Detection of Late Blight in Potato Leaves Based on Multi-Feature and SVM Classifier

Wenjie Liu¹, Yongjun Zhang¹,a, Haisheng Fan²,b, Yongjie Zou¹ and Yongbin Qin⁴

¹,³Key Laboratory of Intelligent Medical Image Analysis and Precise Diagnosis of Guizhou Province, College of Computer Science and Technology, Guizhou University, Guiyang, China
²ZHUHAI ORBITA AEROSPACE SCIENCE&TECHNOLOGY Co., LTD. Oribita Tech Park, 1 BaiSha Road, TangJia DongAn, ZhuHai, China
⁴College of Computer Science and Technology, Guizhou University

azyj6667@126.com; bfan@myorbita.net

Abstract. Due to the influence of germs and viruses, plants often show various symptoms of diseases and insect pests during the growth process, which leads to a large economic loss of fruit farmers. It also brings a certain economic loss to our society, so prevent earlier and advise growers about plant diseases and insect pests have important value and significance. In this case, this paper proposes a detection method which is based on the combination of HOG, LBP and CSS features with Support Vector Machine (SVM) classifier. This method extracts the histogram of oriented gradients, texture, and color self-similar features of potato leaves, and then training samples with SVM classifier to detect late blight as early as possible in the early stages of potato growth. In addition, this paper proposes a method to increase virtual samples, that is, generating symmetrical samples according to the original samples. Due to the limitation of the number of collected samples, increasing symmetrical samples can expand the diversity of samples. The results show that this method can obtain a detection rate of 92.7%, and has better detection and recognition performance in practical application.

1. Introduction
Potato late blight is one of the important factors threatening its yield. The detection of potato leaves with late blight has been widely studied and concerned by researchers [1-3]. At present, some methods have been proposed. Y. Hu et al. [4] studied the hyperspectral imaging characteristics of leaves which is influenced by late blight, and used hyperspectral imaging systems to obtain hyperspectral data of potato samples with different degrees of infection and healthy potato samples to detect different degrees of potato late blight. M. Franceschini et al. [5] described the spectral changes during the
occurrence of potato late blight by using sub-demif optical drone imaging technology. A. Pande et al. [6] combined the symptom-based diagnosis method with plant disease prediction model to improve the accuracy of potato late blight detection.

For the past few years, computer vision and pattern recognition is developing rapidly, and machine learning methods have a good performance on target detection and recognition. Object detection based on machine learning mainly includes two stages: feature extraction and classification. At present, many methods have been proposed for feature extraction. The classic features include HOG feature [7], LBP feature [8], CSS feature [9], SIFT feature [10], HAAR feature [11], and so on.

Therefore, this paper proposes a method using HOG features, LBP features, CSS features to combined with SVM classifier to detect potato blight. The histogram of oriented gradients (HOG) [7] method proposed by Dalal, and it has achieved good results when applied to the fields of pedestrian detection and face recognition. In particular, Dalal applied HOG features to pedestrian detection and achieved excellent results. T. Ojala proposed the local binary pattern (LBP) feature [8]. After that, T. Ojala summarized the characteristics of LBP [12], which attracted wide attention. LBP features are well applied in many fields, such as texture classification and segmentation. According to the common characteristics of color features, walk proposed color self-similar (CSS) features [9], and applied them in various fields. SVM classifier [13] is a better classification method, which has used by many people.

2. The algorithm proposed in this paper

2.1. Data preprocessing

The experimental data in this paper are all from the data set published by the AI Challenger global AI challenge, and then the potato late blight samples are extracted through a script program. The disease-free samples are taken as negative samples and the late blight samples are used as positive samples. The proportion of the number of samples in the training set and the test set is 2:1, while the validation set is composed of different images from the training and test samples. Due to the number of training samples is not enough, this paper proposes to generate virtual samples to increase the sample size, that is, to expand the data by turning the original samples left and right, and then turning them up and down. The generated virtual samples not only expand the sample size, but also reflect the diversity of samples.

2.2. Algorithm flow

This paper proposes a method based on the combination of HOG, LBP, CSS features with SVM classifier to detect potato late blight. In this paper, the detection of potato late blight can be divided into two stages: training stage and detection stage. In the training stages, firstly, we need to create data sets for training, preprocess the data sets for training and detection; then extract the features of HOG, LBP and CSS from the existing data sets; after extracting the features, we need to train SVM classifier; finally, we get the final classifier.

In the detection stage, firstly input the detection image; then extract the characteristics of HOG, LBP and CSS from the input image; then detect whether the potato leaves suffer from late blight through the trained classifier; finally get the detection results. The algorithm flow is shown in Figure 1.

![Figure 1. Flowchart of algorithm](image-url)
3. Feature extraction

3.1. Histogram of oriented gradients feature and extraction method
Histogram of Oriented Gradients (HOG) feature is a kind of feature descriptors for calculating gradient amplitude and gradient direction. It has obtained great success in target detection and recognition. The extraction steps of hog features are as follows: Computing the gradient; Creating cell histogram; Combining cells into large blocks; Block normalization; Generate HOG feature description vector.

3.2. Local texture features and extraction methods
Local binary pattern (LBP) is a descriptor used to describe local texture features, which is mainly used for texture feature extraction. Its idea is to take the local area around each pixel, take the pixel value of the center pixel as the threshold, and use the generated binary value as the descriptor of the local image. The original LBP operator is defined in the $3 \times 3$ window, and the gray value of the pixel in the center of the window is used as a threshold to compare the gray values of adjacent 8 pixels. The position of the pixel point is marked as 1. If the adjacent pixel value is less than the center pixel value, the position of the pixel point is marked as 0. In this way, 8-bit binary numbers can be generated in the $3 \times 3$ fields. Converting a binary number to decimal is the LBP value of the central pixel, and obtain LBP feature description vector.

3.3. Color self-similar features and extraction methods
Color information is usually obtained in three channels in the color space. According to the similarity between the late blight with and without the blight in the leaf part, and the background also have a certain similarity. This similarity can be used to distinguish between late blight and no blight. The color self-similarity (CSS) feature can be used for detection of potato late blight. The CSS feature calculation steps are described as follows: Converting color space; Dividing blocks and counting color histograms; Calculating the similarity among blocks; The feature vector is normalized by L2 norm, and finally we can obtain an 8128-dimensional CSS color self-similarity feature vector.

4. Analysis of experimental results

4.1. Experimental samples
Due to the limitation of the number of original samples, this paper proposes a method to generate symmetrical samples based on the original samples to increase the diversity of the samples. As shown in Figure 2, the original positive and negative samples are first flipped left and right, and then flipped up and down to get the corresponding virtual samples. Figure 2(a) is a generated partially symmetric training positive sample, and Figure 2(b) is a generated partially symmetric training negative sample.

The experimental samples in this paper include training samples, test samples, and detection samples. The training samples have 1,248 negative samples and 1,208 positive samples, which are respectively inverted from 624 original training negative samples and 604 original training positive samples. The test samples are 640 negative samples and 560 positive samples, which are respectively inverted from 320 original training negative samples and 280 original training positive samples, and there are 140 detection samples. The positive samples are all images with late blight, the negative samples are disease-free images, and the training positive and test positive samples are normalized. The images of the training positive samples are normalized to $96 \times 160$ size, the test positive sample images are normalized to $70 \times 134$ size.
4.2. Comparison of LBP, HOG and CSS features
In this paper, LBP features, HOG features and CSS features of image are extracted and compared. As shown in Figure 3. Figure 3 is a det curve, which is a standard criterion used to measure the algorithm in target detection and target recognition. The vertical coordinate is the missed detection rate of the window. The lower the missed detection rate, the higher the detection rate. The abscissa is the false alarm rate of the window. The lower the false positive per window (FPPW), the better the detection effect. It is generally judged when the false alarm rate is $10^{-4}$.

It can be seen from Figure 3 that when the value of FPPW is $10^{-4}$, the performance of HOG feature is the best, which means that the detection rate of HOG feature is the highest, that of CSS feature is the lowest, and that of LBP feature is higher than that of CSS feature. Their detection rate is shown in Table 1. Because CSS features are easy to be influenced by the environment and light factors, the detection rate of CSS features in the target detection is generally low, it is rarely used in the target detection alone, so in the detection of potato late blight, the detection effect of extracting image CSS features is poor.

4.3. Comparison of LBP and HOG features and the combination of LBP and HOG features
LBP features extract the texture of potato leaves, and HOG features extract the contour information of potato leaves. When extracting potato leaves features, they can complement each other and detect the late blight of potato leaves more accurately. Therefore, this paper combines LBP features with HOG features, as shown in Figure 4. When the value of FPPW is $10^{-4}$, the performance of the LBP + HOG features is significantly better than that of LBP features and HOG features. Their detection rates are shown in Table 1, indicating that the LBP + HOG features can obtain good results in the detection of potato late blight.

4.4. Comparison of LBP and CSS features and the combination of LBP and CSS features
As can be seen from Figure 5, CSS features have obtained poor results in detecting potato late blight, but the combination of CSS features and LBP features can obtain high detection rate. As shown in Figure 5, when the value of FPPW is $10^{-4}$, the performance of the LBP + CSS features is significantly better than that of LBP features and CSS features, and their detection rates are shown in Table 1. The results showed that LBP + CSS features could be complementary to each other in the detection of potato late blight.

4.5. Comparison of CSS and HOG features and the combination of CSS and HOG features
The above content introduces the combination of LBP and HOG features. The combination of CSS and LBP features can complement each other in the detection of potato late blight and improve the detection rate. Therefore, the CSS features and HOG features are also combined. The results are shown in Figure 6. When the value of FPPW is $10^{-4}$, the performance of CSS + HOG features is
slightly better than HOG features, indicating that the detection rate of the HOG + CSS features is slightly higher than that of HOG features. The CSS + HOG features is used to detect potato blight. The complementary effect played by China is not obvious.

4.6. Comparison of HOG, CSS and LBP features fusion with other features

Although the effect of combining CSS features with HOG features is not good, the detection rate of combining LBP, HOG and CSS features is significantly improved, as shown in Figure 7. When the value of FPPW is $10^{-4}$, the performance of the LBP + HOG + CSS features is significantly better than that of LBP + CSS, LBP + HOG and CSS + HOG features, which shows that the combination of the three features can obtain better feature complementation in the detection of potato late blight, and the detection rate of the LBP + HOG + CSS features reaches 92.7%.

![Figure 3. Comparison of LBP feature, HOG feature and CSS feature](image3.png)

![Figure 4. Comparison of LBP feature, HOG feature and the combination LBP and HOG feature](image4.png)

![Figure 5. Comparison of LBP feature, CSS feature and the combination of LBP and CSS feature](image5.png)

![Figure 6. Comparison of CSS feature, HOG feature and the combination of CSS and HOG feature](image6.png)
Detection result

The combination of multiple features is a commonly used method for target detection. In this paper, the three features of LBP, HOG, and CSS are combined to train a model using the SVM classifier. Partial results obtained by using this model to detect potato detection samples are shown in Figure 8. The test samples include potato leaves with late blight and disease-free potato leaves. The first three lines are potato leaves with late blight, and the last line is potato leaves with no disease. As can be seen from the figure below, for late blight, all potato leaves can be detected, but for potato leaves without late blight, there may still be some false detections, such as the eighth picture in the last row. In general, the detection effect using three features combined with the SVM classifier is better.

### Table 1. Detection rate and dimension of different features

| Features      | Dimension | Detection rate |
|---------------|-----------|----------------|
| LBP           | 6195      | 67.8%          |
| CSS           | 8128      | 41.25%         |
| HOG           | 3780      | 71.15%         |
| LBP+CSS       | 14323     | 87.7%          |
| LBP+HOG       | 9975      | 86.15%         |
| HOG+CSS       | 11908     | 72.8%          |
| LBP+HOG+CSS   | 18103     | 92.7%          |
5. Conclusion
This paper proposes a multi-feature combination method based on machine learning to detect potato leaves with late blight. Early detection of potato leaves with late blight can take relevant methods to treat potatoes with late blight as early as possible, thereby reducing certain economic loss. This method combines LBP, HOG and CSS features and uses SVM classifiers to achieve better detection results. Due to the limitation of the number of samples, this paper also proposes a method of generating symmetrical samples to increase the number of samples. This method can also be extended to samples detected by other targets.

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