school	28	7.33
Middle school	17	4.44
High school	178	46.60
Associate's degree	83	21.73
Bachelor's degree	76	19.90
Total	382	100.00

When the occupational status of the participants was examined, it was found that 57.85% were students and 13.35% were civil servants (Table 3).

It was found that 61.52% of the consumers read the labels on the food products with geographical indications. According to the consumers, the most important of the properties stated on the packaging is the storage conditions (4.23), followed by the trademark (4.18) and quality certificate (4.17) (Table 7).

When which member of the family doing the shopping was examined, it was found that generally the mother (38.74%) and the father (27.49%) do the shopping (Table 4).

It was found that 81.15% of the consumers participating in the current study consume products with geographical indications. In the study carried out by Thangaraja and Abirami (2018), it was determined that the positive experiences of consumers to do with geographical indications had a positive effect on the decision to purchase products with geographical indications in the future. Henseleit *et al.* (2009) found that regional foods have a higher level of food safety, therefore consumers prefer to buy foods grown in the region.

Table 3. Consumers' occupational status.

Occupational status	f	%
Worker	25	6.54
Civil servant	51	13.35
Tradesman	13	3.40
Retired	27	7.07
Housewife	8	2.09
Self-employed	37	9.70
Student	221	57.85
Total	382	100.00

Table 4. The member of the family doing the shopping.

	f	%
Mother	148	38.74
Father	105	27.49
Mother-Father	95	24.87
Older children	10	2.62
The whole family	24	6.28
Total	382	100.00

Table 5. Consumers' knowledge of geographically indicated products.

	f		%	
	Yes	No	Yes	No
Zile molasses	281	101	73.56	26.44
Niksar walnuts	182	200	47.64	52.36
Turhal Yoğurtmacı	207	175	54.19	45.81
Tokat kebabs	356	26	93.19	6.81
Erbaa Narince vine leaves	271	111	70.94	29.06
Zile churchkhela	204	178	53.40	46.60
Tokat Narince pickled vine leaves	244	138	63.87	36.13

Table 6. Consumers' perceptions of geographical indications.

Statements	Mean	SE Mean
The product is produced in a particular geographic area	4.6	0.0281
Independent auditing is performed on the product	2.5	0.0642
Sustainable quality is ensured for the product	2.3	0.0542
The possibility of deception in relation to the product is weak	2.6	0.0545
The product is healthy	2.6	0.0572
The product is tasty	3.0	0.0625
The production process of the product is more meticulous	2.4	0.0551
The income of the agricultural workers can increase	2.4	0.0603
The product will be sold at higher prices	2.2	0.0571
The product is produced using traditional production methods	2.8	0.0665
The product is handmade and difficult to produce	3.0	0.0634

1. Strongly Disagree, 2. Disagree, 3. Undecided, 4. Agree and 5. Strongly Agree

Table 7. Properties explained on the packaging.

	Mean	SE Mean
Nutritional Value/Calories	4.14	0.0410
Trademark	4.18	0.0415
Storage conditions	4.23	0.0451
Date of expiry	4.15	0.0507
Environmentally friendly	4.20	0.0432
Quality Certificate	4.17	0.0475
Content	4.06	0.0532

1. Strongly Disagree, 2. Disagree, 3. Undecided, 4. Agree and 5. Strongly Agree

Among the reasons why the consumers consume products with geographical indications was their contribution to the economy of the region (4.73). This was followed by the products being tastier (4.51) (Table 8). Similarly, in the study conducted by Dhamotharan *et al.* (2015), the reasons found for the consumers consuming the products with geographical indications were found to include supporting the production of local products, the importance of quality and locality. In the study conducted by Garanti (2019), trust was determined to be an important factor that determined the tendency to purchase geographically marked halloumi cheese. Roselli *et al.* (2018) determined that there is a significant relationship between the consumers' purchase of geographically marked olive oil and consumer age, education level, household size and income level. In the study carried out by Cacic *et al.* (2011), it was determined that there is a relationship between the high socio-economic status of the consumers and the geographically marked wine preferences.

Findings related to the decision tree: In the current study, the percentage split method was used first. For this purpose, the group was divided into two. The first group was used as the training group and the second group as the testing group. Regarding the data, 66% was used for training and 34% for testing. When the results obtained with the percentage split method were examined, the Naive Bayes algorithm produced the best result with an accuracy rate of 80.7692%. The MAE value was found to vary between 0.253 and 0.2766. The RMSE value was found to vary between 0.3921 and 0.3943 (Table 10).

In the current study, the cross-validation method was also used. In the 10-fold cross-validation method, the data set was divided into 10 sub-sections. One of the sub-sections was used for the testing of the model while the other 9 sub-sections were used as the training group. The cross-validation process was repeated 10 times for each sub-section that was going to be used as the test data. When the results obtained through the cross-validation method were examined, the Random Forest algorithm produced the best result with an accuracy rate of 84.555%. The MAE and RMSE values should be close to zero. Thus, the best MAE value was yielded by the Random Forest algorithm and the best RMSE value was yielded by REPTree algorithm (Table 11).

Table 8. Consumers' reasons for consuming geographically indicated products.

	Mean	SE Mean
Healthier	3.73	0.0649
Tastier	4.51	0.0337
Less harmful to the environment	2.79	0.0725
Higher quality	3.20	0.0706
Contributes to the economy of the region	4.73	0.0313

1. Strongly Disagree, 2. Disagree, 3. Undecided, 4. Agree and 5. Strongly Agree

The most important reason for the consumers not consuming products with geographical indications was found to be their contentment with other products (4.79) (Table 9).

Table 9. Consumers' reasons for not consuming geographically indicated products.

	Mean	SE Mean
Very expensive	4.06	0.177
They have a bad look	2.79	0.178
I cannot find the products	2.26	0.182
I do not trust their labels	4.16	0.137
I cannot see any logo	4.05	0.133
I do not like their taste	4.48	0.0884
I am content with other products	4.79	0.0482

1. Strongly Disagree, 2. Disagree, 3. Undecided, 4. Agree and 5. Strongly Agree

Table 10. Results of the different algorithms (percentage split).

	Kappa statistic	Correctly classified instances (%)	MAE	RMSE	Precision	Recall	F-Measure
J48	0.2121	80	0.2766	0.3943	0.765	0.800	0.774
Random Tree	0.2439	76.1538	0.2636	0.4779	0.765	0.762	0.763
Random Forest	0.2763	79.2308	0.253	0.3993	0.777	0.792	0.783
NaiveBayes	0.1287	80.7692	0.2969	0.3994	0.761	0.808	0.757
REPTree	0.2927	77.6923	0.2571	0.3921	0.780	0.777	0.779

Table 11. Results of the different algorithms.

	Kappa statistic	Correctly classified instances (%)	MAE	RMSE	Precision	Recall	F-Measure
J48	0.1885	82.9843	0.2606	0.369	0.820	0.830	0.778
Random Tree	0.327	81.9372	0.2277	0.4205	0.799	0.819	0.805
Random Forest	0.3793	84.555	0.235	0.366	0.828	0.846	0.825
NaiveBayes	0.0223	81.4136	0.2968	0.3894	0.849	0.814	0.733
REPTree	0.1947	83.2461	0.2495	0.3628	0.833	0.832	0.780

The decision tree produced various rules, which are presented in Fig 4 and Table 12.

- The consumers who know that Niksar walnut is a geographical indication. They have a high income and consume products with geographical indications.
- The consumers who know that Niksar walnut is a geographical indication. They have low incomes and a low level of monthly walnut consumption. They consume products with geographical indications.
- The consumers who know that Niksar walnuts are a geographical indication. They have low incomes, a high level of monthly walnut consumption and are willing to pay more for geographical indications. They consume products with geographical indications.
- The consumers who know that Niksar walnuts are a geographical indication. They have low incomes, a high level of monthly walnut consumption, are not willing to pay more for products with geographical indications and read the labels on the product packaging with geographical indications. They do not consume products with geographical indications.
- The consumers who know that Niksar walnuts are a geographical indication. They have low incomes, a high

- level of monthly walnut consumption, are not willing to pay more for products with geographical indications and do not read the labels on the product packaging with geographical indications. They consume products with geographical indications.
- The consumers who do not know that Niksar walnuts are a geographical indication who have a low level of monthly walnut consumption. They consume products with geographical indications.
- The consumers who do not know that Niksar walnuts are a geographical indication have a high level of monthly walnut consumption and they are willing to pay for more geographical indications. They consume products with geographical indications.
- The consumers who do not know that Niksar walnuts are a geographical indication have a high level of monthly walnut consumption, are not willing to pay for geographical indications. They do not consume products with geographical indications.

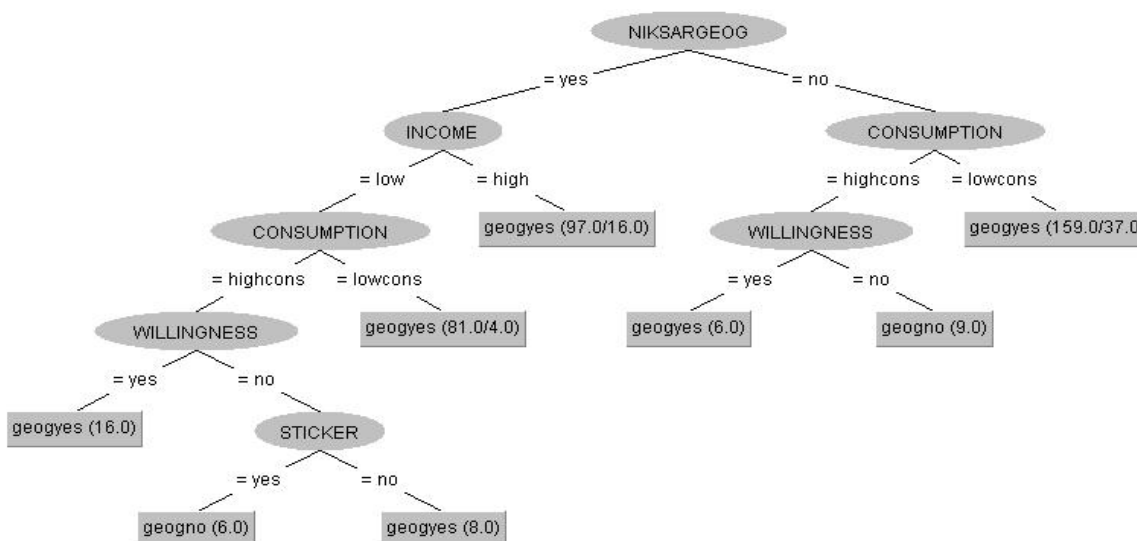


Fig 4. The decision tree obtained using the J48 algorithm

Table 12. Rules created by the decision tree (J48).

Rule no	Rules
1	If it is =yes niksargeog and =high income then geogyes
2	If it is =yes niksargeog and =low income and =lowcons then geogyes
3	If it is =yes niksargeog and =low income and =highcons and =yes willingness then geogyes
4	If it is =yes niksargeog and =low income and =highcons and =no willingness and =yes sticker then geogno
5	If it is =yes niksargeog and =low income and =highcons and =no willingness and =no sticker then geogyes
6	If it is =no niksargeog and =lowcons then geogyes
7	If it is =no niksargeog and =highcons and =yes willingness then geogyes
8	If it is =no niksargeog and =highcons and =no willingness then geogno

Findings related to Artificial Neural Networks: In the current study, the feed-forward multilayer perceptron algorithm was used. The classification accuracy rate of the algorithm was found to be 75.3846% for the percentage split method and 82.199% for the cross-validation method. Similarly, Precision, Recall and F-Measure values were found to score higher in the cross-validation method (Table 13).

The resulting artificial neural network is shown in Fig 5. In the artificial neural network, there are 12 attributes, 1 hidden layer and 7 hidden neurons in the hidden layer.

Table 13. Results of the multi-layer perceptron algorithm.

	Percentage split	Cross-validation
Kappa statistic	0.1827	0.3783
Correctly classified instances (%)	75.3846	82.199
MAE	0.2512	0.2152
RMSE	0.4339	0.3808
Precision	0.746	0.811
Recall	0.754	0.822
F-Measure	0.750	0.816

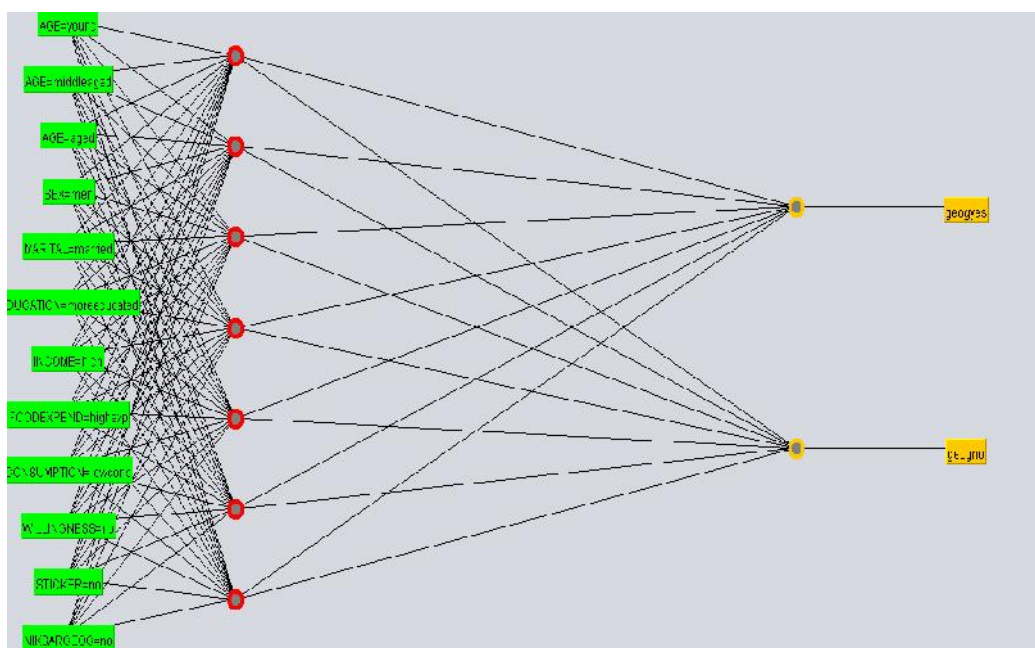


Fig 5. The artificial neural network used in the study

Conclusion: In the current study, decision tree and artificial neural network models were used to determine the factors affecting the consumers in the city of Tokat regarding their consumption of products with a geographical indication. When the results of the study were examined, it was found that many factors are involved in the consumption of GIP by the consumers. The factors include the consumers’ monthly walnut consumption, the consumers’ knowledge that Niksar walnuts are a geographical indication product, the consumers’ monthly income, the consumers’ willingness to pay more for geographical indication products and the

consumers’ engagement with the activity of reading the labels on the product packaging with geographical indications marked.

In the current study, it was determined that the knowledge of geographical indications in the province of Tokat by the consumers varies and that the best-known geographical indication product is Tokat kebab. It was also found that the majority of consumers consume products with a geographical indication. This shows that the consumers are aware of the importance of geographical indications and that their level of consciousness related to the issue is high.

REFERENCES

- Ahrendsen, B.L. and E. Majewski (2017). Protected geographical indication recognition and willingness to pay: a case of grojec apple. *Applied Stud. Agribusi. Commerce*. 11(3-4): 73-80.
- Adinolfi, F., M. de Rosa, and F. Trabalzi (2011). Dedicated and generic marketing strategies : The disconnection between geographical indications and consumer behavior in Italy. *British Food J*. 113(3): 419-435.
- Anonymous. (2019). Concepts. [online] Available at: <https://www.turkpatent.gov.tr/TURKPATENT/resources/temp/6B3F914C-E72C-437C-8A30-F50C51DE0A23.pdf;jsessionid=CA404248B7B ABD475998A99793B13329>.
- Aydemir, E., (2019). *Artificial Intelligence with Weka*, Seçkin Publishing, Ankara, 231p.
- Babcock, B. A. and R. Clemens (2004). Geographical Indications and Property Rights: Protecting Value-Added Agricultural Products. MATRIC Briefing Paper 04-MBP 7, Midwest Agribusiness Trade Research and Information Center Iowa State University.
- Brandão, F.S., A.C. Ceolin, M.E.A. Canozzi, J.P.P. Révillion and J.O.J. Barcellos (2012). Confiança e agregação de valor em carnes com indicação geográfica. *Arq. Bras. Med. Vet. Zootec*. 64(2): 458-464.
- Byeon, H. (2019). Development of depression prediction models for caregivers of patients with dementia using decision tree learning algorithm. *Intl. J. Gerontology*. 13: 314-319.
- Cacic, J., M. Tratnik, J.G. Kljusuric, D. Cacic, and D. Kovacevic (2011). Wine with geographical indication – awareness of Croatian consumers. *Brit. Food J.*, 113(1): 66-77.
- Çukur, F. and T. Çukur (2017). Evaluation of geographically indication products and rural development: the case study of Muğla province. *Turk. J. Agri. Econ.*, 23 (2): 187-194.
- De Rosa, M. (2015). The role of geographical indication in supporting food safety: a not taken for granted nexus. *Italian J. Food Safety*. 4(493): 186-191.
- Dhamotharan, P.G., S. Devadoss and K.N. Selvaraj (2015). Estimation of consumers' willingness to pay for geographic indications bananas using conjoint analysis. *J. Int. Food & Agribus. Marketing*. 27: 65-78.
- Divya, N.D. and K.K. Anoop (2018). Rural development through geographical indication. *Intl. J. Pure and Applied Math*. 199 (16): 1385-1391.
- Dokuzlu, S. (2016). Geographical indications, implementation and traceability: Gemlik table olives. *Brit. Food J*. 118(9): 2074-2085.
- Dong, W. (2019). A case study on Chinese consumers' willingness to pay for geographical indication products. *The Front. Society, Sci. Techn*. 1(7): 95-103.
- Durand, C. and S. Fournier (2017). Can geographical indications modernize Indonesian and Vietnamese agriculture? analyzing the role of national and local governments and producers' strategies. *World Develop.*, 98: 93-104.
- Fernandez-Ferrin, P., B. Bande, M.M. Galan-Ladero, D. Martín-Consuegra, E. Diaz, and S. Castro-Gonzalez (2019). Geographical indication food products and ethnocentric tendencies: The importance of proximity, tradition, and ethnicity. *J. Cleaner Prod.*, 241: 1-9.
- Fotopoulos, C. and A. Krystallis (2003). Quality labels as a marketing advantage the case of the “pdo zagora” apples in the Greek market. *Euro. J. Marketing*. 37(10): 1350-1374.
- Garanti, Z. (2019). GenZ willingness to purchase products with geographical indications. *Akdeniz Uni. J. Econ. Admin. Sci.*, 19(2): 299-325.
- Giovannucci, D., T. Josling, W. Kerr, B. O'Connor, and M.T. Yeung (2009). *Guide to Geographical Indications Linking Products and Their Origins*. The International Trade Centre, 207p.
- Gracia, A., T. de Magistris, and R.M. Nayga (2012). Importance of social influence in consumers' willingness to pay for local food: are there gender differences? *Agribusiness*. 28(3): 361-371.
- Henseleit, M., S. Kubitzki and R. Teuber (2009). Determinants of consumer preferences for regional food products, in Canavari, M., Cantore, N., Castellini, A., Pignatti, E. and Spadoni, R. (Eds), *International Marketing and Trade of Quality Food Products*, Wageningen Academic Publishers, Wageningen, 263-278.
- Kim, K. and S.H. Yoon (2018). Assessment of building damage risk by natural disasters in South Korea using decision tree analysis. *Sustainability*. 10(1072): 1-22.
- Kirchner, K., K.H. Tölle, and J. Krieter (2004). The analysis of simulated sow herd datasets using decision tree technique. *Computers and Electronics in Agriculture*. 42: 111-127
- Likoudis, Z., D. Sdrali, V. Costarelli and C. Apostolopoulos (2015). Consumers' intention to buy protected designation of origin and protected geographical indication foodstuffs: the case of Greece. *Intl. J. Consumer Stud.*, 40:283-289.
- Meral, Y. and A. Şahin (2013). Consumers' Perceptions of Product with Geographical Indication: The Case of Gemlik Olives. *Kahramanmaraş Sütçü İmam Uni. J. Natu. Sci.*, 16(4): 16-24.
- Newbold, P., 1995, *Statistics for Business and Economics*, Prentice-Hall International, New Jersey, 867p.
- Oh, H.J., M.S. Park, K.J. Cho, S.I. Choi, H.M. Kang, and H. Kim (2018). Geographical indication and development plans in South Korea: a study on dried persimmons. *Forest Sci. Techno.*, 14(1): 41-46.

- Öztemel, E. (2016). Artificial Neural Networks. Papatya Press, İstanbul, 230 p.
- Raimondi, V., C. Falco, D. Curzi and A. Olper (2019). Trade effects of geographical indication policy: The EU case. *J. Agri. Econo.* 71: 330-356.
- Roselli, L., G. Giannoccaro, D. Carlucci, and B. De Gennaro (2018). EU quality labels in the Italian olive oil market: How much overlap is there between geographical indication and organic production?. *J. Food Prod. Marketing.* 24(6): 784-801.
- Seetisarn, P. and Y., Chiaravutthi (2012). Thai consumers willingness to pay for food products with geographical indications. *Electronic Business J.*, 11(8): 441-450.
- Sitepu, F.Y. (2018). The potential of geographical indications and its legal protection. *E3S Web of Confer.*, 52 (17): 1-6.
- Skuras, D. and A. Vakrou (2002). Consumers' willingness to pay for origin labelled wine A Greek case study. *Brit. Food J.* 104(11): 898-912.
- Supekova, S., M. Honza, and D. Kacenova (2008). Perception of Slovak foodstuffs designated by protected geographical indication by Slovak consumers. *J. Food Nutr. Res.*, 47(4): 205-208.
- Teuber, R. (2011). Consumers' and producers' expectations towards geographical indications Empirical evidence for a German case study. *Brit.Food J.* 133(7): 900-918.
- Thangaraja, A. and A. Abirami (2018). The consumer experience on geographical indicators and its impact on purchase decision: An empirical study. *Intl. J. Pure and Appl. Math.*, 118(20): 2625-2630.
- Zhan, H., S. Liu, and J. Yu (2017). Research on factors influencing consumers' loyalty towards geographical indication products based on grey incidence analysis. *Grey Systems: Theory and Application.* 7(3):397-407.
- Zhang, X., F. Lin, Y. Jiang, K. Wang and M.T.F. Wong (2008). Assessing soil Cu content and anthropogenic influences using decision tree analysis. *Environmental Pollution.* 156, pp.1260-1267.
- Zografos, D. (2008). Geographical indications and socio-economic development. *SSRN Electronic J.* [online] Available at: https://www.researchgate.net/publication/228313378_Geographical_Indications_and_Socio-Economic_Development.