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Texture Analysis of Citrus Leaf Images Using BEMD for Huanglongbing Disease Diagnosis

Sumanto[1], Agus Buono[2], Karlisa Priandana[3], Bib Paruhum Silalahi[4], Elisabeth Sri Hendrastuti[5]
[1,2,3] Department of Computer Science, IPB University, Indonesia
[4]Department of Mathematics, IPB University, Indonesia
[5]Department of Plant Protection, IPB University, Indonesia

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ABSTRACT

Plant diseases significantly threaten agricultural productivity, necessitating accurate identification and classification of plant lesions for improved crop quality. Citrus plants, belonging to the Rutaceae family, are highly susceptible to diseases such as citrus canker, black spot, and the devastating Huanglongbing (HLB) disease. Conventional disease detection methods rely on expert knowledge and time-consuming laboratory tests, which hinder rapid and effective disease management. This study aims to explore an alternative method that combines the Bidimensional Empirical Mode Decomposition (BEMD) algorithm for texture feature extraction and Support Vector Machine (SVM) classification to improve HLB diagnosis in citrus plants. The method used in this research involves the BEMD algorithm decomposes citrus leaf images into Intrinsic Mode Functions (IMFs) and a residue component. Classification experiments were conducted using SVM on the IMFs and residue features. This research found that the achieved classification accuracies, ranging from 61% to 77% for varying numbers of classes, indicate that the residue component achieved the highest classification accuracy, outperforming the IMF features. The combination of the BEMD algorithm and SVM classification presents a promising approach for accurate HLB diagnosis, surpassing the performance of previous studies that utilized GLCM-SVM techniques. This research contributes to developing efficient and reliable methods for early detection and classification of HLB-infected plants, which are essential for effective disease management and the preservation of agricultural productivity.

Corresponding Author:

Sumanto,
Department of Computer Science, Faculty of Mathematics and Natural Science, IPB University
Jl. Raya Dramaga, Babakan, Kec. Dramaga, Kabupaten Bogor, Jawa Barat 16680
Email: sto_sumanto@apps.ipb.ac.id

1. INTRODUCTION

Plant diseases are a significant concern in agriculture because they can decrease the overall quality of agricultural output. It is crucial to accurately identify and classify plant lesions to advance the economy, as this can substantially improve the quality of plant production [1]. Citrus plants are the most widely distributed agricultural product worldwide and are members of the Rutaceae family. Citrus plants, which include lemons, grapefruit, oranges, limes, and citrons, are susceptible to citrus canker, black spot, and citrus greening (HLB), among others [2]. Citrus greening disease, commonly known as Citrus Huanglongbing (HLB), is a major concern for citrus orchards worldwide, causing substantial damage to the citrus sector and posing a significant economic threat. The illness is brought on by three strains of gram-negative proteobacteria that are phloem-limited and belong to the -subdivision of bacteria. These strains are known as Candidatus Liberibacter asiaticus (Ca. Las), Candidatus Liberibacter americanus (Ca. Lam), and Candidatus Liberibacter africanus (Ca. Laf), respectively [3]. Plants affected by citrus greening disease typically exhibit stunted growth, with infected branches gradually drying out as the illness advances. In addition, these diseased plants tend to be more fragile than their healthy counterparts and are particularly vulnerable to extreme temperatures and moisture [4]. Examples of leaves affected by huanglongbing disease and healthy leaves in the citrus leaf dataset are shown in Figure 1.

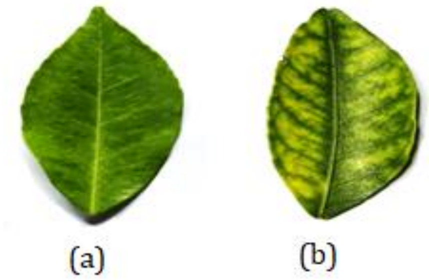

Figure 1. Leaf samples used in this study: (a) healthy, (b) HLB-infected

The conventional method for preventing and controlling HLB in agriculture relies on the knowledge of seasoned farmers or professionals to promptly identify and remove diseased plants [5]. Plants showing only subtle signs of HLB may be accurately determined using PCR (Polymerase Chain Reaction) and other biotechnological methods. This precise technique allows diagnosing and curing the illness in its earliest phases of plant infection. This method, however, requires trained professionals to spot infected plants and transport them to a lab for DNA confirmation, which can be time-consuming. Preparing a machine to take the position of the expert in the identification process can significantly speed up the detection process [6]. Leaves are the most delicate part of plants, exhibiting disease symptoms at an early stage. Therefore, early detection of plant leaf diseases is crucial [7]. HLB disease can be recognized by the rough texture of the leaves [8]. The surface is used for image retrieval and classification purposes. In agriculture, many researchers point to the consistency of plant leaves as the most significant feature for identifying plants [2][9]. Research related to huanglongbing disease with texture extraction features using citrus leaves dataset has been carried out, and an accuracy of 70,31% was obtained using GLCM-SVM [7], and using GLCM-MSVM got an accuracy of 88% [10].

Huang proposed the Hilbert Huang Transformation (HHT) in 1998, and it incorporates a crucial feature called Empirical Mode Decomposition (EMD) [11][12]. Unlike its predecessors, the Empirical Mode Decomposition (EMD) is a data-driven, direct, intuitive, and adaptable decomposition method. It has been extensively utilized in numerous fields, such as financial series analysis and earthquake motion. As modified by J.C. Nunes, bidimensional Empirical Mode Decomposition (BEMD) enables the simultaneous extraction and segmentation of texture features without the need for preprocessing stages. Bidimensional Empirical Mode Decomposition (BEMD) differs from Fourier and wavelet transform techniques because it does not employ fundamental functions. Images are instead decomposed into a set of Bidimensional Intrinsic Mode Functions (BIMFs) or modes. The implementation of BEMD for texture extraction demonstrated that when it comes to extracting texture features, no other method performs adequately for all image types besides BEMD [13]. In this research, textural picture data was analyzed using the BEMD technique, in which the data was divided into intrinsic mode functions (IMFs), and the feature vectors were produced using fractal dimensions [14] [15].

In previous studies, the classification methods employed for identifying Huanglongbing (HLB) had limitations in accuracy and complexity [1] [4][5][6][7]. Consequently, this research addresses these challenges by exploring a novel and improved approach for classifying HLB. The proposed method focuses on utilizing texture features derived from orange leaves to enhance the accuracy of HLB classification. This research seeks a more reliable and efficient solution for identifying and categorizing Huanglongbing disease using this technique. In addition, this research is the first step in detecting Huanglongbing disease in various categories (mild, moderate, and severe).

2. METHOD

The proposed methodology (PM) flow chart for this study is shown in Figure 2. The PM decomposed the processed images of citrus leaves into IMFs using the Bivariate Empirical Mode Decomposition (BEMD) method. These deconstructed IMFs were then used to calculate texture characteristics. The next step was to choose the best features from the retrieved collection of elements. At last, a Support Vector Machine (SVM) classifier was used on the data based on these well-chosen, highly discriminatory characteristics. By employing this methodological approach, this research aims to enhance the accuracy and usability of categorizing Huanglongbing (HLB) based on citrus leaves.

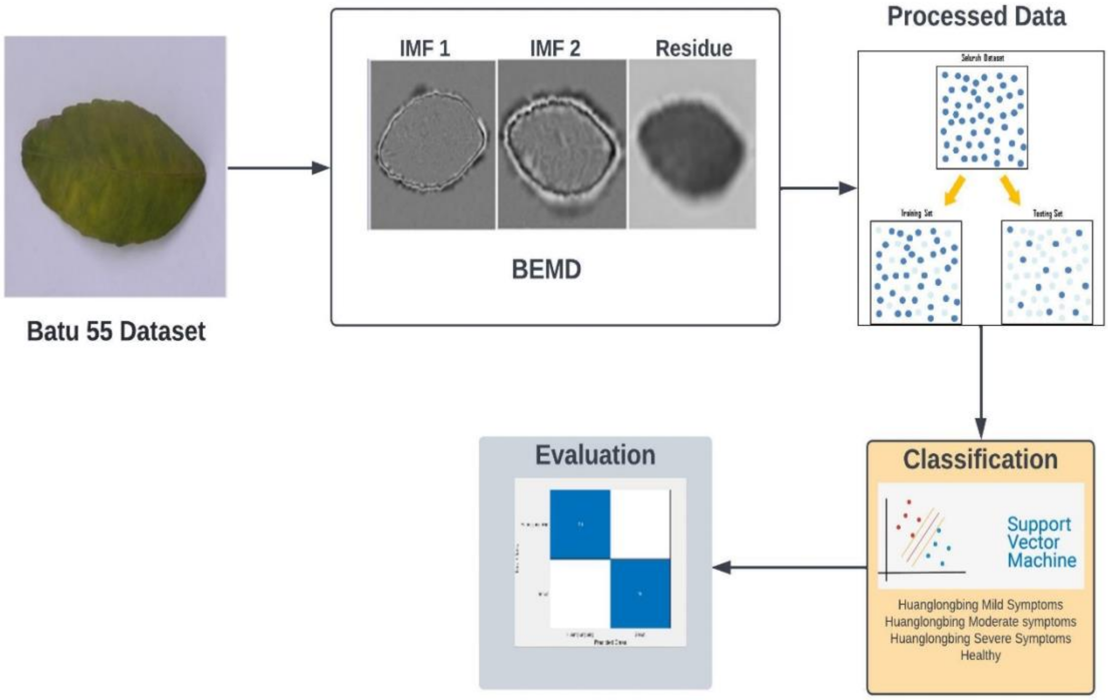

Figure 2. Research Procedure BEMD

2.1. Data Collection

This article utilized a dataset of 400 photographs of citrus leaves obtained from citrus plantations in Malang, explicitly focusing on the Batu 55 Malang orange variety. The data collection process involved rigorous validation by experts specializing in Huanglongbing disease, ensuring the accuracy and reliability of the dataset. Furthermore, to ensure the presence of huanglongbing disease, the collected samples underwent PCR tests at the Plant Pathology Laboratory of the Institute Pertanian Bogor (IPB) Plant Protection Department. Detailed information regarding this dataset can be found in Table I, providing valuable insights into the characteristics of the samples used in this study.

Table 1. Distribution Of Huanglongbing Disease Dataset Batu 55 Malang

Class	Number
Huanglongbing Mild Symptoms	100
Huanglongbing Symptoms Moderate	100
Huanglongbing Severe Symptoms	100
Healthy	100
Total	**400**

2.2. Bidimensional Empirical Mode Decomposition (BEMD)

BEMD is an extension of EMD that allows for data analysis in more than two dimensions. Images can be segmented[14], edges can be detected[16], noise can be reduced[17], textures can be

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synthesized[18], images can be compressed[19], fused[20], and watermarked[14] using BEMD. In this study, the orange leaf dataset was processed using BEMD to extract texture; the number of images shifts to remove texture features using two changes so that the results of this BEMD process are IMF 1, IMF 2, and the remaining growth is called the residue. Data processing using the BEMD algorithm is contained in the bemd algorithm flow. Experiments were conducted using two classes (Huanglongbing and Healthy), three classes (Huanglongbing Mild Symptoms, Huanglongbing Severe Symptoms, and Healthy), and four classes (Huanglongbing Mild Symptoms, Huanglongbing Moderate Symptoms, Huanglongbing Severe Symptoms, and Healthy). Data processing using the bemd algorithm is contained in the BEMD algorithm flow.

Algorithm 1. BEMD

1: Initialize $r_0\ (m,n) = I\ (m,n), i = 1$
2: Set $h_0\ (m,n) = r_{i-1}\ (m,n), j = 1$
3: Maximal envelopment construction $E_{max}\ (m,n)$ along with the minimum envelope $E_{min}\ (m,n)$ Using a 2D interpolation function to estimate the values between the maximum and minimum points.
4: Create the average envelope : $E_M\ (m,n) = \ (E_{max}\ (m,n) + \ E_{min}\ (m,n)\ )/2$
5: Calculate $h_j\ (m,n) = \ h_{j-1}\ (m,n) - E_M\ (m,n)$
6: If $h_j\ (m,n)$ Is BIMF then
$BIMF_i\ (m,n) = \ h_j\ (m,n)$
Else
Goto step 3, with $j = j + 1$
7: Set $r_i\ (m,n) = \ r_{i-1}\ (m,n) - BIMF_i\ (m,n)$
8: If $r_i\ (m,n)$ has two extrema, then
The composition is completed
Else
Go to step 2 with $i = i + 1$

2.3. Classification using SVM

In this study framework, classification tasks were performed using SVM classifiers. SVM is a supervised learning method. The decision boundaries for the SVM classification have been created using a hyperplane. The result of type is healthy leaves or leaves with Huanglongbing disease (Mild Symptoms, Moderate Symptoms, Severe Symptoms). After completing all the processes, the model was further evaluated using the confusion matrix.

3. RESULT AND DISCUSSION

The BEMD method was used for 400 datasets of four classes: Healthy, Moderately Healthy, Heavily Healthy, and Huanglongbing Symptoms Mild. In Table 1 below, you'll find the whole citrus leaf data dataset.

A separate training dataset and test dataset were created using the gathered information. In this study, we utilized the training dataset to build learning models and the testing dataset to examine their efficacy. One hundred images, three hundred of which are of leaves with huanglongbing disease, are utilized to create a predictive model. The researcher divided the dataset into two halves, one for training and one for evaluation. The distribution of the datasets used in this analysis is shown in Table 2.

Table 2. Distribution of the dataset

No	Dataset	Sample
1	Data Training (80%)	80
2	Data Testing (20%)	20
	Total Images	**100**

In this study, BEMD was utilized to deconstruct images. Huanglongbing citrus leaves' textural properties are derived from the IMF's breakdown. An expression for the BEMD is

$$I(m,n) = \ \sum_{i=1}^{N} IMF_i\ (m,n) + R(m,n) \tag{1}$$

The raw picture is denoted as IMF(m, n), where IMF is the intrinsic mode function, and R(m, n) is the residual. Figure 3 displays the outcomes of BEMD processing.

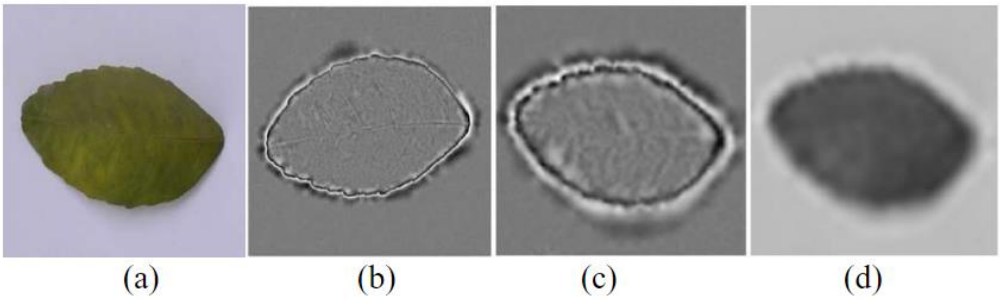

Figure 3. Results of image processing using BEMD, (a) original image, (b) IMF 1, (c) IMF 2, and (d) Residue.

The purpose of texture extraction in the Bidimensional Empirical Mode Decomposition (BEMD) algorithm in processing orange leaf dataset images is to improve image quality. After decomposition, the results obtained from the BEMD algorithm will be further processed for the classification stage using the SVM algorithm.

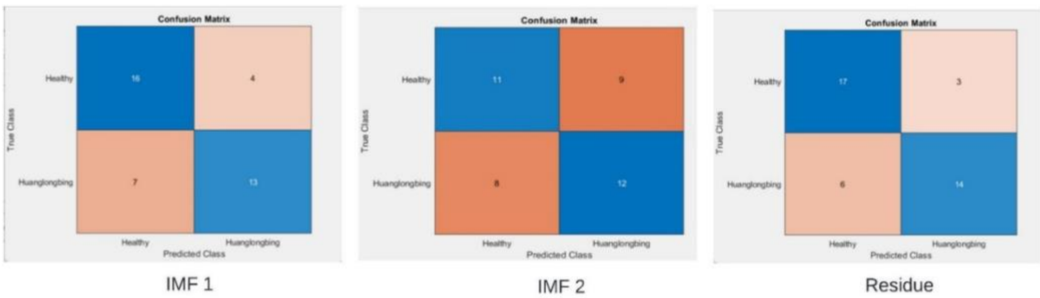

Figure 4. Results of Huanglongbing two classes classification using SVM.

The BEMD method was used to analyze the orange leaf picture shown in Figure 4. The decomposition process generates several intrinsic mode functions (IMFs) that capture different scales of texture information. In this case, IMF 1 represents 72.5% of the total image content, significantly contributing to the overall texture. In contrast, IMF 2 accounts for 57.5% of the image content, indicating another important texture component. In addition, the residual, which represents the information left over after parsing, performed exceptionally well in predicting huanglongbing disease at 77.5% of the image content. These percentages provide insight into each component's relative importance and contribution, helping analyze and interpret the extracted texture features for Huanglongbing disease diagnosis. Among the three BEMD features, the texture feature of residue is the best in predicting Huanglongbing disease for Batu 55 Malang orange leaf data.

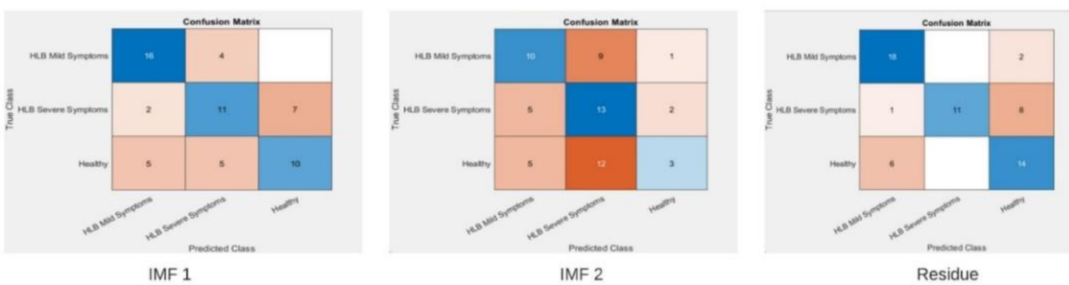

Figure 5. Results of Huanglongbing three classes classification using SVM.

Figure 5 illustrates the classification results for three classes using the proposed texture analysis approach. Using the BEMD technique, the decomposition process produces three components: IMF 1, IMF 2, and residue. Among these components, IMF 1 contributes 62% of the total image content, followed by IMF 2 with 43%. The residue component accounts for 72% of the remaining image information. The residue result is the highest accuracy achieved in the classification result corresponding to the class with the best prediction performance. This finding is almost similar to the processing of Huanglongbing disease using two categories.

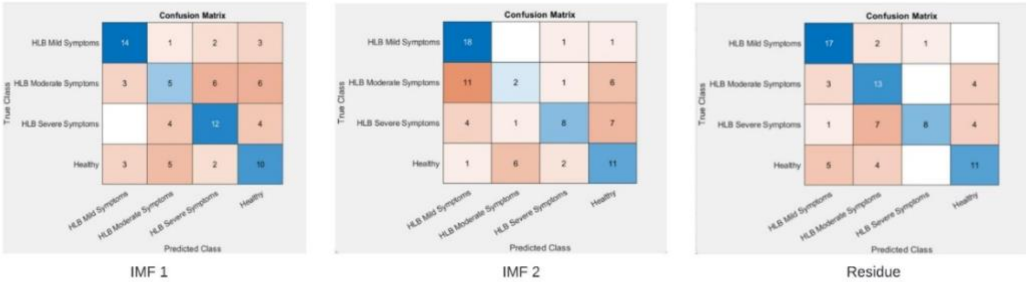

Figure 6. Results of Huanglongbing four classes classification using SVM.

Figure 6 illustrates Bidimensional Empirical Mode Decomposition (BEMD) processing results for four classes. The decomposition process produces three components: IMF 1, IMF 2, and residue. Among these components, IMF 1 obtained an accuracy of 51% of the total image content, followed by IMF 2 with an accuracy of 48%. The residue component achieved the highest accuracy result of 61.25% of the remaining image information. Notably, the highest accuracy in the prediction results corresponds to the class with the best prediction performance. This finding aligns with the experiments for two categories and three types, where the residue results are always superior to both IMF 1 and IMF 2 components. The results of the whole investigation for two, three, and four classes can be seen in Table 3.

Table 3. The function of Power Supply Components

No	Number of classes	File Name	Accuracy Result
1	Two Classes	IMF 1	72,5%
		IMF 2	57,5%
		Residue	77,5%
2	Three Classes	IMF 1	62%
		IMF 2	43%
		Residue	72%
3	Four Classes	IMF 1	51%
		IMF 2	48%
		Residue	61,25%

4. CONCLUSION

Based on the findings of this study, it can be concluded that the combination of BEMD algorithm processing for texture extraction and SVM classification emerges as a practical approach for digital image processing. In this study, image processing was performed by applying the BEMD algorithm to extract texture features, resulting in IMF components and image residuals. Each texture feature, including IMF 1, IMF 2, and residue, underwent classification using the SVM algorithm. Regarding classification accuracy, this study showed that the texture features derived from the image residue achieved the highest accuracy of 77% for two classes, 72% for three categories, and 61% for four categories. On the other hand, IMF 1 can be considered an alternative option to selecting texture features derived from the BEMD algorithm, as IMF 1 obtained the second-best results after image residue. The highest accuracy achieved by IMF 1 was 72% for two classes, while the lowest accuracy was observed in the four-class experiment, with a rate of 51%. As for IMF 2, it produced the most insufficient accuracy among the texture features, with 43% for three classes and the highest accuracy of 57% for two categories. These findings emphasize the importance of image residue in this study, as it consistently outperformed the IMF component regarding classification accuracy, indicating its reputation as a valuable feature for image processing and disease diagnosis. In addition, this study exceeded previous research conducted by D. Sruthi and P. Prakash in huanglongbing disease detection using GLCM-SVM, which only obtained an accuracy of 70.31%. For further research, image residue should be examined to diagnose plant diseases. Investigating the best methods for increasing the beneficial properties of the residual image could improve classification accuracy.

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