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Data Mining and Pixel Distribution Approach for Wood Density Prediction

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Abstract

The wood material has strategic importance in economic development. Innovations are the basic premise of commercial success in the wood industry, as in all industries. The density of wood provides valuable information about the physical and mechanical properties of the wood, and it is also directly related to the productivity in the forest industry. Many non-destructive test studies have been conducted to evaluate the physical properties of wood structures. This study was conducted to predict the density of wood in the species of oak (*Quercus robur*) and beech (*Fagus orientalis* L.) using the number of pixels in a grayscale image and data mining. To this purpose, pixel density of data was processed with the data collected from the images of wood specimens. This data was used as descriptor variables in artificial neural networks and random forest algorithm. The designed artificial neural network model and random forest algorithm allowed the prediction of density with an accuracy of 95.19% and 96.36%, respectively for the testing phase. As a result, this study showed that pixel density and data mining have the potential to be used as an instrument for predicting the density of wood.

Keywords: *Data mining, artificial neural networks, random forest, digital images, wood*

Odun Yoğunluğu Tahmini için Veri Madenciliği ve Piksel Dağılımı Yaklaşımı

Öz

Ahşap, ekonomik kalkınmada stratejik bir öneme sahiptir. Yenilikler, tüm endüstrilerde olduğu gibi ahşap endüstrisinde de ticari başarının temelini oluşturur. Ahşabın yoğunluğu, ahşabın fiziksel ve mekanik özellikleri hakkında değerli bilgiler sağlar ve ayrıca orman endüstrisindeki verim ile de doğrudan ilgilidir. Ahşap yapıların fiziksel özelliklerini değerlendirmek için birçok tahribatsız test çalışmaları yapılmıştır. Bu çalışma, gri tonlamalı görüntüdeki piksel sayısı ve veri madenciliğini kullanarak meşe (*Quercus robur*) ve kayın (*Fagus orientalis* L.) ağacının yoğunluğunu tahmin etmek için yapıldı. Bu amaçla, ahşap görüntülerden elde edilen piksel yoğunluğu verileri kaydedildi. Bu veriler yapay sinir ağları ve rastgele orman algoritmalarında tanımlayıcı değişkenler olarak kullanılmıştır. Tasarlanan yapay sinir ağı ve rastgele orman algoritmaları, test aşamasında sırasıyla % 95,19 ve %96,36 doğrulukla yoğunluk tahmini sağlamıştır. Sonuç olarak, bu çalışma piksel yoğunluğunun ve veri madenciliğinin ahşabın yoğunluğunu öngörmede bir araç olarak kullanılma potansiyeline sahip olduğunu göstermiştir.

Anahtar Kelimeler: Veri madenciliği, yapay sinir ağları, rastgele orman, dijital görüntüler, odun

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1. Introduction

The potential that the wood industry offers for international economies cannot be underestimated. One of the most important parameters for determining wood quality is density (Diaconu et al., 2016). Wood density is a significant wood feature for both solid wood and fiber products in both conifers and hardwoods, and it affects the performance of most wood products (Osborne et al., 2016; Zobel and Jett 1995). At the same time, it is related to the cutting power requirement in woodworking machinery (Chuchala et al., 2014). There are several methods currently used for the quality control of wood density.

Data mining has seen a rapid increase over the years and is being used successfully in various applications. Data science techniques have the potential to benefit other scientific disciplines (Komi et al., 2017). Data mining is the term that is used for methods of discovering hidden patterns and correlations through data to predict the outcomes (Eskandarian et al., 2017). Presently, machine learning is used in many industries. Artificial neural network (ANN) is a numerical model based on the structure and working features of biological neural networks (Simon 1999). The networks can discover the relationship between inputs and outputs (Lin and Lee 1996; Schinker et al., 2003; Tiryaki et al., 2015; Rapidminer 2018). ANN can be used to evaluate data collected by optical, acoustic or other sensors. The important piece of the study research explains the applications for the forecast of technological and sensory aspects by means of different regression tools of ANN. (Lana et al., 2006; Foca et al., 2011). A typical ANN consists of three consistent layers; input layer made of the independent factors, output layer represented by the responses, and a hidden layer(s) in-between made of a certain number of nodes connecting the input layer to the output layer (Tang et al., 2004; Youshia et al., 2017). As shown in Figure 1, the main components of an artificial neuron are inputs, weights, summation function, activation function, and output.

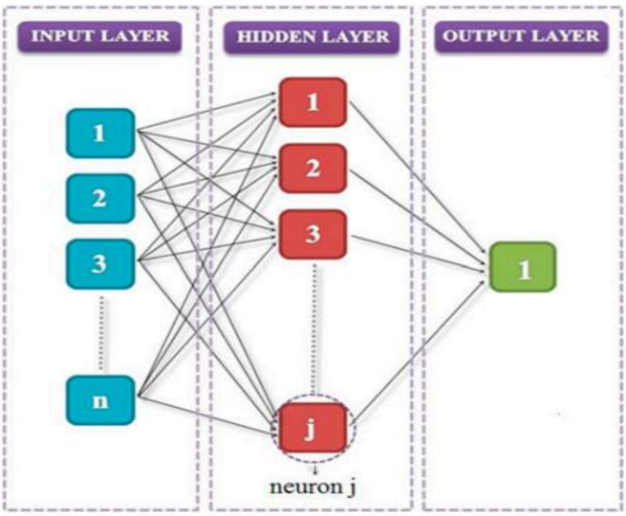


Figure 1. A typical multilayered ANN architecture. (Sözen et al., 2018; Tiryaki et al., 2015).

Random Forest (RF) is a group learning algorithm based on the concept of randomized decision trees. This algorithm has great potential to solve real-world problems (Ao et al., 2019). Random forests models have excellent classification and regression performance. There are two main parts of the theory related to random forests models. The primary is the consistency of the models, i.e. whether they can converge to an optimal resolution as the data set grows infinitely large. The second is the rate of convergence (Sun et al., 2018).
Many studies have shown that digital image processing is a very effective and reliable method for various usage areas (Wu et al., 2012; Zor et al., 2016; Gogebakan and Erol 2018). Image analysis can be defined as the extraction of meaningful information from images. A pixel is the basic logical unit in digital image (Wu and Zhang 2019). Digital 8-bit gray images have the number of pixels at different each grayscale intensity. These pixels can have values in the range of 0 to 255. The values provide information about how bright the image is. (Wang et al., 2019). Bright pixel intensities are represented with high numerical values. 255 is the maximum value. Dark pixels are represented with low values. 0 is the minimum value. Vision technology has existed in the forest product industry since the early 1980s. The most research has been done in the development of automatic visual inspection methods in the wood industry for the presence of defects, However, to the authors' knowledge, studies on the prediction of wood density are quite limited (Khalid et al., 2008). Digital image analysis has the potential to provide more information for wood density measurements (Hryniewicz et al., 2015).

In this paper, a novel method is proposed based on pixel distribution and data mining to predict the density of wood. The results obtained demonstrated that Pixel Intensity, Number of Pixels give valuable information about wood density.

2. Material and Methods

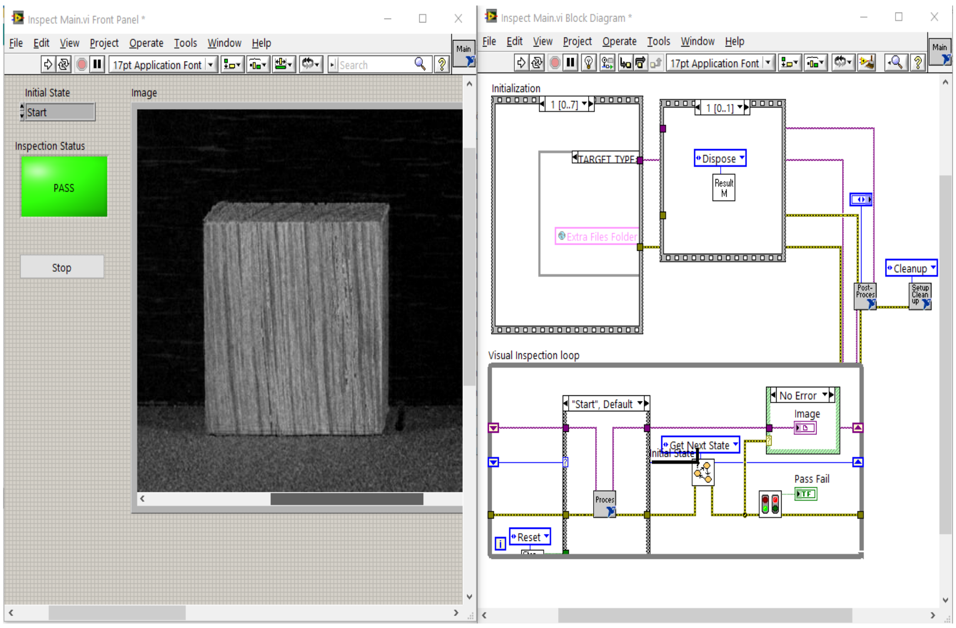
2.1. Materials

In this study, oak (*Quercus robur*) and beech (*Fagus orientalis*) wood were used at different densities. These selected wood samples are frequently used in the forest industry. The moisture content of all samples was 12%. Air dried samples were cut to nominal dimensions of 55 mm x 25 mm x 25 mm. The density of the wood materials was calculated and recorded in accordance with the standard TS 2472.

2.2. Methods

2.2.1. Color Image acquisition and conversion to gray images

Digital images were recorded using LabVIEW Vision Builder AI (National Instruments Corporation, Austin, USA). LabView is a graphical programming language that is produced by National Instruments (Luna-Moreno et al., 2015). The software has many advantages, including the strong connection between the camera and the computer (Shi et al., 2016; Wang et al., 2012). The camera used in the study had a resolution of 1624 px x 1234 px. A computer was connected to the camera with firewire (IEEE1394). All experiments were conducted on CPU i7, 6GB RAM, 2TB Hard Disk Drive (HDD). RGB color images have red, green and blue color spaces. Each color space is 8-bit. With Labivew software, red color space was extracted from color image and gray images at 8 bit depth were obtained. Figure 3 shows the color image and the gray image obtained from the color image with the LabView software and its corresponding code.



a) Color image and the gray image b) LabView software code

Figure 2 The gray image obtained from the color image.

2.2.2. Collecting pixel data from gray image

The total number of pixels in each grayscale value from gray wood images was recorded with the Labview software. Figure 3 shows a graphical representation of the quantitative distribution of pixels per grayscale value for a sample.

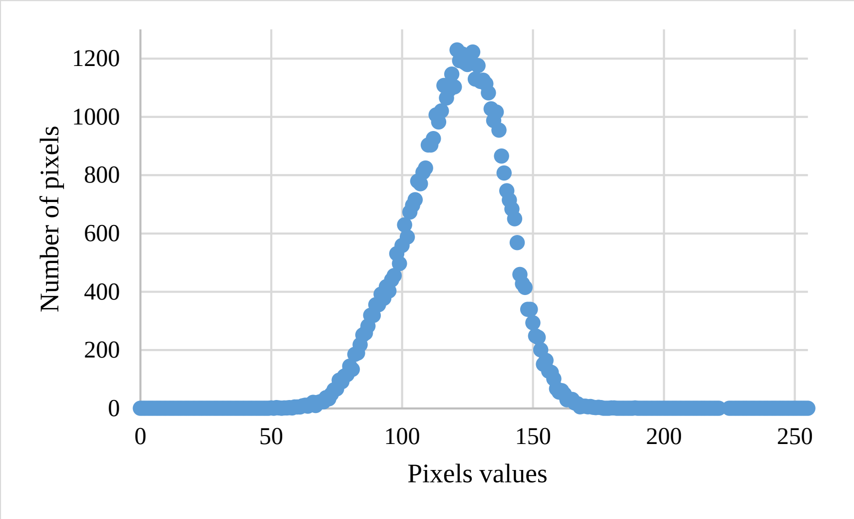


Figure 3. Graphical representation of the quantitative distribution of pixels per grayscale value for a sample.

The data set was created in the number of pixels, pixels values, wood type and wood density obtained. Table 1 shows a part of the data set used in the study. The data set has 1 special attribute, 257 regular attributes. The number of pixels with a value of 0 to 255 and wood type were considered the inputs of the models, while the wood density was the output.

Table 1. A part of the data set used in the study.

Number of samples	Wood density	Wood type	The number of pixels with a value of 0	The number of pixels with a value of 1	The number of pixels with a value of 2
1	0,76	Oak	0	0	0
2	0,72	Oak	0	0	0
3	0,74	Oak	0	0	0
4	0,76	Oak	0	0	0
5	0,69	Oak	0	0	0
6	0,67	Beech	0	0	0
7	0,64	Beech	0	0	0
8	0,81	Beech	0	0	0
9	0,68	Beech	0	0	0
10	0,66	Beech	0	0	0

2.2.3. Models training

RapidMiner software (RapidMiner, Inc., Boston, USA) was used to interrogate the Pixel distribution dataset and build an ANN and RF classifier for predicting the wood density. RapidMiner is a code free modern analytics platform that includes predictive analytics. However, it is widely used in the world and consists of machine learning algorithms (Yadav et al., 2015). This software is used to measure the predicting performance. The number of pixels with a value of 0 to 255 and Wood type were considered the inputs of the ANN and RF models, while the wood density was the output. The dataset consisted of a total 257 attributes and 480 instances. The recorded data was divided into two parts: training (80%) and testing data (20%). RapidMiner is used with operators and there is an operator for every need of data mining. Figure 4 shows RapidMiner operation for model production (Random Forest and Artificial neural networks) with operators.

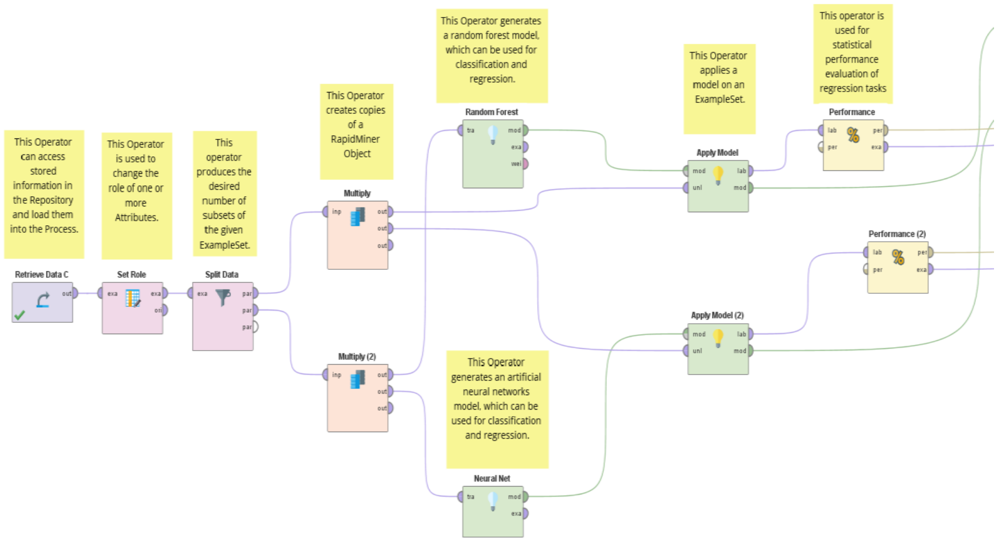


Figure 4. RapidMiner operation for model production (Random Forest and Artificial neural networks) with operators.

The parameters of the models are optimized with the rapidminer software. Figure 5 shows the process used for optimization (Number of trees, maximal depth, hidden layers and training cycles).

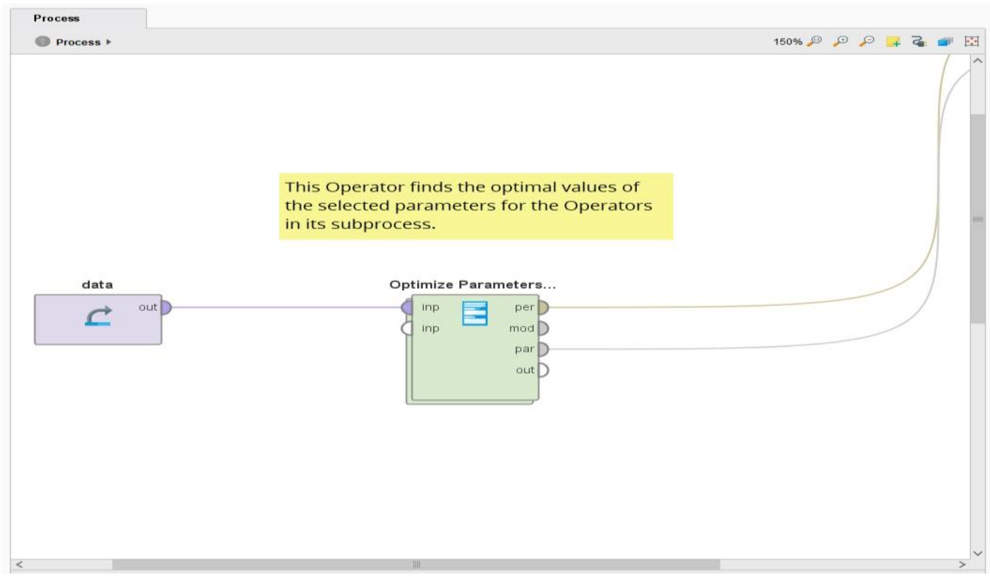


Figure 5 The process used for optimization.

To test model efficiency, the correlation, root mean squared error, absolute error, relative error, spearman rho and kendall tau were calculated. Table 2 shows the parameters of the models.

Table 2. The parameters of the models.

Decision Tree		**Artificial neural network**	
Number of trees	32	Hidden layers	2
Criterion	least square	Training cycles	200
maximal depth	19	Learning rate	0,01

The average relative error (E_r), root mean square error (RMSE) and are good indicator of the performance of a particular model. The equations used for performance are shown below:

$$E_r = \frac{|O - A|}{A} x100 \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=}^{N}(t_i - td_i)} \quad (2)$$

In Equations (1-2), O is is the predicted values, A is the experimental values, ti is the experimental values, tdi is the predicted values, N is the total number of samples, and is the average of predicted values.

3. Result and Discussion

3.1. Wood Density

The density values of the oak and beech wood are given in Table 3. Density values of the samples varied between 0.572 and 0.891 g/cm^3.

Table 3. The density values of the oak and beech wood.

Wood Type	Average (g/cm^3)	Deviation	Number of Samples
Oak	0,749	0,0534	240
Beech	0,704	0,0540	240

3.2. Artificial Neural Networks and Random Forest

In the present study, ANN and RF model were used to evaluate the prediction results for wood density. The error between the experimental and predicted values of wood density for testing data are given in Table 4.

Table 4. the error between experimental and predicted values of wood density for testing data.

Sample number	Wood density	ANN Prediction (Wood density)	RF Prediction (Wood density)	Error (%) ANN	Error (%) RF
1	0,762	0,744	0,703	2,30	7,67
2	0,791	0,796	0,778	-0,63	1,64
3	0,714	0,730	0,730	-2,25	-2,25
4	0,741	0,754	0,735	-1,70	0,81
5	0,771	0,879	0,766	-13,94	0,72
6	0,750	0,759	0,758	-1,17	-1,08
7	0,768	0,760	0,768	1,05	0,00
8	0,700	0,753	0,710	-7,55	-1,36
9	0,728	0,726	0,748	0,32	-2,69
10	0,681	0,643	0,700	5,57	-2,85

Table 3 continues

11	0,721	0,745	0,738	-3,26	-2,41
12	0,821	0,789	0,775	3,89	5,64
13	0,710	0,768	0,758	-8,16	-6,83
14	0,700	0,722	0,710	-3,14	-1,36
15	0,801	0,840	0,811	-4,92	-1,28
16	0,732	0,752	0,726	-2,75	0,78
17	0,648	0,733	0,761	-13,15	-17,48
18	0,724	0,741	0,759	-2,37	-4,94
19	0,689	0,722	0,701	-4,74	-1,73
20	0,691	0,700	0,687	-1,24	0,62
21	0,686	0,701	0,694	-2,25	-1,23
22	0,768	0,727	0,722	5,29	6,03
23	0,765	0,724	0,702	5,29	8,16
24	0,725	0,742	0,714	-2,33	1,54
25	0,603	0,684	0,667	-13,40	-10,57
26	0,712	0,689	0,670	3,30	5,93
27	0,711	0,661	0,675	7,06	5,10
28	0,680	0,616	0,648	9,38	4,61
29	0,639	0,704	0,703	-10,22	-10,05
30	0,608	0,695	0,658	-14,30	-8,17
31	0,608	0,665	0,638	-9,30	-4,93
32	0,675	0,710	0,697	-5,16	-3,22
33	0,733	0,720	0,720	1,71	1,75
34	0,698	0,714	0,708	-2,36	-1,50
35	0,713	0,721	0,713	-1,07	-0,01
36	0,779	0,753	0,745	3,29	4,38
37	0,768	0,774	0,770	-0,81	-0,23
38	0,794	0,754	0,770	5,00	2,98
39	0,723	0,723	0,719	0,01	0,51
40	0,692	0,666	0,664	3,77	4,02
41	0,672	0,652	0,650	3,05	3,28
42	0,712	0,760	0,750	-6,76	-5,37
43	0,754	0,741	0,745	1,62	1,13
44	0,759	0,746	0,753	1,77	0,78
45	0,757	0,780	0,763	-3,12	-0,81
46	0,754	0,755	0,751	-0,22	0,32
47	0,759	0,748	0,760	1,32	-0,20
48	0,750	0,768	0,777	-2,48	-3,69
49	0,779	0,790	0,785	-1,37	-0,74
50	0,649	0,633	0,665	2,46	-2,49
51	0,800	0,781	0,798	2,38	0,30
52	0,820	0,791	0,791	3,63	3,60
53	0,775	0,764	0,772	1,39	0,32

Table 3 continues

54	0,767	0,767	0,762	0,10	0,63
55	0,739	0,752	0,750	-1,74	-1,37
56	0,710	0,743	0,718	-4,63	-1,14
57	0,625	0,742	0,707	-18,66	-13,02
58	0,718	0,719	0,707	-0,17	1,50
59	0,789	0,726	0,743	8,05	5,84
60	0,779	0,799	0,770	-2,60	1,15
61	0,760	0,722	0,733	4,97	3,57
62	0,813	0,734	0,710	9,70	12,64
63	0,610	0,714	0,660	-17,12	-8,30
64	0,658	0,704	0,691	-7,04	-5,03
65	0,693	0,720	0,712	-3,91	-2,68
66	0,703	0,677	0,673	3,66	4,24
67	0,696	0,720	0,720	-3,51	-3,43
68	0,751	0,720	0,689	4,20	8,29
69	0,621	0,721	0,656	-16,11	-5,76
70	0,603	0,697	0,654	-15,61	-8,57
71	0,772	0,718	0,688	7,07	10,99
72	0,677	0,598	0,655	11,68	3,16
73	0,711	0,646	0,712	9,08	-0,10
74	0,750	0,746	0,730	0,53	2,72
75	0,757	0,743	0,735	1,93	2,95
76	0,772	0,751	0,739	2,77	4,25
77	0,781	0,786	0,755	-0,62	3,27
78	0,654	0,752	0,643	-15,04	1,62
79	0,763	0,755	0,744	1,09	2,46
80	0,708	0,733	0,754	-3,64	-6,57
81	0,722	0,744	0,700	-3,00	2,99
82	0,701	0,756	0,724	-7,90	-3,37
83	0,726	0,745	0,735	-2,50	-1,20
84	0,789	0,761	0,741	3,55	6,03
85	0,784	0,789	0,748	-0,54	4,67
86	0,774	0,784	0,765	-1,31	1,22
87	0,747	0,746	0,750	0,15	-0,30
88	0,797	0,732	0,765	8,27	4,01
89	0,776	0,796	0,766	-2,52	1,27
90	0,675	0,720	0,695	-6,60	-2,95
91	0,674	0,667	0,670	1,00	0,53
92	0,760	0,698	0,709	8,08	6,75
93	0,722	0,677	0,668	6,27	7,43
94	0,731	0,722	0,716	1,21	2,04
95	0,748	0,721	0,729	3,65	2,55
96	0,656	0,714	0,685	-8,93	-4,50
			Average error:	% 4,81	% 3,64

Figure 6 shows the relationship between the experimental and predicted wood densities for training.

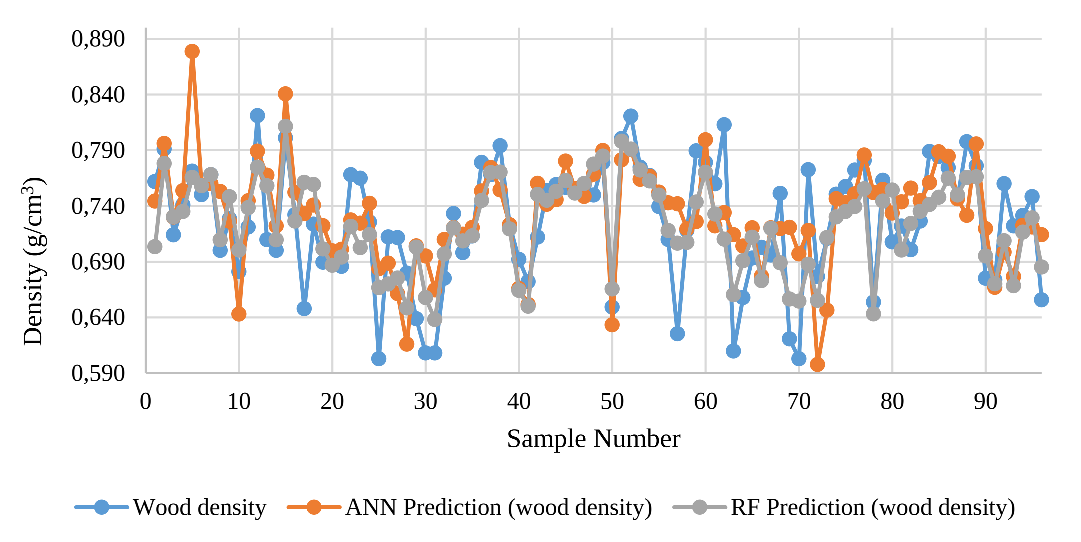


Figure 6. The relationship between experimental and predicted wood density for training

Various performance measures related to the ANN and RF model have shown in Table 5.

Table 5. Various Performance Measures Related ANN and RF Model

Model	Test Type	The correlation	Root mean squared error	Absolute error	Relative error	Spearman rho	Kendall tau
ANN	Testing	0.617	0.044	0.034	4.81%	0.706	0.519
	Training	0.686	0.047	0.036	5.05%	0.695	0.506
RF	Testing	0.761	0.034	0.026	3.64%	0.755	0.581
	Training	0.976	0.015	0.011	1.58%	0.972	0.862

Consequently, a satisfactory prediction profile was obtained with the correlation of determination (R), which the R > 0.7 value for a predictable the RF model. The ANN model had a lower correlation rate (R =0.617) for testing. The accuracy of RF and ANN model were respectively 96,36% and 95.19% for testing. According to the literature, these results were successful (Wadie et al., 2006). There were correlations between wood density and wood anatomy (Pritzkow et al., 2014). It is reported that, in general, most wood with a higher density is likely to have a darker color with a reddish hue, while most species with a lower density is likely to have a lighter color with a yellowish hue (Rojas and Martina 1996; Nishino et al., 1998; Janin et al., 2001; Masanori and Nakano 2004; Montes et al., 2007). This can be explained by the relationship between color and genetic variation (Montes et al., 2007). The results of this study coincide with the results of the literature.

4. Conclusion

1. The modern research in data mining on digital image issues is in a continuous evolving stage. The contribution of this study lied in the development of ANN and RF model to predict the wood density based on Pixel distribution and data mining.
2. According to the obtained results, the presented study was promising for estimates. The RF model performed with an accuracy of 96.36% for testing phase and 98.42% for training. The ANN model performed with an accuracy of 95.19% for testing phase and 94.95% for training.
3. Density is an effect on efficiency and quality in wood products. For example, density is related to pulp yield and timber strength. The determination of the required results by experiment is time-consuming. The method suggested in the study can be considered as a rapid and alternative way.

4. Data mining and image analysis can be used for quality control in the forest industry. However, further research is needed in this regard.

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