Evaluating CNN and SVM Models in Smart Agriculture: A Case Study on Bell Pepper Leaf Disease Classification

Komang Wibisana
Computer Science
Universitas Pendidikan Ganesha
Singaraja, Indonesia
wibisana@undiksha.ac.id

Luh Joni Erawati Dewi
Computer Science
Universitas Pendidikan Ganesha
Singaraja, Indonesia
joni.erawati@undiksha.ac.id

I Ketut Purnamawan
Computer Science
Universitas Pendidikan Ganesha
Singaraja, Indonesia
purna@undiksha.ac.id

Siu Sun CHUNG
University Library
The University of Hong Kong
Hong Kong SAR
sunchung@ieee.org

Gede Indrawan
Computer Science
Universitas Pendidikan Ganesha
Singaraja, Indonesia
gindrawan@undiksha.ac.id

Fieter Brain Pasaribu
Computer Science
Universitas Pendidikan Ganesha
Singaraja, Indonesia
fieter@student.undiksha.ac.id

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Abstract**—** This research aims to develop a classification model for bell pepper leaf disease images to support modern agriculture in Smart Green House (SGH). Diseases on bell pepper leaves caused by pests, fungi, and viruses have caused a decrease in crop yields. To solve these issues, an image classification method called Convolutional Neural Network (CNN) and Support Vector Machine (SVM) is used. The datasets are grouped into four classes: healthy (healthy leaf), pest (leaf disease caused by pest), fungus (leaf disease caused by fungus), and virus (leaf disease caused by virus). The dataset used in this study consists of 173 images, divided into 139 training data (80%) and 34 testing data (20%). The training data were then combined using traditional augmentation methods, increasing the total number of images to 1,390. To obtain robust results, early stopping trials with a patience of 5, followed by 50 epoch and 100 epoch approaches were conducted on the CNN model. On the other hand, SVM using manually extracted features from color (RGB, HSL) and texture (Sobel) components was tested with scenarios such as the use of linear, polynomial, and RBF kernels. The best evaluation results were delivered by CNN with early stopping with 97% accuracy. However, SVM also performed quite well with 94% accuracy on the polynomial kernel. These results indicate that CNN excels in classifying leaf diseases, and the results of this study are expected to help develop a system for detecting diseases in bell pepper plants.

Keywords: *CNN, Classification, Bell Pepper Leaf, Smart Green House, SVM*

I. Introduction

Agriculture is a vital sector in providing food and improving community welfare, especially in rural areas [1]. One of the horticultural commodities with high economic value is bell pepper (Capsicum annuum) [2], which is widely cultivated in Pancasari Village, Buleleng Regency, Bali [3]. This region has ideal natural conditions for the growth of peppers, especially through the application of Plantation technology such as Smart Green House (SGH) [4], [5].

Although SGH technology has been used in cultivation, farmers still face serious problems in the form of disease attacks on plant leaves. One of the farmers in Pancasari Village reported a decrease in yield from 300 kg to only 100 kg per week due to diseases caused by Thrips pests, Cercospora capsici fungus, and Xanthomonas campestris virus [6], [7]. These diseases cause leaf curling, brown spots, and yellow discoloration, which directly affects the quality of the bell pepper crop.

The plantation system in SGH used today is only limited to monitoring temperature and humidity through IoT sensors [8]. There is no system that is able to detect leaf diseases automatically using a digital image-based approach. In fact, early detection is crucial for stopping the further spread of illness and speeding up the process of treatment.[9], [10], [11].

As artificial intelligence technology has advanced, Techniques in machine learning and deep learning have gained widespread application for detecting and classifying plant diseases [12], [13], [14]. Convolutional Neural Network (CNN) which is a part of deep learning is adept at extracting visual characteristics from images autonomously and has been proven to be efficient for leaf image classification [15], [16]. On the other hand, Support Vector Machine (SVM) which is a part of machine learning excels in small datasets with manual features such as color and texture [17], [18].

Various studies have found that CNN and SVM are capable of performing disease classification in plants. However, only a limited number of studies utilize data directly from farms and ascertain the most accurate model for classifying diseases in bell pepper plant leaves. Consequently, this research aims to evaluate the accuracy performance of CNN and SVM models in identifying bell pepper leaf diseases using the original image dataset from SGH in Pancasari Village. This research aims to evaluate the accuracy, precision, recall and F1-score of each model, and is expected to contribute to the development of image-based disease detection systems on plant leaves.

II. Methods

This study uses a comparative quantitative approach to evaluate and compare the accuracy performance of two image classification models, namely CNN and SVM. CNN is known to have the ability to automatically extract visual features and works very well on image data, while SVM with manually determined features. The overall flow of the stages of this research can be seen in Fig. 1.

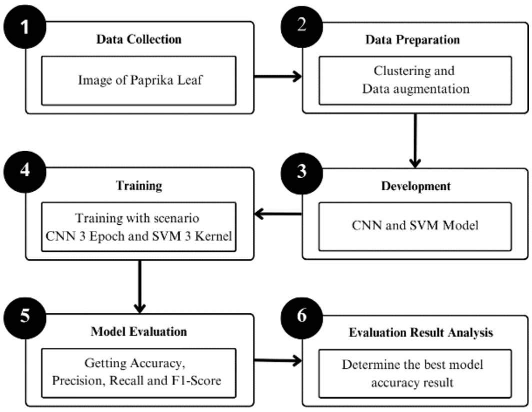

Fig. 1. Research Stage

The dataset used in this study is 173 images of bell pepper leaves collected directly from the Smart Green House (SGH) plantation in Pancasari Village, Buleleng Regency, Bali [4]. The images were categorized into four classes, namely healthy leaves (42 images), leaves affected by pests (38 images), leaves affected by fungi (44 images), and leaves affected by viruses (49 images). Image capture was done using a smartphone camera perpendicular to the leaf object under stable lighting conditions to maintain image quality consistency. Examples of images from each class of bell pepper leaves can be seen in Fig. 2.

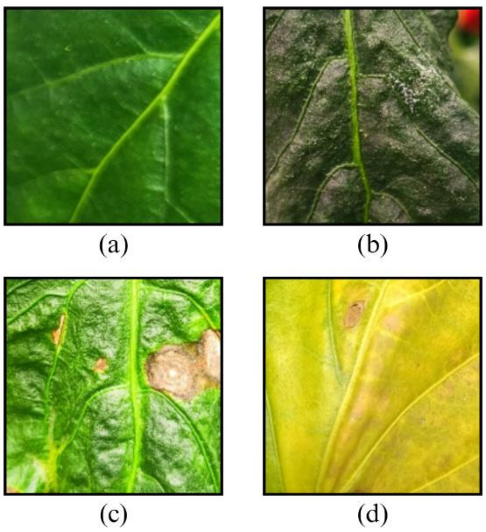

Fig. 2. Example images of bell pepper leaves: (a) Healthy, (b) Pest, (c) Fungus, and (d) Virus

The dominant color in an images can be employed for tasks like image searching, adjusting colors, creating palletes, and various other uses. The dataset is subsequently split into two sections, with 80% designated for training purposes and 20% allocated for testing purpose. Details of the amount of data distribution are described in Table 1.

Table 1 Data Distribution per Class

Class	Number of Original Image	Training Data	Testing Data
Healthy	42	34	8
Pest	38	30	8
Fungus	44	36	8
Virus	49	39	10
Total	173	139	34

To increase the variety in the training data and prevent overfitting, image augmentation was performed using rotation techniques at eight different angles, namely 15°, 30°, 45°, 60°, 90°, 120°, and 180°, as well as horizontal and vertical flip [21], [22]. This augmentation process resulted in a total of 1,390 images for the training data. An illustration of the augmentation results for the bell pepper leaf image is presented in Fig. 3.

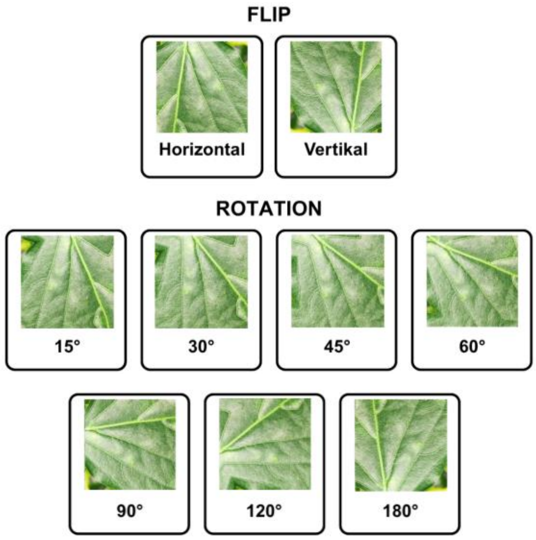

Fig. 3. Bell pepper leaf Image Augmentation

The CNN architecture utilized in this research is constructed with two successive convolutional layers, incorporating 32 and 64 filters of size 3×3 combined with a ReLU activation function, complemented by two 2×2 max pooling layers [16], [23]. The output from the convolutional layer is flattened through a flatten layer and then forwarded to a dense layer containing 128 neurons with ReLU activation. To mitigate the risk of overfitting, a dropout rate of 0.5 is implemented before the output layer, which is comprised of four neurons using softmax activation functions in accordance with the number of classes. The CNN model underwent training using the Adam Optimizer with a learning rate of 0.001 and a batch size of 32. The model was evaluated under three training conditions: early stopping with a patience of 5, training for 50 epochs, and training for 100 epochs. The entire training process was performed on the Google Colab platform using a T4 GPU for computation. The computational complexity of model training, especially on large datasets, requires significant computing resources [24].

Unlike CNN, the SVM model relies on manually extracted features. The process starts with resizing the image to 256×256 pixels, then extracting colour features (mean and standard deviation of RGB and HSL channels) and texture features using the Sobel operator in the horizontal and vertical directions [25]. All generated features were then normalized using StandardScaler for scale uniformity. SVM models were tested using three types of kernels, namely linear, polynomial, and radial basis function (RBF), with parameters C = 100 and gamma = 'scale' [17]. Details of SVM can be seen in Table 2.

Table 2 Details of SVM

No	C	Degree	Gamma	Kernel	Training Accuracy(%)
1	**100**	2	**Scale**	Polinomial	94.00
2	100	2	0.1	Polinomial	93.70
3	10	2	0.1	Polinomial	93.20
4	100	2	0.01	Polinomial	92.90
5	10	2	Scale	Polinomial	92.60
6	1	2	0.1	Polinomial	92.00
7	100	2	Auto	Polinomial	91.80
8	0.1	2	0.1	Polinomial	90.50
9	10	2	Auto	Polinomial	89.80
10	**100**	–	**Scale**	RBF	91.00
11	100	–	0.1	RBF	86.90
12	100	–	0.01	RBF	86.50
13	10	–	Auto	RBF	85.20
14	10	–	0.01	RBF	84.70
15	10	–	0.001	RBF	83.00
16	1	–	0.01	RBF	82.30
17	**100**	–	**Scale**	Linear	88.00
18	100	–	0.1	Linear	87.50
19	10	–	–	Linear	87.20
20	10	–	Auto	Linear	86.10
21	1	–	–	Linear	85.40
22	10	–	0.01	Linear	85.00
23	0.1	–	–	Linear	82.80

Performance evaluation of each model was conducted using convolutional matrix and classification report to see accuracy, precision, recall, and F1-score. This evaluation is important to understand the effectiveness of the model in handling multiclass data that tends to be unbalanced [15], [16], [26].

III. RESULTS AND DISCUSSION

Convolutional Neural Network (CNN) and Support Vector Machine (SVM) models were trained using training data from augmented bell pepper leaf images consisting of four classes: healthy, pest, fungus, and virus. Evaluation is carried out on the testing data to assess the ability of the model to classify bell pepper leaf diseases based on accuracy, precision, recall, and F1-score. The evaluation results are displayed in the form of confusion matrix and classification report, which describes the performance of each model in each class.

CNN models were tested in three training scenarios, namely early stopping with patience = 5, 50 epochs, and 100 epochs. In the first scenario, the CNN model uses the early stopping technique, where the training is automatically stopped when the validation accuracy does not increase for five consecutive epochs. In this study, the CNN model with early stopping achieved its best performance at epoch 16 with a testing accuracy of 97%. Using early stopping with a patience of 5 causes training to stop if there is no performance improvement. The relatively small data also makes the training process not take long, but adding epochs can actually cause the model to overfit. The pest, healthy, and virus classes were classified successfully (precision and recall = 1.00), while the fungus class had a precision of 0.89 and recall of 0.88. Confusion matrix and evaluation metric of early stopping scenario can be seen in Fig. 4 and Table 3.

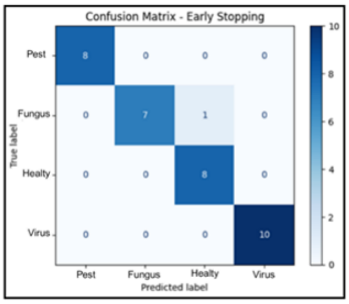

Fig 4. Confusion matrix of the CNN model tested using early stopping

Table 3. Evaluation Metric of Early Stopping Scenario

Class	Precision	Recall	F1-Score	Number of Data (Support)
0 (Pest)	1.00	1.00	1.00	8
1 (Fungus)	0.89	0.88	0.94	8
2 (Healthy)	1.00	1.00	1.00	8
3 (Virus)	1.00	1.00	1.00	10
Accuracy			0.97	34

In the second scenario, 50 epoch training, the model accuracy decreased to 88%. Although the classification in the pest and virus classes remained good, the performance in the healthy and fungus classes decreased. This is due to the limited duration of training which is not enough to optimize the learning of features that distinguish between classes, especially between fungus and healthy. Confusion matrix and evaluation metric of 50 epoch scenario can be seen in Fig. 5 and Table 4.

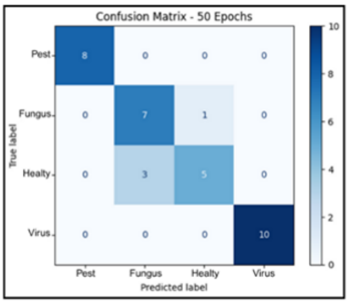

Fig 5. Confusion matrix of the CNN model tested in 50 epoch

Table 4. Evaluation Metric of 50 Epoch Scenario

Class	Precision	Recall	F1-Score	Number of Data (Support)
0 (Pest)	1.00	1.00	1.00	8
1 (Fungus)	0.70	0.88	0.78	8
2 (Healthy)	0.83	0.63	0.71	8
3 (Virus)	1.00	1.00	1.00	10
Accuracy			0.88	34

The third scenario with 100 training epochs resulted in 91% accuracy. Although slightly higher than 50 epochs, the precision and recall values for the healthy and fungus classes stagnated at 0.75. The healthy and fungus classes are often confused, likely due to the similar leaf characteristics compared to other classes. Although the fungus class has brown spots on its leaves, it also has a dominant green color similar to the healthy class, increasing the difficulty for the model to differentiate between the two. Furthermore, prolonged training can also lead to overfitting, resulting in lower accuracy on testing data [20]. Confusion matrix and evaluation metric of 100 epoch scenario can be seen in Fig. 6 and Table 5. While Fig. 7 is the loss and accuracy graph.

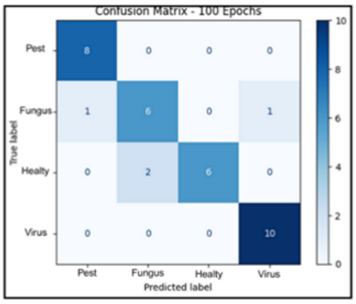

Fig. 6. Confusion matrix of the CNN model tested in 100 epoch

Table 5. Evaluation Metric of 100 Epoch Scenario

Class	Precision	Recall	F1-Score	Number of Data (Support)
0 (Pest)	1.00	1.00	1.00	8
1 (Fungus)	0.75	0.75	0.75	8
2 (Healthy)	0.75	0.75	0.75	8
3 (Virus)	1.00	1.00	1.00	10
Accuracy			0.91	34

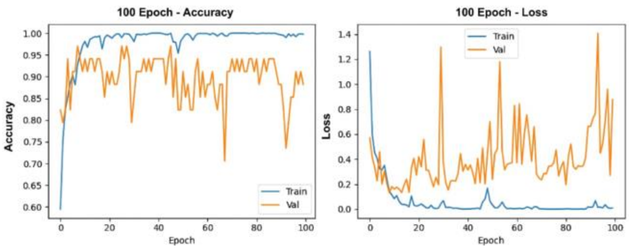

Fig. 7. The loss and accuracy graph of CNN tested in 100 epoch

Furthermore, SVM models were tested using three types of kernels, namely linear, polynomial, and radial basis function (RBF). All SVM models were trained using manually extracted training data, which included the mean and standard deviation of color in RGB and HSL space, and texture using the Sobel operator in the horizontal and vertical directions. This extraction process is done before the classification stage, so the performance of the model is highly dependent on the quality of the features generated from image preprocessing.

SVM with a linear kernel showed an accuracy of 88% against the testing data. Although it performed well, the model misclassified the fungus and healthy classes. This is due to the limitation of the linear kernel in separating classes that have non-linear feature distributions [26]. Confusion matrix and evaluation metric of SVM model with linier kernel scenario can be seen in Fig. 8 and Table 6.

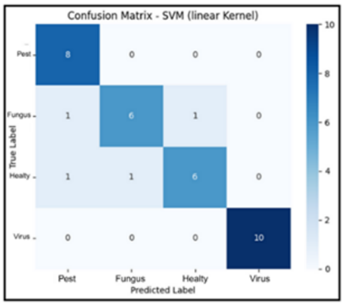

Fig. 8. Confusion Matrix of SVM Model with Linier Kernel

Table 6. Evaluation metric of Linear Kernel Scenario

Class	Precision	Recall	F1-Score	Number of Data (Support)
0 (Pest)	0.80	1.00	0.89	8
1 (Fungus)	0.86	0.75	0.80	8
2 (Healthy)	0.86	0.75	0.80	8
3 (Virus)	1.00	1.00	1.00	10
Accuracy			0.88	34

Meanwhile, the SVM model using a polynomial kernel performed the best, achieving an accuracy of 94%. This kernel was able to recognize non-linear relationships between color and texture features more effectively, and recorded a precision and recall of 1.00 in the fungus and virus classes. Similar to the CNN model, the SVM also struggled to distinguish between the fungus and healthy classes. This is thought to be due to their similar dominant feature, which is predominantly green. This is reinforced by the virus class, which has a perfect score. The virus class itself has a very distinct characteristic compared to other classes, namely a yellowish color. Furthermore, the advantage of the polynomial kernel lies in its flexibility in modeling complex decision boundaries between classes [1], [17]. Confusion matrix and evaluation metric of SVM model with polynomial kernel scenario can be seen in Fig. 9 and Table 7.

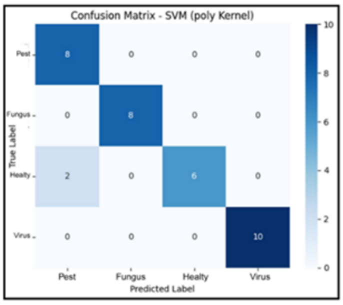

Fig. 9. Confusion Matrix of SVM Model with Polynomial Kernel

Table 7. Evaluation metric of Polynomial Kernel Scenario

Class	Precision	Recall	F1-Score	Number of Data (Support)
0 (Pest)	0.80	1.00	0.89	8
1 (Fungus)	1.00	1.00	1.00	8
2 (Healthy)	1.00	0.75	0.86	8
3 (Virus)	1.00	1.00	1.00	10
Accuracy			0.94	34

Finally, SVM with RBF kernel also recorded an accuracy of 88%. However, its performance tends to be unstable, especially in the healthy class which only obtained a recall of 0.62. This is most likely due to the sensitivity of the RBF kernel to the gamma parameter. If the setting of this parameter is not optimal, the model tends to overfitting on the training data and failing to recognize varied patterns on the testing data [9], [26]. Confusion matrix and evaluation metric of SVM with RBF kernel scenario can be seen in Fig. 10 and Table 8.

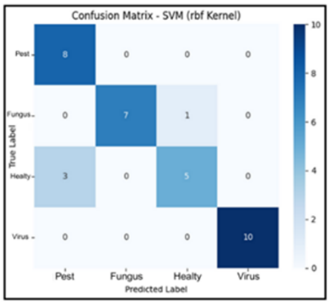

Fig. 10. Confusion Matrix of SVM Model with RBF Kernel

Table 8. Evaluation Metric of RBF Kernel Scenario

Class	Precision	Recall	F1-Score	Number of Data (Support)
0 (Pest)	0.73	1.00	0.84	8
1 (Fungus)	1.00	0.88	0.93	8
2 (Healthy)	0.83	0.62	0.71	8
3 (Virus)	1.00	1.00	1.00	10
Accuracy			0.91	34

The evaluation results showed that the SVM with a polynomial kernel performed best with 94% accuracy, as well as high precision, recall, and F1-score values across all classes, particularly the fungus and virus classes, which achieved a perfect score (1.00). The RBF kernel followed with 91% accuracy, but there was still a decrease in recall in the healthy class. Meanwhile, the linear kernel achieved 88% accuracy, with fairly frequent classifications of the fungi and healthy classes. Based on the confusion matrix and evaluation metrics, the polynomial kernel was the most consistent and accurate in recognizing all four classes of bell pepper leaves.

Comparative analysis showed that the CNN model with the early lighting scenario performed best with a peak accuracy of 97%, followed by the SVM model with a polynomial kernel, which achieved 94% accuracy. The CNN model with 100 epochs of training achieved 91% accuracy, while the 50 epoch scenario achieved 88% accuracy. The three SVM kernels showed varying results, but the linear kernel only achieved 88% accuracy and the RBF 91% accuracy, with less stable performance across classes. From these findings, it can be inferred that the CNN employing early stopping stands out as the optimal model for categorizing bell pepper leaf diseases in this study. More information about the ranking of models based on accuracy can be seen in Table 9.

This study also found that although the fungus and healthy classes differ, their similar dominant characteristics make it difficult for both CNN and SVM models to classify them. This is demonstrated by the virus class, which has a perfect score due to its very different features.

Table 9. Ranking Based on Accuracy

Rank	Model	Scenario/Kernel	Accuracy (%)
1	CNN	Early Stopping	97
2	SVM	Kernel Polynomial	94
3	CNN	100 Epoch	91
4	SVM	Kernel RBF	91
5	CNN	50 Epoch	88
6	SVM	Kernel Linear	88

Next, for model testing, the best CNN model and the best SVM model were implemented into a web-based application using Streamlit. This application enables users to submit a image of bell pepper foliage, and the application then categorizes it using either the CNN or SVM algorithm. The inference process in the application utilizes a CNN model in .h5 format and an SVM model in .pkl format, which have been integrated into the Streamlit system.

In the web application, the user can input, for example, an image of a pest-infested leaf, as shown in Fig. 11. The CNN and SVM models both successfully predict it as pest-infested. However, when the user inputs an image of a healthy leaf, as shown in Fig. 12, the SVM model predicts it as pest-infested, while the CNN model correctly identifies it as healthy.

Fig. 11 Leaf with Pest

Fig. 12 Healthy Leaf

This error indicates that the SVM feature extraction process, which is based on RGB mean values, HSL, and Sobel edges, is not fully capable of distinguishing the visual characteristics of healthy leaves from pest-infested leaves. In this image, the green color of the leaves appears uniform and the surface texture is quite smooth. However, it is likely that certain leaf patterns or color intensities cause the resulting numerical features to resemble the characteristics of pest-infested leaves. This is a weakness of the manual feature-based approach, as the model relies heavily on statistical representations of the image, which may not necessarily reflect the actual biological conditions. Meanwhile, the CNN model using a deep learning approach is able to capture more complex and contextual visual patterns, resulting in a more accurate classification.

IV. CONCLUSIONS AND SUGGESTIONS

This study looks at how well two image classification methods, Convolutional Neural Network (CNN) and Support Vector Machine (SVM), work in identifying leaf diseases in bell pepper plants. Based on the evaluation results of the testing data, the CNN model with a training scenario using early stopping techniques achieved the highest accuracy of 97%, which indicates its ability to prevent overfitting and produce good generalization to new data. This study also found that although leaf classes have different characteristics, if they have more dominant similar features, they are also more likely to be difficult to distinguish.

The main advantage of the CNN model lies in its ability to automatically and thoroughly extract visual features directly from the image data, such as leaf shape, damage pattern and texture. This gives it an advantage over SVM models that rely on manual feature extraction from RGB and HSL colour channels, as well as texture features using the Sobel operator. Although the SVM model with a polynomial kernel also performed comparatively effective with an accuracy of 94%, it is more dependent on proper feature and kernel selection, and is more sensitive to variations in data distribution between classes.

As a recommendation, future research is suggested to explore more complex CNN architectures or apply transfer learning approaches such as ResNet, MobileNet, or EfficientNet, to improve the accuracy and efficiency of model training. In addition, it is necessary to increase the amount and variety of image data by considering various lighting conditions, backgrounds, and capture angles to expand the generalization ability of the model in the field. Increasing the dataset size can also be achieved by generating synthetic data using the Generative Adversarial Network (GAN) method.

The CNN model that has been developed is also recommended to be implemented in the form of desktop or mobile-based applications, so that it can be utilized directly by farmers in the field as an automatic and practical leaf disease early detection system. Thus, the findings of this study aid in the establishment of a bell pepper plant disease classification system embedded within the Smart Green House to enhance contemporary agricultural practices in Pancasari Village.

REFERENCES

[1] Bali Express, "Lika-liku petani paprika Pancasari tak tumbang walau dijajah pandemi dan produk luar Bali," *Bali Express*, Aug. 16, 2023. [Online]. Available: https://baliexpress.jawapos.com/bali/672755012/lika-liku-petani-paprika-pancasari-tak-tumbang-walau-dijajah-pandemi-dan-produk-luar-bali

[2] Mariani, R., Perdana, F., Mawaddah, L. R. ., & Wibowo, D. P. . (2024). Physicochemical Parameters, Phytochemical Screening, and Antioxidant Activity of Capsicum annuum var. grossum Leaves From Indonesia. *Journal of Midwifery and Nursing*, *6*(2), 514-521. https://doi.org/10.35335/jmn.v6i2.5039

[3] Prabawa P.S., Sumbertiasih N M., "Pengembangan agrowisata pertanian guna meningkatkan kesejahteraan petani di Desa Pancasari," Saraswati: *Jurnal Kelitbangan Kabupaten Buleleng*, vol. 1, no. 2, 2022. https://ejurnal.bulelengkab.go.id/index.php/saraswati/article/view/31/13

[4] I. N. Mara, "Petani paprika dari Pancasari maju dan sukses dengan sistem pertanian digital," *Tatkala.co*, Aug. 16, 2023. https://tatkala.co/2023/08/16/i-nyoman-mara-petani-paprika-dari-pancasari-maju-dan-sukses-dengan-sistem-pertanian-digital/

[5] Kompas, "Petani milenial kembangkan varietas baru untuk agro-wisata di Buleleng," *Kompas.com*, Mar. 8, 2023. https://biz.kompas.com/read/2023/03/08/165509828/petani-milenial-kembangkan-varietas-baru-untuk-agro-wisata-di-buleleng-dengan

[6] Dinas Pertanian Buleleng, "Pengendalian serangan thrips pada tanaman paprika," 2022. [Online]. Available: https://distan.bulelengkab.go.id/informasi/detail/artikel/pengendalian-serangan-thrips-pada-tanaman-paprika-22

[7] M. Isnaini, A. Rohyadi, I. Muthahanas, and W. Astiko, "Kemampuan Trichoderma sp. untuk menekan penyakit secara alami pada tanaman paprika di dataran medium," *Prosiding SAINTEK*, vol. 3, pp. 217–224, 2021. https://jurnal.lppm.unram.ac.id/index.php/prosidingsaintek/article/view/225

[8] U. Ristian, I. Ruslianto, and K. Sari, "Sistem monitoring smart greenhouse pada lahan terbatas berbasis Internet of Things (IoT)," *JEPIN*, vol. 8, no. 1, pp. 87–94, 2022. https://doi.org/10.26418/jp.v8i1.52770

[9] Muslih and A. D. Krismawan, "Tomato leaf diseases classification using convolutional neural networks with transfer learning ResNet-50," *KINETIK*, vol. 9, no. 2, pp. 149–158, 2024. https://kinetik.umm.ac.id/index.php/kinetik/article/view/1939

[10] G. V. Nivaan, J. Sumah, and D. Y. Metiary, "Sistem cerdas deteksi penyakit tanaman pala menggunakan metode Convolutional Neural Network (CNN)," *JATI (Jurnal Mahasiswa Teknik Informatika)*, vol. 8, no. 6, pp. 12921–12925, 2024.

[11] R. Sharma et al., "Plant disease diagnosis and image classification using deep learning," *Computers, Materials & Continua*, vol. 71, no. 2, pp. 2126–2140, 2022. https://doi.org/10.32604/cmc.2022.020017

[12] P. Wang, E. Fan, and P. Wang, "Comparative analysis of image classification algorithms based on traditional machine learning and deep learning," *Pattern Recognition Letters*, vol. 7991, 2020. https://doi.org/10.1016/j.patrec.2020.07.042

[13] V. Salim, A. Abdullah, and P. Y. Utami, "Klasifikasi citra penyakit tanaman pada daun paprika dengan metode transfer learning menggunakan DenseNet-201," *Indonesian Journal of Computer Science*, vol. 13, no. 2, pp. 3001–3014, 2024. https://ijcs.stmikindonesia.ac.id

[14] P. Kulkarni et al., "Plant disease detection using image processing and machine learning," *arXiv preprint*, 2021. https://doi.org/10.48550/arXiv.2106.10698

[15] C. Janiesch, P. Zschech, and K. Heinrich, "Machine learning and deep learning," *Electronic Markets*, vol. 31, no. 3, pp. 685–695, 2021. https://doi.org/10.1007/s12525-021-00475-2

[16] L. Alzubaidi et al., "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, no. 53, 2021. https://doi.org/10.1186/s40537-021-00444-8

[17] A. Nasution, A. S. Lubis, and D. Kiswanto, "Identifikasi variasi paprika berdasarkan jenis warna paprika berbasis analisis citra digital menggunakan algoritma Support Vector Machine (SVM)," *Jurnal Informasi, Sains dan Teknologi*, vol. 7, no. 2, pp. 209–220, 2024. https://doi.org/10.55606/isaintek.v7i2.282

[18] D. M. Abdullah and A. M. Abdulazeez, "Machine learning applications based on SVM classification: A review," Technical College of Informatics, Akre, Duhok Polytechnic University, 2021. [Online]. Available: https://doi.org/10.48161/qaj.v1n2a50

[19] Y. Chang and N. Mukai, "Color feature based dominant color extraction," *IEEE Access*, vol. 10, pp. 93055–93061, 2022. https://doi.org/10.1109/ACCESS.2022.3202632

[20] X. Guan and H. V. Burton, "Bias-variance tradeoff in machine learning: Theoretical formulation and implications to structural engineering applications," *Advanced Engineering Informatics*, vol. 52, 101596, 2022. https://doi.org/10.1016/j.aei.2022.101596

[21] C. Shorten and T. M. Khoshgoftaar, "A survey on image data augmentation for deep learning," *Journal of Big Data*, vol. 6, no. 60, pp. 1–48, 2019. https://doi.org/10.1186/s40537-019-0197-0

[22] J. Li, "Research on image texture feature extraction based on digital twin," *Mathematical Problems in Engineering*, vol. 2022, Article ID 6788719. https://doi.org/10.1155/2022/6788719

[23] W. Silvani, S. Aurelia, N. Zulatifa, and T. Agustin, "Pengaruh jumlah epoch terhadap akurasi model Convolutional Neural Network dalam klasifikasi penyakit pada tanaman padi," *Seminar Nasional Amikom Surakarta (SEMNASA)*, pp. 179–190, 2024. e-ISSN: 3031-5581.

[24] A. R. Pratama et al., "The impact of machine learning in modern industries," *Nian Tana Sikka*, vol. 3, no. 1, pp. 177–182, 2025. https://doi.org/10.59603/niantanasikka.v3i1.680

[25] F. Putrawansyah and T. Susanti, "Penerapan metode Support Vector Machine terhadap klasifikasi jenis jambu biji," *JIKO (Jurnal Informatika dan Komputer)*, vol. 8, no. 1, pp. 193–204, 2024. https://doi.org/10.26798/jiko.v8i1.988

[26] D. Krstinić, M. Braović, L. Šerić, and D. Božić-Štulić, "Multi-label classifier performance evaluation with confusion matrix," *Computer Science & Information Technology (CS & IT)*, vol. 10, no. 8, pp. 1–14, 2020. https://doi.org/10.5121/csit.2020.100801