Convolutional neural network vs bag of features for bambara groundnut leaf disease recognition

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Article Info

ABSTRACT

This paper investigates bambara groundnut leaf disease recognition using two popular techniques known as Convolutional Neural Network (CNN) and Bag of Features (BOF) with Speeded-up Robust Feature (SURF) and Support Vector Machine (SVM) classifier. Leaf disease recognition has attracted many researchers because the outcome is useful for farmers. One of the crops that provide high income for farmers is bambara groundnut but the leaves are easily infected with diseases especially after the rain. This could affect the crop productivity. Thus, automatic disease recognition is crucial. A new dataset that consists of 400 images of the infected and non-infected leaves of bambara groundnut has been constructed. The experimental results indicate that both of these techniques produce excellent leaf disease recognition accuracy.

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1. INTRODUCTION

Bambara groundnut, or the scientific name Vigna subterranea (L) Verdc. is originally planted in the African continent and has been cultivated in tropical Africa for centuries [1]. It has been planted in Malaysia due to similar weather condition but one of the challenges planting it here is that it can easily be infected with leaf diseases after heavy rains [1]. In order to minimize the leaf disease that induced damage during the growth of bambara groundnut, harvest and post-harvest processing, as well as maximize productivity and ensure agricultural sustainability, automatic leaf disease recognition is highly important [2]. The existing method for leaf plant disease recognition is simply applying the naked eye observation by experts [3]. In doing so, a large team of experts as well as continuous monitoring of plant is required, which incur costs for large farms [3]. Plant disease recognition by visual way is more laborious and time consuming and at the same time, less accurate and can be done only in limited areas [4].

In order to adapt to this fast changing environment, appropriate and timely plant leaf disease recognition is crucial. However, most plant leaf diseases generate some kind of manifestation in the visible spectrum, so the naked eye examination of a trained professional is the prime technique adopted in practice for plant disease recognition [5]. An automated plant leaf disease recognition system could be of great help for amateurs in the gardening process and also trained professionals as a verification system in disease diagnostics [6]. Various features and classifiers have been investigated to recognize plant diseases automatically [7]-[10]. Colour features and Back-Propagation Neural Network (BPNN) have been used for cotton and groundnut diseases classification [7]. Shape and colour features with Support Vector Machine (SVM) classifier have been utilized to classify rice-plant diseases [8]. SVM has also been used to classify

cotton leaf spot disease in [9]. A comparative study has been performed among various texture features namely Local Binary Pattern (LBP) and Gray Level Co-occurrence Matrix (GLCM) and classifiers that are Probabilistic Neural Network (PNN), BPNN, SVM and Random Forest (RF) to classify diseases in grapes and the results indicate that GLCM with RF achieve the best recognition results [11]. Convolutional Neural Network (CNN) is getting popular in object recognition problems such as leaf recognition [13-14], fruit recognition [15-16], character recognition [17], vehicle recognition [18] and palm oil fresh fruit bunch ripeness grading recognition [19]. Plant disease classification based on CNN produce outstanding accuracy results [20]. BoF, one of the many machine learning techniques, has also shown good performance in object recognition [21-22]. Due to promising results produced by BoF and CNN, this research plans to investigate their performances in recognizing bambara groundnut leaf disease.

2. RESEARCH METHOD
2.1. Convolutional Neural Network (CNN)
The architecture of CNN is structured as a series of layers, that consists of three layers which are convolve layer, pooling layer and Rectified Linear unit (ReLu) [16]. Convolve layer extracts features of an image using filter and image patch that strides over the input image. ReLu layer replaces all negative pixel values in the feature map with zero while pooling layer allows the feature map to be down-sampled after ReLu layer to reduce the dimensionality. Max-pooling computes the maximum local of feature map. Neighboring pooling takes input from feature maps that are shifted or stride by more than one rows or columns. Figure 1 shows the architecture of a CNN [23].
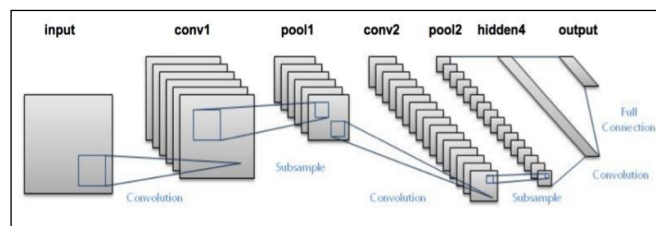

Figure 1. The architecture of CNN [26]

2.2. Bag of Features (BoF)
One method that represents images as orderless collections of local features is called Bag of Features (BoF) [22]. In this project, Speeded up Robust Features (SURF) has been used in BoF because the performance of this feature is excellent and only require low computational cost [24]. It is a descriptor that is based on Hessian matrix measures and an image detector. For a descriptor which uses only 64 dimensions leading to quick feature extraction, and it also uses a 2D Haar wavelet transform [24].The two common perspectives for the BoF image representation explanation which the first one is the by analogy from the Bag of Words representation. One represents a document that normalizes histogram of word counts with Bag of Words, [25]. Figure 2 shows the process for BoF image representation.
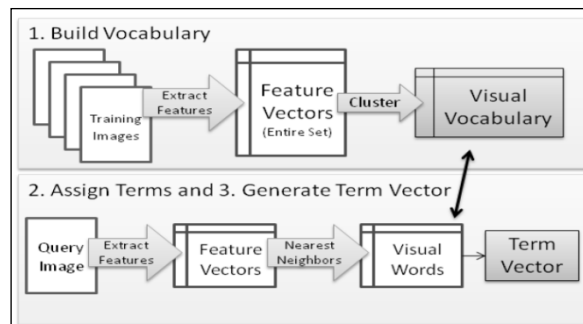

Figure 2. Process for BoF image representation [22]

3.   RESULTS AND ANALYSIS
3.1. The Dataset

A new dataset of the bambara groundnut leaf images has been constructed that consists of 200 images of the non-infected leaves and 200 images of leaves with diseases. They were captured from a farm in Semenyih, Selangor using a mobile phone. Some sample images of bambara groundnut with and without diseases are illustrated in Figure 3 and Figure 4.
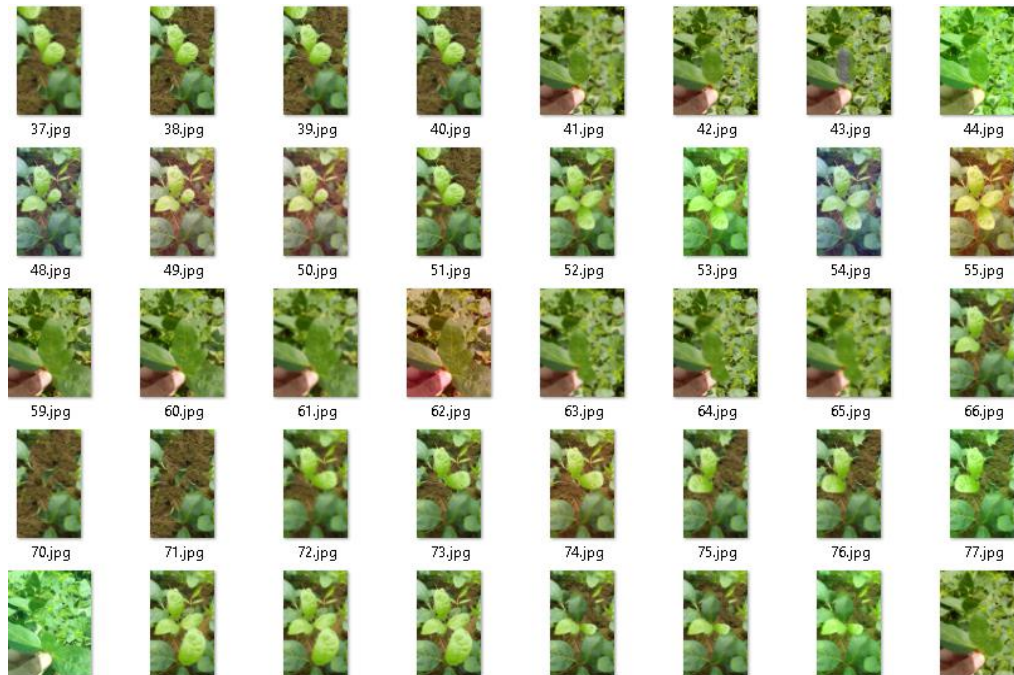
Figure 3. Some sample images of bambara groundnut without leaf diseases

Figure 4. Some sample images of bambara groundnut with leaf diseases

3.2. CNN

A stack of CNN consist of convolve layer, pooling layer and ReLu layer while additional stack of layers can be added to improve the performance. CNN takes color images and the features are automatically extracted by the convolve layers. The size of filters in the convolve layer and the value of stride in the pooling layer represent the number of columns to be skipped for the sliding window through the image. These values can be changed as they can affect the result of the recognition performance. Besides that, the values of epochs represent the number of iteration for the training process and initial learning rate that represent the value of the weight to be adjusted during the training process, can be changed to view their effect to the recognition rate. The image size required for basic CNN is 224 x 224 pixels. Experimental results were conducted on the combination of these values and the results are shown in Table 1. The first column represents the size of the filter and the number of filters in the convolve layer. By referring to Table 1, we can see that a 100% accuracy is achieved with [5,20] in the first convolve layer and [3,32] in the second convolve layer, and Figure 5 shows the results of this training and validation processes.
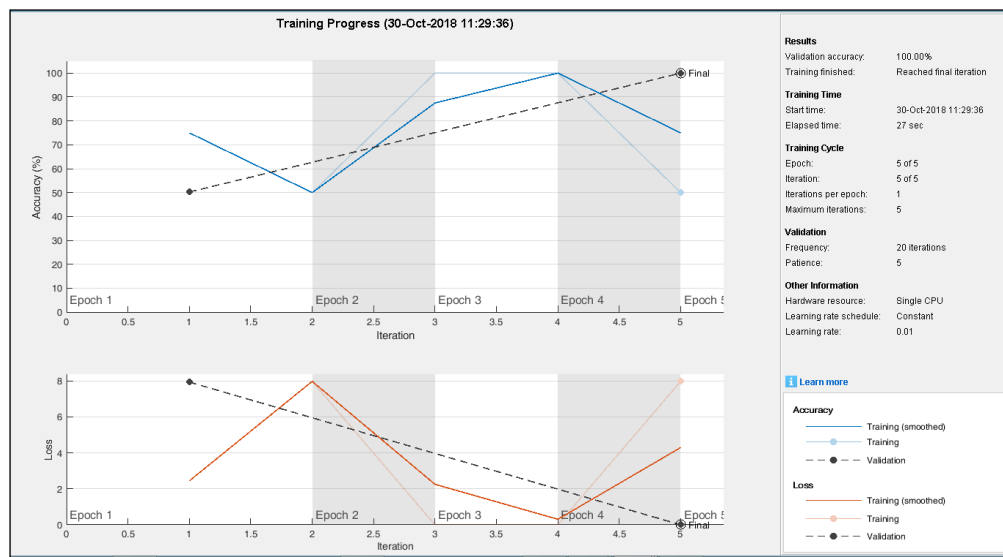

Figure 5. The result of CNN with [5,20] in the first convolve layer and [3,32] in the second convolve layer

Table 1. Experimental Results on Parameter Tuning for Basic CNN

No of Stack of Layers	Convolve Layer	Pooling layer and Stride	Accuracy (%)	Total Time/s
1	[3,16]	3	78.82	30 sec
	[5,20]	3	83.59	28 sec
2	[3,16] [3,32]	3	91.79	27 sec
	[5, 20][3,32]	2	100.00	27 sec
3	[5, 20][3,32] [3, 32]	2	75.90	41 sec
	[5, 20][3,32] [3,16]	2	74.87	34 sec

By looking at Table 1, we can see that as the number of layers increases, the accuracy is also increased. But when the number of layers is more than 3, the accuracy begins to drop. This means that two stacks of layers plus 1 classification layer produce the best accuracy for bambara groundnut lead disease recognition.

3.3. Bag of Features (BoF)

The size of an image used for BoF is 227 x 227 pixels and the accuracy produced is 100%. Figure 6 shows the result of visual words occurrence produced by BoF for our dataset. Speeded-Up Robust Feature (SURF) and Support Vector Machine (SVM) is being utilized in the BoF.
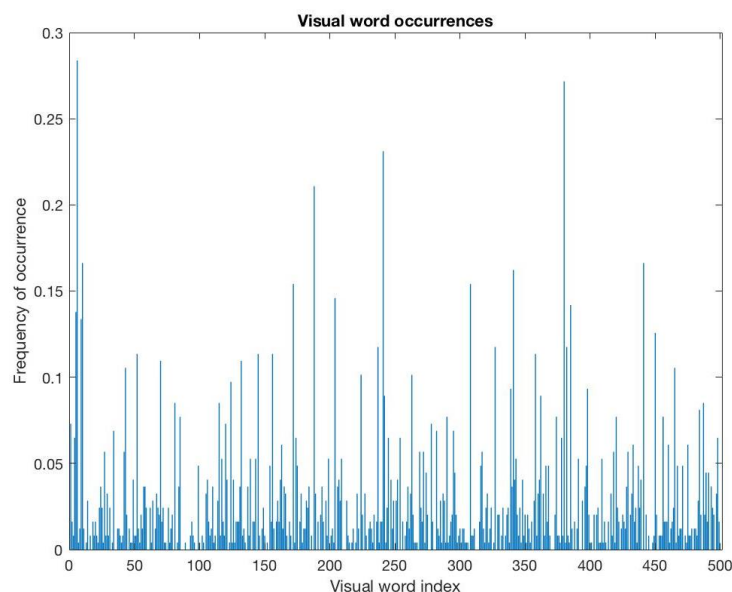
Figure 6. Visual word occurrences result

Table 2 shows an overview of the accuracy performance of CNN compared to BoF based on our bambara groundnut leaf dataset. By looking at Table 2, we can see that BoF is better than basic CNN but it took a longer time to achieve this result. This is because extracting of the SURF features is longer compared to the time to extract the low-level and middle level features by the CNN.

Table 2. The Performance Overview for Basic CNN and BoF for Bambara Dataset

Model	Basic CNN	BoF
Validation accuracy	100	100
Elapsed Time (s)	27	31

4. CONCLUSION

In this paper, a comparison between CNN and BoF was performed with respect to accuracy and elapsed time. The experiment results show that BoF achieved the same accuracy rate as CNN which is 100%. However, BoF requires a higher elapsed time due to the large number of SURF features required to be extracted. Although the number of layers affects the accuracy performance, the complexity of the CNN architecture does not guarantee a better result. The experimental results in this research indicate that two stacks of layers produce better accuracy compared to three stacks of layers. The use of CNN is recommended for leaf disease recognition if the processing time is not an issue. For future work, more deep learning models and publicly available datasets will be tested.

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