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## **Vegetative Rice Growth Quality Classification Using Artificial Neural Network Based on Nitrogen Content and Leaf Width Features**

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### **Abstract**

Rice farming land in Indonesia has been decreasing annually, affecting rice productivity. Optimal fertilizer application is crucial to maintain rice quality and yield. Previous studies focused only on nitrogen content measured by leaf color, while rice plant growth quality is determined by more than just nitrogen content. Therefore, this study proposes a classification model of rice plant health in the vegetative phase based on nitrogen content and leaf width, using artificial neural networks. The proposed model uses digital imagery and computer vision to classify rice plants into low, medium, and high health levels. The model includes image acquisition, quality improvement, segmentation, feature extraction, and classification using backpropagation neural networks. The proposed method achieved an average accuracy of 85.9% and a Misclassification Error of 14.1%. This research can assist farmers in identifying rice plant health levels for optimal fertilizer application.

**Keywords:** Artificial neural network, Digital image processing, Leaf, Nitrogen, Rice

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### **1. Introduction**

Rice is a staple food in Southeast Asia, where Indonesia is one of the largest rice-producing countries in the world. Based on data from the Indonesian Central Bureau of Statistics, land area and rice production in Indonesia are decreasing yearly. In 2018, the land area was 11,377,934.44 hectares, yielding 59,200,533.72 tons; in 2019, the land area decreased to 10,677,887.15 hectares, with a harvest of 54,604,033.34 tons; in 2020, the land area further declined to 10,657,274.96 hectares, producing 54,649,202.24 tons; and in 2021, the land area decreased again to 10,411,801.22 hectares, yielding 54,415,294.22 tons [1]. In addition, climate change also directly or indirectly contributes to reduced rice production [2]. Based on the data above, the area of rice farming land in Indonesia tends to decrease yearly and affects Indonesia's productivity in producing rice. Reduced agricultural land and rice production have threatened Indonesia and the world. Besides being influenced by land area and climate change, the quantity and quality of rice plant growth are also affected by two key variables: genetic and environmental factors [3]. Genetic variables can include the type of rice planted, while environmental variables may encompass the nutrient content in the soil required by the plants.

Regarding leaf width, rice plants that are fertile and have their nutritional needs met tend to exhibit broader leaves than those that are nutrient-deficient. In terms of nutrition, one of the nutrients which is very important and needed by plants, including rice, is Nitrogen (N) [4,5]. Plants can absorb nitrogen in the soil in the form of nitrate and ammonia and then use it for growth. Nitrogen is an essential nutrient because it is closely related to the chlorophyll content of the leaves. In addition to growth, nitrogen plays a vital role in photosynthesis and biomass production for grain-producing plants such as rice [3,6,7]. If the plant is deficient in nitrogen, the chlorophyll content in the leaves and biomass production will be reduced, which will negatively impact both the quantity and quality of the grain. However, excessive nitrogen in fertilizer application can reduce nitrogen use efficiency,

leading to increased production costs, decreased water and air quality due to gas emissions, and detrimental effects on biodiversity [3,8,9]. Other facts also show that the use of N fertilizer in a certain amount affects the quality of the rice produced [10]. Therefore, using fertilizers with a certain nitrogen content is vital in agriculture [11,12].

Various methods can be used to determine nitrogen in rice leaves. One logical method to identify the nitrogen content in rice plants is by examining the green color of the leaves and their chlorophyll [11]. Several other studies use chemical analysis techniques [13] or the Kjeldahl method to measure nitrogen in rice plant leaves [14]. Additionally, some studies employ special sensors to detect the nitrogen content in leaves [15]. However, the complicated and expensive assistance process has encouraged researchers to look for other methods to identify nitrogen in rice plant leaves. Until now, the technique that has been developed is based on digital image processing.

Several studies have been conducted to estimate the nitrogen content in the leaves of a plant. A study was conducted to assess the nitrogen content of rice plants during the heading stage by using hyperspectral imagery and incorporating temperature data. The study found that combining reflectance and temperature data was effective in developing a model for estimating the nitrogen content of rice plants during the heading stage [16]. Research has been conducted on chlorophyll and nitrogen concentration estimation using a digital still color camera under natural light [17]. A significant correlation was found between Soil-Plant Analysis Development (SPAD) readings, leaf nitrogen concentration, and 13 color indicators calculated from digital camera images in HSV, RGB, and Lab\* color spaces. Research on the response of rice leaf thickness, SPAD readings, and the ratio of chlorophyll a/b to different supply levels in rice fields has also been carried out [6]. This study aimed to determine the effect of different nitrogen levels on several leaf morphological features and chlorophyll content at different leaf ages. The results showed that increasing the supply of nitrogen to rice plants resulted in thinner leaves and a decrease in the ratio of chlorophyll a/b. Other studies on leaf color dynamics modeling based on Red-Green-Blue (RGB) channels values of rice leaf images have been carried out [18]. The study developed a colour model of rice leaves treated with various nitrogen amounts. The results indicated that the RGB value of leaf colour decreased from light green to a stable green value in the first stage, then increased gradually until the end. Finally, the colour changed from green to yellow in the third stage.

Research on the discrimination of nitrogen concentrations in corn fertilized with algae and polymer extracts based on the image of the leaves has also been carried out [3]. This study used computer vision and Support Vector Machine (SVM) to discriminate nitrogen concentrations in corn leaves based on their RGB values. The results of the research show that the proposed model can classify corn leaf nitrogen concentrations into low and high classes with high accuracy. Other studies have also developed a method to estimate the nutritional nitrogen index of rice based on RGB UAV (Unmanned Aerial Vehicle) imagery combined with machine learning [19]. The results of this research show that the random forest method can provide high accuracy in predicting the target nitrogen nutrient index in each plant phase. Other research estimated leaf nitrogen content using hyperspectral data above the canopy [11]. This study proposed a drone-based model to estimate leaf nitrogen content in maize fields treated with varying water and nitrogen levels, using pure 400–1000 nm pixels from above. The analysis included the relationship between nitrogen content and water content in the leaves. Research has been conducted on estimating nitrogen nutrition using RGB imagery using machine learning [20]. The results showed that the right combination of digital imagery and machine learning could be used to estimate nitrogen nutrition in rice plants.

A study was also carried out on estimating nitrogen content in corn leaves in summer [21]. This research combined plant height, canopy coverage, and vegetation index from UAV-based RGB imagery. The results showed that the accuracy of estimating the nitrogen concentration in the leaves was relatively high. A study of the Nitrogen Concentration Detection Model of Rubber Leaves Based on Spatial Spectral Information with NIR Hyperspectral Data has been conducted [22]. This research proposes that the Kernel PCA- Gaussian Mixture Model clustering (KPCA-GMM) method utilizes clustering to obtain spatial information from rubber leaf images. The developed model identifies the optimal number of clusters for detecting nitrogen content in the rubber leaf area. Other researchers have also developed a model for estimating leaf nitrogen content based on Gene Expression Programming and spectral reflectance in leaves [4]. The experimental results show that the first derived local band model obtained based on GEP has better estimation accuracy compared to other regression algorithms. The selected local bands are less affected by humidity.

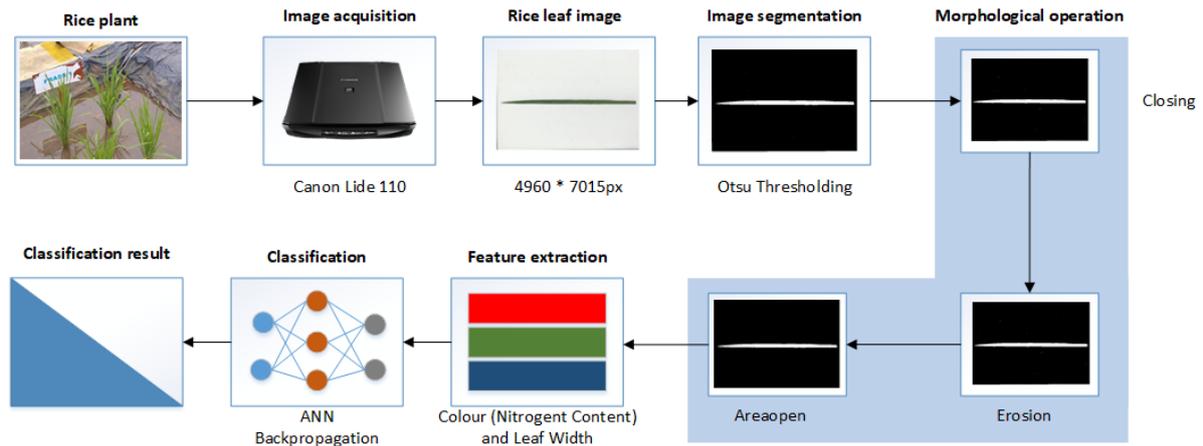
Another study also tried to estimate nitrogen content and crop yield using UAV images [23]. The proposed method can be utilized to map the distribution of nitrogen content and yield quite accurately. Another research evaluated the effectiveness of remote sensing-based models in predicting mid-season nitrogen status in commercial-scale rice using machine learning models [24]. Calibration with three local field samples improved predictions and helped farmers optimize fertilization. This study highlights the potential of remote sensing-based models to increase rice productivity and encourage further research to reduce local sample collection.

In this study, we propose a classification of rice fertility levels based on nitrogen content and leaf width features using an Artificial Neural Network (ANN) based on digital image processing. The proposed discrimination model utilizes digital imagery and computer vision to differentiate the growth quality of rice plants based on the leaves into three classes: low, medium, and high. The stages in the model start with image acquisition,

image quality improvement, segmentation using the Otsu method, morphological operations, color and shape feature extraction, and classification using backpropagation neural networks. Therefore, the novelty of the proposed method is in the form of a new image capture technique using a scanner, which ensures that the resulting images are more consistent and not disturbed by changes in light intensity. In addition, the proposed method uses a combination of nitrogen and leaf width features that represent plant fertility well. The proposed method is more affordable and easier to implement but can yield fairly accurate results.

## 2. Materials and methods

The general stages of the method for classifying the quality level of rice plant growth based on nitrogen content and leaf width can be seen in Figure 1.



**Figure 1** Stage of classification of rice plant growth quality based on nitrogen content and leaf width.

### 2.1 Image Acquisition Stage

The image acquisition process was carried out by taking leaf samples in the vegetative phase at the same position for each plant taken. According to previous research [25], the part of the rice leaf that best represents the nitrogen content extends from the tip of the leaf to two-thirds of its length. Leaf samples were taken periodically every two weeks. The leaf samples were then scanned using a Canon Lide 110 with normal settings of 600 dpi without auto enhancement. A dataset was sampled using a scanner, as it provides greater consistency in capturing images regardless of environmental light conditions. Auto enhancement was not used so that the resulting image was consistent. The leaf datasets used were 90 rice leaves taken from each bed. The leaf samples were scanned immediately to ensure that the original color remained unchanged, allowing for the accurate measurement of intensity values.

### 2.2 Image Segmentation Stage

At this stage, we separated the object and background components of the image to be processed, where the object is a rice leaf and the remaining area constitutes the background. We first extracted the Blue channel from the input image. The value of the Blue channel image was then used as input for segmentation. The Blue channel exhibited a high contrast between the object (rice leaf) and the background. Therefore, at this stage, we employed the Otsu Thresholding method. The Otsu thresholding method separated objects and backgrounds by calculating the input image histogram statistics. The basic assumption of the Otsu method is that an image with objects and a background will produce a normal distribution with two peaks. These two peaks represent the object and background clusters [26]. Therefore, the object and background can be separated by finding the dividing point between the two peaks. This method can then determine the thresholds on the histogram automatically. The intersection point is then used as a reference to distinguish between the background and the object.

### 2.3 Morphological Operation Stage

The morphological operation stage was applied to refine the segmentation results obtained in the previous stage. The initial results may yield incorrect segmentations; therefore, it is necessary to enhance them. The morphological operations applied are dilation, closing, erosion and areaopen operations. The dilation operation

was applied to increase the edge of the object area, and then the closing operation was applied. Furthermore, in the closing results, the erosion operation was applied again to ensure that the edges of the background do not become part of the object. The application of erosion ensured that the area entered as an image object was the area of rice leaves. In binary images, the results of erosion operations usually leave other objects that are not needed in the image area. Therefore, the areaopen technique was applied. Areaopen removed unnecessary objects from the image area. All objects with connected component pixels smaller than 1000 were deleted so that only one object was left in the image, namely the rice leaf image.

#### *2.4 Feature Extraction Stage*

In the feature extraction stage, the feature values used as input at the ANN training stage were taken from well-segmented object areas. The accuracy of feature values is dependent on the accuracy of the segmentation results in the previous stage. At this stage, the feature values used were the average intensity of rice leaf objects in the Red channel in the RGB colour space, the L channel in the LAB colour space, the S channel in the HSV colour space, and the minor axis shape feature that represents the width of the leaf. These four main features were the feature values inputted into the classification method used in the next stage.

The input variables were selected based on the results of the experiments that had been conducted. In this case, the combination of channel R in RGB color space, channel L in Lab\* (LAB) color space, and Channel S in Hue-Saturation-Value (HSV) color space represents the nitrogen content of rice leaves. While the minor axis feature represents the width of rice leaves. In this study, the feature that most effectively represents the fertility level of rice plants in the vegetative phase was selected based on the results of the experiments conducted, which are detailed in the Results and Discussion section of this paper.

#### *2.5 Classification Stage*

This stage consists of two main parts: training and testing. During the training phase, the feature values of the leaf objects were used as input for training the artificial neural network (ANN), allowing for the development of an accurate ANN model capable of distinguishing object areas in feature space. Once the optimal ANN model had been identified, it was tested and classified. The accuracy of the classification results depends on the effectiveness of the ANN model produced during the training process.

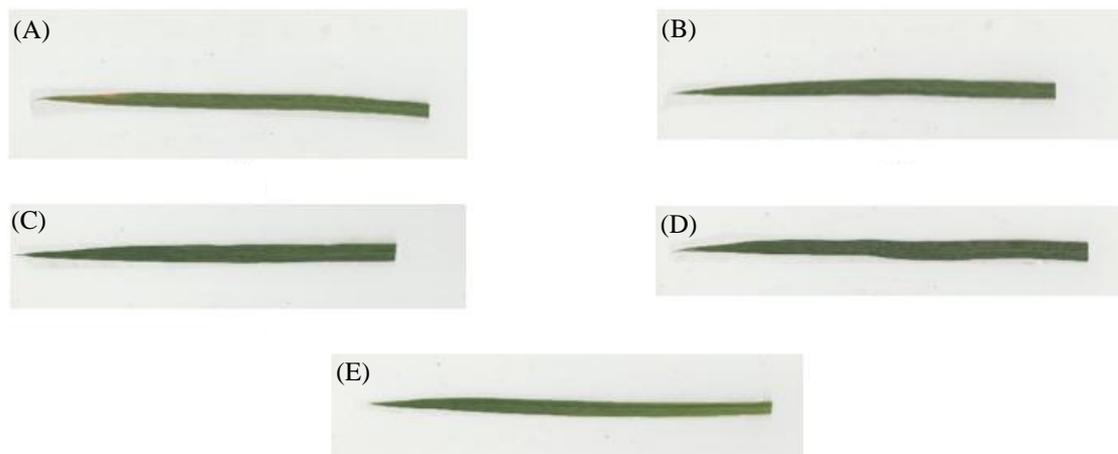
The utilization of ANN Backpropagation in computer vision has been extensively researched and implemented across various domains. Image classification is among the most prevalent applications [27–29]. ANN backpropagation is widely used because it has several advantages. One significant advantage is its capability to handle intricate and non-linear relationships between input and output variables. This versatility makes it suitable for various applications, including prediction, classification, and pattern recognition. Another advantage of ANN backpropagation is its ability to learn from large datasets. Furthermore, ANN backpropagation is a flexible algorithm that can be adapted to various types of ANNs and optimization problems.

However, the classification accuracy of Backpropagation ANN is highly dependent on the training data used. Therefore, it is necessary to have highly correlated input variables resulting from feature extraction at the digital image processing stage.

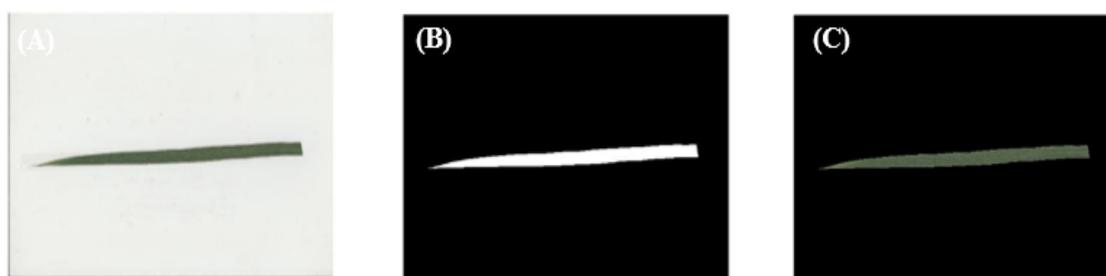
### **3. Result**

#### *3.1 Image Acquisition Stage Result*

The results of image acquisition using the Canon Lide 110 can be seen in Figure 2. The resulting image is not disturbed by inconsistent external light. Therefore, the consistency of the intensity obtained from the scan results can be guaranteed. An example of the resulting image can be seen in Figure 2. Acquisition using a Canon Lide 110 scanner produces an image of rice leaves measuring 4960 x 7015 pixels. The resolution of this image acquisition is sufficient to represent the details of the rice leaves.



**Figure 2** Image acquisition results of rice leaves, (A-B) Medium growth quality, (C-D) High growth quality, and (E) Low growth quality.



**Figure 3** Example of image segmentation results, (A) Original image, (B) Image from segmentation and morphological operations, (C) Leaf object.

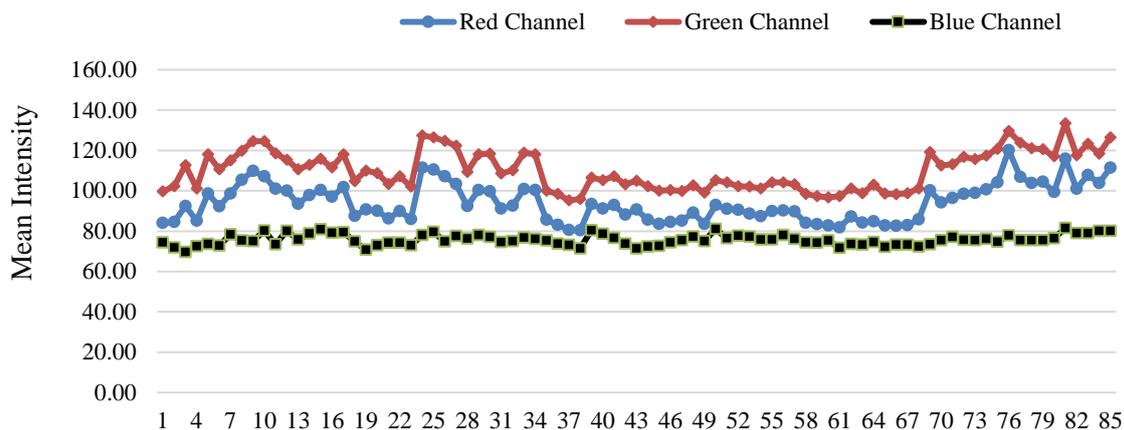
### 3.2 Image Segmentation and Morphological Operation Stage Result

After the leaf image was obtained, it was segmented to identify the area of the object from which to extract feature values. The segmentation results were then refined using morphological operations in spatial space to ensure that only one clean and accurate object remained in the image. An example of the image segmentation results can be seen in Figure 3.

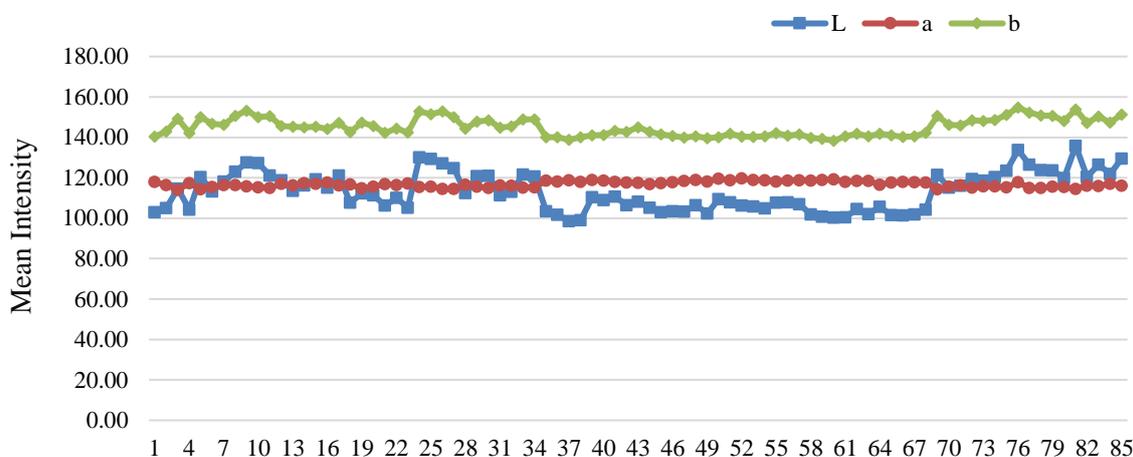
In Figure 3, it can be seen that the original image as input is segmented so that a binary image is obtained from the segmentation results using Otsu method [26] and morphological operations (Closing, erosion, and areaopen). The white part indicates that the area is the object area, and the black area is the background area in the image. After marking the pixels, which are the object areas, this marking was applied to the original image so that part of the object from the original image was obtained (c). In the next stage (feature extraction), only this part of the object whose feature value will be extracted.

### 3.3 Feature Extraction Stage Result

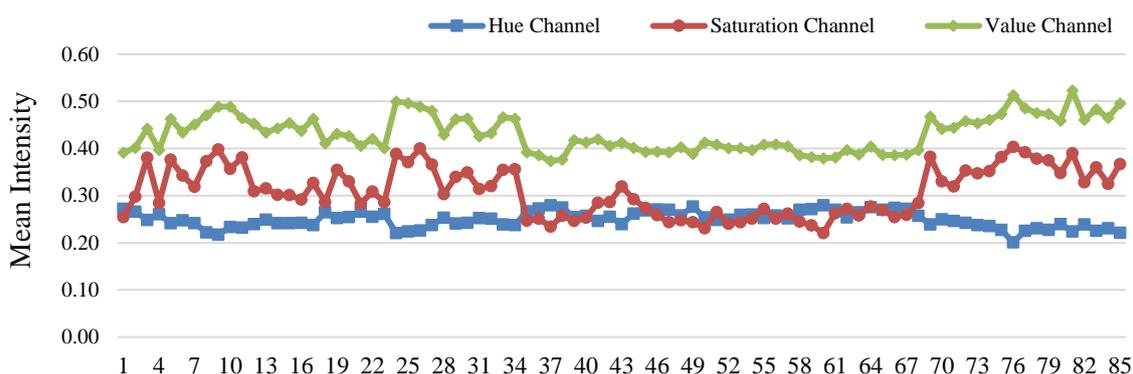
At the feature extraction stage, we conducted experiments in three color spaces: RGB, LAB, and HSV. The average intensity of the rice leaf image samples in the RGB color space is illustrated in Figure 4. Based on the graph, the average intensity of rice leaves in the high-growth quality class (sample 35 – 68) tends to be lower than that in the medium (sample 1 – 34) and low-quality (sample 69 – 85) growth classes. The graph also indicates that rice with low growth quality tends to exhibit higher or brighter color intensity in the red and green channels. In the blue channel, the intensity across the three leaf classes tends to be similar.



**Figure 4** The mean intensity of the training data samples in the RGB color space



**Figure 5** The average intensity of the training data samples in the LAB color space.

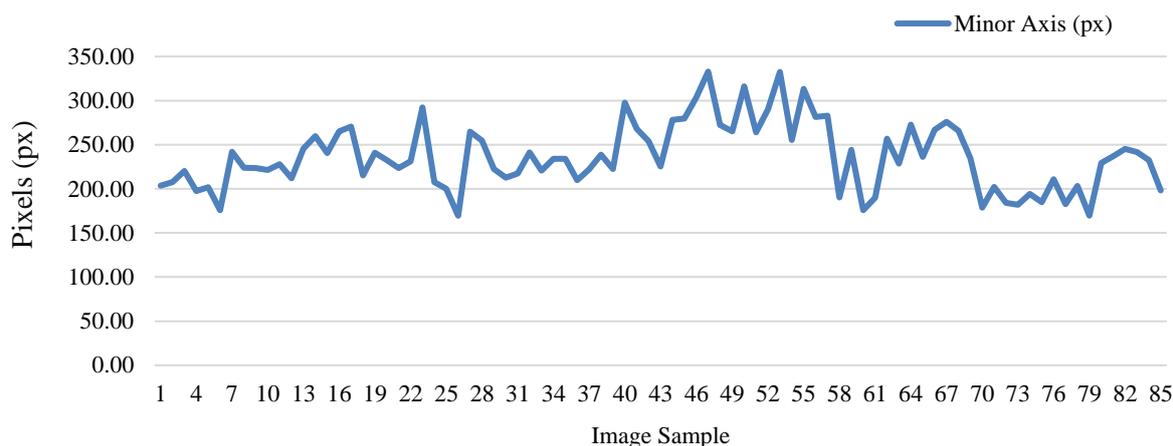


**Figure 6** The average intensity of the training data samples in the HSV color space.

In the LAB colour space, the average intensity of leaf image samples is presented in Figure 5. Based on the graph shown in Figure 5, it can be seen that rice leaves with a high growth quality class have a lower L channel intensity value compared to the other two quality classes. Rice intensity value compared to the other two quality classes. Rice leaves with a high growth quality class are also seen in channel B, where the intensity of rice leaves with high growth quality tends to be lower. This graph shows that the image of rice leaves with low or medium growth quality exhibits high-intensity values in the L and B channels.

Meanwhile, in Channel A, the three classes show an average intensity that tends to be the same. In the average intensity of image samples in the HSV color space, as illustrated in Figure 6, rice leaves exhibiting high growth quality have lower intensity values in the S and V channels compared to other leaf classes. The graph also indicates that as the quality of rice growth decreases, the intensity of leaf color in the S and V channels increases.

In addition to the colour features, at this stage, the value of the minor axis feature is also generated, representing the rice leaf's width. The minor axis chart can be seen in Figure 7. As Figure 7 indicates, healthy rice leaves tend to have a greater minor axis value compared to the other two leaf classes. Rice with low growth quality tends to have leaves with a lower minor axis. Based on the features that have been extracted, it can be seen that rice with a high growth quality tends to have lower intensity values in the R, G, L, S, and V channels, as well as a smaller minor axis. Conversely, leaves with low growth quality tend to have higher intensity values and lower minor axis.



**Figure 7** The leaf width value (minor axis) of the rice leaf image sample.

### 3.4 Classification Stage Result

At the classification stage, several test scenarios were conducted by combining features to maximize the accuracy of the classification results. The experimental scenarios and the level of accuracy obtained can be seen in Table 1. A comparison of accuracy and misclassification errors can be seen in Figure 8.

Table 1 and Figure 8 demonstrate that the seventh scenario, which combines the features of the Red (R) channel, Lightness (L), Saturation (S), and Minor Axis (M), yields the highest classification accuracy of 85.9%, with a misclassification error of 14.1%. Based on the experimental results, the proposed model effectively distinguishes among three classes of rice growth quality (low, medium, and high) using color features that reflect nitrogen content and minor axis features that represent leaf width.

**Table 1** Classification accuracy based on test scenarios.

Testing Scenario	Feature										Accuracy(%)	ME (%)
	R	G	B	L	A	B	H	S	V	M		
1	√	√	√	√	√	√	√	√	√	√	83,5	16,5
2	√	√		√				√	√	√	84,7	15,3
3		√		√					√	√	83,5	16,5
4	√	√	√								78,8	21,2
5							√	√	√		80	20
6				√	√	√					80	20
7	√			√				√		√	85,9	14,1

**Table 2** F1-Score results from the proposed method.

Class	Precision	Recall	F1-Score
High	0.91	0.94	0.93
Medium	0.88	0.82	0.85
Low	0.72	0.76	0.74

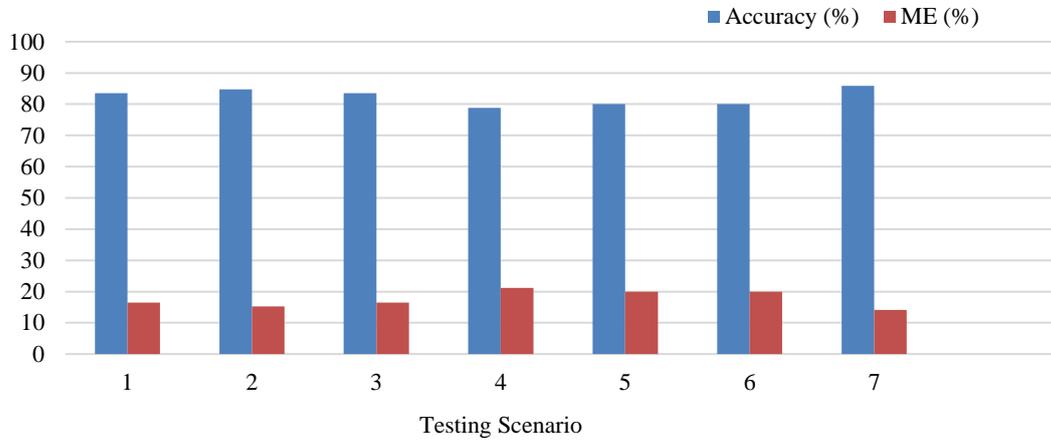
**Figure 8** Testing scenarios result.

Table 2 presents an evaluation of the performance of the proposed method using precision, recall, and F1-score metrics. As the table indicates, the High class demonstrates the best performance, with a precision value of 0.91, a recall of 0.94, and an F1-score of 0.85. This indicates that the model effectively recognizes the High class in terms of both prediction accuracy and the success rate in identifying the correct data. In contrast, the Low class exhibits lower classification results compared to the other two classes. This discrepancy arises because the Low and Medium classes tend to share similar characteristics, leading to some predictions being interchanged between these two classes. Nevertheless, the proposed method achieved an overall F1-score of 0.84, indicating that, on average, it can effectively classify the three classes.

Based on the observations, it is evident that the fertility of the rice plant is directly proportional to leaf width and the intensity of green color, which correlates with the nitrogen content of the leaves. This relationship is represented by the R, L, and S channels.

The color feature values and leaf width measurements are normalized prior to being used as input variables in the ANN backpropagation process. This normalization is performed to prevent feature dominance, accelerate convergence, and enhance stability and generalization.

#### 4. Discussion

In the image acquisition process, image samples of rice leaves were collected every two weeks during the vegetative phase. The selection of leaves was conducted consistently at the same position and location on the rice stalks. The leaf samples were then immediately scanned using a scanner. A scanner was used because it produces images that are more consistent and less affected by dynamic external lighting. During the scanning stage, we ensured that the scanner captured images without auto-enhancement, thereby maintaining a consistent shooting mode for all samples. At the image segmentation stage, channel analysis was first conducted in RGB space to determine which channel exhibited sufficient contrast between the rice leaves and the background. Given that the rice leaves are green and the background resulting from the scanning process is white, observations indicate that the intensity value of channel B demonstrates a higher level of contrast with the background compared to the other channels. Consequently, the Otsu Thresholding method was applied to the Blue channel of the input image during the segmentation stage.

The output of this segmentation is quite accurate, given that the color difference between the leaf object and the background in the blue channel is significant. Therefore, it is relatively straightforward to determine the thresholding value for segmentation using the Otsu method. However, there are instances where certain parts of the image cannot be segmented perfectly. For example, some objects in other areas of the image may be incorrectly classified as part of the leaf, while portions of the leaf edges may encroach upon the background but are still considered part of the object. Failing to address these issues can disrupt the feature extraction process and lead to inaccurate extracted feature values. Consequently, after obtaining the segmented image (binary image),

morphological operations are applied to refine the segmentation results. The operations performed include closing, erosion, and area opening. The closing operation is used to smooth the edges of the leaf object, while the erosion operation removes leaf edges that are mistakenly classified as part of the background. The area opening operation is employed to eliminate other unnecessary objects (connected components) in the image. The output of these morphological operations yields improved image segmentation results, resulting in intact leaf images free from noise disturbances.

In the feature extraction stage, this research proposes a combination of color features from the R, L, and S channels, along with leaf width features (minor axis). These features were selected because, after analyzing and experimenting with all channels in the RGB, LAB, and HSV color spaces, they were found to be the most accurate in representing the level of nitrogen content in rice leaves. The feature value for each channel is derived from the average intensity of all pixels considered part of the leaf image. This average value effectively represents the leaf object. It is also observed that higher nitrogen content in rice leaves corresponds to lower intensity values in the R, L, and S channels. Additionally, the width of the rice leaves serves as a reliable indicator of the growth quality of the plants; as nitrogen content increases, the width of the rice leaves tends to increase as well. This correlation between color features and leaf width justifies the inclusion of the leaf width feature in the classification stage. These findings are consistent with earlier studies that have demonstrated that the leaf width gene LW5/D1 plays a role in regulating nitrogen utilization efficiency, which in turn affects the plant architecture and yield of rice. [30].

Furthermore, at the classification stage, the dataset feature values are divided into three parts: 70% for training data, 15% for validation data, and 15% for test data. Based on the results obtained, the combination of the R, L, and S channels, along with the minor axis/leaf width (M), has been shown to yield accurate classification results using artificial neural networks. This accuracy is demonstrated in the test scenario results table, which combines several features.

## 5. Conclusion

Based on the accuracy and misclassification results obtained, the proposed classification method, which combines R, L, S, and leaf width features, can provide fairly accurate classification results for assessing the quality of rice plant growth. The test scenario results and feature extraction indicate that higher nitrogen content in rice leaves correlates with lower color intensity (in the R, L, and S channels) and wider leaf size. The model developed can assist farmers in determining the growth quality of their rice plants, enabling them to apply fertilizer optimally. Although the achieved accuracy is commendable, there is still room for improvement in the classification results. Future research could focus on developing image capture techniques that are easier and real-time while maintaining accuracy. Additionally, further development could explore other features that may better represent the fertility of rice plants.

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## 7. Author Contributions

Kaswar, AB.: Conceptualization, Methodology, Software, Writing – original draft; Djawad, YA.: Formal analysis, Validation, Writing – review & editing, Project administration; Andayani, DD.: Data curation, Visualization; Jumadi, O.: Resources, Supervision, Validation.

## 8. Conflict of interest

The authors declare no conflicts of interest relevant to the content of this article.

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