Pixel-Based Classification Method for Detecting Unhealthy Regions in Leaf Images

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Abstract: In this paper, we present a pixel-based, non-probabilistic classification algorithm for the automatic detection of unhealthy regions in leaf images. The algorithm is designed to distinguish image pixels as belonging to one of the two classes: healthy and unhealthy. The task is performed in three steps. First, we perform segmentation to divide the image into foreground and background. In the second step, support vector machines are applied to predict the class of each pixel belonging to the foreground. And finally, we do further refinement by neighborhood-check to omit all falsely-classified pixels from second step. The result shown in this work is based on a model plant (*Arabidobsis thaliana*), which forms the ideal basis for the usage of the proposed algorithm in biological researches concerning plant disease control mechanisms.

1 Introduction

During the last years, image classification tasks have found tremendous appreciation in biological researches where a number of tasks are being simplified with the help of automated image classification. Plant diseases need to be controlled not only to maintain the quality of food produced by growers around the world but also to reduce food-borne illnesses from infected plants. Thus, automatic extraction of unhealthy regions in leaf images is useful for various biological research based on disease control mechanisms. There is a wide variety of plant diseases caused by environmental factors (nutrition, moisture, temperature etc) or by organisms (fungi, bacteria, viruses) that attack plants but in most cases one common symptom is changes in the color intensities in the infected regions of leaves. A good color variation model can be employed to distinguish healthy and unhealthy regions in leaf images. A probabilistic algorithm, employing a Gaussian mixture model (GMM) and a Bayesian classifier for classifying disease symptoms in *Arabidopsis* plants was presented in [SSK+10]. The results from Bayes-like classifiers can be inaccurate, because the estimation of a robust GMM is not always possible from real data. To

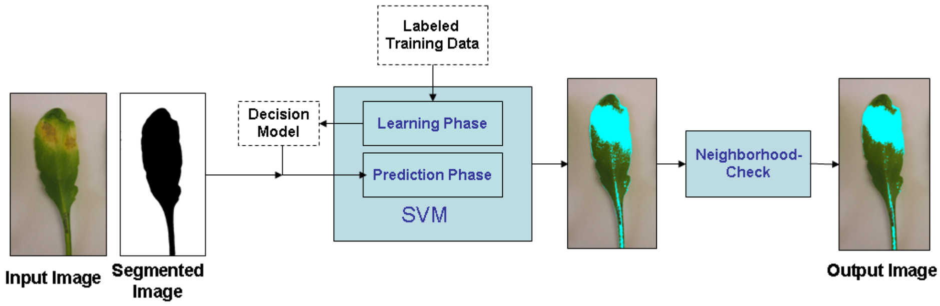


Figure 1: Overview of the proposed algorithm

overcome these limitations we propose here a different classification strategy. The algorithm described in this paper uses color feature space as input to a well-known machine learning algorithm (SVM) to classify an unlabeled pixel. Figure 1 gives an overview of the steps described in this paper. First a segmentation method, described in section 2, is applied to obtain a binary image with only foreground and background information. Then each pixel belonging to the foreground region is given as an input to a linear SVM classifier (described in section 3) for predicting the class to which it belongs. After all the pixels belonging to the foreground are classified, the neighborhood information is used to alter the result of pixels classified as unhealthy but does not match with the visual perception. The neighborhood-check method is described in section 4.

2 Segmentation

Besides reducing the computational cost in the next step, a good segmentation method can also improve the overall result. Therefore, we divide the image into foreground and background so that only the pixels belonging to the foreground could be considered for classification in the next step. The most influential region based image segmentation model was introduced by Mumford and Shah in 1989 [MS89]. Many models based on this functional and its derivatives have been proposed, e.g. [CV01, UPCB08]. In this work we use the segmentation method proposed in [SSK$^+$10]. The method uses convex energy functional [SHRW09] but with the I1I2I3 color space [Haf99] instead of HSV. Following [SHRW09] a convex energy functional in the I1I2I3 color space can be written as:

$$E(u, \boldsymbol{\mu}_{\text{obj}}, \boldsymbol{\mu}_{\text{bgd}}) = \int\limits_{\Omega} \left(f(I_{123}(\mathbf{x}), \boldsymbol{\mu}_{\text{obj}}) - f(I_{123}(\mathbf{x}), \boldsymbol{\mu}_{\text{bgd}}) \right) u(\mathbf{x}) \mathrm{d}\mathbf{x} + \lambda \int\limits_{\Omega} |\nabla u(\mathbf{x})| \mathrm{d}\mathbf{x}, \tag{1}$$

with

$$f(I_{123}(\mathbf{x}), \boldsymbol{\mu}) = w_1([I_{123}(\mathbf{x})]_{\text{I1}} - \boldsymbol{\mu}_{\text{I1}})^2 + w_2([I_{123}(\mathbf{x})]_{\text{I2}} - \boldsymbol{\mu}_{\text{I2}})^2 + w_3([I_{123}(\mathbf{x})]_{\text{I3}} - \boldsymbol{\mu}_{\text{I3}})^2 \tag{2}$$

denoting a weighted squared sum of the individual channels. For the results presented in this paper we use $w_{\text{I1}} = 0.1$ and $w_{\text{I2}} = w_{\text{I3}} = 0.45$. As additional input we use mean values for the foreground $\boldsymbol{\mu}_{\text{obj}}$ and background $\boldsymbol{\mu}_{\text{bgd}}$ and a smoothing parameter $\lambda \in \mathbb{R}$. The desired segmentation is a binary image $u : \Omega \subseteq \mathbb{R}^2 \to \{0, 1\}$. We minimize (1) using successive over-relaxation (SOR) to estimate the optimal u.

3 SVM classification

Support vector machine (SVM) is a state-of-the-art machine-learning algorithm that have found wide acceptance in recent years because of its ability to classify linear and non-linear data. SVMs have been applied with great success in many challenging classification problems processing large data sets. The basic concept was introduced in [CV95]. SVM is based on learning from examples, which means, it requires a separate set of training and testing data. The training algorithm builds a model that predicts the class of unknown input data. Thus SVM is a non-probabilistic classification method.

Training phase - offline

Suppose we have L number of training vectors belonging to two different classes, $(\mathbf{x}_i, y_i)$ where $i = 1, ..., L$ and y_i is either 1 (healthy) or -1 (unhealthy), indicating the class to which x_i belongs. SVM is based on the concept of finding a hyperplane which can be described by a set of points satisfying the equation:

$$\mathbf{w} \cdot \mathbf{x} + b = 0, \quad \mathbf{w} \in \mathbb{R}^n,\ b \in \mathbb{R} \tag{3}$$

where $\mathbf{w}$ is normal to the hyperplane and $b/||\mathbf{w}||$ is the perpendicular distance from the hyperplane to the origin. The goal here is to choose $\mathbf{w}$ and b so as to maximize the margin

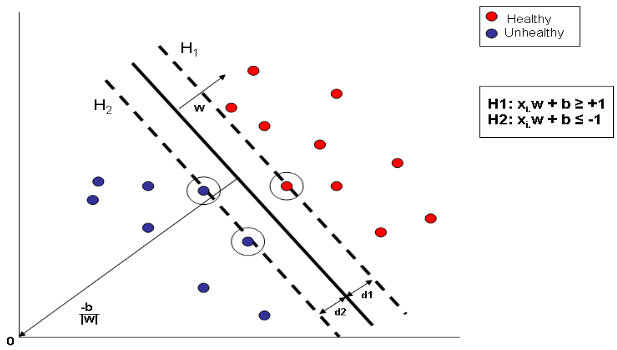


Figure 2: Hyperplane through two linearly separable classes. Points on the hyperplanes are called support vectors and forms the basis for predicting the class of unlabeled data

between two parallel hyperplanes H1 and H2 (see Figure 2). Thus our training data can be described by equation: $y_i(\mathbf{w} \cdot \mathbf{x_i} + b) - 1 \geq 0\ \forall_i$. The training part of SVM algorithm finds a $\mathbf{w}$ that leads to the largest b. The solution is well described in [Bur98].

Training data: We need a labeled training data, which serves as an input to the learning function. Like many other pixel-based classification methods, we exploit the color variation property of image co-ordinates in order to form a decision model. Since the components of I1I2I3 color space are uncorrelated, statistically it is the best way for detecting color variations. While I1 contains the illumination information, I2 and I3 mainly contains color information. Hence, we use only I2 and I3 in order to provide invariance to illumination changes. Thus the training data comprises of 2D color values, selected from healthy and unhealthy leaf images and labeled into three different classes. Though, inherently, SVMs are binary classifiers but it is easily possible to do a multi-class classification with SVMs by building a set of one-verses-one classifiers.

Prediction phase - online
In the prediction phase, all pixels labeled as foreground pixel in step 2 are classified into one of the two classes - healthy or unhealthy. Each new pixel, $\mathbf{x}'$ is classified by evaluating: $y' = \text{sign}(\mathbf{w} \cdot \mathbf{x}' + b)$, where $\mathbf{w}$ and b are obtained from the training part of the SVM algorithm.

4 Neighborhood-Check

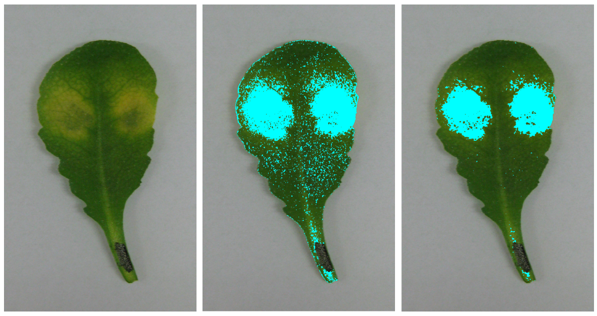
Output from the classification shows lot of pixels labeled as unhealthy, which to human eye looks otherwise. Here, we exploit the fact that usually the infected regions should be densely populated with infected pixels. We can, therefore, use the neighborhood classification information to alter the result of isolated pixels, classified as unhealthy. The algorithm works as follows: For each $(\mathbf{x}_i, y_i)$ with $y_i = -1$ (unhealthy), define the number of pixels which are classified as unhealthy in the neighborhood radius $n \in \mathbb{Z}$ as c_i. We perform the following:

$$\text{if } c_i < \frac{(2n+1)^2 - 1}{2}, \text{ then set } y_i = +1 \text{ (healthy)} \tag{4}$$

We used $n = 2$ to obtain the results presented in this paper. Figure 3 shows an example where the result from step 2 could be improved remarkably with the help of neighborhood-check.

5 Results

Figure 4 shows some outputs from the classification algorithm described above. The algorithm have been tested extensively on more than 500 infected leaf images. The testing images were obtained from biological experiments done in University of Gießen. The plants were infected with *Salmonella* bacteria and observed through time to investigate how the plant reacts and defends itself against the disease. The results obtained from this algorithm were quite convincing and could be easily used for such biological experiments. Figure 5 shows a comparison between the proposed and a probabilistic method [SSK+10].



(a) Input image (b) Before (c) After

Figure 3: (c) shows improved performance after applying neighborhood-check

It can be easily seen that the proposed algorithm outperforms the probabilistic method.

6 Conclusion

An automatic pixel-based classification method for detecting unhealthy regions in leaf images is presented in this paper. The algorithms have been tested extensively and promising results were obtained. Linear SVM has been used to classify each pixel. We have also shown how the results from SVM could be improved remarkably using the neighborhood-check technique. The presented algorithm could well be extended for other detection tasks which also mainly rely on color information, but extension to other features is easily possible.
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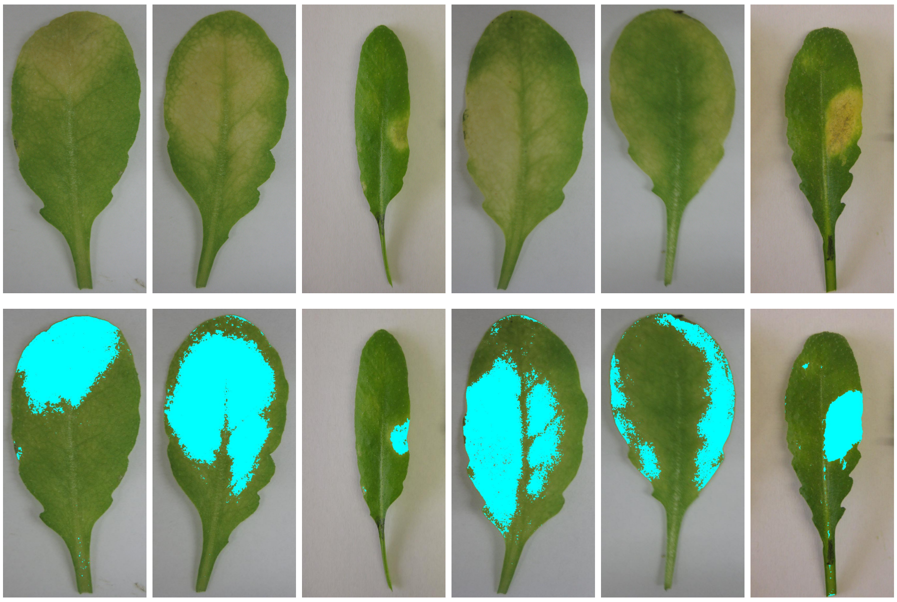
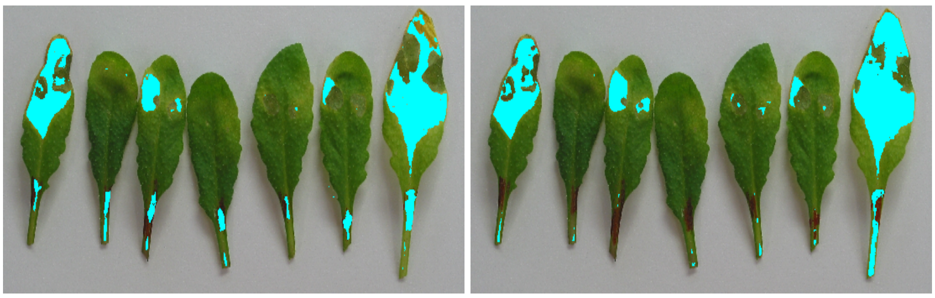


Figure 4: Classification Results - Top row shows input images and the bottom row shows outputs from the proposed classification algorithm



(a) Bayesian Classifier

(b) SVM Classifier

Figure 5: Example image showing result from probabilistic and SVM classification. Higher accuracy could be achieved by using SVM in the second step.

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