Maize Leaf Disease Image Classification Using Bag of Features

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Abstract — Image classification is an image grouping based on similarities features. The features extraction stage is a crucial factor for classifying an image. In the conventional image classification, the features commonly used are morphology, color, and texture with various derivative features. The type and number of appropriate features will affect the classification results. In this study, image classification by using the Bag of Features (BOF) method which can generate features automatically. It consists of 4 stages: feature point location by using grid method, feature extraction by using Speed Up Robust Feature (SURF), clustering word-visual vocabularies by using k-means, and classification by using Support Vector Machine (SVM). The classification data are maize leaf images from the PlantVillage-Dataset. The data consists of 3 types of images: RGB, grayscale, and segmentation images. Each type includes four classes: healthy, Cercospora, common rust, and northern leaf blight. There are 50 images for each class. We used two scenarios of testing for each type of data: training and validation, 70% and 80% images for training, and the rest for validation. Experimental results showed that the validation accuracies of RGB, grayscale, and segmentation images were 82%, 77%, and 85%.

Keywords – Bag of features; Classification; Maize leaf disease images; Speeded-up Robust Features, Support Vector Machine.

I. INTRODUCTION

Image classification is a grouping of images that have similar features. The conventional images classification requires a determination of features manually. Commonly used features are morphology, color, and texture with all derivative features. Morphology features include axis ratio, diameter, perimeter, complexity, rectangularity, and sphericity. Color features include mean, skewness, and kurtosis. Texture features include the Gray Level Co-Occurrence Matrix (GLCM) [1], [2], [3], [4]. Type and number of features affect the classification results.

The leaf image is one object to classify diseases. In this study, the classification of diseases on maize leaves was carried out. Several studies using maize leaf, including Al Hiary et al. classified images of 16 types of food crops including maize. The classification was carried out to detect six disease classes. These classes were early scorch, cottony mold, as mold, late scorch, and normal. Image processing applied to the research were preprocessing to convert RGB images to green channels, segmentation using thresholds, Gray Level Co-occurrence Matrix (GLCM) for feature extraction, and classification using the Backpropagation Neural Network method. The results showed the classification accuracy rate up to 94.67% [5].

Cao et al. conducted maize disease detection based on six classes: maize big spot disease, small maize spot disease, maize gray spot disease, maize curvularia lunata, maize circle spot disease, and maize brown spot disease. The image size used for the testing process was 148x256 pixels. The Backpropagation Neural Network method was used as the Classification method. Stages of the classification process were preprocessing, threshold segmentation, and feature extraction. The feature extraction was performed based on area, perimeter, circular degree and position of gravity. The Accuracy results showed a percentage of up to 88.2% [6].

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Alehegn classified the maize diseases into four classes: common rust, leaf blight, healthy leaf, and leaf spot. The testing data is 800 images with 200 images of each class. The test results showed that the average level of accuracy is 94.4% [7].

Mohanty et al. Classified 14 types of food crops, including maize. Disease classes consist of 26 classes. The testing used images in vast numbers, i.e., 54,306 images. Deep Learning Conventional Neural Network (CNN) used for classification while the CNN architecture was AlexNet and GoogleNet. The classification results showed an accuracy of 31.4% [8].

Aravin et al. performed the classification of maize plant diseases with Bag-Features and Support Vector Machine. The classes consist of 4 categories, namely Cercospora, common rust, northern blight leaf, and healthy leaf. The testing results of the BOF and the statistical feature extraction method produced an accuracy of 83.7% and 81.3%, respectively [9]. Research [5-7] still uses manual feature extraction, research [8] obtained low accuracy, and research [9] has the opportunity to increase accuracy.

In this study, classification was carried out on maize leaf images. The images consist of 4 classes: normal, downy mildew, leaf blight, and leaf rust. The novelty of this research is classification using Bag-of-Feature consisting of 4 stages: divide image with grid method, feature extraction using Speeded-Up Robust Features (SURF), clustering word visual vocabulary by using k-Means and Classification by using Support Vector Machine.

II. RESEARCH METHOD

Bag-of-Feature Method (BOF) is a collection of features contained in an image. For example, in the human face image, the features consist of ears, nose, mouth, hair, chin, earrings, background color, and so on.

In the image of maize leaves, features can be leaves, leaf bones, leaf color, disease, background color, etc. BOF does not need to define the features. It can instantly recognize automatically through the features contained in an image.

Generally, BOF consists of 3 stages, i.e., feature extraction, word vocabulary clustering, and BOF feature construction, by checking the number of features existing in each cluster. The application of the BOF method has been used for medical images [10], [11], satellite images [12], [13], and images for agricultural purposes [14], [15].

A. Feature Extraction Using SURF

SURF is a feature detection method that was first made by Bay et al. in Zurich [16]. SURF emphasizes noise reduction, quick calculation, and in-plane rotation invariant. SURF procedures can be divided into three parts:

1. Interest point detection
2. Interest point description
3. Interest point matching

a) Interest Point Detection

Interest point is the best point of an image containing much information and is stable against interferences. The detector used to detect interest points is blob detection. A blob is a region in the image having constant values or variation of specific values. Blob detection is used to determine the Hessian matrix determinant of an image [17]–[19]. For an identified image I, there is the Hessian matrix H (x, σ) = at x with the scale σ shown in equation 1,

$$H\,(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \qquad (1)$$

with $L_{xx}(x,\sigma)$ is a convolution of the second Gaussian derivative $\frac{\partial^2}{\partial x^2}\,g\,(\sigma)$ in the image I at point x. This also applies to $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$.

Determinants of the Hessian matrix use the Haar wavelet function [20], [21]. The Hessian matrix determinant has an invariant nature of scale, a stable algorithm, and a good loop.

When the image has a different size, the comparison of image features will be difficult. One of the solutions is by using a scale comparison method. The operation executed on the image is smoothing operation with Gaussian and then followed by sub-sampling which is performed from the lowest to the highest level of the pyramid. Filters used in this method can be a matrix of different sizes. [22].

b) Interest Point Description

The feature description is observing the dominant orientation of the image interest point. The next step is to comparing interest points with the related features in the comparison image by using Haar wavelet. Feature descriptions in the Haar wavelet use gradient histogram in four groups as shown in Equation 2,

$$v = \left(\textstyle\sum d_x, \sum d_y,\, \sum|d_x|,\, \sum|d_y| \right) \qquad (2)$$

with d_x is haar wavelet horizontal response, and d_y is a haar wavelet vertical response.

c) Interest Point Matching

At this stage, the comparison of the results of the calculation process has been made. If there is a difference, it will be indicated by the Hessian trace matrix.

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B. Word Visual Vocabulary Clustering Using K-Means

Word vocabulary is a term to display all words that appear in text classification. This is the same as applied to an image that shows all possible features. Clustering is needed to group similar features. Clustering uses the k-means method.

K-means clustering works iteratively until it reaches a stable class condition. With k-means clustering, the features can be reduced by only using 80% of the features that have existed through the previous process [23].

C. Support Vector Machine

Support Vector Machine (SVM) determines the best hyperplane that separates data between classes. The best hyperplane is the most significant margin between classes. Distance is measured from the outermost data points of each class. In Fig.1, an illustration of SVM is shown.
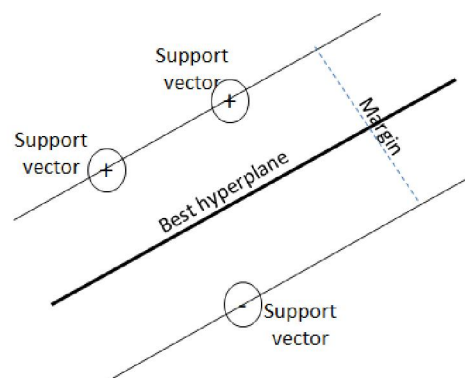

Fig.1. Support Vector Machine [24]

D. Experimental Data

This study uses the data standards of maize leaves from PlantVillage-Dataseta. PlantVillage is an online collection of data and information about more than 200 agricultural plants. The data consists of 3 types: RGB, grayscale, and segmented images. Each type includes four disease classes: healthy, Cercospora, common rust, and northern leaf blight. There are 50 images for each class. Fig.2 shows the visualization of pests and diseases.
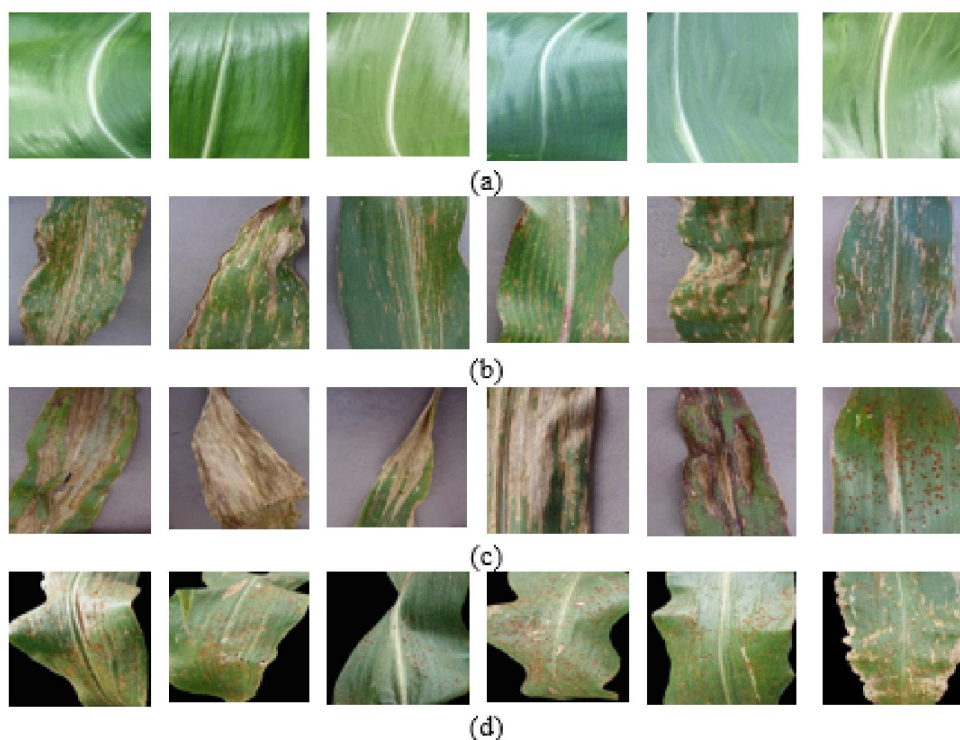

Fig.2. **M**aize Leaf Image Classes: (a) Healthy, (b) Cercospora, (c) Common Rust, and (d) Northern Leaf Blight.

E. Maize Diseases

a) Cercospora

Cercospora is the most often disease found in maize plants. Cercospora attacks maize plants aged 1 to 2 weeks. Symptoms of Cercospora on maize leaves appear as the increasing of the chlorotic, which is parallel to the leaf bone. This disease also attacks the whole maize plant so it cannot produce fruit. If it produces fruits, they have poor quality and inconsumable. Cercospora is caused by Peronosclerospora maydis and Peronosclerospora philippinensis fungi [25].

b) Common rust

Common rust is caused by Helmithosporium turcicum. The initial symptoms of Common rust are small patches, which then develop elongated and elliptical. Hawar has a length of 2.5 to 15 cm. if common rust is not treated as soon as possible, the plants will die [25].

c) Northern leaf blight

Northern leaf blight is caused by Puccinia polysora. Northern leaf blight symptoms are similar to hawar, but the causes are different. Initially, the Northern leaf blight is small and round in size. The symptoms are found in the upper and lower maize leaves. The disease spreads through wind and can occur throughout the season [25].

III.   RESULT

In this study, the Bag of Feature algorithm was constructed as follows:

1. Initialize the number and name of the category or class. Split the data into two groups for each category; 35 images for training and 15 images for validation.
2. Select feature points locations using the Grid method by dividing the image into several equal parts. The Grid size is [8 8], and the block width size is [32 64 96 128].
3. Extracting the features of training images for each category produce 143,360 features per category. The number of features for all categories were 4 x 143,360 = 458,752 features. Feature extraction by using the SURF method. Choose the best 80% features for each category. The remaining features are 367,001
4. Use K-mean clustering to create 500-word visual vocabularies of the image. Determine the cluster center. Perform iteration 12 times, out of its maximum 100 iterations.
5. Classification by using Support Vector Machine. The BOF stages are shown in Fig.3.

The testing images were divided into three different maize leaf image groups: RGB, grayscale, and segmented images. Each scenario consists of 200 images with four categories. There were 50 images for each category. Tables 1, 2, and 3 show the testing results for color RGB images, grayscale images, and segmentation images respectively with training data 70%. Tables 4, 5, and 6 with training data 80%.
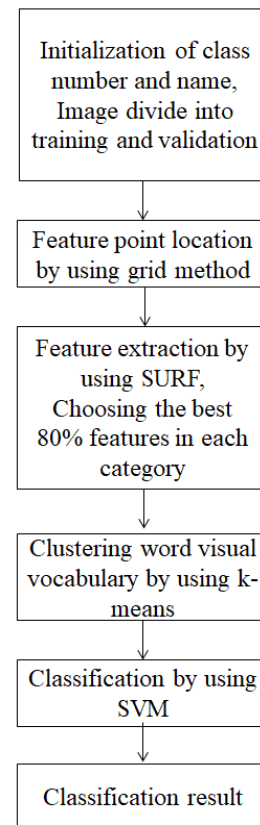

Fig.3. BOF Stages

IV.   DISCUSSION

We used two scenarios of testing for each type of data: training and validation. The first scenario uses 140 images for training and the rest (60 images) for validation. The validation accuracies for each scenario were 82%, 77%, and 85%. The testing results showed that the segmented image scenario had the best accuracies for the validation stage.

The second scenario is 160 images for training and the rest (40 images) for validation. The validation accuracies for each scenario were 85%, 83%, and 78%. The testing results showed that the RGB image scenario had the best accuracies for the validation stage.

The testing results from this work are then compared with previous works to measure the testing success level according to the method. A comparison of the accuracy of the testing results is found in Table 7. For the training stages, the accuracies achieved were relatively high, up to 96%, while the validation accuracies were less compared to previous studies. This could be improved by increasing the amount of training data so that the learning process could be more extensive.

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Table 1. Testing Results for RGB Scenario (70% Training Data)

Image types	Testing				Validation			
	detected as				detected as			
	Cercospora	common rust	healthy	Northern leaf blight	Cercospora	common rust	healthy	Northern leaf blight
Cercospora	91	0	3	6	80	0	13	7
common rust	0	100	0	0	0	100	0	0
healthy	0	0	100	0	7	0	87	7
northern leaf blight	3	0	3	94	20	0	20	60
	Training accuracy: 96%				Validation accuracy: 82%			

Table 2. Testing Results for Grayscale Scenario (70% Training Data)

Image types	Testing				Validation			
	detected as				detected as			
	Cercospora	common rust	healthy	Northern leaf blight	Cercospora	common rust	healthy	Northern leaf blight
Cercospora	83	0	9	9	67	0	0	33
common rust	0	100	0	0	0	100	0	0
healthy	0	0	100	3	13	0	87	0
northern leaf blight	11	0	3	86	13	0	33	53
	Testing accuracy:92%				Validation accuracy: 77%			

Table 3. Testing Results for Segmented Images Scenario (70% Training Data)

Image types	Testing				Validation			
	detected as				detected as			
	Cercospora	common rust	healthy	Northern leaf blight	Cercospora	common rust	healthy	Northern leaf blight
Cercospora	89	3	0	9	87	0	13	0
common rust	0	100	0	0	0	100	0	0
healthy	0	0	100	0	0	0	100	0
northern leaf blight	20	60	11	63	27	13	7	3
	Testing accuracy: 88%				Validation accuracy: 85%			

Table 4: Testing Results for RGB Scenario (80% Training Data)

Image types	Testing				Validation			
	detected as				detected as			
	Cercospora	common rust	healthy	Northern leaf blight	Cercospora	common rust	healthy	Northern leaf blight
Cercospora	82	0	7	10	80	10	0	10
common rust	0	100	0	0	0	100	0	0
healthy	0	0	100	0	0	0	80	20
northern leaf blight	5	0	3	93	10	0	10	80
	Training accuracy: 94%				Validation accuracy: 85%			

Table 5. Testing Results for Grayscale Scenario (80% Training Data)

Image types	Testing				Validation			
	detected as				detected as			
	Cercospora	common rust	healthy	Northern leaf blight	Cercospora	common rust	healthy	Northern leaf blight
Cercospora	88	3	5	5	80	0	0	20
common rust	0	100	0	0	0	100	0	0
healthy	0	0	97	3	0	0	90	10
northern leaf blight	5	0	5	90	20	0	20	60
Testing accuracy:94%					Validation accuracy: 83%			

Table 6. Testing Results for Segmented Images Scenario (80% Training Data)

Image types	testing				Validation			
	detected as				detected as			
	Cercospora	common rust	healthy	Northern leaf blight	Cercospora	common rust	healthy	Northern leaf blight
Cercospora	82	3	3	13	80	10	0	10
common rust	0	100	0	0	0	100	0	0
healthy	0	0	100	0	0	10	90	0
northern leaf blight	13	60	3	85	20	20	20	40
Testing accuracy: 92%					Validation accuracy: 78%			

Table 7. Comparison Between The Result of This Study and Other Studies

Author	Method	Number of classes	Accuracies
Al Hiary et al. [5]	GLCM+BPNN	6	94,67%
Cao et al. [6]	Threshold + BPNN	6	88,25%
Alehegn [7]			94,4%
Mohanty et al. [8]	CNN	26	31,4%
Aravind et al. [9]	BOF+SVM	4	83,7%,
	GLCM		81,3%
Proposed method	BOF using SURF + SVM	4	testing: 88%-96% validation :77%-85%

V.   CONCLUSION

In this article, the image classification of leaves on maize plants has been carried out using the Bag-Of-Feature method. This method consists of feature extraction with SURF, clustering with k-Means, and classification using Support Vector Machine. This method is quite useful, with the accuracy up to 96% for the testing and 85% for the validation. To get better results, training can use more data or use deep learning methods for high classification speed and accuracy.

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