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Leaf-based plant species recognition based on improved local binary pattern and extreme learning machine

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HIGHLIGHTS

- A novel image descriptor is presented.
- The proposed image descriptor is used to classify plants.
- A noise robust method is presented.
- The proposed method outperforms high success rates.

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ABSTRACT

Over the past 15 years, many feature extraction methods have been used and developed for the recognition of plant species. These methods have mostly been performed using separation operations from the background based on a pre-processing stage. However, the Local Binary Patterns (LBP) method, which provides high performance in object recognition, is used to obtain textural features from images without need for a pre-processing stage. In this paper, we propose different approaches based on LBP for the recognition of plant leaves using extracted texture features from plant leaves. While the original LBP converts color images to gray tones, the proposed methods are applied by using the R and G color channel of images. In addition, we evaluate the robustness of the proposed methods against noise such as salt & pepper and Gaussian. Later, the obtained features from the proposed methods were classified and tested using the Extreme Learning Machine (ELM) method. The experimental works were performed using various plant leaf datasets such as Flavia, Swedish, ICL, and Foliage. According to the obtained performance results, the calculated accuracy values for Flavia, Swedish, ICL and Foliage datasets were 98.94%, 99.46%, 83.71%, and 92.92%, respectively. The results demonstrate that the proposed method was more successful when compared to the original LBP, improved LBP methods, and other image descriptors for both noisy and noiseless images.

1. Introduction

Plants play an important role in the environment and for human beings. Plants are a unique factor that provide ecological balance as well as everyday needs such as nutrients, medicinal and industrial products. It is therefore important to be able to recognize plant species and to preserve their diversity [1,2]. Such processes are carried out by experts such

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as botanists and agricultural engineers. Traditional methods involve time-consuming, exhaustive, and complex processes. In studies conducted in the field of computer vision and developing technologies, applications have been developed for object recognition to be carried out faster and with greater accuracy without the need of experts.

Plant identification applications are generally based on factors such as a plant's leaves, roots, branch fruit and veins. Recently, plant recognition based on leaves has become a popular topic as plant leaves contain rich distinctive features such as shape, texture, and color [1–5]. There are studies in the literature based on numerous image descriptors for the classification of plant species using datasets composed of different plant leaves such as Flavia [6], Swedish [7], ICL [8], and Foliage [9]. Most of these image descriptors are based on shape, texture and color features. In previous shape feature-based studies, methods such as geometric or morphological features [1,2,6,8–11], Hu's Invariant Moment [7,12,13], Zernike Moment [3,13,14], Fourier Descriptor [7,9,15,16], and Centroid-Center Distance [4,17,18] have been employed. In previous studies based on texture features, methods such as Gray-Level Co-occurrence Matrix (GLCM) [3,9,14,19] and Histogram of oriented gradient (HOG) [20,21] have been used. In previous studies based on color features [3,9,14,19,22,23], statistical formulas such as mean, kurtosis, skewness, and standard deviation have been employed.

In the current study, we propose three new image descriptors called Region Mean-LBP, Overall Mean-LBP, and ROM-LBP for the recognition of plant species. These methods are improved versions of the LBP, which is one of the known image descriptors. These methods work by considering the region and overall mean instead of center pixel. However, while the original LBP method uses gray images, Region Mean-LBP and Overall Mean-LBP methods use the R and G color channels of the images, respectively. The ROM-LBP method is based on a combination of both the Region Mean-LBP and Overall Mean-LBP methods. In addition, we evaluated the effectiveness and robustness of the proposed methods against noisy images. The attribute parameters obtained from these methods were classified using the ELM method. The main reason for using the ELM method is that it has both quick training and good performance among the classifier methods. However, we used four different leaf datasets; specifically, Flavia, Swedish, ICL, and Foliage, in order to calculate the performance of the proposed methods.

The contributions of this paper are as follows:

- The proposed methods do not require any additional cost to extract more characteristics than the LBP method.
- The proposed methods are practical and applicable as real-time for the recognition of the plant species class.
- The proposed methods have higher classification accuracy than improved LBP methods and other methods such as HOG, GLCM, Color Features, and Shearlet Transform.
- The proposed methods showed improved recognition of plant species as a classification problem and solving it using filtering such as regional and overall mean based on the R and G color channel of images.
- The proposed methods achieved improved performance, significantly outperforming improved LBP methods for plant recognition with the Flavia, Swedish, ICL, and Foliage datasets.
- Noisy or undesirable images greatly affect the performance of image descriptors. The current study evaluated the robustness of the proposed methods against noises such as salt & pepper and Gaussian, and then compared its performance against existing methods. As a result, it was observed that the proposed methods were more robust and effective than other methods against noisy images.

The remainder of this paper is organized as follows. Section 2 outlines the previous works related to the LBP method, whilst Section 3 details the material and methods of the current study. Section 4 provides detail of the proposed method and experimental work, and the results are detailed in Section 5. Finally, Section 6 provides a discussion of the results, and outlines the contribution of the study.

2. Related work

The majority of previous studies performed for the recognition of plant species were mostly based on shape, texture, and color features. Until approximately 10 years ago, LBP was one of the best feature extraction methods. In the literature, many studies can be found based on improved LBP method and LBP method for plant recognition. Ahmet et al. [24] used SVM classify and basic LBP method which high accuracy and computational efficiency to classify of the broadleaf and grass weed images. Different parameters of the LBP method were evaluated to obtain the best performance value for an automated weed classification. Muthevi et al. [25] used different versions of the Completed LBP (CLBP) method such as signed CLBP, magnitude CLBP and centered CLBP for leaf classification. Herdiyeni and Santoni [26] proposed a combined system based on texture, shape, and color features for medicinal plant recognition. Local Binary Pattern Variance (LBPV) used to extract texture features of leaf and the classification of obtained features was performed by using Probabilistic Neural Network method. Lukic et al. [27] proposed a combined system based on SVM as a classifier and Hu's Invariant Moments and uniform LBP method as feature extraction for plant species recognition. Le et al. [28] proposed a system based on the combination of LBP methods and SVM method for plant classification. They obtained the best classification performance by using parameters such as the number of neighbors, the radius and a rotation invariant uniform for LBP method. Naresh et al. [29] proposed an approach using modified LBP, with symbolic representation based on the structural relationship between neighboring pixels by replacing the hard threshold approach of the original LBP. Wang et al. [30]

Table 1
Improved LBP-based methods.

Descriptor	Reference	Explanation
LQPAT	[35]	Local Quadruple Pattern (LQPAT) method defined an efficient encoding structure with optimal feature length. The proposed descriptor encodes relations amongst neighbors in quadruple space.
LGS	[36]	Local Graph Structure (LGS) method, based on dominating set points for a graph of the image.
S-LGS	[37]	Symmetric Local Graph Structure
VS-LGS		Vertical Symmetric Local Graph Structure
V-LGS	[38]	Vertical Local Graph Structure
ZH-LGS		Zigzag Horizontal Local Graph Structure
ZV-LGS		Zigzag Vertical Local Graph Structure
ZHM-LGS		Zigzag Horizontal Middle Local Graph Structure

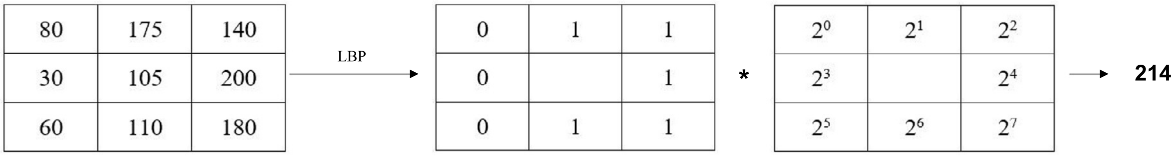


Fig. 1. Application of the LBP method.

used an approach based on dual-scale decomposition and local binary descriptors (DS-LBP), combining the texture and contour features of leaves.

In object pattern studies, new methods have been developed based on the LBP method, but have not yet been applied to plant recognition [31–38]. The best-developed approaches from these LBP-based studies are given in Table 1.

Table 1 shows improved LBP methods used to face and texture recognition. In the current study, we obtained performance results by using these methods with plant leaf datasets, and then performed comparisons with the proposed methods. The experimental results and comparisons are given in Section 5 of this paper.

3. Material and methods

In this section, theoretical background-related algorithms, and datasets are detailed under subheadings.

3.1. Local Binary Pattern (LBP)

The Local Binary Pattern method, as proposed by He and Wang [39], is a feature extraction algorithm widely used in object recognition studies. The LBP method produces a code consisting of a one and a zero for each pixel of the image by comparing the center pixel with its neighboring pixels [40–44]. The LBP code of a pixel is calculated as follows:

$$LBP_{P,R} = \sum_{i=0}^{P-1} L * 2^i \qquad L = \begin{cases} 1 & (M_i - M_c) \geq 0 \\ 0 & (M_i - M_c) < 0 \end{cases} \tag{1}$$

where R represents the distance of the neighboring pixels from the center pixel, P represents the total number of neighboring pixels, M_c represents the center pixel, and M_i represents the neighborhood pixels. Fig. 1 shows the values obtained using the LBP method for a sample pixel.

3.2. Extreme Learning Machine (ELM)

Huang et al. proposed a learning algorithm called ELM in order to train the single-hidden layer feedforward networks (SLFN) [45]. Unlike traditional SLFN learning approaches, the input layer weights and hidden layer bias of the ELM method are randomly initiated and remain constant. The output layer weights are then calculated analytically. The mathematical model of this approach is shown in Eq. (2).

$$\sum_{i=1}^{N} \beta_i g\left(w_i.x_j + b_i\right) = y_j,\ \ j = 1, \ldots, K \tag{2}$$

where $[x_i, y_i]$ is the input–output, the w_i is the input weight, b_i is the bias of the hidden layer, β is the output weight, and K is the number of training samples. In Eq. (2), if $g\left(w_i.x_j + b_i\right)$ is indicated by H (hidden layer matrix), $Y = H\beta$ equation

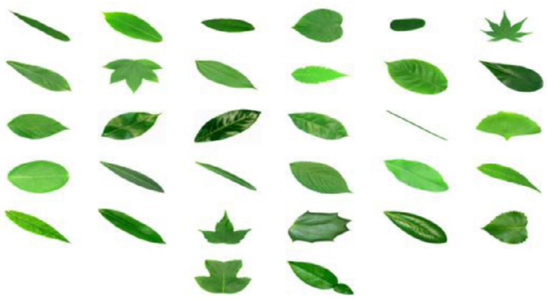


Fig. 2. Samples of plant leaves in Flavia dataset.

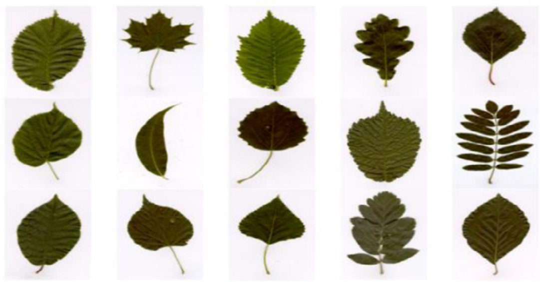


Fig. 3. Samples the plant leaves in Swedish dataset.

is obtained. H hidden layer output matrix is calculated using Eq. (3):

$$H = \begin{bmatrix} g\left(w_1.x_1 + b_1\right) & \cdots & g\left(w_N.x_1 + b_N\right) \\ \vdots & \cdots & \vdots \\ g\left(w_1.x_M + b_1\right) & \cdots & g\left(w_N.x_M + b_N\right) \end{bmatrix}_{NxM} \tag{3}$$

ß is calculated with Least Squares (LS) solution using Eq. (4);

$$\beta = H^{\dagger} Y \tag{4}$$

where the Moore–Penrose generalized inverse of H is shown with H† [45–49].

3.3. Datasets

In order to test the proposed method, we used plant leaf datasets recognized in the literature, namely ICL, Flavia, Foliage, and Swedish. These datasets are detailed in the following subsections.

3.3.1. Flavia leaf dataset

The Flavia dataset consists of a total of 1907 leaf images belonging to 32 different plant varieties. Each image in this dataset consists of 1600×1200 resolution color images. Several representative image samples from the dataset are shown in Fig. 2.

3.3.2. Swedish Leaf dataset

The Swedish dataset consists of a total of 1125 leaf images belonging to 15 different plant varieties. Each image in this dataset consists of different resolution color images. Several representative image samples from the dataset are shown in Fig. 3.

3.3.3. ICL Leaf dataset

The ICL dataset consists of a total of 350 leaf images belonging to 31 different plant varieties. Each image in this dataset consists of 960×720 resolution color images. Several representative image samples from the dataset are shown in Fig. 4.

3.3.4. Foliage leaf dataset

The Foliage dataset consists of a total of 7200 leaf images belonging to 60 different plant varieties. Each image in this dataset consists of different resolution color images. Several representative image samples from the dataset are shown in Fig. 5.

Fig. 4. Samples of plant leaves in ICL dataset.

Fig. 5. Samples of plant leaves in Foliage dataset.

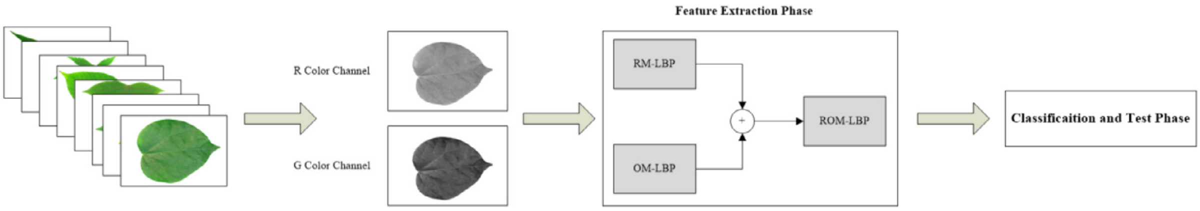


Fig. 6. General flowchart of the proposed system.

4. Proposed approach

In this study, we proposed methods involving different approaches inspired from the original LBP method. These methods include filtering operations based on regional and overall mean. However, while the original LBP converts color images to gray tones, we applied R color channel in the Overall Mean-LBP method, and G color channel in the Region Mean-LBP method. Then, we proposed another approach by combining the parameters obtained from both the Region Mean-LBP and Overall Mean-LBP methods called ROM-LBP, based on a combination of the two proposed methods with both R and G color channels of an image. The general processing steps of the current study are shown in Fig. 6.

In this study, we proposed three new approaches, as Region Mean-LBP, Overall Mean-LBP, and ROM-LBP methods by using R and G color channels of images based on the original LBP methods. Prior to the application of methods, morphological operations of size reduction and color channel separation were performed. These methods and pre-processing phase are detailed in the following subsections.

4.1. Pre-processing phase

In the pre-processing stage, operations of size change and color channel separation were performed for the images in the datasets to be used in this study. The size change operation for each dataset was determined by the following experimental approach:

- Flavia dataset images resized as 600×800.
- Swedish dataset images resized as 896×512.
- ICL dataset images resized as 960×720.
- Foliage dataset images resized as 256×256.

These datasets consist of color images including R, G, and B channels. The methods proposed in previous studies are generally applied using gray tone images. In the current study, the proposed methods calculated classification

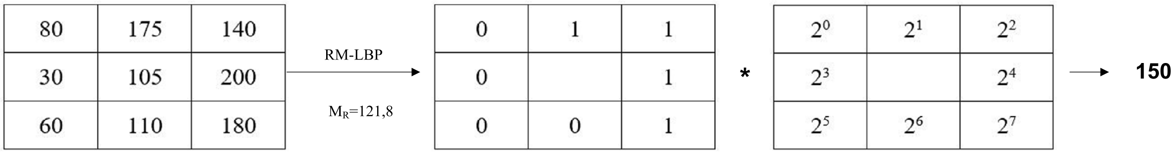


Fig. 7. Implementation of the RM-LBP method.

performances by applying R, G, and B channels of images separately. With this experimental approach, R color channel was determined for the Overall Mean-LBP method, and G color channel for the Region Mean-LBP method.

4.2. Region mean - LBP

The proposed Region Mean-LBP method is based on comparison with neighboring pixels after comparison of the regional average of the image with the center pixel, unlike in the original LBP. In this method, we first selected the largest value by making a comparison between the center pixel and the region mean. Then, this value was given a binary number by comparison of the pixels in the 3×3 neighborhood of the center pixel.

The region means are computed using Eq. (5):

$$RM = \frac{\sum_{i=1}^{n} M_i}{n} \tag{5}$$

where M_i represents the neighborhood pixels, and n represents the number of neighbors. In this study, we determined n as the value 8, the number of neighbors. In other words, we used a filtering structure of 3 × 3.

The operation logic of the Regional Mean-LBP (RM-LBP) is given as Eq. (6):

$$RM - LBP = \sum_{i=1}^{8} K * 2^{i-1} \tag{6}$$

The K value in Eq. (6) is calculated as follows;

$$K = \begin{cases} 1, & if\,(RM \geq M_C) \text{ and } (RM \leq M_i) \\ 0, & elseif\,(RM \geq M_C) \text{ and } (RM > M_i) \\ 1, & elseif\ (RM < M_C) \text{ and } (M_C \leq M_i) \\ 0, & otherwise \end{cases} \tag{7}$$

where M_c represents the center pixel. As can be seen in Eq. (7), the maximum value is selected by comparing the RM and center pixel (M_c) values. Then, the LBP code is generated through comparison with the neighboring pixels (M_i). An example of the RM-LBP is shown in Fig. 7.

Fig. 7 shows the value obtained from the RM-LBP method for an example pixel (3 × 3 pixels neighborhood). This value obtained from the RM-LBP method was observed to be different from the obtained value using the original LBP, as shown in Fig. 1. In this example, the RM value is compared to its neighboring pixels as the value is larger than the center pixel value. Also, if the center pixel is greater than the RM value, the same operations are performed again taking the center pixel into account.

4.3. Overall mean - LBP

The proposed Overall Mean-LBP method is based on comparison with neighboring pixels after comparison of the average of a whole image with the center pixel, unlike in the original LBP. In this method, we first selected the largest value by making a comparison between the center pixel and the overall mean. Then, this value was given a binary number by comparison of the pixels in the 3×3 neighborhood of the center pixel.

The overall means are computed using Eq. (8):

$$OM = \frac{\sum_{i=1}^{P} \sum_{j=1}^{R} N_{(i,j)}}{K * L} \tag{8}$$

where N represents image matrix of $P \times R$ size. The operation logic of the Overall Mean-LBP (OM-LBP) is given as Eq. (9):

$$OM - LBP = \sum_{i=1}^{8} K * 2^{i-1} \tag{9}$$

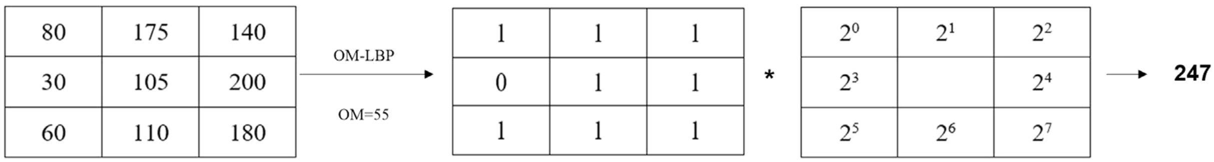


Fig. 8. Implementation of the OM-LBP method.

The K value in Eq. (9) is calculated as follows;

$$K = \begin{cases} 1, & if (OM < M_C) \text{ and } (OM < M_i) \\ 0, & elseif (OM < M_C) \text{ and } (OM \geq M_i) \\ 1, & elseif\ (OM \geq M_C) \text{ and } (M_c < M_i) \\ 0, & otherwise \end{cases} \tag{10}$$

As can be seen in Eq. (10), the minimum value is selected by comparing the RM and center pixel (M_c) values. Then, in comparison with the neighboring pixels (M_i), the LBP code is generated. An example of the OM-LBP is shown in Fig. 8.

Fig. 8 shows the value obtained from the OM-LBP method for an example pixel (3 × 3 pixels neighborhood). This value obtained from the OM-LBP method was observed to be different from the obtained values using the RM-LBP method (see Fig. 7), and the original LBP method (see Fig. 1). In this example, the OM value is compared to its neighboring pixels as the value is smaller than the center pixel value. Also, if the center pixel is smaller than the RM value, the same operations are performed again taking the center pixel into account.

4.4. ROM-LBP

The proposed ROM-LBP method is based on combining the parameters obtained from both the Region Mean-LBP and Overall Mean-LBP methods. For example, in the samples shown in Figs. 7 and 8, the LBP codes obtained from OM-LBP and RM-LBP are combined and the ROM-LBP parameter as [150 247] is obtained. This method allows different and distinctive parameters to be obtained by using R and G channels of an image. The pseudo code of the ROM-LBP is shown in Algorithm 1.

Algorithm 1. Pseudo code of the ROM-LBP method

```
Input: Plant image (I) with size of W x H
Output: The extracted features (F)
Load I
for i=1 to W-2 do
    for j=1 to H-2 do
        block=I(i:i+2,j:j+2); // Divide 3 x 3 sized overlapping blocks
        Apply Eq. 5-7 to calculate RM values of the block which is RMV(i,j)
        Apply Eq. 8-10 to calculate OM values of the block which is OMV(i,j)
    end for j
end for i
H1 = hist(RMV) // Calculate histogram of the RMV.
H2 = hist(OMV) // Calculate histogram of the OMV.
F = H1 ⊕ H2 // Concatenate histograms to obtain features.
```

5. Experimental studies

In this paper, we proposed three methods, named Overall Mean-LBP, Region Mean-LBP, and ROM-LBP, based on Local Binary Patterns (LBP) for recognition of plant leaves. While the Overall Mean-LBP method extracted texture features from plant leaves using the R color channel, the Region Mean-LBP method extracted texture features using the G color channel. The ROM-LBP method is a combination of both the Region Mean-LBP and Overall Mean-LBP methods. These proposed methods calculated performances by using the ELM method. The parameters of this classifier were determined by an experimental approach using sigmoid as the activation function, and hidden layer neuron number in the range of [1000–10000] with step size 100.

In previous studies, the random separation method was used, which takes into account a certain percentage ratio in the separation of training and test data. The disadvantage to this approach is that it can produce different results when calculating the performance of the system. In the current study, a 10-fold cross-validation method has been used, which has both a high level of reliability and is accepted in the literature. Thus, it is aimed to increase the reliability of the system by eliminating the possibility of generating different results. The MATLAB platform was used for experimental studies. In addition, all the applications were performed using the computer which features such as i7 2.8 GHz processor, GTX 950 m 8GB GPU card and 16GB RAM.

In the following subsections, we detail the experimental results and performance comparisons.

Table 2
Classification performances of LBP and proposed methods.

Method	Flavia	Swedish	ICL	Foliage
Original LBP	98.05%	98.12%	70.57%	87.86%
RM-LBP	97.94%	98.30%	71.42%	91.11%
OM-LBP	97.89%	**99.46%**	76.57%	88.75%
ROM-LBP	**98.94%**	99.19%	**83.71%**	**92.92%**

Table 3
Execution times of the proposed methods and original LBP method (second/sec).

	Flavia	ICL	Swedish	Foliage
LBP	0.0914	0.1858	0.1059	0.0068
RM-LBP	0.0745	0.1766	0.0863	0.0064
OM-LBP	0.0693	0.1482	0.0788	0.0062
ROM-LBP	0.1313	0.2993	0.1632	0.0108

Table 4
Comparison of LBP-based previous studies with proposed methods.

		Flavia	Swedish	ICL	Foliage
Previous studies	[25]	84.78%	88.89%	–	90.88%
	[27]	94.13%	–	–	–
	[29]	97.55%	96.83%	–	90.62%
	[30]	–	99.25%	–	–
RM-LBP		97.94%	98.30%	71.42%	91.11%
OM-LBP		97.89%	**99.46%**	76.57%	88.75%
ROM-LBP		**98.94%**	99.19%	**83.71%**	**92.92%**

5.1. Results based on LBP and proposed methods

In this study, we calculated classification accuracies by using the ICL, Flavia, Foliage, and Swedish datasets with LBP, RM-LBP, OM-LBP and ROM-LBP methods. Each of these methods were classified using the ELM method, and the success rates are illustrated in Table 2.

As can be seen in Table 2, the proposed methods obtained a higher level of performance than the original LBP method. While the highest accuracy for the Flavia, Foliage, and ICL datasets was obtained using the ROM-LBP method, the highest accuracy for the Swedish dataset was obtained using the OM-LBP method. According to the obtained performance results;

- The highest accuracy achieved for the Flavia dataset was 98.94%, using the ROM-LBP method. The ROM-LBP method provided a success rate increase of about 1% based on the original LBP method.
- The highest accuracy achieved for the Swedish dataset was 99.46%, using the OM-LBP method. The OM-LBP method provided a success rate increase of about 2% based on the original LBP method.
- The highest accuracy achieved for the ICL dataset was 83.71%, using the ROM-LBP method. The ROM-LBP method provided a success rate increase of about 12% based on the original LBP method.
- The highest accuracy achieved for the Foliage dataset was 92.92%, using the ROM-LBP method. The ROM-LBP method provided a success rate increase of about 5% based on the original LBP method.

In addition, ROC diagrams of the obtained best performance results using proposed methods for Flavia, Swedish, ICL and Foliage datasets (98.94%, 99.46%, 83.71%, and 92.92%, respectively) were shown in Fig. 9.

The execution times of the original LBP method and the proposed methods are given in Table 3 and these times are calculated for an image. In addition, since the dimensions of the images in the data sets used in this study are different, the execution times of each are given.

As shown in Table 3, OM-LBP showed the lowest training time among the three methods, while the LBP method was slightly slower than the ROM-LBP method. In addition, the execution times for RM-LBP and OM-LBP methods were almost equal.

5.2. Comparison of image descriptors, previous studies and proposed methods

The proposed methods were compared with the classification accuracy of previous studies based on LBP methods developed for the recognition of plant species. These comparisons were made by taking into consideration the datasets used in the current study. In addition, all of the images in these datasets were used in both the experimental studies of the current study and in previous studies. These results are shown in Table 4.

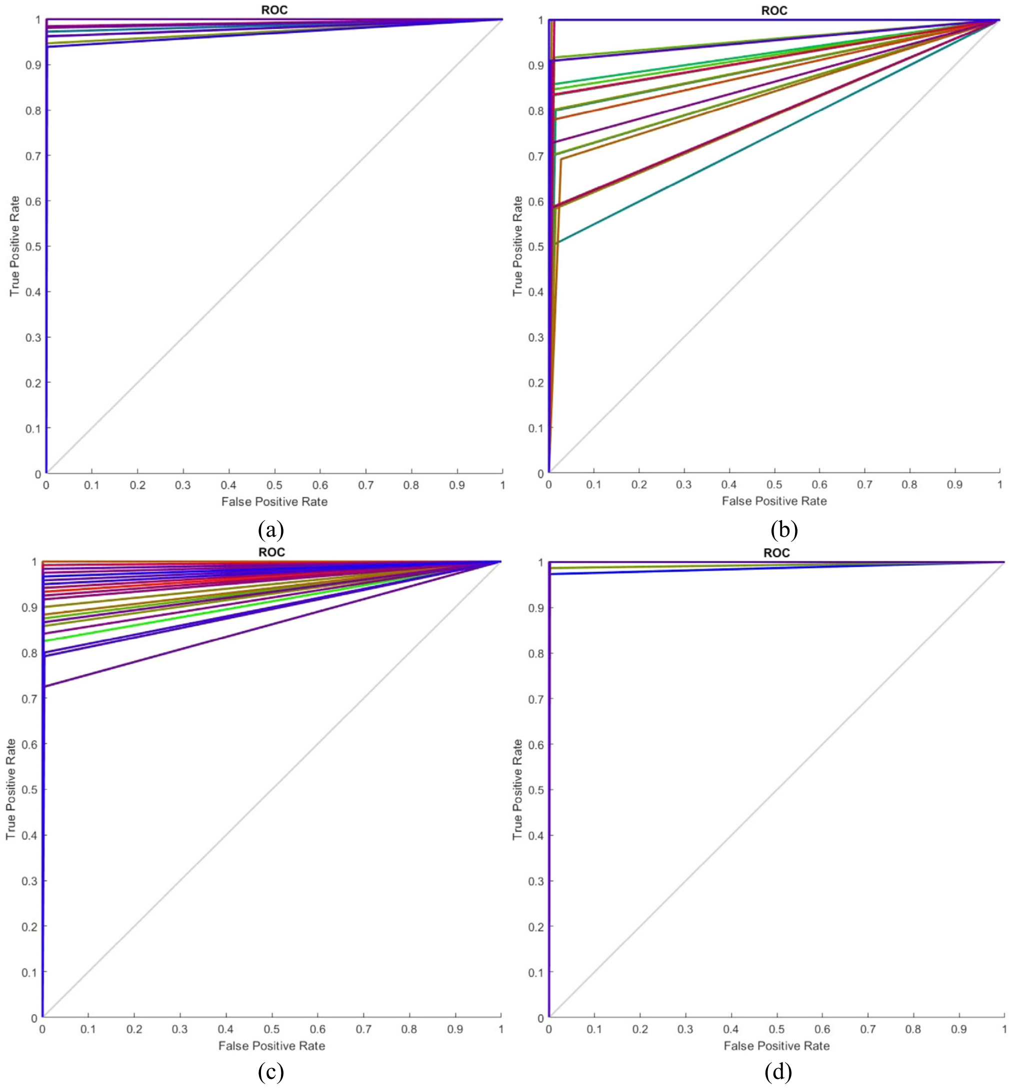


Fig. 9. ROC diagrams of the best performance results of the proposed methods, (a) Flavia dataset, (b) ICL dataset, (c) Foliage dataset, (d) Swedish dataset.

Table 5
Comparison of image descriptors with the proposed methods.

	Flavia	Swedish	ICL	Foliage
Shearlet transform	59.47%	75.00%	34.57%	30.38%
GLCM	63.21%	75.98%	37.71%	53.51%
Color features	85.31%	84.91%	68.28%	82.88%
HOG	94.78%	98.75%	82.85%	89.76%
RM-LBP	97.94%	98.30%	71.42%	91.11%
OM-LBP	97.89%	**99.46%**	76.57%	88.75%
ROM-LBP	**98.94%**	99.19%	**83.71%**	**92.92%**

As can be seen in Table 4, the proposed methods showed the highest classification accuracy for the four different datasets compared to previous LBP-based studies. However, we calculated the classification performance of image descriptors such as GLCM, HOG, Color Features, and Shearlet Transform by using the Flavia, ICL, Swedish, and Foliage datasets. These descriptors are widely used in studies related to object recognition and also have high reported classification performance.

Table 6
Comparison of other methods with the proposed methods.

	Flavia	Swedish	ICL	Foliage
LQPAT	96.57%	98.48%	69.71%	88.33%
LGS	97.68%	96.96%	79.71%	94.16%
S-LGS	98.47%	97.41%	82.28%	94.13%
VS-LGS	98.21%	97.76%	82.00%	93.90%
V-LGS	97.89%	97.41%	80.85%	**94.62%**
ZH-LGS	98.26%	97.94%	75.71%	88.62%
ZV-LGS	97.68%	97.67%	74.28%	89.63%
ZHM-LGS	97.84%	97.85%	79.14%	93.52%
RM-LBP	97.94%	98.30%	71.42%	91.11%
OM-LBP	97.89%	**99.46%**	76.57%	88.75%
ROM-LBP	**98.94%**	99.19%	**83.71%**	92.92%

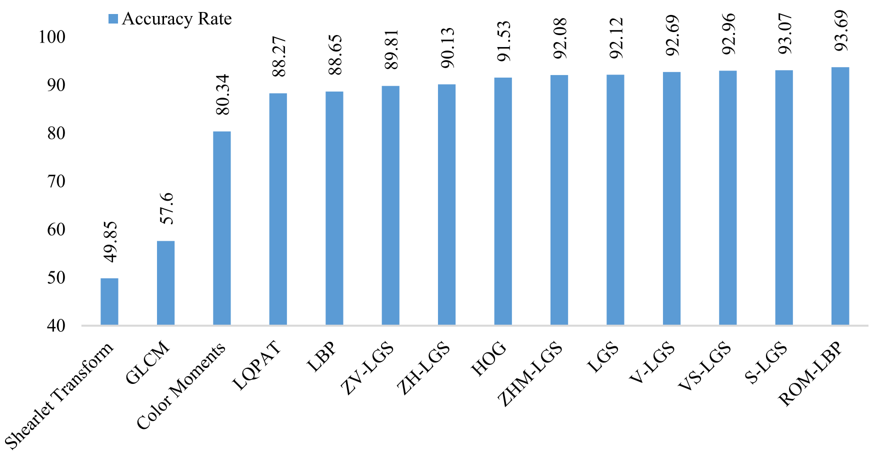


Fig. 10. The average performance results of four datasets.

In Table 5, the proposed methods have been observed to have higher classification accuracy than image descriptors in the Flavia, Swedish, ICL, and Foliage datasets. However, the highest accuracy among image descriptors was obtained using the HOG method for all four datasets.

5.3. Comparison of other improved LBP and proposed methods

In the object recognition field, there have been many studies based on the LBP method. The LBP-based methods in these studies used solutions to different problems such as face recognition rather than plant recognition. We calculated classification accuracies of these improved methods by using the Flavia, Swedish, ICL, and Foliage datasets. The obtained results compared with the proposed OM-LBP and ROM-LBP methods are shown in Table 6.

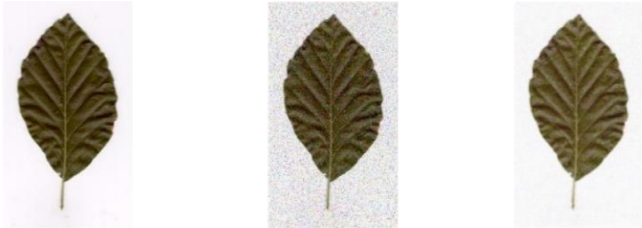
In Table 6, the OM-LBP and ROM-LBP methods are compared with the nine best performing LBP-based methods developed in the field of object recognition. According to the results obtained;

- The highest accuracy for the Flavia dataset was 98.94%, using the ROM-LBP method.
- The highest accuracy for the Swedish dataset was 99.46%, using the OM-LBP method.
- The highest accuracy for the ICL dataset was 83.71%, using the ROM-LBP method.
- The highest accuracy for the Foliage dataset was 94.62%, using the V-LGS method.

As a result, the proposed methods were observed to have higher classification performance than the improved LBP-based methods, except for the Foliage dataset. For the four datasets utilized in this study, the performance results of the proposed method, original LBP, improved LBP methods, and other image descriptors were averaged and shown in Fig. 10.

5.4. Comparison of other methods and the proposed methods against noise

The image descriptors developed based on object recognition are generally tested using noiseless and specially obtained images. However, in real-time applications, images obtained through tools such as phones and cameras may not always



(a) (b) (c)

Fig. 11. Noise added sample images, (a) Original image, (b) Salt & pepper noise added image, (c) Gaussian noise added image.

Table 7
Comparison performances of the proposed and other methods based on salt & pepper noise.

	Flavia	Swedish	ICL	Foliage
LBP	92.63%	94.19%	55.42%	70.06%
LQPAT	92.15%	92.85%	58.57%	67.43%
LGS	97.10%	95.26%	78.00%	90.54%
S-LGS	97.21%	95.44%	77.71%	**90.76%**
V-LGS	88.52%	90.71%	37.14%	87.55%
VS-LGS	97.26%	96.16%	79.14%	90.66%
ZH-LGS	85.42%	91.62%	31.42%	81.86%
ZV-LGS	87.36%	91.25%	32.85%	84.83%
ZHM-LGS	85.68%	92.41%	39.14%	85.63%
RM-LBP	96.10%	96.78%	66.28%	83.75%
OM-LBP	94.73%	98.30%	64.57%	79.79%
ROM-LBP	**97.31%**	**98.48%**	**81.14%**	87.84%

Table 8
Comparison performances of the proposed and other methods based on Gaussian noise.

	Flavia	Swedish	ICL	Foliage
LBP	74.84%	77.67%	20.00%	28.22%
LQPAT	77.31%	80.71%	22.85%	38.76%
LGS	73.57%	67.50%	28.28%	34.86%
S-LGS	86.26%	76.96%	36.85%	47.75%
V-LGS	68.26%	70.08%	23.14%	27.93%
VS-LGS	86.58%	76.69%	32.57%	49.15%
ZH-LGS	64.94%	68.39%	18.85%	19.61%
ZV-LGS	66.89%	71.33%	19.62%	21.19%
ZHM-LGS	60.21%	72.23%	26.00%	26.33%
RM-LBP	69.73%	74.46%	19.42%	33.31%
OM-LBP	**86.68%**	**85.62%**	**51.71%**	46.33%
ROM-LBP	85.31%	84.73%	31.14%	**49.52%**

be as desired. Therefore, in the current study we evaluated the effectiveness and robustness of the proposed methods against noisy images.

In this study, we used salt & pepper and Gaussian noise, which are both popular noise addition methods (see Fig. 11). These noises were applied separately to the Flavia, Swedish, ICL, and Foliage datasets. Then, we calculated the performances of the existing methods with the proposed methods, and these results are shown in Tables 7 and 8.

In Table 7, the proposed methods are compared with the performances of other methods based on salt & pepper noise. According to the results obtained;

- The highest accuracy for the Flavia dataset was 97.31%, using the ROM-LBP method.
- The highest accuracy for the Swedish dataset was 98.48%, using the ROM-LBP method.
- The highest accuracy for the ICL dataset was 81.14%, using the ROM-LBP method.
- The highest accuracy for the Foliage dataset was 90.76%, using the S-LGS method.

According to the results given in Table 7, the best performance against the salt & pepper noise was achieved with the ROM-LBP method among the proposed methods.

In Table 8, the proposed methods are compared with performances of other methods based on Gaussian noise. According to the results obtained;

- The highest accuracy for the Flavia dataset was 96.68%, using the ROM-LBP method.
- The highest accuracy for the Swedish dataset was 85.62%, using the OM-LBP method.
- The highest accuracy for the ICL dataset was 51.71%, using the OM-LBP method.
- The highest accuracy for the Foliage dataset was 49.52%, using the ROM-LBP method.

According to the results given in Tables 7 and 8, the best performance against the salt & pepper noise was achieved with the ROM-LBP method, while the OM-LBP method obtained the best performance against Gaussian noise. However, it was observed that the highest performance for both noisy and noiseless Flavia, Swedish, and ICL datasets was obtained using the proposed method. For the noiseless Foliage dataset, the proposed method showed a lower performance compared to other improved LBP-based methods. In addition, while the proposed method exceeded the performance of many methods against the salt & pepper noise, the proposed method achieved the highest performance compared to all other methods against Gaussian noise. As a result, the proposed methods can be said to be more robust, provide an improved level of performance, and are easier to implement than other LBP-based methods of plant species identification.

The advantages of the proposed method according to results are given below.

- The proposed method extracts distinctive features. As a result, 98.94%, 99.46%, 83.71%, and 92.92% success rates were calculated for Flavia, Swedish, ICL and Foliage datasets, respectively.
- The execution time analysis clearly demonstrated that the proposed method has a short execution time.
- The proposed method has a robust structure against noise attack.
- Implementation of the proposed is simple because it has no complex mathematical background.

6. Conclusion

In this paper, we proposed the Region Mean-LBP, Overall Mean-LBP, and ROM-LBP methods as improved versions of the LBP method for the recognition of plant leaves. These methods work by considering the region and overall mean instead of the center pixel for coding by way of filtering. However, while the original LBP converts color images to gray tones, the Region Mean-LBP and Overall Mean-LBP methods were applied using R and G color channels of the images, respectively. The ROM-LBP method is based on a combination of the parameters obtained from both methods. In addition, we evaluated the robustness of the proposed methods against noises such as salt & pepper and Gaussian. The performances of these methods were calculated by ELM classifier. In order to test the proposed methods, the Flavia, Swedish, ICL, and Foliage plant leaf datasets were used. According to the obtained performance results, the best classification accuracies for Flavia, Swedish, ICL, and Foliage datasets were calculated as 98.94%, 99.46%, 83.71%, and 92.92%, respectively. The experimental results clearly showed that the proposed methods have higher levels of classification accuracy than the original LBP, improved LBP methods, and other image descriptors for both noisy and noiseless images. In the future, these proposed methods could help farmers in plant recognition without the need for experts. In addition, it is aimed to develop Convolutional Neural Network-based systems using the proposed methods.

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