KHATULISTIWA SMART : JOURNAL OF ARTIFICIAL INTELLIGENCE
e-ISSN : 3089-9710
p-ISSN : XXXX-XXXX

Khatulistiwa Smart : Journal of Artificial Intelligence
Vol. 2 No. 1 (2025) : 117 – 125
Available online at : https://journal.literasikhatulistiwa.org/index.php/smart

Classification Of Rice Leaf Disease Images Using Convolutional Neural Network (CNN) Algorithm

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Submitted: 28 Nov 2025 Revision: 14 Dec 2025 Accepted: 20 Dec 2025 Published: 31 Dec 2025

Abstract Rice (Oryza sativa) is a major commodity that plays an important role in Indonesia's food security. However, rice productivity often decreases due to leaf diseases, such as neck blast, leaf blight, and rice leafhopper. Manual disease identification still has limitations, as it requires a long time, depends on farmers' expertise, and may lead to misclassification. To address these issues, this study develops a rice leaf disease classification system using a Convolutional Neural Network (CNN) algorithm. The dataset used was from Kaggle, consisting of a total of 3,631 images divided into three disease classes. The data was split with a ratio of 80% for training, 10% for validation, and 10% for testing. The pre-processing steps included resizing, augmentation, and image normalization. The CNN architecture was custom-built with several convolutional, pooling, flatten, and dense layers. The training results showed that the model could achieve a training accuracy of 97.80% and a validation accuracy of 97.42%. The model was then implemented into a web application based on Flask, allowing users to upload images of rice leaves and obtain classification results quickly, accurately, and in real-time. Based on the research results, CNN has been proven effective in classifying rice leaf diseases with a high level of accuracy. This system is expected to help farmers detect diseases early, reduce the risk of crop failure, and support the implementation of smart farming in Indonesia.

Keywords ***CNN, image classification, rice leaves, deep learning, Flask.***

1. INTRODUCTION

Rice (Oryza sativa) is a major agricultural commodity in Indonesia and plays an important role in maintaining national food security. As an agrarian country, most of the Indonesian population depends on rice as a primary source of consumption, making the improvement of its productivity and quality a key priority[1]. However, rice productivity is often hindered by leaf diseases such as neck blast, leaf blight, and leafhopper infestations, which can reduce crop yields, increase production costs, and cause economic losses. Manual disease identification has limitations because it is time-consuming, relies on farmers' expertise, and carries a risk of errors due to the similarity of symptoms among diseases.

Traditional identification methods through visual observation are also considered less efficient and have low accuracy, especially on a large scale. This situation necessitates the application of modern technology that is faster, more accurate, and reliable[2]. The development of artificial intelligence, particularly in digital image processing, has introduced the Convolutional Neural Network (CNN) method, which is designed to automatically recognize visual patterns. CNN has been proven capable of extracting image features, such as color, texture, and shape, enabling the classification of rice leaf diseases with high accuracy.

By utilizing CNN, the process of detecting rice leaf diseases can be carried out in real-time, reducing dependence on experts, and supporting the implementation of smart farming [3]. This system not only helps farmers perform early detection and precise disease control, but also has the potential to improve pesticide use efficiency, reduce production costs, and prevent crop yield losses. Therefore, this study aims to develop an accurate, efficient, and easily implementable CNN-based rice leaf disease image classification system through a web application, making it directly accessible to farmers and agricultural extension workers as a practical solution in the field [4].

Previous research has developed a corn plant disease classification system using the CNN method. The dataset consisted of 2,000 images with two types of diseases, namely leaf blight and leaf rust[5]. The CNN model built was trained using images sized 150×150 pixels over 100 epochs. The research results showed an accuracy of 97.5% on the training data, 100% on the validation data, and 94% on the testing data with new data,[6] and accuracy above 98% on images of other plant diseases after the resizing and normalization process. In addition to CNN, it was developed as a lightweight and efficient model, making it suitable for use in mobile- or web-based applications. Various studies have shown that CNN can provide classification results equivalent to or better than conventional CNN with fewer parameters and lower computation time[7].

This study proposes the development of a web-based rice leaf disease classification system using the Flask framework, which implements CNN. The dataset used includes three classes (neck blast, leaf blight, and rice hispa) and undergoes preprocessing steps such as resizing, limited augmentation, and normalization. The trained model is then integrated into a web application so that users can upload images of rice leaves and obtain classification results directly. This approach is expected to be an innovative solution for detecting rice leaf diseases quickly and accurately, minimizing manual identification errors, and supporting more adaptive modern agriculture. This study also contributes to the development of lightweight, AI-based agricultural systems that are accessible via web and mobile platforms.

2. RESEARCH METHODS

2.1. Research Framework

This research framework is designed to illustrate the workflow systematically. The model used is Convolutional Neural Network (CNN). The first stage begins with data collection, data preprocessing, implementation (CNN), evaluation, and Flask web implementation.

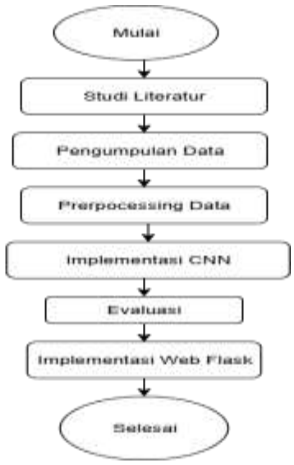


Figure 1. Research Framework

2.2. Research Method

This study uses a mixed methods approach by combining quantitative and qualitative analysis in evaluating the performance of Convolutional Neural Networks (CNNs) for classifying rice leaf disease images. Quantitatively, the study focuses on measuring the accuracy and efficiency of the CNN model, while qualitatively it examines the context of field application, including farmers' perceptions and needs. The integration of these two approaches is expected to produce solutions that are both technically accurate and relevant to agricultural practices.

2.3. Development Method

This research designs a rice leaf disease classification system using CNN in the topic of Smart Computing. The development process consists of three main stages:

a. User Interface (UI) Design – Designing a simple and user-friendly Flask-based web interface for uploading images of rice leaves and displaying the classification results.
b. Coding – Integrating the trained MobileNet model into the Flask system, including image pre-processing (resizing, normalization, augmentation) and classification functions into three categories: neck blast, leaf blight, and rice hispa.
c. Testing – Testing the system functions and user interface using various images of rice leaves to ensure classification accuracy and ease of use.

2.4 Testing Method

The testing method of this study aims to evaluate the performance of the CNN model with an architecture in classifying rice leaf diseases[8]. The evaluation is conducted using several key metrics:

1. Accuracy – Measures the percentage of correct predictions out of all predictions using the formula:

$$Accuracy = \frac{(TP) + (TN)}{TP + TN + FP + FN}$$

2. Precision – Evaluating the accuracy of the model in classifying rice leaves with neck blast disease, leaf blight, and brown planthopper as positive cases.

$$Presisi = \frac{TP}{TP + FP}$$

3. Recall (Sensitivity) – Measures the model's ability to identify all truly positive data.

$$Recall = \frac{TP}{TP + FN}$$

4. F1 Score – A combination of precision and recall to show the balance of model performance.

$$F1\ score = 2\frac{Precision\ x\ Recall}{Preccision\ +\ Recall}$$

5. Confusion Matrix – Shows the number of correct and incorrect predictions in each class to analyze the model's error patterns

3. Result and Discussion

3.1. Data Collection

This study uses a dataset obtained from Kaggle, consisting of 3,631 images of diseased rice leaves. The dataset includes three classes, namely neck blast disease (1,000 images), leaf blight (1,332 images), and rice hispa (1,299 images).

TABLE 1. DETAILS OF THE RICE LEAF DISEASE IMAGE DATASET

Sample	Amount of Data	Source Data
Neck Blast	1.000	Kaggle
Leaf Blister	1.332	
Rice Hispa	1.299	

Figure 2. Shows details of rice leaf images from 3 classes, namely neck blast, leaf blight, and brown planthopper infestation.

(a)

(b)

(c)

Figure 2. Detail of Rice Leaf Image

In Figure 2 (a), it shows rice leaves affected by neck blast disease, indicated by symptoms in the form of lesions or grayish-brown spots that appear on the neck of the panicle or the stem near the panicle. This infection causes the neck tissue to weaken, causing the panicle to collapse or break before fully maturing. Figure 2 (b) is an image of rice leaves infected with leaf blister disease, marked by grayish or whitish spots surrounded by brown edges.

These spots usually spread irregularly on the leaf surface, causing the leaf tissue to dry, curl, or even die if the infection is severe. Figure 2 (c) shows an image of a rice leaf with brown planthopper disease, where the leaf exhibits damage in the form of elongated white lines parallel to the leaf veins due to insect bites on the leaf surface. Severe attacks can cause the leaves to dry, appear scorched, and interfere with the plant's photosynthesis process.

3.2. Data Preprocessing

The data used consists of images of rice leaves infected with diseases, consisting of three classes: Neck Blast, Leaf Blight, and Rice Hispa. The total dataset amounts to 3,631 images obtained from an open source (Kaggle). This dataset is divided into training data (80%), validation data (10%), and testing data (10%) to support the model training and evaluation process.

TABLE II. DATASET DISTRIBUTION

Dataset	Training	Testing	Validasi
Neck Blight	800	100	100
Leaf Blister	1065	134	133
Rice Hispa	1039	130	130
Total	2904	364	363

Table 2 shows the data distribution, where the training data consists of 2,904 image data, the testing data consists of 364 image data, and the validation data consists of 363 image data.

In order for the computation process to be performed faster without reducing the accuracy of the system, a 128x128 pixel resizing process is applied to each image data. Data augmentation is also used during the training phase so that there are many variations in the training data. Data augmentation is a process in image data processing by modifying images in such a way that it can be understood that the altered image is a different image. The presence of data augmentation makes the model better at generalizing. Some augmentation variations used are zoom, rotation, horizontal_flip, width_shift, and height_shift. Normalization of data is done to standardize the scale of pixel values in images before being used in the model training process. Generally, digital images have pixel values ranging from 0 to 255.

3.3. Model Training

After all the libraries have been successfully imported and the images of rice leaves have been processed through augmentation and normalization stages, the next step is to build the image classification model architecture using a Convolutional Neural Network (CNN) approach from scratch (custom CNN). This model is built manually without using transfer learning so that the architecture is simpler and can be specifically tailored to the characteristics of the rice leaf dataset.

Layer (type)	Output Shape	Param #
conv2d_6 (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d_6 (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_7 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_7 (MaxPooling2D)	(None, 30, 30, 64)	0
flatten_3 (Flatten)	(None, 57600)	0
dense_5 (Dense)	(None, 128)	7,372,928
dense_6 (Dense)	(None, 3)	387

Total params: 7,392,707 (28.20 MB)
Trainable params: 7,392,707 (28.20 MB)
Non-trainable params: 0 (0.00 B)

Architectural image

During the training process, several experiments with the number of epochs were conducted to determine the optimal amount of training for the model's performance. The experiments were carried out three times with different epoch variations, namely

5, 10, and 20 epochs. The model's accuracy results on the evaluation data for each experiment can be summarized in the following table.

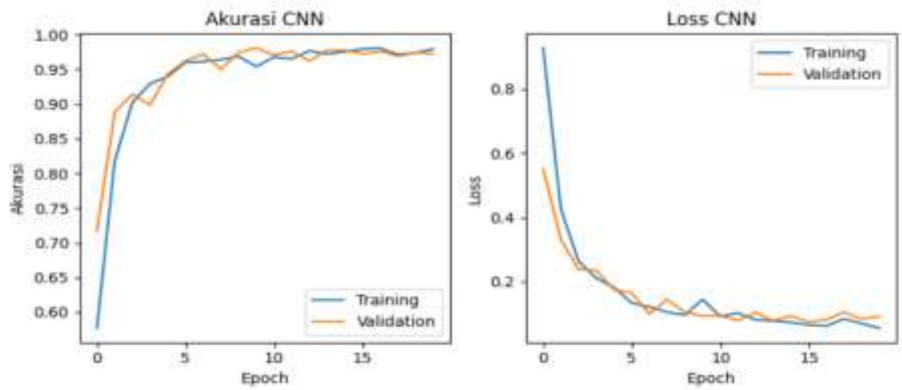
Tabel Hasil Epoch

Epoch	Accuracy Validation	Training Loss	Accuracy Testing	Accuracy Loss
5	0.8833	0.1275	0.9592	0.1499
10	0.9333	0.753	0.9738	0.1414
20	0.9833	0.0696	0.9780	0.0792

Based on these results, an epoch count of 10 was chosen as the best configuration. This is because at 10 epochs, the model shows a balance between training and evaluation performance, namely:

a. Training accuracy of 0.9738
b. Evaluation accuracy of 0.9780

The relatively small difference between the training and evaluation results over 10 epochs indicates that the model has learned optimally without experiencing overfitting. The graphs for model accuracy and model loss can be seen in the image



Model Accuracy and Loss Chart

3.4. Model Evaluation

After the model is saved, the next step is to evaluate the model's performance using test data. The evaluation process begins by loading the trained model that has been saved in .keras format, then preparing the test data using ImageDataGenerator with a preprocessing function. This evaluation aims to measure the model's accuracy when given new data that it has never seen before, to determine how well the model can generalize its classification results.

Confusion Matrix Image

3.5. Flask Web Implementation

The web implementation is carried out using the Flask framework, where the application functions to classify diseases in rice plants based on leaf images by utilizing a previously trained and saved model.

a) Home Page

Image Home Page

On the homepage, users are provided with an image upload feature via the "Choose File" button, which allows them to select leaf images directly from their device to be sent to the system for prediction, and the classification results will be displayed on the next page.

b) Classification Results Page

Image Classification Results Page

4. CONCLUSION

This study successfully developed a web-based rice leaf disease classification system using CNN and Flask. The model trained on 364 images achieved an accuracy of 97.80% in recognizing three rice leaf conditions (neck blast, leaf blight, and brown planthopper). The system has proven to be practical and efficient, and has the potential to be developed into a mobile application to support smart farming.

ACKNOWLEDGEMENTS (10 PT)

The author would like to express their deepest gratitude to all parties who have provided support in the preparation and completion of this research. Special thanks are extended to Mr. Syaiful M.Kom and Mrs. Amalia Herlina S.IIP., M.MT for their guidance, direction, and valuable input that have been instrumental in providing facilities, data, and research funding.

Thanks are also due to family, friends, and all parties who cannot be mentioned individually for their prayers and moral support throughout this research and the writing of this journal.

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