

Pest Detection on Oil-Palm Leaves Using the K-Nearest Neighbor Algorithm and Image Analysis

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Abstrak

Oil palm is a strategic commodity whose productivity is often threatened by leaf-feeding pests such as bagworms and nettle caterpillars, underscoring the need for rapid, objective early detection. This study develops an image-based pest detection system using the K-Nearest Neighbor (KNN) algorithm with Gray Level Co-occurrence Matrix (GLCM) texture features—energy, contrast, homogeneity, and correlation—extracted from images of healthy and infested leaves. The workflow comprises preprocessing (resizing, grayscale conversion, thresholding), GLCM feature extraction, normalization, and KNN classification with Euclidean distance and an empirically selected k . Performance is assessed on three classes (healthy, bagworm, nettle caterpillar) using a confusion matrix alongside precision, recall, and F1-score, with cross-validation to gauge generalization. The model reliably distinguishes classes, with classwise metrics ranging from 0.71 to 0.83 evaluation on new samples yields predictions consistent with ground truth. These findings indicate that the GLCM-KNN combination is an effective and affordable approach for early pest detection in oil-palm leaves, supporting timely, data-informed decisions in the field. Future improvements include enlarging and diversifying the dataset, parameter optimization and feature selection, comparative baselines with SVM/CNN, and integration into IoT and UAV monitoring pipelines for plantation-scale surveillance.

Keyword: Image analysis; K-Nearest Neighbor (KNN); leaf pests; oil palm; texture features (GLCM)

1. INTRODUCTION

Oil palm (*Elaeis guineensis*) is one of Indonesia's leading plantation commodities, playing an important role in the national economy. Indonesia is the world's largest producer of palm oil, with most of its production exported to various countries as raw material for the food, cosmetics, biofuel, and other industries. Given the importance of oil palm to the country's economy, efforts to maintain its productivity are crucial. However, one of the main challenges in oil palm cultivation is pest and disease infestation, especially on the leaves, which are an important part of the plant's photosynthesis process.

Pest attacks on palm oil leaves can have a negative impact on plant productivity. Pests such as bagworms (*Metisa plana*) and fireworms (*Setothosea asigna*) are known to damage leaf tissue, reducing the area of healthy leaves that can perform photosynthesis, thereby inhibiting growth and reducing yields. Early detection of pest attacks is crucial so that control measures can be taken quickly and effectively, before the attack spreads to other parts of the plant or even to larger areas of the plantation. Conventional methods for detecting pests are usually carried out manually by skilled workers through direct observation in the field. This method is not only costly, but also prone to human error and time-consuming, especially in large plantations.

With the development of technology, particularly in the fields of digital image processing and artificial intelligence, various algorithm-based methods have been proposed to automatically detect pests through leaf image analysis. One promising algorithm is the K-Nearest Neighbor (KNN) algorithm. The KNN algorithm is a Machine Learning algorithm based on Instance-Based Learning that is quite simple and performs well in classifying image data. In the context of pest detection on oil palm leaves, the KNN algorithm can be used to classify leaf images into healthy or pest-infected categories based on certain features extracted from leaf images, such as color, texture, and damage shape. This process involves the image feature extraction stage, where features relevant to the condition of the leaves will be identified, followed by a classification process using the KNN algorithm to distinguish between healthy leaves and those infected with pests.

This study aims to develop a pest detection model on oil palm leaves using the KNN algorithm with the hope of helping to accelerate the process of identifying and handling pest attacks. This method is also expected to be applicable in various scales of plantations, both large and small, so that it can provide broader benefits to the palm oil industry. The use of image processing technology also supports the concept of precision agriculture, where digital technology is used to improve efficiency and effectiveness in plantation and agricultural management.

Through the application of this algorithm, the automatic pest detection system is expected to reduce dependence on experts to conduct manual field monitoring. This will enable quick and precise pest control so that oil palm productivity can be improved sustainably. This research will also be the first step in the use of artificial intelligence for the cultivation of strategic crops in Indonesia, with broad adaptation potential for other crops that are also affected by pest attacks.

In addition, the application of KNN algorithms in image-based pest detection also has the potential to be further developed into a more intelligent system by integrating other technologies such as deep learning, which can expand the detection capacity for various types of pests and diseases simultaneously. Such a system will support the application of information technology in the agricultural sector in the digital era, making pest detection systems more efficient and capable of providing real-time data to farmers and plantation managers for faster and more accurate decision making.

Thus, this research is expected to not only provide practical solutions in pest detection, but also contribute to the development of more integrated smart agricultural technology.

2. RESEARCH METHOD

2.1 Tools and Materials Used in Research

- Intel/Ryzen 5 processor or higher.
- Random Access Memory (RAM) 4 GB or more.
- Hard drive with a minimum capacity of 500 GB or more.
- Mouse.

2.2 Research Design

The steps of the image processing procedure carried out in this study are shown in Figure 1.



Figure 1. Identification Process Flowchart

This study uses a digital image analysis method with the K-Nearest Neighbor (KNN) algorithm to detect pests on oil palm leaves. This study is experimental and aims to develop a classification model capable of recognizing patterns and characteristics of damage caused by pests on oil palm leaf images.

2.3 Data Collection

The data used in this study consisted of images of oil palm leaves infected with pests and those not infected. The data was obtained from a collection of images taken directly from oil palm plantations in the field using a high-resolution camera. A total of 45 images were used, consisting of 15 images of leaves infected with bagworm pests, 15 images of leaves infected with fireworm pests, and 15 images of healthy leaves.

2.4 Data Pre-processing

Image data obtained in advance through the pre-processing stage, which includes:

2.4.1 Resize

Resizing is the process of changing both the horizontal and vertical resolution of an input image. The image is processed by reducing the pixels to a size of 550x250 pixels, with the aim of making the image more complex so that it requires less memory. An example of an image that has been resized can be seen in the following image.

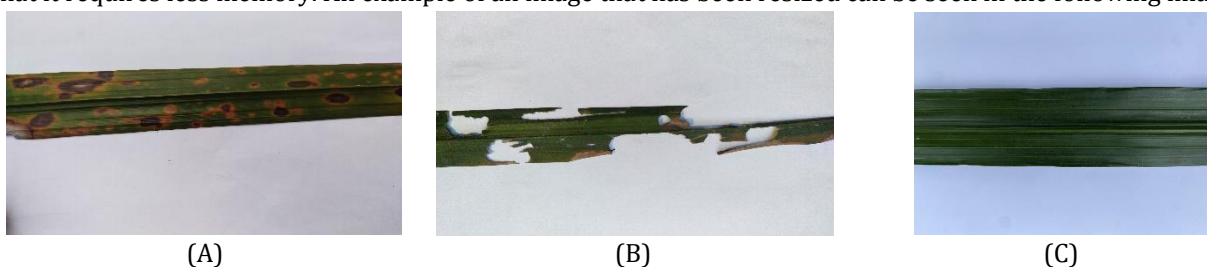


Figure 2. (A) Image of Bagworm Damage (B) Image of Fireworm Damage (C) Image of Healthy Leaves

2.4.2 Greyscale

A grayscale image is an image that only has one channel value, meaning Red = Green = Blue. The image is displayed in different shades of gray, unlike a "black and white" image, which consists of only two colors, black and white. Grayscale imaging is a technique for converting images into shades of gray. In this process, leaf images that have been converted to grayscale images will be converted into images divided into regions based on the similarity of the parameter values used. For the grayscale stage, the grayscale value can be calculated using the following formula (1):

$$y = \frac{r+g+b}{3} \tag{1}$$

From the known color value matrix in Figure 3.3, the next step is to convert the color value matrix into a grayscale value matrix. The following are the calculations on the reference image value matrix (x1, y1) on the image matrix of the impact of bagworms and fireworms.

$$y = \frac{208+201+215}{3} = 211 \quad y = \frac{209+211+212}{3} = 210 \quad y = \frac{175+189+223}{3} = 196 \tag{2}$$

2.4.3 Threshold

In the K-Nearest Neighbor (KNN) algorithm, the threshold is a limit value that helps determine the class of the test sample based on the calculation of the distance to the nearest neighbors. KNN is a classification algorithm that works by calculating the distance between the test data and the training data and selecting the class based on the majority of the K nearest neighbors. The threshold in KNN, although not always a key parameter, can help improve prediction accuracy in certain situations. For example, by using a threshold, we can set specific requirements for deciding when test data can be classified into a particular class.

2.5 Gray Level Co-Occurrence Matrix (GLCM)

Calculating GLCM on grayscale images. For each pixel in the image, we will find neighboring pixels with a predetermined distance and angle, then fill the GLCM matrix with the frequency of occurrence of corresponding pixel intensity pairs. The purpose of this process is to classify the results of the leaf image.

2.6 Implementation of the K-Nearest Neighbor (KNN) Algorithm

The next stage is the classification of new oil palm leaf image objects based on training data using the KNN method. Once the training data has been prepared and the K parameters determined, the next stage is the classification of new oil palm leaf image objects. This process is carried out by comparing new leaf images with training data based on extracted features, such as texture, shape, or color. The KNN method will calculate the distance between the new image and each data point in the training dataset, usually using a distance matrix such as Euclidean. The new image is then classified into the category most commonly found among its K-Nearest Neighbors. This step ensures accurate classification results in accordance with the training data pattern.

2.7 Model Evaluation

The evaluation of the model in this study aims to determine how well the K-Nearest Neighbor (KNN) algorithm performs in detecting pests on oil palm leaves.

2.8 Testing Implementation

This study uses Python software with the OpenCV library for image pre-processing and Scikit-Learn for KNN algorithm implementation. The testing process was conducted using test data, with classification results and evaluation matrices recorded for analysis.

3. RESULT AND DISCUSSION

3.1 Image Pre-processing Results

The raw images collected from the plantation exhibited variations in size, illumination, and background. The pre-processing steps described in Section 3.4 were applied uniformly to all 45 images. This subsection presents the outcomes of each pre-processing stage.

3.1.1 Resizing Results

All original images (3024 × 4032 pixels) were resized to **550 × 250 pixels** using bilinear interpolation. This dimension was chosen to maintain the aspect ratio while significantly reducing computational load.

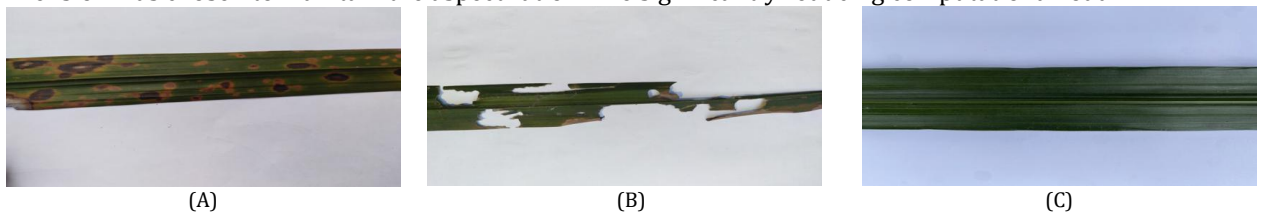


Figure 3. (A) Image of the Resizing Process Impact of Bagworms (B) Image of the Resizing Process Impact of Fireworms (C) Image of the Resizing Process of Healthy Leaves

R : 208	R : 206	R : 202	R : 196	R : 209	R : 209	R : 206	R : 206	R : 175	R : 171	R : 173	R : 178
G : 210	G : 207	G : 202	G : 194	G : 211	G : 209	G : 208	G : 209	G : 189	G : 185	G : 187	G : 192
B : 215	B : 213	B : 208	B : 200	B : 212	B : 212	B : 211	B : 211	B : 223	B : 221	B : 224	B : 228
R : 92	R : 76	R : 55	R : 59	R : 177	R : 170	R : 179	R : 197	R : 90	R : 78	R : 82	R : 103
G : 86	G : 73	G : 51	G : 55	G : 180	G : 172	G : 182	G : 200	G : 105	G : 93	G : 96	G : 116
B : 62	B : 48	B : 28	B : 32	B : 177	B : 170	B : 183	B : 203	B : 105	B : 93	B : 99	B : 122
R : 172	R : 176	R : 184	R : 189	R : 126	R : 128	R : 171	R : 166	R : 78	R : 62	R : 70	R : 96
G : 167	G : 173	G : 181	G : 186	G : 132	G : 132	G : 173	G : 167	G : 94	G : 78	G : 85	G : 110
B : 168	B : 177	B : 189	B : 194	B : 118	B : 119	B : 173	B : 166	B : 84	B : 68	B : 78	B : 108
R : 198	R : 205	R : 193	R : 181	R : 213	R : 214	R : 214	R : 212	R : 187	R : 181	R : 181	R : 184
G : 197	G : 203	G : 190	G : 179	G : 218	G : 218	G : 217	G : 215	G : 202	G : 195	G : 195	G : 198
B : 205	B : 209	B : 198	B : 188	B : 221	B : 221	B : 221	B : 220	B : 237	B : 230	B : 229	B : 233

Figure 4. (A) Color Image Value Matrix of Bagworm Impact (B) Fireworm (C) Healthy Leaves

3.1.2 Grayscale Conversion Results

Colour images were converted to grayscale using the luminance formula $Y = 0.299R + 0.587G + 0.114B$. The resulting grayscale images contain only intensity information (0–255), which is sufficient for texture analysis. The matrix results obtained from the channel values above:

Table 1. (A) Matrix of Calculated Impact Values for Caterpillars (B) Bagworms (C) Normal Leaves

211	208	203	195	210	210	208	208	195	192	194	199
78	64	44	51	178	170	181	200	100	88	92	113
172	178	187	189	125	126	172	166	85	69	77	104
199	205	193	182	217	217	217	215	208	202	201	205

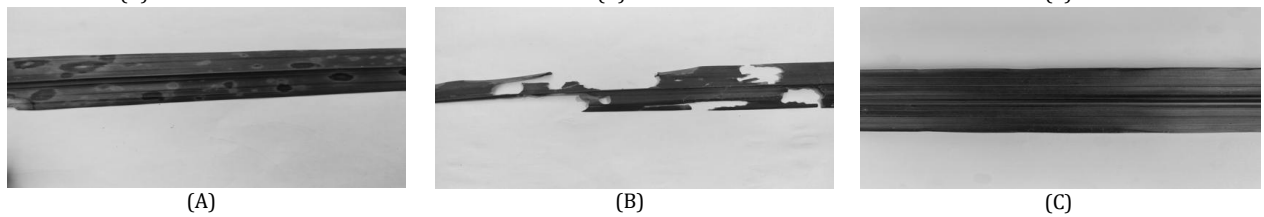


Figure 5. (A) Grayscale Impact of Bagworm Pests (B) Impact of Fireworm Pests (C) Healthy Leaves

3.1.3 Thresholding Results

Binary thresholding was applied using Otsu’s method to separate the leaf region from the background and to highlight damaged areas. The optimal threshold value was determined automatically for each image.

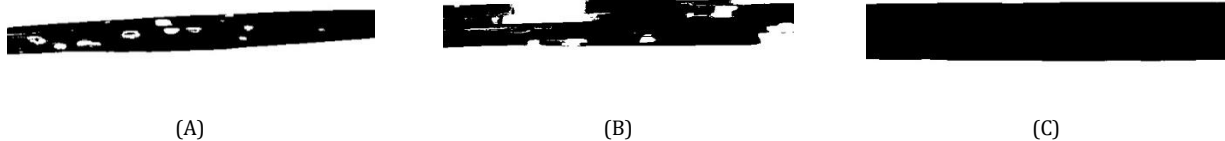


Figure 6. Binary Process Images (A) Impact of Bagworms (B) Impact of Fireworms (C) Healthy Leaves

3.2 Feature Extraction Results

3.2.1 GLCM Results

The calculation process in the Gray Level Co-Occurrence Matrix (GLCM) method is as follows:

- The matrix is rearranged based on the relationship between pixels and the framework matrix called the GLCM matrix.

Table 2. (A) GLCM Matrix Impact of Bagworms (B) Impact of Fireworms (C) Normal Leaves

1	0	0	0	0	0	0	0	0	0	0	0
1	1	0	0	0	1	1	0	0	1	1	0
0	0	3	0	0	0	3	1	0	0	3	1
0	0	1	5	0	0	0	6	0	0	0	6

- The next step is normalization, where the pixel values are divided by their neighboring pixels. Pixel values of 0 are not included in the formula.

Table 3. GLCM matrix after normalization (A) Affected by bagworm pests (B) Affected by fireworm pests (C) Normal leaves

0.08	0.04	0	0	0	0	0	0	0	0	0	0
0.04	0.08	0	0	0	0.08	0.04	0	0	0.08	0.04	0
0	0	0.25	0.04	0	0.04	0.25	0.04	0	0.04	0.25	0.04
0	0	0.04	0.41	0	0	0.04	0.5	0	0	0.04	0.5

- Sum the values of each feature for each zone.

Table 4. Calculation of Feature Values for Bagworm Impact

GLCM	0°	45°	90°	135°
Energy	0.2569	0.1172	0.0937	0.0987
Correlation	-59.5612	-44.6829	-45.0208	-45.2209

Concentration	0.1666	3.2222	3.2499	3.3333
Homogeneity	0.9166	0.3981	0.4444	0.4629

Table 5. Calculation of Feature Extraction Values on the Impact of Fireworm Pests

GLCM	0°	45°	90°	135°
Energy	0.3263	0.2530	0.1666	0.1481
Correlation	-176.8450	-146.6585	-146.08	-146.6585
Concentration	0.1666	1.3333	1.3333	1.3333
Homogeneity	0.9166	0.4814	0.5555	0.6296

Table 6. Calculation of Extraction Feature Values in Healthy Leaves

GLCM	0°	45°	90°	135°
Energy	0.3437	0.2345	0.2291	0.2222
Correlation	-63.4060	-52.9464	-54.0574	-58.2857
Concentration	0.0833	2.0	1.9166	1.6666
Homogeneity	0.9583	0.5925	0.5972	0.6111

3.3 KNN Classification Results

The main advantage of this research lies in its ability to provide fast and objective classification results, thereby minimizing the risk of human error that often occurs in conventional field inspections. The use of the KNN algorithm offers ease of implementation due to its simple yet robust structure for handling image texture feature data. This provides cost and time efficiency for plantation managers in monitoring plant health in large areas, which ultimately contributes to protecting Fresh Fruit Bunch (FFB) production from potential economic losses due to pest attacks.

The following are the results of these calculations:

Table 7. Average four-directional results for each feature in the bagworm impact image

GLCM	0°	45°	90°	135°	Average
Energy	0.2569	0.1172	0.0937	0.0987	0.1416
Correlation	-59.5612	-44.6829	-45.0208	-45.2209	-48.6215
Concentration	0.1666	3.2222	3.2499	3.3333	2.4930
Homogeneity	0.9166	0.3981	0.4444	0.4629	0.5555

Table 8. Average four-way results in each feature on the image of the impact of the fire moth

GLCM	0°	45°	90°	135°	Average
Energy	0.3263	0.2530	0.1666	0.1481	0.2235
Correlation	-176.8450	-146.6585	-146.08	-146.6585	-154.0605
Concentration	0.1666	1.3333	1.3333	1.3333	1.0416
Homogeneity	0.9166	0.4814	0.5555	0.6296	0.6458

Table 9. Average four-way results in each feature on normal leaf images

GLCM	0°	45°	90°	135°	Average
Energy	0.3437	0.2345	0.2291	0.2222	0.2574
Correlation	-63.4060	-52.9464	-54.0574	-58.2857	-57.1739
Concentration	0.0833	2.0	1.9166	1.6666	1.4166
Homogeneity	0.9583	0.5925	0.5972	0.6111	0.6898

Each average value from the four directions on each feature is used as a criterion in the KNN calculation to determine the cluster group. Here are the results of the calculation.

Table 10. Calculation Result

Data to-	R_CONTRAS	R_CORELASI	R_HOMOGENITY	R_ENERGY	Class
D1	2.49	-48.62	0.55	0.14	Bag Caterpillar
D2	1.04	-154.06	0.64	0.22	Fire Caterpillar
D3	1.41	-57.17	0.68	0.25	Healthy Leaf
D4	1.50	-95.23	0.58	0.21	Bag Caterpillar
D5	0.80	-197.87	0.72	0.20	Fire Caterpillar
D6	0.85	-103.09	0.70	0.23	Healthy Leaf
D7	0.11	-318.84	0.94	0.78	?

Start calculating the Euclidean distance using equation. The results are the distances for data 1, data 2, data 3, data 4, and data 5.

$$D1 = \sqrt{(0,11 - 2,49)^2 + (-318,84 - (-48,62))^2 + (0,94 - 0,55)^2 + (0,78 - 0,14)^2} = 270,23 \quad (3)$$

$$D2 = \sqrt{(0,11 - 1,04)^2 + (-318,84 - (-154,06))^2 + (0,94 - 0,64)^2 + (0,78 - 0,22)^2} = 154,065 \quad (4)$$

$$D3 = \sqrt{(0,11 - 141)^2 + (-318,84 - (-57,17))^2 + (0,94 - 0,68)^2 + (0,78 - 0,25)^2} = 261,6739 \quad (5)$$

$$D4 = \sqrt{(0,11 - 1,50)^2 + (-318,84 - (-95,23))^2 + (0,94 - 0,58)^2 + (0,78 - 0,21)^2} = 223,6153 \quad (6)$$

$$D5 = \sqrt{(0,11 - 0,80)^2 + (-318,84 - (-197,87))^2 + (0,94 - 0,72)^2 + (0,78 - 0,20)^2} = 120,9736 \quad (7)$$

$$D6 = \sqrt{(0,11 - 2,72)^2 + (-318,84 - (-63,56))^2 + (0,94 - 0,60)^2 + (0,78 - 0,25)^2} = 255,2941 \quad (8)$$

The results of the summation process are entered into a table to determine whether the data will be classified into the fire caterpillar or bag caterpillar class. The data is sorted based on the smallest Euclidean distance value, resulting in the following results:

Table 11. Sorted data based on the smallest Euclidean distance value

Data to-	Euclidean Result	Class Group
D5	120,9736	Fire Caterpillar
D2	154,065	Fire Caterpillar
D4	223,6153	Bag Caterpillar
D6	255,2941	Fire Caterpillar
D3	261,6739	Healthy Leaf
D1	270,23	Bag Caterpillar

From the table, using $k=3$, three data points with the smallest distances from data point 1 to data point 6 are selected. The results show that there are three data points belonging to the caterpillar class, two data points belonging to the bagworm class, and one data point belonging to the healthy leaf class. Therefore, the class for the 7th data point is caterpillar. After this calculation, the process can continue to the next test data, which is the 8th data point, and so on. After obtaining the distance results and the selected class groups, the data is reordered based on the smallest distance of k that has been determined. This process is repeated for each new test data to determine its class group.

4. CONCLUSION

This study concludes that the implementation of the K-Nearest Neighbors (KNN) algorithm integrated with Gray-Level Co-occurrence Matrix (GLCM) feature extraction has proven effective in automatically detecting and classifying pest types on oil palm leaves. This system successfully addresses the main research problem regarding the efficiency of identifying fireworms (*Limacodidae*) and bagworms (*Mahasena corbetti*) through digital image analysis. By utilizing texture parameters such as contrast, correlation, energy, and homogeneity, the model is able to distinguish between healthy and infected leaves with better consistency compared to manual visual observation methods. The main advantage of this research lies in its ability to provide fast and objective classification results, thereby minimizing the risk of human error that often occurs in conventional field inspections. The use of the KNN algorithm offers ease of implementation due to its simple yet robust structure for handling image texture feature data. This provides cost and time efficiency for plantation managers in monitoring plant health in large areas, which ultimately contributes to protecting Fresh Fruit Bunch (FFB) production from potential economic losses due to pest attacks. However, this study has certain limitations, particularly in terms of the model's sensitivity to variations in lighting conditions and the quality of image resolution taken directly in the field. The quality of input data greatly affects the accuracy of GLCM feature extraction, so that uncontrolled image capture environments can reduce classification performance. In addition, the current detection coverage is still limited to two main types of pests, requiring the addition of a more diverse dataset to recognize other plant diseases or disorders more comprehensively. For future development, the results of this study have broad application potential through integration into Unmanned Aerial Vehicle (UAV)-based monitoring systems or mobile applications for real-time detection. Such applications will enable practitioners in the field to obtain instant information on pest attacks, so that control measures such as pesticide spraying can be carried out with precision and only in affected areas. This step not only increases sustainable plantation productivity, but also supports the acceleration of digital transformation towards Smart Farming in the Indonesian palm oil industry.

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