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Classification Of Rice Plant Diseases Based on Leaf Images Using the Multi Class Support Vector Machine (M-SVM) Method

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Abstract

The rice farming sector plays an important role in the Indonesian economy, considering that rice is the main staple food. According to IRRI, rice farmers experience crop losses of up to 37% each year due to pests and diseases. This study aims to classify rice plant diseases using the Multi-Class Support Vector Machine (M-SVM) method based on leaf images. This study aims to provide education to farmers in recognizing and overcoming diseases in rice plant leaves. The types of rice leaf diseases classified in this study include Blast, Kresek, and Tungro. The data used in this study amounted to 1200, which were divided by varying training and testing data ratios, from 10% training and 90% testing to 90% training and 10% testing. Each variation of features and data division was evaluated by calculating the model performance parameters. The features used for classification include color (RGB) and texture (GLCM) from leaf images. The test results showed that the best accuracy obtained was 85.5% using a combination of color and texture features.

Keywords: *Accuracy, Disease Classification, GLCM, leaf image, M-SVM, Rice.*

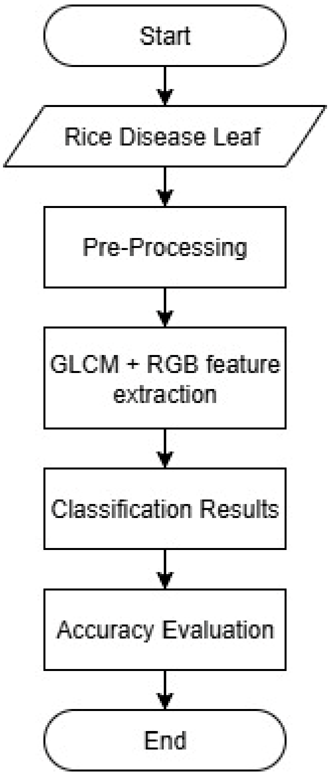
I. Introduction

The rice farming sector plays an important role in contributing to the Indonesian economy, because rice is one of the largest commodities. Many countries, including Indonesia, make rice their main staple food. Therefore, Indonesia needs to continue to innovate so that the rice supply remains abundant and stable [1]. Agriculture itself is an activity that utilizes nature to produce food, one of which is rice cultivation. However, rice plants are often attacked by various diseases, such as leaf blight (kresek), blast, tungro and others [2].

The development of digital image processing technology and artificial intelligence (AI) provides potential solutions in the agricultural sector, especially in terms of identifying plant diseases. With the help of machine learning algorithms, such as Support Vector Machine (SVM), the classification process can be carried out [3], Multi-Class Support Vector Machine (MSVM) is a variant of the Support Vector Machine (SVM) method used to solve multi-class classification problems. SVM is basically a classification algorithm designed to handle two-class problems (binary classification) [4] Based on the background of this problem, researchers propose a solution by using the Multi-Class Support Vector Machine (M-SVM) method. The use of the M-SVM algorithm allows disease classification based on patterns and textures on rice leaves, so that each type of disease can be recognized more quickly and accurately.

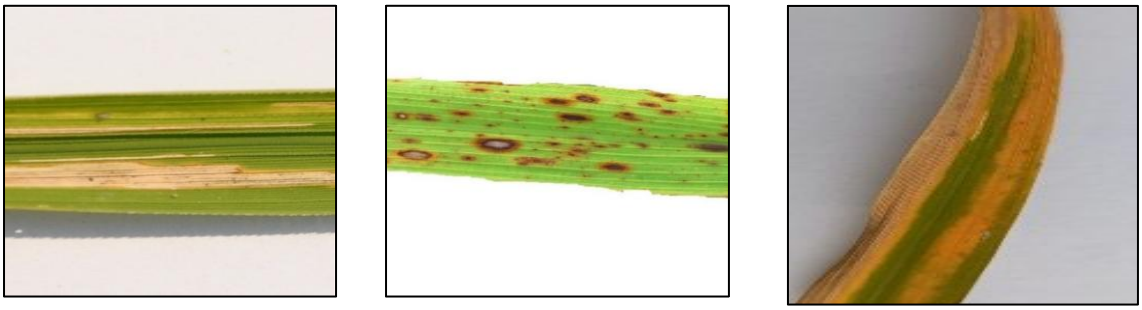
II. Methods

In (Figure 1) it will explain the research stages including several steps carried out systematically to achieve the objectives of the research, the research stages include starting, input of rice leaves, analysis of the problem identification system, implementation, trial, success.



. Figure 1. Research stage flowcart.
(Source: Personal Preparation)

1. Input data for rice disease leaves:



(a). Leaf blight (kresek) (b). Blast (c). Tungro
Figure 2. Image of rice leaves

In (Figure 2) we will explain about 3 diseases of rice as follows:

a. Bacterial leaf blight is a very common disease found in rice fields. The main cause of this disease is the bacteria Xanthomonas oryzae. Symptoms of bacterial leaf blight on leaf blades are characterized by damage that usually begins a few centimeters from the edge, which appears as lines and blisters, then spreads to the wavy edges [1].
b. Blast disease caused by Pyricularia grisea is an important disease in rice plants in Indonesia, especially in upland rice in dry land. grisea infects the leaves and causes disease symptoms in the form of diamond-shaped brown spots called leaf blast [5].
c. Tungro is a disease caused by a double infection of 2 different types of viruses. The second virus in question is Rice Tungro Spherical Virus (RTSV) and Rice Tungro Bacilliform Virus (RTBV).

Symptoms of tungro disease are that the leaves will turn yellow starting from the tips of the leaves that are still in the growth stage [5].

Rice plants are susceptible to various types of diseases. In this study, we focus on three main types of diseases in rice plants, namely tungro disease, leaf blight, and leaf blast. The data used consists of 1200 leaf images divided into 3 classes, namely 400 Leaf blight (kresek) image data, 400 leaf blast image data, 400 tungro image data. Data division is carried out for training data (80%) and test data (20%) [3].

2. Pre-processing

Pre-processing is a crucial step that is carried out before the image is used for feature extraction or classification model development. The main purpose of this stage is to prepare the image so that it is more ready for further analysis and can improve accuracy [6]. The disease detection system at this processing stage includes: Normalization, Contraction, Cropping, Resize.

3. GLCM and RGB feature extraction

GLCM (Gray Level Co-occurrence Matrix) and RGB (Red, Green, Blue) feature extraction are used to analyse the texture and color of rice leaf images, especially in detecting and classifying diseases that attack rice leaves [7]. When rice leaves are infected with disease, both the texture and color of the leaves will experience different changes from healthy leaves. Infection can cause color changes, such as yellowish or brownish, as well as the appearance of spots with certain intensities, which can be analyzed through RGB features [8]. In addition, changes in texture patterns such as spots, lines, or holes on leaves can be evaluated using the GLCM method which extracts features such as Contrast and Correlation. By combining texture analysis using GLCM and color analysis using RGB, we can obtain more complete information about the condition of rice leaves, thereby increasing the accuracy of disease identification and classification [9].

4. M-SVM Classification

Classification using the Multi-Class SVM (MSVM) method is divided into two stages, namely training and testing, where the image dataset goes through a feature extraction process using the GLCM and RGB methods. GLCM is used to extract texture information, such as Contrast and Correlation, while RGB is used to analyse colour characteristics in rice leaf images. Furthermore, the extracted images are classified using Multi-Class SVM. Through this classification process, it can be identified whether the input leaves are included in the category of normal leaves or diseased rice leaves, and can be separated based on their respective classes by considering a combination of texture and colour features to improve identification accuracy [10],[11],[12].

5. Accuracy Evaluation

At this stage there are several steps taken, namely:

a. Confusion Matrix

Use a confusion matrix to see how well the model classifies diseases. The confusion matrix will show the number of correct and incorrect predictions for each disease class (e.g., Leaf Blight, Leaf Blast, and Tungro) that exist [9], [13], [14].

b. Accuracy

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (1)$$

c. Precision

$$\text{Precision} = \frac{TP}{TP+FP} \times 100\% \quad (2)$$

d. Recall

$$\text{Recall} = \frac{TP}{TP+FN} \times 100\% \quad (3)$$

The research will be conducted at Jl. Sudimoro, behind the Sawah cafe, and is targeted to take place from November 2024 to February 2025. This extended period will provide sufficient time for the researcher to make necessary preparations, such as understanding the research problems, objectives, methods, and the tools required for the research process [15].

III. Results and Discussions

a. Feature extraction using Gray Level Co-occurrence Matrix (GLCM) and RGB

Feature extraction using the Gray Level Co-occurrence Matrix (GLCM) method is a technique in image processing used to obtain texture information from images. GLCM analyzes the spatial relationship between pixels based on gray levels to form a co-occurrence matrix, from which texture features such as Contrast, Correlation can be calculated. At this stage, the method is used to detect rice leaf images. In addition, the basic color values of the image are also used by taking RGB (Red, Green, Blue) values directly from each pixel as additional features that represent image color information.

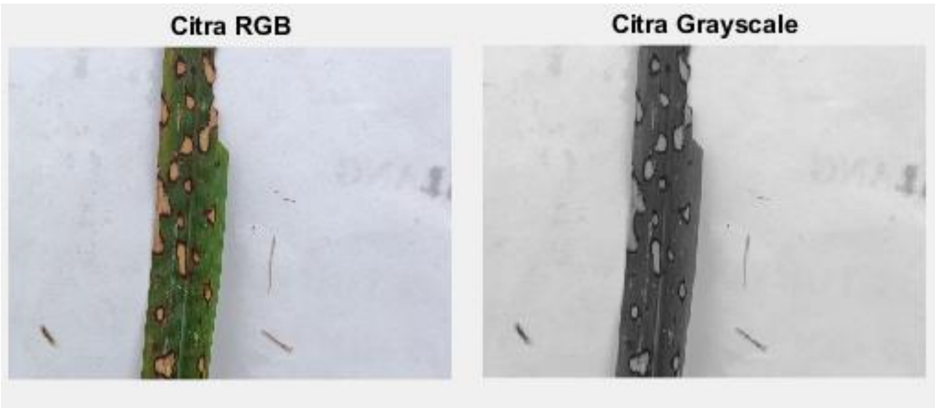


Figure 3. Blast image capture interface design

In (Figure 3.) to convert data from image form into numeric form, a data conversion process design is needed that utilizes a graphical interface (GUI) using the Matlab programming language. This process is important for the purposes of texture analysis with the M-SVM method. The blast, kresek and tungro data values obtained from the feature extraction results consist of several fields that can be displayed in (Table 1).

Tabel 1. Blast, Kresek and Tungro Image Datasets

Project_ID	Contrast	Correlation	Red	Greend	Blue	Results
blast111.jpg	0.091126	0.96395	0.7276	0.74142	0.75599	blast
blast144.jpg	0.09572	0.95864	0.74756	0.72766	0.69713	blast

kresek11.jpg	0.15015	0.93488	0.56585	0.62566	0.76428	plastic bag
kresek109.jpg	0.1193	0.95152	0.74032	0.72572	0.71702	plastic bag
tungro1.jpg	0.073608	0.96713	0.7847	0.72117	0.66278	tungro
tungro100.jpg	0.053928	0.97586	0.79111	0.73136	0.65979	tungro

b. Training Data *Multiclass Support Vector Machine* (M-SVM) method

Table 2. Results of Polynomial M-SVM Training Evaluation

M-SVM(POLYNOMIAL)						
Split ratio		Accuracy	Precision	Recall	Data	
Training	Testing				Train	Test
10%	**90%**	**88%**	**83.3751%**	**83.3333%**	120	1080
20%	**80%**	**89.7222%**	**84.5861%**	**84.5833%**	240	960
30%	70%	85.1852%	78.8981%	77.7778%	360	840
40%	60%	85.5556%	78.7160%	78.3333%	480	720
50%	50%	85.7778%	78.5025%	78.6667%	600	600
60%	40%	85.2778%	77.8825%	77.9167%	720	480
70%	30%	85.2381%	79.2707%	77.8571%	840	360
80%	20%	84.5833%	77.1485%	76.8750%	960	240
90%	10%	85.1852%	77.9073%	77.7778%	1080	120

In (Table 2) it is explained that the results of the training data evaluation using the M-SVM Polynomial method obtained a high accuracy score, namely at a split ratio of 20:80, the number of training data is 240 with an accuracy score of 89.7222%. Precision 84.5861% and Recall 84.5833. and the results of the M-SVM Polynomial graph and the calculation of the confusion matrix with the highest value at a split ratio of 20:80, can be seen in (Figure 4) and (Figure 5) below.

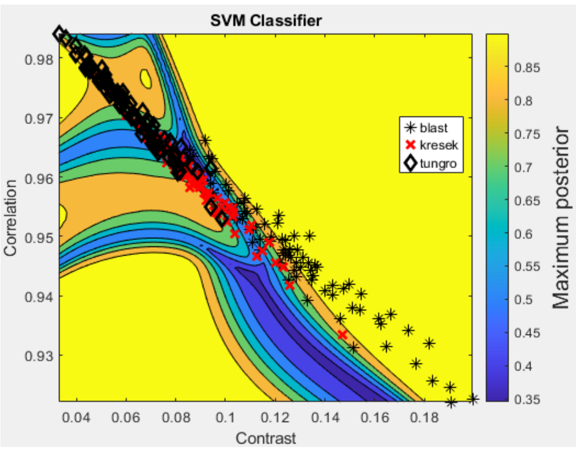


Figure 4. M-SVM Polynomial 20:80 graph

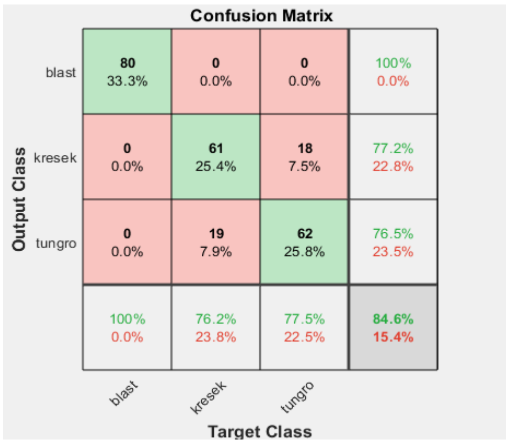


Figure 5. CM M-SVM Polynomial 20:80

Table 3. Linear M-SVM Training Evaluation Results

M-SVM(LINEAR)						
Split ratio		Accuracy	Precision	Recall	Data	
Training	Testing				Train	Test
10%	90%	87.2222%	81.2963%	80.8333%	120	1080
20%	**80%**	**89.4444%**	**84.1667%**	**84.1667%**	**240**	**960**
30%	70%	84.8148%	77.3130%	77.2222%	360	840
40%	60%	86.2500%	79.5291%	79.3750%	480	720
50%	50%	84.4444%	76.7066%	76.6667%	600	600
60%	40%	84.9074%	77.2398%	77.3611%	720	480
70%	30%	84.2063%	76.4328%	76.3095%	840	360
80%	20%	84.5833%	76.7444%	76.8750%	960	240
90%	10%	84.3827%	76.7453%	76.5741%	1080	120

In (Table 3), it can be seen that the M-SVM Linear method shows performance variations at various split ratios of training and testing data. At a split ratio of 20:80, the M-SVM Linear model obtained very good results with the highest accuracy score of 89.4444%, followed by a precision score of 84.1667% and a recall of 84.1667%. and the results of the M-SVM Linear graph and the calculation of the confusion matrix with the highest value at a split ratio of 20:80, can be seen in (Figure 6) and (Figure 7) below.

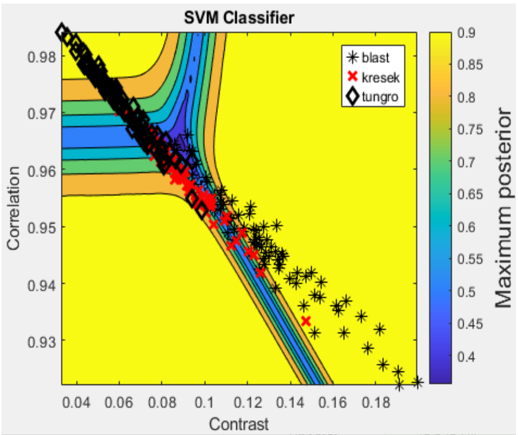


Figure 6. M-SVM Linear graph 20:80

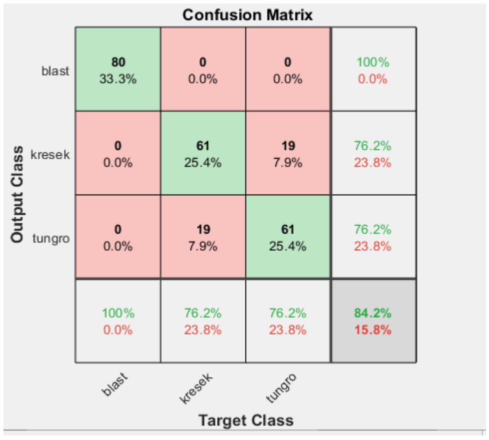


Figure 7. CM M-SVM linear 20:80

Table 4. Results of Gausian M-SVM Performance Evaluation

M-SVM(POLYNOMIAL)						
Split ratio		Accuracy	Precision	Recall	Data	
Training	Testing				Train	Test
10%	**90%**	**80%**	**77.5360%**	**76.6667%**	120	1080
20%	80%	79.2125%	75.7534%	75.8333%	240	960
30%	70%	79%	69.3777%	70%	360	840
40%	60%	77.2222%	65.0255%	65.8333%	480	720

50%	50%	76%	62.9947%	64%	600	600
60%	40%	74.6296%	60.8490%	59.5833%	720	480
70%	30%	71.1905%	55.6062%	56.7857%	840	360
80%	20%	71.5278%	54.3445%	57.2917%	960	240
90%	10%	71.2346%	53.6462%	56.8519%	1080	120

In (Table 4) it is explained that the Gaussian M-SVM method on training data obtained the highest accuracy at a split ratio of 10:90, with a total of 120 data. At this split ratio, the accuracy obtained was 80%, precision 75.7534%, and recall 75.8333%. The Gaussian M-SVM graph and confusion matrix calculation for a split ratio of 10:90 can be seen in (Figure 8) and (Figure 9).

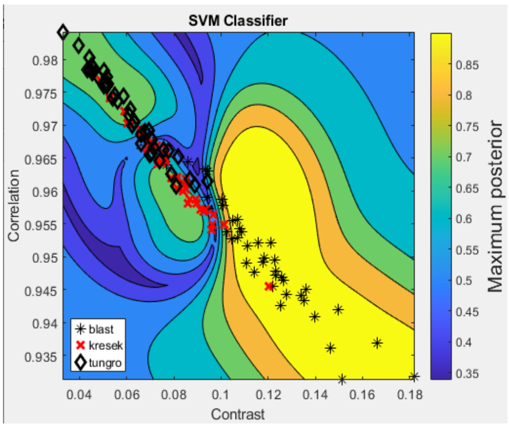


Figure 8 Gaussian M-SVM graph 10:90

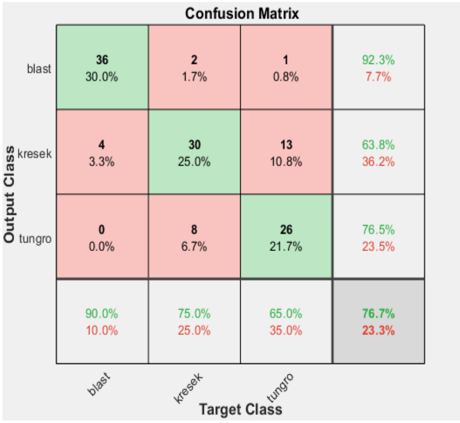


Figure 9 Gaussian CM M-SVM 10:90

c. Test data for the Multiclass Support Vector Machine (M-SVM) method

Table 5. Results of the M-SVM Polynomial Test Evaluation

M-SVM(POLYNOMIAL)						
Split ratio		**Accuracy**	**Precision**	**Recall**	**Data**	
Training	**Testing**				**Train**	**Test**
10%	90%	71.2346%	53.6462%	56.8519%	1080	120
20%	80%	71.5278%	54.3445%	57.2917%	240	960
30%	70%	71.7460%	53.2519%	57.6190%	360	840
40%	60%	75.7407%	62.1921%	63.6111%	480	720
50%	50%	77.4444%	64.9680%	66.1667%	600	600
60%	40%	78.7500%	67.4113%	68.1250%	720	480
70%	30%	80.7407%	70.9712%	71.1111%	840	360
80%	**20%**	**85.5556%**	**77.9906%**	**78.3333%**	960	240
90%	**10%**	**85%**	**77.5126%**	**77.5%**	120	1080

In (Table 5) explains that the results of the evaluation of test data using the M-SVM Polynomial method obtained the highest accuracy score, namely at a split ratio of 80:20 with an accuracy score = 85.5556%, precision = 78.9906%, and recall = 78.3333%. and the results of the calculation of the confusion matrix M-SVM polynomial with the highest value can be seen in (Figure 10).

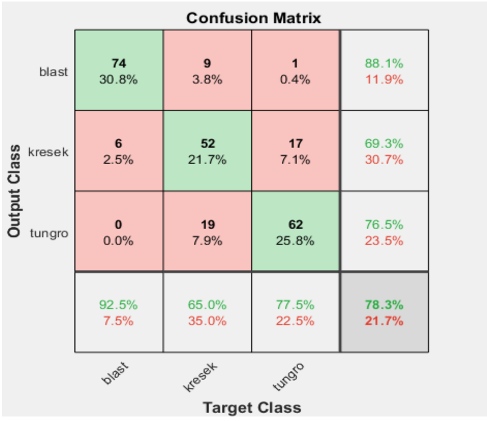


Figure 10. CM M-SVM polynomial 80:20

Table 6. M-SVM Linear Test Evaluation Results

M-SVM(LINEAR)						
Split ratio		**Accuracy**	**Precision**	**Recall**	**Data**	
Training	**Testing**				**test**	**Lati**
10%	90%	71%	52.5762%	56.6219%	1080	120
20%	80%	71.1078%	54.4445%	57%	960	240
30%	70%	71.1905%	55.6062%	56.7857%	840	360
40%	60%	73.0556%	58.3109%	59.5833%	720	480
50%	50%	72.8889%	57.9054%	59.3333%	600	600
60%	40%	77.7778%	66.9101%	66.6667%	480	720
70%	30%	80%	69.8135%	70%	360	840
80%	**20%**	**84.4444%**	**76.5757%**	**76.6667%**	240	960
90%	10%	83.8889%	76.2121%	75.8333%	120	1080

In (Table 6) it is explained that the results of the evaluation of the test data using the M-SVM Linear method obtained the highest accuracy score, namely at a split ratio of 80:20 with an accuracy score = 84.4444%, precision = 76.5757%, and recall = 76.6667%. High accuracy, precision, and recall at a ratio of 80:20 occur because the model has enough data for training (80% of data for training). and the results of the calculation of the M-SVM Linear confusion matrix with the highest value can be seen in (Figure 11).

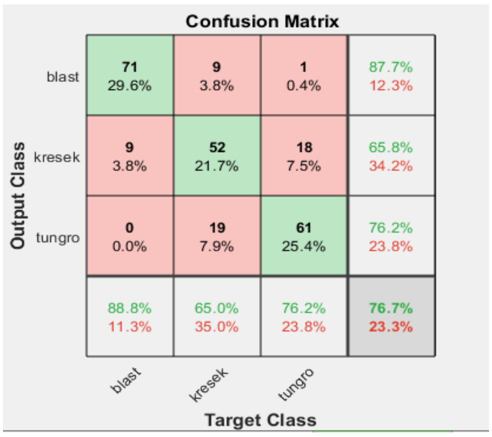


Figure 11 CM M-SVM linear 80:20

Table 7 Gaussian M-SVM Test Evaluation Results

M-SVM(GAUSIAN)						
Split ratio		**Accuracy**	**Precision**	**Recall**	**Data**	
Training	**Testing**				**test**	**Lati**
10%	90%	61.7778%	45.8540%	42.6667%	1080	120
20%	80%	61.7778%	45.9603%	46.7%	960	240
30%	70%	63.4286%	47.992%	45.1429%	840	360
40%	60%	67.4074%	50.0876%	51.1111%	720	480
50%	50%	67.4667%	49.7449%	51.2%	600	600
60%	40%	67.7778%	49.9405%	51.6667%	480	720
70%	30%	73.2593%	55.5506%	56.8889%	360	840
80%	20%	76.8889%	58.8763%	59.3333%	240	960
90%	**10%**	**79.8889%**	**64.7186%**	**65.3333%**	120	1080

In (Table 7) it is explained that the results of the evaluation of the test data using the Gausian M-SVM method obtained the highest accuracy score, namely at a split ratio of 90:10 with an accuracy score = 69.7778%, precision = 52.5284%, and recall = 54.6667%. and the results of the calculation of the Gausian M-SVM confusion matrix with the highest value at a split ratio of 90:10 can be seen in (Figure 12)

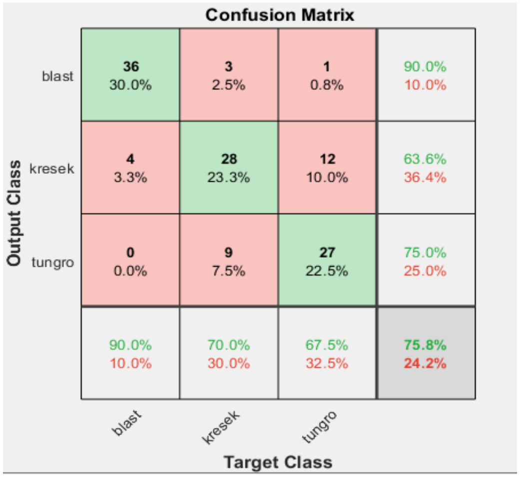


Figure 12. CM M-SVM Gaussian 90:10

d. Results of comparison of training accuracy of Multiclass Support Vector Machine (M-SVM)

The accuracy results of the Multiclass Support Vector Machine (M-SVM) method training are shown in the comparison in (Table 8). The table provides an overview of how effective the M-SVM method is in classifying data, and shows the variation in performance based on the composition of the data used. This allows for evaluating the advantages and disadvantages of the method in different contexts.

Table 8 Results of Training Accuracy Data Comparison

split ratio	**Accuracy**		
	polynomial	**linear**	**Gaussian**
10;90	**88%**	**87.2222%**	**80%**
20;80	**89.7222%**	**89.4444%**	**79.2125%**
30;70	85.1852%	84.8148%	79%
40;60	85.5556%	86.2500%	77.2222%
50;50	85.7778%	84.4444%	76%
60;40	85.2778%	84.9074%	74.6296%
70;30	85.2381%	84.2063%	71.1905%
80;20	84.5833%	84.5833%	71.5278%
90;10	85.1852%	84.3827%	71.2346%

Based on the results of the accuracy comparison in (Table 8), it can be concluded that the method with the polynomial kernel shows the highest accuracy value of 89.7222% at a ratio of 20:80, and in general the performance of the polynomial kernel is superior to the linear and gaussian kernels. The linear kernel recorded the highest accuracy value of 88.4444% at a ratio of 20:80, while the gaussian kernel had the lowest performance, with the highest accuracy of only 80% at a ratio of 10:90.

Overall, polynomial kernels are more effective in handling larger training data, while linear kernels show better results at more balanced data ratios between training and testing data. Gaussian kernels, although inferior, still provide good performance at more dominant testing data ratios, but not as high as polynomial and linear kernels.

e. Results of comparative accuracy of Multiclass Support Vector Machine (M-SVM) testing

The accuracy results of the testing data from the Multiclass Support Vector Machine (M-SVM) method are shown in the comparison results in (Table 9). The table provides an overview of how effective the M-SVM method is in classifying data, and shows variations in performance based on the composition of the data used.

Table 9 Results of Comparison of Test Accuracy Data

split ratio	**Accuracy**		
	polynomial	**linear**	**Gaussian**
10;90	71.2346%	71%	61.7778%
20;80	71.5278%	71.1078%	61.7778%
30;70	71.7460%	71.1905%	63.4286%
40;60	75.7407%	73.0556%	67.4074%
50;50	77.4444%	72.8889%	67.4667%
60;40	78.7500%	77.7778%	67.7778%
70;30	80.7407%	80%	73.2593%
80;20	**85.5556%**	**84.4444%**	76.8889%
90;10	**85%**	**83.8889%**	**79.8889%**

Based on the results of the accuracy comparison in (Table 9), it can be concluded that the methods with polynomial kernel and linear kernel show better performance compared to the Gaussian kernel. The polynomial kernel has the highest accuracy value of 85.5556% at a ratio of 80:20, while the linear kernel achieves the highest accuracy value of 84.4444% at a ratio of 80:20. Meanwhile, the Gaussian kernel is recorded with the highest accuracy value of 79.8889% at a ratio of 90:10.

Overall, the polynomial kernel tends to be more effective in handling larger test data, with more stable accuracy across data ratios. The linear kernel, although slightly lower, still shows consistent results, while the gaussian kernel produces lower accuracy across almost all test data ratios. This suggests that the polynomial and linear kernels are more suitable for this rice leaf disease classification than the gaussian kernel

IV. Conclusions

This study successfully built a rice leaf disease classification system using the Multi-Class Support Vector Machine (M-SVM) method. The test results showed that the polynomial kernel provided the highest accuracy of 85.56% at a training and testing ratio of 80:20, followed by the linear kernel (84.44%) and Gaussian (79.89%). GLCM and RGB-based feature extraction proved effective in supporting model performance through leaf texture and color analysis.

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