IDENTIFICATION OF TREE SPECIES BASED ON THE COMBINATION OF TREE TRUNK IMAGE TEXTURE INFORMATION AND HIGH-LEVEL FEATURES

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Abstract

Forests are known as global capitals, therefore forests are rich resources and provide many human needs. One of the most important roles of forests around the globe is to provide most of the oxygen used by living organisms. In a way that forests are said to be the lungs of the planet. Therefore, the preservation of forests is of great importance. The necessity of preserving forests is to identify plant species and trees in it. Identification of trees helps to make the right decisions for their conservation. In this research, a method for identifying tree species based on their bark images was presented. The proposed method is based on vision and machine learning. Since in machine vision, images are classified based on machine learning algorithms, extracting appropriate features from images is of great importance. The bark of trees can be separated and differentiated in terms of structure. In this research, a method for the structural classification of trees based on the appearance of their bark was presented. Therefore, three methods were used to extract features. The first method; Using the local binary pattern, the second method; The use of convolutional neural network and the third method are the use of ResNet to extract features from the image. Finally, the extracted features were combined and the final feature vector was presented. Finally, with the help of decision tree and random forest classification models, the image classification process was done. The results show that the feature extraction method based on the convolutional neural network and the combined method have much better results than the other two methods. Also, random forest has shown better performance than decision tree. So, in the case of combination of features, the accuracy of the random forest and decision tree classification was equal to 99.49 and 79.18 percent, respectively. This superiority is observed in all feature extraction models.

Keywords: Identification of trees, machine vision, structural features, deep learning, local binary pattern, convolutional neural network, Random forest

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1. Introduction

A tree can be defined as a large perennial woody plant. Although there is no fixed definition of its size, it can be said that a mature tree is usually at least 4.5 meters (15 feet) tall and its branches are attached to a main stem. Trees are important components of natural landscapes and essential elements in the construction of green spaces.

Trees have a longer lifespan compared to other plant species. Few species of trees grow more than 100 meters (300 feet) and some of them live for thousands of years. The components of a tree are: roots, stems, branches, twigs and leaves, the stem of a tree is mostly composed of supporting and transfer tissues (xylem and phloem), in fact, wood is made of xylem cells and bark, basically Phloem is formed [1]. There are many types of trees, each of which has its own characteristics. Therefore, botanists and geological researchers should identify these species by spending material costs and sometimes lives. New studies show that the trunk structure of many trees has a unique texture and this can be an effective parameter in distinguishing different species [2]. As mentioned, due to natural dangerous environments such as forests and plateaus, etc., identifying the types of trees is a time-consuming matter and in some cases can cause accidents.

One of the ways to identify and classify plants is to use the structure of their skin. Normally, each tree has a unique structure in its bark. The bark of trees can have various structures such as smooth, smooth and unbroken, many lenticular (holes), deep furrows, sediments and plates, etc. Figure 1 shows an example of tree bark structure.

Figure (1): Examples of different tree bark structures

Therefore, the

texture of the image can be used to categorize it. The distribution pattern of the light intensity of pixels along the entire length of an image is called its texture [3]. Therefore, a textured image is an image in which a pattern is repeated in the entire image or parts of it. Texture images are usually classified into two groups: smart texture and natural texture. Images with smart texture are images that have a repetitive pattern produced by humans. But images with natural texture refer to images that naturally have such structures.

Texture, along with color and shape, are the three main components to identify the nature of an image [4]. So far, several operators have been proposed to extract image texture features. Textural features are generally called low-level features in machine vision. New results have shown that low-level features alone cannot provide sufficient accuracy in many applications such as pattern and image classification. Therefore, the necessity of combination with high and deep level features is strongly felt.

Deep convolutional networks, due to the successive filtering of the input image, produce a feature map in each layer that deals with the internal relationship of pixels with each other and can be used as high-level features.

According to the mentioned cases, in this article, the combination of low-level features and high-level features was used to increase the accuracy of recognizing tree types based on the analysis of tree trunk images, compared to existing articles. For this purpose, the local binary pattern operator will be used to extract texture features. Also, a deep convolutional network such as ResNet is used to extract high-level features. The feature vector obtained from the LBP operator is connected to the feature vector obtained from the ResNet network and the final feature vector is produced for each image. Finally, the non-random forest classifier is used to classify and label the new image.

Based on the mentioned cases, the structure of the article is as described. In the second part of the article, some of the works done in the field of the article are examined. In the third part, the tools used and the proposed method of the article are given. In the fourth section, the results of the proposed method are presented and analyzed. In the fifth section, the general results of the proposed method will be given.

2. Related works

As mentioned in the previous section, the main goal of this thesis is to identify the types of trees based on the image analysis of tree trunks. In this regard, the combination of low-level textural features along with high-level deep features will be used. This is a new problem, but in the last few years, various articles have been published in this field, which will be analyzed in the thesis based on the year of publication and the degree of connection with the proposed method. So far, many works have been done based on image processing techniques and artificial algorithms in the field of tree identification based on tree trunk image analysis. Almost all the proposed methods include two stages of training and testing. Most methods follow one of the following two goals in the training phase:

• Extract distinctive features as input for classifiers

• Training classifiers such as neural networks based on spatial information of the image such as intensity, brightness, magnitude, spatial coordinates, etc.

Boudra et al. in [5] , have used low-level features to analyze the texture of the tree trunk image. In [5], the potential of the LBP operator at different scales is compared for retrieving tree trunk bark images. The experimental results in [5] show that multi-scale descriptors of LBP perform better than the original version of LBP and improved binary patterns. Multi-block local binary patterns and multi-scale local binary patterns gave almost similar results on average in the Trunk12 dataset.

In [6], a method for classifying tree types that jointly uses tree bark and leaf image information. The innovation of the mentioned method is to propose a strategy to create a matrix of confusion that can be created between several species, when the shape of a leaf or the shape of a shell is common to a number of tree species. In [7], an approach to identify trees from bark based on a new local texture descriptor called macrostatistical binary pattern is proposed. The main innovation in the SMBP operator is the extraction of statistical information from the local texture descriptor. Several new structures to define the local neighborhood have been tested to achieve the highest accuracy.

As one of the few articles that used deep learning to recognize tree species, we can refer to [8], which was published in 2018. In this paper, several different versions of deep convolutional networks such as ResNet34 and ResNet18 are used. In this paper, first, the input image is divided into several windows without overlapping, and then each window is presented as a separate input image to the deep network that is previously trained by the ImageNet database. Finally, in the classification stage, a simple majority voting technique has been used between the labels of the windows. The calculation load of the method presented in [8] is extremely high due to the consecutive use of a deep convolutional network and cannot be used in real space.

In [9], the authors proposed a LBP-like texture descriptor for tree trunk bark image classification. The gradient local binary pattern (GLBP) is proposed in [9] to encode local texture information based on the gradient and its magnitude. The classification in this article is done using the K-nearest neighbor classifier. Color features are among the low-level features that have been used in some articles to increase recognition accuracy. In this regard, some researchers tried to jointly combine the features of color and texture. In 2019, Ratajczak et al proposed an approach for tree trunk bark classification based on color-texture information jointly [10].

In [10], two different algorithms are proposed to reduce the dimensions of color-texture features. The combination of local binary pattern light with color histogram descriptor has provided the highest accuracy.

In one of the most recent articles presented in this field, texture information is used along with multi-layer perceptron neural network. In [11], an improved version of the local triple patterns operator is used for the feature extraction step. Then a multi-layer perceptron neural network with a hidden layer is trained on the database images. Finally, to increase the classification accuracy, four different ideas for the number of hidden layer neurons are presented. In the paper [12], published in 2021, a set of statistical radial binary patterns is presented. Researchers in this article have tried to define the characteristics of sSRBP by using the LBP operator at different scale levels along with a statistical sampling method that is not sensitive to image scale change. One of the weaknesses of this article is the need to adjust different input parameters to get the best input result. The efficiency of the proposed method in [13] has also been evaluated on the AFF and Trunk12 databases, which are compared in the table below. In the table below, some of the articles presented in this field are compared with each other from the point of view of feature extraction method and classification accuracy.

3. suggested method

In this part, the tools used in this article are described first. Then the proposed method will be explained. The general process of the proposed method is shown in Figure 2.

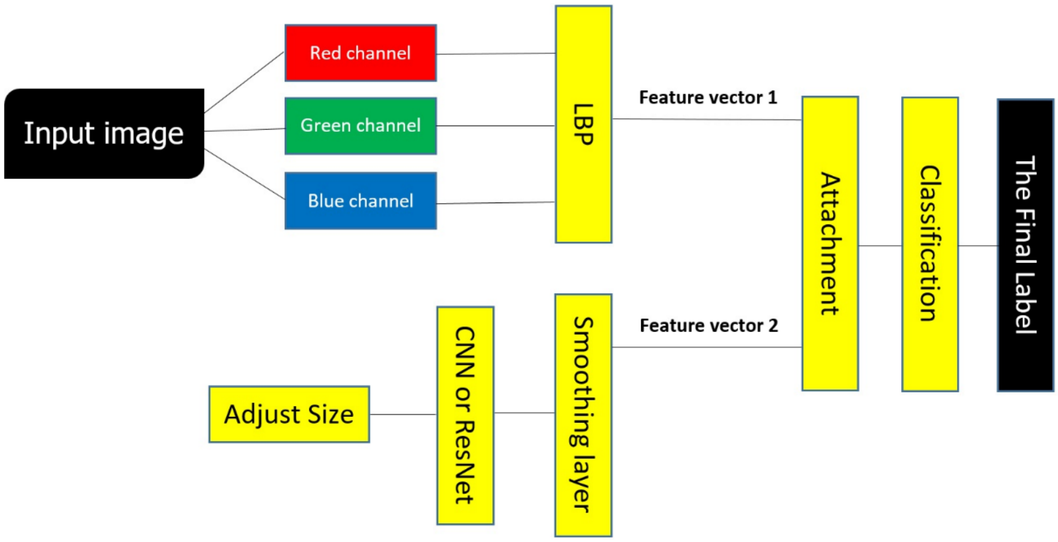


Figure (2): General process of the proposed method

According to Figure 2, two types of features are extracted from the image and connected to each other and finally sent to a category. To recognize the type of tree based on the extracted features. In the following, each of these cases will be explained.

3.1. Local binary pattern (LBP)

The local binary pattern algorithm was invented in 1994 [14]. The LBP algorithm is one of the most powerful feature extraction algorithms in machine vision, and it is also one of the methods that has been widely used in face research and face restoration. Local binary patterns are an effective method to explain the efficiency of textures, which can be used to measure the extraction of features of adjacent textures in images. The advantage of using this method is that the operator of local binary patterns has rotation invariance and high gray level invariance, and it is possible to overcome the problems of imbalance in position change, rotation and lighting by using this method. In addition, the LBP operator has very simple calculations.

LBP is a simple and very useful texture operator that represents the numbers of each image with the calculation threshold of each pixel and considers the result as a binary number. Due to its high resolution and computational simplicity, the LBP texture operator has become a common approach in various applications. It can be seen as a unified approach to traditional statistical and structural models of tissue analysis. Perhaps the most important feature of the LBP operator in real-world applications is its ability to handle monochromatic gray variations that cause light variations. Another important feature is its computational simplicity, which enables image analysis in challenging real-time settings.

The main idea for the development of the LBP operator is that the surface texture can be described by two complementary methods: local spatial patterns and grayscale comparison. The basic LBP operator [14] constructs patches for image pixels with a threshold of 3x3 range of each pixel with the center value and considering the result as a binary number. This histogram of 8^2=256 on different adhesives can be used as a texture descriptor. This operator was used using a simple local comparison method and provided excellent performance in unsupervised texture segmentation. After this, many related methods have been designed for texture and color texture segmentation. The LBP operator was scaled to use different neighborhoods. By using circular neighborhood and bipolar values between values in non-integer pixel coordinates, it allows any radius and number of pixels in the neighborhood. The grayscale variance of the local neighborhood can be used as a complementary comparison measure. In the following, the notation (P,R) is used for pixel neighborhoods, which means sampling points P in a circle of radius R. In Figure 3, some examples of circular symmetric neighbors with different radii (R) and number of neighbors (P) are shown.

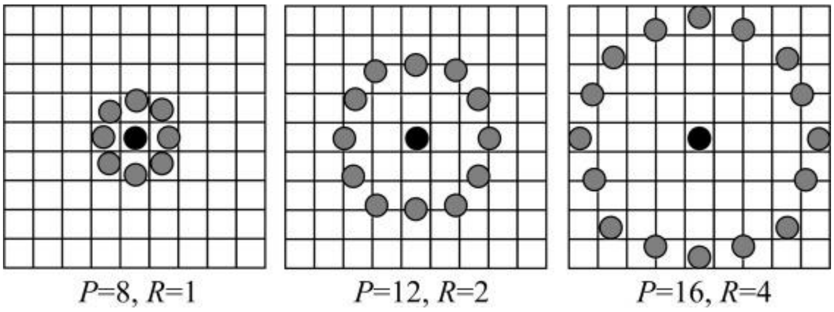


Figure (3): Examples of symmetric circular local neighborhood

Then, the LBP value for each neighborhood is extracted based on the difference between the brightness intensity of the center and its neighbors.

3.2. ResNet Network

In this research, the ResNet network is used to extract high-level features. ResNet or Residual Network is one of the famous deep networks. This network was introduced by Shaoqing Ren, Kaiming He, Jian Sun and Xiangyu Zhang in 2015 [15]. Rosenet model has been one of the most popular and successful deep learning models so far. This model was the winner of the ILSVRC challenge in 2015. The reason for the success of ResNet is that it allowed us to train very deep neural networks with more than 150 layers. Before ResNet, very deep neural networks had problems due to the problem of Vanishing Gradient.

For example, the schematic structure of the ResNet-18 network is shown in the figure below [16]. The difference between this network and normal networks is that it has a shortcut connection that passes through one or more layers and does not consider them; In fact, it takes a shortcut and connects a layer to a further layer.

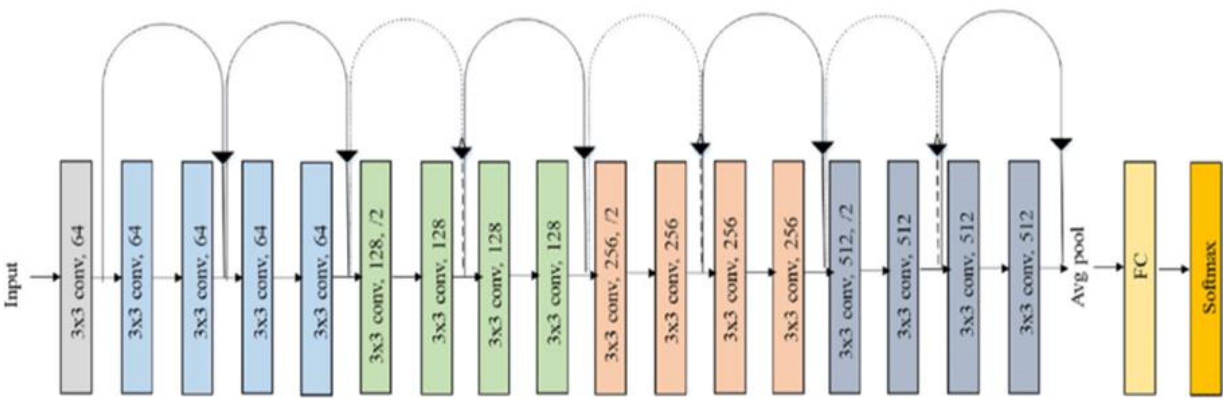


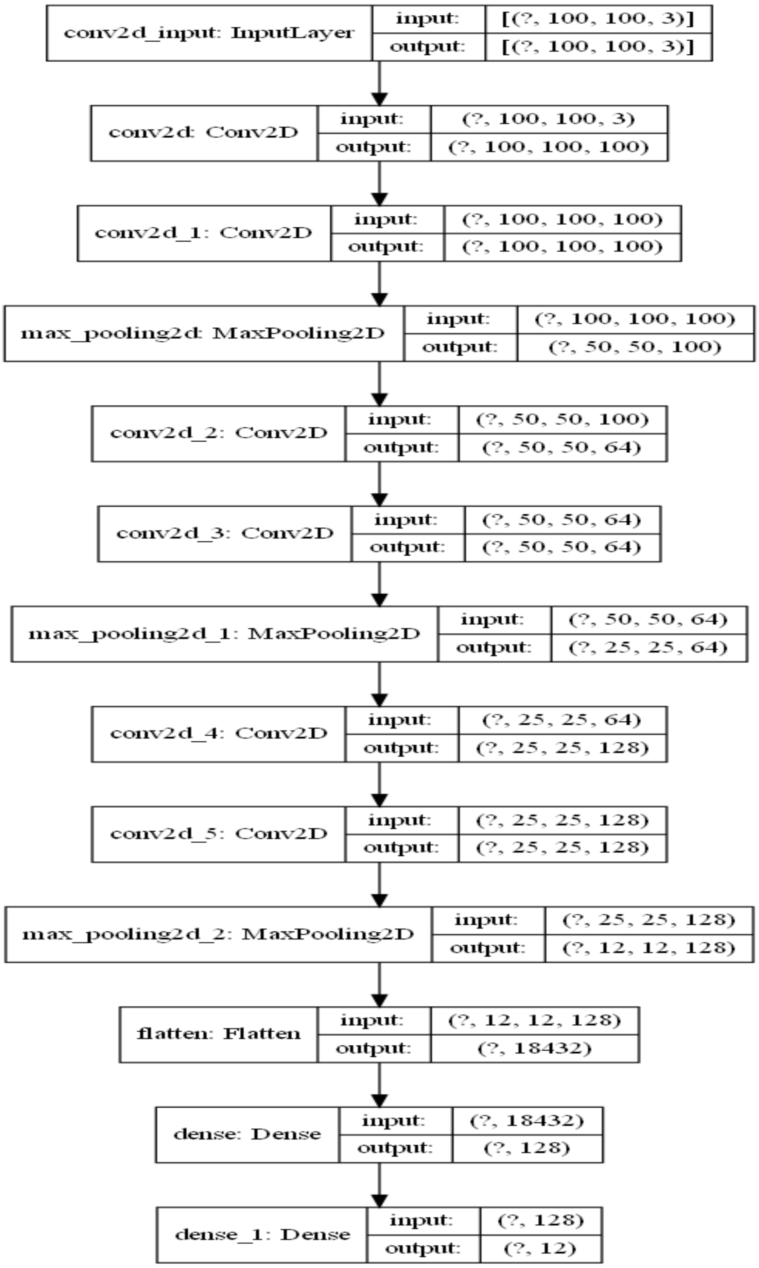
Figure (4): Structure of ResNet-18 network layers

As can be seen, the structure of ResNet-18 is a deep convolutional structure. The output of each convolution layer is called feature map. In the initial layers, the dimensions of the output are high and burden the calculations. On the other hand, in the basic layers, the features are still considered at a low level. The output dimension of the last convolution layer is 7x7x512, which after entering the average pooling layer is greatly reduced and the feature map is reduced to a three-dimensional matrix with dimensions of 512x1x1.

The fully connected layer plays the role of a fully connected network and finally the Softmax layer performs the final classification. The aim of this thesis is to combine deep features with low-level texture features. Therefore, the fully connected and softmax layers are removed. The output of the Average pooling layer is transferred to a new layer called the smoother, and finally we will have a numerical feature vector with specific dimensions. The smoothing layer transforms the 3D matrix into a flat feature vector like an array without manipulating the values.

In this article, the output vector of ResNet network has a length equal to 64. CNN is also used in this article for feature extraction. Figure 5 shows the CNN structure used in this study.

Figure (5): CNN network structure used



The output of CNN and ResNet networks is combined with the output of LBP and finally the final feature vector is made. Next, this vector is sent to the random forest classifier to get the final result.

3.3. Random Forest

Random forest algorithm is a group algorithm with a set of decision trees. The classification accuracy of the random forest method has been significantly improved by building a set of trees and voting among them to obtain the category with the highest number of votes. Two important features in constructing random forests are bagging method and random selection in each node.

- Bagging method

Bagging method was proposed by Leo Berryman 17 in 1996. The bagging algorithm process is as follows; Consider a training set D of size m. Bagging produces a new training set Di with initial size m by uniform sampling and by replacing samples from D. Sampling with replacement allows some samples to be repeated in each Di. This type of sampling is known as self-starting sampling.

- Random features method

The characteristic of random features is that in each node of each tree, a small group of input features is randomly selected, and to divide the node, instead of searching among all features, among the features of this subgroup, the best feature with the most information is selected. It is selected for tree growth. The number of these features is less than the number of main features. Each tree in the random forest grows using the card decision tree algorithm with the maximum size and without pruning. Berryman has used the number of $\lfloor \log_2 M \rfloor+1$ features in each node, where M is the total number of input features [17].

Random forest is a classifier consisting of a set of decision tree classifications. Each classifier for each input sample is $h(x, \theta_k)$, where x is an input sample and θ_k is the training set for the kth tree. The θs are independent of each other but with the same distribution. For each sample, x, each tree provides a prediction for sample category x, and finally, the category with the highest number of votes of the trees on input x is selected as the sample category. This process is called random forest [17] The random forest algorithm can increase the prediction accuracy compared to the individual classification tree. In the individual tree, with small changes in the training set, there is instability, which causes a disturbance in the prediction accuracy in the test sample. But being a group of random forest algorithm makes it adapt to changes and eliminates instability.

Based on the above, the proposed method is as follows:

- In the first step, morphological features are extracted from the image with the help of LBP.
- In the second step, high-level features will be extracted with the help of ResNet and CNN.
- Finally, with the help of the random forest classifier, the act of classification will be based on the combination of features extracted in the previous two steps.

4. Experimental Results of the proposed method

In this section, the results of the proposed method are given and the results are compared with other works. For this purpose, first, the data set used will be described. Then the evaluation criteria are described. Finally, the results of the proposed method will be stated and compared with other works that were presented in the field of research based on the data set used.

4.1. Data sets

The dataset used in this research is the images in the TRUNK12 dataset [18]. This dataset contains about 393 images of the bark of 12 different trees found in Slovenia [19]. In this research, no special pre-processing was done on the images and only the dimensions of the image were changed to 100x100. Also, the class number of each tree species for using machine learning tools is given in Table 1. It should be noted that one hot coding was used for use in ResNet and CNN networks.

Species Name	Number of Samples	Class Number	Species Name	Number of Samples	Class Number
alder	34	1	horse chestnut	33	7
beech	30	2	linden	30	8
birch	37	3	oak	30	9
chestnut	32	4	oriental plane	32	10
ginkgo biloba	30	5	pine	30	11
hornbeam	30	6	spruce	45	12

Table (1): Numbering of different tree species classes in TRUNK12 data

4.2. Evaluation criteria

Proportional criteria are used to measure classification algorithms to evaluate the proposed method. Therefore, the confusion matrix is used for this purpose. Table 2 shows the confusion matrix.

		Actual Class	
		Positive (**P**)	Negative (**N**)
Predicted Class	Positive (**P**)	True Positive (**TP**)	False Positive (**FP**)
	Negative (**N**)	False Negative (**FN**)	True Negative (**TN**)

Table (2): confusion matrix

Due to the 12 classes of the data set, the accuracy criterion is used to measure the efficiency of the model, and the disturbance matrix is given for different situations. Based on the above table, the accuracy value is calculated as follows:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

4.3. Results

Different modes are given to evaluate the proposed method. Therefore, to evaluate the proposed method, experiments were designed as follows:

1. Calculation of the results in the case where only LBP was used for feature extraction and classification was done with the help of decision tree and random forest.

2. Calculation of the results in the case where only ResNet was used for feature extraction and classification was done with the help of decision tree and random forest algorithms.

3. Calculation of the results in the case where only CNN was used for feature extraction and classification was done with the help of decision tree and random forest algorithms.

4. Calculation of the results in the combined mode based on the idea of the proposed method.

It should be noted that in this research, 50% of the data is used for training and 50% for testing. To better understand the results, the confusion matrix for the test data for the decision tree and random forest classifiers based on the stated experiments is given.

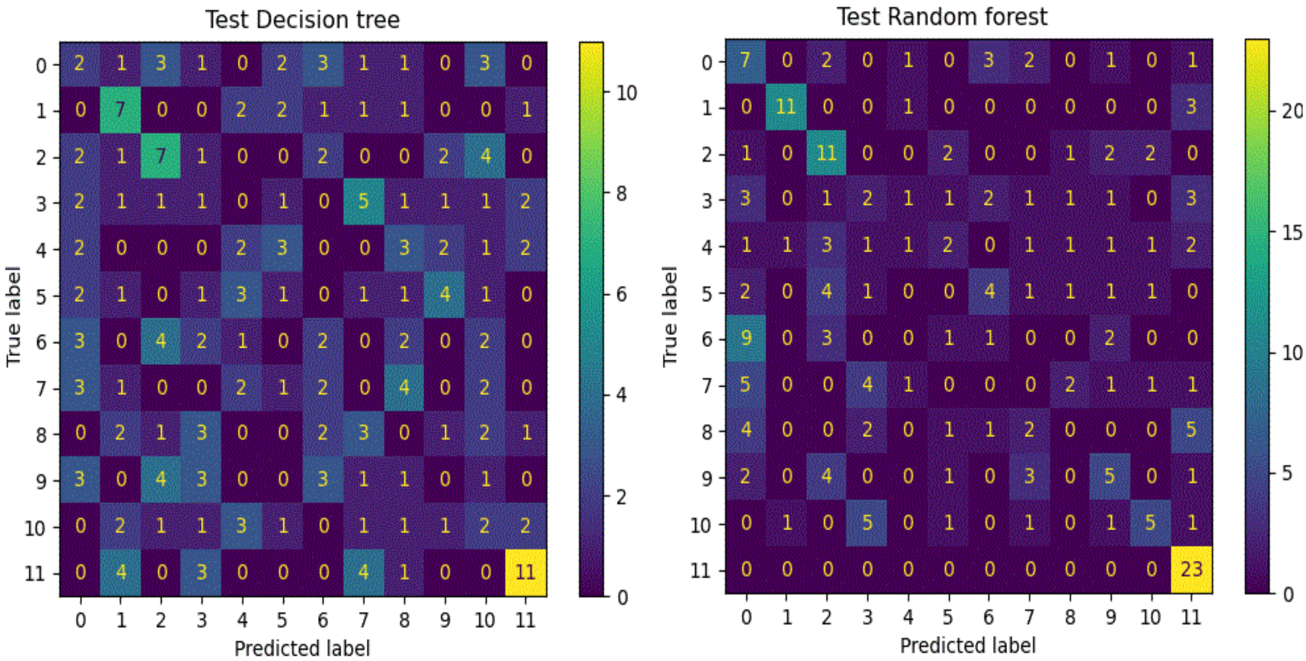


Figure (6): confusion matrix for test data in the first experiment based on decision tree (left) and random forest (right)

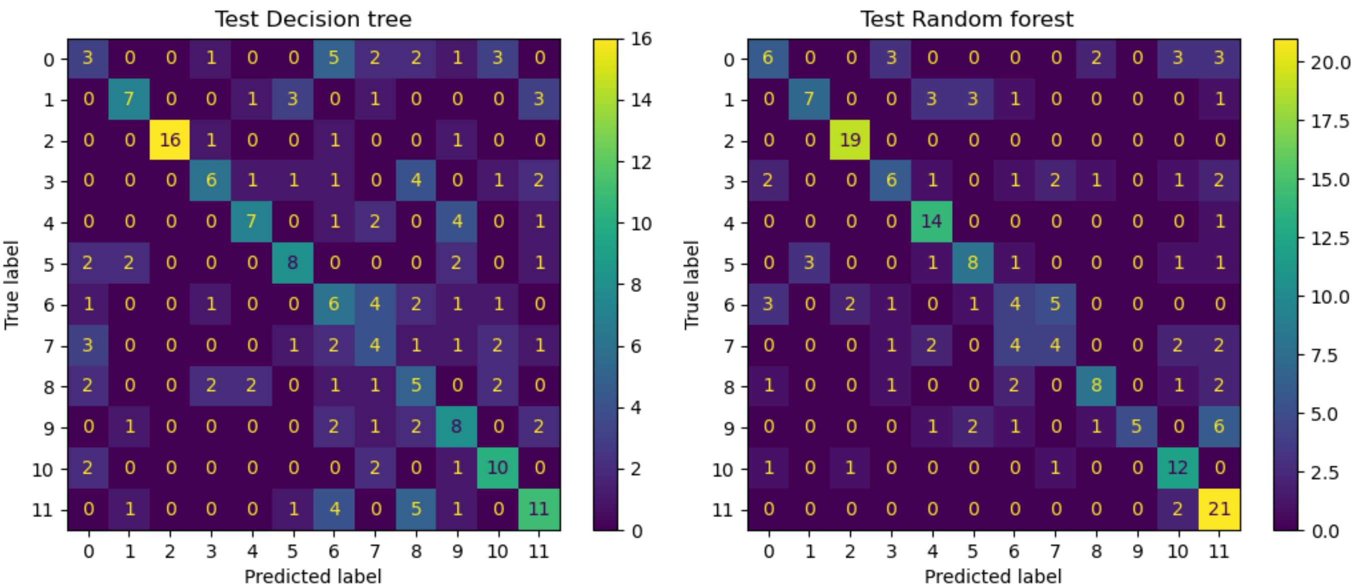


Figure (7): Confusion matrix for test data in the second experiment based on decision tree (left) and random forest (right)

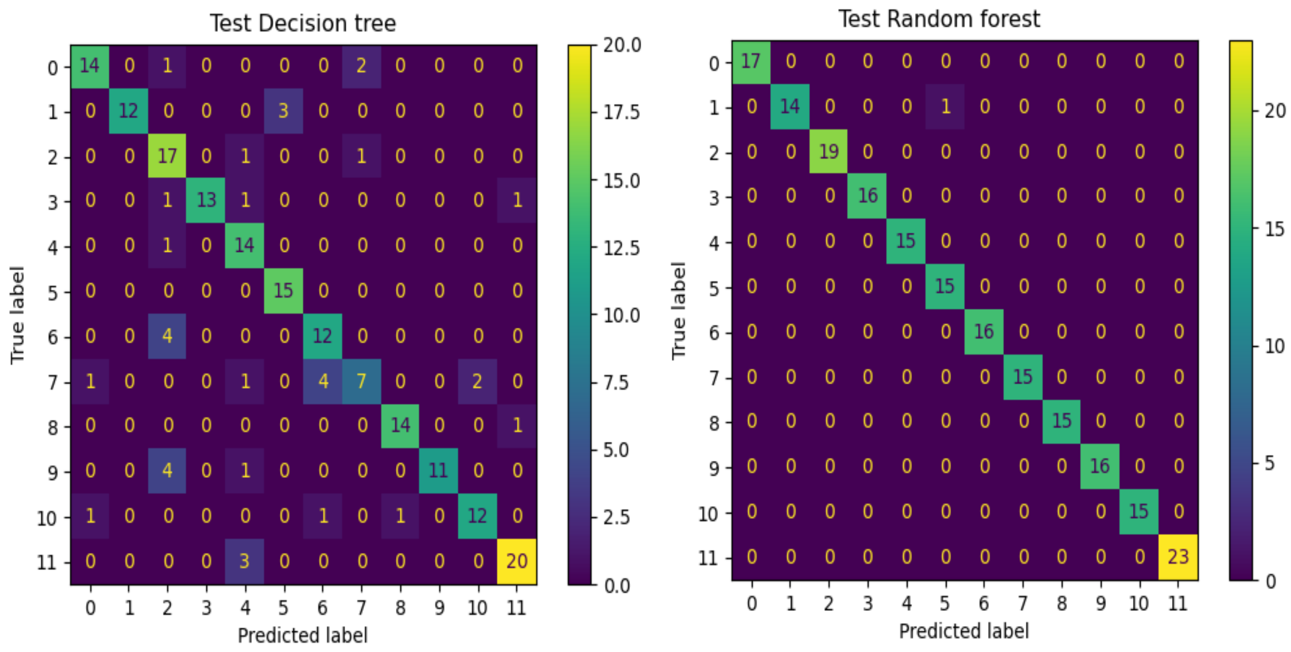


Figure (8): Confusion matrix for test data in the third experiment based on decision tree (left) and random forest (right)

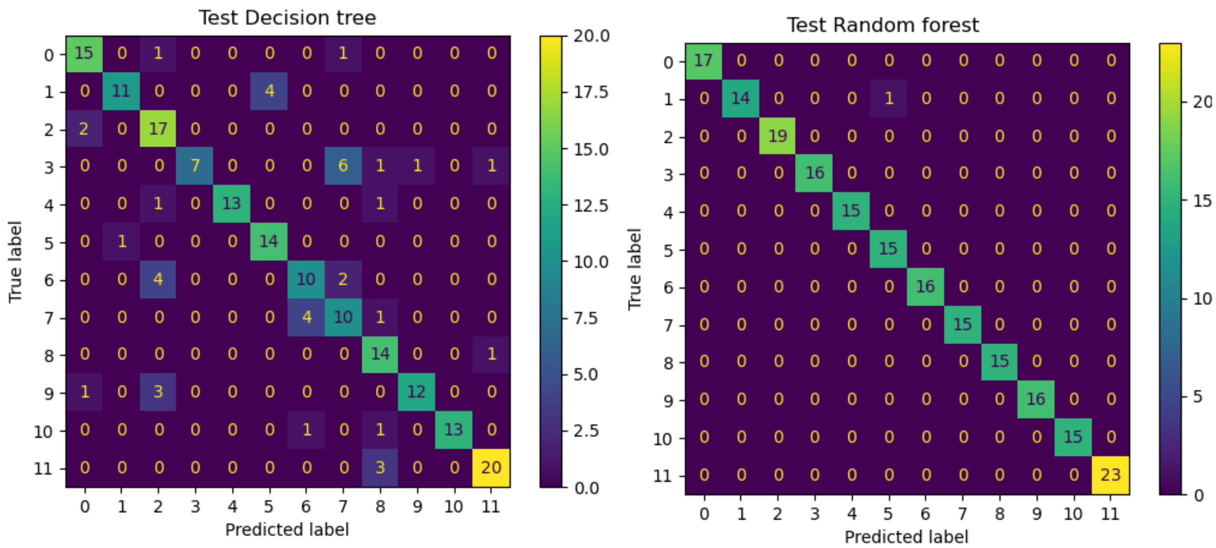


Figure (9): Confusion matrix for test data in the proposed method (fourth test) based on decision tree (left) and random forest (right)

It should be noted that in the disturbance matrix, the more the number of elements on the main diameter are closer to or equal to the number of samples of that class, the better the model performance. Also, the elements that are not located on the main diameter, if their value is closer to or equal to zero, the efficiency of the model will be better. Therefore, in figures 6 to 9, in all situations, the random forest has a better performance than the decision tree.

4.4. Evaluation and comparison of results

In this part, the results of the proposed methods are examined with each other and with some other works.

4.4.1. Comparison of the effectiveness of the proposed methods

In Figure 10, the proposed works of this research are compared. The efficiency of the models in the training data has been equal and the comparison is only based on the test data.

Figure (10): Comparison of the results of the proposed methods based on the test data

Based on Figure 10, it can be said :

1) Random forest has a better performance than decision tree.

2) The best feature extraction model is CNN.

3) The combined method has worked well.

4) In general, deep learning methods have a very good performance compared to the traditional LBP method.

4.4.2. Comparison with other works

In this part, the best proposed method which is based on CNN and the combined method is compared with other works. This comparison is given in Table 3.

Table (3): Comparison of the results of the proposed method with other works

Classification accuracy	**Solution provided**	**year of publication**	**Reference**
Trunk12			
65.13	Kernel-based multiscale local binary patterns	2013	[13]
71.00	SMBP	2018	[7]
74.3	Gabor wavelet + color histogram with ratio H=30	2018	[6]
76.1	Gabor wavelet + color histogram with ratio H=80	2018	[6]

89.37	Deep convolutional networks	2018	[8]
64.43	Color histogram with ratio H=30	2019	[10]
69.00	Color histogram with ratio H=80	2019	[10]
84.2	Color histogram with H=80 ratio + improved local smoke patterns	2019	[10]
84.2	Color histogram with H=30 ratio + improved local smoke patterns	2019	[10]
73.45	Separate combination of local binary patterns and local gradients	2019	[9]
78.39	Local binary pattern gradient	2019	[9]
78.03	Local ternary patterns	2020	[11]
86.76	Improved local ternary patterns	2020	[12]
88.04	A set of radius-based statistical binary patterns	2021	[12]
99.9	**Random forest using features extracted with CNN**	**Suggested Method**	
99.9	**Random forest using features extracted with LBP+CNN+ResNet**	**Suggested Method**	

According to Table 3, the proposed method has a better performance than other works. The point to be noted is that:

- The construction time of the CNN model with 50 iterations was about 45 minutes.

- The time to build the ResNet model with 50 iterations is about 55 minutes.

- The time to extract features using LBP is about 30 seconds.

Based on the above, deep neural network-based methods provide good accuracy compared to other methods, while they require more time.

5. Discussion and conclusion

Image processing and machine vision play an essential role in recognizing tree species using their skin. The basic step in machine vision is feature extraction from the image. Appropriate features that provide sufficient differentiation for image classification and identification. Accordingly, in this research, various methods have been presented to extract features from tree bark images to recognize its species. The methods used in this research to extract features are:

- LBP with a neighborhood radius of 1 and the number of neighbors equal to 8. In this, LBP is applied to each image, and considering that the dimensions of the original image have been changed to 100x100, the image is divided into 16 images of 25x25 and in each The image subsection of the histogram action is applied. Therefore, the output of the LBP-based process from each image is a feature vector with a length of 4096 = 256 * 16. This method is an unsupervised method of feature selection.

- ResNet whose structure was explained in the third chapter. It is a method with a supervisor. 64 features will be extracted from this network. For ResNet training, the number of repetitions was equal to 50.

- CNN, whose structure was examined in the third chapter. This method is a supervised method in feature extraction. The number of iterations for CNN training was considered equal to 50. In this case 128 features are extracted.

- Combined feature vector: In this step, the feature vectors of each image are connected using the extracted methods and sent to the classification unit.

After the features are extracted from the image with the help of algorithms; 1) decision tree, 2) random forest with the number of basic learners equal to 50, tree species have been identified. The results showed that the combination of CNN+RF had better results. Also, the combined feature vector has also worked well. Based on the reviews and comparisons, the proposed method has been able to show good performance. In a way that it has been more effective than the works that have been done in the field of research.

The disadvantage of the proposed method can be the time spent to build CNN or deep learning based models. Although their good performance can cover this weakness. On the other hand, considering that this time is done only once when building the model (model training) based on the data and it has a good speed during use, it is possible to create better and heavier models with strong systems.

In general, we can say; 1) Deep learning methods can extract suitable features for classical machine learning models such as random forest, which leads to good model performance. 2) The efficiency of deep learning methods such as CNN can come with the help of traditional methods and provide acceptable results.

Conflicts of interest

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of this article.

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