INTERNATIONAL JOURNAL OF APPLIED ARTIFICIAL INTELLIGENCE AND ROBOTICS
E-ISSN: 3124-1212, DOI: 10.67745/ijaic.v2i2.24
Vol. 2 No. 2 2026 pp. 33-41

Classification of Cayenne Pepper Leaf Nutritional Deficiencies Using Convolutional Neural Networks

Alya Shifa[1], Hendrawaty[2*], Rahmad Hidayat[3], Rani Irma Handayani[4]

[1,2,3] Information Technology and Computer Departement, Politeknik Negeri Lhokseumawe Lhokseumawe, Aceh, Indonesia
[3] Program Studi Sistem Informasi, Jurusan Teknologi Informasi, Universitas Nusa Mandiri, Jakarta, Indonesia

*Corresponding Author: hendrawaty@pnl.ac.id

Article info: Received 01/09/2026, Revised 07/09/2026, Accepted 17/10/2026

This is an open access article under the CC BY-SA license.

Abstract

Cayenne pepper (Capsicum frutescens L.) is one of the horticultural commodities with high economic value in Indonesia. Pest attacks and nutrient deficiencies can reduce crop quality and yield. Identification of these conditions is commonly conducted through visual observation, which can be subjective and time-consuming. This study aims to classify nutrient deficiency conditions in cayenne pepper leaves using the Convolutional Neural Network (CNN) method. The dataset consisted of primary data collected directly from the field and secondary data obtained from the Chili Plant Leaf Disease and Growth Stage Dataset from Bangladesh. The research stages included image preprocessing, data augmentation, CNN model training, and model evaluation. The CNN model was developed using three convolutional layers to classify cayenne pepper leaves into healthy and nutrient deficiency classes. The experimental results showed that the proposed model achieved high classification performance, with an accuracy of 98% on the primary dataset and 97% on the secondary dataset. These results indicate that the CNN method can effectively classify nutrient deficiency conditions in cayenne pepper leaves and maintain consistent performance across datasets.

Keywords: Cayenne Pepper, Leaves, Nutrient Deficiency, Classification, Convolutional Neural Network (CNN)

1. Introduction

Cayenne pepper (Capsicum frutescens L.) or chili is one of the strategic horticultural commodities in Indonesia, with high economic value and an important role in food stability and farmers' income. According to the National Food Agency, national chili production remains sufficient to meet domestic consumption needs [1]. In December 2025, the production of large chili was estimated at 127.8 thousand tons, while cayenne pepper production reached approximately 108.6 thousand tons, with national consumption estimated at around 76–78 thousand tons per month [2]. Chili production centers are mainly concentrated in Java and Sumatra, which serve as major regions supporting the national chili supply. In addition to its role as a food commodity, chili also contributes to food price inflation, making the sustainability of its production an important concern in the agricultural sector [3].

The productivity of cayenne pepper plants is influenced by their physiological condition, particularly leaf health, which plays an essential role in photosynthesis. Physiological disturbances caused by nutrient deficiencies or pathogen attacks can inhibit plant growth, reduce photosynthetic activity, and produce symptoms such as wilting, chlorosis, and leaf spots, which may subsequently reduce crop productivity and quality [4]. Plants require essential nutrients, including nitrogen (N), phosphorus (P), and potassium (K), to support vegetative growth and crop development. Deficiencies in these nutrients can cause changes in leaf color and shape, inhibit plant growth, reduce fruit production, and even accelerate plant death [5]. Identifying nutrient deficiencies in cayenne pepper plants remains challenging because their symptoms may resemble those caused by diseases and other plant disorders. Nutrient deficiencies generally exhibit relatively symmetrical symptoms on leaves of similar physiological age, whereas disease or pest attacks tend to appear more randomly. However, these characteristics can still be difficult

to distinguish through visual observation, particularly during the early stages of plant growth, potentially resulting in misidentification of leaf conditions [6]. Observations conducted in cayenne pepper fields in Ujong Pacu Village showed that farmers still experienced difficulties in distinguishing diseased leaves from leaves affected by nutrient deficiencies due to the similarity of their symptoms. Identification is still commonly performed manually and relies heavily on farmers' experience, which may lead to misdiagnosis, inappropriate treatment, increased production costs, and reduced crop yields [7].

The development of computer vision and deep learning technologies provides an opportunity to assist in the automatic identification of plant conditions. One of the widely used methods for image classification is the Convolutional Neural Network (CNN), which is capable of automatically extracting visual features from images and using them for classification [8]. Several studies have demonstrated the application of machine learning and CNN-based approaches for plant condition identification. Kaur et al. [9] achieved an accuracy of 85–89% using CNN-SVM to detect Cercospora disease on chili leaves. Arie et al. [10] applied the SVM method to identify nutrient deficiencies and achieved an accuracy of 84.4%. Adi et al. [11] developed a CNN-based system with an accuracy above 85%, while a CNN approach using UAV imagery achieved an accuracy of 94.6% [12]. These findings indicate that image-based approaches have considerable potential for assisting plant condition identification. However, the application of CNN specifically to distinguish healthy cayenne pepper leaves from leaves affected by nutrient deficiencies still requires further investigation, particularly by incorporating primary field data and secondary data as a comparative basis.

Therefore, this study aims to develop a CNN model to classify cayenne pepper leaves into two classes: healthy leaves and leaves affected by nutrient deficiencies. The model is evaluated using a primary dataset collected directly from the field and a secondary dataset obtained from a public dataset to assess its performance across different data sources.

2. Methods

2.1 Research Design and Stages

The research stages consisted of CNN model training and testing. The training stage began with image datasets undergoing preprocessing, followed by data augmentation to increase image variation. The preprocessed and augmented images were then processed using CNN for feature extraction and classification model development. The trained model was used to classify chili leaf conditions into two classes, namely healthy and nutritionally deficient leaves. The testing stage was conducted using an image dataset that underwent preprocessing. The image features were then extracted using CNN and classified using the trained model. The workflow of the CNN model training and testing stages is presented in Figure 1.

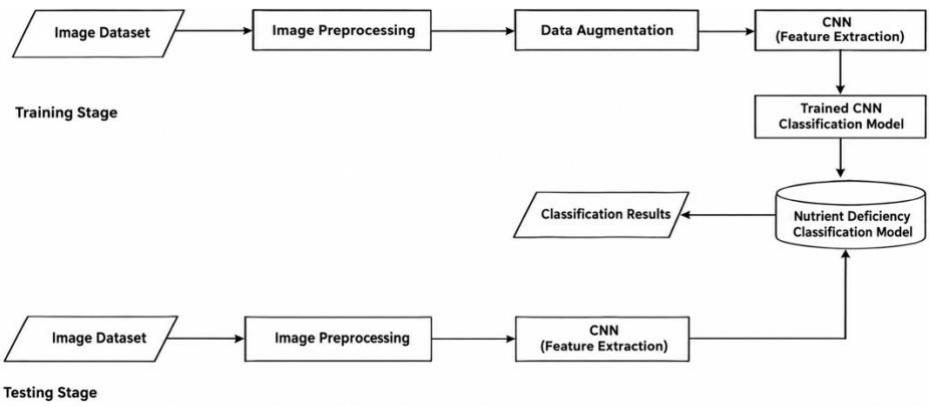


Figure 1. Flowchart of the Cayenne Pepper Leaf Nutritional Deficiency Classification System

2.2 Dataset Collection and Splitting

The dataset used in this study consisted of primary and secondary datasets. The primary dataset was collected directly from chili plantations in Ujong Pacu Village, while the secondary dataset was obtained from the Chili Plant Leaf Diseases and Growth Stage Dataset from Bangladesh. Both datasets consisted of two classification classes, namely Healthy and Nutrition Deficiency. Each dataset was processed and evaluated separately to assess the CNN model's ability to classify chili leaves under different data sources.

a. Primary Dataset

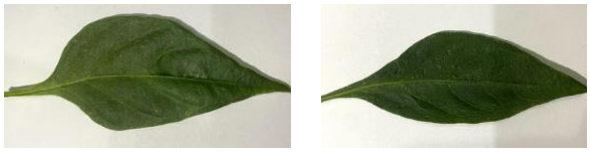
The primary dataset consisted of 458 chili leaf images collected directly from chili plantations in Ujong Pacu Village. Image acquisition was performed using the main camera of an iPhone 11 with a resolution of 4032 × 3024 pixels (12 MP). The distance between the camera and the chili leaves was approximately 15–25 cm to obtain clear images while maintaining consistency during data collection. Previous studies have used mobile phone cameras with

imaging distances of approximately 15–20 cm and 15–30 cm for plant image acquisition [13]. The primary dataset contained 203 images of healthy leaves and 255 images showing nutrient deficiency symptoms. The dataset was divided into training, validation, and testing data using an 80:10:10 ratio. The distribution of the primary dataset is presented in Table 1.

Table 1. Composition of the Dataset Used in the Study

Class	Total Images	Training	Validation	Testing
Healthy	203	162	20	21
Nutrition Deficiency	255	204	25	26
Total	458	366	45	47

Examples of images from the primary dataset are shown in Figure 2.



a. Healthy



b. Nutritional Deficiency

Figure 2. Examples of Primary Dataset Images

b. Secondary Dataset

The secondary dataset was obtained from the Chili Plant Leaf Diseases and Growth Stage Dataset from Bangladesh developed by Nirob et al. (2025) and available through Mendeley Data [14]. The dataset contained 902 chili leaf images consisting of 458 Healthy images and 444 Nutrition Deficiency images. The secondary dataset was used to evaluate the consistency of the CNN model when applied to data obtained from a different source. Similar to the primary dataset, the secondary dataset was divided into training, validation, and testing data using an 80:10:10 ratio. The distribution of the secondary dataset is presented in Table 2.

Table 2. Distribution of the Secondary Dataset

Class	Total Images	Training	Validation	Testing
Healthy	458	366	45	47
Nutrition Deficiency	444	355	44	45
Total	902	721	89	92

Examples of images from the secondary dataset are shown in Figure 3.



a. Healthy



b. Nutritional Deficiency

Figure 3. Examples of Secondary Dataset Images

2.3 Image Preprocessing and Augmentation

Preprocessing was performed to ensure that the images had an appropriate size and pixel scale for model input. Each image was resized to 224 × 224 pixels [15]. In this study, normalization was performed by dividing the value of each pixel by 255, changing the pixel value range from 0–255 to 0–1. The purpose of normalization was to standardize the input values so that the model training process became more stable and the model could learn image patterns more effectively [16]. Augmentation was applied *on-the-fly* to the training data. The techniques included random rotation with a maximum range of 15 degrees, *horizontal flipping*, *vertical flipping*, and brightness adjustment within a range of 80%–120%. The use of augmentation was intended to provide variations in the training images without manually adding new original data. This approach is consistent with findings in the literature indicating that geometric and photometric variations can help models handle different image conditions, although their effectiveness depends on the characteristics of the dataset [17].



a. Original b. Horizontal Flip c. Vertical Flip d . Contrast Adjusment e. Rotate 15^0

Figure 4. Variations of Chili Leaf Images After Augmentation

2.4 Convolutional Neural Network Architecture

The CNN architecture consisted of three convolutional blocks. The first block used 32 filters, the second block used 64 filters, and the third block used 128 filters. Each convolutional layer used a 3 × 3 kernel, a stride of 1, *same* padding, and ReLU activation. Each block was followed by a 2 × 2 MaxPooling layer to reduce the feature dimensions. After the convolutional blocks, the output was flattened using a Flatten layer and then processed by a Dense layer with 128 units and ReLU activation. A dropout rate of 0.5 was applied before the output layer to reduce the risk of overfitting. The output layer consisted of two neurons with Softmax activation to generate the probabilities for the healthy and nutritional deficiency classes [18].

Table 3. CNN Architecture Configuration

Component	Configuration
Input	224 x 224 x 3
Conv Block 1	32 filter, kernel 3 x 3, ReLU + MaxPooling 2 x 2
Conv Block 2	64 filter, kernel 3 x 3, ReLU + MaxPooling 2 x 2
Conv Block 3	128 filter, kernel 3 x 3, ReLU + MaxPooling 2 x 2
Flatten	Flatten
Dense	128 unit, ReLU
Dropout	0,5
Output	2 unit, Softmax

2.5 Model Evaluation

The Confusion Matrix was used to evaluate the performance of the classification model by comparing the model's predictions with the actual classes. This matrix shows the number of correct and incorrect predictions for each class. The results of the Confusion Matrix were used to calculate several evaluation metrics, namely *accuracy*, *precision*, *recall*, and *F1-score* [19].

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

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$F1 - Score = 2x \frac{precision\ x\ recall}{recall + precision} x100\% \quad (4)$$

Description:
TP (True Positive) represents the number of positive-class samples that were correctly predicted as positive.
TN (True Negative) represents the number of negative-class samples that were correctly predicted as negative.
FP (False Positive) represents the number of negative-class samples that were incorrectly predicted as positive, whereas
FN (False Negative) represents the number of positive-class samples that were incorrectly predicted as negative.

2.6 System Testing

System testing was conducted using Black Box Testing to examine whether each user-facing function operated according to the specified requirements, while White Box Testing was used to examine the logical flow of important processes, particularly preprocessing and model processing [20]. This testing complemented the numerical evaluation of the model by ensuring that the application implementation could perform the classification process from input to output.

3. Results and Discussion

3.1 System Implementation

The implementation results showed that the CNN model could be integrated into a web-based application to receive chili leaf images and display the classification results. The detection interface provided an image upload area and displayed the analysis results after the image was processed by the backend. The confidence score allowed users to observe the model's confidence level in the predicted class, although the confidence value was not intended to replace agronomic diagnosis.

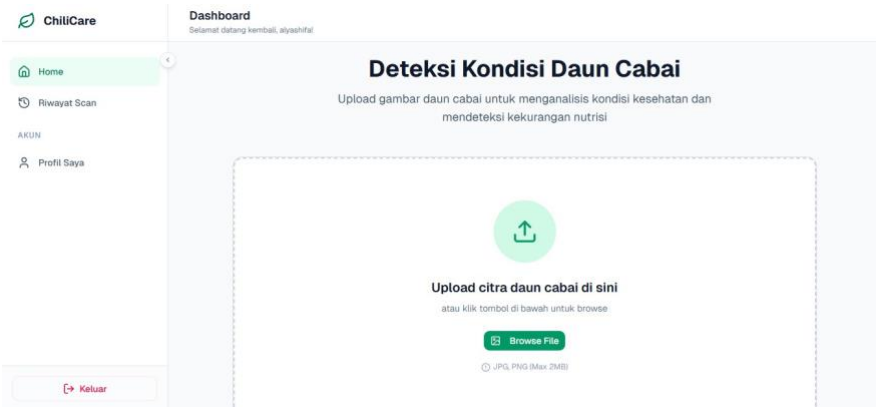


Figure 5. Interface of the Chili Leaf Condition Detection Page in the Web-Based System

3.2 Training and Testing Results on the Primary Dataset

For the primary dataset, the training curve shows that the training accuracy increased from approximately 49% in the early epochs to nearly 99%, while the validation accuracy increased to nearly 100%. The training and validation loss values generally decreased as the number of epochs increased. This pattern indicates that the model was able to learn the visual characteristics of the two classes in the local dataset effectively.

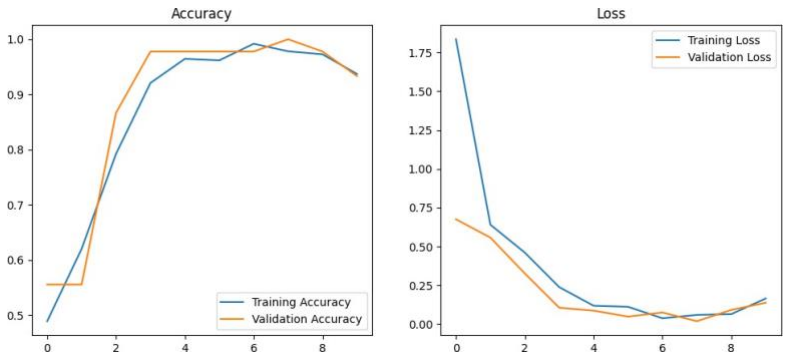


Figure 6. Training Accuracy and Loss Graph on the Primary Dataset

The confusion matrix for the primary dataset shows that 26 nutritional deficiency images were correctly classified, with no nutritional deficiency images misclassified as healthy. For the healthy class, 20 images were correctly predicted, while 1 image was predicted as nutritional deficiency. Thus, 46 out of 47 test images were correctly classified, corresponding to approximately 97.9%, which was rounded to 98%. This pattern indicates that the recall for the nutritional deficiency class reached 100% on the primary test data.

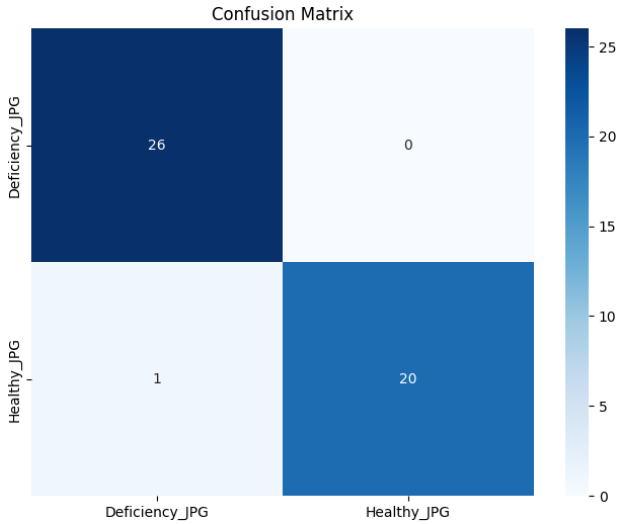


Figure 7. Confusion Matrix of the Primary Dataset

3.3 Training and Testing Results on the Secondary Dataset

For the secondary dataset, the training accuracy increased from approximately 51% at the beginning of training to around 95%, while the validation accuracy increased to approximately 99%. The training and validation loss values generally decreased, although several fluctuations occurred across epochs. These results indicate that the model was able to learn visual patterns from a data source different from the primary dataset.

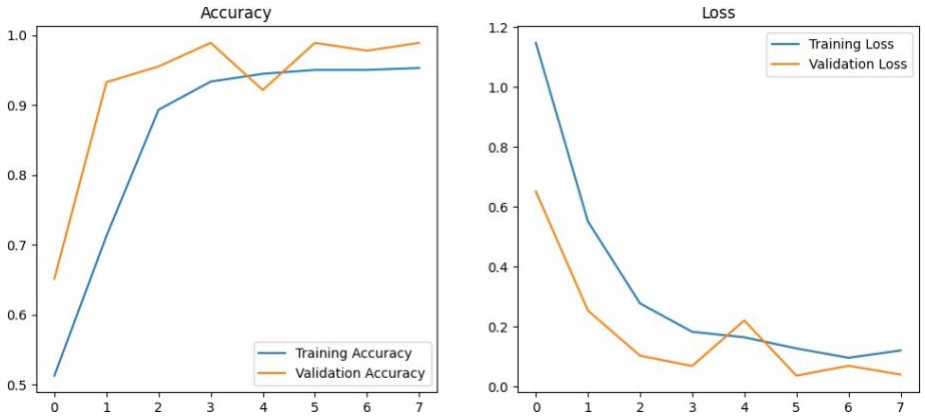


Figure 8. Training Accuracy and Loss Graph on the Secondary Dataset

The confusion matrix for the secondary dataset shows that 44 nutritional deficiency images were correctly predicted, while 1 nutritional deficiency image was predicted as healthy. For the healthy class, 45 images were correctly predicted, while 2 images were predicted as nutritional deficiency. Of the 92 test images, 89 were correctly classified, resulting in an accuracy of approximately 96.7%, or 97% after rounding. The single error in the nutritional deficiency class represents a false negative, indicating that this error pattern should still be considered when the system is used to assist in the initial identification of nutritional conditions.

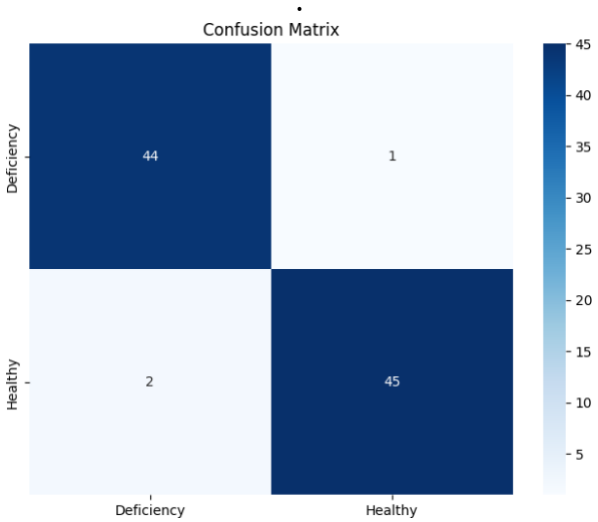


Figure 9. Confusion Matrix of the Secondary Dataset

3.4 Classification Report

Table 4 shows that the performance of the two models was relatively similar. The primary dataset achieved an accuracy of 98%, while the secondary dataset achieved 97%. The precision for the nutritional deficiency class was 96% for both datasets, while the recall for the nutritional deficiency class decreased from 100% on the primary dataset to 98% on the secondary dataset. The F1-score remained high, reaching 98% on the primary dataset and 97% on the secondary dataset. The 1% difference in accuracy indicates a relatively small change in performance when the model was evaluated on different data sources. However, these results are not sufficient to claim broad generalization because the study only used two classes and one local dataset.

Table 4. Classification Report Results for the Primary and Secondary Datasets

Metric	Primary Dataset	Secondary Dataset
Accuracy	98%	97%
Precision - Deficiency	96%	96%
Recall - Deficiency	100%	98%
F1-score - Deficiency	98%	97%
Precision - Healthy	100%	98%
Recall - Healthy	95%	96%
F1-score - Healthy	98%	97%

3.5 Error Analysis and Implications

Classification errors on the primary dataset occurred in only one healthy image that was predicted as nutritional deficiency, whereas the secondary dataset contained one nutritional deficiency image predicted as healthy and two healthy images predicted as nutritional deficiency. This pattern indicates that the model was relatively sensitive to nutritional deficiency conditions, particularly on the primary dataset. However, the presence of a false negative on the secondary dataset remains a concern because users may interpret a problematic leaf as healthy. In the context of a decision support system, the classification results should therefore be positioned as preliminary information rather than the sole basis for cultivation decisions. The differences in results between the primary and secondary datasets also indicate the influence of the data source. Although both datasets used the same two labels, image acquisition conditions, varieties or environmental conditions, backgrounds, lighting, and visual characteristics may differ. Research on plant disease classification emphasizes that field conditions and data diversity are

important challenges in developing robust models [23]. Since this study evaluated two different data sources, the results provide an initial indication that the model can maintain high performance when moving across domains; however, multi-location evaluation is still required.

From a methodological perspective, augmentation was one of the components that helped the model obtain image variations during training. Recent literature indicates that augmentation of plant images can reduce limitations associated with small datasets and improve the ability of models to handle certain variations. However, overly aggressive augmentation techniques may also generate unrealistic patterns [24]. In this study, rotation was limited to 15 degrees, while brightness was varied within the range of 80%–120%, keeping the image modifications relatively close to the original object conditions. The model used in this study was also relatively simple compared with modern architectures such as EfficientNet, ConvNeXt, and hybrid CNN-transformer models. Several recent studies have shown that transfer learning and more complex architectures can achieve high accuracy in leaf disease classification. Nevertheless, a simple architecture remains relevant when the primary objective is to develop a pipeline that is easy to train, maintain, and integrate into a web-based application with relatively low computational requirements [25].

3.6 Research Limitations

This study has several limitations that should be considered. First, the classification was limited to two classes, so the system could not distinguish specific types of nutritional deficiencies based on individual nutrients such as nitrogen, phosphorus, or potassium. Second, the primary dataset was relatively limited and collected from a single location, meaning that the diversity of field conditions was not fully represented. Third, the system did not include an explainability analysis to identify the leaf regions that most influenced the model's decisions. Fourth, performance comparisons with modern models were not systematically conducted through controlled ablation experiments.

These limitations also affect the interpretation of the 98% and 97% accuracy results. The high accuracy values on the test data indicate the model's performance under the experimental conditions of this study, but they do not automatically guarantee the same performance when the model is applied in fields with substantially different cameras, lighting conditions, varieties, or locations. Future development could expand the dataset across multiple locations, add classes based on specific nutrients, conduct external validation, and evaluate lightweight architectures as well as transfer learning approaches.

4. Conclusion

The results of this study show that the web-based chili leaf nutritional deficiency classification system successfully performed image uploading, classification using the Convolutional Neural Network (CNN) method, and presentation of prediction results in the form of Healthy and Nutrition Deficiency classes along with their confidence scores. Model evaluation on the primary dataset using a confusion matrix resulted in an accuracy of 98%. For the Nutrition Deficiency class, the model achieved a precision of 96%, recall of 100%, and F1-score of 98%, while the Healthy class achieved a precision of 100%, recall of 95%, and F1-score of 98%. These results demonstrate that the model has good capability in distinguishing healthy leaves from leaves experiencing nutritional deficiencies.

Evaluation on the secondary dataset resulted in an accuracy of 97%, indicating that the model was also able to perform well on data outside the primary dataset. The model trained on the primary dataset achieved slightly higher accuracy than the model evaluated on the secondary dataset. In addition, Black Box and White Box testing showed that the system functions and main model processes operated according to the design. Overall, the developed system is capable of supporting the classification of chili leaf conditions based on images with good performance.

REFERENCES

[1] Badan Pangan Nasional, Mobilisasi Cabai. Jakarta: Badan Pangan Nasional, 2025.
[2] Badan Pusat Statistik, Peran Komoditas Hortikultura terhadap Inflasi Pangan. Jakarta: Badan Pusat Statistik, 2024.
[3] Direktorat Jenderal Hortikultura, Panduan Teknis Budidaya Cabai Rawit. Jakarta: Kementerian Pertanian Republik Indonesia, 2024.
[4] Y. S. Rahayu, Yuliani, and S. K. Dewi, "Penyakit tanaman akibat defisiensi unsur hara," Unesa University Press, vol. 2, no. 1, pp. 101–115, 2024, doi: 10.1234/unesa.2024.04.
[5] A. Qur'ania, L. Karlitasari, S. Maryana, C. Sudrajat, and Z. Zolla, "Identifikasi defisiensi unsur hara pada tanaman cabai menggunakan support vector machine," J-ICON: Jurnal Komputer dan Informatika, vol. 12, no. 1, pp. 62–67, 2024, doi: 10.35508/jicon.v12i1.1023.
[6] M. E. Dwiastuti, A. Triwiratno, and U. N. Taflikan, "Hubungan gejala blotching, defisiensi Zn dan Fe dengan hasil deteksi penyakit CVPD jeruk dengan polymerase chain reaction," Jurnal Hortikultura, vol. 14, no. 2, pp. 131–137, 2024, doi: 10.21082/jhort.v14n2.2024.
[7] J. Zhang et al., "Consequences of Nutrient Misdiagnosis in Crop Management," Agricultural Water Management, vol. 245, no. 1, pp. 106–115, 2024, doi: 10.1016/j.agwat.2024.106115.

[8] J. Lu, L. Tan, and H. Jiang, "Review on Convolutional Neural Network (CNN) Applied to Plant Leaf Disease Classification," Agriculture, vol. 14, no. 8, pp. 707–719, 2024, doi
[9] P. Kaur, G. Singh, and S. Kaur, "CNN-SVM for Cercospora Leaf Spot Disease Recognition in Chilli Plants," Multimedia Tools and Applications, vol. 83, no. 4, pp. 11201–11218, 2024, doi: 10.1007/s11042-024-15201-w.
[10] A. Qur'ania et al., "Identifikasi Defisiensi Unsur Hara pada Tanaman Cabai Menggunakan Support Vector Machine," JICON: Jurnal Informatika dan Komputer, vol. 12, no. 2, pp. 88–95, 2024, doi: 10.35508/jicon.v12i2.2024.
[11] Adi et al., "Implementasi Sistem Deteksi Otomatis pada Tanaman Cabe Rawit Menggunakan Convolutional Neural Network (CNN) Berbasis TensorFlow untuk Optimasi Pertanian Modern," PNACIA, vol. 5, no. 1, pp. 45–53, 2024, doi: 10.1234/pnacia.2024.11.
[12] A. K. Rangarajan et al., "A Low-Cost UAV for Detection of Cercospora Leaf Spot Using DCNN," Multimedia Tools and Applications, vol. 83, no. 2, pp. 4511–4528, 2024, doi: 10.1007/s11042-024-14202-y.
[13] H. Nurfauziah and I. Jamaliyah, "Perbandingan metode testing antara blackbox dengan whitebox pada sebuah sistem informasi," Jurnal Visualika, vol. 10, no. 2, pp. 105–113, 2024, doi: 10.32639/visualika.v10i2.2024.
[14] M. M. Nirob et al., "Chili Plant Leaf Diseases and Growth Stage Dataset from Bangladesh," Mendeley Data, vol. 1, no. 1, pp. 1–10, 2025, doi: 10.17632/w9mr3vf56s.1.
[15] V. D. B. Sebayang and I. G. N. L. W. Kusuma, "Klasifikasi jenis jerawat berdasarkan citra menggunakan convolutional neural network dengan arsitektur MobileNetV2," Jurnal Fasilkom, vol. 14, no. 3, pp. 766–774, 2024, doi: 10.37859/jf.v14i3.766.
[16] D. P. Ayuni, Jasril, M. Irsyad, F. Yanto, and S. Sanjaya, "Augmentasi data pada implementasi convolutional neural network arsitektur EfficientNet-B3 untuk klasifikasi penyakit daun padi," ZONAsi: Jurnal Sistem Informasi, vol. 6, no. 1, pp. 239–249, 2024, doi: 10.31849/zn.v6i1.13874.
[17] P. P. Vedanty, M. W. A. Kesiman, and I. M. G. Sunarya, "Pengaruh data augmentasi pada identifikasi penyakit daun tanaman obat menggunakan K-nearest neighbor," JATI (Jurnal Mahasiswa Teknik Informatika), vol. 9, no. 2, pp. 2094–2100, 2025, doi: 10.36040/jati.v9i2.12961.
[18] A. M. Tama and R. C. N. Santi, "Klasifikasi Jenis Tanaman Hias Menggunakan Metode Convolutional Neural Network (CNN)," Journal of Information Technology and Computer Science (INTECOMS), vol. 7, no. 1, pp. 112–120, 2024, doi: 10.31539/intecoms.v7i1.2024.
[19] F. R. Valerian, M. Syarief, and D. A. Fatah, "Klasifikasi tingkat obesitas menggunakan metode GBM dan confusion matrix," JATI (Jurnal Mahasiswa Teknik Informatika), vol. 9, no. 2, pp. 1500–1508, 2025, doi: 10.36040/jati.v9i2.2025.
[20] T. Kumar, R. Brennan, A. Mileo, and M. Bendechache, "Image data augmentation approaches: A comprehensive survey and future directions," IEEE Access, vol. 12, pp. 187536–187571, 2024, doi: 10.1109/ACCESS.2024.3470122.
[21] Andreyas and D. Alamsyah, "Color and texture feature extraction for disease identification in chili leaves using K-nearest neighbors," INOVTEK Polbeng - Seri Informatika, vol. 11, no. 1, pp. 183–192, 2026, doi: 10.35314/isi.v11i1.2026.
[22] Nabila, R. Rahmanda, and D. Oktaviany, "Implementasi arsitektur MobileNetV2 untuk klasifikasi penyakit pada daun cabai berbasis convolutional neural network," JIK: Jurnal Ilmu Komputer, vol. 10, no. 1, pp. 22–29, 2025, doi: 10.47007/komp.v10i1.2025.
[23] K. Antwi, K. E. Bennin, D. K. P. Asiedu, and B. Tekinerdogan, "On the application of image augmentation for plant disease detection: A systematic literature review," Smart Agricultural Technology, vol. 9, Art. no. 100590, pp. 1–15, 2024, doi: 10.1016/j.atech.2024.100590.
[24] W. Zeng, "Image data augmentation techniques based on deep learning: A survey," Mathematical Biosciences and Engineering, vol. 21, no. 6, pp. 6190–6224, 2024, doi: 10.3934/mbe.2024272.
[25] S. Parez, N. Dilshad, and J. W. Lee, "A channel attention-driven optimized CNN for efficient early detection of plant diseases in resource constrained environment," Agriculture, vol. 15, no. 2, Art. no. 127, pp. 1–18, 2025, doi: 10.3390/agriculture15020127.