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Corn Plant Disease Identification Using SURF-based Bag of Visual Words Feature

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***Abstract*— Feature selection is the most important step in picture classification due to its influence on accuracy. The objective of this study was to diagnose corn plant illnesses using visual features extracted from leaf photos with Bag of visual words (BoVW) and the Support Vector Machine (SVM) classification approach. The SURF approach was implemented in order to extract and describe the features of each and every corn leaf image that was included in the training dataset. The approach of K-Means clustering is utilized in the process of organizing k Centroids derived from visual Word. The arrangement of the BoVW feature based on the histogram of k clusters of visual words provides the input for the SVM classification algorithm. The original contribution of this study is to investigate how the classification accuracy is impacted by factors such as the number of K-Means clusters and the proportion of the most important features that are represented by keypoints. The experiment was conducted using the plantvillage public dataset. The experiment results indicate that the best classification accuracy is 85%, with the number of clusters 800 and the proportion of the strongest keypoints features 80%.**

Keywords*—*BoVW, Cluster, Corn, K-Means, Plant Disease, SURF

I. INTRODUCTION

Abiotic and biotic restrictions contributed to maize (Zea mays L.) crop failure. Grey leaf spot disease, the most deadly leaf disease, rust, and northern leaf blight are examples of biotic constraints [1]. Plant growth and development are hampered by the illness, resulting in lower agricultural output [2]. Farmers, on the other hand, are unaware of the disease and are unable to recognize plant signs visually. Because leaves are plentiful throughout the year, they are regarded the most dependable source of information in identifying plant illnesses. Researchers have investigated leaf features such as color, shape, texture, fiber, and other morphological characteristics[3],[4]. Who can use the visual signs that appear on the leaves to detect and treat the disease in its early stages[5].

Several authors have proposed the utilization of automatic leaf image detection systems as a method for diagnosing diseases based on the disease's earliest symptoms as a potential diagnostic tool. Sannakki et al.[6]have presented a method that is able to automatically evaluate the presence of disease in the plant's leaves. In order to detect the location of a disease in a satisfying manner, Siricharoen et al[7] developed a method that analyzes an image in a way that makes it possible to detect the location of a disease in a satisfactory manner. This method makes use of a combination of color, form, and texture features. In this study, identifying leaves that were affected by the same disease rather than looking for early warning signs was the primary focus.

Feature selection can yield leaf attributes, according to previous research. The most critical phase in computer vision leaf classification[8]. Minimum inter-class similarity and maximum intra-class similarity are required for the chosen features. The accuracy of the classification algorithm can be determined by the best features. A leaf image is used as the input, and the output is a feature vector that reflects the differentiating feature[10]. The initial stage in pattern recognition is to find and extract the descriptor for the desired spot in the image. The classification algorithm can then compare the descriptors to uncover relationships between images in order to conduct matching and recognition tasks.[11]. Therefore, the performance of the image classification or pattern recognition system is heavily dependent on the descriptor.

The Bag of Visual Word (BoVW) technique delivers feature-based picture content specific to the local area. The effectiveness of this strategy is extensively researched when it comes to pattern recognition or image classification. The BoVW local feature extraction method generates positive outcomes through the use of image descriptors. defining characteristics of This method is straightforward, useful, adaptable, and does not affect the final image's transformation in any way. The following steps are involved in the generation of local features using the BoVW approach [12]:1. Identifying and providing a description of sites of interest; 2. The development of one's vocabulary through the use of figurative words; 3. The development of a histogram including the visual word frequency for each image. In the BoVW approach, the feature extractor plays a significant part in defining the level of precision and accuracy achieved by the method. The performance of the Speeded Up Robust Feature (SURF) feature extractor method as a BoVW extractor for image classification is at its highest possible [13], [14]. Because it contains an integrated keypoint detection technique that is compatible with BoVW, the SURF local feature extractor has been the subject of much research.

The objective of this study is to identify corn plant diseases using leaf image analysis and visual characteristics. Who used the features collected from all of the corn leaf images included in the training dataset by the SURF method to describe and extract them. The method of K Means Clustering is used to arrange the K Centroid of the visual Word. The Support Vector Machine (SVM) classification algorithm takes the histograms of k visual word clusters as input, and uses those histograms to arrange the feature representations that BoVW generates. The analysis of the effect of the number of K-Means clusters and the percentage

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of the strongest keypoint characteristics on the classification performance is the scientific contribution of this research. The organization of the paper is as follows: Section 1 offers the background of the work, Section 2 presents the related work, Section 3 presents the recommended study material and methods, Section 4 presents the research results, and Section 5 closes the content and suggests future research.

II. Related Work

A. Identification of Plant Leaf Disease based Handcrafted Feature

Figure 1 illustrates a workflow for image classification [15], which is utilized as a preliminary step for conventional leaf disease detection. Depending on the class's ground truth information, images are captured. Preprocessing is performed in order to obtain a higher-quality image. When performing preprocessing on a picture, it is common practice to either resize the image, increase its sharpness, remove noise, or flatten the image's histogram value. There are two stages of segmentation, each of which is carried out with a distinct objective in mind. In the initial phase of segmentation, the leaf area is determined. The object of the lesion region is obtained by the execution of the second stage of the segmentation procedure. Extraction of features includes the mining of segmented data [16]. The learning algorithm is responsible for recognizing new visual features that have been collected from the environment. Classification is the process of matching an input vector of features to one of the classes learnt during training[17].

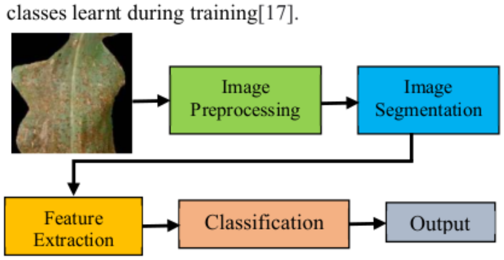

Figure 1. Handcrafted method of feature extraction and classification process

B. Bag of Visual Words Feature Extraction

The feature set is depicted in this image as a representation. Initially, the BoVW model extracts local invariant features from an image. Secondly, it encodes each feature to its nearest visual word, and finally, it represents the image as a histogram of occurrences of visual words [18]. A image's features are the salient characteristics and defining characteristics that set it apart from other images. The vocabulary and frequency histogram aspects of the image can be constructed using these components [19]. This image feature set is being sent into the classification process as an input.

Pires, et al[20] implemented BoVW as a feature for automatically detecting diseases in soybeans as part of an experiment. Encoding input vectors for classifiers using this method is achieved through the utilization of local descriptors and the Bag of Values (BOV) method. This is not necessary to segment a picture in order to use the solid local descriptor for occlusion. After then, the SVM is used to define two classes, a sick class, and a healthy class, as part of the

Figure 2. Three prevalent corn diseases based on leaf visual characteristics: Gray leaf spot, Rust, and Northern leaf blight.

classification process. Meanwhile, Katoch et al. came up with a method that makes use of the BoVW model to recognize Indian sign language alphabets (A-Z) and digits (0-9) in a live video stream, and it outputs the predicted labels as text and audio[21].

III. Method

A. Dataset

PlantVillage is a database that can be accessed at https://plantvillage.psu.edu/. The data for this research experiment was selected from [22] This data is being used to support a computer vision approach to solving the problem of crop production loss caused by infectious illnesses. The plantvillage database image of corn used contains four classes: grey leaf spot, rust, northern leaf blight, and healthy image. For the experiment, 500 images were employed for each class of corn imagery. The image representation of the corn PlantVillage dataset is shown in Figure 2.

B. Method

SURF is used to create scale and rotation-invariant point of interest detectors and descriptors. As illustrated by Figure 4, this research stage includes generating feature vectors from the input image using a robust local feature extractor. BoVW used K Means to group the descriptors into k centroids after extracting all of the key points and descriptors from the training picture set. The fundamental assumption of this paper is that the retrieved descriptors are self-contained and may thus be used as BoVW in the image. The Support Vector Machine classification technique uses this BoVW feature as an input (SVM).

1) SURF

The image's features and descriptors were retrieved using the SURF detector-descriptor approach established by Bay et al. [23]. The SURF descriptor is produced by generating a rectangular region centered on the detected point of interest and designed to align with its principal orientation. This window has a size of 20s, where s is the scale from the location of the point of interest that was detected. The regions. At *5x5* sample points, *dx* and *dy* (respectively, for each sub) were determined for each sub. To enhance resilience against geometric deformation and localization mistakes. Region of interest is then subdivided into smaller

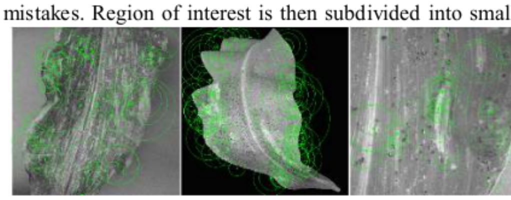

Figure 3. The Results of Keypoint Detection on the Corn Image

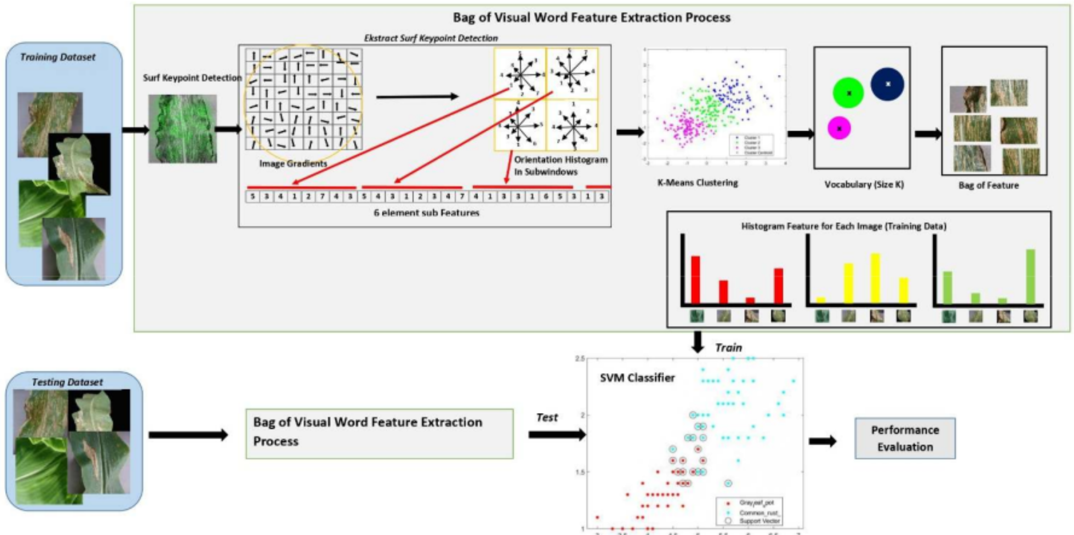

Figure 4. Corn Disease Classification using Bag of Visual Word and SVM Workflow

4x4 sub-For each sub-region, the wavelet responses *dx* and *dy* are added together and included in the feature vector *v*, which is calculated using the formula 1:

$$v = \left(\sum d_x, \sum |d_x|, \sum d_y, \sum |d_y|\right) \qquad \text{Eq(1)}$$

The formulation is then computed for each of the 4 x 4 subregions, which results in a feature descriptor with a length of 4 x 4 x 4, which equals 64 dimensions. SURF reduces the length of this descriptor to 64 floating point values so that it may be stored more efficiently. A gradient orientation histogram was applied to the local environment around each key point in order to build 64 lengths of descriptor vectors [24]. The feature descriptor is then normalized to a unit vector in order to diminish the lighting impact. Visualization Figure 3 is a visual representation of the surf keypoint detection performed on the image of the corn leaf.

2) K-Means Clustering

The K-means unsupervised learning algorithm was used to carry out this operation after all of the important points and descriptors from the training image had been extracted and grouped into K centroids. K-means clustering was used to group the extracted descriptors from the training images into groups of visual words. The Euclidean distance metric is used to group a descriptor into a centroid cluster. In this investigation, the test will determine the value of K.

3) SVM Classifier

In this paper, the SVM supervised learning algorithm is investigated. In the K-means step, a histogram vector is created, which is then used by the learning algorithm to classify the images. SVM is a binary classifier, but it is frequently investigated for image classification of more than two groups (multiclass). The SVM was used to classify images based on their BoW characteristics within the framework that was proposed in this research.

IV. Result and Discussion

This experiment scenario evaluates the number of clusters of the best features and the proportion of each image's best features. Which of the 350 photos in each class contained a percentage of 70% BoVW feature vector data. A total of 150 images were utilized to validate and test each class, according to the researcher. The first experiment was conducted with a variety of different numbers of clusters so that the influence of N clusters derived from the BoVW feature on the performance of the SVM classification accuracy could be determined. Which of the four picture classes has the ability to depict the frequency of the histogram equalization of the visual words in the cluster that has been specified. Figure 5 is a visual representation of the histogram equalization of a visual word with an 800-point keypoint. All experiments are implemented on a PC computer with memory size 128 GB and processor 11th Gen Intel(R) Core(TM) i9-11900K @ 3.50 GHz.

Table 1. Number of Cluster Perform

Cluster Time/ iteration	Iteration Convergence	Testing Accuracy	Number of Cluster	Silhouette
6.42	25	0.84631	900	0.75041986
6.39	**14**	**0.85631**	**800**	**0.41857147**
6.15	24	0.84536	700	0.33072457
6.25	33	0.8475	600	0.74483043
6.01	41	0.84214	500	0.86869907
5.77	46	0.83536	400	1
5.58	31	0.84036	300	0.82414174
5.39	12	0.83381	200	0.80912292
4.82	46	0.8244	100	0.91049981
4.19	22	0.79464	50	0.84999287

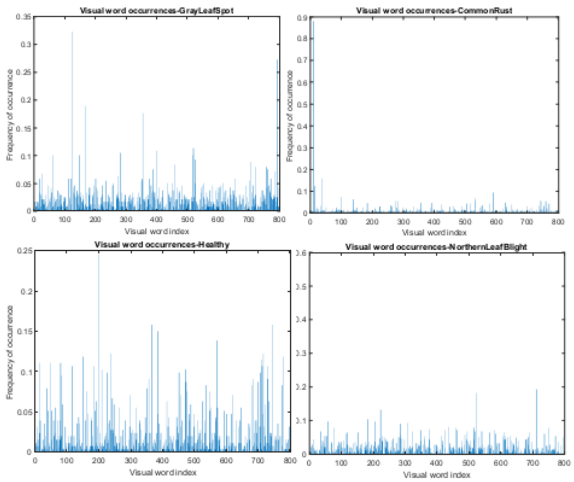

Figure 5. Histogram Equalization of each class's Features

The proposed experiment consists of a few different stages, each of which helps determine which keypoint is the most compelling. The discrepancies in the classification results that were acquired from a number of distinct clusters are displayed in table 1 as the results of the first stage, which can be found here. For each feature vector that is generated, the number of clusters that are employed ranges from fifty to nine hundred. Table 1 displays the variance in the number of iterations required to reach convergence for the various numbers of clusters. The table reveals that the number of clusters that result in the highest level of accuracy corresponds to cluster 800, and that convergence is reached on the 14th iteration. The classification performance test revealed, based on the number of different clusters, that the cluster with the highest accuracy performance does not also provide the maximum performance via silhouette testing.

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Table 2. Confusion Matrix for each image class

Class	**Common_ rust**	**Gray_ leaf_spot**	**healthy**	**Northern_ Leaf Blight**
Common_ rust	0,99	0,01	0,01	0,00
Gray_ leaf_spot	0,01	0,81	0,10	0,09
healthy	0,01	0,05	0,95	0,00
Northern_ Leaf_ Blight	0,01	0,31	0,19	0,49

The second experiment was conducted using the proportion of BoVW's most strong features. In the first experiment, it was determined that 800 clusters were optimal. The number of clusters was then evaluated using the percentage of images with the strongest features. Table 2 shows the testing results for the several strongest feature methods that choose between 60 and 100 percent of the strongest features. Even if the iteration convergence of the clusters created is faster, the proportion of BoVW's strongest features in the corn image has not demonstrated the greatest performance. The testing results indicate that 80 percent of the strongest features are responsible for the greatest classification performance.

According to the findings of the experiment conducted in the initial scenario, each class had significantly varied accuracy scores. The confusion matrix representing the classification performance of each class is presented in Table 2. Following the healthy and gray leaf spot classes in terms of accuracy performance against itself is the common rust class, which achieves a pretty high performance of 99 percent. The northern leaf blight class has the worst performance when it comes to accuracy. The visual appearance of the northern leaf blight class combines a variety of complicated lesion morphologies, including dots and irregular rounds. This is different from gray leaf spots and common rust, both of which have a more regular and uniform form of visual symptoms, as shown in Figure 3. In contrast, this has a more irregular and variable appearance.

Table 3. Percentage of Strongest Features Perform

Cluster Time Sec/ iteration	**Iter Conv**	**Number of Features**	**% of Strongest Features**	**Testing Accuracy**
5.51	24	3.440.640	60	0.84964
5.51	24	4.014.080	70	0.85131
6.39	**14**	**4.587.520**	**80**	**0.85631**
6.73	14	4.874.240	85	0.84774
7.15	10	5.160.960	90	0.84726
7.48	10	5.447.680	95	0.84631
7.83	13	5.734.400	100	0.83798

The detection of corn plant diseases is presented by an investigation of the visual characteristics of leaf imagery in this research work. The SURF approach was used as a descriptor for the purpose of extracting features from each and every corn leaf image that was included in the training dataset. K Means Clustering is the approach that is used to construct the K Centroid of a visual Word. Input for the Support Vector Machine (SVM) classification algorithm is provided by BoVW, which is a representation of image features ordered according to a histogram of k visual word clusters. The impact of a variety of conditions on the classification performance was analyzed, and both the number of K-Means clusters and the percentage of the strongest keypoint characteristics were subjected to testing.

The results of the tests demonstrate that the classification accuracy is affected differently depending on the number of clusters. Therefore, the proportion of the most prominent BoVW characteristics present in the corn image has not demonstrated the optimal performance, despite the fact that doing so minimizes the iterative convergence of the newly formed cluster. Considering that BoVW can affect such a wide variety of plant diseases and plant species, the focus of current and future research is on investigating BoVW at many important points and data. In order to obtain a classification performance that is more optimal, it is possible to investigate non-handcrafted classification approaches that are based on transfer learning or reuse learning. The resultant vector features are amenable to re-optimization thanks to a learning strategy that is reusable.

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