CHAPTER V
CONCLUSION

5.1. Conclusion

Based on the results of the research and testing that have been conducted on the combined K-Means and K-Nearest Neighbor (KNN) method for rice leaf disease classification, several conclusions are obtained as follows:

1. Effectiveness of the Combination of K-Means and K-Nearest Neighbor (KNN) Methods

   The combination of K-Means for segmentation and K-Nearest Neighbor (KNN) for classification proved capable of classifying types of rice leaf diseases with quite high accuracy. K-Means is able to group image areas based on similar visual features, while K-Nearest Neighbor (KNN) works well in determining the disease class based on patterns that have been grouped by K-Means.

2. Effect of Data Split Ratio on Accuracy

   Testing using various data split ratios shows that the 90:10 ratio provides the best classification results with the highest accuracy. This indicates that the model has more stable performance when more data is used for training. Conversely, the 60:40 ratio results in a quite significant decrease in accuracy, which indicates that a smaller amount of training data can impact the model's accuracy in classifying images.

3. Choosing the K Value in K-Nearest Neighbor (KNN)

   The test results show that choosing the optimal K value greatly influences classification performance. A K value that is too small can cause the model to be too sensitive to noise, while a K value that is too large makes the model less specific in determining the class. From the experiments conducted, K=3 to K=5 provide the best accuracy in most testing scenarios.

4. Model Performance on Various Types of Diseases

   The model can recognize Bacterial Blight, Blast, Brown Spot, and Tungro diseases well. However, there are several classification errors, especially in diseases that have similar spot patterns to each other, such as Brown Spot and Blast. This indicates that the model still has limitations in distinguishing several types of diseases with similar visual characteristics.

5. Visualization and Confusion Matrix Analysis

   From the confusion matrix results, it can be seen that the model is able to classify most of the images correctly, although there are still some prediction errors. This shows that the method used is quite effective, but can still be improved further with improvements in image preprocessing or optimization of model parameters.

6. Implementation in an Image-Based Classification System

   The application of the combination of K-Means and K-Nearest Neighbor (KNN) in an image-based classification system has shown promising results in automatically detecting rice leaf diseases. This system can be used as a tool for farmers or researchers to identify plant diseases more quickly and efficiently compared to manual methods.

5.2. Development Suggestions

Based on the results of the research that have been conducted, there are several suggestions for future research development, including:

1. **Development using more complex methods**

   Future research is advised to use deep learning methods such as Convolutional Neural Network (CNN) to improve classification accuracy.

2. **Addition and variation of the dataset**

   The dataset needs to be expanded with variations of real-world conditions such as lighting, background, and image quality so that the model is more robust.

3. **Use of more diverse image features**

   In addition to grayscale, color features (RGB/HSV/Lab) and texture can be used to improve the model's ability to recognize disease patterns.

4. **Systematic parameter optimization**

   Determining the K value in KNN and the number of clusters in K-Means can be optimized using methods such as cross-validation or grid search..

5. **Development of user-based applications**

   The system can be developed into a mobile or web-based application so that it can be used directly by farmers in the field.

6. **Development of a real-time system**

   Future research can develop a real-time disease detection system using a camera to improve identification efficiency.