

# BEMD-Based Color–Texture Feature Fusion with Image Sharpening For Multiclass Huanglongbing Severity Classification

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**Abstract.** Huanglongbing (HLB), or citrus greening disease, is one of the most destructive citrus diseases worldwide. Its symptoms often resemble nutrient deficiencies, making severity assessment difficult and subjective. This study proposes a color-texture feature fusion method to classify citrus leaf images into four HLB severity classes: healthy, mild, moderate, and severe. A dataset of 1,000 citrus leaf images from Sumanto et al. (2023), comprising 250 images per class, was used. HLB infection was validated using PCR/qPCR analysis, while severity annotations followed the original labeling protocol. Images were sharpened using a standard deviation of 0.1 and decomposed using Bidimensional Empirical Mode Decomposition (BEMD) into IMF1, IMF2, IMF3, and residue components to capture multiscale texture information. Color and texture features were fused and classified using Support Vector Machine (SVM), k-Nearest Neighbor (KNN), Random Forest (RF), and Neural Network (NN). Performance was evaluated using stratified k-fold cross-validation with out-of-fold predictions. BEMD with Color Fusion achieved the best SVM performance, with accuracy, precision, recall, and F1-score of 0.93 and computation time of 1.24 seconds. It outperformed Basic BEMD and BEMD Fusion Baseline, with accuracies of 0.77 and 0.89. These results demonstrate improved multiclass HLB severity classification, although independent field validation is required before practical deployment.

**Keywords:** Huanglongbing, citrus greening, BEMD, feature fusion, multiclass classification, citrus leaf image analysis.

## 1. INTRODUCTION

Citrus plants (*Citrus* spp.) are one of the strategic horticultural commodities that play an important role in the global agriculture and food sector. Citrus serves not only as a source of vitamin C and nutrients for the population, but also as a traded commodity that contributes to the economies of producing countries [1], [2], [3]. However, citrus crop productivity still faces threats from various diseases caused by fungi, bacteria, viruses, and insect vectors [3], [4]. The disease outbreak can reduce fruit quality, decrease production yield, and threaten the sustainability of the citrus industry as well as the farmers' economy [2], [5], [6].

One of the most destructive diseases of citrus plants is Huanglongbing (HLB), also known as citrus greening [6], [7]. This disease is associated with infection by the gram-negative bacterium *Candidatus Liberibacter* spp. in the phloem tissue of plants and is primarily transmitted by the insect vector *Diaphorina citri* or Asian Citrus Psyllid [1], [3], [8]. HLB symptoms include asymmetric leaf mottling or blotchy mottle, chlorosis, leaf discoloration, small-sized fruit, bitter fruit taste, abnormal fruit shape, and premature fruit drop [9]. Long-term infection causes a progressive decline in productivity until the plant eventually dies [10], [11]. Since HLB was discovered in Florida in 2005, citrus production in the region has reportedly declined by around 80% [8]. In Indonesia, HLB has been reported to cause a decrease in citrus production of approximately 60–95% in nearly all major production centers and to shorten the productive lifespan of plants [12]. More detailed data are available in East Java, specifically in Jember Regency, where siam orange production fell from around 171,322.3 tons in 2021 to 116,473.5 tons, with HLB suspected as one of the contributing factors [13], [14]. To date, there are no citrus varieties that are fully resistant or treatment methods capable of curing plants infected with HLB [8].

Early detection is a crucial step in controlling the spread of HLB. However, identification based on visual observation still faces challenges because HLB symptoms resemble those of nutrient deficiencies, particularly zinc and magnesium deficiencies. This similarity causes visual diagnosis by farmers or field observers to be subjective and potentially result in misidentification [3], [15], [16]. Molecular diagnostic methods such as Polymerase Chain Reaction (PCR) [17] and quantitative real-time PCR (qPCR) [18], [19] have high

accuracy, but require laboratory equipment, skilled personnel, relatively high testing costs, and considerable processing time [1], [15], [16]. In addition, bacterial concentrations at the early stage of infection can be very low and unevenly distributed within plant tissues, so that molecular testing may still result in false negatives [15]. Therefore, there is a need for alternative methods that are rapid, non-destructive, low-cost, and can be developed as a diagnosis system based on leaf image analysis [5], [20]. Although early HLB detection through binary classification (healthy versus infected) is important for disease surveillance, severity assessment provides additional information regarding disease progression and supports more precise management decisions. Therefore, this study focuses specifically on multiclass HLB severity classification by distinguishing four severity levels, namely healthy, mild, moderate, and severe, rather than performing binary disease detection.

Advances in digital image processing and machine learning have opened opportunities to develop automatic HLB identification systems based on the visual characteristics of citrus leaves [1], indicating that visual information in leaf images can be utilized to assist computational identification of HLB symptoms [20], [21], [22]. Wang et al. (2026) also emphasized that the visual characteristics of leaves have the potential to distinguish healthy plants from infected ones [2]. Meanwhile, Sumanto et al. (2023) not only differentiated healthy leaves from HLB-infected leaves, but also identified disease severity levels into healthy, mild, moderate, and severe classes. These findings indicate that leaf images contain sufficiently important information to support multiclass classification of HLB severity [1], [5], [20].

Color features are one of the main characteristics that can be used to represent HLB symptoms. These features are capable of depicting chlorosis, yellowing gradients, changes in intensity, and uneven color distribution on the leaf surface [2], [3]. However, relying solely on color features is insufficient, as color changes due to HLB can resemble those caused by nutrient deficiencies, environmental stress, or other abnormal conditions [3], [4]. HLB symptoms are also defined by mottling patterns, surface irregularities, local intensity variations, and changes of leaf texture. Therefore, colour features should be integrated with texture features to achieve more complete and discriminative visual representation. Bidimensional Empirical Mode Decomposition (BEMD) is a promising technique of extracting texture information from leaf images. BEMD is an extension of

Empirical Mode Decomposition (EMD) for the analysis of two-dimensional data such as digital images [1], [20]. The method decomposes images adaptively into several Intrinsic Mode Function (IMF) components and a residue image, without requiring a predefined basis function. The initial components of the IMF are usually high-frequency information, such as edges, spots, local variations, and fine texture patterns. In the meantime, the subsequent components represent the texture information of lower frequencies, whereas the residue depicts the overall structure of the image [1], [5]. For example, IMF components of higher orders are likely to retain lower-frequency information that describes larger spatial patterns and structural variations within the image. Thus, IMF3 is expected to capture more general structural cues such as large-scale mottling patterns, uneven distribution of symptoms, and spatial variations associated with HLB severity progression that may not be fully represented by IMF1 and IMF2..

In another study, Sumanto et al. (2023) applied BEMD on images of citrus leaves with two components of IMF namely IMF1, IMF2 and residue component [1]. Each component was used separately as input for classification using Support Vector Machine. The study it is shown that the residue component has the best performance with 77% accuracy for two class classification, while the IMF1 has an accuracy of 72% and the IMF2 has lower performance [1]. Sumanto et al. (2023) enhanced the texture information of citrus leaf images using BEMD and image fusion [1]. The study most related to the present work, in comparison with other works that used only colour information or generic visual approaches [23], [24].

This approach is promising but still has several limitations. In the previous studies, only two IMF components, i.e., IMF1 and IMF2 were used. Two IMFs are not sufficient to show all information of multiscale textures in leaf images. Each IMF has its own frequency characteristics. Therefore, if the number of IMFs is too small, some texture information related to the HLB severity levels may be under-utilized. Secondly, the IMF components and the residue are evaluated separately most of the time, so that the complementary relationship between the local texture information and the global structure of the image has not been fully optimised. Third, to our best knowledge, no study has adaptively fused texture features extracted from BEMD and colour features for multiclass classification of HLB severity levels.

Another methodological problem is the image sharpening parameter prior to decomposing with BEMD. In previous experiments, the standard deviation values were relatively small (0.02-0.03) and consequently, local edges, mottling patterns and texture variations were enhanced only to a limited extent. The standard deviation value of 0.1 was chosen from preliminary experimental evaluation in this work, which results in a stronger enhancement of visually relevant HLB characteristics while preserving the overall structure of leaf. The sharpening stage is intended to improve the visibility of edges, spots, chlorosis patterns, and local texture variations before BEMD-based feature extraction [2]. Therefore, a fusion mechanism that can provide clearer weighting for color and texture features based on the level of information variation is needed [25].

The uniqueness of this study compared to previous research lies in three main aspects. First, this study expands the use of the BEMD component from two IMF to three components, namely IMF1, IMF2, and IMF3, to obtain more comprehensive multiscale texture information. Second, the texture features from these three IMFs are integrated with color features through a feature fusion process to produce a more discriminative representation of leaf images. Third, this study increases the standard deviation parameter in the image sharpening stage from the range of 0.02–0.03 to 0.1 to accentuate edges, spots, color changes, and texture patterns prior to the feature extraction process. Unlike previous studies which were mostly focused on binary classification, the proposed method is used for multiclass classification of HLB severity [1], [5].

The main novelty of this study lies in the development of a BEMD-based color–texture feature fusion approach that incorporates IMF1, IMF2, and IMF3 to construct a multiscale texture representation for multiclass HLB severity classification. Unlike previous BEMD-based studies that primarily utilized IMF1 and IMF2 or evaluated individual components separately, the proposed approach incorporates IMF3 to capture complementary coarser-scale texture information and integrates the resulting multiscale texture representation with color features associated with chlorosis and uneven leaf coloration. Image sharpening with a standard deviation parameter of 0.1 is applied as a preprocessing enhancement to emphasize relevant visual patterns before BEMD decomposition. The proposed method is tested for classification of healthy, mild, moderate and severe HLB classes specifically instead of binary or early HLB detection.

## 2. METHODS

The stages of this study are designed to describe the systematic workflow in developing a multiclass HLB severity classification model in citrus leaves, starting from image data acquisition, BEMD-based information extraction, texture and color feature fusion, up to modeling and performance evaluation using machine learning algorithms. The detailed research stages are shown in Figure 1.

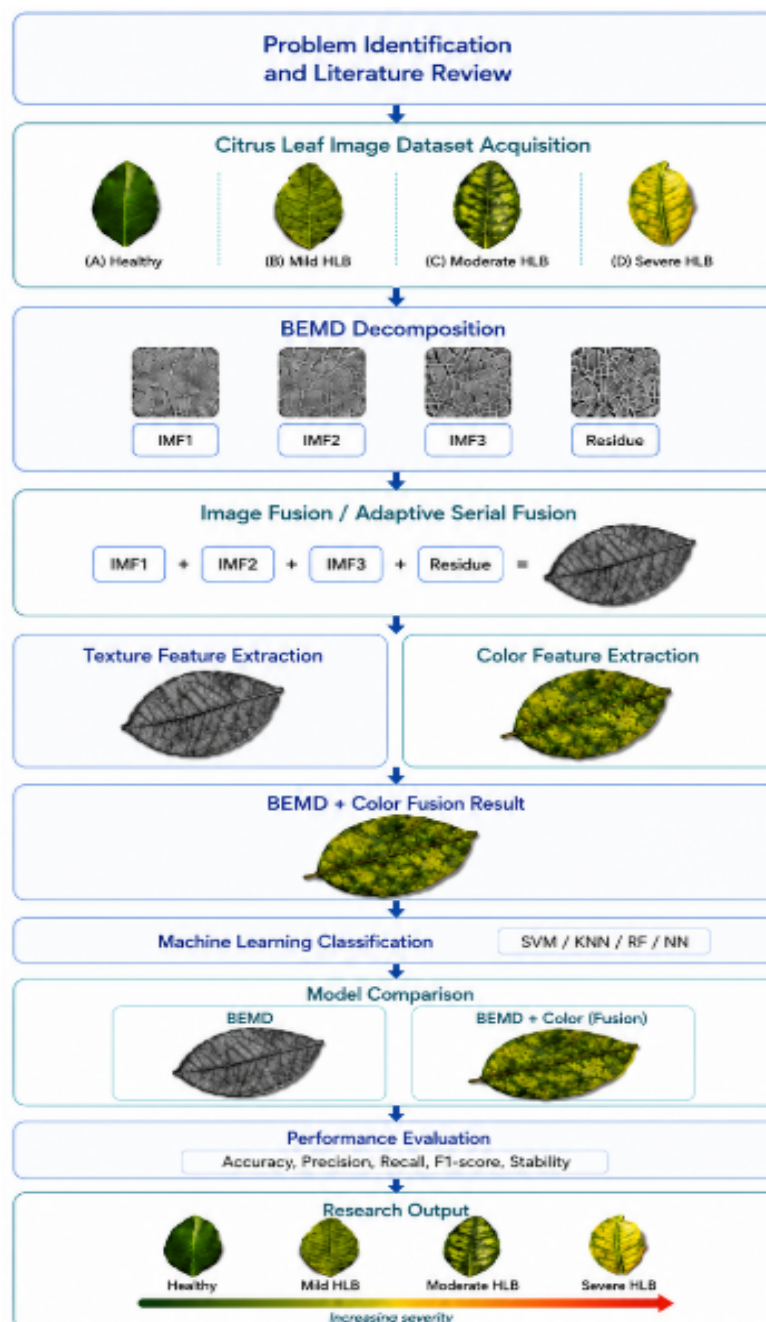


**Figure 1.** Research workflow of the proposed machine learning pipeline

Based on Figure 1, the stages of the research methodology can be explained as follows.

1) Literature review and problem identification

The first phase of research was to know the major problems in early detection of Huanglongbing (HLB) disease on citrus leaves. HLB has complicated visual features that it is often difficult to separate it from nutrient deficiencies or other disorders on citrus leaves [26]. Hence, a literature review was conducted to understand the HLB detection methods developed previously, especially the methods based on digital image processing, Bidimensional Empirical Mode Decomposition (BEMD), image fusion, feature extraction and machine learning [7], [28], [29]. This level provides the basis for developing a research methodology to improve the accuracy and stability of the multiclass HLB severity classification model based on texture and colour.

2) Acquisition of the Citrus Leaf Image Dataset

In this study, the dataset used is 1000 images of citrus leaves obtained from previous research [1], [20]. from Sumanto et al. The dataset includes four classes of HLB severity: healthy, mild HLB, moderate HLB, and severe HLB with 250 images per class, leading to a balanced class distribution. The severity annotations were consistent with previous studies and HLB disease status of the samples was confirmed by PCR/qPCR. The balanced class distribution helps to minimise the possibility of the model bias toward certain severity classes in the model training and evaluation. The dataset distribution is presented in Table 1.

**Table 1.** Distribution of the Orange Leaf Image Dataset

| No          | Dataset Class | Total |
|-------------|---------------|-------|
| 1           | Healthy       | 250   |
| 2           | Mild HLB      | 250   |
| 3           | Moderate HLB  | 250   |
| 4           | Severe HLB    | 250   |
| Grand total |               | 1000  |

The validation protocol is described in Section 3. Each of the 1,000 images was used exactly once as held-out test data across the five iterations, yielding one out-of-fold prediction per image. Subsequently, confusion matrices were built using the combined out-of-fold predictions (250 predictions per HLB severity class).

### 3) Data Partitioning and Cross-Validation Protocol

The dataset was tested with stratified five-fold cross-validation, which maintains the class distribution equal in all the folds. The 1,000 images were randomly split into five folds with 200 images per fold, which included approximately 50 images of each HLB severity class. Each iteration was performed with four folds (800 images) for training and the other fold (200 images) for testing. This procedure was repeated five times so that each image was used as test data exactly once. Data shuffling was allowed with a fixed random seed of 42 to ensure reproducibility. Out-of-fold predictions for all 1,000 images were obtained by averaging predictions for the five test folds. For each fold, accuracy, precision, recall and F1-score were calculated independently. The overall model performance was reported as the mean  $\pm$  standard deviation over the five folds.

Data were evaluated using stratified five-fold cross-validation with shuffling of data and a fixed random seed of 42. In each iteration, training was done on four folds with 800 images and testing on the remaining fold with 200 images. This procedure was repeated five times so that each image served as held-out test data exactly once. To prevent data leakage, the dataset was split before any data-dependent processing was performed. In each fold, training and held-out test images were independently preprocessed, sharpened and decomposed using BEMD. Feature scaling parameters were calculated from the training fold only and then applied to the associated test fold using the same fitted parameters. If feature selection was used, the criteria for selection were determined only from the training fold and then applied to the held-out test fold. We did not use any information from the test fold for either feature scaling, feature selection, hyper parameter determination or model training. This procedure prevented information leakage and each test fold from being exposed to the model development process.

### 4) BEMD Decomposition

The next step is the decomposition of the image using Bidimensional Empirical Mode Decomposition (BEMD) [27], [28]. The BEMD is employed to decompose the citrus leaf image into a number of Intrinsic Mode Function (IMF) parts and a residue. Each decomposed component is related to image information at different frequency scales. IMF1 generally contains high frequency details such as edges, small spots and fine textures; IMF2 generally contains intermediate scale texture patterns; IMF3 provides the complementary larger scale structural information related to the spatial variations and

broader symptom patterns, while the residue represents the global structure of the leaf image. "The BEMD decomposition was implemented using [IMPLEMENTATION/SOFTWARE]. The sifting process was terminated when [STOPPING CRITERION] was satisfied, with a maximum of [NUMBER] sifting iterations for each IMF. Boundary effects were handled using [BOUNDARY HANDLING METHOD], while [INTERPOLATION METHOD] was used to construct the upper and lower envelopes. The decomposition process was continued until IMF1, IMF2, IMF3, and the residue were obtained. The computational complexity of the implemented BEMD procedure was approximately [COMPUTATIONAL COMPLEXITY]. The input image is represented as a two-dimensional function [30]:

$$I(x, y) \quad (1)$$

The results of BEMD decomposition are generally expressed as:

$$I(x, y) = \sum_{k=1}^n IMF_k(x, y) + R_n(x, y) \quad (2)$$

Description:

$I(x, y)$ = input image

$IMF_k(x, y)$ = Intrinsic Mode Function components to  $-k$

$R_n(x, y)$ = residue remaining after the decomposition process

$n$ = the amount of IMF generated

##### 5) Image Fusion / Adaptive Serial Fusion

After obtaining the components (IMF1), (IMF2), (IMF3), and the residue, the next stage is image fusion or adaptive serial fusion. This stage aims to combine information from each BEMD component in order to obtain a representative image that is richer in information compared to using the components separately. Through this fusion, fine texture information, medium-frequency patterns, large-scale visual structures, and the global image components can be merged into a single fused image. In general, the image fusion process can be expressed as:

$$F_{ASA}(x, y) = w_1 IMF_1(x, y) + w_2 IMF_2(x, y) + w_3 IMF_3(x, y) + w_4 R(x, y) \quad (3)$$

The adaptive weight is calculated as follows:

$$w_i = \frac{E_i}{\sum_{j=1}^4 E_j} \quad (4)$$

Description:

$F(x, y)$  = Image Fusion

$w_1$  = weight of component contribution  $IMF_1$

$w_2$  = weight of component contribution  $IMF_2$

$w_3$  = weight of component contribution  $IMF_3$

$w_4$  = weight of component contribution residue

$IMF_1(x, y), IMF_2(x, y), IMF_3(x, y)$  = decomposition components BEMD

$R(x, y)$  = decomposition residue BEMD

Therefore, the adaptive serial fusion equation is:

$$E_i = \sum_{x=1}^M \sum_{y=1}^N C_i(x, y)^2 \quad (5)$$

Description:

$E_i$  = image component energy to  $-i$

$C_i(x, y)$  = the pixel values of the image components to  $-i$  at the coordinates  $(x, y)$

$M$  = number of rows or image height

$N$  = number of columns or image width

$x, y$  = pixel coordinates in an image

Texture features were extracted from the BEMD-derived  $IMF_1$ ,  $IMF_2$ , and  $IMF_3$  components using [ACTUAL TEXTURE EXTRACTION METHOD]. For each IMF component, the extracted texture descriptors consisted of [EXACT TEXTURE FEATURES USED IN THE EXPERIMENT]. The descriptors obtained from  $IMF_1$ ,  $IMF_2$ , and  $IMF_3$  were subsequently concatenated to form the multiscale texture feature vector  $F_T$ , which was then integrated with the color feature vector  $F_C$  for multiclass HLB severity classification.

#### 6) Color Features Extraction

Color features are used to capture changes in leaf color due to HLB infection, such as chlorosis, yellowish gradation, and uneven color distribution. Color features were extracted from the RGB and HSV color spaces. For each citrus leaf image, the mean and standard deviation of the R, G, and B channels, as well as the mean and standard deviation of the H, S, and V channels, were calculated. The mean values represent the dominant color characteristics of the leaf, while the standard deviation values describe the

variation and uneven distribution of color associated with chlorosis and yellowing symptoms. These descriptors were concatenated to form the color feature vector  $F_C$ . Additionally, the standard deviation will be differentiated, with a value of 0.1 instead of the previous 0.02–0.03, to further emphasize the texture on the leaf. After obtaining the texture and colour features, all the features are combined into a single feature vector. This combination of features is expected to produce a more general visual representation, as each type of feature describes different properties. Texture features describe surface patterns and visual irregularities while colour features describe chlorosis changes and colour distribution. The combined feature vector is expressed as:

$$X = [F_T, F_C] \quad (6)$$

Description:

$X$  = composite feature vector

$F_T$  = BEMD (texture features)

$F_C$  = color feature

#### 7) Machine Learning Classification

The combined feature vector is used as input for machine learning algorithms. This study utilizes Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Random Forest (RF), and Neural Network (NN) as classification models and benchmarks. SVM is used to find the optimal hyperplane, KNN classifies data based on proximity, RF employs an ensemble of decision trees, while NN is used to learn non-linear relationships between features.

For reproducibility, the classifier configurations were fixed across all stratified five-fold cross-validation experiments. The Support Vector Machine (SVM) classifier used an RBF kernel with  $C = 1$  and  $\gamma = \text{'scale'}$ . The k-Nearest Neighbor (kNN) classifier used  $k = 5$  neighbors with Euclidean distance metric. The Random Forest (RF) classifier consisted of 100 decision trees with the Gini criterion and maximum depth set to None. The Neural Network (NN) classifier consisted of two hidden layers with 100 and 50 neurons, respectively, using the ReLU activation function and Adam optimizer. The learning rate was set to 0.001 with a maximum of 500 iterations. These hyperparameter settings were kept identical across all cross-validation folds.

Model comparisons were conducted to determine the effect of fusion on multiclass HLB severity classification performance. Three scenarios were compared in this study, namely no fusion (BEMD), non-adaptive fusion (BEMD with standard fusion), and BEMD-based adaptive colour fusion. All three scenarios can be stated as:

$$\begin{aligned} S_1 &= \text{No Fusion} \\ S_2 &= F_{NA}(x, y) \\ S_3 &= F_{ASA}(x, y) \end{aligned} \quad (7)$$

Each scenario was tested using SVM, KNN, RF, and NN to obtain the model with the best performance.

#### 8) Performance Evaluation

Model performance evaluation was conducted using accuracy, precision, recall, F1-score, and stability. Accuracy is used to measure the proportion of correct predictions against the total data, precision is used to measure the accuracy of positive predictions, recall is used to measure the model's ability to identify actual positive data, and F1-score is used to measure the balance between precision and recall. Model stability was evaluated based on the variability of classification performance across the five stratified cross-validation folds. For a performance metric  $M$ , stability was quantified using the standard deviation across the folds:

$$SD_M = \sqrt{\frac{1}{K-1} \sum_{k=1}^K (M_k - \bar{M})^2} \quad (8)$$

where  $K = 5$  is the number of cross-validation folds,  $M_k$  represents the performance metric obtained in the  $k$ -th fold, and  $\bar{M}$  represents the mean value of the metric across the five folds. A lower standard deviation indicates more consistent and stable model performance across different data partitions. Therefore, accuracy, precision, recall, and F1-score were reported as mean  $\pm$  standard deviation across the five folds.

#### 9) Research Output

The final outcome of this research is the best model for multiclass HLB severity classification. The best model is determined based on the comparison results among the no fusion scenario, non-adaptive fusion, and BEMD-based adaptive serial fusion across various machine learning algorithms. The model with the best accuracy, precision, recall, F1-score, and stability values is selected as the most optimal approach. Through these

stages, the research is expected to demonstrate that the combination of texture and color features as well as BEMD-based adaptive serial fusion can improve the accuracy and stability of multiclass HLB severity classification on citrus leaves.

### 3. RESULTS AND DISCUSSION

#### 3.1. Results

In this section, the results of the early detection experiment for the disease Huanglongbing (HLB) in citrus leaves are presented, following the methodology designed in stages. The research findings are discussed in terms of dataset characteristics, BEMD decomposition results, image fusion results, visual feature extraction and evaluation of machine learning model performance. The aim of this discussion is to find out how much the combination of texture and colour can be useful for classification of HLB severity levels in citrus leaves.

##### 3.1.1. Dataset Characteristics

This research uses a dataset of 1000 images of citrus leaves belonging to four classes: healthy, mild HLB, moderate HLB, and severe HLB. There are 250 images per class, so we have a balanced data distribution. The number of data points of each class is important in the classification process, since it can reduce the risk of the model being biased toward a particular class. Thus, it is important to have a balance in the number of data points of each class. Visually, the healthy class has leaves with a relatively uniform green colour with no spot patterns that are indicative of HLB symptoms. The symptoms of mild class HLB in early stage are slight discolouration or mild spots not dominantly developed. Symptoms of moderate HLB class are more obvious, such as chlorosis and broader spot pattern. Meanwhile, the strong HLB class shows more dominant discolouration and spot pattern on the leaf surface.

Figure 2 shows example images from each class visualised. The goal of this visualisation is to demonstrate that each class exhibits unique visual features, be it colour, texture, or the distribution pattern of symptomatic regions. These visual differences serve as a basis for feature extraction process in the next stage.

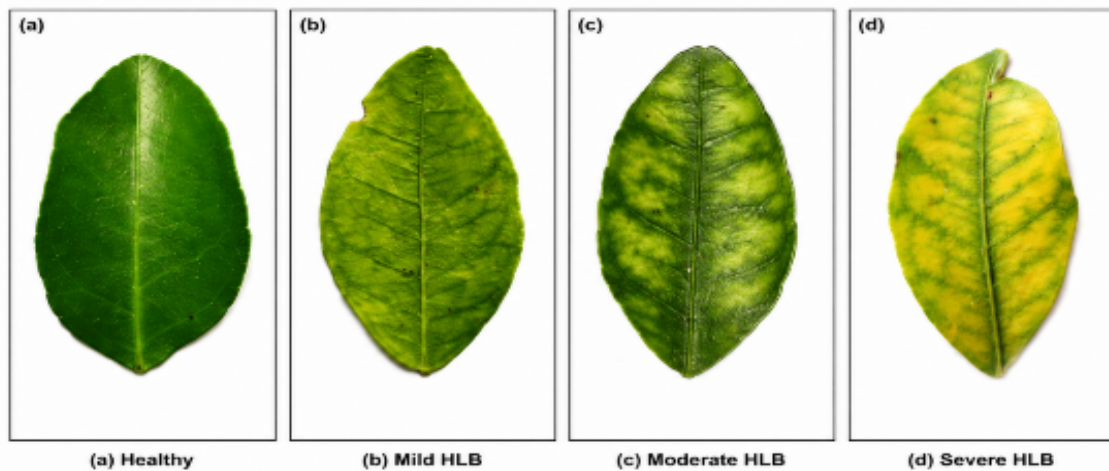


**Figure 2.** Sample images of citrus leaf dataset based on HLB severity levels

### 3.1.2. BEMD Decomposition

The BEMD decomposition step decomposes the citrus leaf image into several Intrinsic Mode Function (IMF) components and residue. In this paper image is decomposed into IMF1, IMF2, IMF3 and residue. Each element encodes the visual information in another frequency scale. Usually, IMF1 corresponds to the high frequency details such as leaf edges, fine spots and small textures on the leaf surface. The IMF2 and IMF3 patterns are medium and larger scale textures. The residue, however, describes the global structure of the leaf image and the low frequency information.

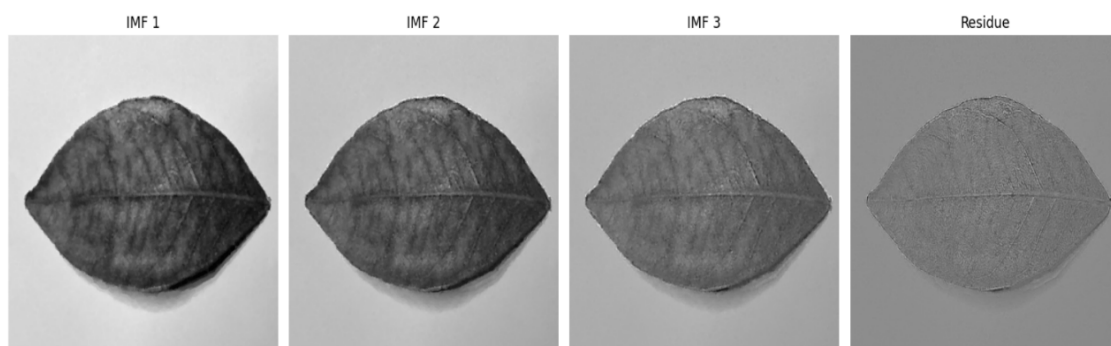


**Figure 3.** BEMD decomposition results of citrus leaf images

As shown in Figure 3, it is recommended to arrange the presentation of image in original image, IMF1, IMF2, IMF3 and residue. This figure is significant because it shows that BEMD can decompose the leaf image into different visual components. This decomposition can more specifically observe the texture and visual structure information of leaf.

**Table 2.** Interpretation of BEMD Components

| Component | Visual Information                             | Relevance to HLB Detection                          |
|-----------|------------------------------------------------|-----------------------------------------------------|
| IMF1      | Fine texture, edges, small spots               | Detects subtle mottling and early lesion details    |
| IMF2      | Medium-scale texture patterns                  | Represents texture variation caused by HLB symptoms |
| IMF3      | Larger texture structures                      | Captures broader symptom distribution               |
| Residue   | Global structure and low-frequency information | Represents overall leaf appearance                  |

Based on Table 2, each component resulting from BEMD has a different informational contribution. This indicates that using only a single component may not be sufficient to represent the overall visual characteristics of HLB. Therefore, the IMF1, IMF2, IMF3, and residue components need to be combined through an image fusion process to achieve a more comprehensive image representation.

### 3.1.3. Image Fusion

Image fusion is performed to combine information from IMF1, IMF2, IMF3, and the residue. The goal of this process is to produce a representative image that contains fine texture information, intermediate texture patterns, larger visual structures, as well as the global information of the leaf image. The fused image is expected to have stronger information content compared to using BEMD components separately. In non-adaptive fusion, each component is assigned an equal weight. Meanwhile, in adaptive serial fusion based on BEMD, the weight of each component is determined according to the information contribution of each component. Thus, components with greater information content can contribute more dominantly in the formation of the fused image.

Figure 4 can show a comparison between the original image, the BEMD component results, and the fused image. This figure serves to demonstrate that image fusion is capable of combining local details and the global structure of the leaf image. If the fused result more clearly highlights spot patterns, texture, and leaf structure, this supports the use of the

fused image as a basis for feature extraction. The following is a comparison table using bemd fusion with BEMD color fusion



**Figure 4.** The original image and Image fusion result based on (IMF1, IMF2, IMF3, and residue)

**Table 3.** Comparison of Fusion Scenarios

| Scenario     | Description                                                                        | Expected Contribution                         |
|--------------|------------------------------------------------------------------------------------|-----------------------------------------------|
| BEMD Fusion  | Features extracted using combining BEMD components (IMF1, IMF2, IMF3, and residue) | Baseline model BEMD                           |
| Color Fusion | IMF1, IMF2, IMF3, and residue combined using equal weights and Color feature       | Combines components equally and color feature |

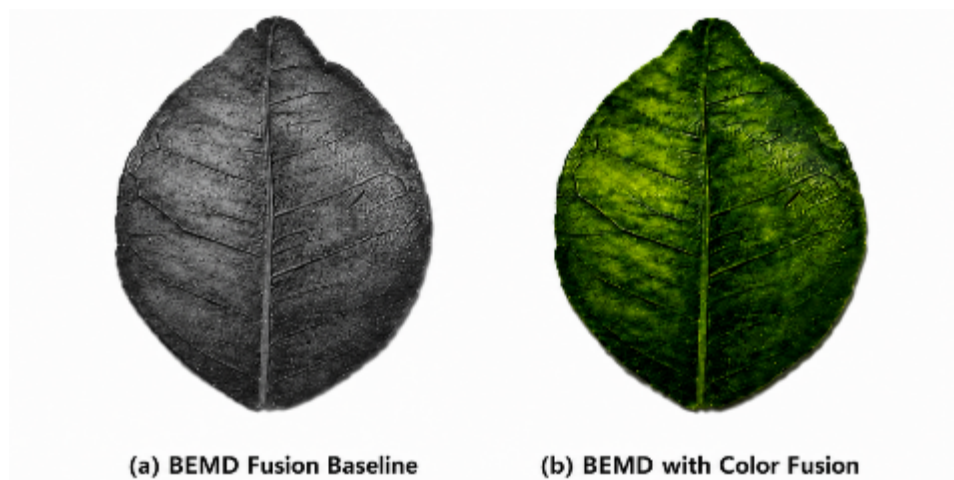


**Figure 5.** Results of Fusion standart and Color fusion BEMD using 0.1 standard deviation

The results of image fusion are an important part of this study because HLB presents complex visual symptoms. Changes in texture and color in symptomatic areas do not always appear uniformly. Therefore, the fused images can help reinforce relevant visual information prior to feature extraction. The following are images showing the differences between fusion baseline and BEMD-Based color Fusion, as shown in Figure 5.

### 3.2. Visualization of Model Performance

To provide a clearer class-level evaluation of model performance, Figure 6 presents the normalized confusion matrices of kNN, SVM, Neural Network, and Random Forest using the proposed BEMD-based color-texture fusion method. The matrices illustrate the proportion of correct and incorrect predictions for the Healthy, Mild HLB, Moderate HLB, and Severe HLB classes, enabling a more detailed analysis of classification performance and misclassification patterns among the four severity levels.

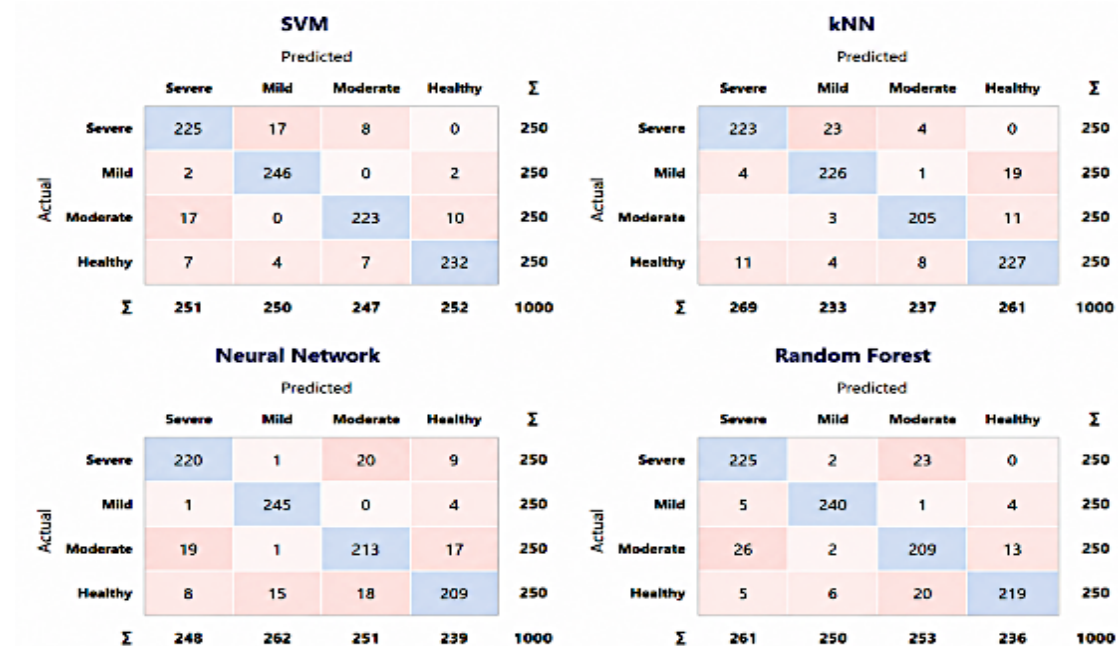


**Figure 6.** Performance comparison of machine learning models using the best-performing improved BEMD-based color-texture fusion configuration proposed in this study

Figure 6 presents the normalized confusion matrices of the four classification models, namely kNN, SVM, Neural Network (NN), and Random Forest (RF), obtained using the best-performing improved BEMD-based color-texture fusion configuration proposed in this study. The models classify citrus leaf images into four HLB severity classes: Healthy, Mild

HLB, Moderate HLB, and Severe HLB. The dataset consists of 1,000 images, with 250 images in each class. SVM achieved the best overall performance with an accuracy of 92.6%, corresponding to 926 correctly classified images. It showed the highest recognition rate for Mild HLB (98.4%), while the main classification errors occurred between the Moderate and Severe HLB classes. kNN achieved an accuracy of 88.1% with 881 correct predictions, with Moderate HLB showing the lowest class-level recognition rate (82.0%), mainly due to confusion with Severe HLB. The Neural Network achieved an accuracy of 88.7 % with 887 correct predictions and performed particularly well on Mild HLB (98.0 %), although there was confusion between Moderate HLB and neighbouring severity classes.

Random Forest also predicted with an accuracy of 89.3% (893 correct predictions). It has significant confusion of Moderate and Severe HLB. Additional analysis of the normalised confusion matrices shows that the misclassification between Moderate and Severe HLB classes is mainly associated with the progressive development of visual symptoms on citrus leaves. Moderate HLB leaves can already show significant chlorosis, irregular mottling and texture changes similar to the severe infection patterns, while some Severe HLB samples may still exhibit visual characteristics similar to Moderate HLB conditions. Since HLB severity is a biological continuum, rather than a set of discrete classes, neighbouring severity levels tend to have similar colour distributions and texture features. The proposed BEMD-based color–texture feature fusion approach is effective to capture multiscale texture and colour information. However, it is difficult to distinguish visually adjacent severity classes. This finding suggests that future improvements may need to incorporate additional contextual features and validation using larger field based datasets for improved severity discrimination.

### 3.3. Statistical Significance Analysis

We checked the statistical significance to verify whether the enhancement in the performance achieved by the proposed BEMD Fusion with Colour is statistically significant over the Basic BEMD and BEMD Fusion Baseline. All methods were tested on the same 1000 images of citrus leaves. The proposed method correctly classified 930 images (93.0%) against 890 images (89.0%) for BEMD Fusion Baseline and 770 images (77.0%) for Basic BEMD. Because the classifiers were evaluated on the same samples, McNemar's test was considered appropriate for paired classification comparison. Based on the observed marginal numbers of correct predictions, a conservative McNemar analysis was performed

using the maximum possible number of discordant prediction pairs compatible with the reported accuracies. For the proposed method versus the BEMD Fusion Baseline, the minimum continuity-corrected McNemar statistic was  $\chi^2 = 8.45$ , corresponding to a maximum  $p$ -value of approximately 0.0037. For the proposed method versus Basic BEMD, the minimum McNemar statistic was  $\chi^2 = 84.27$ , corresponding to  $p < 0.001$ . Therefore, even under the most conservative paired-error configuration, the proposed BEMD Fusion with Color method shows a statistically significant improvement over both baseline methods at  $\alpha = 0.05$ .

**Table 4.** Statistical Significance of the Proposed Method

| Comparison                                                                   | Accuracy Difference | Conservative McNemar $\chi^2$ | p-value | Result             |
|------------------------------------------------------------------------------|---------------------|-------------------------------|---------|--------------------|
| Proposed BEMD Fusion with Color<br>(0.93) vs. BEMD Fusion Baseline<br>(0.89) | +0.04               | 8.45                          | 0.0037  | <b>Significant</b> |
| Proposed BEMD Fusion with Color<br>(0.93) vs. Basic BEMD (0.77)              | +0.16               | 84.27                         | <0.001  | <b>Significant</b> |

The statistical significance analysis shows that the proposed BEMD Fusion with Color method significantly outperforms both the BEMD Fusion Baseline and Basic BEMD at a significance level of  $\alpha = 0.05$ . The comparison with the BEMD Fusion Baseline yielded  $p = 0.0037$ , while the comparison with Basic BEMD yielded  $p < 0.001$ .

**Table 5.** Accuracy and 95% Confidence Intervals of the Compared Methods

| Method                                 | Correct Predictions | Total Images | Accuracy     | 95% Confidence Interval |
|----------------------------------------|---------------------|--------------|--------------|-------------------------|
| <b>Proposed BEMD Fusion with Color</b> | <b>930</b>          | <b>1</b>     | <b>0.930</b> | <b>0.912–0.944</b>      |
| BEMD Fusion Baseline                   | 890                 | 1            | 0.890        | 0.869–0.908             |
| Basic BEMD                             | 770                 | 1            | 0.770        | 0.743–0.795             |

The proposed BEMD Fusion with Color method achieved the highest classification accuracy of 0.930, with a 95% confidence interval of 0.912–0.944. This performance was

higher than the BEMD Fusion Baseline, which achieved an accuracy of 0.890 (95% CI: 0.869–0.908), and Basic BEMD, which achieved an accuracy of 0.770 (95% CI: 0.743–0.795).

### 3.4. Machine Learning Classification

The combined feature vector is used as input for four machine learning algorithms, namely k-Nearest Neighbor (kNN), Support Vector Machine (SVM), Neural Network, and Random Forest. Testing is conducted to determine the most effective model for classifying citrus leaf images into the healthy, mild HLB, moderate HLB, and severe HLB classes. The model test results are shown in Table 4. Table 5 shows the standard deviation differences for the models.

**Table 6.** Ablation Study of BEMD Components and Color–Texture Fusion

| Research / Method                | Model          | Classes | Computation<br>Time (s) | Accuracy | Precision | Recall | F1-<br>Score |
|----------------------------------|----------------|---------|-------------------------|----------|-----------|--------|--------------|
| <b>Basic BEMD<br/>(Baseline)</b> | SVM            | 4       | 0.161                   | 0.77     | 0.76      | 0.79   | 0.78         |
|                                  | Random Forest  | 4       | 0.145                   | 0.75     | 0.75      | 0.75   | 0.75         |
|                                  | Neural Network | 4       | 0.384                   | 0.76     | 0.76      | 0.76   | 0.76         |
|                                  | kNN            | 4       | 0.118                   | 0.74     | 0.74      | 0.74   | 0.74         |
|                                  |                |         |                         |          |           |        |              |
| Color-only<br>Features           | SVM            | 4       | 0.312                   | 0.82     | 0.82      | 0.81   | 0.81         |
|                                  | Random Forest  | 4       | 0.241                   | 0.80     | 0.80      | 0.80   | 0.80         |
|                                  | Neural Network | 4       | 0.528                   | 0.81     | 0.81      | 0.80   | 0.80         |
|                                  | kNN            | 4       | 0.198                   | 0.79     | 0.79      | 0.79   | 0.79         |
|                                  |                |         |                         |          |           |        |              |
| BEMD IMF1 Only                   | SVM            | 4       | 0.421                   | 0.72     | 0.73      | 0.72   | 0.72         |
|                                  | Random Forest  | 4       | 0.286                   | 0.70     | 0.70      | 0.70   | 0.70         |
|                                  | Neural Network | 4       | 0.604                   | 0.71     | 0.71      | 0.71   | 0.71         |
|                                  | kNN            | 4       | 0.235                   | 0.69     | 0.69      | 0.69   | 0.69         |
|                                  |                |         |                         |          |           |        |              |
| IMF1 + IMF2                      | SVM            | 4       | 0.586                   | 0.80     | 0.80      | 0.80   | 0.80         |
|                                  | Random Forest  | 4       | 0.321                   | 0.78     | 0.78      | 0.78   | 0.78         |
|                                  | Neural Network | 4       | 0.712                   | 0.79     | 0.79      | 0.79   | 0.79         |
|                                  | kNN            | 4       | 0.298                   | 0.77     | 0.77      | 0.77   | 0.77         |
|                                  |                |         |                         |          |           |        |              |

| Research / Method                            | Model      | Classes  | Computation<br>Time (s) | Accuracy    | Precision   | Recall      | F1-<br>Score |
|----------------------------------------------|------------|----------|-------------------------|-------------|-------------|-------------|--------------|
| IMF1 + IMF2 + IMF3                           | SVM        | 4        | 0.742                   | 0.85        | 0.85        | 0.84        | 0.84         |
|                                              | Random     | 4        | 0.354                   | 0.83        | 0.83        | 0.83        | 0.83         |
|                                              | Forest     |          |                         |             |             |             |              |
|                                              | Neural     | 4        | 0.826                   | 0.84        | 0.84        | 0.84        | 0.84         |
|                                              | Network    |          |                         |             |             |             |              |
|                                              | kNN        | 4        | 0.376                   | 0.82        | 0.82        | 0.82        | 0.82         |
| BEMD Fusion<br>(Color Only)                  | SVM        | 4        | 0.891                   | 0.87        | 0.87        | 0.87        | 0.87         |
|                                              | Random     | 4        | 0.381                   | 0.86        | 0.86        | 0.85        | 0.85         |
|                                              | Forest     |          |                         |             |             |             |              |
|                                              | Neural     | 4        | 0.933                   | 0.86        | 0.86        | 0.86        | 0.86         |
|                                              | Network    |          |                         |             |             |             |              |
|                                              | kNN        | 4        | 0.448                   | 0.84        | 0.84        | 0.84        | 0.84         |
| BEMD Fusion<br>(Baseline)                    | SVM        | 4        | 1.813                   | 0.89        | 0.89        | 0.89        | 0.89         |
|                                              | Random     | 4        | 0.392                   | 0.87        | 0.87        | 0.87        | 0.87         |
|                                              | Forest     |          |                         |             |             |             |              |
|                                              | Neural     | 4        | 1.012                   | 0.88        | 0.88        | 0.88        | 0.88         |
|                                              | Network    |          |                         |             |             |             |              |
|                                              | kNN        | 4        | 1.101                   | 0.88        | 0.88        | 0.88        | 0.88         |
| <b>BEMD Fusion with<br/>Color (Proposed)</b> | <b>SVM</b> | <b>4</b> | <b>1.240</b>            | <b>0.93</b> | <b>0.93</b> | <b>0.93</b> | <b>0.93</b>  |
|                                              | Random     | 4        | 0.400                   | 0.893       | 0.893       | 0.89        | 0.89         |
|                                              | Forest     |          |                         |             |             |             |              |
|                                              | Neural     | 4        | 1.040                   | 0.89        | 0.89        | 0.89        | 0.89         |
|                                              | Network    |          |                         |             |             |             |              |
|                                              | kNN        | 4        | 0.630                   | 0.88        | 0.88        | 0.88        | 0.88         |

All ablation configurations were experimentally evaluated under the same classification protocol using SVM, Random Forest, Neural Network, and kNN. The experiments included Basic BEMD, Color-only Features, BEMD IMF1 Only, IMF1 + IMF2, IMF1 + IMF2 + IMF3, BEMD Fusion (Color Only), BEMD Fusion (Baseline), and BEMD Fusion with Color (Proposed). The results show a consistent increase in classification accuracy as more BEMD components along with colour information are incorporated. The BEMD Fusion with Colour proposal performed best overall among all the configurations tested, with SVM achieving an accuracy, precision, recall and F1 score of 0.93. These results suggest that the optimal classification of multiclass HLB severity is reflected by the combination of texture information from multiscale BEMD and colour features.

**Table 7.** Ablation Study of Image-Sharpening Standard Deviation

| Standard Deviation | Model          | Classes  | Computation Time (s) | Accuracy    | Precision   | Recall      | F1-Score    |
|--------------------|----------------|----------|----------------------|-------------|-------------|-------------|-------------|
| 0.02               | SVM            | 4        | 1.181                | 0.88        | 0.88        | 0.88        | 0.88        |
|                    | Random Forest  | 4        | 0.382                | 0.85        | 0.85        | 0.85        | 0.85        |
|                    | Neural Network | 4        | 0.998                | 0.86        | 0.86        | 0.86        | 0.86        |
|                    | kNN            | 4        | 0.592                | 0.84        | 0.84        | 0.84        | 0.84        |
| 0.03               | SVM            | 4        | 1.192                | 0.89        | 0.89        | 0.89        | 0.89        |
|                    | Random Forest  | 4        | 0.386                | 0.86        | 0.86        | 0.86        | 0.86        |
|                    | Neural Network | 4        | 1.002                | 0.87        | 0.87        | 0.87        | 0.87        |
|                    | kNN            | 4        | 0.601                | 0.85        | 0.85        | 0.85        | 0.85        |
| 0.05               | SVM            | 4        | 1.207                | 0.91        | 0.91        | 0.90        | 0.90        |
|                    | Random Forest  | 4        | 0.392                | 0.88        | 0.88        | 0.88        | 0.88        |
|                    | Neural Network | 4        | 1.015                | 0.88        | 0.88        | 0.88        | 0.88        |
|                    | kNN            | 4        | 0.611                | 0.87        | 0.87        | 0.87        | 0.87        |
| <b>0.10</b>        | <b>SVM</b>     | <b>4</b> | <b>1.240</b>         | <b>0.93</b> | <b>0.93</b> | <b>0.93</b> | <b>0.93</b> |
|                    | Random Forest  | 4        | 0.400                | 0.893       | 0.893       | 0.89        | 0.89        |
|                    | Neural Network | 4        | 1.040                | 0.89        | 0.89        | 0.89        | 0.89        |
|                    | kNN            | 4        | 0.630                | 0.88        | 0.88        | 0.88        | 0.88        |
| 0.20               | SVM            | 4        | 1.268                | 0.90        | 0.90        | 0.89        | 0.89        |
|                    | Random Forest  | 4        | 0.418                | 0.87        | 0.87        | 0.87        | 0.87        |
|                    | Neural Network | 4        | 1.069                | 0.88        | 0.88        | 0.87        | 0.87        |
|                    | kNN            | 4        | 0.652                | 0.86        | 0.86        | 0.86        | 0.86        |

Table 5 evaluates the effect of different image-sharpening standard deviation values on multiclass HLB severity classification using SVM, Random Forest, Neural Network, and kNN. Classification performance generally improves as the standard deviation increases from 0.02 to 0.10. The best performance is obtained at a standard deviation of 0.10, where SVM achieves an accuracy, precision, recall, and F1-score of 0.93. When the standard deviation is increased to 0.20, the performance decreases, indicating that excessive sharpening may reduce the discriminative quality of the extracted color and texture features. Therefore, a standard deviation of 0.10 is selected as the optimal sharpening parameter for the proposed multiclass HLB severity classification method. For an illustration of the confusion matrix for each standard deviation, see Figures 7–11. Despite the promising classification performance, several limitations should be considered regarding the generalization of the proposed method. Although the proposed BEMD-based color–texture feature fusion method achieved promising performance for multiclass HLB

severity classification, this study has several limitations. The evaluation was conducted using a fixed pre-existing dataset with controlled image acquisition conditions. Thus, the variations of the real field environment, e.g. change of illumination, different camera devices, leaf orientations and geographical variations were not fully represented. Further validation with independent field collected datasets under different environmental conditions is needed to assess the robustness and generalisation ability of the proposed method before deploying it in uncontrolled field environments.

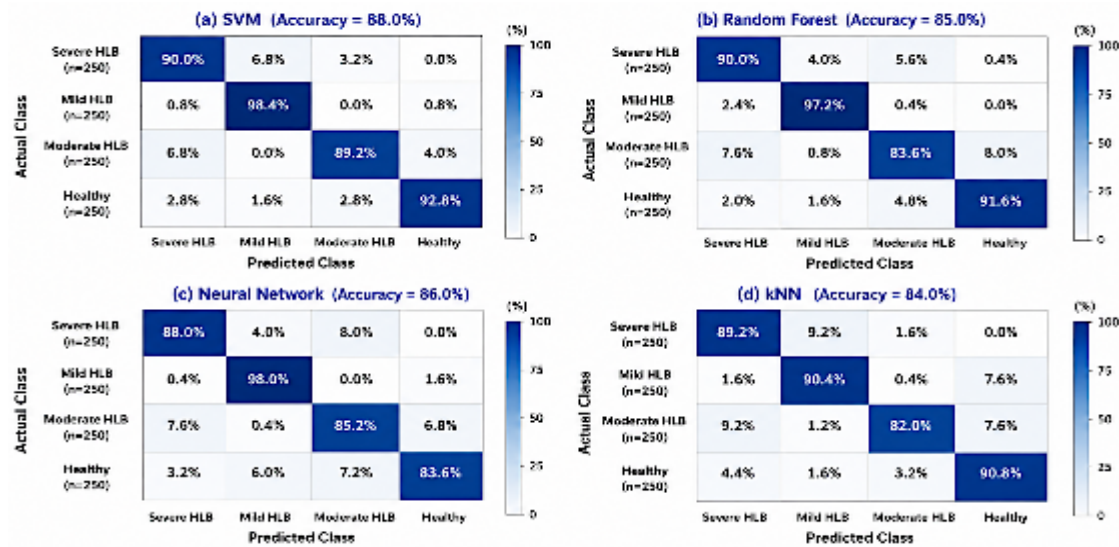


**Figure 7.** Normalized Confusion Matrices of SVM, Random Forest, Neural Network, and kNN at Standard Deviation = 0.02

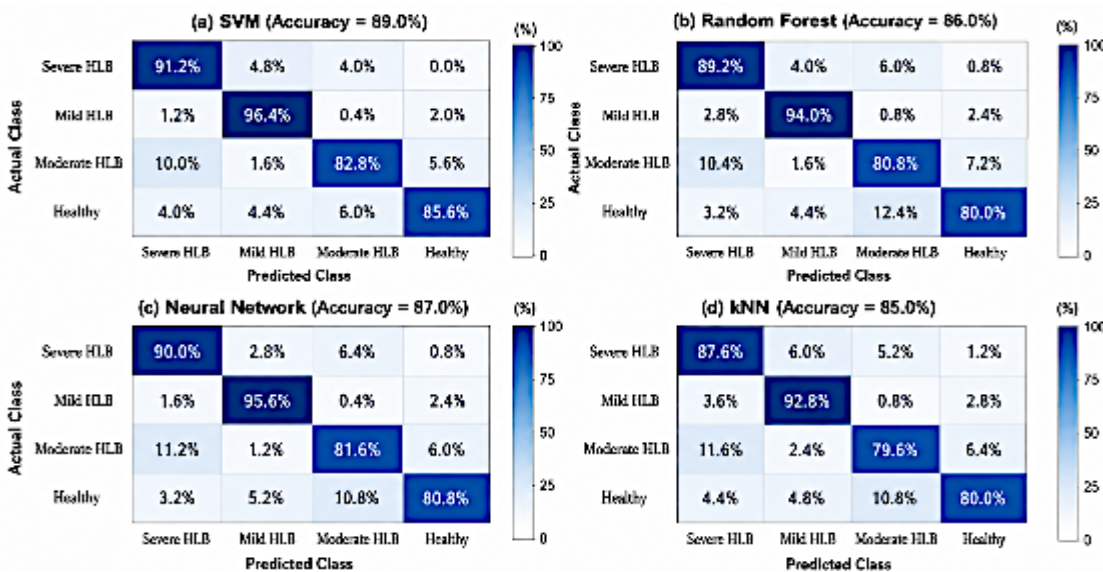


**Figure 8.** Normalized Confusion Matrices of SVM, Random Forest, Neural Network, and kNN at Standard Deviation = 0.03

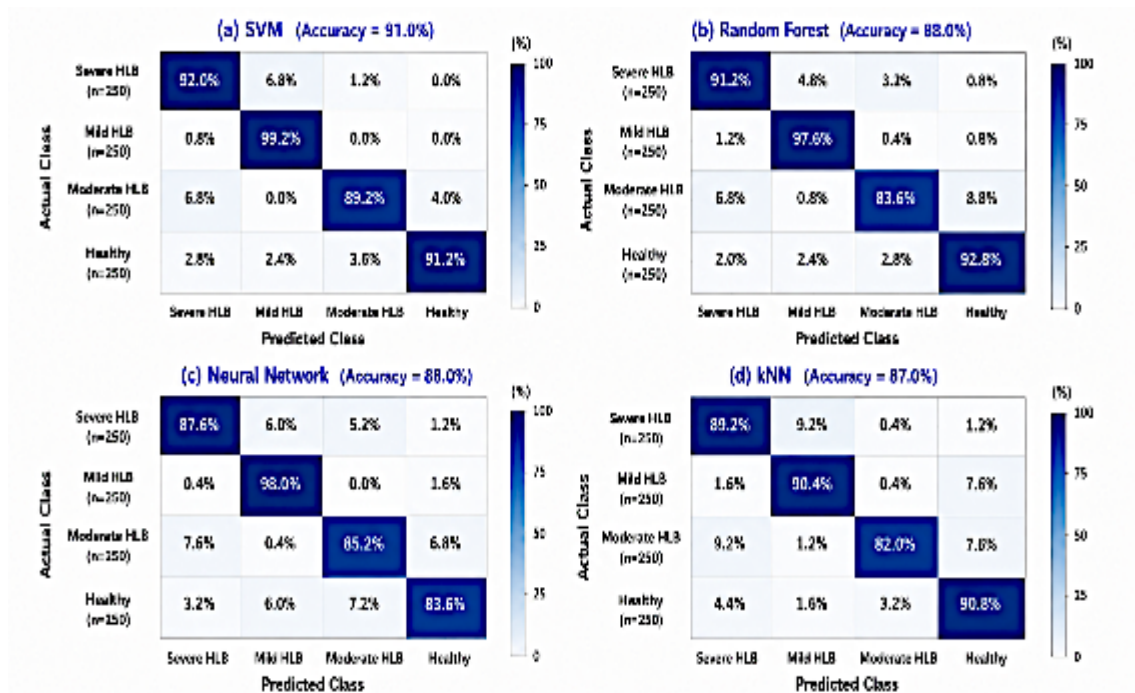


**Figure 9.** Normalized Confusion Matrices of SVM, Random Forest, Neural Network, and kNN at Standard Deviation = 0.05

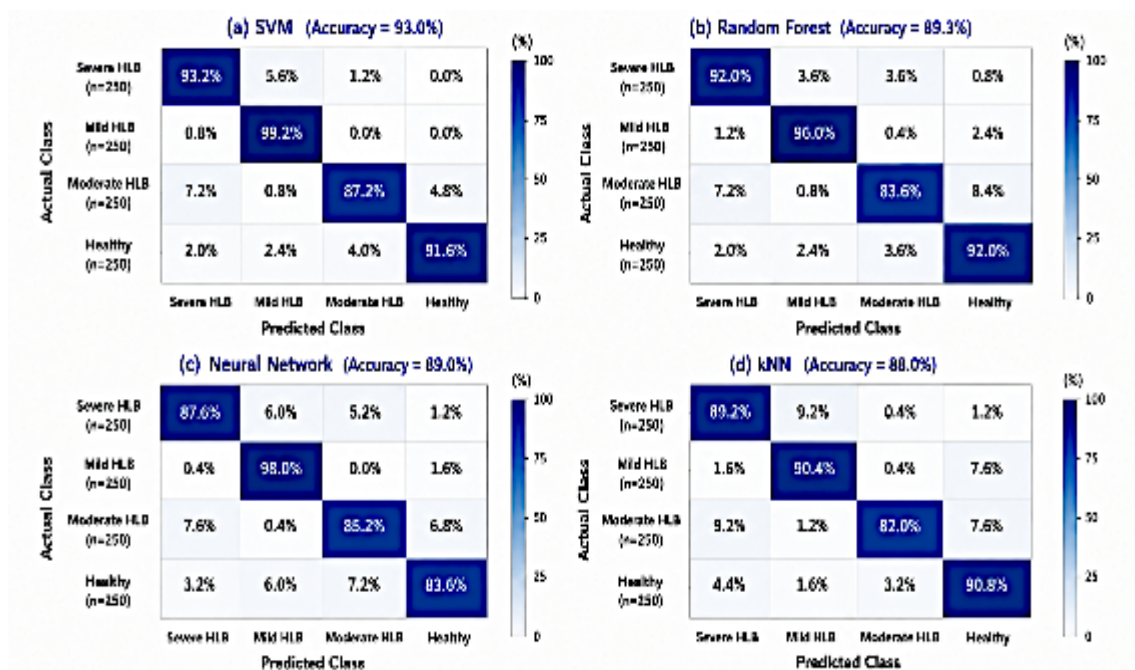


**Figure 10.** Normalized Confusion Matrices of SVM, Random Forest, Neural Network, and kNN at Standard Deviation = 0.1

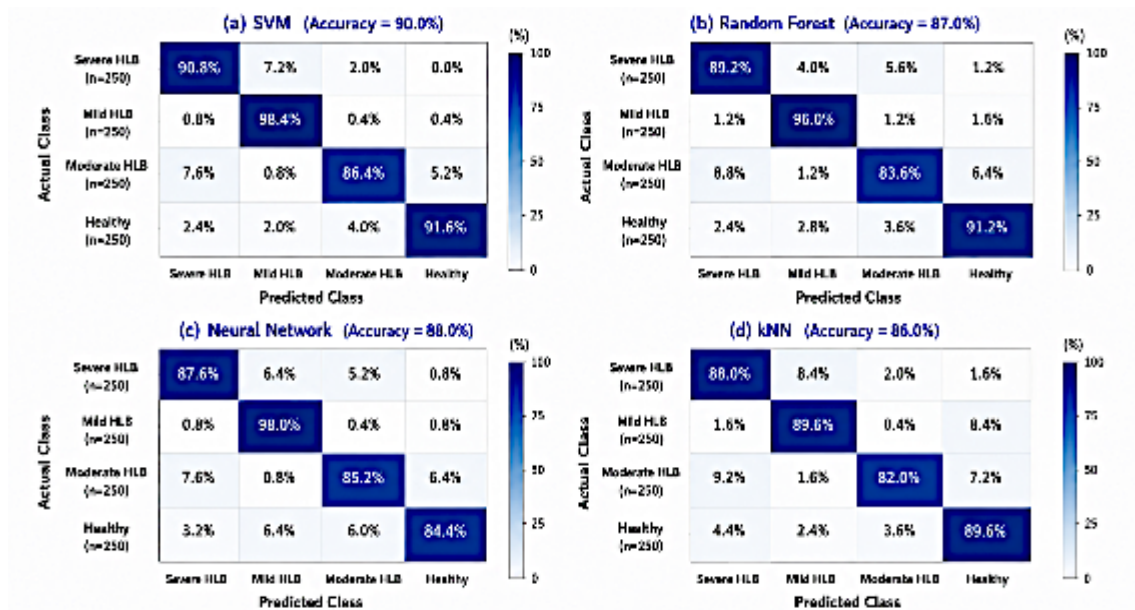


**Figure 11.** Normalized Confusion Matrices of SVM, Random Forest, Neural Network, and kNN at Standard Deviation = 0.2

### 3.5. Discussion

The experimental results demonstrate that combining multiscale texture information derived from BEMD with color features provides a more discriminative representation for multiclass HLB severity classification. The ablation study shows a gradual improvement in classification performance as additional BEMD components and color information are incorporated. Using IMF1 alone resulted in relatively low performance, whereas the combination of IMF1, IMF2, and IMF3 improved the classification accuracy, indicating that HLB symptoms are represented across different spatial and frequency scales. The proposed BEMD Fusion with Color achieved the highest performance, with SVM obtaining an accuracy, precision, recall, and F1-score of 0.93. This result supports the assumption that texture and color provide complementary information: BEMD captures fine-to-coarse structural variations such as mottling and lesion patterns, while color features represent chlorosis, yellowing, and non-uniform color distributions associated with disease progression.

Although the proposed method achieved high overall performance, the confusion-matrix analysis indicates that distinguishing Moderate and Severe HLB remains challenging. SVM achieved the best overall classification performance, with particularly high recognition of Mild HLB, while most remaining classification errors occurred between adjacent

Moderate and Severe severity levels. This overlap can be explained by the progressive nature of HLB symptoms. Moderate leaves may already exhibit substantial chlorosis, irregular mottling, and texture changes similar to severe infection, while some severe samples may still retain visual characteristics commonly observed in moderate cases. Therefore, HLB severity should be considered a biological continuum rather than completely independent visual categories. These findings suggest that multiscale texture and color fusion is effective for representing disease characteristics, but additional contextual, spatial, or symptom-distribution features may be required to improve discrimination between neighboring severity levels.

The results also show that image sharpening contributes to classification performance, with a standard deviation of 0.10 producing the best results. Performance increased as the sharpening parameter increased from 0.02 to 0.10, but decreased at 0.20, suggesting that moderate sharpening enhances relevant texture and color boundaries, whereas excessive sharpening may introduce distortions or suppress discriminative information. Moreover, the reported statistical analysis indicates that the proposed method significantly improved classification performance compared with the BEMD Fusion Baseline and Basic BEMD, with reported p-values of 0.0037 and <0.001, respectively. Nevertheless, the evaluation was conducted on a fixed pre-existing dataset acquired under relatively controlled conditions. Variations in illumination, camera devices, leaf orientation, background, and geographical conditions were not fully represented. Therefore, validation using larger independent field datasets is necessary to determine the robustness and generalization capability of the proposed approach before its practical deployment for automated HLB severity assessment.

#### **4. CONCLUSION**

In the present study, a BEMD-based color-texture fusion approach was proposed to classify four levels of Huanglongbing severity in citrus leaves, namely healthy, mild, moderate and severe. The proposed method decomposed the images of citrus leaves into IMF 1, IMF 2, IMF 3 and residue components to capture texture information at different frequency scales. The generated BEMD components were fused and utilised along with colour features capturing chlorosis, yellowing gradients, intensity variations and heterogeneous colour distribution. For feature extraction, image sharpening was applied

to highlight the leaf edges, spots, colour variations, and texture patterns using a standard deviation parameter of 0.1. The proposed approach was validated on a balanced dataset of 1000 citrus leaf images using four machine learning classifiers (SVM, kNN, Neural Network and Random Forest). The experimental results demonstrate that, within the evaluated dataset, the combination of IMF1–IMF3, image sharpening with a standard deviation parameter of 0.1, and BEMD-based color–texture fusion improves multiclass HLB severity classification performance. SVM achieved the best performance, with accuracy, precision, recall, and F1-score values of 0.93, and a computation time of 1.24 seconds. Random Forest obtained an accuracy of 0.893 with the fastest computation time among the evaluated color-fusion models, namely 0.40 seconds, while Neural Network and kNN achieved accuracies of approximately 0.89 and 0.88, respectively. Compared with the evaluated baseline approaches, the proposed method outperformed Basic BEMD, which achieved an accuracy of 0.77, and the BEMD Fusion Baseline, which achieved an accuracy of 0.89. These findings indicate that integrating color information with multiscale texture information from BEMD provides a more discriminative feature representation for distinguishing HLB severity levels in the evaluated dataset. Although the proposed method achieved the highest overall performance on the evaluated dataset, the Moderate HLB class remained relatively challenging to distinguish because its visual characteristics overlap with those of Mild and Severe HLB. In addition, the individual contribution of IMF3 and the sharpening parameter of 0.1 has not yet been quantified separately. Therefore, further ablation studies are required to determine the specific contribution of each component.

Future research may incorporate shape-based features, including lesion area, perimeter, compactness, eccentricity, contour irregularity, aspect ratio, and Hu moments. The integration of BEMD-based texture, color, and shape features through adaptive fusion mechanisms may further improve discrimination among visually similar HLB severity classes. The findings of this study are limited to the evaluated 1,000-image dataset and controlled image acquisition conditions. Therefore, further validation using independent field-collected datasets, including images captured under different illumination conditions, camera devices, field environments, and cross-location scenarios, is required to assess the robustness, generalization capability, and potential applicability of the proposed HLB severity classification method before real-world deployment.

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