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A Digital Image Processing–Based Moler Disease Detection System for Shallot Leaves

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Abstract

This study aims to design and develop a leaf moler disease detection system on shallots (Allium cepa L.) based on digital image processing in Enrekang Regency, South Sulawesi. Moler disease caused by the fungus Fusarium oxysporum f. sp. cepae is one of the main factors that reduce the quality and productivity of shallots. So far, disease identification is still done manually through direct observation by farmers, which is subjective and time-consuming. To overcome this problem, this study applies the Convolutional Neural Network (CNN) algorithm to automatically classify shallot leaf images into two categories, namely healthy and infected with moler disease. The number of datasets used is 502 images, consisting of 251 healthy images and 251 infected images, with data division of 70% for training, 15% for validation, and 15% for testing. The CNN architecture used consists of convolution, pooling, flatten, and fully connected layers with ReLU and sigmoid activation functions in the output layer. The training process used the Adam optimizer with a learning rate of 0.001 and a binary cross-entropy loss function. Test results showed a training accuracy of 97.14%, a validation accuracy of 94.73%, and a testing accuracy of 97.37%, indicating the model has a good level of precision and generalization ability without overfitting. This system is implemented as a Flask-based web application that allows users to upload leaf images and obtain detection results instantly. This system is expected to help farmers detect diseases more quickly and increase shallot productivity in Enrekang Regency.

Introduction

Shallots (*Allium cepa L.)* are one of the most widely cultivated horticultural commodities in Indonesia, particularly on the islands of Java and Sulawesi (Nur et al., 2022). Enrekang Regency in South Sulawesi Province is a major shallot-producing region, where shallot cultivation has become a crucial agricultural activity and a primary source of livelihood for the local community.

Since the 1980s, farmers in Enrekang have begun intensively cultivating shallots, particularly in highland areas such as Anggeraja, Baraka, and Cendana Districts (Tussadia & Halim, 2023; Pujawiyatna, 2024; Muhiddin, 2022; Summase et al., 2019). Fertile volcanic soil and increasing market demand have made shallots a leading commodity in this region (Simanjuntak & Manalu, 2022; Panjaitan, 2023). Enrekang farmers are enthusiastic; they even

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install lighting on their farms to extend the duration of photosynthesis during the rainy season or when sunlight intensity is low, ensuring optimal plant growth and increasing yields.

However, in recent years, the quality and productivity of shallots in Enrekang have fluctuated due to environmental factors and an increase in plant disease attacks (Resiani et al., 2025; Astaman et al., 2025; Yusriadi et al., 2024; Kodrat, 2024; Resiani et al., 2021). One of the most detrimental diseases is moler disease, which is caused by the fungus *Fusarium oxysporum f. sp. cepae.* (Cahyaningrum et al., 2023) This fungus attacks the root system and vascular tissue of plants, causing stunted growth, yellowing of leaves, and the formation of small, rotten bulbs. If not treated promptly, this disease can cause crop failure and significant economic losses for farmers (Vurro et al., 2010; Savary et al., 2012; Duveiller et al., 2007). Based on a 2025 report, moler disease is one of the main causes of decreased quality and quantity of shallot harvests in Enrekang Regency.

Figure 1. Comparison of Healthy Onions with Sick Onions

Currently, the disease identification process is still carried out manually through visual observation by farmers, which relies heavily on individual experience (Mahlein, 2016; Bock et al., 2020; Abbas et al., 2023; Shoaib et al., 2023; Wani et al., 2022). This approach is subjective, time-consuming, and prone to diagnostic errors. Research shows that approximately 30% of farmers in Enrekang lack the ability to accurately recognize plant disease symptoms, putting them at risk of treatment errors. This situation highlights the need for technological innovation to assist farmers, both experienced and novice, in detecting diseases more quickly and accurately.

Previous research by Prahesta (2025) and Mahmood et al. (2024) developed a disease detection system for shallots using a Convolutional Neural Network (CNN) algorithm with a MobileNet architecture, achieving 90.63% accuracy and demonstrating satisfactory classification results. Based on this research, this study aims to design a leaf moulting disease detection system for shallots based on digital image processing using a CNN algorithm. This system is expected to assist farmers in early, rapid, and accurate detection of moulting disease symptoms, thereby increasing agricultural productivity and the sustainability of shallot cultivation in Enrekang Regency.

Methods

Hardware and Software Requirements

The hardware and software requirements used in this research include several essential components that mutually support the system design and testing process. For hardware, a mobile phone served as the primary device for capturing shallot leaf images in the field, and a laptop served for data processing, training the Convolutional Neural Network (CNN) model,

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and application development. Meanwhile, for software, this research utilized the Python programming language as the basis for building the CNN model and digital image processing. Furthermore, Visual Studio Code served as the Integrated Development Environment (IDE) for writing and running the program code, while Google Chrome served as the platform for accessing, testing, and displaying the results of the developed web-based application.

Research Location

This research was conducted in a shallot farming area in Enrekang Regency, South Sulawesi Province. The location was selected based on several scientific and methodological considerations, making Enrekang highly relevant for research on shallot leaf spot disease. Enrekang Regency is a center for shallot production, supported by fertile volcanic soil with good drainage, making it highly suitable for cultivating Allium cepa L. This area has a tropical highland climate with an average temperature ranging from 18–28°C, relatively high humidity, and annual rainfall of around 1,500–2,500 mm. These environmental factors not only support optimal shallot growth but also have the potential to trigger the development of the fungus Fusarium oxysporum f. sp. cepae, the primary cause of shallot leaf spot disease. Therefore, Enrekang is a representative and strategic location for collecting field data on healthy and infected leaves. Data collection was conducted directly on several agricultural plots to ensure sample variation and representativeness. Leaf samples came from different plants within the same field to avoid data redundancy. Healthy and infected leaves were selected based on visual characteristics, such as yellowing, leaf curl, and stunted plant growth, so the dataset reflects the diversity of natural conditions in the field. To maintain data consistency, image capture was conducted using the same mobile device under relatively uniform lighting conditions. Camera distance and leaf orientation were maintained consistently to minimize the influence of environmental factors. This approach increased the reliability of the dataset and ensured that the resulting model could be replicated by other researchers in the future.

Research Methods

The method used in this research is a Convolutional Neural Network (CNN), a highly effective deep learning algorithm for image classification. The CNN was applied to classify shallot leaf images into two categories: healthy leaves and leaves infected with moler disease. The CNN method was chosen based on its ability to automatically extract visual features from image data without requiring manual extraction (Liu et al., 2021; Latif et al., 2019; Rehman et al., 2019). It is hoped that the developed CNN model will achieve high accuracy in efficiently detecting plant diseases and can be implemented as a decision support system for farmers in the field.

Research Stages

This research was conducted through several interrelated stages to build and test a leaf spot detection system for shallots based on digital image processing using a Convolutional Neural Network (CNN) algorithm.

The figure illustrates the interrelated research stages in developing a shallot leaf spot detection system based on digital image processing using the Convolutional Neural Network (CNN) algorithm (Gülmez, 2025; Lidyawati et al., 2025; Susanto et al., 2025; Gupta et al., 2025). The research flow begins with a literature study, which aims to examine theories, methods, and previous research related to plant leaf diseases, digital image processing, and CNN implementation. The next stage is image data collection in the form of shallot leaf images representing healthy conditions and those infected with leaf spots. The collected image data

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then undergoes image preprocessing, such as resizing, normalization, and image quality improvement, to suit the input requirements of the CNN model. Next, the processed dataset is divided (dataset sharing) into training data and test data. Based on this dataset, a CNN architecture design is carried out, including determining the number of layers, kernels, and model parameters. The designed architecture is then used in the CNN model training stage to recognize leaf spot patterns in images. The final stage is system testing to demonstrate the model's performance in detecting and classifying shallot leaf conditions. With this flow, the leaf detection system is built systematically from conceptual to model performance evaluation.

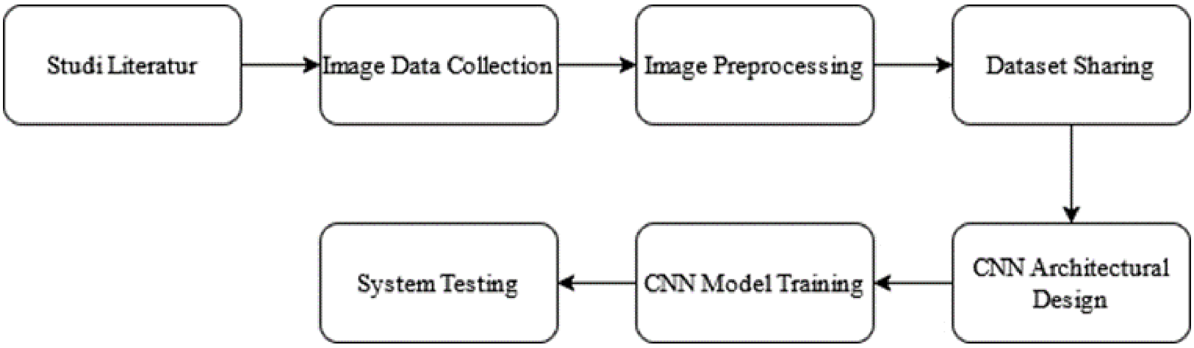

Figure 2. Research Stages

Results and Discussion

Preprocessing

Figure 3. Image Before and After Resizing

The data preprocessing process in this study consists of two main steps: resizing and normalization. In the resizing stage, all images are converted to a uniform size of 128 × 128 pixels. This dimension standardization is performed to ensure that each image meets the input format required by the CNN model and maintains the consistency of the data structure being processed. Next, the normalization stage is performed by converting pixel values from the initial range of 0–255 to the range of 0–1. This process is performed by dividing each pixel value by 255. Normalization plays a crucial role in accelerating the model training process, reducing the risk of instability during weight updates, and improving model accuracy because the pixel values are on a smaller and more uniform scale. These preprocessing steps overall aim to ensure that the image data used has optimal quality and structure so that the CNN

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model can learn visual patterns more effectively (Sarki et al., 2021; Tayal et al., 2022; Tayal et al., 2022; Archana & Jeevaraj, 2024).

Dataset Division

The dataset used in this study consisted of 502 images, consisting of 251 images of healthy leaves and 251 images of leaves infected with moler disease. The dataset was then divided into three main parts for training and evaluating the CNN model: 70% for training, 15% for validation, and 15% for testing. While this ratio is commonly used in machine learning research, its use in this study is based on the relatively small characteristics of the dataset. With the limited data, allocating 70% for training was necessary to ensure the model gained sufficient information to learn visual patterns. However, 30% of the data was left for validation and testing to ensure the model's performance evaluation remained representative and unbiased. This division aimed to maintain a balance between training needs and evaluation reliability.

The dataset was divided using a stratified random sampling technique (Sadaiyandi et al., 2023; Kim et al., 2013; Zhao et al., 2023; Padilla et al., 2015). This technique ensures that the class distribution (healthy and infected) remains balanced in each data subset, thus preventing class imbalance and the risk of data leakage. A fixed random seed was also used to ensure the division process can be consistently replicated in future studies. Although the dataset in this study was balanced (50% healthy and 50% infected), this does not necessarily reflect the actual situation in the field, where disease prevalence can vary depending on season, location, and cultivation techniques. This limitation can impact model performance when applied to unbalanced real-world conditions.

Cross-validation techniques, such as k-fold cross-validation, were also considered as alternatives because they provide more stable performance estimates on small datasets (Lumumba etal., 2024; Wong, 2015; Yadav & Shukla, 2016). However, to maintain a strict separation between training and testing data in the context of system implementation, this study decided to use a fixed split. Cross-validation is still recommended for use in further research to improve the robustness and statistical validity of the model.

Data Collection and Preprocessing

The data used in this study consisted of 502 shallot leaf images, consisting of 251 healthy leaf images and 251 leaf images infected with moulting disease. Before the data was used in model training, a preprocessing stage was performed to standardize the size and pixel values of each image so that they could be properly processed by the Convolutional Neural Network (CNN) algorithm. This preprocessing process involved two main steps: resizing and normalization. In the resizing stage, all images were converted to a uniform size of 128x128 pixels to ensure they had the same dimensions and met the input requirements of the CNN model. Next, in the normalization stage, the image pixel values, which were originally in the range 0–255, were converted to the range 0–1. This normalization aims to accelerate the model training process and improve stability and accuracy in the image classification process.

CNN Model Training Process

Training was conducted using 350 training images, the results of the previous data splitting process. Each image underwent preprocessing, including resizing (128x128 pixels) and normalizing pixel values to the 0–1 range to facilitate CNN processing. The training process was conducted with several key parameters: (1) Epoch: 10; (2) Bath Size: 16; (3) Optimizer: Adam; (4) Loss Function: binary_crossentropy; (5) Learning Rate: 0.001. The training stage

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involved the system repeatedly processing each image (per epoch), calculating the error (loss), and adjusting the network weights to increase prediction accuracy.

Training and Validation Results

The results of the training and model validation are presented in the following table:

Table 1. Training Test Results

Category	Healthy	Moler	Total
Total Correct Test Data	169	171	340
Total of All Tested Data	175	175	350
$\text{Accuracy} = \frac{Correct\ Test\ Data}{Total\ Test\ Data} 100\% = \frac{340}{350} \times 100 = 97{,}14\%$			

Table 2. Validation Test Results

Category	Healthy	Moler	Total
Total Correct Test Data	36	36	72
Total of All Tested Data	38	38	76
$\text{Accuracy} = \frac{Correct\ Test\ Data}{Total\ Test\ Data} 100\% = \frac{72}{76} \times 100 = 94{,}73\%$			

Evaluasi Model (Confusion Matrix)

Table 3. Confusion Matrix Structure

Moler's Prediction	Healthy Prediction
37 (TP)	1 (FN)
1 (FP)	37 (TN)

Based on the confusion matrix above, the evaluation metric value can be calculated using the followingformula:

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

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

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

$$F1 - Score = 2 \times \frac{\text{Precision} \times \text{Recall}}{Precision + Recall} \quad (4)$$

The calculation results are as follows:

$$\text{Accuracy} = \frac{37 + 37}{37 + 37 + 1 + 1} \times 100\% = \frac{74}{76} \times 100\% = 97{,}37\% \quad (1)$$

$$Precision = \frac{37}{37 + 1} \times 100\% = 97{,}37\% \quad (2)$$

$$Recall = \frac{37}{37 + 1} \times 100\% = 97{,}37\% \quad (3)$$

$$F1 - Score = 97{,}37\% \quad (4)$$

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Use Case Diagram

The use case diagram below illustrates the interaction between a user and a shallot moulting disease detection system. This diagram shows the main functions the user can perform and how the system processes those actions. A use case diagram makes the system's requirements flow clearer, simplifying the implementation and testing stages (Beimel, D., & Kedmi-Shahar, 2019).

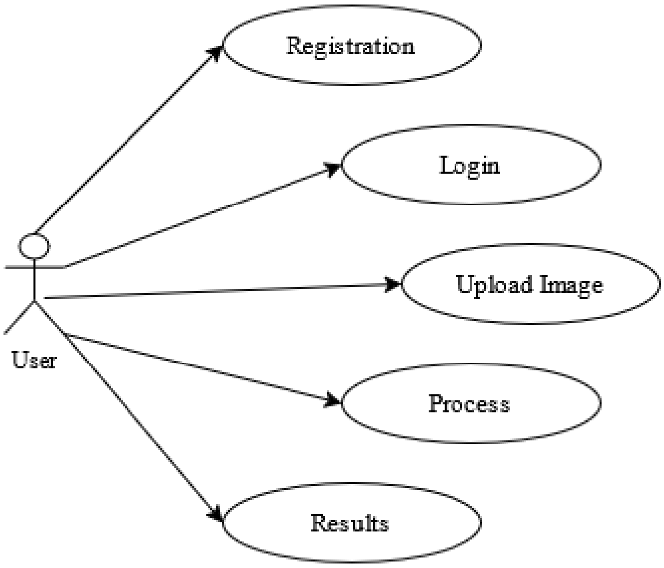

Figure 4. Use Case Diagram

Model Convolutional Neural Network (CNN)

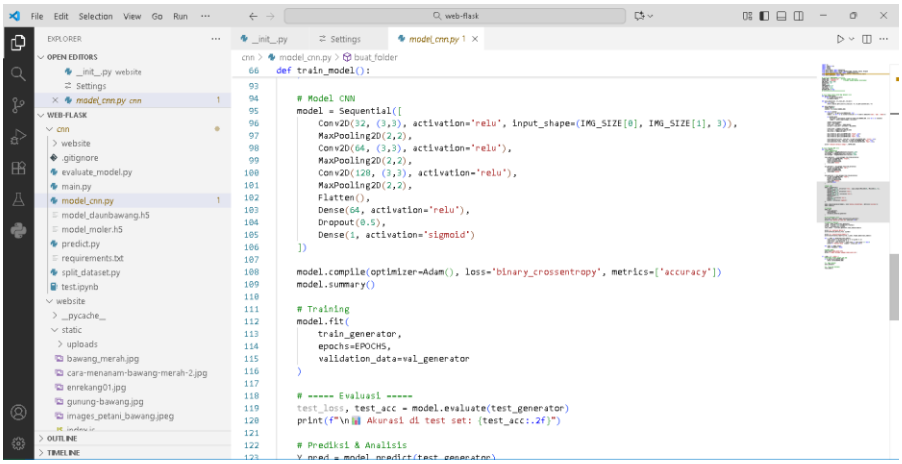

Figure 5. Model Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN) architecture used in the shallot classification system consists of several layers designed to gradually extract important features from images. Initially, the input image passes through three convolutional layers with an increasing number of filters: 32, 64, and 128, each with a 3x3 kernel size and a ReLU activation function. Each convolutional layer is followed by a 2x2 max pooling layer, which reduces the feature dimensionality and prevents overfitting by reducing data complexity. After passing through a series of convolutional and pooling layers, the extracted features are converted into one-dimensional vectors through a flattening layer.

The data is then passed to a fully connected (Dense) layer with 64 neurons and a ReLU activation function, which performs the classification process based on the previously

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extracted features. To improve performance and prevent overfitting, a dropout layer with a dropout value of 0.5 is used. At the end of the architecture, there is an output layer (Dense) with one neuron and a sigmoid activation function, as this model uses a binary classification approach to distinguish between two image classes. This CNN model was compiled using the Adam optimizer, with a binary_crossentropy loss function and an accuracy evaluation metric. After the training process was complete, the model was tested using test data to evaluate its ability to automatically recognize and classify shallot plant images.

Application

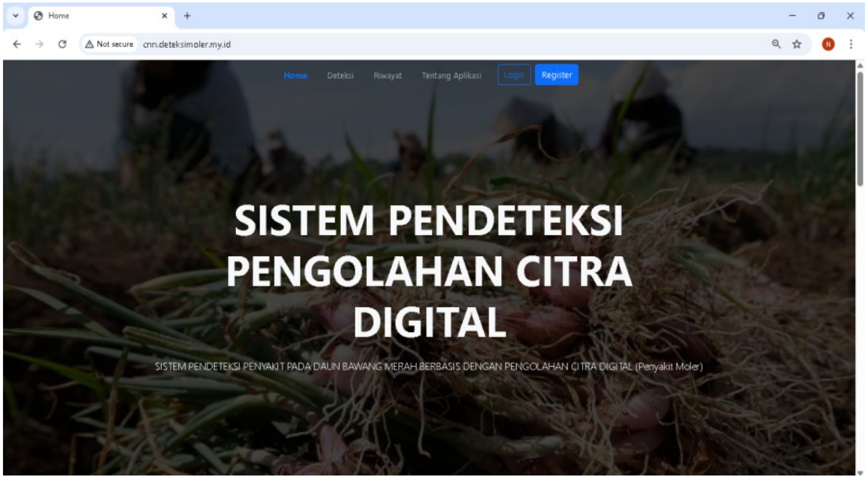

Figure 6. Initial Dashboard View

Figure 6. Dashboard Display: The initial interface of the application, which serves as an introduction to the digital image processing-based disease detection system for shallots. This page displays the system's title and brief description, along with a navigation menu that directs users to key features such as Detection, History, and About the Application. The use of a shallot field as a background image reinforces the application's visual identity, reflecting the context of the issues raised.

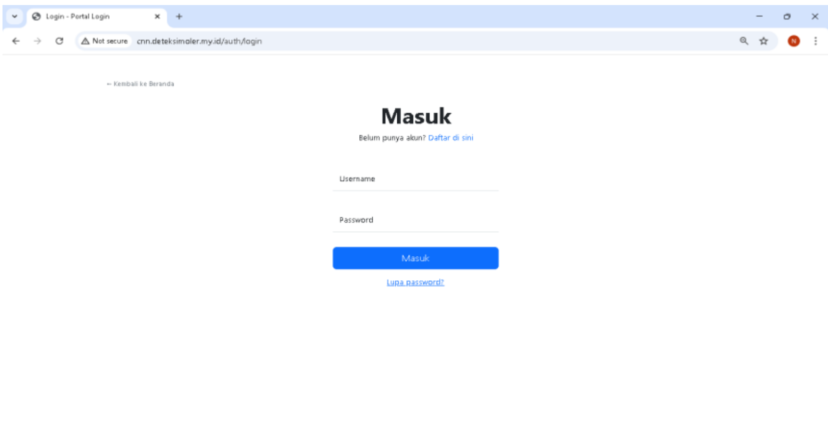

Figure 7. Login Page

Figure 7. The login page is where users enter their username and password before accessing the system. This page provides an authentication form, a registration link for new users, and status notifications such as the "Successfully logged out" message that appears when a user exits an application session.

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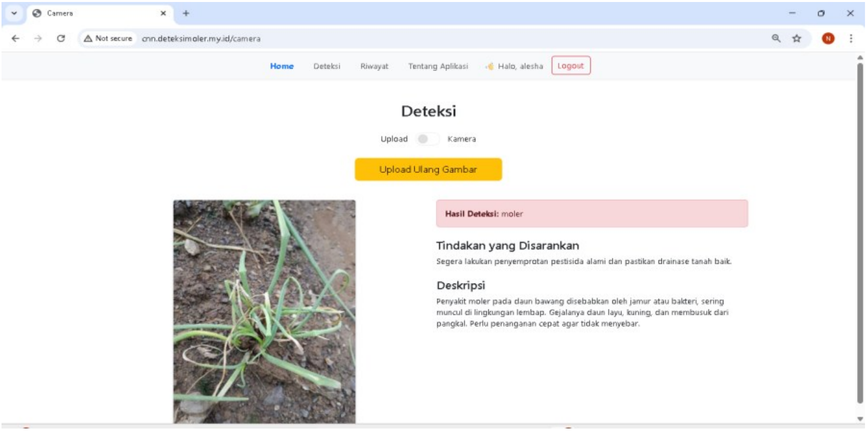

Figure 8. Detection Page Display on the System

Figure 8. The detection results after the analysis process displays the disease identification results on shallot leaves. The image shows the uploaded plant image along with the detection label "moler." This page also provides additional information in the form of recommended actions and a disease description to help users understand the plant's condition and treatment steps.

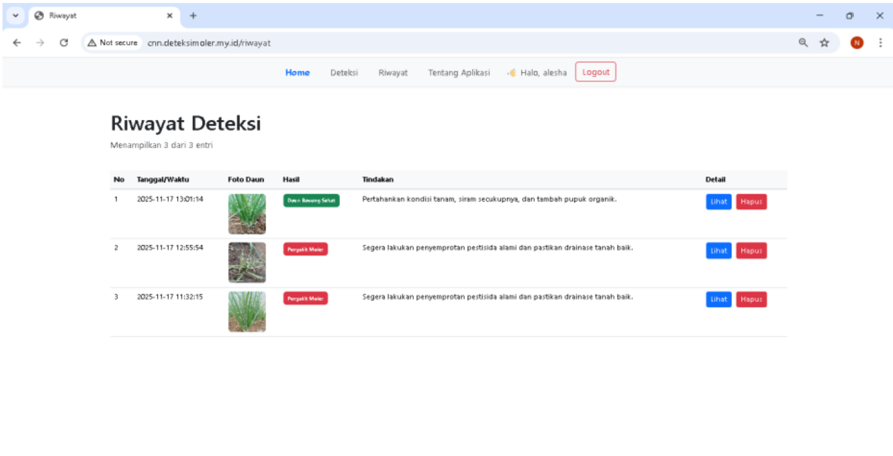

Figure 9. History Page View

Figure 9. shows the Detection History page, which displays all detection results performed by the user. This page displays a table containing important information such as the sequence number, detection date and time, a photo of the analyzed leaf, disease identification results, recommended actions, and action buttons such as "View" to display detection details and "Delete" to delete historical data. This display makes it easier for users to monitor, review, and manage the disease detection track record in shallot plants.

Conclusion

Based on the research results, it can be concluded that the digital image processing-based shallot leaf molar disease detection system has been successfully designed and built. This system is capable of automatically detecting molar disease symptoms in shallot leaves through digital image processing, providing faster and more accurate information on plant condition. The implementation of this system can help farmers in Enrekang Regency identify molar disease early, allowing for more effective prevention and treatment. Therefore, this system has the potential to improve the quality and quantity of shallot production, while reducing losses due to disease attacks.

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