Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 4, October 2023
DOI : https://doi.org/10.33395/sinkron.v8i4.12974
e-ISSN : 2541-2019
p-ISSN : 2541-044X

Detection And Classification of Citrus Diseases Based on A Combination of Features Using the Densenet-169 Model

M. Haikal Firdaus[1)*], Ema Utami[2)], Dhani Ariatmanto[3)]
[1,2,3)] Universitas AMIKOM Yogyakarta, Indonesia
[1)] mhaikalfirdaus22@students.amikom.ac.id, [2)] ema.u@amikom.ac.id, [3)] dhaniari@amikom.ac.id

Submitted : Sep 6, 2023 | **Accepted** : Sep 12, 2023 | **Published** : Oct 1, 2023

Abstract: This research is motivated by the urgent need to improve the capability of detecting diseases in citrus plants, which play a crucial role in maintaining agricultural sector productivity. Diseases such as blackspot, canker, and greening can have a serious impact on harvest yields and overall plant health. Therefore, this research aims to enhance the accuracy in classifying diseases in citrus plants by applying a Deep Learning approach. In this study, we chose to adopt the DenseNet-169 architecture and conducted experiments with two different scenarios: one using original features and the other using a combination of features. This method was employed to classify four different classes, namely blackspot, canker, greening, and healthy plants, using an LDI dataset consisting of 3,000 images. This dataset was divided into three parts, namely training, testing, and validation sets. The experimental results indicate that the DenseNet-169 model with the use of feature combination achieved the highest accuracy rate at 96.66%, whereas the model using only original features achieved 91.33%. This significant improvement of 5.33% in accuracy provides strong evidence that the feature combination approach has a highly meaningful positive impact on the model's ability to identify and classify diseases in citrus plants. These findings confirm that the use of feature combinations is a highly effective strategy in improving the model's performance in disease classification tasks in citrus plants.

Keywords: Citrus Disease, Classification, CNN, DenseNet, Feature Combination

INTRODUCTION

Citrus are an important fruit commodity in Indonesia with high economic value. However, some regions in Indonesia have experienced a decrease in orange harvest yields in the past year, such as North Sumatra, Riau, and Bali (BPS, 2023). This lower yield can impact the production and supply of oranges in these respective regions. According to (Parananda, 2022) with input from orange farmers like Mr. I Ketut Mangku Sugata, the cause of the reduced orange harvest is attributed to frequent rainfall. This makes orange plants susceptible to pest and disease attacks. This finding aligns with research conducted by (Lestari et al., 2018), where the reasons for decreased harvests were linked to pest and disease infestations. The impact of these diseases can result in lower-quality fruits, emphasizing the importance for farmers to ensure their crops remain free from pests and disease-causing agents (Mangla et al., 2022). Despite various plant disease control methods being employed, early identification and accurate diagnosis remain crucial in reducing disease spread and plant damage (Syed-Ab-Rahman et al., 2022).

In the last five years, intensive research on plant diseases has been conducted. AI-based techniques such as machine learning and deep learning in image processing have demonstrated high resilience and

*name of corresponding author

consistency with cost-effectiveness, high precision, and the ability to quickly assess (Dhiman et al., 2023). One reliable algorithm for image processing is Convolutional Neural Network (CNN), as explained by (Ahmed et al., 2022).

Research by (Saputra et al., 2023), utilized a deep learning approach with the CNN algorithm and DenseNet architecture to detect diseases in rice leaves. DenseNet was used to enhance information flow and gradients, reduce parameter counts, improve model accuracy, and address the vanishing gradient problem. The research results showed that the highest accuracy was achieved by DenseNet-121 at 91.67%. Another study by (Elaraby et al., 2022) proposed feature combination and transfer learning techniques using the CNN algorithm with pretrained AlexNet and VGG19 models on the ImageNet dataset for recognizing citrus diseases. The AlexNet model with SGDM optimizer achieved the highest classification accuracy of 94.3% for the leaf disease image (LDI) dataset and 93.5% for the fruit disease image (FDI) dataset. The VGG19 model with SGDM optimizer achieved a classification accuracy of 92.9% for the LDI dataset and 92.6% for the FDI dataset.

Another study by (Shireesha & Reddy, 2022) used the DenseNet-121 model to detect healthy citrus fruit and leaves affected by diseases such as blackspot, greening, scab, and canker. This model achieved a high accuracy rate of 96% with 50 epochs. According to research by (Huang et al., 2017), DenseNet-169 has higher accuracy than DenseNet-121 on the ImageNet dataset because it has 169 layers with a growth rate of 32, while DenseNet-121 has 121 layers with a growth rate of 32. Based on testing results, DenseNet-169 had a top-1 error rate of 23.80% with single-crop testing, while DenseNet-121 had a top-1 error rate of 25.02%. With ten-crop testing, the top-1 error rate reduced to 22.08% for DenseNet-169 and 23.61% for DenseNet-121. Therefore, the use of the CNN algorithm with the DenseNet-169 architecture is proposed in this research.

Based on the above description, the use of the CNN algorithm has shown significant potential in detecting plant diseases. However, this method has some potential drawbacks, such as the need for a large amount of data to train an effective CNN model and longer training times compared to traditional methods due to high computational complexity. To address these issues, some research has leveraged image processing to improve CNN algorithm performance. In a study conducted by (Safdar et al., 2019) they put forward an automatic method for recognizing and classifying diseases in citrus plants using computer image processing techniques. This method succeeded in achieving the highest classification accuracy level of 95.5% using M-SVM. Another research conducted by (Singh et al., 2020) has tried to utilize texture and color features in image processing to increase accuracy in classifying diseases on citrus leaves. The research showed improved classification performance with an average accuracy of 84.32% compared to previous methods.

Therefore, this research aims to compare methods for detecting and classifying citrus diseases using the DenseNet-169 architecture with and without feature combination. Additionally, this research will analyze and compare detection and classification results based on accuracy, precision, and recall of each tested model to provide a deeper understanding of the use of feature combination techniques in CNN models and the DenseNet-169 architecture in detecting and classifying citrus diseases. The results of this research are expected to contribute to disease control and prevention in citrus production to support higher-quality orange production in Indonesia.

LITERATURE REVIEW

In recent years, the detection and classification of citrus diseases using deep learning techniques have garnered significant attention. Various studies have focused on developing models capable of accurately classifying citrus diseases. In a study conducted by (Kukreja & Dhiman, 2020), the impact of citrus diseases on fruit quality, quantity, market competitiveness, and production costs was emphasized. They proposed a deep convolutional neural network (CNN) approach with data augmentation and pre-processing, which improved the model's performance in detecting and classifying citrus diseases. The research results showed that this method outperformed standard deep CNN approaches, achieving an accuracy of 89.1%. However, the dataset used was limited to citrus fruit diseases and did not include citrus leaves.

A similar approach was taken by (Soini et al., 2019) They employed computer vision and deep learning techniques with a retrained Inception model for 4000 iterations to classify infected citrus fruits

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 4, October 2023
DOI : https://doi.org/10.33395/sinkron.v8i4.12974
e-ISSN : 2541-2019
p-ISSN : 2541-044X

from images of citrus trees. The proposed model achieved a validation accuracy of 93.3% and outperformed other classification models in detecting citrus diseases. However, the proposed algorithm could only detect HLB infection in citrus fruits with clear visual symptoms and relied on the quality of the images of citrus trees.

(Syed-Ab-Rahman et al., 2022) proposed a two-stage deep learning model based on Faster R-CNN to detect and classify citrus diseases. This model successfully detected and classified black spots, bacterial canker, and Huanglongbing (HLB) with high accuracy, outperforming other methods in terms of F1-score, precision, recall, and accuracy.

In another study conducted by (Elaraby et al., 2022), they utilized transfer learning techniques with previous CNN models, namely AlexNet and VGG19, to recognize and classify citrus diseases. The use of data augmentation increased the training data and helped overcome overfitting issues. The research results showed that the AlexNet model with stochastic gradient descent with momentum (SGDM) optimization achieved the highest accuracy at 94.3%, while VGG19 with Adam optimization achieved 93.5%.

(Ganesh et al., 2019) employed a deep learning-based segmentation approach, namely Mask R-CNN, to detect and separate oranges from images of citrus trees. Using multi-modal input data consisting of RGB and HSV images of citrus trees, their approach successfully improved detection and segmentation performance compared to RGB-based approaches alone.

(Dhiman et al., 2023) proposed a framework for detecting and classifying citrus diseases using a combination of CNN and LSTM (Long Short-Term Memory) with edge computing. This model achieved an accuracy of 98.25% with pruning and quantization, outperforming the basic CNN model without compression techniques.

Additionally, (Xing et al., 2019) introduced the Weakly Dense Connected Convolution Network (Weakly DenseNet) to recognize and classify citrus pests and diseases. This model successfully reduced parameters and achieved high classification accuracy, reaching 93.42% on validation data and 93.33% on test data.

Overall, recent research on the detection and classification of citrus diseases has shown significant progress through the application of deep learning techniques. Models that utilize data augmentation, pre-processing, transfer learning, as well as combinations with LSTM and edge computing have demonstrated high performance in accurately and efficiently detecting and classifying citrus diseases. Advances in disease detection play a crucial role in preventing disease spread, increasing citrus production, and reducing economic losses for farmers and the citrus industry.

METHOD

This research involves several key stages, namely dataset preparation, dataset pre-processing, and training a detection and classification model using a CNN model with the DenseNet-169 architecture for training, validation, and model evaluation. Evaluation metrics are used to analyze the results and draw conclusions. Figure 1 below illustrates the main research stages along with the processes within them.

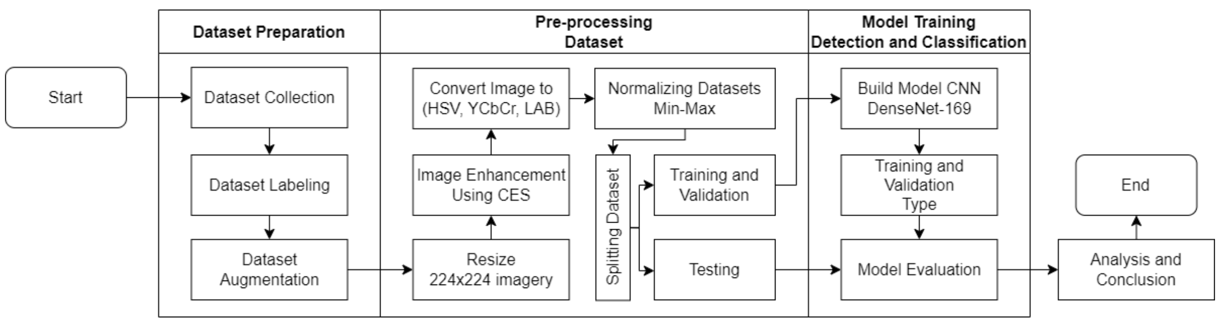

Fig. 1 Research Workflow

Dataset Preparation

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 4, October 2023 e-ISSN : 2541-2019
DOI : https://doi.org/10.33395/sinkron.v8i4.12974 p-ISSN : 2541-044X

In this stage, there are three data preparation processes: dataset collection, dataset labeling, and dataset augmentation. The dataset collected in this research is the Leaf Disease Image (LDI) dataset developed by (Syed-Ab-Rahman et al., 2022), consisting of 596 citrus leaf images. The LDI dataset is used to identify diseases on citrus leaves and includes images of both infected and healthy citrus leaves. The dataset consists of four classes, comprising three types of citrus leaf diseases: blackspot, canker, and greening, as well as one class for healthy leaves. The collected citrus disease dataset is then labeled based on the information provided in the images. Subsequently, dataset augmentation is employed to increase variation in the dataset, prevent overfitting, and enhance model quality. Data augmentation involves various techniques such as rotation, translation, flipping, image resizing, filling empty pixels, and image distortion. Prior to augmentation, the LDI dataset contains 596 images, and after augmentation, the dataset size increases to 3000 images, with each class comprising 750 images. Figure 2 provides a visualization of the dataset used in this research.

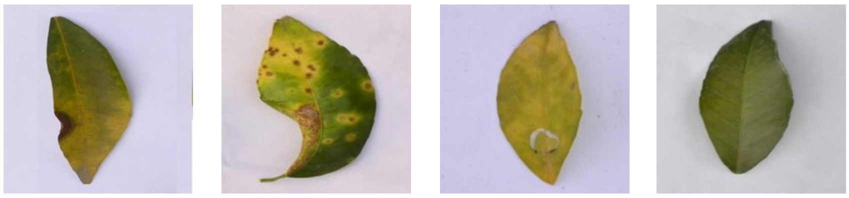

Fig. 2 Citrus Leaf Dataset

Dataset Pre-processing

In this stage, several processes are performed, starting with resizing the images to 224x224 pixels, enhancing image quality using the CES (Color Enhancement by Scaling) technique, converting the images using various techniques, normalizing the dataset, and dividing the data to proceed to the next step, which is creating the CNN model. However, after improving the image quality with the CES technique, there are two different testing scenarios: one without additional image conversion techniques and one with additional image conversion processes. At the end of this stage, the dataset is divided into three parts: 80% for training data, 10% for testing data, and 10% for validation data.

Detection and Classification Model Training

The pre-processed citrus disease dataset is then input into the convolutional layers using the DenseNet-169 model, which has previously been trained using the ImageNet dataset and modified by adjusting the final layers. Relevant features from the citrus leaf images are extracted using the DenseNet-169 model. These features encompass visual characteristics such as texture, color, and shape that can indicate the presence of diseases in citrus plants. The model is trained, validated, and evaluated in each scenario, and evaluation metrics such as accuracy, precision, and recall are employed to assess performance. Figure 3 illustrates the architecture of DenseNet-169.

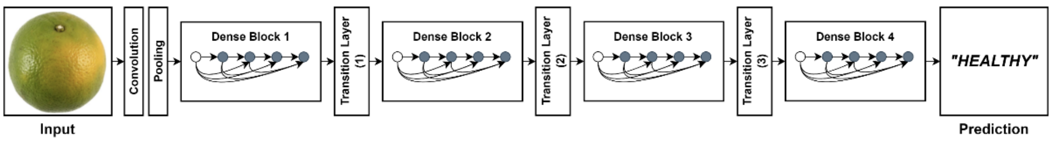

Fig. 3 DenseNet-169 Architecture

1) DenseNet-169

DenseNet-169 is one of the convolutional neural network (CNN) architectures developed by (Huang et al., 2017) to enhance the performance and efficiency of CNNs in object recognition tasks. Figure 7.3 illustrates the schema of the dense block, which is a key component of the DenseNet architecture. The dense block consists of multiple convolutional layers that are directly connected, so each layer receives all feature maps from the previous layers as input and produces k new feature maps as output. The parameter k is referred to as the growth rate because

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 4, October 2023
DOI : https://doi.org/10.33395/sinkron.v8i4.12974
e-ISSN : 2541-2019
p-ISSN : 2541-044X

it determines how much new information is added by each layer. Thus, the dense block facilitates the flow of information and gradients between layers in the network and encourages the reuse of learned features. Figure 4 depicts an example of a dense block with 5 layers and k = 4.

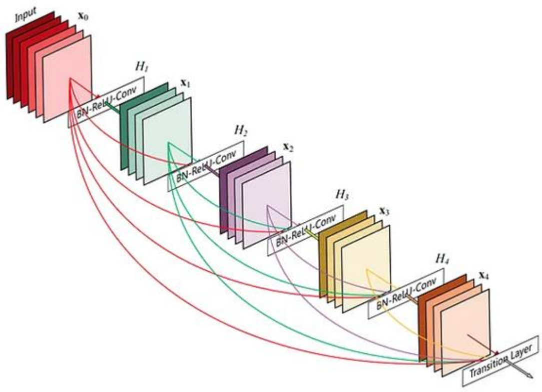

Fig. 4 Solid Block with 5 Layers and k = 4

2) DenseNet-169 with Feature Combination
DenseNet-169 Feature Combination is a term referring to the DenseNet-169 model that utilizes feature combination. In this context, "feature combination" indicates that the model leverages various features or different data representations to perform a specific classification or analysis task. DenseNet-169 itself is a type of artificial neural network architecture known in the field of deep learning. When this model uses "feature combination," it means that the model may integrate information from various sources or features in decision-making. The use of feature combination can enhance the model's ability to extract and utilize relevant information from the given data.

Analysis and Conclusion

This analysis aims to gain a deeper understanding of the model's performance, identify its strengths and weaknesses, and pinpoint aspects that need improvement or optimization. Based on this analysis, we can draw conclusions regarding the success or failure of the model in classifying skin disease types. These conclusions will provide crucial information for evaluating whether the developed model has achieved the research objectives or requires further refinement. They can also serve as the basis for decision-making or providing recommendations related to the model's application in clinical practice or further research.

Performance Evaluation

Performance evaluation is the process of assessing the performance of a system, model, or entity based on specific metrics and criteria. In the context of the presented results, performance evaluation is conducted on the DenseNet-169 model and feature combination for the classification task on the citrus plant disease dataset.

1. Accuracy: Accuracy measures how well the model can correctly classify data. It is calculated by dividing the number of correct predictions (True Positives and True Negatives) by the total number of data points.
$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (1)$$
2. Precision: Precision measures how accurately the model's positive predictions are. It is the ratio of True Positives to the total positive predictions (True Positives and False Positives).
$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$
3. Sensitivity: Sensitivity, also known as Recall or True Positive Rate (TPR), measures how well the model can detect all true positive cases. It is the ratio of True Positives to the total true positive cases (True Positives and False Negatives).

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 4, October 2023
DOI : https://doi.org/10.33395/sinkron.v8i4.12974
e-ISSN : 2541-2019
p-ISSN : 2541-044X

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

4. F1-Score: The F1-Score is a combined measure of precision and recall. It balances the model's ability to identify positive classes correctly (precision) and its ability to detect all positive cases (recall).

$$F1 - Score = \frac{(2\times Precision\ \times Recall)}{(Precision\ \times Recall)} \quad (4)$$

RESULT

The experiments in this research were conducted on 3,000 images sourced from the LDI dataset, comprising 750 images from four different classes: blackspot, canker, greening, and healthy. Each testing finding is discussed in this section. The DenseNet-169 architecture model and DenseNet-169 with CNN-based Feature Combination were used in the experiments using training, validation, and testing data. The dataset was split into 80% for training, 10% for testing, and 10% for validation. The presented test results are for the DenseNet-169 model for the multi-class classification task on the citrus plant disease dataset. Table 1 shows the accuracy and loss for both the training and validation data for each pre-trained CNN-based model. The experiments demonstrated that DenseNet-169 with feature combination outperformed the DenseNet-169 model in terms of performance, with a validation accuracy of 96.67%.

Table. 1 Accuracy, Loss and Validation Models

Pre-train Model	Training Accuracy (%)	Validation Accuracy (%)	Training Loss (%)	Validation Loss (%)
DenseNet-169	100	91.33	32.05	59.97
DenseNet-169 Feature Combination	100	96.67	32.90	43.50

Table 1 also displays the validation losses for each trained DenseNet-169 model. With a value of 43.50%, DenseNet-169 with feature combination becomes the architecture with the lowest training loss, followed by DenseNet-169 with a value of 59.97%. The accuracy and loss curves achieved during the training phase are shown below in Figures 5 and 6.

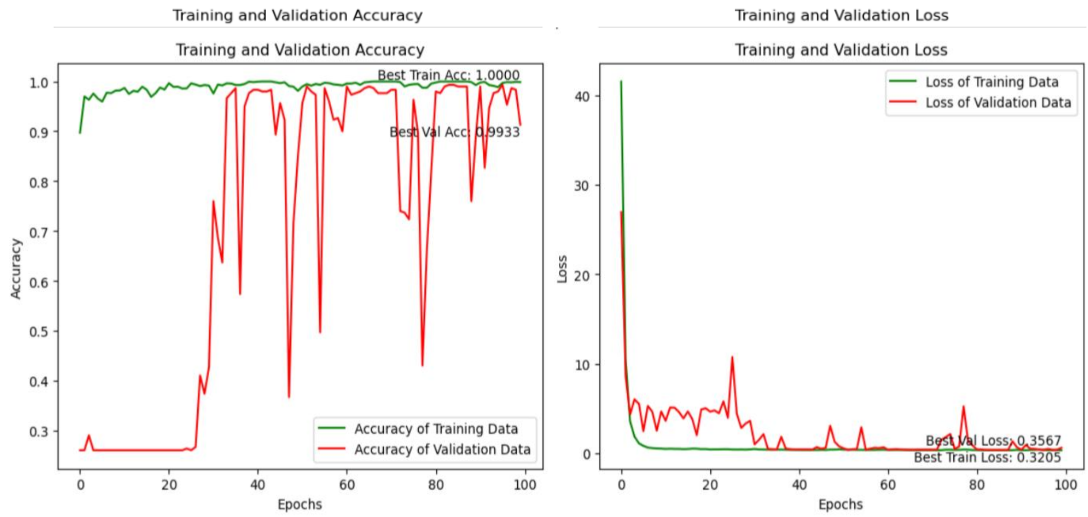

Fig. 6 Accuracy and Loss Graph of DenseNet-169 Model

Table. 2 Class Based Accuracy of the Proposed Model

No	Model	Class

*name of corresponding author

		Blackspot	Canker	Greening	Healthy
1	DenseNet-169	92.86%	71.62%	100%	100%
2	DenseNet-169 Feature Combination	97.14%	98.65%	91.18%	98.86%

The results of the experiments show the performance comparison between two models, DenseNet-169 and DenseNet-169 Feature Combination, in classifying four classes of citrus plant diseases: Blackspot, Canker, Greening, and Healthy.

DenseNet-169 model produced varying accuracies, with the highest rates in the "Greening" and "Healthy" classes reaching 100%, while the "Blackspot" class achieved 92.86%, and "Canker" reached 71.62%. On the other hand, the DenseNet-169 Feature Combination model showed a significant improvement in accuracy. For the "Blackspot" class, accuracy increased to 97.14%, and for "Canker," it reached 98.65%. Although the accuracy for the "Greening" class was slightly lower at 91.18%, and there was a minor change in the "Healthy" class with an accuracy of 98.86%, the overall results indicate that the use of feature combination is effective in enhancing the model's ability to identify diseases in citrus plants.

Therefore, the DenseNet-169 model with feature combination offers a significant performance improvement in the task of citrus plant disease classification, which can support efforts for plant health monitoring and more sustainable agriculture. To examine the experimental results and evaluate the models, we compared the performance of two models, DenseNet-169 and DenseNet-169 Feature Combination, considering accuracy, precision, recall, and F1 score, as shown in Table 3.

Table. 3 Performance evaluation of trained models with testing data

No	Performance	DenseNet-169	DenseNet-169 Feature Combination
1	Accuracy	91.33%	96.66%
2	Precission	91.18%	96.46%
3	Recall	91.11%	96.45%
4	F1-Score	90.66%	96.43%

In the table above, there is a performance comparison between the DenseNet-169 model in two different scenarios: using original features and using feature combination on the citrus plant disease dataset. The DenseNet-169 model with original features achieved an accuracy rate of 91.33%. However, the DenseNet-169 model that utilizes feature combination managed to achieve a higher accuracy rate, reaching 96.66%. Thus, the model that combines features has better capabilities in accurately classifying data compared to the model that relies solely on original features.

It is important to note that the 5.33% increase in accuracy achieved through the use of feature combination indicates a significant enhancement in the model's ability to identify and classify citrus plant diseases. This provides strong evidence that the utilization of feature combination can be an effective strategy to enhance the model's performance in the classification task on this dataset.

*name of corresponding author

SinkrOn
JURNAL & PENELITIAN TEKNIK INFORMATIKA
Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 4, October 2023
DOI : https://doi.org/10.33395/sinkron.v8i4.12974
e-ISSN : 2541-2019
p-ISSN : 2541-044X

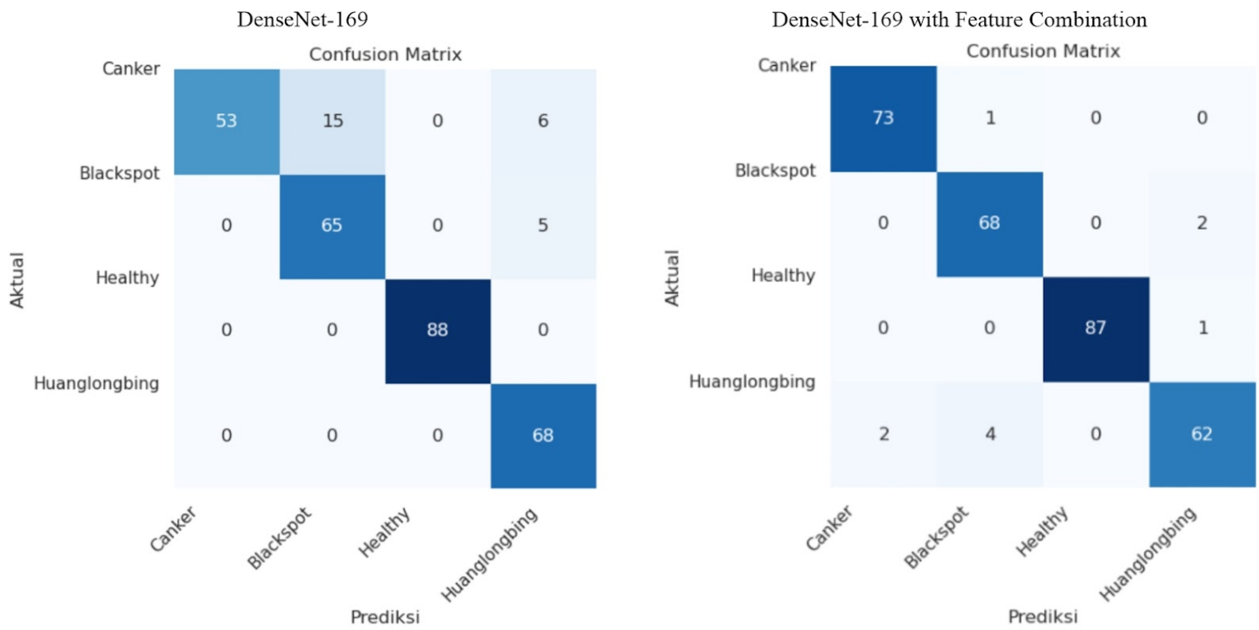

Fig. 5 Confusion Matrix of DenseNet-169 and DenseNet-169 with Feature Combination

The confusion matrices related to the testing data on the DenseNet-169 architecture and DenseNet-169 with feature combination have been presented in Figure 7. From the illustration in Figure 7, there are several samples that have been misclassified. In the confusion matrix of DenseNet-169, there are 26 data samples that were misclassified during testing. Meanwhile, in the confusion matrix of DenseNet-169 with feature combination, only 10 data samples were misclassified out of the total tested data samples. These results indicate that the DenseNet-169 architecture enriched with feature combination demonstrates improved performance compared to the DenseNet-169 model that does not utilize feature combination.

DISCUSSIONS

In this research, trials have been carried out using 3000 images from the LDI dataset which consists of 750 images from four different classes, namely blackspot, canker, greening, and healthy. This dataset is then divided into three parts: 80% is used for training, 10% for testing, and 10% for validation.
The test results we present show that the DenseNet-169 model has been used for multiclass classification tasks on citrus plant disease datasets. We performed two test scenarios: one using the original features and the other with a combination of features.

The research results show that by using a combination of features, the model achieves the highest level of accuracy of 96.66%, while the model that only uses original features achieves an accuracy of 91.33%. This increase in accuracy of 5.33% indicates that the use of combination features is very effective in increasing the model's ability to recognize and classify diseases in citrus plants.

The importance of this research lies in its theoretical and practical implications. From a theoretical perspective, this research shows that the use of combined features in image processing can result in significant improvements in model performance in multiclass classification tasks. This illustrates the importance of a more holistic approach to image processing for plant health monitoring.

From a practical perspective, the results of this research have significant positive implications in the context of plant health monitoring and agriculture. More accurate models in identifying diseases in citrus crops can help farmers and researchers detect problems early, take necessary actions, and thereby, increase crop yields and reduce losses. Thus, this research can make a valuable contribution in supporting sustainable agriculture and food security.

*name of corresponding author

Sinkron : Jurnal dan Penelitian Teknik Informatika
Volume 7, Number 4, October 2023
DOI : https://doi.org/10.33395/sinkron.v8i4.12974
e-ISSN : 2541-2019
p-ISSN : 2541-044X

CONCLUSION

From the results of this study, it can be concluded that the use of the DenseNet-169 model in the classification of citrus plant diseases has great potential to improve plant health monitoring and agricultural efficiency. In tests involving 3000 images from the LDI dataset with four different classes, namely blackspot, canker, greening, and healthy, the use of a combination of features in image processing resulted in a significant increase in model accuracy, reaching the highest level of 96.66%. This indicates that a holistic approach by combining various features can improve the model's ability to recognize and classify diseases in citrus plants

REFERENCES

Ahmed, H., Hossain, M. A., Hossain, I., Akhi, S. S., & Lima, I. J. (2022). Detection and classification of plant diseases in leaves through machine learning. *Indonesian Journal of Electrical Engineering and Computer Science*, *28*(3), 1676–1683. https://doi.org/10.11591/ijeecs.v28.i3.pp1676-1683

Dhiman, P., Kaur, A., Hamid, Y., Alabdulkreem, E., Elmannai, H., & Ababneh, N. (2023). Smart Disease Detection System for Citrus Fruits Using Deep Learning with Edge Computing. *Sustainability (Switzerland)*, *15*(5), 1–18. https://doi.org/10.3390/su15054576

Elaraby, A., Hamdy, W., & Alanazi, S. (2022). Classification of Citrus Diseases Using Optimization Deep Learning Approach. *Computational Intelligence and Neuroscience*, *2022*. https://doi.org/10.1155/2022/9153207

Ganesh, P., Volle, K., Burks, T. F., & Mehta, S. S. (2019). Deep Orange: Mask R-CNN based Orange Detection and Segmentation. *IFAC-PapersOnLine*, *52*(30), 70–75. https://doi.org/10.1016/j.ifacol.2019.12.499

Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, *2017-Janua*, 2261–2269. https://doi.org/10.1109/CVPR.2017.243

Kukreja, V., & Dhiman, P. (2020). A Deep Neural Network based disease detection scheme for Citrus fruits. *Proceedings - International Conference on Smart Electronics and Communication, ICOSEC 2020*, *Icosec*, 97–101. https://doi.org/10.1109/ICOSEC49089.2020.9215359

Lestari, F. R., Sari, J. Y., Sutardi, & Purwanti, I. (2018). *Deteksi Penyakit Tanaman Jeruk Siam Berdasarkan Citra Daun*. *December*, 276–283.

Mangla, M., Mehta, V., Mohanty, S. N., Sharma, N., & Preetham, A. (2022). Statistical growth prediction analysis of rice crop with pixel-based mapping technique. *International Journal of Artificial Intelligence and Soft Computing*, *7*(3), 208–227. https://doi.org/https://doi.org/10.1504/IJAISC.2022.126342

Parananda, E. (2022). *PETANI JERUK TERANCAM GAGAL PANEN*. Bali Post. https://www.balipost.com/news/2022/12/18/311628/Petani-Jeruk-Terancam-Gagal-Panen.html

Safdar, A., Khan, M. A., Shah, J. H., Sharif, M., Saba, T., Rehman, A., Javed, K., & Khan, J. A. (2019). Intelligent microscopic approach for identification and recognition of citrus deformities. *Microscopy Research and Technique*, *82*(9), 1542–1556. https://doi.org/10.1002/jemt.23320

Saputra, A. D., Hindarto, D., & Santoso, H. (2023). Disease Classification on Rice Leaves using DenseNet121, DenseNet169, DenseNet201. *Sinkron*, *8*(1), 48–55. https://doi.org/10.33395/sinkron.v8i1.11906

Shireesha, G., & Reddy, B. E. (2022). Citrus Fruit and Leaf Disease Detection Using DenseNet. *2022 International Conference on Smart Generation Computing, Communication and Networking (SMART GENCON)*. https://doi.org/https://doi.org/10.1109/SMARTGENCON56628.2022.10083852

Singh, H., Rani, R., & Mahajan, S. (2020). Detection and Classification of Citrus Leaf Disease Using Hybrid Features. *Advances in Intelligent Systems and Computing*, 737–745.

Soini, C. T., Fellah, S., & Abid, M. R. (2019). Citrus greening infection detection (CIGID) by computer vision and deep learning. *ACM International Conference Proceeding Series*, 21–26. https://doi.org/10.1145/3325917.3325936

*name of corresponding author

Syed-Ab-Rahman, S. F., Hesamian, M. H., & Prasad, M. (2022). Citrus disease detection and classification using end-to-end anchor-based deep learning model. *Applied Intelligence*, *52*(1), 927–938. https://doi.org/10.1007/s10489-021-02452-w

Xing, S., Lee, M., & Lee, K. K. (2019). Citrus pests and diseases recognition model using weakly dense connected convolution network. *Sensors (Switzerland)*, *19*(14). https://doi.org/10.3390/s19143195

*name of corresponding author