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Early Detection of Chili Leaf Diseases Using Convolutional Neural Network Based on Leaf Images

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ABSTRACT

Chili plants (*Capsicum sp.*) are one of the important horticultural commodities in Indonesia with high economic value. However, chili productivity is often reduced due to leaf diseases such as leaf curl, yellow leaf virus, and leaf spot disease. Manual disease identification conducted by farmers still has several limitations because it requires considerable time, experience, and is prone to observation errors. Therefore, an automatic system is needed to support early detection of chili leaf diseases quickly and accurately.

This study aims to develop a chili leaf disease classification system using a *Convolutional Neural Network* (CNN) based on leaf images. The dataset used in this study consists of chili leaf images categorized into four classes, namely healthy leaves, leaf curl, yellow leaf, and leaf spot. The research stages include dataset collection, image preprocessing, data augmentation, CNN model training, and model evaluation using a *confusion matrix* with performance metrics including accuracy, precision, recall, and F1-score.

The results show that the CNN model is capable of classifying chili leaf diseases with satisfactory performance. Based on the evaluation results, the model achieved a precision value of 0.75, a recall value of 0.53, and a *mean Average Precision* (mAP@0.5) value of 0.60. The developed system is also able to display classification results along with the confidence score of the prediction. Therefore, the CNN method has strong potential to be implemented as an image-based early detection system for chili leaf diseases to assist farmers in monitoring plant conditions more effectively.

INTRODUCTION

In Indonesia, chili (*Capsicum sp.*) plays an important role as a horticultural commodity due to its strong economic value and widespread consumption (Inaya et al., 2022). In addition to its economic value, chili offers nutritional benefits that support human health (Wali et al., 2025). Chili production is often disrupted by plant diseases that impact both the quantity and quality of harvests. Leaf curl disease is one of the major issues, causing abnormal leaf shape, color changes, and limited plant development, which contribute to yield loss (Suyanto et al., 2023). Other diseases, such as yellow leaf and leaf spot, also play a role in reducing chili production (Homepage et al., 2023).

The occurrence of leaf curl disease is often related to viral pathogens, including Yellow Leaf Curl Virus (YLCV), which are typically carried and transmitted by whiteflies (Gita Fakhira et al., n.d.). Failure to identify the disease at an early stage can cause ineffective management, rising production expenses, and reduced farmer income. Thus, early detection becomes essential to prevent wider transmission and limit potential losses (Rizki Ridhwan & Hudori, 2026).

Current disease identification practices largely rely on human observation, making them prone to bias and inefficiency. In contrast, recent technological developments have enabled the use of artificial intelligence, especially deep learning, as a more reliable method for automatic detection (Raup et al., 2022). In image classification tasks, deep learning approaches tend to outperform traditional methods. One of the most commonly applied models is the Convolutional Neural Network (CNN), which is capable of learning meaningful features from image data without manual extraction (Suhardin et al., 2021). Several earlier studies have shown that approaches based on CNN can successfully identify plant diseases (Rizki Ridhwan & Hudori, 2026).

Previous studies on chili leaf disease detection have reported promising classification performance using CNN-based models. Nevertheless, most studies rely on controlled datasets with limited environmental variability, which may lead to reduced performance when applied in real-world agricultural settings. Furthermore, several studies focus on binary classification or a small number of disease categories, limiting their usefulness for practical disease diagnosis. The lack of studies utilizing field-acquired images with diverse backgrounds and lighting conditions highlights a research gap in developing more robust and practical disease detection systems. Therefore, this study develops a CNN-based classification model using real-world chili leaf images to detect healthy leaves, leaf curl, yellow leaf, and leaf spot diseases. The contribution of this research lies in evaluating the capability of CNN models to classify multiple chili

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leaf diseases under realistic field conditions, thereby improving the applicability of deep learning techniques in precision agriculture.

LITERATURE REVIEW

Image Processing and Computer Vision in Agriculture

The use of computer vision and image processing has grown in agricultural applications, particularly for identifying plant diseases. Through these methods, visual data can be interpreted to extract important information from digital images by analyzing color, texture, and spatial patterns (Nyaga et al., 2020). In digital images, each pixel represents specific values related to color and spatial positioning (Dengan Operator & Dan, n.d.). Various methods such as segmentation, feature extraction, and classification are commonly applied to interpret image data effectively (Kulkarni et al., 2021).

Computer vision technology allows systems to process and understand visual data similarly to how humans perceive it, and it has been extensively utilized in agriculture for tasks such as crop observation and disease recognition (Hanum & Artikel, 2024). Image-based systems have advantages over traditional methods, including faster analysis, improved consistency, and the ability to scale efficiently.

Machine Learning and Deep Learning Approaches

Machine learning refers to an approach in artificial intelligence where systems are trained to recognize patterns from data and perform predictions independently, without relying on predefined rules (Diana et al., 2023). In many cases, traditional machine learning models use manually defined features, which can limit their ability to handle complex and dynamic environments effectively.

Deep learning approaches leverage multi-layer neural architectures that can learn meaningful representations directly from raw data without manual feature design (Raup et al., 2022). This technique has substantially improved image classification performance, as it is capable of representing complex patterns more effectively compared to traditional methods.

Convolutional Neural Network (CNN)

Among deep learning models, Convolutional Neural Networks (CNN) are extensively utilized for processing and analyzing visual information (Suhardin et al., 2021). CNN models process visual data by applying convolution operations to learn spatial patterns and features. The architecture usually comprises several components, including convolutional layers, activation functions, pooling stages, and fully connected layers for classification (Gunawan et al., 2021).

With this structure, the model is able to learn features in multiple levels, from simple visual elements such as edges and textures to more complex forms like shapes and objects. This hierarchical learning ability enables CNN to perform effectively in plant disease classification tasks.

Findings from recent research highlight that CNN-based approaches maintain high effectiveness in image classification tasks, including their use in agricultural domains (Mienye & Swart, 2024), (Minaee et al., 2022). More advanced architectures, including EfficientNet, are designed to achieve better efficiency while preserving high levels of accuracy (Muthulakshmi & Jayalakshmi, 2025). Moreover, transfer learning approaches are frequently applied to enhance model effectiveness, particularly when the amount of training data is limited (Iman et al., 2023). The use of data augmentation helps models generalize better and prevents overfitting during the training process (Zeng & Zeng, 2024). In addition, classification performance is often assessed using metrics derived from the confusion matrix, which provide a comprehensive evaluation (Riehl et al., 2023).

Dataset and Data Augmentation

Deep learning model performance largely depends on the availability of sufficient data as well as the quality of the dataset used (G Hermawan, 2024). For better generalization, the dataset should capture a wide range of conditions, such as changes in lighting, orientation, and surrounding environment.

Dataset diversity can be improved through data augmentation, which also helps strengthen model robustness. Typical transformations applied include rotation, flipping, scaling, and translation.

Evaluation Metrics for Classification Models

To evaluate model performance, several metrics based on the confusion matrix are used, including accuracy, precision, recall, and F1-score (Fergus & Chalmers, 2022). The use of these metrics allows for a detailed assessment of classification performance, particularly in cases of imbalanced datasets. Furthermore, CNN-based approaches are extensively utilized in image classification tasks and have proven to be highly accurate in identifying patterns (Ucan et al., 2022). Recent findings suggest that deep learning approaches can capture complex patterns from large-scale data and significantly enhance classification performance (Khan et al., 2023). Moreover, the use of data augmentation helps create more diverse datasets and supports better generalization in deep learning models (Fahd & Miah, 2023).

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Previous Research and Research Gap

Applying data augmentation techniques allows the dataset to become more varied and helps deep learning models perform better on unseen data (Rizki Ridhwan & Hudori, 2026). A number of existing studies are based on controlled environments, making their performance less reliable in real-world applications. Furthermore, several of these studies utilize limited data or concentrate on only a few disease categories.

These limitations highlight the need for studies that rely on real-world datasets and produce models that are both reliable and applicable in practical settings. To address this, the present study employs a CNN-based approach for detecting chili leaf diseases using data obtained directly from field conditions.

METHOD

Research Design

This study employs a quantitative framework based on supervised learning with a Convolutional Neural Network (CNN) for image classification tasks. The main objective is to create an automated system that can recognize multiple chili leaf diseases using digital leaf images. The research workflow is carried out through several stages, including data acquisition, preprocessing, model construction, training, and performance evaluation.

System Workflow

The proposed system consists of two main processes, namely the training phase and the implementation phase. In the training phase, a dataset of chili leaf images is used as input to train the Convolutional Neural Network (CNN) model. The dataset is processed through the CNN architecture, allowing the model to learn important features and patterns from the images. This process results in a trained CNN model that is capable of performing classification tasks.

In the implementation phase, the system begins by receiving input data in the form of images or video frames. The input data then undergoes a preprocessing stage, which includes normalization and resizing to ensure consistent input quality. After preprocessing, the data is passed into the trained CNN model for feature extraction and classification. The model analyzes the input and produces the final prediction result in real-time. The output represents the classification of chili leaf conditions, such as healthy, leaf curl, yellow leaf, or leaf spot.

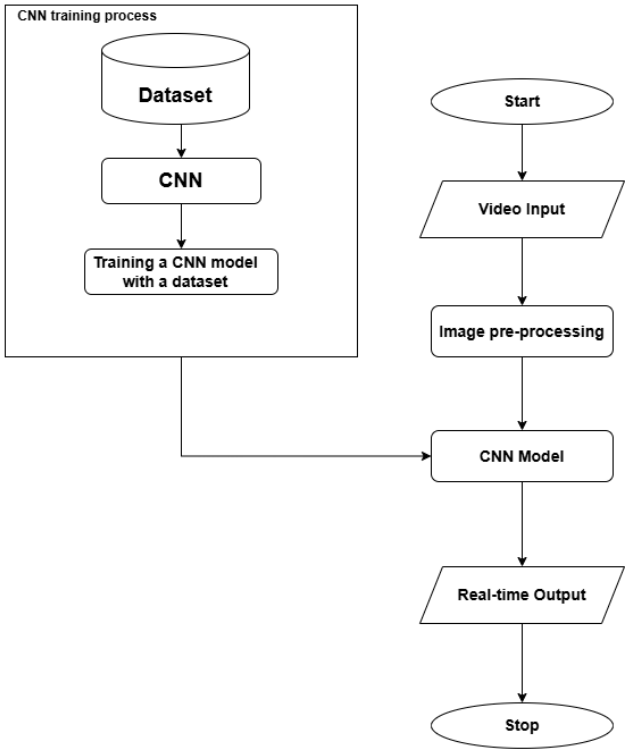


Figure 1. System Workflow of Proposed Model

Data Collection

The dataset used in this research consists of chili leaf images sourced directly from farmers in field environments. These images are classified into four categories, namely healthy, leaf curl, yellow leaf, and leaf spot. The data collection process was conducted under real-world conditions to include variations in lighting, background, and leaf orientation. To ensure reliable classification, each image was carefully labeled manually. Representative samples of the dataset are illustrated in Figure 2.

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Figure 2. Sample images of chili leaf dataset (healthy, leaf curl, yellow leaf, and leaf spot)

To support model development, the dataset is partitioned into three groups: 70% for training, 20% for validation, and 10% for testing. This split enables effective learning, hyperparameter adjustment, and unbiased performance assessment.

Data Preprocessing

Before training the model, preprocessing is applied to standardize the input data and improve overall model performance. This process involves resizing all images to a fixed dimension to ensure consistency and reduce computational complexity. In addition, pixel values are normalized to a range of 0–1 to accelerate the training process and enhance convergence. Furthermore, data cleaning is performed by removing blurry, duplicated, or irrelevant images to maintain the overall quality of the dataset.

Data Augmentation

To increase dataset diversity and reduce the risk of overfitting, data augmentation techniques are applied by generating variations from existing images. These transformations include rotation, horizontal flipping, and vertical flipping, which allow the model to learn more robust and invariant features. As a result, the model is better able to generalize and perform effectively under different environmental conditions.

CNN Model Architecture

The model used in this study is a Convolutional Neural Network (CNN) designed for multi-class image classification. The architecture processes input images through several layers to extract and learn important visual features. Initially, convolution operations are applied to capture relevant patterns from the images, followed by activation functions such as ReLU to introduce non-linearity and enable the model to learn more complex relationships. The feature maps are then reduced in size through pooling operations, which help minimize computational complexity and reduce overfitting. After that, the extracted features are processed through fully connected layers to perform classification. Finally, the output layer generates prediction results in the form of class probabilities, including healthy, leaf curl, yellow leaf, and leaf spot. The model is implemented using the TensorFlow/Keras framework to support efficient training and deployment.

Model Training

The training process is carried out by feeding the training dataset into the CNN model while adjusting its parameters to minimize classification errors. In this study, the training utilizes the Adam optimizer and categorical crossentropy as the loss function, with the number of epochs determined based on convergence and the batch size adjusted according to system capability. During training, the model performs forward propagation to generate predictions and backpropagation to iteratively update the weights. In addition, validation data is used to monitor model performance and help prevent overfitting throughout the training process.

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Model Evaluation

After the training phase, the model is evaluated using the testing dataset to assess its performance on unseen data. The evaluation is carried out using metrics derived from the confusion matrix, including accuracy, precision, recall, and F1-score. Accuracy reflects the overall correctness of predictions, while precision measures how accurate the positive predictions are. Recall indicates the model's ability to correctly identify positive cases, and F1-score provides a balanced measure by combining precision and recall. Together, these metrics offer a comprehensive evaluation of the model's classification performance.

RESULT

The training and validation performance of the CNN model is illustrated in Fig. 3. The training results show that the loss values decrease consistently as the number of epochs increases. In addition, the precision improves and reaches approximately 0.75, while the recall stabilizes around 0.53. The mAP@0.5 also increases and reaches approximately 0.60. These results indicate that the model successfully learns relevant features from the dataset and improves its performance over time.

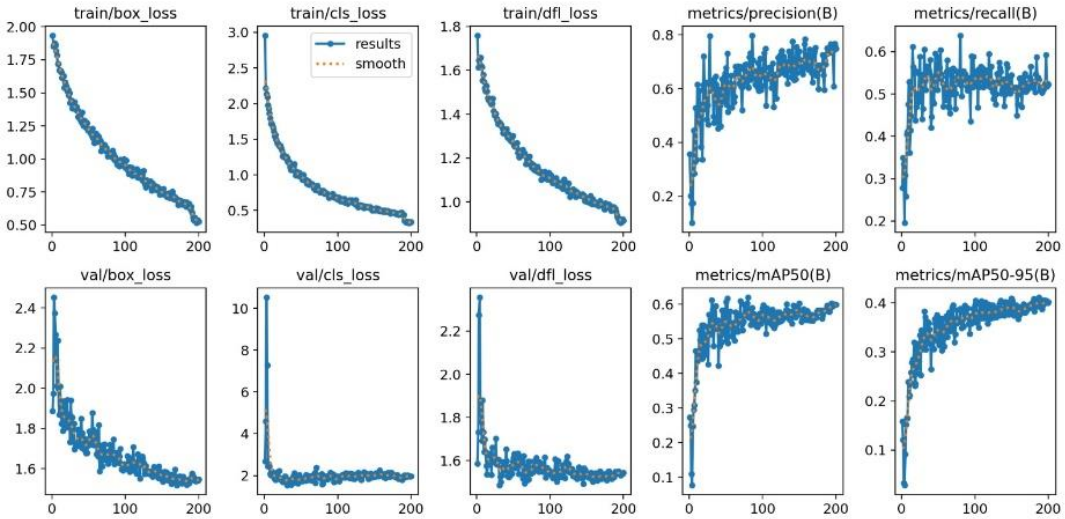


Figure 3. Training and validation performance of the CNN model

CNN Model Performance Evaluation

Table 1. Model Performance Evaluation

Class	Precision	Recall	mAP@0.5
Leaf Spot	0.86	0.86	0.86
Leaf Curl	0.55	0.55	0.55
Yellow Leaf	0.38	0.38	0.38
Healthy	0.71	0.71	0.71

Based on Table 1, the CNN model achieved the best performance in classifying the Leaf Spot class, with precision, recall, and mAP@0.5 values of 0.86. The Healthy class also showed good classification capability with a score of 0.71. Meanwhile, the Leaf Curl class obtained moderate performance with a value of 0.55. The Yellow Leaf class produced the lowest result, with a score of 0.38, indicating that the model still experienced difficulty distinguishing this class from other disease categories due to similarities in color and texture characteristics.

To further analyze the classification performance and identify patterns of misclassification among classes, the normalized confusion matrix is presented in Figure 4.

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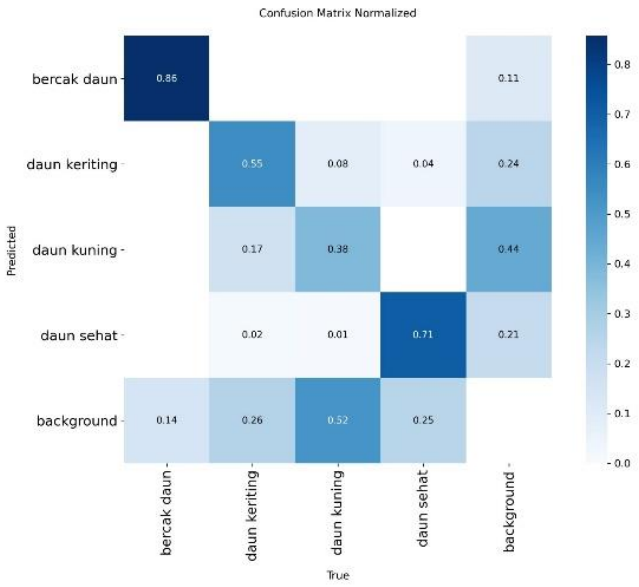


Figure 4. Normalized Confusion Matrix of CNN Model

Confusion Matrix Analysis

The confusion matrix results indicate that the model performs very well in classifying the leaf spot class, achieving the highest accuracy of approximately 0.86. The healthy leaf class also shows good performance with an accuracy of around 0.71. Meanwhile, the leaf curl class demonstrates moderate performance with an accuracy of approximately 0.55. The yellow leaf class shows relatively low performance, with an accuracy of around 0.38, indicating difficulty in distinguishing this class from others. Some misclassification occurs between the leaf curl and yellow leaf classes, suggesting that these classes share similar visual characteristics such as color and texture patterns.

DISCUSSION

The findings of this study indicate that the proposed Convolutional Neural Network (CNN) model is capable of performing multi-class classification of chili leaf diseases with satisfactory results. Based on the evaluation, the model achieves a precision of 0.75, recall of 0.53, and mAP@0.5 of 0.60, suggesting that it can correctly classify a considerable portion of the dataset, although improvements are still needed, particularly in recall performance.

During training, the model shows stable learning behavior, reflected by the continuous reduction in loss values and gradual improvement in evaluation metrics such as precision and mAP. This trend indicates that the model is able to capture relevant patterns from the dataset effectively without experiencing significant overfitting. In addition, the application of preprocessing and data augmentation contributes to improving the model's ability to generalize under different conditions.

The confusion matrix analysis further reveals that the model performs best in identifying the leaf spot class, achieving the highest level of accuracy. This performance is likely influenced by the distinctive visual characteristics of leaf spot, such as clear and consistent patterns that are easier for the model to recognize. The healthy class also demonstrates strong performance, indicating that the model can effectively differentiate between normal and diseased leaves.

On the other hand, the classification performance for the leaf curl and yellow leaf classes is relatively lower. The leaf curl class shows moderate accuracy, while the yellow leaf class has the lowest performance among all categories. This limitation can be explained by the similarity in visual features between these classes, including overlapping color patterns and subtle texture differences. As a result, the model encounters difficulties in distinguishing between them, leading to several misclassification cases.

The results obtained in this study can be compared with previous CNN-based plant disease classification studies. Rizki Ridhwan and Hudori (2026) reported promising performance in detecting yellow leaf virus disease in chili plants using a CNN-based approach. Similarly, Suhardin et al. (2021) demonstrated that CNN models can achieve high classification performance when trained using datasets with relatively uniform image characteristics and controlled environmental conditions. Compared with these studies, the performance achieved in this research is relatively lower. However, this difference can be attributed to the use of images collected directly from field conditions, which contain variations in lighting, background complexity, leaf orientation, and disease symptoms. These factors increase the difficulty of classification while providing a more realistic evaluation scenario. Therefore, although the performance

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metrics are lower than those reported in some previous studies, the proposed model demonstrates stronger applicability for practical deployment in real agricultural environments.

Overall, this study demonstrates that CNN-based approaches have strong potential for supporting early detection of chili leaf diseases. However, further refinement is necessary to improve accuracy and ensure better performance under real-world conditions.

CONCLUSION

This study presents the development of a CNN-based system for early detection of chili leaf diseases, with evaluation results showing a precision of 0.75, recall of 0.53, and mAP@0.5 of 0.60. These findings suggest that the model is able to perform classification tasks with acceptable performance. The implementation of CNN highlights its potential as a reliable approach for automated disease detection in agricultural applications.

Despite these results, several limitations remain, particularly in distinguishing classes with similar visual characteristics. Therefore, further improvements are necessary, including expanding the dataset and refining the model to enhance overall accuracy and performance.

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