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Recognition of Paddy Plant Diseases Based on Histogram Oriented Gradient Features

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Abstract: In the field of agriculture, paddy cultivation plays a very important role. But the growth of paddy plants is affected by various diseases. There will be a decline in the production, if the diseases are not recognized at an early stage. The main goal of this work is to build up an image recognition system that can classify the paddy plant diseases affecting the cultivation of paddy plant namely brown spot, bacterial blight and leaf blast. The features from the disease affected portion are extracted using Histogram Oriented Gradient (HOG) features. Then these features are given as input to the Support Vector Machine (SVM) in order to recognize their category. By this approach one can detect the disease at an early stage and thus can take necessary steps in time to minimize the loss of production. The disease recognition accuracy rate is 97.73%.

Keywords: Agriculture, Accuracy Rate, Computer Vision, HOG, Pattern Classification, SVM Classifier.

1. INTRODUCTION

India is an agriculture based country that has many people working in the agriculture industry. The agricultural sector plays an important role in economic development by providing rural employment. Paddy is one of the nation's most important products as it is considered to be one of India's staple food and cereal crops and because of that, many efforts have taken to ensure its safety, one of them is crop management of paddy plants. Paddy plants are affected by various fungi and bacterial diseases. This work focuses on recognizing two paddy plant diseases, namely Bacterial Blight Disease (BBD) and Leaf Blast Disease (LBD). The proper detection and recognition of the disease is very important in applying required fertilizer. BBD is caused by Xanthomonas oryzae. It causes wilting of seedling and yellowing and drying of leaves. LBD is caused by fungus Magnaporthe oryzae. Initial symptoms appear as white to gray-green lesions or spots, with dark green borders. Older lesions on the leaves are elliptical or spindle-shaped and whitish to gray centers with red to brownish borders. Some resemble a diamond shape, wide in the center and pointed toward either end. The main objective of this work is to develop a system for recognizing the paddy plant diseases using image processing technique. This paper is organized as following sections. Related work is described in section 2. The proposed work is described in section 3. Feature Extraction is described in section 4. Classification is described in section 5. Experimental results are discussed in section 6. Conclusion and future work are illustrated in section 7.

2. RELATED WORK

Paddy plant disease recognition system has the potential to be a natural and powerful tool supporting many farmers and agriculture based industry. This recognition system helps in applying required fertilizer at an early stage to minimize production. This has motivated many researchers in developing image based recognition system of paddy plant diseases as a very active research area. A work based on pattern recognition systems is proposed for identification and classification of three cotton leaf diseases, namely Bacterial Blight, Myrothecium, Alternaria. Image Segmentation is done using active contour models. Adaptive Neuro-fuzzy inference system used Hu's moments as features for the training method. The classification accuracy is 85 percent [1].

A work has addressed the problem of diagnosis of diseases on cotton leaves using Principal Component Analysis and Nearest Neighborhood Classifier. It involves diseases like Blight, Leaf Narcosis, Gray Mildew, Alternaria and Magnesium Deficiency. The classification accuracy is 95 percent [2]. A novel method was presented for robust and early Cercospora leaf spot detection in sugar beet using hybrid algorithms of template matching and support vector machine. This method is robust and feasible for early detection and continuous quantization under natural daylight conditions. In some cases the detection becomes complex due to the complex changes of external environment [3].

A paper has incorporated the digital image processing techniques to eliminate the manual inspection of diseases in rice plant that usually occur in Philippine's farmlands namely Bacterial leaf blight, Brown spot and Rice blast. The disease identification accuracy is 100 percent around 134 sample images [4]. This work has attempted to identify the four major paddy diseases in the Indonesia, namely leaf blast, brown spot, bacterial leaf blight and tungro. Fractal descriptors are used to analyze the texture of the lesions. The disease identification accuracy is 83 percent [5].

A mobile application for paddy plant disease identification system was developed using fuzzy entropy and Probabilistic neural network classifier that runs on Android mobile's operating system. It involves four types

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of diseases, namely brown spot, leaf blast, tungro and bacterial leaf blight. The accuracy of paddy disease identification is 91.46 percent [6]. A prototype system was developed for diagnosing paddy diseases, namely blast disease, brown spot and narrow brown spot disease. RGB images are converted into binary images using automatic thresholding based on local entropy threshold and Ostu method. The paddy diseases are recognized with 94.7 percent accuracy [7].

A diagnostic system was developed to recognize the paddy diseases, namely blast disease, brown spot and narrow brown spot. RGB images are converted into binary images using variable, global and automatic threshold based on Ostu method. The paddy diseases are recognized with 87.5 percent accuracy [8]. An image recognition system was developed to recognize paddy diseases commonly found in Sri Lanka, namely rice blast, rice sheath blight and brown spot. The classification accuracy is 70 percent around 50 sample images [9]. A software prototype system which involves both image processing and soft computing technique was described for rice disease detection based on the infected images of various rice plants. The diseased images are classified using Self Organizing Map (SOM) neural network. The transformed image does not yield a better classification compared to the original image [10].

3. PROPOSED METHODOLOGY

This work proposes an image recognition system for identifying the paddy plant diseases that first involves pre-processing, feature extraction and classification.

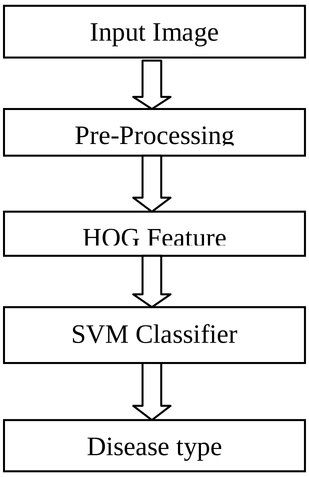

Fig1. Block diagram of the proposed work

In pre-processing, the particular affected portion is manually cropped and then it is converted into gray images for further processing.

4. FEATURE EXTRACTION

4.1 Histogram Oriented Gradient (HOG) Features

The Histogram of Oriented Gradient (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The procedure includes events of angle introduction confined bits of a picture. This technique is like a scale-invariant element change descriptors, however, vary in that it is processed on a thick framework of consistently divided cells and utilizations covering nearby different standard for enhanced precision.

4.1.1 Gradient Computation

In order to find the gradient, the gray scale image is filtered to get the x and y derivatives of filters The most common method is to apply the 1-D centered, point discrete derivative masking. Specifically, this method requires filtering the color or intensity data of the image with the following filter kernels:

D_x= [-1 0 +1] and D_y= [-1 0 +1] ^{T}

After finding x and y derivatives (Ix and Iy), the magnitude and orientation of the gradient are calculated:

$$|G| = \sqrt{I_x^2 + I_y^2} \quad \text{and } \theta = \arctan \frac{I_y}{I_x}$$

The orientation calculation method returns values between [-180◦, 180◦]. Since unsigned orientations are desired for this implementation, the values which are less than 0◦ is summed up with 180◦.

4.1.2 Orientation Binning

The next step is to calculate the cell histogram for descriptor blocks. The 8x8 pixel size cells are computed with 9 orientation bins for [0◦,180◦] interval. For each pixel's orientation, the corresponding orientation bin is found and the orientation's magnitude |G| is voted to this bin.

4.1.3 Descriptor Blocks

To normalize the cells' orientation histograms, they should be combined into blocks. From the two main blocks, geometric, the implementation uses R-HOG geometry. Each R-HOG block has 2x2 cells and adjacent R-HOGs are overlapping each other for a magnitude of half-size of a block.

4.1.4 Block Normalization

Although there are three different methods for block normalization, L2-Norm normalization is implemented using norm (vec) method:

$$f = \frac{v}{\sqrt{||v||_2^2 + e^2}}$$

4.1.5 Detection Window

Each R-HOG block has 2x2 cells in which each cell is 8x8 pixels, which also has 1x9 histogram vector each. So the overall size of R-HOG descriptor of a window is given by 144 values. Final vector size= 2 blocks horizontally x 2 blocks vertically x 4 cells per block x 9 bins per histogram = 144 values.

5. CLASSIFICATION

5.1 SVM Classifier

Support Vector Machine (SVM) is based on the principle of Structural Risk Minimization (SRM). Like Radial Basis Function Neural Network (RBFNN), SVM machines can be used for pattern classification and nonlinear regression. SVM builds a direct model to gauge the cache capacity utilizing non-straight class limits taking into account support vectors. In the event that the information is

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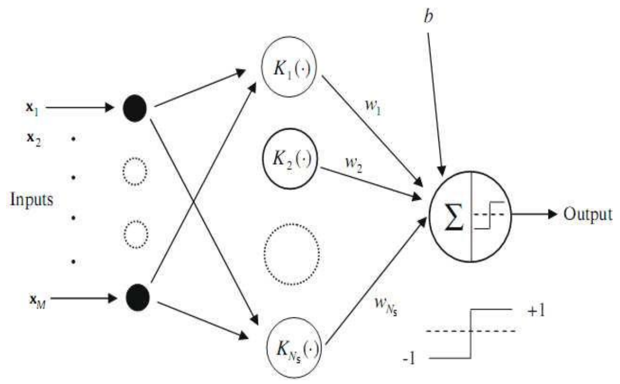
directly isolated, SVM trains straight machines for an ideal hyper plane that isolates the information without blunder and into the most extreme separation between the hyper plane and the nearest preparing focuses. The preparation indicates that are nearest the ideal isolating hyper plane are called support vectors.



In figure 1, feature vector (termed as pattern) is denoted by x= (x_1, x_2, · · ·, x_M) and its class label are denoted by y such that y = {+1, −1}. SVM maps the info designs into a higher dimensional element space through some nonlinear mapping picked from the earlier. A direct choice surface is then built in this high dimensional element space. Consequently, SVM is a direct classifier in the parameter space, however, it turns into a nonlinear classifier as an after effect of the nonlinear mapping of the space of the info designs in the high dimensional component space.

6. EXPERIMENTAL RESULTS

In the training phase, Histogram Oriented Gradient features are extracted to identify three classes of diseases brown spot, bacterial blight and leaf blast disease. 144 HOG features are extracted from the diseased region and they are invariant to geometric and photometric transformations. While testing the disease, the same 144 features are extracted. Using SVM the test features compare with train features and it recognizes the accurate disease based on maximum distance value.
Total number of diseases affected images (3 classes) = 120 images.
Total number of training images = 90 images (each class contains 30 images)
A total number of testing images = 30 images (each class contains 10 images).

Table1. Confusion Matrix for HOG using SVM

Paddy Plant Diseases Name	TP	FN	FP	TN
Brown Spot	10	0	0	20
Leaf Blast	9	1	1	19
Bacterial Blight	9	1	1	19

Table2. Performance Table for HOG using SVM

Feature + Classifier	Precision (%)	Recall (%)	Accuracy (%)	F -score (%)
HOG+SVM	93.33	93.33	97.73	93.33

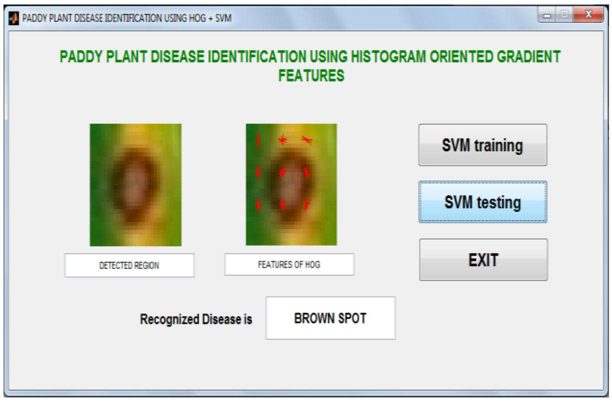


Fig2. GUI for brown spot disease recognition using HOG+SVM

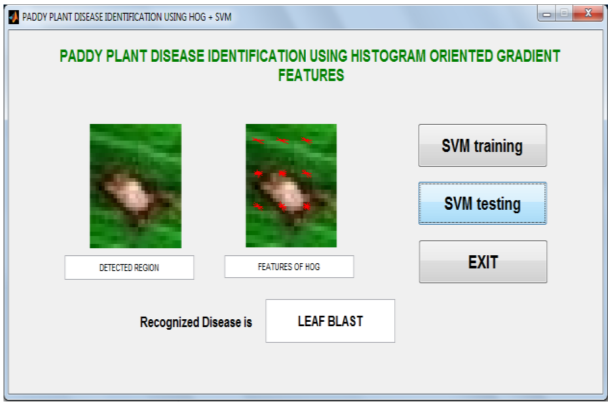


Fig3. GUI for leaf blast disease recognition using HOG+SVM

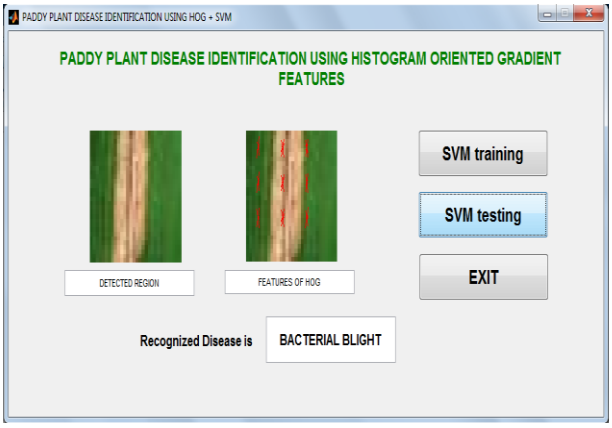


Fig4. GUI for bacterial blight disease recognition using HOG+SVM

7. CONCLUSION AND FUTURE SCOPE

The image processing techniques were used to establish the classification system. In this work HOG feature is used to extract features from the disease affected images. Then these features are used to recognize and classify the images using SVM. This work mainly concentrates on three main diseases of paddy plant, namely Brown spot, Leaf blast and Bacterial blight. It is valuable for ranchers and farming related inquires about. Result demonstrated that the model is skilled to anticipate the sickness with precision of 97.73% utilizing SVM.

For future work, some option strategies can be utilized to concentrate highlights and some different classifiers can be utilized to enhance the outcome exactness.

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