Indonesian Journal of Data and Science

Volume 6 Issue 2
ISSN 2715-9936
https://doi.org/10.56705/ijodas.v6i3.255

Research Article

Performance Analysis of Convolutional Neural Networks and Naive Bayes Methods for Disease Classification in Tomato Plant Leaves

Nadya Salsabilah [1,*]; Irawati [2]; Lilis Nur Hayati [3]
[1] Universitas Muslim Indonesia, Makassar, Indonesia, 13020210302@umi.ac.id
[2] Universitas Muslim Indonesia, Makassar, Indonesia, irawati@umi.ac.id
[3] Universitas Muslim Indonesia, Makassar, Indonesia, lilis.nurhayati@umi.ac.id

Correspondence should be addressed to Thomas Edyson Tarigan; tarigan@utdi.ac.id

Received 10 August 2025; Accepted 15 October 2025; Published 31 December 2025

Abstract:
Tomatoes are one of the most widely cultivated and consumed crops, but they are highly susceptible to disease attacks. The main diseases that often attack tomato plants are early blight and late blight. This study compares two machine learning-based classification methods, namely Convolutional Neural Network (CNN) and Naïve Bayes, in detecting tomato leaf diseases. The dataset used consists of 1,255 images obtained from Kaggle, which have been processed and divided into three data ratio scenarios (70:30, 80:20, and 90:10) for training and testing. The results showed that CNN is superior to Naïve Bayes, with the highest accuracy reaching 83.01%, while Naïve Bayes only achieved 34%. With better stability and accuracy, CNN has the potential to help farmers detect diseases more quickly and increase agricultural productivity.

Keywords: *Convolutional Neural Network* (CNN), *Naive Bayes*, Tomato Leaf Disease.

Dataset link: https://www.kaggle.com/datasets/muhammadmasdar/tomato-disease-ready

1. Introduction

Tomato (*Solanum lycopersicum*) is one of the leading horticultural commodities that plays an important role in Indonesia's economy. As a fruit vegetable, tomato has great potential for agribusiness development due to its high nutritional content and significant economic value [1]. Tomato plant diseases commonly affect the leaves, where changes in color and shape often indicate infection. However, such symptoms are difficult to detect with the naked eye, making early diagnosis by farmers challenging. This can lead to mistreatment, reduced yields, and a higher risk of crop failure [2] The main diseases commonly found on tomato leaves are late blight and early blight. [3] These two diseases can lead to a decrease in the quality and quantity of tomato yields and have a negative impact on farmers' profits [4]. Therefore, it is important to correctly recognize tomato leaf diseases. However, because the symptoms are similar, it is often difficult to distinguish them simply by looking at them. [5] Therefore, a more accurate method is needed so that diseases can be identified correctly and crop yields can be increased.

Previous research used a CNN method with the VGG 16 model to classify tomato plant diseases. The results showed that this system achieved an accuracy rate of 98% in the training phase and 82% in the validation phase. Furthermore, this research successfully developed a website-based classification system that is expected to assist users in identifying tomato plant diseases practically. [6] Another study used a web-based Naive Bayes Classifier to identify tomato plant diseases based on leaf color and shape, with a success rate of 82.98%. However, light and noise can affect the identification results, resulting in less accurate image features. [7] Meanwhile, research on shallot disease classification using Naive Bayes and CNN with GLCM features demonstrated excellent results. With 320 images and classification using two disease classes, this method achieved an accuracy rate of up to 100% in tests using the Naive Bayes, GLCM-CNN, and CNN algorithms. [8]

This study aims to implement and evaluate the performance of the Convolutional Neural Networks (CNN) method in detecting types of diseases in tomato plants through leaf image analysis. In addition, it compares the performance of CNN with the Naïve Bayes algorithm in classifying two major diseases: *early blight* and *late blight*. Unlike previous studies that only applied a single approach, this research compares both methods through several stages, including dataset input, data preprocessing, classification, and performance evaluation. The main objective is to determine the accuracy and effectiveness of each algorithm in accurately classifying tomato leaf diseases.

2. Method

This study employs the Convolutional Neural Network (CNN) and Naive Bayes algorithms to construct a classification model for detecting diseases in tomato plant leaves. Subsequently, the performance accuracy of both algorithms will be evaluated and compared.

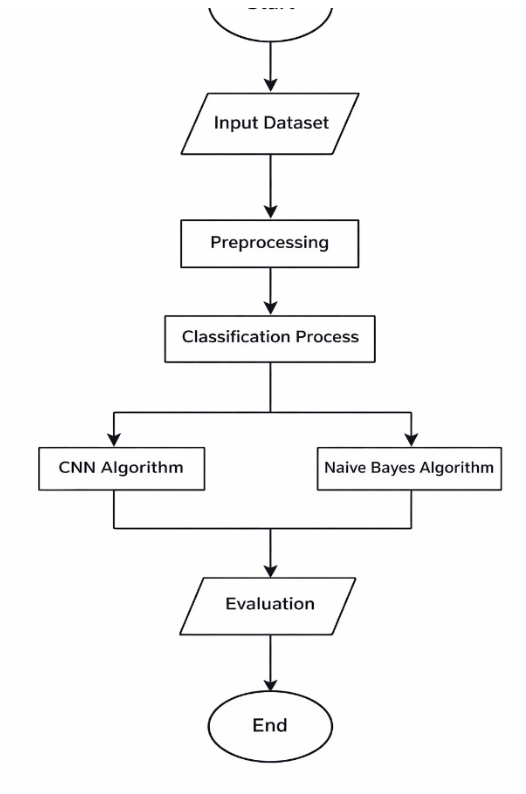

Figure 1: Research Flow

Input Data

The data used in this study comes from www.kaggle.com. The dataset consists of 1255 images in .jpg, .jpeg, .png, .bmp, .gif, and .tiff formats with an RGB color scheme, each with a resolution of 255 x 255 pixels [9]. This study focuses on the classification of two types of tomato leaf diseases: late blight (628 images) and early blight (627 images). Since it only covers two categories, other potential diseases are not accommodated. [10]

Preprocessing

The preprocessing stage is performed to adjust the input image size to match the structure of the model used. Dataset preprocessing involves several steps, including feature selection, data cleaning, and data transformation. [11]

In this study, the data preprocessing stage began by organizing the dataset into two folders: a "train" folder for model training and a "validation" folder for model testing.

After grouping, a data cleaning process was conducted by checking all files to ensure that only valid image files were used. Accepted image formats included .jpg, .jpeg, .png, .bmp, .gif, and .tiff. Files with other extensions were considered invalid and removed from the dataset.

The next step was resizing the images uniformly to a target resolution of 255x255 pixels. This was followed by a normalization process, where each pixel value was divided by 255, converting the range from 0–255 to 0–1. This normalization aimed to accelerate and simplify the classification process in subsequent stages.

Classification

Convolutional Neural Network (CNN)

Convolutional Neural Networks (CNN) are a type of deep learning model most widely used for image classification. The architecture of CNNs is based on the functioning of receptive fields in the human visual cortex. CNNs belong to the category of feedforward neural networks and are hierarchically constructed through several main layers, namely convolutional layers, pooling layers, and fully connected layers. [12]

Convolutional Neural Networks (CNN) make optimal use of two-dimensional input data, such as signals. This process divides a large number of parameters into smaller parts, simplifying the data training process and speeding up training time. [13] The main advantage of CNNs is their ability to classify images with very high accuracy. This advantage stems from their ability to reduce the number of free parameters and handle deformations in the input image, such as shifts, rotations, and scale changes. [14]

Naïve bayes

Naive Bayes is a classification algorithm based on Bayes' theorem, assuming that each explanatory variable is independent of the others. This method assumes that the occurrence of an event in a group is not influenced by the environment or the occurrence of other events. [15]

In this algorithm, Bayes' Theorem is used to combine the prior probability (P(H)) with the conditional probability (P(X|H)), which then allows the calculation of the posterior probability (P(H|X)) for each classification. [16] As can be seen in equation 1, the naive bayes proximity formula.

$$P(H|X) = P(X|H)\frac{P(H)}{P(X)} \tag{1}$$

Information :
X : data with unknown class
H : data hypothesis is a specific class
P(H|X) : probability of hypothesis H based on condition X (posteriori probability) P(H) : probability
of hypothesis H (prior probability)
P(X|H) : probability of X based on the conditions in hypothesis H P(X) : probability
X

Evaluation

This evaluation was conducted to assess the performance of the implemented algorithm. Testing was conducted using a method aimed at measuring the system's success in diagnosing tomato leaf diseases, namely through a confusion matrix. The table in the confusion matrix displays test data that was correctly classified and data that was misclassified. [17] [18] Confusion matrix is applied as an evaluation method in this study, which involves four main components, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). [19] An overview of the confusion matrix table can be seen in Table 1.

Table 1. Contoh Confusion Matrix

Class Prediction	Class Actual	
	Positive	*Negative*
Positive	TP	FN
Negative	FP	TN

In the classification process, there are several test metrics used to assess model performance, including accuracy, precision, recall, and f1-score. [20]

Table 2. Rumus Evaluasi Performa Metode

Performance Metrics	**Formula**
Accuracy	$\frac{TP+TN}{TP + TN + FP + FN}$ X 100%
Recall	$\frac{TP}{TP + FN}$ X 100%
Precision	$\frac{TP}{\quad}$ X 100%

Accuracy measures the proportion of correct predictions compared to the total data analyzed. Recall is used to assess the ratio between the number of correct positive predictions and the total number of data that are actually positive. On the other hand, precision shows how accurate the predictions are for the positive class, namely by comparing the number of correct predictions with all data predicted as positive. [21] Meanwhile, precision is the ratio between the number of correct positive predictions and the total number of data predicted as positive. This can be calculated using the formula [22].

3. Result and Discussion

This study used 360 validated images, consisting of 180 images of late blight and 180 images of early blight, each stored in a separate folder. The data was divided into three ratios: 70:30, 80:20, and 90:10, with the larger percentage used for training and the remainder for testing. Classification of tomato leaf diseases was performed using the Convolutional Neural Networks (CNN) dan Naïve Bayes.

Classification using *Convolutional Neural Networks*

Classification of tomato leaf plant diseases using CNN models showed varying performance based on the data split ratio for training and testing.

```
Model 70_30:
  - Accuracy: 83.06%
  - Loss: 0.3785
```

Figure 2. Model Accuracy 70:30

Figure 2 shows a model with a 70:30 data split, resulting in an accuracy of 83.06% and a loss of 0.3785. This demonstrates good ability to classify tomato leaf diseases.

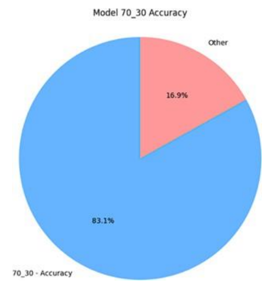

Figure 3. Algorithm results CNN Rasio 70:30

The pie chart illustrates the accuracy of a tomato disease classification model with 70% training data and 30% testing data. The model achieved 83.1% accuracy, as indicated by the blue area, indicating that 83.1% of the test data was accurate were correctly classified. Meanwhile, 16.9% represented misclassified data. This indicates good and fairly stable model performance.

```
Model 80_20:
  - Accuracy: 75.56%
  - Loss: 0.4857
```

Figure 4. Model Accuracy 80:20

The 80:20 data split model yielded an accuracy of 76.56% and a loss of 0.4857. This indicates that the model still has decent classification performance, but is slightly more prone to prediction errors than the previous model.

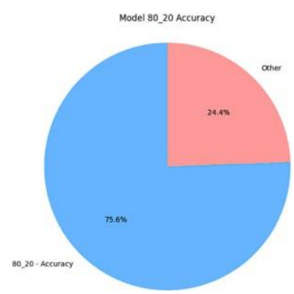

Figure 5. Algorithm results CNN Rasio 80:20

The pie chart shows the accuracy of the tomato disease classification model. 75.6% represents correctly classified data, while 24.4% represents misclassified data. This indicates a decrease in accuracy compared to the previous model, but the model still performs quite well.

```
Model 90_10:
  - Accuracy: 77.22%
  - Loss: 0.4507
```

Figure 6. Model Accuracy 90:10

The model with a 90:10 data split produced an accuracy of 77.02%, and a loss of 0.4507 indicating a low level of prediction error.

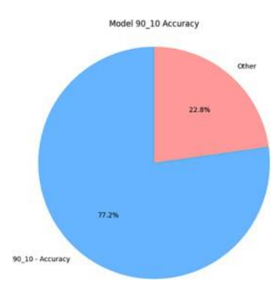

Figure 7. Algorithm results CNN Rasio 90:10

The pie chart above shows the accuracy of the tomato disease classification model, with an accuracy of 77.2% and a classification error of 22.8%. Despite the larger training dataset, the accuracy results are not significantly different from the 80:20 model and are still considered good for classifying tomato leaf diseases.

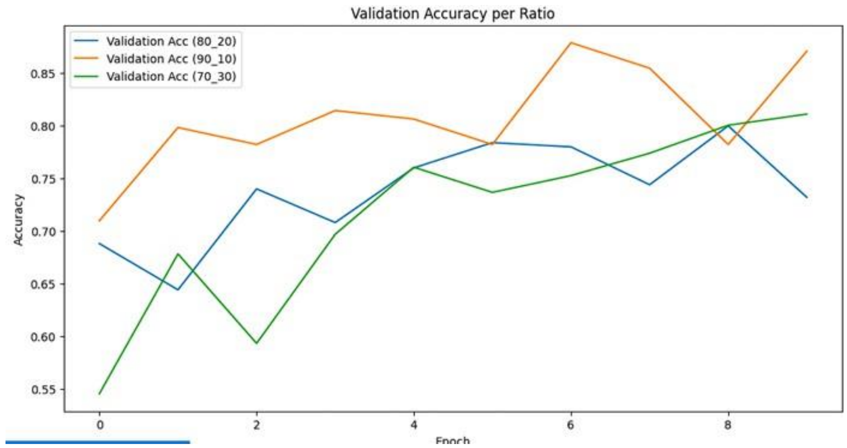

Figure 8. Algorithm results

The graph above shows the development of validation accuracy of tomato plant disease classification models based on data split ratios (80:20, 90:10, and 70:30) over 10 epochs. The blue line represents the 80:20 ratio, the orange line the 90:10 ratio, and the green line the 70:30 ratio. The 90:10 model showed the highest accuracy across several epochs, although the results fluctuated. The 80:20 model tended to be stable but with lower accuracy. The 70:30 model showed consistent, gradual improvement. Overall, this graph shows that each ratio has its own advantages, with 70:30 excelling in stability and 90:10 in highest accuracy.

Classification using *Naïve Bayes*

```
Melatih model dengan rasio 70_30...

Laporan Klasifikasi untuk rasio 70_30:
              precision    recall  f1-score   support

early_blight       0.69      0.76      0.72       177
 late_blight       0.77      0.70      0.73       200

    accuracy                           0.73       377
   macro avg       0.73      0.73      0.73       377
weighted avg       0.73      0.73      0.73       377

Akurasi untuk rasio 70_30: 72.68%
```

Figure 9. Algorithm Result Naive Bayes Rasio 70:30

In Figure 9, the naive Bayes model was able to classify tomato leaves affected by early blight with 76% accuracy and late blight with 70% accuracy. The tomato disease classification model with a 70:30 data split ratio achieved an accuracy of 72.68%. Based on the classification report, the model demonstrated fairly balanced performance across both classes.

```
Melatih model dengan rasio 80_20...

Laporan Klasifikasi untuk rasio 80_20:
              precision    recall  f1-score   support

early_blight       0.67      0.76      0.72       109
 late_blight       0.80      0.72      0.76       142

    accuracy                           0.74       251
   macro avg       0.74      0.74      0.74       251
weighted avg       0.74      0.74      0.74       251

Akurasi untuk rasio 80_20: 73.71%
```

Figure 10. Algorithm Results Naive Bayes Rasio 80:20

In Figure 10, the naive Bayes model was able to classify tomato leaves affected by early blight with 76% accuracy and late blight with 70% accuracy. The tomato disease classification model with a data split ratio of 80:20 achieved an accuracy of 73.71%. Based on the classification report results, the model performed quite well in both classes.

```
Melatih model dengan rasio 90_10...

Laporan Klasifikasi untuk rasio 90_10:
              precision    recall  f1-score   support

early_blight       0.64      0.75      0.69        55
 late_blight       0.77      0.68      0.72        71

    accuracy                           0.71       126
   macro avg       0.71      0.71      0.71       126
weighted avg       0.72      0.71      0.71       126

Akurasi untuk rasio 90_10: 70.63%
```

Figure 11. Algorithm Results Naive Bayes Rasio 90:10

In Figure 11, the naive Bayes model was able to classify tomato leaves affected by early blight with 64% accuracy and late blight with 77% accuracy. The tomato disease classification model with a 90:10 data split ratio achieved an accuracy of 70.63%. Based on the classification report, the model demonstrated fairly balanced performance across both classes.

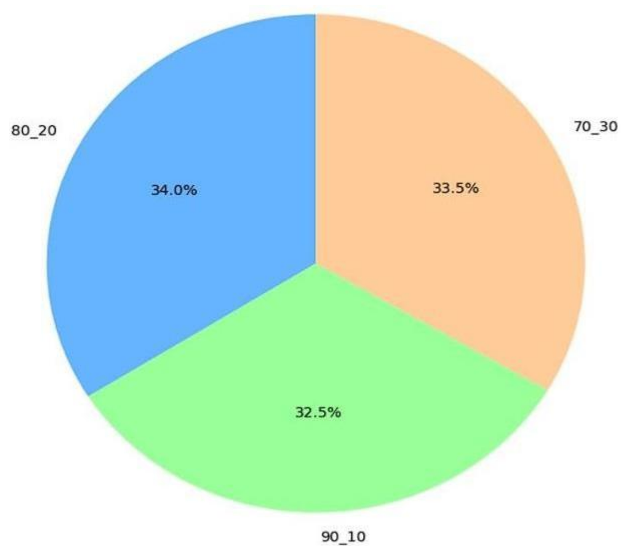

Figure 12. Comparison of Naive Bayes Model Accuracy

The pie chart illustrates the distribution of accuracy percentages for tomato disease classification models based on three data sharing ratios: 80:20, 70:30, and 90:10. The 80:20 ratio showed the highest accuracy at 34.0%, followed by the 70:30 ratio at 33.5%, and the 90:10 ratio at 32.5%.
These results indicate that the 80:20 model had a slightly superior accuracy compared to the other two ratios. Although the difference is small, this finding suggests that variations in data sharing ratios affect model performance in classifying tomato diseases.

4. Conclusion

This study aims to compare the performance of Convolutional Neural Networks (CNN) and Naïve Bayes methods in classifying tomato plant diseases, namely early blight and late blight. The dataset used consisted of 1,255 images obtained from Kaggle, which were then processed through several stages, including preprocessing, normalization, and data division into three ratio scenarios (70:30, 80:20, and 90:10) for training and testing purposes.

Based on the evaluation results, the CNN method demonstrated a higher level of accuracy than Naïve Bayes. In the best scenario with a data ratio of 80:20, CNN achieved an accuracy of 83.01%, while Naïve Bayes only achieved an accuracy of 34%. Furthermore, the CNN model also demonstrated more stable performance across various test scenarios. Thus, it can be concluded that the CNN method is more effective in classifying tomato plant diseases than Naïve Bayes. Implementation of this model has the potential to help farmers detect diseases more accurately, thereby minimizing the risk of misdiagnosis and increasing crop productivity.

References:

[1] A. Universitas and S. Ratulangi, "Jurnal Agroekoteknologi," vol. 4, pp. 84–93, 2023.

[2] Nining Putri Ningsih, Emi Suryadi, Lalu Darmawan Bakti, and Bahtiar Imran, "Klasifikasi Penyakit Early Blight Dan Late Blight Pada Tanaman Tomat Berdasarkan Citra Daun Menggunakan Metode Cnn Berbasis Website," *J. Kecerdasan Buatan dan Teknol. Inf.*, vol. 1, no. 3, pp. 27–35, 2022, doi: 10.69916/jkbti.v1i3.10.

[3] Lely Sahrani, "Klasifikasi Penyakit Daun Tomat Berdasarkan Ekstraksi Tekstur Daun Menggunakan Gabor Filter Dan Algoritma Support Vector Machine," *Repos. Univ. Islam Negri Sumatera Utara Medan*, pp. 1–100, 2021.

[4] L. G. Mugao, B. M. Gichimu, P. W. Muturi, and E. K. Njoroge, "Essential Oils as Biocontrol Agents of Early and Late Blight Diseases of Tomato under Greenhouse Conditions," vol. 2021, 2021, doi: 10.1155/2021/5719091.

[5] N. Awalia and A. Primajaya, "Identifikasi Penyakit Leaf Mold Daun Tomat Menggunakan Model DenseNet-121," *J. Ilm. Ilmu Komput.*, vol. 8, no. 1, pp. 49–54, 2022, [Online]. Available: http://ejournal.fikom-unasman.ac.id

[6] R. Soekarta, N. Nurdjan, and A. Syah, "Klasifikasi Penyakit Tanaman Tomat Menggunakan Metode Convolutional Neural Network (CNN)," *Insect (Informatics Secur. J. Tek. Inform.*, vol. 8, no. 2, pp. 143–151, 2023, doi: 10.33506/insect.v8i2.2356.

[7] F. A. , I. R. , Muhammad Diponegoro, "Identifikasi Penyakit Pada Tanaman Tomat Berdasarkan Warna Dan Bentuk Daun Dengan Metode Naive Bayes Classifier Berbasis Web," *Coding J. Komput. dan Apl.*, vol. 5, no. 1, 2017, doi: 10.26418/coding.v5i1.19171.

[8] Dian, Purnawansyah, H. Darwis, and L. Nurhayati, "Klasifikasi Penyakit Bawang Merah Menggunakan Naïve Bayes dan Convolutional Neural Network," *Indones. J. Comput. Sci.*, vol. 12, no. 4, pp. 1932–1943, 2023, doi: 10.33022/ijcs.v12i4.3265.

[9] H. Apriyani and K. Kurniati, "Perbandingan Metode Naïve Bayes Dan Support Vector Machine Dalam Klasifikasi Penyakit Diabetes Melitus," *J. Inf. Technol. Ampera*, vol. 1, no. 3, pp. 133–143, 2020, doi: 10.51519/journalita.volume1.isssue3.year2020.page133-143.

[10] M. Khan, F. Gulan, and A. Riaz, "Early and late blight disease identi fi cation in tomato plants using a neural network-based model to augmenting agricultural productivity," vol. 107, no. 3, pp. 1–27, 2024, doi: 10.1177/00368504241275371.

[11] B. P. Esther, J. S. Paul, S. Sunil, and S. Pandey, "Detection of Diseases in Plant Leaf Using CNN Technique," vol. 14, no. 03, pp. 878–884, 2022.

[12] V. S. Dhaka, S. V. Meena, G. Rani, D. Sinwar, M. F. Ijaz, and M. Wo, "A Survey of Deep Convolutional Neural Networks Applied for Prediction of Plant Leaf Diseases," 2021.

[13] C. U. Aji, Wasito Galih, "Jurnal Teknologi Terpadu Learning," *J. Teknol. Terpadu*, vol. 8, no. 1, pp. 89– 94, 2022.

[14] Sandy Andika Maulana, Shabrina Husna Batubara, Tasya Ade Amelia, and Yohanna Permata Putri Pasaribu, "Penerapan Metode CNN (Convolutional Neural Network) Dalam Mengklasifikasi Jenis Ubur-Ubur," *J. Penelit. Rumpun Ilmu Tek.*, vol. 2, no. 4, pp. 122–130, 2023, doi: 10.55606/juprit.v2i4.3084.

[15] J. Arfah, Purnawansyah, H. Darwis, and R. Sastra, "Klasifikasi Penyakit Bawang Merah Menggunakan Naive Bayes dan CNN dengan Fitur GLCM," *Indones. J. Comput. Sci.*, vol. 12, no. 3, pp. 1231–1240, 2023, doi: 10.33022/ijcs.v12i3.3236.

[16] A. Nurjulianty, P. Purnawansyah, and H. Darwis, "Perbandingan Metode Naïve Bayes dan K-NN dengan Ekstraksi Fitur GLCM pada Klasifikasi Daun Herbal," *J. Media Inform. Budidarma*, vol. 7, no. 4, p. 1740, 2023, doi: 10.30865/mib.v7i4.6262.

[17] A. Agustina, F. Yanto, E. Budianita, I. Iskandar, and F. Syafria, "Klasifikasi Penyakit Tanaman Padi Menggunakan Metode Cnn Arsitektur Densenet-121 Dan Augmentasi Data," *J. Inf. Syst. Informatics Eng.*, vol. 8, no. 1, pp. 124–134, 2024.

[18] A. Nurdin, D. Satria, Y. Kartika, A. Rezha, and E. Najaf, "Klasifikasi Penyakit Daun Tomat Dengan Metode Convolutional Neural Network Menggunakan Arsitektur Inception-V3," no. 1, pp. 1–6, 2024.

[19] I. As'ad, "Advancing Healthcare Diagnostics: A Study on Gaussian Naive Bayes Classification of Blood Samples," *Int. J. Artif. Intell. Med. Issues*, vol. 1, no. 2, pp. 115–123, 2023, doi: 10.56705/ijaimi.v1i2.120.

[20] A. B. Prakosa, Hendry, and R. Tanone, "Implementasi Model Deep Learning Convolutional Neural Network (CNN) Pada Citra Penyakit Daun Jagung Untuk Klasifikasi Penyakit Tanaman," *J. Pendidik. Teknol. Inf.*, vol. 6, no. 1, pp. 107–116, 2023.

[21] E. Yuninsar *et al.*, "Analisis Perbandingan Metode Convolutional Neural Network (CNN) Dan Artificial Neural Network (ANN)," no. 03, pp. 321–333, 2024.

[22] S. A. Hakim *et al.*, "Klasifikasi Citra Generasi Artificial Intelligence Menggunakan Metode Fine Tuning Pada Residual Network Ai Generated Image Classification Using Fine Tuning on Residual Network," vol. 11, no. 3, pp. 655–666, 2024, doi: 10.25126/jtiik.938118.