Automatic Detection of Cabbage Pest Attacks Based on Leaf Images with Machine Learning Approach

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***Abstract*— Farmers in cabbage farming face many problems, one of which is pest attack. Plutella xylostella L. is a major pest on cabbage (known as cabbage leaf caterpillar) which can cause a decrease in production of up to 100 percent. Decision Support System (DSS) was developed to classify the attack rate of Plutella to reduce the negative effects of using various types of high doses of pesticides and short spraying intervals but causing residual effects and killing natural enemies. DSS has a role in helping farmers to make decisions regarding the time of pesticide treatment needed to minimize negative effects and increase productivity. In this study, DSS was developed to detect damage to cabbage (*Brassica oleracea L*) crops so that farmers can determine pesticide doses and spraying intervals based on a website. The results of the system is presented in the form of images and the percentage of damage to cabbage plants. Therefore, the CART method can be used to analyze the level of damage to plants that are attacked by pests.**

***Keywords*— Cabbage pest, CART, Classification, Leaf Image, Decision Support System.**

I. Introduction

Indonesia is one of the world's agrarian countries, but ironically in recent years Indonesia has imported foodstuffs from abroad [1]. According to data [2], cabbage production in Indonesia experienced significant fluctuations. This happens because of the attack of cabbage pests and their management. So according to mele et al, 2001 required some knowledge and innovation for maximum production results. In nowadays era, several combined methods have been developed for increasing crop production on a large scale. Increasing crop production is no longer conducted by opening new agricultural land, but implementing multidisciplinary science (intensification). One of the attempts is the application of methods to detect pests, plants disease or other plant growth disorders. The trend in the detection of plant disorders and diseases by utilizing innovative information technology [3].

The trend of knowing the nature of plant diseases now refers to the study of visual patterns in a particular plant. Research by Patil, et.al. [4], provides rapid development in various methods used to study plant diseases/traits using image processing. The method is to increase throughput and reduce subjectivity from human expertise in detecting plant diseases.

Utilizes digital image processing techniques to detect, measure and classify plant diseases from digital images in the visible spectrum [5]. Although disease symptoms can manifest in any part of the plant, the method only explore symptoms in leaves and stems. Moreover, Barbedo includes three parts, namely detection, degree of quantification, and classification [6]. Each class, in turn, is divided according to the main technical solutions used in the algorithm.

Research development by Raza, et. al. [7], combined a thermal and visible light image data with in-depth information and developed a machine learning system on plants infected with the powdery mildew fungus Oidium neolycopersici tomato. His method extracts a new set of features from image data using local and global statistics and shows that combining in-depth information can vastly improve the detection accuracy of diseased plants.

Research on the implementation of the image processing method was also carried out for fungal diseases of various plants [8]. Another research by Holsteen, et. al. have detected stem disease of flax plant which is one of the most important cash crops in several Asian countries [9]. An automated system based on an Android application has been implemented to take pictures of the diseased stems of hemp plants and send them to a dedicated server for feature extraction. On the server side, the affected portion of the image will be segmented using threshold formula which is adjusted based on hue segmentation. The consequential feature values will be extracted from the segmented portion for texture analysis using the color methodology. However, this research is still in progress and has not been applied to the community.

Recent research introduced a color-based segmentation model defined to segment infected areas and assign them to the relevant classification [9]. Plant diseases can be detected by image processing techniques. Disease detection involves steps such as image acquisition, image pre-processing, image segmentation, feature extraction and classification. It shows percentages the part of the leaf that is affected.

Crop cultivation plays an important role in agriculture. Currently, yield loss is mainly caused by infected plants, which reflectively reduces production rates. It is necessarily needed to identify plant diseases at an early stages. The main problem is to reduce the use of pesticides in agriculture and to increase the quality and quantity of production levels. Therefore, this research encourage farmers and land owners to identify the cabbage damage to apply an appropriate treatment.

II. LITERATURE REVIEW

Cabbage (Brassica oleracea) is an important horticultural commodity in various countries, including Indonesia. However, cabbage production is very susceptible to pest attacks, especially *Plutella xylostella* (cabbage leaf caterpillar), *Hellula undalis*, and *Brevicoryne brassicae* (cabbage aphid). Accurate detection and classification of pest attack levels are essential for decision making in integrated pest management (IPM). The development of data processing technology and artificial intelligence (AI) provides a new approach to combining and classifying pest attacks automatically and efficiently.

According to research by Sarfraz et al., cabbage leafworm (*Plutella xylostella*) is one of the most destructive and difficult to control pests due to its resistance to various insecticides [10]. Other pests that commonly attack cabbage include *Hellula undalis* (inchworm), *Brevicoryne brassicae* (cabbage aphid), *Pieris rapae* (cabbage butterfly). Classification of attacks from each of these pests is based on visual symptoms such as leaf damage, holes, discoloration, and plant deformation. The pest attack classification process generally consists of four main stages: (1) data acquisition, (2) data preprocessing, (3) feature extraction, and (4) classification. Each stage greatly determines the accuracy and efficiency of the entire automatic pest detection system.

The main data in pest classification research comes from digital images of leaves or plants. Conventional RGB cameras, multispectral cameras, and hyperspectral and thermal cameras are used depending on the level of accuracy and detection needs. RGB images are accurate enough to detect visual damage due to pest attacks, but the use of multispectral sensors can increase the sensitivity of the system to physiological changes in plants [6]. Ramcharan et al. [11], noted that the use of mobile phone cameras for field image collection provides a practical and inexpensive solution in developing countries. In the context of cabbage, images are usually taken from the top of the plant because most pest symptoms (such as holes, curling, or leaf discoloration) appear on the upper leaf surface.

Preprocessing steps are essential to prepare the data so that relevant features can be extracted effectively. Some common methods include resizing and normalization to ensure uniform pixel sizes and values [12]. Segmentation to separate plant objects from the background. Popular techniques include adaptive thresholding, Otsu method, and cluster-based segmentation (k-means). Data augmentation to increase the size of the dataset and prevent overfitting. Techniques include rotation, flipping, zooming, and translation [13].

Feature extraction is a crucial step in identifying the characteristics of pest damage. Commonly used features in classification include:

- Color features: RGB, HSV, LAB histograms to detect color changes in leaves. The color distribution of healthy and infected leaves is very different and can be detected automatically [14].
- Texture features: GLCM (Gray-Level Co-occurrence Matrix), LBP (Local Binary Pattern), or HOG (Histogram of Oriented Gradient) are used to identify texture patterns due to leaf bites or holes [15].
- Morphological features: damage contour, wound area, damage length, used to distinguish bite patterns from various types of pests.

One of the machine learning methods that can be used for classification is Decision Tree. A decision tree-based classification method that maps input attributes into output decisions through a branching structure. Each internal node in the tree represents a test of an attribute, a branch represents the test result, and a leaf node represents the final class label. Decision Tree is a popular method because it is easy to understand, does not require much preprocessing, and can handle categorical and numeric data [16]. The process of forming a decision tree involves attribute selection, data separation, recursion, and pruning.

A study developed a web-based decision support system for early detection of pest attacks on cabbage plants. This system uses the Decision Tree algorithm to analyze images of cabbage leaves and determine the level of damage caused by pests. By utilizing image processing and classification technology, this system helps farmers identify pest attacks quickly and accurately, so that control measures can be carried out more effectively [17].

III. METHODOLOGY

Wardani et. al. [18], research has introduced a method of imbalance data for cabbage. This method can be adapted for decision-making determination from cabbage pest attacks. The research methods include data collection of cabbage photos, preprocessing of cabbage photos, processing and extraction of images, classification models, and system evaluation. Classification models using Classification and Regression Tree (CART) have been widely implemented [19][20][21]. The step of the research method can be seen in the figure below.

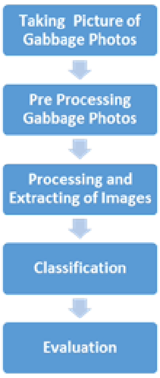


Fig 1: Steps of Research Method

A. Taking Picture of Cabbage Photos:

The picture of cabbage was taken in a cabbage field in the Poncokusumo, Malang, East Java. The age of cabbage plants reaches to 70 days after planting. The image of cabbage is divided into two classes, cabbage with plants (positive and majority class) and cabbage without plants (negative and minority class). Image acquisition is taken randomly using a camera with at least 13 MP

B. Preprocessing Cabbage Photos:

In the preprocessing stage, there are 3 steps to process the image, namely cropping the image, scaling the image and converting the RGB image to grayscale form. The cropping technique is done to cut and take the core of the cabbage and leaves from the image. Moreover, cutting is done based on the whole part (leaves, buds and shoots) of the cabbage plant. The cutting process aims to remove the background / photo background that is not part of the cabbage plant. This process utilizes Photoshop software. Following this, all cropped image data is converted to the same scale. Last but not least, the scaled image which is still in RGB form is converted into grayscale. The complete process is presented as follows:

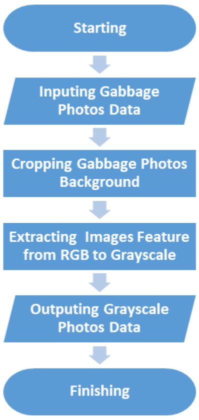


Fig 2: Steps of Preprocessing Cabbage Photos

C. Processing and Extracting Photo Images:

The research utilizes the Gray Level Co-occurrence Matrix (GLCM) method as an extraction method. Research zhang et al has provided evidence of results using GLCM provides good results and can be applied to plant types [22]. Gray Level Co-occurrence Matrix (GLCM) is used for texture analysis/ feature extraction. Moreover, GLCM will describe the frequency of the appearance of pairs of two pixels with an intensity in a certain distance and direction from the image [23]. The coordinates of a pair of pixels have a distance d and an angle orientation θ. Distance is represented in pixels, while angle in degrees. Angle orientation is formed based on four corner directions, namely, 0°, 45°, 90° and 135°, and the distance between pixels is 1 pixel [24]. The steps in the GLCM calculation are presented as follows:

1) Formation of the initial GLCM matrix from pairs of two pixels aligned in the direction 0°, 45°, 90° or 135°.
2) Form a symmetrical matrix by adding the initial GLCM matrix with its transpose value.
3) Normalize the GLCM matrix by dividing each matrix element by the number of pixel pairs.

The detailed process described in the diagram below:

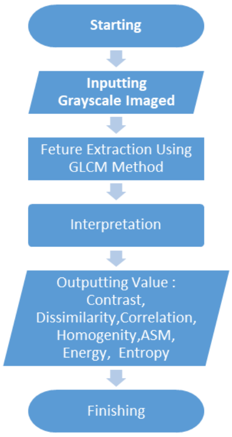


Fig 3: Steps of Processing and Extracting Photo Images

D. Classification using Decision Tree Based Boosting Method:

Following the feature extraction data from the GLCM method, the next processing is the ensemble method. The ensemble method is an algorithm in machine learning. It takes a role as a search engine. Moreover, it offers the best predictive solution compared to other algorithms since the ensemble utilizes several learning algorithms to achieve better predictive solutions rather than algorithms that can only obtain one constituent algorithm learning. Unlike statistical ensembles in statistical mechanics which is usually unlimited, the learning ensemble only consists of a limited set of alternative models, but usually allows for more flexible structures to exist among the alternative models. Evaluation of predictions from ensembles usually requires more computation than evaluation of predictions of a single model, so this ensemble makes it possible to compensate for poor learning algorithms by performing more computations. The ensemble method is classified into 3 which are:

- **Bagging**

Bagging is a method that improve the results of machine learning classification algorithms by combining prediction classifications from several models. It is used to overcome the instability in complex models with relatively small data sets. Bagging is one of the earliest and simplest, yet effective ensemble-based algorithms. Furthermore, it is fit for problems with relatively small training datasets. Bagging has a variation called Pasting Small Votes. This method is designed for problems with large training datasets, following a similar approach, but dividing the large dataset into smaller segments. Individual classifiers are trained with these segments, called bites, before combining them by means of majority voting.

- **Boosting**

Boosting aims to generate multiple models or categories for prediction or classification, and also to combine predictions from multiple models into a single prediction. More to the point, it is an iterative approach to produce a strong classifier, which is able to achieve the minimum possible training error from a group of weak classifiers, each of which cannot do better rather than a random guess.

Boosting is designed for binary class problems, creating sets of three weak classifications at a time. The first classification (or hypothesis) is to process a random subset of the available training data. The second classification is a different subset of the original dataset, where the results of the first classification are correctly classified and half are misclassified. The third classification is then trained with prediction examples where the first classification and the second classification do not work well. These three classifiers are then combined by means of a three-way majority vote.

- **Stacking**

Stacking attempts to combine several models, with the concept of a meta-learner. It is used following bagging and boosting. Unlike bagging and boosting, stacking allows combining models of different types. The basic concept in stacking is to train first-level learners using the original training dataset and generate a new dataset to train second-level learners, where the outputs of the first-level learners are considered as input features while the original labels are still considered as new training data labels. First-level learners are often generated by applying different learning algorithms.

In the training phase of stacking, a new data set needs to be generated from the first level classifier. If the right data used to train the first level classifier is also used to generate a new dataset to train the second level classifier, it will be resulted in overfitting. So, it is recommended that the examples used to generate the new data set are excluded from the sample training data for first-level learners, and the cross-validation procedure.

The reasons for using this method are : (1) Ensembling is a proven method to improve model accuracy and works in most of the cases; (2) Ensembling makes the model more firm and stable that later can provide a proper performance on test cases in most scenarios; (3) To capture a complex linear and simple and non-linear relationships in the data, the method can be conducted using two different models and forming an ensemble of two.

In this section, a classification model will be developed. The method used is Classification and Regression Tree (CART). Below is the steps on the classification:

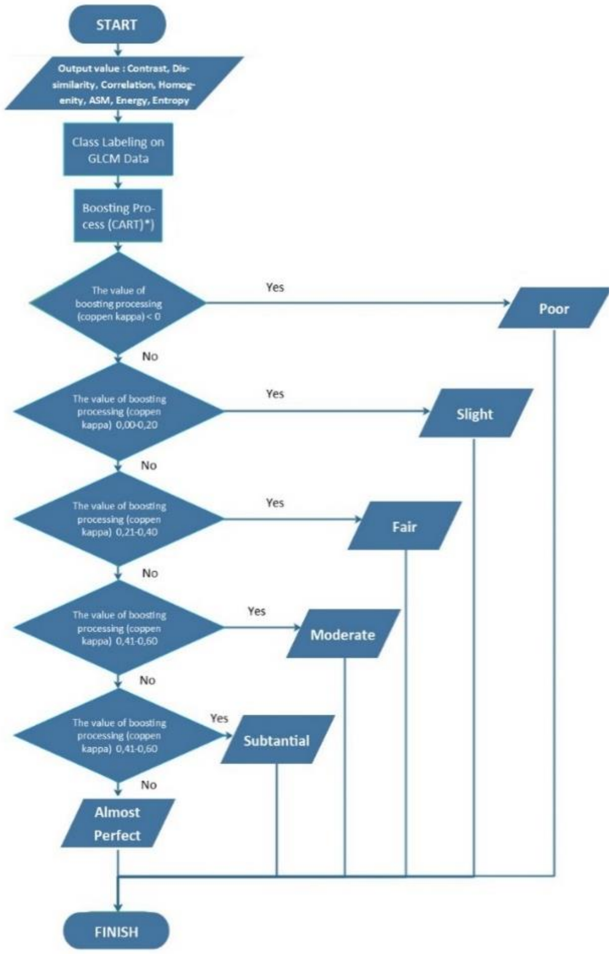


Fig 4: Steps of Classification Using Decision Tree Based Boosting Method

E. Result Evaluation:

The results of the test will be showed in percentage accuracy of the successful classification of pest attacks from photo images. Before being classified, the dataset is divided for the training and testing process. Eighty percent of the data is used for training. The training data consisted of 84 images of cabbage with cropping and 20 images of cabbage without cropping. Meanwhile, the rest is used for data testing. After the training and testing data is done, the feature value is normalized to equalize the scale. Equation (1) describes the function for normalization. The function maps values to intervals [0,1].

$$z_i = x_i - \min(x)/\max(x) - \min(x)$$

F. *System Design:*

A lot of research on image processing has been applied by utilizing website media. An example is the research Dell'Aquila et al has used the website to find out the seeds / seeds [25]. Subsequent research was utilizing the merger with RGB images in detection and quantification in cabbage disease [26]. So this study combines the shortcomings of two previous studies to identify the percentage of attacks and any recommendations. The result of the architectural system design is presented below:

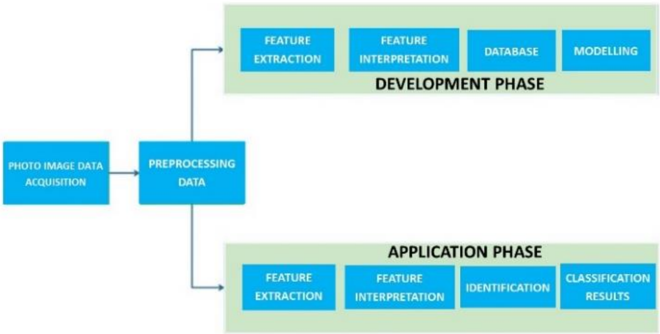


Fig 5: System Design

According to the architectural design of the system above, it can be seen that the system is divided into 2 processes, development or training and application or testing. In the development phase, the data is stored in the database for modeling in the system.

IV. RESULT

The results of this study are divided into the following sections:

A. *System Display:*

The most important part of the website is the display or commonly called the home menu. The results of this study used a home menu to display the title of the application and some other parts of the system. The core is that the system has been divided into three main parts: input, process and output. The initial display of the system shows a system that can be used for analysis. The main page is presented as in the image below.

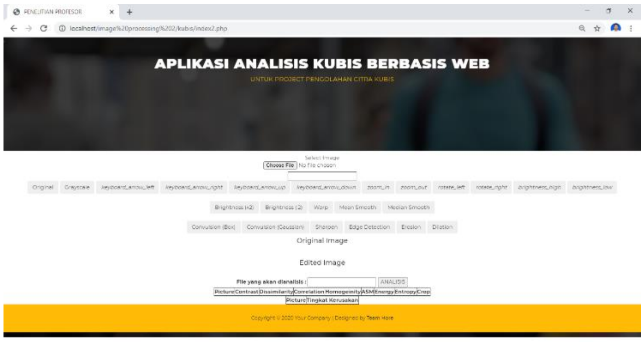


Fig 6: Main Page View

The main display of the page consist of 4 main systems:

1) Input Image, It is used to upload image for analysis

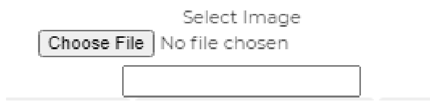


Fig 7: Upload Image Menu

2) Image Manipulation & Modification, This part consist of symbol for edited image

Fig 8: Image Editing Button

There are several types of buttons for editing images, namely:

- Original, it is used to restore the original appearance
- Grayscale, it is used to change original images to grayscale
- keyboard_arrow_left
- keyboard_arrow_right
- keyboard_arrow_up
- keyboard_arrow_down
- zoom_in
- zoom_out
- rotate_left
- rotate_right
- brightness_high
- brightness_low
- Brightness (x2)
- Brightness (:2)
- Warp
- Mean Smooth
- Median Smooth
- Convulsion (Box)
- Convulsion (Gaussian)
- Sharpen
- Edge Detection
- Erosion
- Dilation

3) Input from the Image Manipulation & Modification result, the original image is used to display the image that has been uploaded. While the edited image is used for the results of manipulation / modification.

Fig 9: Image Manipulation and Modification Result

4) The result of analysis displays cabbage image analysis

Fig 10: Result of analysis display

To upload the image, click on the "upload image" button. It will automatically open the computer folder where the image is stored.

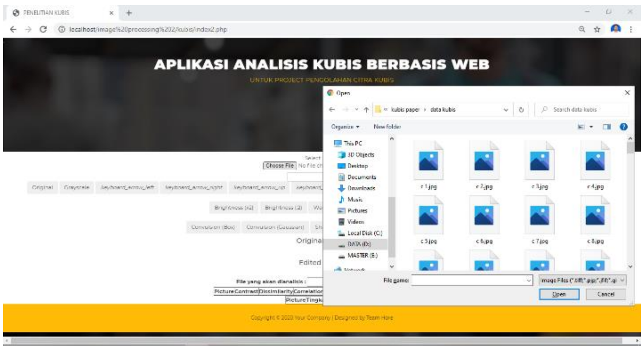


Fig 11: Upload Image Process

Following this, we can choose image which needs to analyze by click "open". The image will be displayed as follows:

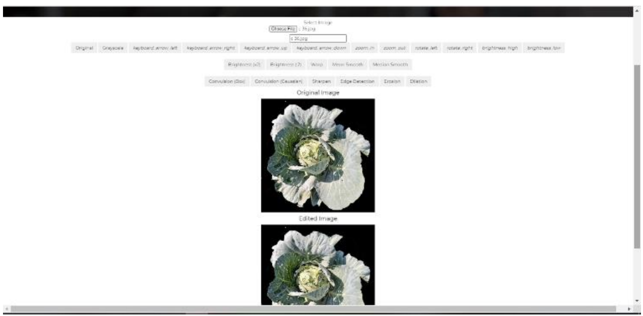


Fig 12: Original Image

The original image is the image that the background has been removed. For the edited image, it is used to accommodate the display of images that can be manipulated.

Manipulation of images can be proceed by clicking manipulation, modification buttons. Since we need a grayscale display, we should press thnde grayscale button.

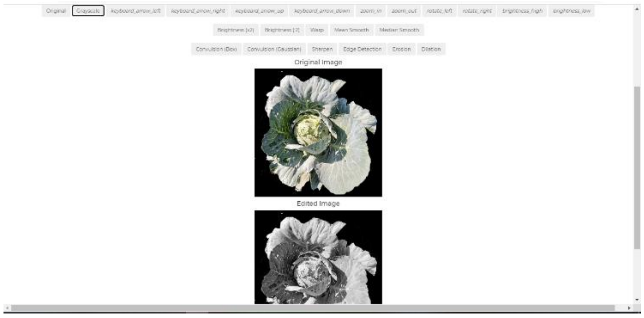


Fig 13: Edited Image

Original image shows its original and whole image. While edited image refers is used to image that has changed into greyscale.

B. *Extraction and Analysis Process:*

After the display is aligned with what is requested, the next step will go to extraction process. The Extraction process will display the results of the GLCM features that have been analyzed. These include Contras, Dissimilarity, correlation, Homogenity, ASM, Energy, Entrophy, Crop. Nevertheless, we have to analyze the appearance of the edited image first by entering the name of the file that has been edited.

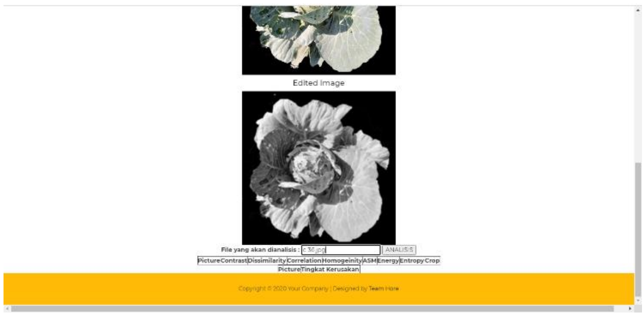
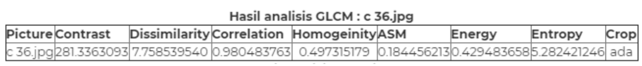


Fig 14: Extracting Image

Then, we can click the analysis button next to the image that has been analyzed. After that, the value of the existing GLCM features will appear. Last but not least, the level of damage in the image can be analyzed. The GLCM analysis will look like this:


Hasil analisis GLCM : c 36.jpg

Picture	Contrast	Dissimilarity	Correlation	Homogeinity	ASM	Energy	Entropy	Crop
c 36.jpg	281.3363093	7.758539540	0.980483763	0.497315179	0.184456213	0.429483658	5.282421246	ada

Fig 15: Result of Analysis

While, the analysis to the leaves and crop observation on the criteria for the category damage intensity:

Table 1. Criteria for the category damage intensity

Category	Percentage	Criteria
0	0	Normal
1	0 – 25	Low
2	25 – 50	Moderate
3	50 – 75	Severe
4	>75	Very Severe

The complete display of feature extraction and the analysis is presented as follows:

File yang akan dianalisis : ANALISIS

Hasil analisis GLCM : c 36.jpg

Picture	Contrast	Dissimilarity	Correlation	Homogeinity	ASM	Energy	Entropy	Crop
c 36.jpg	281.3363093	7.758539540	0.980483763	0.497315179	0.184456213	0.429483658	5.282421246	ada

Hasil analisis : c 36.jpg

Picture	Tingkat Kerusakan
c 36.jpg	Kerusakan Sedang

Fig 16: Complete Display of Feature Extraction and Analysis

The picture of original image and edited image will be removed due to display analysis in extraction process.

V. CONCLUSION

The result of the system is presented in the form of images and the percentage of cabbage crop damage. The CART method can be used to analyze the level of plants damage that have been attacked by pests. The results of the classification process can be used to consider insecticide dosages and insecticide spraying intervals for cabbage plants.

VI. FUTURE SCOPE

Future research in cabbage pest attack classification using image processing can focus on improving data quality and model performance. High-resolution images captured from drones or smartphones under various lighting and weather conditions can enhance image quality and detection accuracy. Expanding datasets to include different seasons and geographic locations will help improve model generalizability. Advanced deep learning techniques, such as Vision Transformers or hybrid CNN-transformer architectures, could significantly improve classification accuracy. Additionally, using semi-supervised or unsupervised learning can reduce reliance on extensive labeled data, making the system more scalable.

Further developments may include extending the model to identify specific pest species, integrating entomological databases for more detailed analysis. Real-time pest monitoring can be made possible through mobile or edge-AI applications, enabling on-site detection and control recommendations. Combining image data with environmental sensor inputs (e.g., humidity, temperature, soil moisture) and time-series analysis can enhance outbreak prediction. Future systems could also estimate the economic impact of pest intensity and offer decision support tools for farmers. Lastly, automated drone-based surveillance with onboard processing can streamline large-scale crop monitoring by optimizing data collection routes and reducing manual labor.

VII. CHALLENGES

One of the main challenges in classifying the intensity of cabbage pest attacks using photo image processing is the variability and quality of image data. Differences in lighting, camera angles, weather conditions, and background clutter can significantly affect the accuracy of image-based analysis. Inconsistent image resolution and occlusion of leaves or pests can make it difficult to accurately detect and classify the extent of damage. Additionally, the lack of large, well-annotated datasets specific to cabbage pest damage poses a barrier to training robust machine learning models, especially deep learning architectures that require vast amounts of data.

Another significant challenge lies in the complexity and diversity of pest symptoms. Different pests may cause similar types of damage, making it hard to distinguish between them solely based on visual cues. Moreover, early-stage infestations might show minimal visible symptoms, which are difficult to detect with conventional image processing techniques. Developing models that can classify both the pest type and the intensity of attack requires integrating domain-specific agricultural knowledge and possibly combining image data with other sources like sensor or weather data. Ensuring real-time processing capabilities and model generalization across different field conditions further adds to the complexity of the system.

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