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Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers

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ABSTRACT

The presented approach demonstrates an automated way of crop disease identification on various leaf sample images corresponding to different crop species employing Local Binary Patterns (LBPs) for feature extraction and One Class Classification for classification. The proposed methodology uses a dedicated One Class Classifier for each plant health condition including, healthy, downy mildew, powdery mildew and black rot. The algorithms trained on vine leaves have been tested in a variety of crops achieving a very high generalization behavior when tested in other crops. An original algorithm proposing conflict resolution between One Class Classifiers provides the correct identification when ambivalent data examples possibly belong to one or more conditions. A total success rate of 95% is achieved for the total for the 46 plant-condition combinations tested.

1. Introduction

Plant disease diagnosis is crucial for crop management and production. It can be successfully achieved through optical observation of plant leaves alterations by scouting specialist but requires a high degree of experience and specialization. Novel technologies employing data analysis by Artificial Intelligence (AI) can improve trustworthiness of diagnosis and thus can be incorporated into tools for appropriate treatment. Approaches combining AI with image feature analysis can contribute to an even more successful plant disease identification. Plant disease identification utilizing visual features is challenging. It becomes even more difficult when automated. And it is difficult not only due to the morphological features but also lighting conditions. Plant disease severity assessment is a necessary step towards not only precise but also effective crop management practices including predictive tools and treatment application models. Fungal diseases causes severe yield depression and economic losses, amounting between 5 and 80% according to the level of infection, environmental factors linked to climate and soil, and genotypic susceptibility (Šrobárová and Kakalíková, 2007). Attention should be paid to the correspondence between different types of abnormalities in crop leaves and their surrounding ecosystem background, and their respective susceptibility to specific stress factors (Gaunt, 1995).

Lamari (2002) introduced a tool for plant disease severity assessment “Assess” while Abramoff et al. (2004) worked on an extension for an open source software called ImageJ. The afore mentioned crop disease recognition approaches have been enhanced eliminating errors and developing into commercial applications.

Feature extraction methods have been widely developed for monitoring several plant conditions. Different attributes such as physical and morphological plant characteristics are used for feature extraction. Zhang et al. (2017) demonstrated a leaf disease identification application in cucumber plants. Initially the application isolated the infected part of the leaf through k-means clustering and color and shape are extracted reaching an accuracy of 85.7%. Similarly, Guo et al., (2014) utilized texture and color features using a Bayesian approach for recognizing downy mildew, anthracnose, powdery, and gray mold infection with respective accuracy rates of 94.0%, 86.7%, 88.8%, and 84.4%. Vianna et al. (2017) developed a neural network based pattern recognition approach for detecting the globally preeminent tomato late blight disease. In the current approach of 20 networks the best prediction level in pixel classification was 97.99%.

Fiel and Sablatnig (2011) have further expanded leaf disease recognition to five tree species by applying Bag of Words with SIFT descriptors, reaching a precision of 93.6%. Kumar et al. (2012) introduced Leafsnap, a curvature-based recognition algorithm and a new user interface for wider application on IOS devices. The two main drawbacks were the necessity of an Internet connection and of a white background. A smartphone application was introduced by Pethybridge and Nelson (2015). This method assessed disease presence based on eight user selected colors defining healthy areas. Regarding the six respective diseases, the effective response of the algorithm to severity assessment was

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evaluated based on targeted selection of 10 color corrected images reaching $R^2 > 0.79$. However, a black background is a prerequisite for image processing and could be potentially confused with similar colored pixels related to disease symptoms. Moreover, due to the destructive sampling procedure this algorithm lacks credibility.

Based on the presented analysis the current state of the art in crop disease detection under ambient conditions, faces many difficulties due to the variability of the conditions experienced in the field, so there is need for flexible and adaptable algorithms so as to address this variability. The current research presents a novel application of ascertaining the presence of four different health conditions including healthy, downy mildew, powdery mildew and black rot in different leaf samples by using One Class Classification. The application is capable of analyzing images taken in situ without further enhancement necessary and can successfully establish the presence of a disease even in its early stages. The proposed methodology includes a training procedure with target data regarding each one of the aforementioned diseases. A new feature vector with unknown class is assessed by a group of one class classifiers. which produce activations according their training data. If multiple activations occur, then a conflict arises of since more than one classifiers claim the new feature vector as belonging to the new class. The innovation of the presented approach lays on the its generalization potential to different crop diseases identification in leaves after been calibrated only with vine leaf samples.

2. Materials and methods

2.1. Employment of LBP algorithm and image segmentation for plant disease identification

Firstly, an image of the infected leaf with visible symptoms is taken using a smartphone or tablet. (Fig. 1a). Then, image segmentation is applied to attain the region of interest and discard the background. Additionally, a Hue Saturation Value (HSV) transform has been applied to the segmented image (Fig. 1b). The GrabCut algorithm is structured are follows:

1. The focal points of the image denote as foreground the surrounding regions denote as background and the unknown part of the image that can be either of them. A rectangle is created surrounding the target area while the pixels inside it are marked as unknown and the outside ones are marked as known.
2. An image segmentation takes place modeling the foreground and background as Gaussian Mixture Models (GMMs) by employing the Orchard-Bouman clustering algorithm.
3. Every pixel in the foreground and background is allocated most credible Gaussian component that belongs to the foreground GMMs and the background ones respectively.
4. The created pixel sets assists the learning procedure for forming new GMMs.
5. A graph is built and GrabCut algorithm is employed for defining a new foreground class.
6. Step 4–6 are repeated until the classification is completed.

Fig. 1a. Arbitrary selected vine leaf image used for training the powdery mildew One Class Classifier.

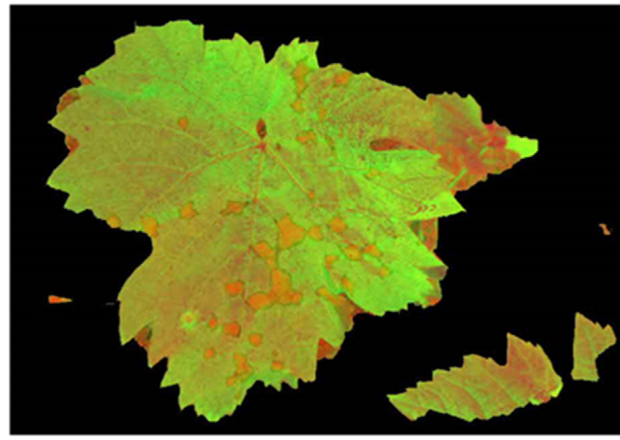

Fig. 1b. Isolation of the region of interest corresponding to the vine leaf depicted in Fig. 1 after HSV transform and described implementation of the GrabCut algorithm.

The GrabCut algorithm forms K components of multivariate Gaussian Mixture Models (GMM) for the background and K components for the foreground regions. The GMM components get their values from the color statistics of each cluster. Homogenous clusters with low variance lead to easier and more reliable segmentation.

2.2. The local binary Patterns (LBPs)

The local binary pattern is a synergistic approach to texture analysis, capable of pixel labelling by setting their boundaries of proximity and provides a binary result. The main LBP advantage in commercial applications is its ability to retain an independent behavior to the occurring gray scale level alterations that take place, e.g., by illumination. and its computational efficiency, processing images in complex real-time environment. Li et al., (2008) and Llado et al., (2009) presented the LBP operator, taking into account the two features of texture: pattern and its relative strength and working with a 3×3 grid, the center value representing a threshold. An LBP code is composed as follows: the thresholded values are multiplied by the respective pixel weights, while the total provides the final result. As the neighborhood is comprised of 8 pixels, a total of $2^8 = 256$ individual labels are attained according to the relative gray values of the threshold and the rest of the grid pixels. The contrast measure (C) is equal to the difference of the average of the pixel values lower than the threshold from the average of pixel values greater to (or equal to) the threshold. In the event that the values of the thresholded pixels are 0 or 1, the contrast value is considered 0. Fig. 2 provides an illustrated application of LBP operator.

The LBP operator is capable of converting an image into a matrix of integer values describing the fine structure of the image at the local level (Fig. 2). These values or their statistics, as the histogram, are the tools for advanced image analysis. The operator is primarily applied not only to monotone images but also multi-channel images, videos and 3D data. The hue channel is extracted from the leaf image as shown in Fig. 3a. Application of the LBP transform on the Hue channel of the segmented image provides an LBP image of the leaf (Fig. 3b).

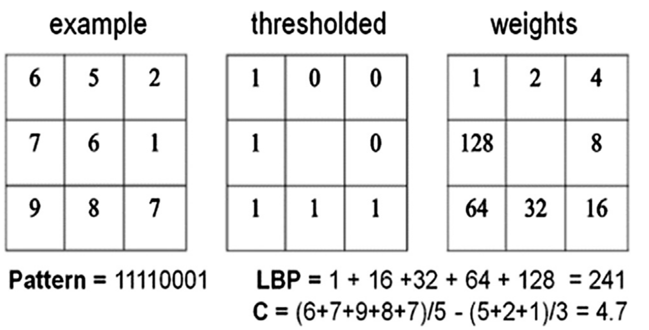

Fig. 2. Depiction of Local Binary Pattern operator structure (Pietikäinen et al., 2011).

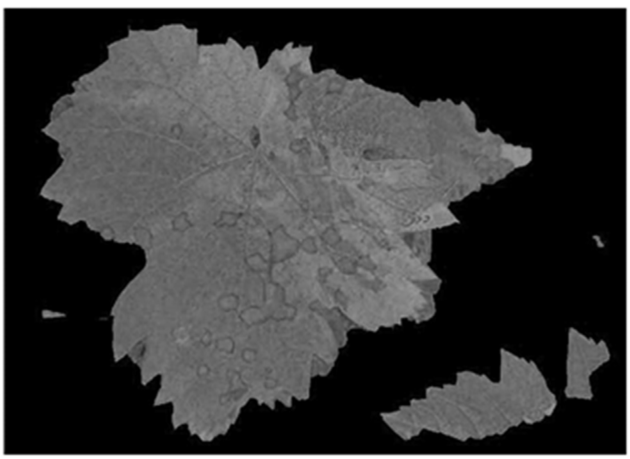

Fig. 3a. Hue channel depiction of the vine leaf.

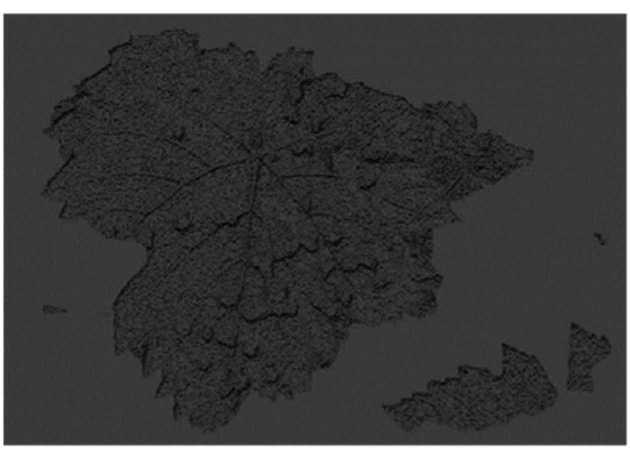

Fig. 3b. Vine leaf LBP image of the vine leaf.

2.3. Derivation of assessment of the LBP histogram

The GrabCut algorithm provides several monochromatic versions of the segmented image due to the fact that the LBP operator functions in individual channels. On the original image obtained in RGB format two different transformation options were assessed. The first option was the original image transformed in HSV format and the second option was the original image transformed to grey scale. From the HSV transformation the Hue and Saturation channels were utilized. It has been established that the Hue channel LBP histogram demonstrated the best results compared to the grey scale transformation regarding the identification of infected plant leaves. The LBP operator is capable of labelling the pixels of obtained images according to their proximity on

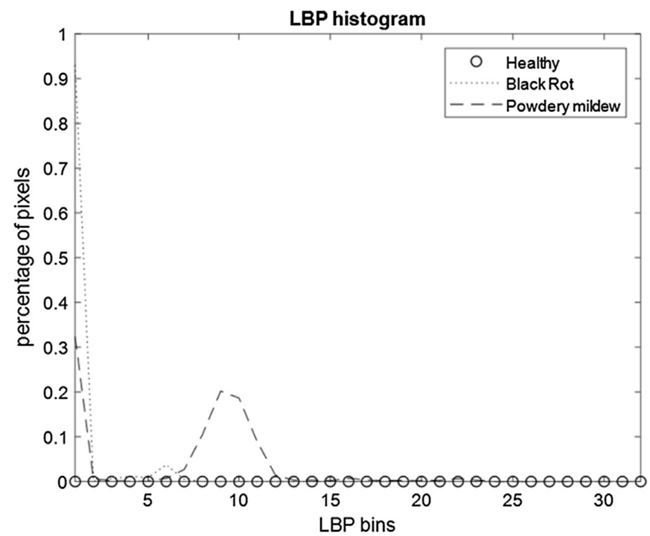

Fig. 4. Local Binary histograms of a powdery mildew infected, healthy, and downy mildew infected vine leaf.

the Hue channel, and thus utilizes the textural features relating to contrast and Hue variation (Fig. 3b). The LBP histogram demonstrates the occurrence rate of proximal values from 0 to 255. The 0–255 histogram has been condensed to 32 bins, for providing less variable feature values. Fig. 4 demonstrates the condensed histogram. The axes × and y represent the number of bins and the percentage of pixels that respectively. The irregularity of symptoms in infected leaves gives to alteration in texture which brings about local changes in texture which are reflected in the LBP histogram as concentration of pixels in specific bins (Fig. 4).

As it is demonstrated in Fig. 4, the healthy condition demonstrates minimal changes in the local texture composition. The concentration in specific bins in the local binary pattern histograms shows other variations of local nature that are concomitant to leaf texture disruption that has been induced by the pathogen activity. Similarly, the black rot indicates high concentration in the first bin and another peak at sixth bin, while powdery mildew has a lower concentration in the first bin and a peak at the ninth bin. This corresponds to the number of pixels that participate in the texture change that differentiates the symptoms between the black rot and powdery mildew. The difference between the healthy and the diseased leaf condition due to the smoothness of the histogram that correspond to the healthy leaf.

2.4. One Class Classification

The LBP histograms were utilized for training One Class Classifiers. More precisely, One Class SVMs were applied for classifying leaf sample images into target class and outliers (healthy condition/other infections). For achieving this classification eight vine leaf samples from each condition (healthy, powdery mildew, downy mildew, black rot) were sufficient database for the training procedure (Figs. 5–8). One Class SVMs were cross validated by being applied to different condition samples (healthy, powdery mildew, downy mildew, black rot), including calibration and random images, demonstrating an accurate performance.

2.5. One Class support vector Machines (OCSVMs)

Classification is applied to separate different types of samples while regression aims to bring about a requested result for provided samples. On the other hand, One Class Classification uses only target data to model a classification problem in binary form as belonging or not to a data target set. Its name is an equivalent to the term domain

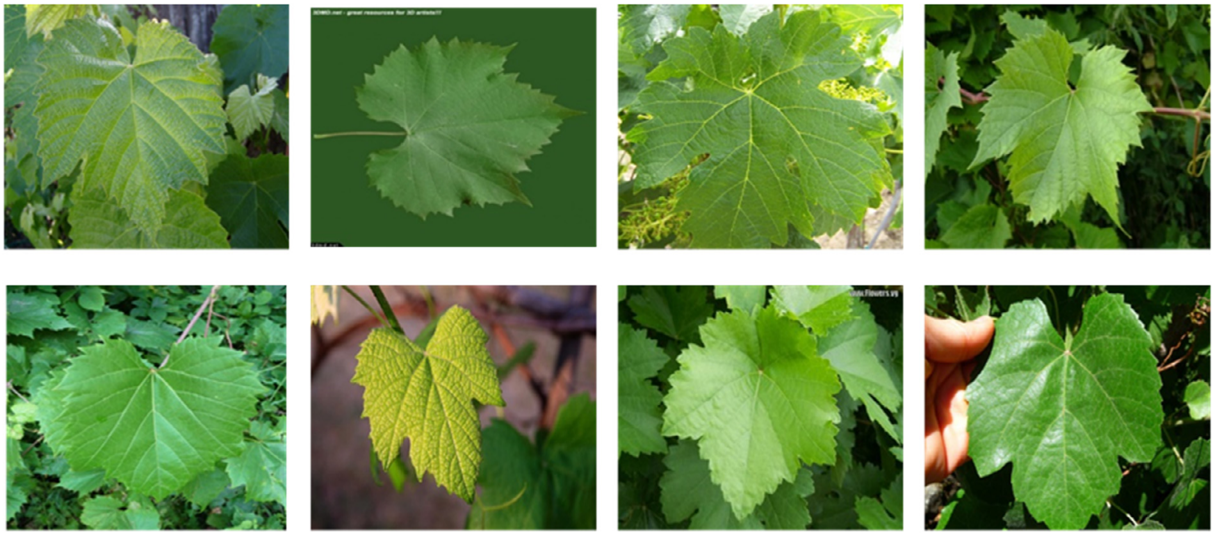

Fig. 5. The dataset utilized for calibrating the One Class SVM model for the healthy condition.

description, defining a group of items, able to discriminate between items similar or dissimilar to the training set. The dissimilar items are labelled as outliers through novelty detection. Several data domain description or outlier detection architectures are available. Tax and Duin (2004) introduced a category of One Class SVM Classification, known as Support Vector Data Description (SVDD). The SVDD classifies an unknown sample into target or outlier, founded on the assumption that target data are confined in the feature space.

A sphere, of a center a and minimum radius R including the majority of N samples, $\{x_i;\ i = 1; :::;\ N\}$. Allowing some exceptions. Slack variables i are presented and the following restrictions arise:

$$(x_i - \alpha)(x_i - a)^T \leqslant R^2 + \xi_\iota$$

$$\xi_\iota \geqslant 0 \tag{1}$$

The radius R and the slack variables are reduced:

$$F(R, a, \xi_i) = R^2 + C\sum_i \xi_\iota \tag{2}$$

where C, represents sphere's volume and the amount of sample exceptions. Then the following LaGrange equation is formed:

$$L(R, a, a_i, \xi_i) = R^2 + C\sum_i \xi_i - \sum_i a_i\{R^2 + \xi_i - (x_i^2 + 2\alpha x_i + \alpha^2)\} - \sum_i \gamma_i \xi_i \tag{3}$$

where $\alpha_i \geq 0$ and $\gamma_i \geq 0$ are multipliers. With partial derivatives equal to zero, the following restrictions arise:

$$\begin{gathered} \textstyle\sum_\iota \alpha_i = 1 \\ a = \frac{\sum_i a_i x_i}{\sum_i a_i} = \textstyle\sum_i a_i x_i \\ 0 \leqslant a_i \leqslant C \end{gathered} \tag{4}$$

After maximization regarding α_ι taking into account the restrictions (4):

$$L = \sum_i a_i(x_i \cdot x_i) - \sum_{i,j} a_i a_j (x_i \cdot x_j) \tag{5}$$

A sample z is included to the sphere when its proximity to the center is less than the radius:

$$(z - a)(z - a)^T = (z \cdot z) - 2\sum_i a_i(z \cdot x_i) + \sum_{i,j} a_i a_j (x_i \cdot x_j) \leqslant R^2 \tag{6}$$

For a small dataset, the training set is described by the Eq. (6) where

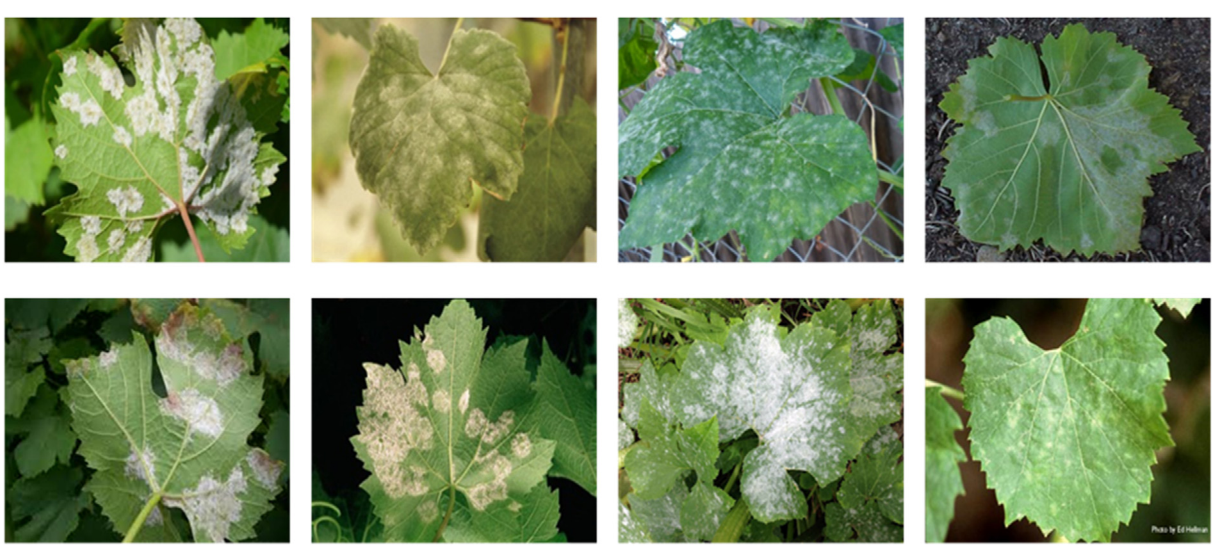

Fig. 6. The dataset utilized for calibrating the One Class SVM model for the powdery mildew infection.

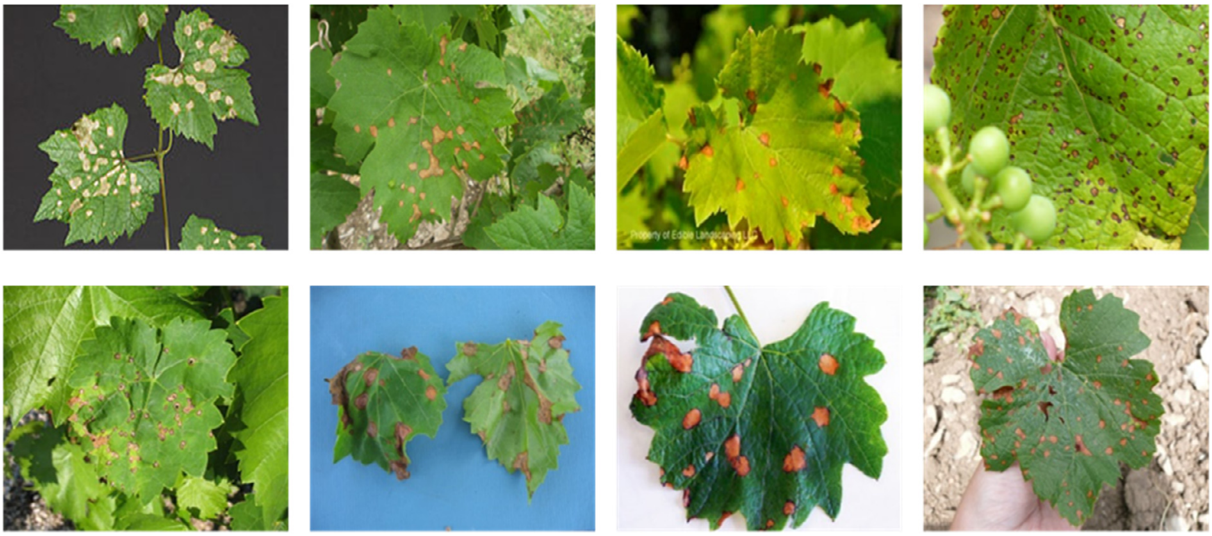

Fig. 7. The dataset utilized for calibrating the One Class SVM model for the black rot infection.

support objects are $\alpha_i \neq 0$. In the occasion that $C < 1$ support objects are equal to C. These objects belong to the outer area of the sphere and are regarded as outliers. This method described above is the Support Vector Domain Description (SVDD).

The OCSVM forms model calibrating from normal samples given by the SVDD. Then, the test samples are labeled using the normal samples deviation (Scholkopf et al., 2001).

2.6. One-Class Support-Vector-Learning for multi class problems

One-Class Classification is often used to offer solutions to multi-value decision problems. Samples are taken randomly representing different classes. For each one of the afore mentioned classes a classifier is constructed and the sphere is built including or excluding each one of the points belonging to the dataset. In the event of a novel sample pattern there are three possible outcomes:

1. In the occasion that one classifier is responsible for a novel sample pattern, it is labelled accordingly.
2. Conflict resolution takes place when two or more classifiers are possibly responsible for this pattern.
3. If a novel sample is introduced and not recognized by a classifier, it is labelled as an outlier.

The conflict is resolved by using the Nearest-Support-Vector Strategy.

2.7. Nearest-Support-Vector Strategy

The new observation's (z) proximity to the support vectors of each classifiers determines its label (Eq. (7)). Taking into account that:

$$SV(t) = \{\hat{x}_1^t, \ldots\ldots, \hat{x}_{1t}^t\} \tag{7}$$

where *SV* represents the support vectors, and *it* their amount corresponding to the classifier *t*.

The decision function *f(z)* compares the support vectors determining the minimum distance in order to classify *z* (Eq. (8)).

$$f(z) = \text{argmin}_{l \in C} \|\hat{x}_i^l - z\| \tag{8}$$

where C represents the conflict situation.

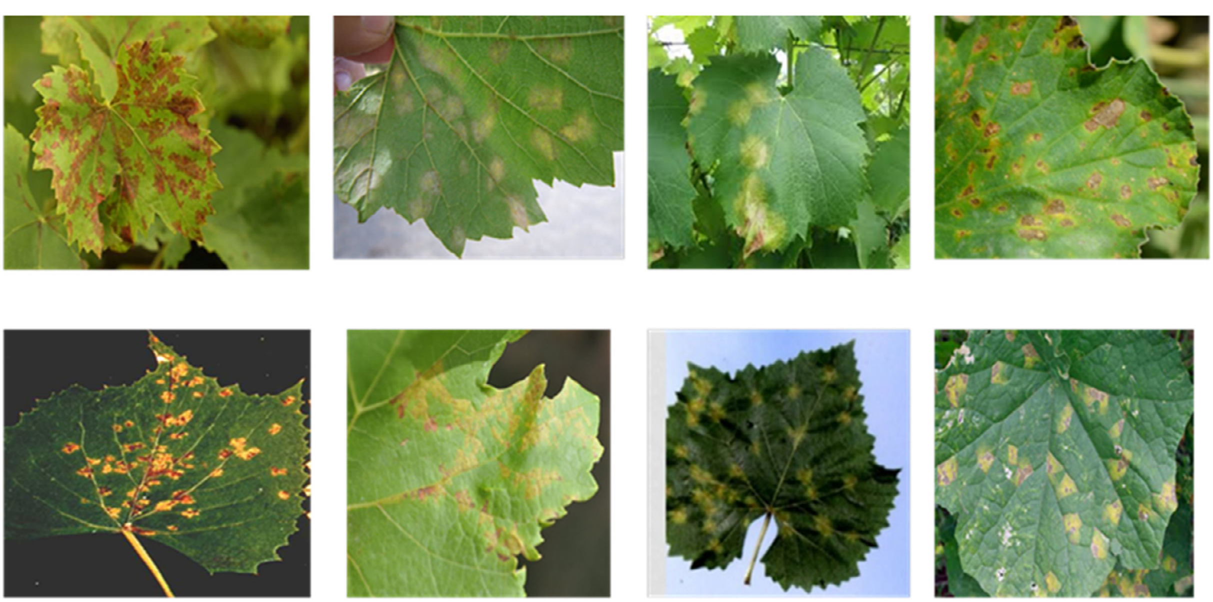

Fig. 8. The dataset utilized for calibrating the One Class SVM model for the downy mildew infection.

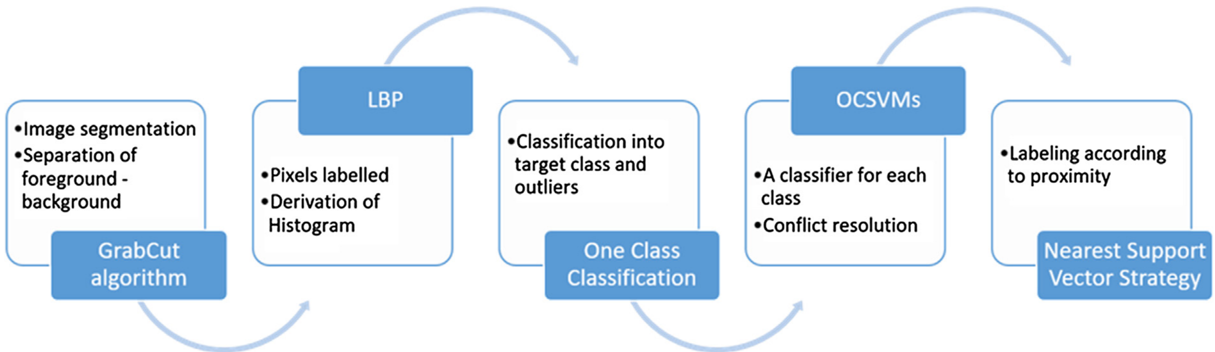

Fig. 9. Schematic depiction of the utilized steps.

All the employed steps of the presented approach are summarized schematically in the following block diagram (Fig. 9).

3. Results

3.1. Validation of the developed disease classification framework

Initially, a total of eight vine leaf pictures concerning each of the four health conditions were utilized healthy condition, powdery mildew, black rot and downy mildew infected) as input data to the One Class SVM. The One Class SVM that was trained in vine leaves and was further applied for disease recognition in 18 different leaf plant species demonstrated an efficient generalization capability for each case. Conflict resolution proved to be crucial, for the accurate classification of more than 50% of the cases, reaching 100%.

The models recognizing the healthy plant condition and the three mentioned diseases (powdery mildew, black rot, downy mildew) have all been trained using vine leaf samples but there is the potential for the recognition of the afore mentioned diseases in variety of crops.

The powdery mildew presence was tested on 10 samples of each crop and appears to be successful either with the direct recognition from One Class Classifier or more One Class Classifiers, resulting in a conflict situation which is resolved with the help of the Nearest Support Vector Strategy. The examined crops were: *Vitis vinifera, Brassica Oleraceae var capitata, Cucurbita pepo, Lagenaria siceratia, Cucumis sativus, Cumis melo, Citrullus lanatus, Cucurbita maxima, Solanum melongena, Cucurbita moschata, Capsicum annuum, Fragaria ananassa, Pisum sativum and Malus pumila.* The only exception of the species that was tested and not successfully recognized was *Solanum lycopersicum.*

Concerning the black rot infection of the following crops the crop status recognition was tested on 10 samples of each crop and appears to be successful with or without the assistance of conflict resolution: *Vitis vinifera, Malus pumila, Fragaria ananassa, Pyrus communis, Brassica oleraceae var italica, Brassica oleracea var capitata.*

As regards downey mildew infection it is tested on 10 samples of each crop and detected with or without conflict resolution at the crops including *Vitis vinifera, Lactuca sativa, Cucumis sativus, Citrullus lanatus, Brassica oleracea var botrytis* except for *Brassica oleraceae var capitata.*

More precisely, the recognition potential concerning the health status for each one of the afore mentioned crop species is presented in Table 1. The marked cells represent the all the tested combinations whether it is successful or not.

As it demonstrated in Table 1, the healthy status is successfully recognized for all the plant samples. In the case of powdery mildew identification, the infection is correctly identified for the majority of the plant sample except for the *Solanum lycopersicum* that is misclassified as health (marked as Fail in Table 1). The models behavior appears to be similar for *Brassica oleraceae var capitata* concerning downy mildew recognition.

According to Table 1, out of a total of 46 tested combinations, the 44 were successfully classified, giving a total success rate of 95%. Regarding its separate condition, the success rate was 100% for the healthy and black rot infected leaf samples, 93% for powdery mildew (14 correctly identified samples out of 15 tested) and 83.3% for downy mildew infection (5 successfully identified out of 6 tested). In order to evaluate the generalization potential of the current application were chosen only from different leaves than the one that were not included in the training set.

Table 1
. Recognition capability of the four health condition tested in leaf samples in a variety of crops.

	Healthy Status	Powdery Mildew	Black Rot	Downey Mildew
Vitis vinifera	x	x	x	x
Brassica oleraceae var. capitata	x	x	x	Fail
Brassica oleraceae var. botrytis	x			x
Brassica oleraceae var. italica	x		x	
Cucurbita pepo	x	x		
Lagenaria siceratia	x	x		x
Lactuca sativa	x			x
Cucumis sativus	x	x		
Cucumis melo	x	x		
Citrullus lanatus	x	x		x
Cucurbita maxima	x	x		
Solanum melongena	x	x		
Cucurbita moschata	x	x		
Capsicum annuum	x	x		
Fragaria ananassa	x	x	x	
Pisum sativum	x	x		
Pyrus communis	x		x	
Malus pumila	x	x	x	
Solanum lycopersicum	x	Fail		

3.2. The generalisation potential of One Class SVM from vines powdery mildew to other plant diseases

The One Class SVM model successfully labels powdery mildew infected vine leaves as ‘powderyHSV’ and stores them as XML. Fig. 10a depicts the testing of the model’s performance on *Cucumis sativus* (cucumber) leaves. A random sample was subjected to the classification process. The generalisation potential of the powderyHSV One Class SVM was proven through the positive identification of the infection on different plant species that the one used on training (Fig. 10b).

PowderyHSV has been further developed using vine images in order to expand its generalisation potential and precise identification regardless of conflict resolution. The generalisation considers powdery mildew was tested for identification in nine species including: *Vitis vinifera, Brassica oleracea, Cucurbita pepo , Lagenaria siceraria, Cucumis sativus, Cucumis melo, Citrullus lanatus, Cucurbita maxima* and *Cucurbita moschata*. For each of the species ten samples were utilized for the testing procedure. To ensure the accurate classification of the sample,

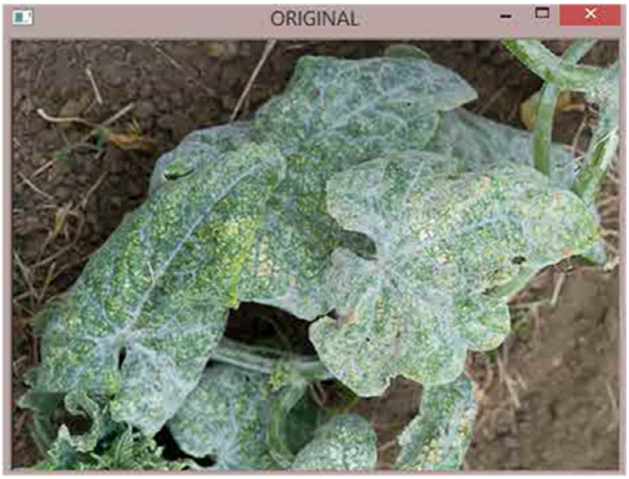

Fig. 10a. Arbitrary image of *Cucumis sativus* leaf used for evaluating the model of powdery mildew One Classifier.

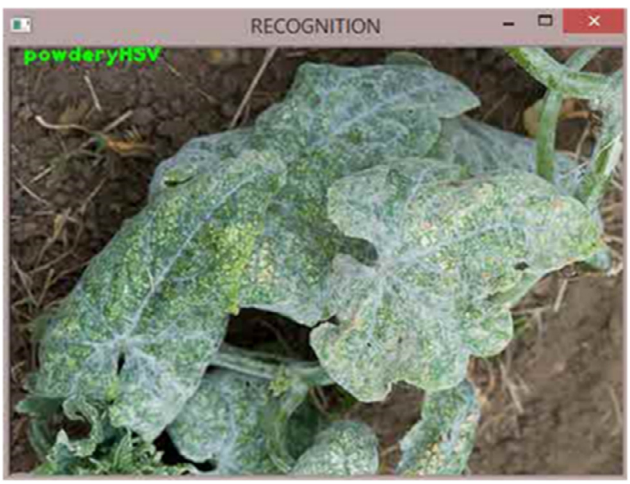

Fig. 10b. Identification of *Cucumis sativus* leaf powdery mildew infection as displayed on screen.

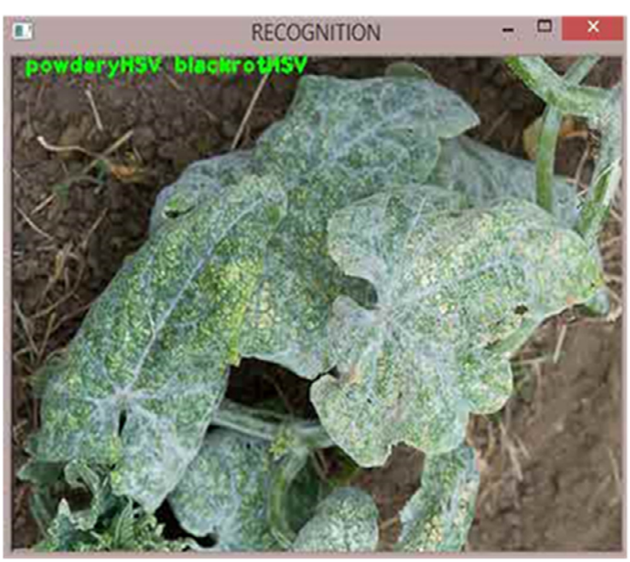

Fig. 11a. Conflict arises between the two One Class SVM models (powdery HSV-blackrotHSV) on a *Cucumis sativus* plant.

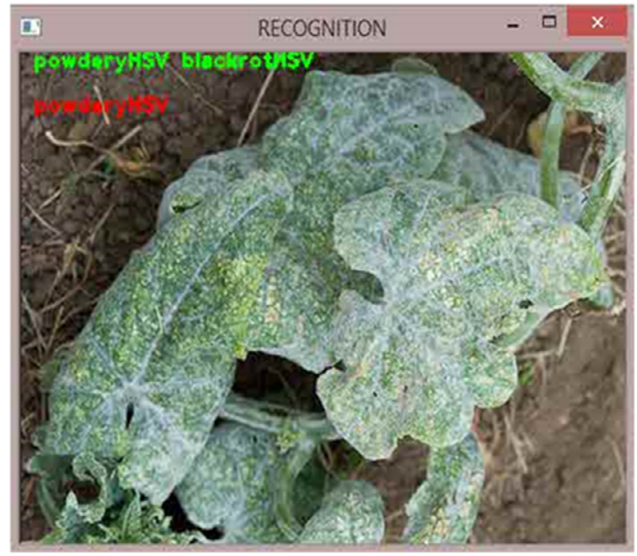

Fig. 11b. Conflict resolution between the two One Class SVM models (powdery HSV-blackrotHSV) leads to correct labelling as infected with powdery mildew.

an additional model ‘blackrotHSV’ has been also applied. Then, the observed symptoms appear to trigger the two models (Fig. 11a). In order to reach a conclusion regarding the leaf condition, conflict is achieved based on the proximity between support vectors and the new sample’s feature vector. The model representing the sample’s condition is correctly identified as powderyHSV (Fig. 11b). Similar conflict resolution was repeatedly achieved including combinations of the presented models (powderyHSV, downyHSV and blackrotHSV) and has always reached the correct conclusion concerning the health condition of the plant.

3.3. Generalisation of the vines black rot model to different crops diseases

The One Class SVM model called ‘blackrotHSV’ successfully labels black rot infected leaves after being trained on vines and it has been stored in XML format. Figs. 12a, 12b and 12c depict the model’s recognition capability on *Fragaria ananassa* leaf samples. For each of the species ten samples were utilized for the testing procedure.

4. Discussion

4.1. Segmentation technique

The presented approach is capable of achieving successful generalization by requiring for the training procedure with Support Vector Machines only 8 vine leaves samples randomly selected for each of the

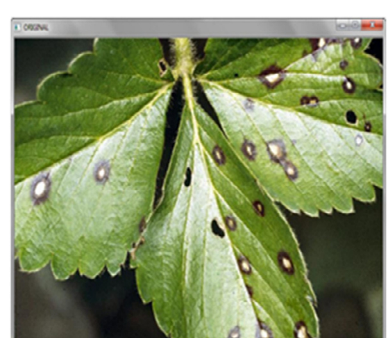

Fig. 12a. Arbitrary image of black rot infected *Fragaria ananassa* leaf that has been used for evaluating the black rot One Class Classifier.

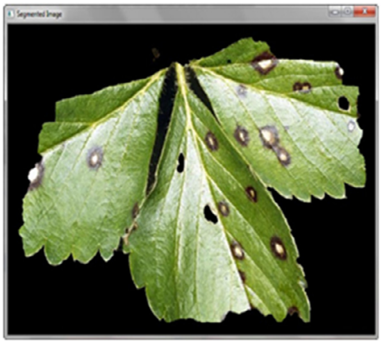

Fig. 12b. Image segmentation on *Fragaria ananassa* automatically captures the areas of interest.

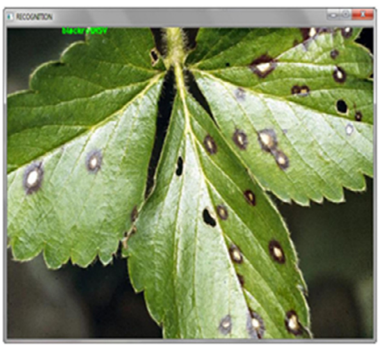

Fig. 12c. Identification of *Fragaria ananassa* black rot infection as displayed on scren.

four different health states (healthy, downy mildew, black rot, powdery mildew). The infected plant pictures were derived by personal collections by authors. The novelty of the current study lays on the GrabCut's algorithm high discerning capability of isolating only the leaf area for the total amount of the leaf samples pictures. In the event that there are more than one leaves that belong to different crop species depicted in the sample image, the GrabCut managed to isolate effectively only the leaf sample that is subjected to testing. For current application there is no special background needed for taking the leaves pictures, since the algorithm works effectively on natural scene. This makes the current application more robust and operational, since it doesn't require any special conditions and under which the pictures should be non-destructively acquired for example, shading, leaf position and geometry and illumination. Furthermore, no special device calibration (camera settings) is necessary such as zoom in, focus and shutter settings. The above mentioned characteristics render the application user friendly, very operational and easily adaptable to all the possible scenarios. The employment of the GrabCut algorithm through Gaussian Mixtures and elementary classification picks image areas that demonstrate significant variance in RGB pixel values.

4.2. Classification process and the features extraction process

The presented method relies on a number of One Class Classifiers are interrogated simultaneously to classify the current image samples from new unseen test leaf images. The classifiers are based on training data that correspond to a single disease and provide a binary classification between the infected and the health leaf. This approach produces a positive detection of certain leaf diseases, which means that is detected as outlier. However, the symptoms in some cases are detected as outliers for other diseases concerning the same crop. This could be explained from the position of the feature vector being in proximity to both one class classifier spheres. The representation of disease and healthy plant in terms of features extracted from the HS layers of healthy plants is the key of the definition of One Class Classifier for vine leaves which can generalize very accurately to the One class definition of many different plants. This capability emanates from the type of feature that have been used in the form of LBP histogram. The LBP provides the needed robustness to image transformation resulting from environmental factors like scaling, translation and rotations or illumination variations. The important information that relates to the health condition of the plant is captured due to the ability of the LBP histogram incorporating texture information corresponding to visual manifestation and the density of the symptoms. Every new image that is provided to the model, enriches its existing database and expands its recognition ability by including it as a new training example so that the new examples can be compared to enhanced database. Some limitations of the presented approach could possibly arise due to extrinsic factors such as image background and capture conditions and to intrinsic factors including segmentation and different disorders with similar symptoms. The above limitations are overcome through the GrabCut algorithm which is capable of overcoming intrinsic factors that may corrupt the segmentation procedure due to image background and capture conditions since it is very robust by isolating and extracting the area of interest (leaf). Additionally, the captured conditions regarding orientation and lighting are overcome by the feature extraction since LBP histograms are invariant to such variations. On the other hand, different disorders can be the source of similar symptoms that cannot be differentiated by the trained models. The conflict resolution overcomes that, by taking into account the proximity to the support vector.

The presented approach combines uniquely the advantages of Artificial Intelligence (AI) techniques with advanced imaging processing like GrabCut algorithm to isolate visual features like LBPs related to crop species health conditions. One Class Classification is a flexible AI technique that allows intelligent systems to discover knowledge in natural environments. The presented work takes advantage of the synergy between One Class Classifiers and achieves very accurate results of crop health condition by conflict resolution between competing classifiers. The presented scheme can further have expanded into detection of crops condition in order to adapt best crop management practices in the field of precision agriculture.

5. Conclusions

In the presented research a novel application of ascertaining the presence of four different health conditions including healthy, downy mildew, powdery mildew and black rot by using One Class Classification is demonstrated. The developed model was trained on vine leaves to identify four different health conditions. The novelty of the current application is high generalization capability which was proven through testing in various leaf samples belonging to different plant species. The results proved that the model was efficient for most of the cases. More specifically, 44 of the 46 tested plant disease combination were successfully classified, giving a total success rate of 95%. Conflict resolution has proven crucial, for the accurate classification of more than 50% of the cases, reaching an identification capability of 100%. Each newly added image that is fed to the model, enriches its existing database and expands its recognition ability. The presented application is capable of identifying the afore mentioned health conditions in plant species other than the already tested and of detecting conditions other than the already tested and classifying them as new categories.

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