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Classification of wooden wastes with machine learning approaches

Ahşap atıkların makine öğrenmesi yaklaşımları ile sınıflandırılması

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Abstract

In this study, 200 wood waste samples from different origins were analysed by Inductive coupled plasma optical emission spectrometry (ICP-OES) and Inductively coupled plasma mass spectrometry (ICP-MS) for 11 elements (lead, cadmium, aluminium, iron, zinc, copper, chrome, arsenic, nickel, mercury and sulphur) that are likely to present in wood waste. In the study, the data as non-hazardous and hazardous was evaluated based on the standard (TS EN ISO 17225-1, 2021). Artificial neural network (ANN) and random forest (RF) analyses were then applied to better analyze and interpret the data. In this way, statistical separation of wood wastes as non-hazardous and hazardous was realized. Accordingly, it was shown that random forest analysis with an accuracy rate of 100% was better than artificial neural network analysis with an accuracy rate of 99%. Results suggested that wood wastes could be recycled and entered the production cycle in a way to contribute to the national economy or be incinerated with appropriate methods in bioenergy production in an environmentally friendly way which would be possible with the accurate classification of these wastes. In this study, the classification of wood wastes as hazardous and non-hazardous with 100% accuracy rate using ICP data with machine learning approaches, which is not encountered in the literature review.

Özet

Bu çalışmada 200 adet farklı kökenden gelen ahşap atık örneğinde İndüktif Eşleşmiş Plazma- Optik Emisyon Spektrometre (ICP-OES) ve Indüktif Eşleşmiş Plazma-Kütle Spektrometresi(ICP-MS) cihazlarında ahşap atıklarda çıkma olasılığı yüksek olan 11 elementin (Pb, Cd, Al, Fe, Zn, Cu, Cr, As, Ni, Hg ve S) analizi yapılmıştır. Çalışmada verilerin tehlikesiz ve tehlikeli şeklindeki değerlendirilmesi TS EN ISO 17225-1 (2021) standardı esas alınarak yapılmıştır. Daha sonra verileri daha iyi analiz edebilmek ve yorumlayabilmek amacıyla, verilere yapay sinir ağı (YSA) ve random forest (RF) analizleri uygulanmıştır. Bu şekilde ahşap atıkların istatistiksel olarak da tehlikesiz ve tehlikeli olarak ayrımının yapılması gerçekleştirilmiştir. Buna göre %100 doğruluk oranı ile random forest analizinin, %99 doğruluk oranı ile yapay sinir ağı analizinden daha iyi bir sınıflandırma yaptığı ortaya konmuştur. Ahşap atıkların geri kazanılarak ülke ekonomisine katkı sağlayacak şekilde üretim döngüsüne girebilmesi veya biyoenerji üretiminde çevre dostu olacak şekilde uygun yöntemler ile yakılabilmesi bu atıkların doğru bir şekilde sınıflandırılması ile mümkün olacaktır. Bu çalışma ileliteratür taramasında rastlanmayan makine öğrenme yaklaşımları ile ahşap atıkların ICP verileri kullanılarak tehlikeli ve tehlikesiz olarak %100 doğruluk oranı ile sınıflandırılması yapılmıştır.

INTRODUCTION

Wood raw material is transformed into various products through processes such as bending, splitting, cutting, peeling, sawing, chipping, fibring, gluing, pressing, steaming, drying, treated etc. in the forest products industry (Hisarlı 1990, ORÜS 1991, Tutuş and Tozluoğlu 2008). Wood wastes arise both in the production processes of these products and due to the disposal of these products after they have completed their functions. In addition, in a country like Türkiye where urban transformation is intensively applied, a significant amount of waste wood is left behind from demolished buildings. As a result of production activities in the forest products industry, process and non-process specific wood wastes are generated. Wood wastes, regardless of the activity in which they are generated, are wastes with potential for utilization, provided that their content is known. In terms of contributing to the solution of increasing raw material prices and the shortage of access to raw materials, the introduction of wood wastes into the production cycle if they have clean content will make a significant contribution to the national economy. It will also significantly reduce the solid waste burden in cities (Hisarlı 1990, Çolak et al. 2005, Demirkır and Çolak 2006). However, the contents of wood wastes vary widely depending on the treatments applied. Wood waste that must be disposed of in disposal facilities because it is absolutely harmful to human and environmental health can also be found in this waste pile. For this reason, waste sorting and classification is a very important issue for wood waste as it is for all solid wastes in terms of how they can be utilized. All predictions are that biomass, which is among the sustainable resources and has an important place due to the finite nature of fossil fuels, will continue to play an important role in the use of biomass as fuel in the future. At the same time, for this reason, the issue of reducing dependence on fossil fuels and minimizing the negative consequences of the climate crisis by limiting the emissions that cause the greenhouse effect, as well as maintaining the carbon sequestration function by processing a carbon storage material into permanent products that can be used instead of fossil-based materials will be of much greater importance. The Renewable Energy Sources (RES) policy of the European Union (EU) and the emission trading system for greenhouse gas emissions are used for this purpose. The RES Policy envisages that by 2020, at least 20% of the total energy consumed in the EU should be derived from renewable energy sources. This implies that the use of wood, which is categorized as carbon neutral within the EU, will increase further. The extensive reuse of log residues and recycled wood forms as raw materials in many European countries contributes to the sustainability of forest resources by maintaining carbon sequestration functions (Davis et al 2013, TOBB 2015, TORID 2017, Özertan and Coşkun 2021). Within these processes, the utilization of wood wastes generated during the production processes in the forest products industry gains particularly great importance. The type and volume of wastes generated during the production stages of the forest products industry can change over time depending on various factors (Davis et al. 2013, Özertan and Coşkun 2021). Such recycling and reuse can be possible by knowing the contents of these wastes and classifying them accordingly. A correct classification will allow wastes without chemicals to be used as raw materials by re-entering the production cycle, while wastes containing various chemicals but with values that do not exceed the upper limits in the TS EN ISO 17225-1 (2021) standard of these chemical compounds will allow energy to be produced by burning in appropriate incineration units (Demirkır and Çolak 2006). In the literature, there is considerable amount of research on metal and heavy metal content in wood and wood waste materials, which are solid wastes.

Huhn et al. (1995) took 9 bark samples of pine from different regions and the samples were prepared for heavy metal analysis. The elemental contents of Cd, Cr, Cu, Fe, Hg, Mn, Ni, Pb and Zn were determined with the help of ICP-AES and ICP-MS, and cluster and factor analyses were performed to evaluate regional heavy metal accumulation using the data obtained. Uhde et al. (1996) studied a technique for the digestion of various coating-material types employing microwave-assisted pressure-digestion has been devised in order to estimate the overall heavy metal content of hardwood furniture coatings. Sequential ICP-AES was used to analyze 13 metals that are important to the environment in the research. This technique was applied to the examination of 62 samples of hardwood furniture coating ranging in age. While many samples had modest metal contents, several samples had contamination levels of some elements that exceeded 1 g/kg. Tafur-Marinos et al. (2016), used different procedures (microwave, wet, dry, ash fusion) to determine Al, Ca, Fe, Mg, P, K, Si, Na, S, Cd, Co, Cr, Cu, Mn, Ni, Pb and Zn in wood by ICP-OES. They used two certified reference materials for accuracy: Beech leaves and olive leaves. Different procedures were found to be more effective for different elements. For ICP-OES, higher substance concentrations are required to obtain accurate results compared to ICP-MS. Different digestion procedures gave more sensitive and accurate results for different elements. Huron et al. (2017) studied various treated waste wood to characterize their chemical structure and evaluate their compatibility with incineration systems. Compared to untreated wood, the heating value and C, H, O composition of the samples did not change. Most importantly, they confirmed the heterogeneity of waste wood with this study. They found that the N element was by far the highest in the panel boards (up to 38g/kg), Cl level was high in the samples with surface coating, metals such as Pb and Zn were caused by paints, and Cr and Cu elements were caused by impregnated samples. Tokalıoğlu et al. (2018) determined the concentration of Cr, Mn, Fe, Co, Ni, As, Cd, Pb and Zn in 9 different species for a total of 69 samples (such as coconut, sumac, sesame, red pepper, thyme) by ICP-MS. Multivariate and univariate statistical techniques such as principal component analysis, cluster analysis, correlation analysis and one-way Anova were applied to interpret the data provided. The 3 principal components explain 79.6% of the total variance. The first component explains Cr, Fe and Pb; the second component explains Mn, As and Cd; the third component explains Ni and Co. Different types of species were classified by principal component and cluster analysis. The certified reference material GBW07605 tea leaves (tea tree leaves) was analyzed to verify the accuracy of the method. Yan et al. (2019) used three typical contaminated biomasses (recycled wood, combustible municipal solid waste and industrial and commercial waste) and waste fuels to identify heavy metal and metalloid contamination in biomass and waste fuels by statistical methods (t-test, significance, correlation, Anova, Manova and principal component analyses (PCA)). They stated that much stronger relationships and predictions can be made about contamination characteristics, relationships between contaminants and potential sources of contamination with the help of statistical analyses. Türk and Osma (2020) took bark, leaf and soil samples of *Pinus nigra* from industrial, roadside, urban and control locations in Ankara province to determine the amount of heavy metal pollution. The concentrations of heavy metals (Al, Cr, Cd, Cu, Fe, Fe, Zn, Mn, Pb, Ni) in these samples were determined by ICP-OES. The data obtained in the study were statistically evaluated with Anova and Dunnett test at 95% confidence level. As a result of the study, it was determined that *P. nigra*, which is widely found in urban areas, can function as a biomonitor in determining heavy metal pollution. Szczepanik et al. (2021) determined the content of heavy metals Cd, Cr, Cu, Fe, Ni, Pb and Zn in ash samples (miscanthus, oak, pine, sunflower husk, wheat straw, and willow). Hierarchical cluster analysis (HCA) and principle component analysis (PCA) were used to classify the raw materials ashed at different temperature (500, 600, 700, 800, 900 and 1000˚C) into the most similar groups and research the structure of data variability. In the study shown that explain more than 88% of the variability of the heavy metals with three principal components. The study provided the results of the heavy metal content of ash samples with the application of multivariate statistical analyses and enabled to draw results about the effect of biomass properties on its chemical properties during combustion.

Heavy metals are well-known hazardous substances and heavy metal pollution causes deterioration of human health and environmental quality. Whether wood waste samples can be used in bioenergy production is evaluated based on TS EN ISO 17225-1 (2021) standard. In order to develop the most appropriate techniques to utilize these resources in a way that contributes to the economy, it is crucial to understand the waste material content correctly. In this study, the results of elemental analysis of 200 wood samples were determined as hazardous and non-hazardous according to TS EN ISO 17225-1 (2021) standard for 11 elements (Pb, Cd, Al, Fe, Zn, Cu, Cr, As, Ni, Hg and S) including heavy metals. Thus, the data obtained from ICP-MS and ICP-OES devices were organized through a series of pre-treatments for the classification of wood-based wastes produced in the timber, board, furniture and impregnation sectors in our country into two categories (non-hazardous and hazardous). The aim of the study is to classify wood wastes into two categories as non-hazardous and hazardous with the highest success by using the data obtained as a result of ICP analysis with the help of ANN and RF analysis methods.

MATERIAL AND METHOD

Material

To occur wood wastes dataset, number of wood wastes were acquired from the different of wood industry sectors such as impregnated, wood based panel, furniture sector etc. These wastes are solid, impregnated, furniture and panel wood wastes (Table 1).

Table 1. List of the waste types

Wood wastes	Observation
Solid wood waste	50
Impregnated wood waste	50
Furniture wastes	50
Panel wood wastes	50

Solid and only including glue wood samples are taken as non-hazardous wood wastes, while treated wood wastes and furniture wood wastes are accepted as hazardous wood wastes according to the model flow chart (Figure 1).

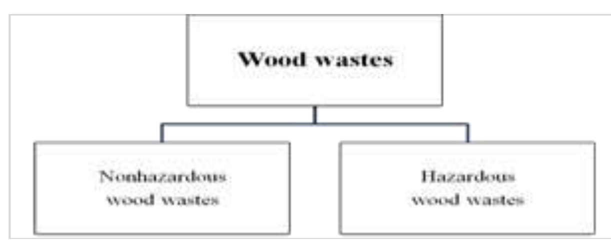

Figure 1. Workflow of the modelling procedure

Preparation of Wood Samples for ICP Analysis

After chipping process, 200 waste wood samples were ground into wood flour for chemical analyses by passing through the grinding machine with the Retsch brand grinder in the laboratory (Figure 2).

Figure 2. Grinding process

ICP Analysis

ICP-MS and ICP-OES devices were used to determine the content of wood wastes in the study. For this purpose, samples were prepared for analysis. Firstly, a homogenised solution was prepared for ICP analysis in Figure 3. After grinding, the samples were dried at 55-60°C for 24 hours. From these dried waste samples, 0.5 g samples were weighed and placed in teflon tubes suitable for microwave processing. Then 5 ml of concentrated nitric acid (HNO_3) was added to these samples. After waiting for 10 minutes in this way, 1 ml of hydrogen peroxide (H_2O_2) was added. In order to make reference measurements, only nitric acid and hydrogen peroxide were added to teflon tubes without samples and treated with the samples in the microwave. The purpose of preparing these reference samples is to eliminate the effect of impurities from nitric acid and hydrogen peroxide on the elements in the analysed samples. These samples were then homogenised into solution in a Berghof Speedway four microwave disintegrator. The solutions were filtered through blue band filter paper and taken into a 50 ml balloon jar and the volume was completed by adding ultrapure water.

Figure 3. The preparation of the sample as a homogeneous solution

After then, measurements of Pb, Cd, Al, Fe, Zn, Cu, Cr, Ni, S elements were carried out in ICP-MS (Perkin Elmer Optima 7000 DV) (Figure 4b) in Istanbul University-Cerrahpaşa (İUC) Forest Faculty at the Department of Soil Science and Ecology. Hg and As were measured by ICP-OES (Figure 4a) in Merlab in the Project Technology Office, Central Laboratory (MERLAB) at the İUC Avcılar campus. A certified sample (NIST 1575a Pine needle) was also analyzed samples on the ICP device. The measurement sensitivity of the device was demonstrated by comparing the certificate values of the certified sample with the values read during the analysis of the by the device. The obtained results were evaluated according to the non-hazardous and hazardous status of the material based on Table B.1, Table B.2 and Table B.3 and upper limits in Annex B of TS EN ISO 17225-1 (2021) standard.

Figure 4. Measurement of ICP analyse (a-ICP-OES, b-ICP-MS)

Method

Artifical Neural Network (ANN) Analysis

ANN is formed by connecting artificial neural cells to each other. ANNs are usually parallel structures consisting of a large number of interconnected processing elements (simple nerves). Figure 5 shows a simple ANN structure. ANNs are analysed in two structures: single layer (consisting of only input and output layer) and multilayer (input layer, at least one hidden layer and output layer) (Benli 2002, Adıyaman 2007, Ataseven 2013). A sample network model occurs an input layer, a hidden layer and an output layer. Input layer; data enters the network through this layer. The data is transferred to the next step which is called the intermediate layer, without being processed. Intermediate (hidden) layer; the number of cells in this layer may vary according to the nature of the problem; it forms the output layer by developing the data in the input layer with appropriate functions. The output layer is obtained by processing the data from the hidden layer in the function used by the network to generate the output (Kılıç 2015, Santos et al. 2021). The input layer consists of the values of 11 elements obtained from ICP-OES and ICP-MS, and the output layer demonstrates two categories (hazardous and nonhazardous) in ANN structure for 200 sample.

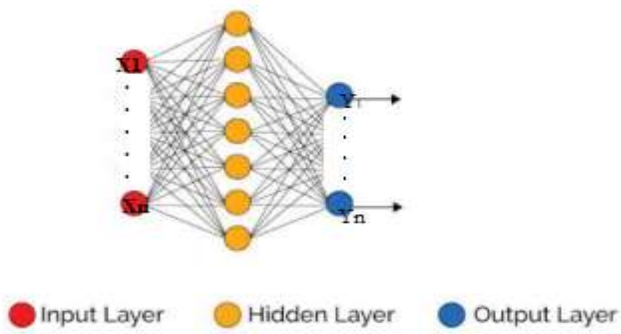

Figure 5. Simple ANN structure (Santos et al. 2021)

Random Forest

Random forest (RF) is an algorithm developed by Leo Breiman, inspired by the earlier work of Amit and Geman (Amit and Geman 1997, Breiman 2001a, Breiman 2001b). RF can be used for a categorical response variable called "classification" or for a continuous response called "regression" (Breiman 2001a, Breiman 2001b). Similarly, the predictor variables can be categoric or continuous (Cutler et al. 2011). RF is an algorithm technique and model that provides classification by generating different models by training each decision tree over multiple decision trees over a different observation sample and allows the degree of importance of variables. This technique is easy and flexible since it handles both classification and regression problems (Akman et al. 2011).

RESULTS AND DISCUSSION

ICP Analysis Results

ICP results were categorised as non-hazardous and hazardous based on the upper limits of the elements in Table B.1, Table B.2 and Table B.3 based on AnnexB in TS EN ISO 17225-1 (2021) standard. The elements were selected from those elements that are likely to be present in the wood content higher than they should be due to the various chemicals used in the industries processing forest products. In this study, the elemental analysis results of 200 wood samples were determined as hazardous and non-hazardous according to TS EN ISO 17225-1 (2021) standard for 11 elements (Pb, Cd, Al, Fe, Zn, Cu, Cr, As, Ni, Hg and S). Based on the upper limits in these three tables in the standard, the analysis results were compared with these upper limits for each element and it was concluded that the sample was hazardous if it exceeded these upper limits. Based on TS EN ISO 17225-1 (2021) standard, wood wastes were classified as non-hazardous wood wastes if ≤ the values in the standard and as hazardous wood wastes if > the values in the standard. The measurements made for the samples with ICP are shown in Tables 2, 3, 4 and 5.

As seen in Table 2 and Table 5, the highest values of all measured elements are lower than the highest values in the relevant standard. Thus, all of these wastes can be considered as non-hazardous waste. On the other hand, since Cu, Cr, As and S’ content values of impregnated (E) wood waste are higher than the standard values of those it can be accepted as hazardous waste (Table 3). In addition, since Fe, Zn, As and S’ content values of furniture waste are higher than the standard values of those it can be also accepted as hazardous wastes (Table 4). The data shown with "**" in the tables were accepted as zero for classification by ANN and RF analysis. The ICP values were normalized and adjusted between 0 and 1 by preprocessing the data for the analysis. After that, ANN and RF were used to classify wood wastes into two categories (non-hazardous and hazardous) according to the adjusted ICP data. ANN and RF analysis were performed using Matlab software to classify wood waste.

The Results of ANN Analysis

For the binary categorical classification as non-hazardous and hazardous, ANN analysis experiments were performed with ICP dataset with 200 observations using different algorithms: Levenberg Marquardt (LM) and Scaled Conjugate Gradient (SCG). The best ANN models were determined with respect to the total classification accuracy percentage over training and test datasets. The outputs of analysis are given in Table 6.

To determine how many neurons should be in the hidden layers, the complexity measures such as Akaike Information Criterion (AIC), Corrected AIC (AICc), Bayesian Information Criterion (BIC) were used. In the training procedure, cross-entropy and MSE were utilized for SCG and LM optimization algorithms, respectively. From Table 6, it can be seen that ICP dataset is partitioned into 0.8-0.1-0.1ratios as training, validation and test, and the estimated ANN model with LM optimization algorithm has 99% classification accuracy over the test data in terms of recognizing the wood samples as non-hazardous and hazardous. Similarly, the estimated ANN model with SCG optimization algorithm has 97% classification accuracy over the test data.

Table 2. ICP results of samples obtained from solid wood waste (MSF)

*The highest value	10	0.5	400	100	100	10	10	1	10	0.05	0.05
Sample\ Element	**Pb**	**Cd**	**Al**	**Fe**	**Zn**	**Cu**	**Cr**	**As**	**Ni**	**Hg**	**S**
MSF-1	0.53	0	38.48	43.43	4.004	0.564	0.147	0.004	**	**	0.018
MSF-2	1.23	0.04	10.04	10.37	4.398	0.418	0.851	0.042	**	**	0.015
MSF-3	0.66	0.03	27	10.36	5.397	0.751	0.239	0.05	**	**	0.022
MSF-4	0.89	0.006	4.637	9.465	0.917	0.606	0.145	0.05	**	**	0.016
MSF-5	0.36	0.03	19.68	4.78	3.874	0.708	0.247	0.0273	0.129	**	0.011
MSF-6	**	**	6.216	13.94	2.609	0.238	0.459	0.0202	**	**	0.013
MSF-7	0.23	**	7.88	5.92	3.23	0.523	0.082	0.01	0.198	**	0.012
MSF-8	0.5	0.024	10	16.33	3.222	2.558	0.685	0.033	**	**	0.015
MSF-9	0.66	0.032	27	10.36	5.4	0.751	0.239	0.029	**	**	0.034
MSF-10	1.23	0.036	10.04	10.37	4.4	0.418	0.851	0.042	**	**	0.033
MSF-11	0.5	0.111	10	10.55	4.667	1.432	0.769	0.038	**	**	0.023
MSF-12	0.5	0.019	10	4.609	2.986	0.622	0.154	0.041	**	**	0.016
MSF-13	0.5	0.082	107.2	10.84	3.63	0.853	0.763	0.043	**	**	0.024
MSF-14	0.5	0.026	1.918	6.598	3.783	1.179	0.4	0.03	**	**	0.022
MSF-15	0.18	0.146	4.384	60.85	3.442	0.808	0.233	0.016	**	**	0.035
MSF-16	0.5	0.066	10	1.78	5.212	1.329	0.276	0.05	**	**	0.030
MSF-17	0.5	0.027	10	2.236	2.383	0.521	0.452	0.043	**	**	0.042
MSF-18	0.23	0.097	7.643	8.034	4.971	0.791	0.151	0.021	**	**	0.045
MSF-19	0.16	**	12	10	2.231	1.297	**	0.016	**	**	0.017
MSF-20	0.26	0.068	10	1.117	3.575	0.48	0.393	0.032	**	**	0.025
MSF-21	0.66	0.093	122	100	10.74	2.327	1.484	0.008	0.01	**	0.032
MSF-22	0.18	0.053	80.9	68.37	3.56	1.47	1.958	0.012	0.161	0.011	0.011
MSF-23	0.26	0.088	138.1	98.8	7.62	1.2	0.711	0.013	**	0.012	0.012
MSF-24	0.19	0.082	256.6	100	3.36	1.42	0.57	0.024	0.024	**	0.019
MSF-25	0.23	0.361	28.36	25.62	6.27	0.88	0.279	0.042	0.26	**	0.01
MSF-26	0.18	0.053	80.9	68.37	3.56	1.47	1.958	0.012	0.161	0.011	0.011
MSF-27	0.5	0.023	1.905	6.459	3.695	1.169	0.3	0.033	**	**	0.016
MSF-28	0.5	0.025	19.115	65.285	3.739	1.17	0.35	0.035	**	**	0.015
MSF-29	0.34	0.106	14.505	31.315	4.327	1.069	0.2545	0.033	**	**	0.012
MSF-30	0.5	0.047	10	2.008	37.975	0.925	0.364	0.045	**	**	0.013
MSF-31	0.36	0.062	4.892	5.135	3.677	0.656	0.302	0.031	**	**	0.028
MSF-32	0.23	0.085	197.35	99	5.49	1.31	0.6405	0.0183	**	**	0.023
MSF-33	0.42	0.073	101.45	97.685	7.15	18.985	1.721	0.01	0.085	**	0.025
MSF-34	0.339	0.038	41.403	37.415	3.628	1.320	1.129	0.022	**	**	0.032
MSF-35	0.5	0.065	10	7.580	3.827	1.027	0.462	0.039	**	**	0.024
MSF-36	0.62	0.018	12.159	7.123	2.396	0.657	0.196	0.048	**	**	0.033
MSF-37	0.58	0.028	18.5	13.345	4.311	16.545	0.462	0.038	**	**	0.025
MSF-38	0.46	0.080	60.412	640.59	71.575	14.035	0.939	0.022	**	**	0.016
MSF-39	0.5	0.050	52.922	77.245	3.308	0.7375	0.459	0.02	**	**	0.013
MSF-40	0.21	0.065	5.412	55.585	2.903	0.8885	**	0.024	**	**	0.020
MSF-41	0.34	0.039	41.406	37.449	3.650	1.322	1.154	0.023	0.081	0.006	0.006
MSF-42	0.58	0.059	61.956	53.264	7.240	1.749	0.917	0.022	0.005	**	0.022
MSF-43	0.44	0.089	159.68	99.500	8.115	1.819	1.062	0.013	0.005	**	0.040
MSF-44	0.26	0.046	61.151	52.892	3.594	1.395	1.544	0.017	0.081	0.006	0.006
MSF-45	0.21	0.084	226.98	99.5	4.425	1.365	0.605	0.021	0.012	**	0.004
MSF-46	0.46	0.048	51.678	52.072	5.423	1.534	1.011	0.021	0.043	**	0.009
MSF-47	0.295	0.074	101.12	52.068	4.584	0.983	0.471	0.025	**	**	0.013
MSF-48	0.337	0.073	32.912	34.809	5.030	1.146	0.469	0.023	**	**	0.029
MSF-49	0.245	0.087	167.73	98.9	6.555	1.255	0.676	0.015	**	0.006	0.006
MSF-50	0.206	0.084	226.98	99.5	4.425	1.365	0.605	0.021	0.012	**	0.021

*The highest value of the relevant element in TS EN ISO 17225-1 (2021) standard, **Values too small to be measured with the analysed devices

Table 3. ICP results of samples obtained from impregnated wood waste (E)

*The highest value	30	3	3000	2000	200	200	40	4	80	2	0.2
Sample\ Element	**Pb**	**Cd**	**Al**	**Fe**	**Zn**	**Cu**	**Cr**	**As**	**Ni**	**Hg**	**S**
E-1	6.45	0.003	19.5	75.94	5.33	0.76	1.47	16.5	0.54	0.04	0.01
E-2	0.05	0.09	17.1	45.89	91.26	2508	7.06	7.61	0.256	0.03	0.02
E-3	1.5	0.05	39.8	69.28	13.03	1633	10.88	5.24	1.079	0.03	0.02
E-4	0.05	0.01	5.3	10.8	5.97	1116	3.18	**	0.1	0.04	0.02
E-5	1.25	0.05	35.8	101.3	20.72	36.36	49.8	27.41	1.171	1.07	0.15
E-6	0.05	0.05	14.9	37.33	3.45	418	864	5.38	0.79	0.02	0.09
E-7	0.05	0.05	13.7	28.72	5	1579	2862	**	2.680	0.02	0.32
E-8	1.47	**	339	918	15.46	64.44	8.93	4.54	3.914	0.04	0.22
E-9	2.82	0.12	3.7	15.3	8.31	5.71	0.98	28.97	0.068	0.05	0.01
E-10	0.05	0.05	57	264	13.57	2436	137	31.821	0.036	0.02	0.1
E-11	0.05	0.05	6.7	11.16	5	1151	2126	1590	0.412	0.03	0.03
E-12	0.05	0.05	10	7.88	2.88	139	277	204	0.1	**	0.03
E-13	0.05	0.03	9.3	15.02	5.24	1547	2.28	**	0.1	**	0.04
E-14	0.05	0.09	13.6	18.54	17.3	1166	8.23	8.94	0.1	0.02	0.05
E-15	0.05	0.05	15.3	21.76	5	1691	3529	105	0.172	0.01	0.04
E-16	0.05	0.05	63	87.46	12.79	1718	12.76	6.506	0.1	0.01	0.075
E-17	0.05	0.05	5.3	7.93	5	1441	2605	5.9	0.011	0.01	0.04
E-18	0.05	0.1	40.3	46.57	15.57	1788	2.95	16.83	0.1	0.01	0.07
E-19	0.05	0.05	4.7	12.17	5	4831	8375	18.54	0.183	0.01	0.05
E-20	0.05	0.05	10.1	12.88	5	1531	3099	8.69	0.1	0.03	0.05
E-21	0.05	0.05	8.9	13.06	16.98	1174	1.21	8.94	0.1	0.02	0.05
E-22	0.5	0.05	4.6	8.41	5	348	639	1854	0.1	0.03	0.03
E-23	0.05	0.05	12.4	14.42	5	4478	8663	**	0.559	**	0.05
E-24	0.05	0.05	8.09	14.59	5	3998	7570	**	0.583	**	0.07
E-25	0.05	0.05	15.8	23.95	4.43	1902	3.94	16.83	0.1	0.01	0.05
E-26	0.05	0.05	54.2	36.79	36.76	5279	12460	13104	0.337	0.02	0.02
E-27	0.05	0.05	74.9	149.4	5	4526	11130	5172	2.161	0.68	0.21
E-28	0.05	0.05	3.1	25.75	5	1227	329	287	0.1	0.03	0.06
E-29	0.05	0.05	13.4	29.36	12.25	1555	1.9	**	0.1	0.04	0.04
E-30	0.05	0.05	12.4	34.89	5	4286	7427	5948	0.47	0.29	0.06
E-31	0.05	0.03	186.2	384	5	1156	1358	**	1.998	**	0.15
E-32	0.05	0.05	6.05	33.97	5.55	1222	201	**	0.1	**	0.05
E-33	0.05	0.05	8.7	36.27	320	427	27.45	102	0.129	0.07	0.02
E-34	0.05	0.05	43	63.01	5	6761	17520	10919	1.834	1.36	0.14
E-35	0.05	0.05	69.4	90.82	10.98	1708	14.48	**	0.1	0	0.06
E-36	0.05	0.11	5.04	9.46	5	439	1245	**	0.414	0.02	0.09
E-37	0.05	0.05	23.02	40.27	10.8	1661	7.59	**	0.1	**	0.05
E-38	4.08	0.05	7.9	26.71	8.32	799	0.78	**	0.034	0.02	0.16
E-39	0.05	0.05	8.3	17.26	5	3216	6370	4634	0.293	**	0.05
E-40	0.05	0.05	20.5	59.16	5	3270	5347	**	0.337	**	0.06
E-41	0.77	0.07	28.4	57.59	52.15	2070.5	8.97	**	0.668	**	0.02
E-42	1.36	0.03	187.5	509.65	18.09	50.4	29.37	15.98	2.543	**	0.18
E-43	2.04	0.08	19.8	58.3	14.51	21.04	25.39	28.19	0.62	**	0.08
E-44	3.25	0.027	36.8	56.37	21.05	2639.88	6230.73	**	0.439	**	0.02
E-45	5.26	0.026	13.7	51.33	6.82	399.9	1.12	8.25	0.287	**	0.09
E-46	2.06	0.05	31.01	31.75	22.54	3039	6230	**	0.186	**	0.09
E-47	5.26	0.026	13.69	51.33	6.82	399.9	1.12	**	0.29	**	0.09
E-48	0.05	0.071	12.72	31.58	48.13	2862	3188.53	**	0.27	**	0.03
E-49	0.774	0.05	30.15	64.22	9.015	2451.5	2678.94	**	0.71	**	0.04
E-50	0.05	0.05	14.42	38.21	5	3243	5858.5	**	0.32	**	0.06

*The highest value of the relevant element in TS EN ISO 17225-1 (2021) standard, **Values too small to be measured with the analysed devices

Table 4. ICP results of samples obtained from furniture waste (M)

*The highest value	30	3	3000	2000	200	200	40	4	80	2	0.2
Sample\ Element	**Pb**	**Cd**	**Al**	**Fe**	**Zn**	**Cu**	**Cr**	**As**	**Ni**	**Hg**	**S**
M-1	0.5	0.02	18.6	2100	6.04	4.57	2.9	0.67	0.5	**	0.11
M-2	0.5	0.09	125.8	67.5	8.11	1.55	2.7	**	1.27	**	0.22
M-3	0.5	0.08	43.5	46.36	26.04	0.54	0.6	0.002	0.1	0.013	0.21
M-4	0.5	0.05	120.7	107.2	9.46	2.21	1.5	1.096	4.61	**	0.22
M-5	0.5	0.02	62.6	82.64	5.02	1.13	1.3	1.032	0.49	**	0.23
M-6	15.5	0.22	53.4	63.72	47	5.57	2	3.205	0.32	0.004	0.99
M-7	0.18	0.1	863.3	1885	12.98	5.86	3.8	**	1.1	**	0.85
M-8	0.5	0.02	70.3	116	12.59	5.47	7	7.930	2.23	**	0.2
M-9	7.76	0.03	51.9	578	30.94	1.09	2.4	0.1	0.69	**	0.21
M-10	0.17	0.19	121.9	623	15.09	3.86	5.1	0.16	4.65	**	0.57
M-11	0.5	0.04	52.5	37	3.48	1.95	2.6	3.439	0.1	**	0.21
M-12	0.06	0.17	167.8	738	13.12	4.5	6.3	1.504	4.79	**	0.72
M-13	0.4	0.12	613.2	1460	15.81	2.1	2.8	0.12	1.21	**	0.53
M-14	0.67	0.13	355.9	1275	10.08	1.86	2.05	**	1.07	**	0.77
M-15	0.5	0.11	265.3	337	5.33	0.59	0.7	**	7.27	**	0.25
M-16	2.4	0.09	514.7	181	10.79	2.34	1.02	**	0.91	**	0.3
M-17	0.5	0.03	123.2	28	3.86	0.49	0.402	0.05	0.1	**	0.34
M-18	1.17	0.05	63	91	13.32	1.26	4.103	**	0.1	**	0.24
M-19	0.12	0.09	87	104	15.98	1.38	2.003	**	0.1	**	0.28
M-20	0.5	0.08	68	37	4.44	0.88	0.997	**	0.24	**	0.21
M-21	0.5	0.09	59	874	6.31	1.47	1.09	**	0.63	**	0.22
M-22	0.5	0.05	184	402	4.24	1.64	1.53	**	0.41	**	0.21
M-23	0.27	0.1	96.4	54.77	14	1.22	0.13	**	0.79	**	0.5
M-24	0.33	0.03	40.7	29.25	4.86	0.96	0.05	0.23	0.45	**	0.22
M-25	0.56	0.05	16.1	106.3	12.73	1.34	0.098	**	1.503	**	0.89
M-26	0.5	0.06	466.8	1000.5	12.79	5.66	5.42	**	1.67	**	0.52
M-27	0.5	0.04	276.3	62.74	5.78	1.24	1.01	**	0.29	**	0.21
M-28	0.5	0.04	24.3	31.59	6.03	1.41	0.57	**	0.42	**	0.25
M-29	0.5	0.05	72.5	69.4	7.75	1.81	1.01	**	2.52	**	0.22
M-30	0.03	0.06	72.9	6103	629	17.9	14.7	0.03	0.4	**	4.55
M-31	0.02	0.03	102.7	1469	2239	1.26	20.3	**	0.18	**	0.12
M-32	0.5	0.06	82.1	76.78	17.75	1.38	1.04	0.55	2.36	**	0.21
M-33	0.5	0.05	72.5	69.4	7.75	1.81	1.01	**	2.52	**	0.22
M-34	0.5	0.03	43.4	57.12	5.52	1.27	0.92	**	0.46	**	0.24
M-35	8.02	0.12	58	73.18	26.16	3.35	1.6	**	0.41	**	0.61
M-36	8.02	0.12	61.8	89.86	29.94	5.52	4.5	**	1.28	**	0.59
M-37	0.5	0.03	95.5	111.6	11.03	3.84	4.2	**	3.42	**	0.21
M-38	0.03	0.05	87.8	3786	1434	9.58	17.5	**	0.29	**	2.34
M-39	0.5	0.03	91.7	94.92	7.24	1.67	1.36	**	2.55	**	0.21
M-40	8.02	0.14	87	85.46	28.38	3.89	1.72	2.15	2.47	**	0.57
M-41	0.5	0.05	72.22	1084	7.08	3.06	2.81	0.34	0.89	**	0.21
M-42	0.5	0.06	82.12	76.78	17.75	1.38	1.04	0.55	2.36	0.007	0.22
M-43	3.96	0.11	86.88	600.5	23.02	2.48	3.78	0.13	2.67	**	0.39
M-44	0.03	0.05	87.78	3786	1434	9.58	17.53	0.02	0.29	**	2.34
M-45	0.02	0.04	95.24	2627.5	1837	5.42	18.93	**	0.24	**	1.23
M-46	0.53	0.12	484.55	1367.5	12.95	1.98	2.43	0.06	1.14	**	0.65
M-47	1.4	0.1	563.95	820.4	13.3	2.22	1.91	0.06	1.06	**	0.42
M-48	1.54	0.11	435.3	727.9	10.44	2.1	1.53	**	0.99	**	0.54
M-49	0.5	0.07	121.7	638.05	5.28	1.55	1.31	**	0.52	**	0.22
M-50	0.5	0.05	371.6	531.62	9.28	3.45	3.22	**	0.98	**	0.37

*The highest value of the relevant element in TS EN ISO 17225-1 (2021) standard, **Values too small to be measured with the analysed devices

Table 5. ICP results of samples obtained frompanel wood waste(T)

*The highest value	30	3	3000	2000	200	200	40	4	80	2	0.2
Sample\Element	**Pb**	**Cd**	**Al**	**Fe**	**Zn**	**Cu**	**Cr**	**As**	**Ni**	**Hg**	S
T-1	0.43	0.03	48.3	65.02	5.82	1.15	2.01	**	0.157	**	0.13
T-2	1.52	0.06	57.79	86.01	7.07	1.21	1.42	**	0.471	**	0.13
T-3	0.5	0.05	43.95	37.39	4.51	0.81	0.65	**	0.1	**	0.18
T-4	0.5	0.03	66.19	85.75	6.48	1.63	2.15	**	0.401	**	0.15
T-5	0.5	0.02	7.04	20.7	5.98	0.7	0.64	**	0.1	**	0.09
T-6	0.5	0.06	312.7	303.7	9.55	2.37	2.74	**	1.007	**	0.2
T-7	0.5	0.04	19.5	31.22	6.73	1.38	2.37	**	0.27	**	0.2
T-8	0.5	0.14	81	106.9	15.72	1.56	4.33	**	0.149	**	0.16
T-9	0.5	0.07	43.7	49.1	7.8	1.03	0.91	**	0.429	**	0.16
T-10	0.18	0.04	91.4	14.15	5.47	0.51	0.29	0.13	0.417	**	0.03
T-11	0.23	0	71.4	62.72	4.44	0.94	0.88	**	0.606	**	0.16
T-12	0.37	0.04	65.1	78.74	5.52	1.57	1.15	0.029	0.734	**	0.02
T-13	0.34	0.05	17.1	42.39	6.8	1.14	0.48	0.103	0.53	**	0.06
T-14	0.66	0.09	121.5	126.7	10.74	2.33	1.48	**	0.307	**	0.2
T-15	0.44	0.06	18.8	23.69	6.03	1.35	0.25	0.151	0.19	**	0.18
T-16	0.5	0.05	42.8	35.81	4.7	0.77	0.44	**	0.1	**	0.15
T-17	0.2	0.09	49.4	67.95	6.8	0.7	0.52	**	0.778	**	0.2
T-18	0.14	**	27.7	36.17	4.2	0.76	1.14	**	1.261	**	0.2
T-19	0.12	0.07	57.1	71.28	3.91	0.8	2.7	**	1.829	**	0.2
T-20	0.53	0.06	102.6	65.29	5.33	0.78	28.5	**	0.496	**	0.02
T-21	0.5	0.05	37.1	45.6	4.54	0.99	0.68	**	0.087	**	0.13
T-22	0.5	0.08	131.2	146.7	6.8	1.29	0.79	**	0.497	**	0.18
T-23	0.5	0.05	662.7	62.58	31.14	1.06	1.08	**	0.1	**	0.19
T-24	0.5	0.05	599.9	70.43	33.38	1.09	0.9	**	0.295	**	0.2
T-25	0.5	0.15	57	63.92	8.65	1.04	0.46	**	0.1	**	0.16
T-26	0.5	0.05	166.1	167.46	8.14	1.88	2.55	**	0.639	**	0.2
T-27	0.5	0.03	13.3	25.96	6.35	1.04	1.5	**	0.1	**	0.14
T-28	0.5	0.11	62.3	78	11.76	1.3	2.62	**	0.289	**	0.16
T-29	0.5	0.06	31.6	40.16	7.26	1.2	1.64	**	0.35	**	0.18
T-30	0.21	**	81.4	38.44	4.95	0.72	0.58	**	0.512	**	0.1
T-31	0.02	**	57.5	55.91	6.12	0.99	0.89	**	0.518	**	0.16
T-32	0.26	0.04	54.3	28.27	6.13	0.82	0.39	0.117	0.474	**	0.05
T-33	0.3	**	68.2	70.73	4.98	1.26	1.01	**	0.67	**	0.09
T-34	0.55	0.08	70.2	75.2	8.38	1.84	0.87	**	0.249	**	0.2
T-35	0.5	0.07	69.3	84.55	8.77	1.73	0.98	**	0.419	**	0.17
T-36	0.5	0.07	46.1	51.88	5.75	0.73	0.48	**	0.3	**	0.2
T-37	0.32	0.07	34.1	45.82	6.41	1.02	0.38	**	0.484	**	0.2
T-38	0.16	0.08	53.3	69.62	5.35	0.75	1.62	**	1.304	**	0.2
T-39	0.5	0.07	55.3	59.71	6.62	0.85	2.3	**	0.747	**	0.2
T-40	0.33	0.07	79.9	68.29	4.62	0.79	15.61	**	1.163	**	0.2
T-41	0.97	0.05	53.05	75.52	6.45	1.18	1.71	**	0.314	**	0.13
T-42	0.5	0.04	55.07	61.57	5.5	1.22	1.4	**	0.251	**	0.16
T-43	0.5	0.04	159.87	162.2	7.76	1.54	1.69	**	0.554	**	0.14
T-44	0.34	0.06	67.57	31.63	6.64	0.77	0.6	0.065	0.423	**	0.09
T-45	0.5	0.05	43.36	36.6	4.6	0.79	0.54	**	0.1	**	0.16
T-46	0.5	0.06	84.15	96.15	5.67	1.14	0.73	**	0.292	**	0.16
T-47	0.5	0.05	349.9	54.09	17.84	1.02	0.88	**	0.094	**	0.16
T-48	0.5	0.05	318.5	58.02	18.96	1.04	0.79	**	0.19	**	0.17
T-49	0.5	0.1	47.02	54.76	6.6	1.02	0.57	**	0.09	**	0.15
T-50	0.5	0.06	396.95	104.64	18.97	1.17	0.93	**	0.3	**	0.19

*The highest value of the relevant element in TS EN ISO 17225-1 (2021) standard, **Values too small to be measured with the analysed devices

Table 6. The research' ANNs model

Neurons	Algorithm	Data fragmentation	MSE	Training MSE	Validation MSE	Test MSE	AIC	AICc	BIC	Time (s)	Taining (%)	Test (%)	Total (%)
50	**LM**	**0.8-0.1-0.1 Single layer**	**0.018**	1.4684	1.6488	1.168	**1465.5**	**-354.06**	**4326.2**	00:00:01	**98.8**	**100**	**99**
30	SCG	0.7-0.15-0.15 Single layer	0.068	1.4011	1.4217	1.167	891.22	-371.82	2554.6	00:00:00	96.4	96.7	95

As can be seen in Figure 6, the accurate classification rates are given over 4 different data sets as training, validation, test and total. In the training data set group, the success level in the first class of binary categorical classification, which is non-hazardous, is 100% and 79 wood wastes are classified as non-hazardous. In the second class of this training dataset, the hazardous waste class, the success rate is 97.5% and 2 non-hazardous and 79 hazardous wastes are classified.

The classification success level of the first group of the data set matrix showing the total classification values is 100% and 100 non-hazardous wood wastes are classified. The success rate in the second class of this total data set matrix is 98%, with 2 non-hazardous and 98 hazardous wastes classified. The overall classification success level for binary categorical classification is 99%.

RF Analysis

The classification values of the training and test data in the RF analysis according to the binary categorical classification (non-hazardous and hazardous) are shown in Figure 7a and Figure 7b. In RF analysis, the data was first split into two parts as 0.90 (training) and 0.10 (test), then the training data was split into 5 parts again (k-fold = 5), and then trained 5 times. From Fig. 7, the classification accuracy rates were obtained as 100% for both training and test datasets. The first class of the training data of the RF analysis consists of 7 non-hazardous wood wastes, while the second class consists of 77 hazardous wood wastes. In the test data set group of the RF analysis, the success level of the first class was 100% and 5 non-hazardous wood wastes were generated, while the success level of the second class was 100% and 3 hazardous wastes were generated.

Figure 6. ANN analysis

Figure 7. RF analysis (a-train confusion matrix, b-test confusion matrix)

According to RF analysis, the most important features are given in Figure 8. From Figure 8, the importance order of the features can be given as Cu, S, As, Cr, Pb, Hg, Zn, Fe, Ni, Al, and Cd from the highest to the lowest, respectively.

In the literature, principal component analysis and cluster analysis methods were generally used for the use of ICP data of wood waste. In this study, after preprocessing the ICP data, a modelling that has not been studied before has been tried with the use of ANN and RF analyses. The study has an original character in this respect.

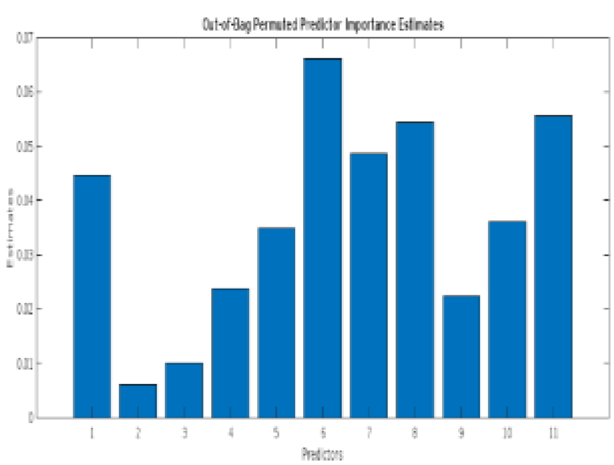

Figure 8. Variables in the RF analysis according to binary categorical classification

CONCLUSION

The 11 elements (Pb, Cd, Al, Fe, Zn, Cu, Cr, As, Ni, Hg and S) selected in the study were analysed by ICP. In this study, Cu, Cr, As, Fe, Zn and S values exceed the upper limits obtained from the tables in the relevant standard. The samples that exceeded these upper limits were obtained from impregnated and furniture waste. A more detailed examination shows that S is the common element exceeding the upper limit for both groups. Cu, Cr, and As are the elements that exceed the upper limits in impregnated wood wastes. This indicates that chemicals containing these compounds are used extensively in impregnation processes and that wood containing these compounds is present in the wood waste load. On the other hand, Fe and Zn are the elements that exceed the upper limits in furniture waste. ICP data combined with statistical analysis showed the variation of elements exceeding the upper limits of the relevant standard in the samples in relation to their concentration content. In the analysis performed with artificial neural network (ANN), two samples were classified as non-hazardous waste in the group that should be considered as hazardous because they exceeded the upper limit value according to the standard. In the random forest (RF) analysis, there is no classification error, that is each group was in its own class. According to analysis results, it can be concluded that RF gives superior performance than ANNs in terms of classifying wood wastes as non-hazardous and hazardous. As a result, advanced statistical analyses and machine learning approaches allow the researchers to interpret chromatography and spectroscopy data much better and to make future predictions accurately.

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