Journal of Research in Artificial Intelligence for Systems and Applications (RAISA)
2025, Vol. 01, No. 02, E-ISSN: 3090-3157

Original Research

Implementation of Convolutional Neural Network (CNN) for Watermelon Plant Diseases Using Lenet-5 Architecture

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Abstract

Watermelon (Citrullus Lanatus) is a horticultural commodity with high economic value that is widely cultivated by farmers in Indonesia, but the productivity of watermelon plants is often hampered by various types of diseases such as anthracnose, leaf spot and viral mosaic which can reduce the quality and quantity of crops. Manual identification of leaf diseases by farmers or agricultural experts is often subjective and takes a short time. Therefore, a plant disease identification method that is fast, accurate and easily accessible is needed. Artificial intelligence technology, especially Convolutional Neural Network (CNN), has proven effective in applying classification and object detection. Lenet-5 architecture is one of the early forms of CNN developed by Yann LeCun which is now widely reused for image classification purposes. The dataset used consists of 4 classes namely Antrachnose, Downy mildew, Healthy leaves and Mosaic virus with a total of 1155 images. The evaluation results of this study obtained the accuracy, recall, precision and F1-score results are 93%, 94% 95% and 94% respectively.

Keywords

CNN, Plant Disease, Watermelon, Lenet-5

1. Introduction

Agriculture is one of the most important sectors in the Indonesian economy. Watermelon (Citrullus lanatus), a popular horticultural commodity, has high economic value and is widely cultivated by farmers. However, watermelon productivity is often hampered by various types of diseases that attack the leaves of the plant, such as anthracnose, leaf spot, and downy mildew. These diseases can significantly reduce both the quality and quantity of the harvest.

Manual identification of leaf diseases by farmers or agricultural experts is often subjective and time-consuming. Additionally, limited access to agricultural experts in some areas leads to delayed disease detection. Therefore, a fast, accurate, and easily accessible method for identifying plant diseases is needed. In this context, the application of artificial intelligence technology presents a highly promising solution.

One branch of artificial intelligence that has proven effective in image processing is deep learning, specifically Convolutional Neural Networks (CNN). CNN is an artificial neural network architecture designed to automatically recognize visual patterns from image data. CNN has been widely applied in object classification and detection, including in the field of digital agriculture such as plant leaf disease identification[1].

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Received: 19 Juli 2025; **Accepted:** 25 Juli 2025; **Published:** 30 Juli 2025

The LeNet-5 architecture is one of the early forms of CNN developed by Yann LeCun and his team. Despite its simplicity, LeNet-5 remains relevant and effective for image classification tasks with low to moderate complexity. This architecture consists of a convolutional layer, subsampling, and a fully connected layer designed to classify handwritten images, but it is now widely reused for other image classification purposes, including in agriculture[2].

Previous studies have demonstrated the success of implementing CNNs in detecting plant leaf diseases. For example, research by [3] showed that CNNs can achieve high accuracy in detecting various diseases in agricultural plants from image datasets. However, the application of CNNs for diseases in watermelon plants, particularly with the LeNet-5 architecture, has not been extensively explored.

This study aims to implement CNN with the LeNet-5 architecture in detecting and classifying diseases in watermelon plants. By using an image dataset containing various types of diseases, this system is expected to learn to recognize visual patterns that are indicators of each type of disease. The results of this study are expected to provide a real contribution to the development of plant disease detection systems based on smart technology.

2. Research Method

The research used was applied research aimed at developing models and testing their accuracy. This research classified diseases in watermelon plants using a lenet-5 architecture with a total of 3 disease classes and 1 healthy leaf class.

2.1. Watermelom Plant Dieseases

This study identified three types of diseases, namely anthrachnose, downy mildew, and mosaic virus.

2.1.1. Antrachnose

Anthracnose disease in watermelon plants is caused by the pathogen C. orbiculare. On leaves, symptoms of this disease begin with yellow spots that turn brown and shiny, causing the leaves to dry out. When it attacks the fruit, it causes brown spots and slime, which then oozes out[4].

Figure 1 Antrachnose

2.1.2. Downy Mildew

Downy mildew, commonly known as downy mildew or kresek, is caused by the fungus Pseudoperonospora cubensis. In addition to watermelon plants, this disease can also attack other plants in the Curcubitaceae family, such as cucumbers, melons, and pumpkins. The symptoms caused by downy mildew in other plants in the Curcubitaceae family differ in terms of shape and color[5].

Figure 1 Downy Mildew

2.1.3. Mosaic Virus

This virus can be spread in various ways, including by aphids. Plant growth becomes curled, with irregular yellow spots and wavy leaves. At severe levels of attack, plants generally fail to form fruit, and even if they do, the fruit is stunted and abnormal[4].

Figure 2 Mosaic Virus

2.2. Lenet-5

Lenet-5 is a network that has multiple layers based on Convolutional Neural Network (CNN), first introduced by Yann Lecun[2] which has been successfully applied to traffic sign recognition[6], facial expression recognition[7], alzheimer's disease recognition[8], and other fields. Lenet-5 is formed from the development of previous versions of Lenet[9].

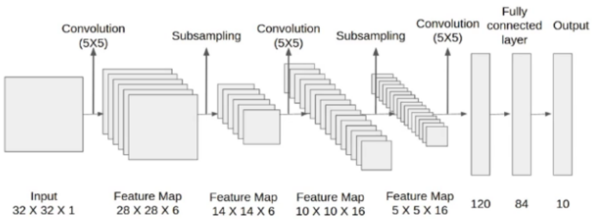

Figure 3 Lenet-5

2.3. Model Design

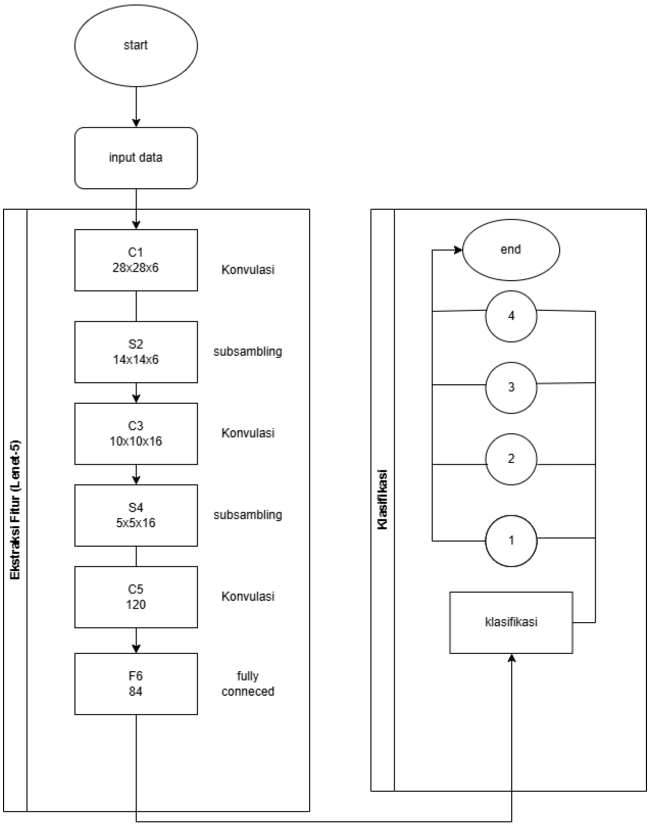

Figure 4 Architecture Lenet-5

Model design is done by using Lenet-5 architecture which is used as a classifier with some adjustments for its use.

2.4. Confusion Matrix

This model uses a confusion matrix, which is then used to calculate the accuracy, precision, recall, and F1 score values.

2.4.1. Accuracy

Accuracy measures how accurately a system is able to find and identify correct information from all available data. The closer the number is to 1, the higher the system's accuracy in finding relevant documents or information.

$$Acurracy = \frac{Tp + Tn}{Tp + Tn + Fp + Fn} \quad (1)$$

2.4.2. Precision

Precision measures how accurately a system is able to find and identify information requested by the user with the answers provided by the system. The closer to 1, the higher the precision value in finding relevant documents or information.

$$Precision = \frac{Tp}{Tp+Fp} \quad (2)$$

2.4.3. Recall

Recall measures how successful the system is in retrieving information. The highest recall value is 1, which means that all documents in the collection were successfully retrieved.

$$Recall = \frac{Tp}{Tp+Fn} \quad (3)$$

2.4.4. F1-Score

The F1-score is the harmonic mean of precision and recall. This metric is used to balance the two.

$$F1\ score = \frac{2xPrecisionxRecall}{precision+Recall} \quad (4)$$

3. Results and Analysis

***Table 1* Model Evaluation Score Results**

Epoch	Training	Validation
13	99%	94.73%
20-24	100%	93.91%
22-50	100%	93.91%
50	100%	93.04%

Table 1 above shows that the highest accuracy occurred between epoch 20 and epoch 50, resulting in overfitting because the training accuracy reached 100% while the validation accuracy decreased, as seen from the validation acc, which no longer increased after epoch 13. However, the validation accuracy only reached a maximum of 94.73% at epoch 13 and then decreased to 93.91%. It even drops to 93.04% by the end. This indicates that the model is very good at memorizing the training data but is unable to maintain generalization to the validation data.

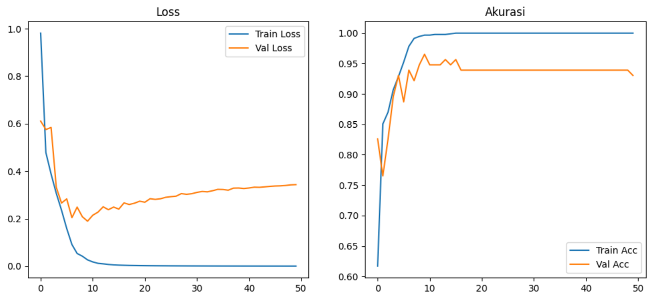

Figure 5 Accuracy and Loss Graph of Lenet-5 Architecture for Data Validation

Figure 6 shows two graphs illustrating the performance of the machine learning model during the training process over 50 epochs. The graph on the left, titled "Loss," displays Train Loss and Validation Loss. The Train Loss curve (blue line) shows a drastic and rapid decline at the beginning of training, approaching zero, indicating that the model is learning very quickly from the training data. However, the Validation Loss (orange line) shows a different pattern after the initial decrease; it begins to rise again gradually after around the 10th epoch, indicating that the model is starting to overfit—it is very good at learning from the training data but does not perform as well on the validation data.

The graph on the right side titled Accuracy displays the Train Accuracy and Validation Accuracy values during the model training process. The Train Accuracy value shown by the blue line experienced a very significant increase to nearly 100% and tended to stabilize after entering the 15th epoch. This indicates that the model was very well suited to the training data used. On the other hand, the Validation Accuracy, shown by the orange line, also experiences a sharp increase in the early stages of training, but then tends to stagnate around 94% and slightly decreases toward the end of the training process. Based on these results, it can be concluded that the model no longer improves its performance on the validation data despite continued training. Overall, the pattern in this graph indicates signs of overfitting in the model, so the application of the early stopping method is necessary to prevent excessive learning on the training data.

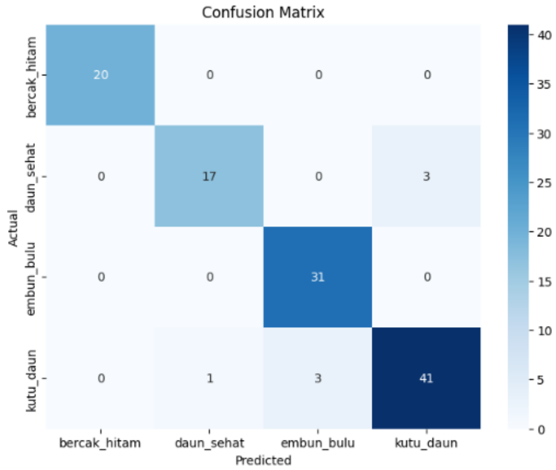

Figure 6 Confusion Matrix Results

Figure 7 shows the confusion matrix, which is a visual representation of the model's classification results for four leaf condition classes: black_spot, healthy_leaf, dew_fuzz, and leaf_insect. This matrix compares the actual labels (vertical axis/"Actual") with the labels predicted by the model (horizontal axis/"Predicted"). The diagonal numbers indicate the number of correct predictions for each class. For example, the model correctly classified 20 black_spot images, 17 healthy_leaf images, 31 dew_fuzz images, and 41 leaf_bug images.

However, there are still some prediction errors, although the number is not too large. For example, the model incorrectly predicted 3 images of healthy leaves as leaf insects, and 3 images of leaf insects as dew. This shows that although the model is quite accurate, there is still some similarity or confusion between certain classes, especially between healthy leaves and leaf insects, or leaf insects and dew. Overall, the model's performance appears to be quite good since most of the data is classified correctly (indicated by the dark blue color on the diagonal), but there is still room for improvement, such as by adding more training data or applying image augmentation techniques to make the model more robust.

4. Conclusion

The CNN method using Lenet-5 architecture in classifying diseases in watermelon plants was able to produce a model with excellent performance and obtained accuracy, recall, precision and F1-score results of 93%, 94%, 95% and 95% respectively.

Acknowledgements

The author is grateful to both parents who always support during the work, the supervisor who has guided during the work and also examiner. And to all parties who cannot be mentioned one by one.

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Biography

Muhammad Ilham Asshidiq is student from the University of Jember studying at the faculty of computer science, having attended SMA Negeri Tempeh in the 2018 graduating year

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