PLANT DISEASE CLASSIFICATION USING TEXTURE AND COLOUR

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Abstract: Plant disease detection and classification is an important topic from the precision agriculture domain. Since diseases have a strong negative impact on agricultural production, they must be detected correctly and as soon as possible in order to be able to take the most appropriate measures. We propose a feature extraction technique which uses texture and colour for the classification of plant diseases. The textural content is extracted from grey-scale images, while the colour distribution in the images is generated from RGB samples. The two types of information are derived independently and are fused together through concatenation. For the experimental evaluation, a public database containing real images of healthy and non-healthy plant leaves was used. We considered 4 setups: corn, grape, potato and tomato disease classification. The colour information added by the proposed approach increases the performance compared to using only the textural information. Even if our technique is not able to surpass a joint texture-colour feature extraction method, it provides more efficiency from the computational time point of view. The proposed method is a good compromise between classification performance and computational complexity.

Keywords: *image classification, plant disease detection, texture, colour.*

I. INTRODUCTION

The agricultural field often faces the problem of diseases affecting crops. This requires quick intervention from the specialists so as the best measures are taken. In this way, it is prevented the loss of the entire crop. Within this context, automatic machine-learning methods can be used to detect and classify diseases affecting plants by considering images of their leaves. These techniques involve using a feature extraction algorithm which generates the most relevant and discriminative features, followed by a machine-learning classifier. Figure 1 shows the general block scheme of a supervised machine-learning classification system.

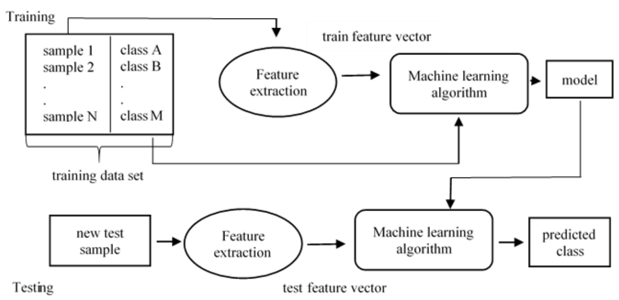

Figure 1. Supervised machine-learning classification system

In a traditional machine-learning classification system, the feature extraction is the most important phase. It provides a compact representation of the input image by keeping only the most relevant features. The machine-learning algorithm learns by example and in the testing phase, it is used to predict the class for a new image.

In literature, there are many traditional machine-learning techniques used in plant disease classification tasks. For example, in [1], the authors propose a method based on the SIFT (Scale Invariant Feature Transform) feature extraction algorithm and the computation of 5 colour statistical features for the classification of tomato leaf diseases. In [2], the authors use features derived from the GLCM (Gray-Level Co-occurrence Matrix) to feed a kNN (k-Nearest Neighbours) classifier for performing disease detection. The GLCM was also used in [3] for the classification of diseases affecting the salad cucumber. The authors implied the Support Vector Machine (SVM) as classifier. The same methods were used in [4] for the detection of diseases affecting citrus leaves.

Recently, deep-learning methods have become more and more used in literature to solve different classification problems. Such methods learn hierarchically relevant features without the need of feature engineering. They were also used for disease detection. For example, in [5], the authors considered a Multilayer Convolutional Neural Network (MCNN) for the detection of a fungal disease affecting mango leaves. The classification of apple leaf diseases is performed in [6] by using a deep CNN (Convolutional Neural Network) based on the AlexNet model. In [7], the authors propose the LeafNet model for the classification of tea plant diseases.

For the plant disease classification task, texture and colour are one of the most relevant features, being able to provide a sufficiently high discrimination power. Within this context, we propose a feature extraction method which generates both types of features independently. The textural content is generated by using the Block Matching and 3D filtering Extended Local Binary Patterns (BM3DELBP) [8] proposed by us in a previous work. This operator works locally on grey-scale images. The colour information is derived by considering an MPEG-7 colour descriptor denoted CLD (Colour Layout Descriptor) [9]. The two types of features are concatenated to form the final feature vector used in the classification task. The advantage of the proposed method is the time efficiency since CLD is a very compact operator.

The paper is organized as follows. Section II reviews two handcrafted feature extraction techniques. One of them is the BM3DELBP operator which is used for generating the textural features in the proposed approach. The other one is the Opponent Colour Colour-Block Matching and 3D filtering Extended Local Binary Patterns (OCCBM3DELBP) operator. This descriptor is a joint texture colour feature extraction algorithm proposed by us in [10]. Section III presents the proposed approach, while the experimental results and related discussion are detailed in section IV. Finally, section V incorporates our conclusions.

II. THEORETICAL BACKGROUND

1. Block Matching and 3D filtering Extended Local Binary Patterns (BM3DELBP)

We introduced in [8] a new texture descriptor characterized by an improved robustness to high Gaussian noise levels. This is achieved by incorporating state-of-the-art filtering techniques in the process of texture feature extraction. The proposed descriptor is labelled Block Matching and 3D filtering Extended Local Binary Patterns (BM3DELBP) and is an LBP-derived operator. The generated features have good invariance properties with respect to rotation, scale and illumination conditions and are robust to Gaussian noise. The illumination invariance is a property specific to the Local Binary Patterns operator, so the features provided by BM3DELBP are also invariant to illumination conditions. The invariance to rotation is achieved by using the rotation invariant coding strategy (*riu2*) and the multiresolution approach is used to gain a degree of invariance to the change of the observation scale.

This operator is derived from the Median Robust Extended Local Binary Patterns (MRELBP) [11]. The RELBP (Robust Extended Local Binary Patterns) is used as feature extractor, but the median filter is substituted by the BM3D (Block Matching and 3D filtering) technique [12].

The BM3D filter is considered state-of-the-art for removing the additive white Gaussian noise. This technique consists of two steps. In the first step, a basic estimate of the input noisy image is obtained by using a hard thresholding technique in the collaborative filtering phase. By using a block-matching method, similar 2D image blocks are grouped together in 3D arrays which are called groups. The collaborative filtering is performed in the 3D transform domain where the representation of a group is sparse because of the similarity between its blocks. A 3D denoising is done by shrinking the transform coefficients. In the second step, both the original noisy image and the basic estimate obtained at the output of the first step are used to provide the final denoised image by using the Wiener technique in the collaborative filtering process.

The BM3DELBP proved to improve the robustness to Gaussian noise of the MRELBP operator since the BM3D filter is able to ensure an efficient noise attenuation without the alteration of texture structures. Figure 2 shows the block scheme which describes how this operator is built.

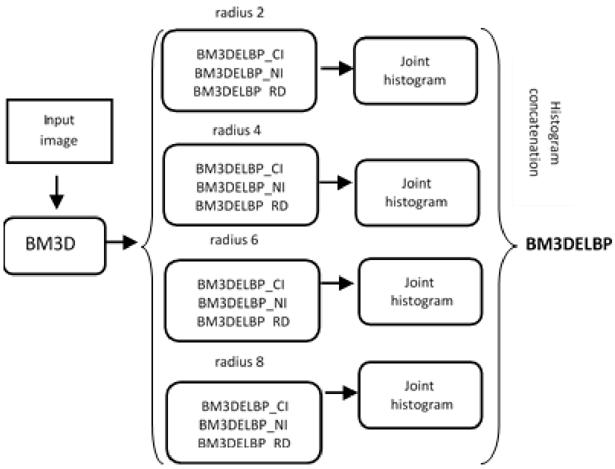

Figure 2. The block scheme of the BM3DELBP operator

At the input of the block scheme shown in Figure 2 there is a noisy textured image. The BM3D filter is used to reduce the noise present in the image and then the filtered sample is analysed at four different scales by considering the following values for the corresponding radii: 2, 4, 6 and 8. For each considered scale, the feature space of BM3DELBP is built by computing three operators: BM3DELBP_CI (BM3DELBP Central pixel intensity), BM3DELBP_NI$^{riu2}_{R,P}$ (BM3DELBP Neighbours' Intensities) and BMM3DELBP_RD$^{riu2}_{R,P}$ (BM3DELBP Radial Difference). We refer to [8] for a complete mathematical description of these operators.

The features generated by the three descriptors are fused together for each scale using a joint histogram. By using a multiresolution approach, all resulting joint histograms from all considered scales are concatenated, forming the final feature vector corresponding to the BM3DELBP descriptor.

2. Opponent Colour Colour-Block Matching and 3D filtering Extended Local Binary Patterns (OCCBM3DELBP)

We proposed in [10] an extension to colour of the BM3DELBP operator by considering a joint texture-colour descriptor labelled OCCBM3DELBP (Opponent Colour Colour-Block Matching and 3D filtering Extended LBP). In [10], we analysed the importance of colour information for the classification of grape leaf diseases. We observed that a joint texture-colour approach brings improvements in the classification performance for this type of application when compared to state-of-the-art grayscale operators derived from LBP, including the BM3DELBP feature extractor.

The opponent colour idea [13] is used to extend the BM3DELBP operator to colour images. The BM3DELBP operator is applied on each colour channel independently, but also on colour channel pairs. The colour channel pairs generate opponent colour patterns. When applying the BM3DELBP operator on channel pairs, the central pixel is considered the one taken from the first channel in that pair and its neighbours are taken from the second channel in the pair. Theoretically, there are 6 possible channel pairs, but only 3 are considered. Pairs such as RB and BR which contain the same channels but in a different order are considered redundant [13]. They do not bring enough important information so that it is worthwhile (considering that in this way the size of the feature vector would be increased). So, after applying the BM3DELBP operator on each individual colour channel, there are obtained 3 intra-channel histograms. The result of working on channel pairs is represented by 3 inter-channel histograms. Figure 3 shows the 6 cases taken into consideration when computing the OCCBM3DELBP.

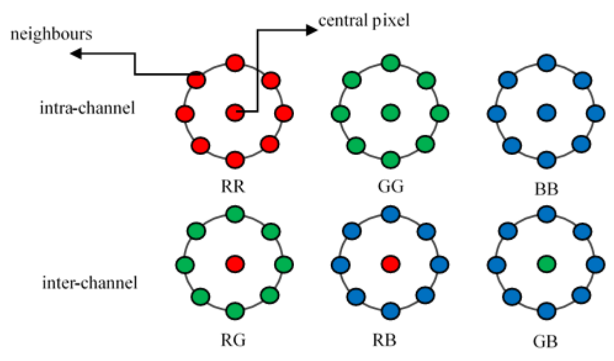

Figure 3. The 6 cases considered in the opponent colour approach

The 6 obtained histograms are concatenated to form the joint texture-colour feature vector. Figure 4 shows the block scheme which details the feature extraction process in case of the OCCBM3DELBP operator.

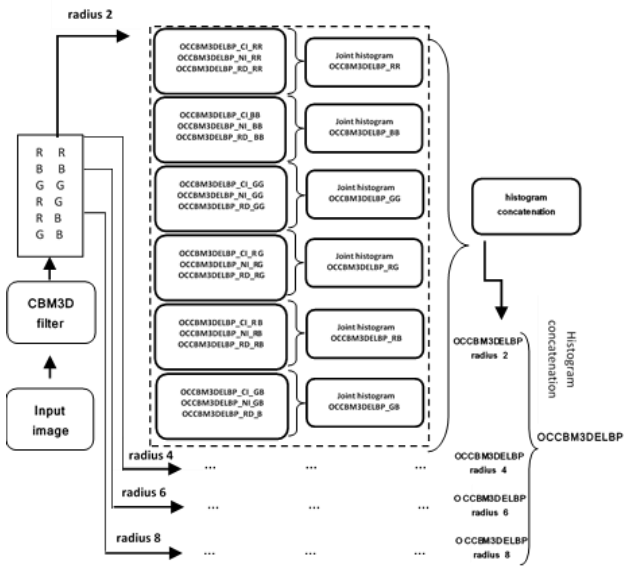

Figure 4. Computation of the OCCBM3DELBP

The first step is the use of the CBM3D filter [12] which is the colour version of BM3D. The filter is used to denoise the input RGB image. In order to build the feature space of the OCCBM3DELBP operator, three components are computed from the filtered image: OCCBM3DELBP_CI (OCCBM3DELBP Central pixel intensity), OCCBM3DELBP_$NI_{R,P}^{riu2}$ (OCCBM3DELBP Neighbours' Intensities) and OCCBM3DELBP_$RD_{R,P}^{riu2}$ (OCCBM3DELBP Radial Difference). They are calculated for each of the 6 cases shown in Figure 3.We refer to [10] for detailed mathematical expressions of the three descriptors.

For each of the 6 cases, a joint histogram is formed by combining the codes obtained using the three components. A multiresolution approach was used to obtain a degree of invariance to the scale. So, 4 different scales were considered (with radii 2, 4, 6 and 8) and the final feature vector is the concatenated version of the feature vectors computed for each scale.

III. PROPOSED APPROACH

The colour information brought by the OCCBM3DELBP approach [10] proved to be able to improve the performance in the classification of grape leaf diseases. However, this operator has an important disadvantage: the feature vector is 6 times larger than the feature vector used for grayscale images, the BM3DELBP one. This implies higher computational times. Therefore, we propose a novel feature extraction approach based both on colour and texture which generates a smaller feature vector and is able to provide higher scores than the grayscale BM3DELBP method. We label the proposed method by TC (Texture and Colour).

The proposed approach fuses two types of information: texture and colour. The texture information is derived from the grayscale version of the images by computing the BM3DELBP feature vector. The colour information is derived from the RGB images by computing the Colour Layout Descriptor (CLD) [9]. Figure 5 shows the diagram corresponding to the proposed descriptor.

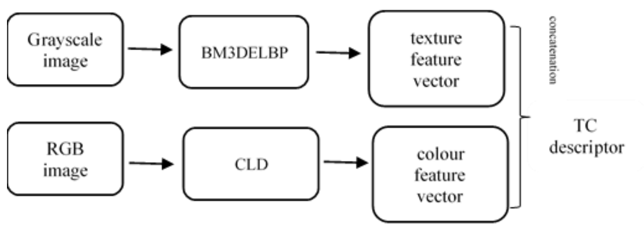

Figure 5. Block scheme of the proposed approach

The texture feature vector is obtained by computing the BM3DELBP descriptor for the grayscale version of the images from the considered dataset.

The colour feature vector is obtained from the RGB samples and is used to describe the colour spatial distribution in the considered images. The considered colour operator is CLD [9] which is an MPEG-7 descriptor used for image retrieval. We chose this descriptor due to its simplicity, speed of computation and compactness. Moreover, this operator is invariant to the scale of observation. The computation of this operator is depicted in Figure 6 using an algorithmic flowchart.

Resize the image so that it will be divisible by 8
Partition the image into 8×8 blocks (64)
for each block
    compute the representative colour (average colour)
    replace all pixels with the average colour
end
Resize the image to be of size 64×64 pixels (each block will be of size 8×8 blocks)
Change the colour space from RGB to YCbCr
for each colour channel (Y, Cb, Cr)
    for each 8×8 block
        apply a DCT (Discrete Cosine Transform) to obtain 64 coefficients
        take only the DC coefficient
    end
end
for each colour channel (Y, Cb, Cr)
    concatenate the coefficients for all blocks
end
Concatenate the coefficients for all channels

Figure 6. Algorithmic flowchart describing the computation of the CLD operator

The first step considered in the CLD approach is the RGB image partitioning into 64 blocks. This provides the invariance to the change of the observation scale of this operator.

The next step consists in finding the representative colour for each selected block of the input image. There are many methods that can be used to compute the representative colour, but in the MPEG-7 standard, the average colour is recommended. The average colour is obtained by computing the average of each colour channel.

The image is then resized to be of size 64×64 pixels and is converted to the YCbCr colour space. The 8×8 DCT transform is then applied to each block of each colour channel (Y, Cb and Cr) so that each block contains 64 DCT coefficients. From these coefficients, only the DC coefficient is non-zero since each block contains 64 pixels of the same colour value. So, only the DC coefficient is kept. This means that there is one coefficient per block for each colour channel, so the total number of coefficients is 3 channels × 64 blocks = 192.

The final feature vector of the proposed method concatenates the BM3DELBP feature vector which contains 800 values and the CLD feature vector consisting of 192 values. The final size is therefore 992, while the OCCBM3DELBP feature vector contains 4800 values.

IV. EXPERIMENTAL RESULTS

1. Datasets

For evaluating the proposed method, we used a publicly available dataset containing images of plant leaves from several species. Some of the images represent healthy leaves, while others are leaves affected by several diseases.

In our experimental configuration, we used the RGB segmented version of the PlantVillage dataset [14] [15]. For performing plant disease classification, we considered 4 setups detailed in Table I.

Table I. Considered setups for plant disease classification

Setup	**Categories and number of samples per class**	
Corn disease classification	1- Corn Cercospora leaf spot (492)	2- Corn Common Rust (1181)
	3- Corn Northern leaf blight (960)	4- Corn healthy (1155)
Grape disease classification	1- Grape Black Rot (1161)	2- Grape Black Measles (1379)
	3- Grape leaf blight (1059)	4- Grape healthy (423)
Potato disease classification	1- Potato Early blight (998)	2- Potato Late blight (998)
	3- Potato healthy (152)	
Tomato disease classification	1- Tomato Bacterial spot (2109)	2- Tomato Early blight (845)
	3- Tomato Late blight (1737)	4- Tomato Leaf mold (838)
	5- Tomato Septoria leaf spot (1720)	6- Tomato Spider mites (1665)
	7- Tomato Target spot (1403)	8- Tomato Yellow leaf curl virus (5336)
	9- Tomato Mosaic virus (370)	10- Tomato healthy (1590)

Some images of the segmented RGB version of the PlantVillage dataset [15] were affected by severe segmentation problems so that they could no longer be recognized. We did not consider these images in our experimental configuration.

Figure 7 shows examples of images of corn and grape leaves and Figure 8 presents examples of potato and tomato leaves for each image category.

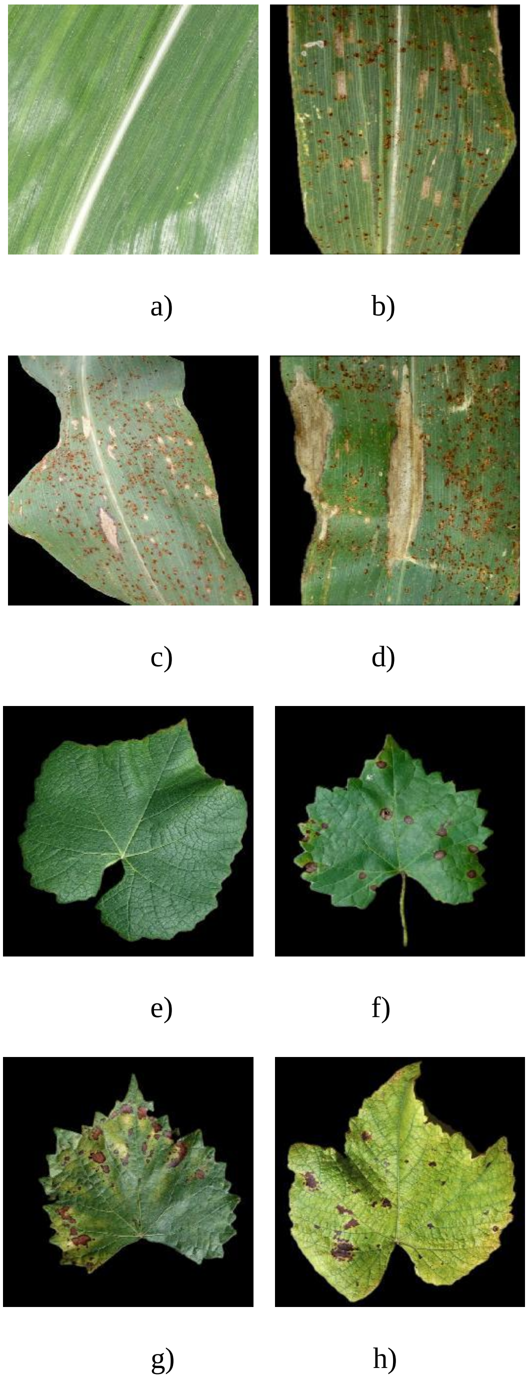

Figure 7. Examples of images from class: a) Corn healthy b) Corn Cercospora leaf spot c) Corn Common Rust d) Corn Northern leaf blight e) Grape healthy f) Grape Black Rot g) Grape Black Measles h) Grape leaf blight

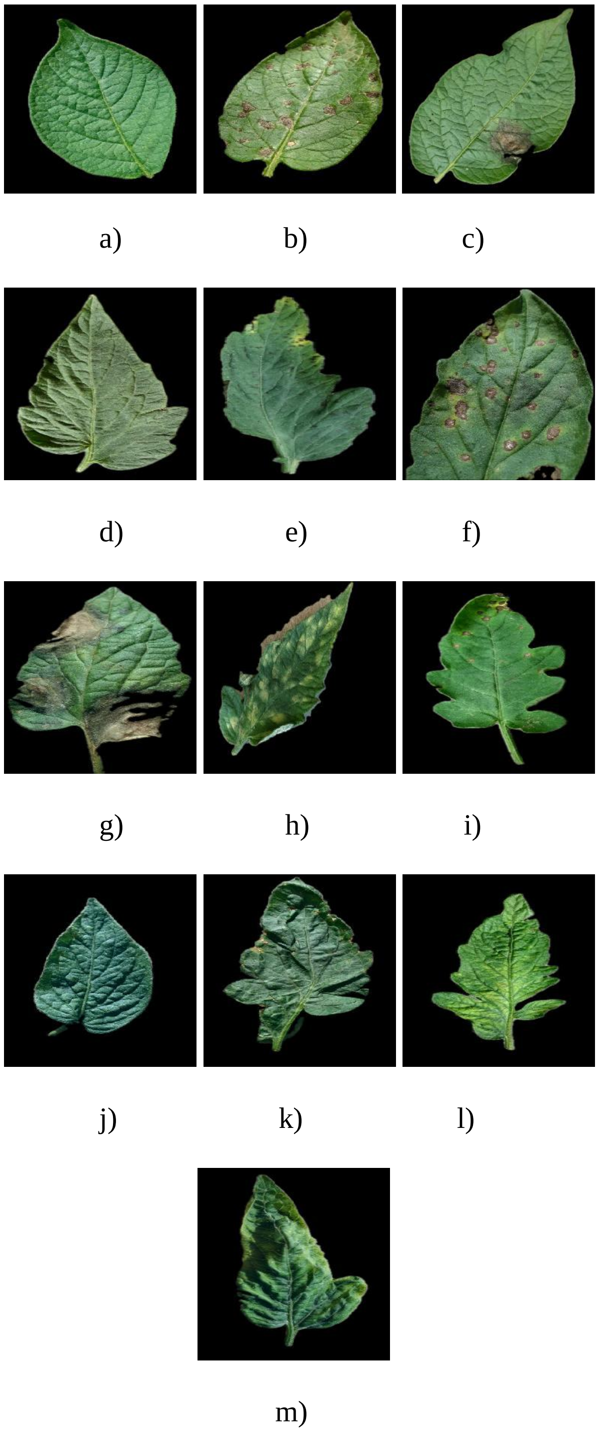

Figure 8. Examples of images from class: a) Potato healthy b) Potato Early blight c) Potato Late blight d) Tomato healthy e) Tomato Bacterial spot f) Tomato Early blight g) Tomato Late blight h) Tomato Leaf mold i) Tomato Septoria leaf spot j) Tomato Spider mites k) Tomato Target spot l) Tomato Mosaic virus m) Tomato Yellow leaf curl virus

2. Results and discussion

In the experimental section, we performed plant disease classification using the proposed approach. We compared the obtained results with the ones obtained using the BM3DELBP operator applied on the same grey-scale images and the OCCBM3DELBP descriptor applied on the same RGB samples. As machine-learning classifier, we used the Support Vector Machine (SVM) algorithm for which we considered the RBF (Radial Basis Function) kernel. The parameters of this classifier (C and γ) [16] were chosen through a grid search in order to maximize the classification accuracy. For each class, 75% of the images were used for the training phase and 25% for testing.

For BM3DELBP and OCCBM3DELBP, the same parameters were used as in [10].

The obtained average accuracy, macro-averaging precision, recall and F1 score for corn, grape, potato and tomato leaves are given in Tables II, III, IV and V, respectively. All results are averaged over 50 random partitions of the train and test sets.

Table II. Classification results for corn leaves [%]

Metric/ Operator	Proposed method (TC)	BM3DELBP [8]	OCCBM3DELBP [10]
Average accuracy	96.16±0.46	93.56±0.82	96.77±0.6
Macro-averaging precision	94.8±0.76	91.79±1.23	95.46±0.78
Macro-averaging recall	94.44±0.68	90.22±1.2	95.44±0.81
Macro-averaging F1 score	94.62	90.99	95.45

Table III. Classification results for grape leaves [%]

Metric/ Operator	Proposed method (TC)	BM3DELBP [8]	OCCBM3DELBP [10]
Average accuracy	97.4±0.3	94.54±0.5	99.07±0.21
Macro-averaging precision	97.98±0.24	95.73±0.4	99.25±0.17
Macro-averaging recall	97.75±0.34	95.4±0.4	99.25±0.17
Macro-averaging F1 score	97.86	95.6	99.25

Table IV. Classification results for potato leaves [%]

Metric/ Operator	Proposed method (TC)	BM3DELBP [8]	OCCBM3DELBP [10]
Average accuracy	97.57±0.55	94.83±0.83	98.9±0.41
Macro-averaging precision	96.98±0.92	94±1.96	97.58±1.23
Macro-averaging recall	93.91±1.88	87.7±2.77	97.66±1.12
Macro-averaging F1 score	95.42	90.75	97.62

Table V. Classification results for tomato leaves [%]

Metric/ Operator	Proposed method (TC)	BM3DELBP [8]	OCCBM3DELBP [10]
Average accuracy	93.82±0.39	84.37±0.35	96.08±0.28
Macro-averaging precision	91.5±0.67	79.83±0.6	94.75±0.44
Macro-averaging recall	91.04±0.67	78.83±0.65	94.57±0.44
Macro-averaging F1 score	91.27	79.33	94.99

Table VI shows the feature extraction time for the considered methods. We used an Intel Core i7-4510U 2.00 GHz processor and NVIDIA GeForce GT 840M 4GB video card.

Table VI. Feature extraction time [minutes]

Metric/ Operator	Proposed method (TC)	BM3DELBP [8]	OCCBM3DELBP [10]	Relative gain
Corn disease detection	252	241	460	45.22 %
Grape disease detection	267	256	488	45.29 %
Potato disease detection	143	137	261	45.21 %
Tomato disease detection	1171	1121	2137	45.2 %

We can observe from the obtained classification results the fact that the proposed operator surpasses the BM3DELBP method in all considered situations. This is due to the fact that the colour information brought by incorporating also the CLD feature vector is relevant for these classification tasks.

However, OCCBM3DELBP still remains the most performant and discriminative, being able to achieve the highest classification scores. In the proposed approach, the texture and colour information are extracted separately as two independent features. The texture information is derived from the grey-scale version of the images, while the considered colour information is derived from the RGB images by computing the colour spatial distribution. On the other hand, for the OCCBM3DELBP algorithm, the extraction of texture and colour features is not performed independently. This approach proves to be better in achieving more discrimination power in this situation. However, the disadvantage of this method is the computational complexity. The feature vector is 6 times longer than the one considered for the BM3DELBP approach which implies longer processing times. The proposed method involves a very short additional time over that required by BM3DELBP (approximately 0.17 seconds/image).

For the corn leaves, the proposed algorithm is able to increase performance by 4%, while OCCBM3DELBP achieves an extra 1%. This is not worth the additional computational complexity and long additional time over that required by BM3DELBP (approximately 3.46 seconds/image).

For the grape disease classification, TC brings an improvement of 2% and OCCBM3DELBP of an extra 2%. For the potato setup, the proposed approach surpasses BM3DELBP with almost 5% and OCCBM3DELBP brings an extra 2%. For the tomato setup, TC brings a 12% improvement, while OCCBM3DELBP achieves an extra 3%.

Even if the proposed approach does not achieve the best performance, it is a very good compromise between classification accuracy and computational complexity. The relative gain regarding the time efficiency is approximately 45% for the considered setups.

V. CONCLUSIONS

We propose a feature extraction method based both on texture and colour features. The textural content is extracted using the BM3DELBP approach and the colour information is generated by using the CLD approach. The two types of features are extracted independently using a parallel approach and concatenated to form the final feature descriptor.

For evaluating the proposed method, we considered 4 experiments in which we performed disease classification for corn, grape, potato and tomato leaves. We compared the results obtained using the proposed descriptor labelled TC to the performance gained by using BM3DELBP and OCCBM3DELBP. The colour information brought by the proposed feature extraction technique is able to increase the classification scores when compared to BM3DELBP. However, OCCBM3DELBP remains the operator with the top performance due to the fact that texture and colour are not considered as independent features. On the other hand, from the computational complexity and processing time point of view, the proposed technique is better, being a good compromise between classification performance and time efficiency.

APPENDIX

The SVM parameters [16] used in the experimental section for the considered feature extraction techniques are given in Table VII. They were chosen through a grid search such as the highest average accuracy is achieved.

Table VII. SVM parameters used in the experimental configuration

Metric/ Operator	Proposed method (TC)	BM3DELBP [8]	OCCBM3DELBP [10]
Corn disease classification	C=10, $\gamma=10^{-3}$	C=100, $\gamma=10^{-5}$	C=100, $\gamma=10^{-5}$
Grape disease classification	C=10, $\gamma=10^{-3}$	C=100, $\gamma=10^{-5}$	C=100, $\gamma=10^{-5}$
Macro-averaging recall	C=10, $\gamma=10^{-3}$	C=100, $\gamma=10^{-5}$	C=100, $\gamma=10^{-5}$
Macro-averaging F1 score	C=10, $\gamma=10^{-3}$	C=100, $\gamma=10^{-5}$	C=100, $\gamma=10^{-5}$

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