407-Bistek-Similarity---

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Implementation of ResNet 101 Architecture in Convolutional Neural Network (CNN) Algorithm to Detect Diseases in Chili Plant Leaves Based on Image Processing

ABSTRACT

Chili plants (Capsicum annuum L.) represent a crucial horticultural crop in Indonesia, with increasing output levels. Chili growers often face challenges, including a lack of understanding of illnesses affecting chili plant leaves and the utilization of technology. The principal diseases identified are leaf spot, curly virus, and gemini virus, which can reduce chili production. The utilization of the ResNet 101 architecture in Convolutional Neural Networks (CNN) for disease detection in plant images constitutes a feasible method. The ResNet 101 architecture in convolutional neural networks is utilized to detect and categorize various diseases in chili leaves, enabling early recognition of disease symptoms. The residual architecture (ResNet 101) captures complex features in images to enhance the accuracy of disease diagnosis.

The study examines the implementation, challenges, and benefits of a disease detection system that employs several approaches, including observation and field research. The procedure involves collecting model image objects from each disease category (leaf spot, curly virus, gemini virus) and healthy leaves to create a dataset, augmented by expert consultations on disease diagnoses and modeling with the ResNet 101 architecture. The study's results demonstrate that the application of the ResNet 101 architecture in convolutional neural networks for detecting diseases in chili leaves, using a dataset of 1,518 images classified into four categories (leaf spot, curly virus, gemini virus, and healthy leaves), achieves a significant overall accuracy of 0.9382. It is imperative to compare this architecture with others to refine model outcomes and expand the dataset employed, thereby significantly improving accuracy levels.

Keywords: Tanaman Cabai, Penyakit Daun Cabai, Arsitektur ResNet 101, Convolution Neural Network (CNN).

INTRODUCTION

Chili plants (Capsicum annuum L.) represent a crucial horticultural crop in Indonesia, with increasing output levels. Chili growers often face challenges, including a lack of understanding of illnesses affecting chili plant leaves and the utilization of technology. The principal diseases identified are leaf spot, curly virus, and gemini virus, which can reduce chili production. The utilization of the ResNet 101 architecture in Convolutional Neural Networks (CNN) for disease detection in plant images constitutes a feasible method. The ResNet 101 architecture in convolutional neural networks

is utilized to detect and categorize various diseases in chili leaves, enabling early recognition of disease symptoms. The residual architecture (ResNet 101) captures complex features in images to enhance the accuracy of disease diagnosis.

The study examines the implementation, challenges, and benefits of a disease detection system that employs several approaches, including observation and field research. The procedure involves collecting model image objects from each disease category (leaf spot, curly virus, gemini virus) and healthy leaves to create a dataset, augmented by expert consultations on disease diagnoses and modeling with the ResNet 101 architecture. The study's results demonstrate that the application of the ResNet 101 architecture in convolutional neural networks for detecting diseases in chili leaves, using a dataset of 1,518 images classified into four categories (leaf spot, curly virus, gemini virus, and healthy leaves), achieves a significant overall accuracy of 0.9382. It is imperative to compare this architecture with others to refine model outcomes and expand the dataset employed, thereby significantly improving accuracy levels.

Yellow viral illness and Cercospora leaf spot are two significant ailments that hinder the cultivation of large red chili peppers. Pseudomonas aeruginosa and Bacillus cereus can alleviate yellow virus disease and Cercospora leaf spot in large red chili peppers, while also influencing the growth of the chili plants (Lestari & Aini, 2021). The yellow curly leaf virus is a notable disease in chili that causes substantial yield decreases (Andarwening et al., 2022).

The implementation of the ResNet101 architecture in the Convolutional Neural Network (CNN) algorithm enables the accurate analysis of chili leaf images, permitting farmers to detect signs of disease swiftly. This early detection allows farmers to implement preventive measures swiftly, hence reducing the risk of crop loss (Lopez-Betancur et al., 2024).

The information system, which employs the ResNet101 architecture within the Convolutional Neural Network (CNN) algorithm, enables disease diagnosis for farmers. Farmers can employ a mobile device or camera to transmit images of potentially infected leaves, and the CNN algorithm will provide a prompt diagnosis. This reduces reliance on manual expertise, allowing even inexperienced farmers to utilize technology using the CNN algorithm (Panigrahi et al., 2024). The CNN algorithm can learn from

historical disease data; therefore, as it analyzes further data, its ability to identify disease trends improves. This enhances detection efficacy and enables the system to provide more accurate treatment recommendations (Al Fathir Rizal Januar et al., 2025).

The integration of the ResNet101 architecture into the CNN algorithm within the plant health information system enhances systematic and coordinated data collection. The collected data can be analyzed to identify disease tendencies in a particular location, aiding farmers in future planning and management of chili cultivation. The study investigates the effectiveness of the ResNet101 architecture within the CNN algorithm for the swift and accurate analysis of chili leaf images to distinguish several disease types (leaf spot, gemini virus, curly virus, and healthy leaves).

RESEARCH METHODS

Research methods

The research technique included several steps, such as:

- **Research Design:** This step involves developing an experimental methodology for the study.
- **Data Selection:** During this phase, images of chili leaves are collected to assemble the dataset.
- **Image Preprocessing:** This stage involves resizing, augmenting, and normalizing the images. This study utilizes the ResNet 101 architecture.
- **Research Method Selection:** At this juncture, the loss function and optimizer are determined.
- **Model Training:** This phase involves training the model using the dataset that has been optimized in the previous steps.
- **Model Evaluation:** This phase evaluates the accuracy and effectiveness of the model using the dataset.
- **Data Analysis:** This phase evaluates the results and determines the model's effectiveness.
- **System Implementation:** This step incorporates the verified model architecture into an information system, such as a web-based or mobile application.

The research method is attached in the image below:

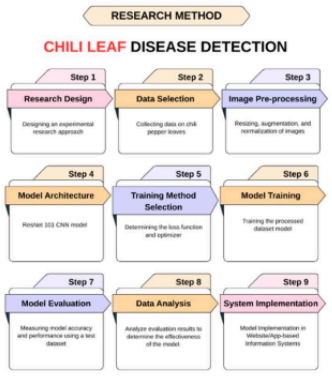


Figure 1. Research method

Development Method

The development technique is crucial throughout the system design phase as it optimizes the creative process and improves both effectiveness and efficiency. Each phase consists of actions based on methodologies, procedures, and tools to achieve objectives (DEMİRAG et al., 2023). This study utilizes the waterfall methodology for system development. The initial phase involves assessing requirements, starting with the existing techniques used by farmers to detect diseases in chili plants and the historical data employed to understand the system's implementation to be developed. This is followed by system design, which employs context diagrams and interactions across tables, along with interface design.

Programming is executed using Python and JavaScript, alongside a MySQL database. The program undergoes testing to identify any errors or issues that may arise. The final phase involves implementing the system on the research subjects. The waterfall method involves the sequential or linear progression of system development. Subsequent phases cannot proceed if the original step is unfinished. The waterfall methodology to be utilized is illustrated in the diagram below.

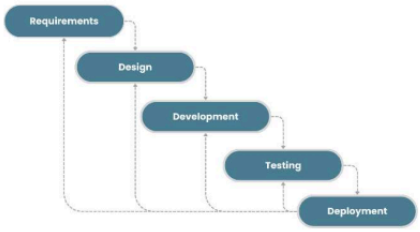


Figure 2. Waterfall models

The study process commences with an examination of the challenges associated with disease detection in chili plants. The study thereafter delineates the issues and articulates the research questions. It subsequently tackles the research issues informed by literature reviews and originality, delineates the analytical methodologies and system creation, executes the system, conducts testing, and assesses the outcomes of the system's application. The research protocols that must be adhered to are illustrated in the diagram below.

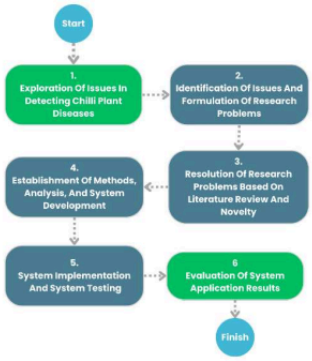


Figure 3. Research procedure

RESULT AND DISCUSSION

The research findings are categorized into multiple phases, from model testing to model deployment into the information system.

Calculating the Number of Datasets per Class

The dataset has the following class distributions: Gemini (391 images), spots (327 photographs), healthy (327 images), and curly (473 images). Figure 4 is attached below—a bar chart illustrating the quantity of photos categorized by class.

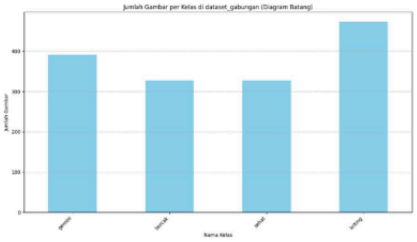


Figure 4. Per-class bar chart of the combined dataset

Additionally, the distribution includes 31.2% for the curly class, 25.8% for the gemini class, 21.5% for the spotted class, and 21.5% for the healthy class. Figure 5 presents the aggregated dataset for each class depicted as a pie chart below.

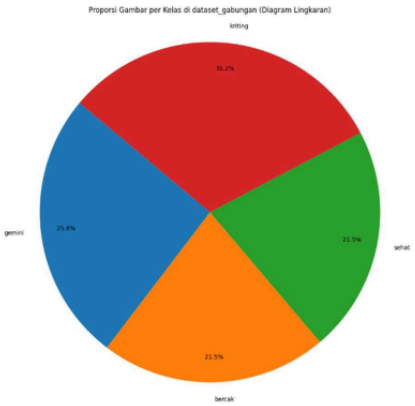


Figure 5. Per-class circle image of the combined dataset

Load Base Model ResNet 101

At the loading phase of the ResNet 101 model, the summary results table for the resnet101_classifier is provided for picture classification. The ResNet architecture comprises 101 levels, as detailed in Table 1 below.

Table 1. Resnet101_classifier model

Layer (type)	Output Shape	Param #	Connected to
input_image (InputLayer)	(None, 224, 224, 3)	0	-
conv1_pad (ZeroPadding2D)	(None, 230, 230, 3)	0	input_image[0][0]
conv1_conv (Conv2D)	(None,	9,472	conv1_pad[0][0]

Layer (type)	Output Shape	Param #	Connected to
	112, 112, 64)		
conv1_bn (BatchNormalization…)	(None, 112, 112, 64)	256	conv1_conv[0][0]
conv1_relu (Activation)	(None, 112, 112, 64)	0	conv1_bn[0][0]
pool1_pad (ZeroPadding2D)	(None, 114, 114, 64)	0	conv1_relu[0][0]
pool1_pool (MaxPooling2D)	(None, 114, 114, 64)	0	pool1_pad[0][0]
…..	…..	…..	…..

Upon categorization into 101 layers, the subsequent results of the ResNet classifier are presented.

Total parameters: 43,183,748 (164.73 MB)

Trainable params: 525,572 (2.00 MB)

Non-trainable params: 42,658,176 (162.73 MB)

Training ResNet 101

During the training process of the ResNet 101 architecture, one component is the training of the head solely, as illustrated in Figure 6 below.

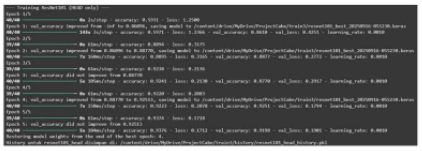


Figure 6. Training (Head Only)

The ResNet 101 model training yielded incremental improvements in accuracy at each epoch, culminating in a peak accuracy of 0.9331 and a notable reduction in loss, indicating enhanced data classification capabilities. The subsequent step in the training phase of the ResNet 101 architecture involves fine-tuning ResNet 101 (partial unfreeze) until epoch 35, achieving an accuracy of 0.9994, a loss of 0.0037, a validation accuracy of 0.9465, and a validation loss of 0.1911, as illustrated in Figure 7 below.

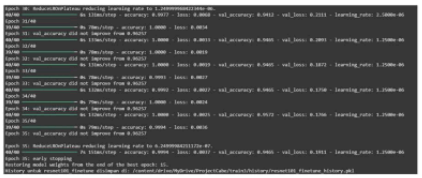


Figure 7. fine-tuning (partial unfreeze)

Training/Validation Loss and Accuracy graphs

In the next phase of assessing the model's performance, we detect overfitting and determine the optimal model, as illustrated in the training/validation loss and accuracy graphs.

The picture below illustrates the training history for ResNet 101 (head training) at epoch 4.0, showing a loss of 0.2. However, the accuracy for ResNet 101 (head training) at epoch 40 exceeds 0.8 and approaches 1.0.

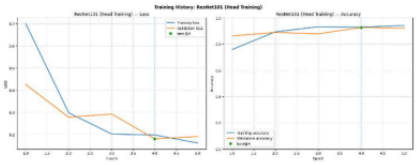


Figure 8. Training history: ResNet 101 (head tanning)

In the training history of ResNet 101 (fine-tuning), epoch 10 has a loss of over 0.10, although the accuracy for epoch 10 approaches 1.0.

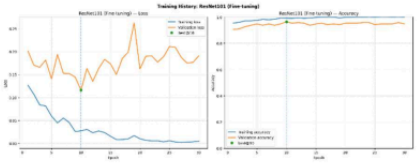


Figure 9. Training history RestNet 101 (fine - tuning)

Accuracy Test

The subsequent information is appended to Table 2 for predictions regarding the Test set of prediction distributions: {'spotted': 20, ' gemini': 22,'curly ': 22, ' healthy': 17}.

Table 2. Model evaluation matrix

Metrics Evaluasi Model (ResNet101)				
Overall Accuracy: 0.9383				
Classification Report (Precision, Recall, F1-Score) per class:				
	Precision	Recall	F1-Score	Support
Spotted	0.8500	0.9444	0.8947	18
Gemini	0.9545	1.0000	0.9767	21
Curly	1.0000	0.9167	0.9565	24
Healthy	0.9412	0.8889	0.9143	18
Accuracy			0.9383	81
Macro avg	0.9364	0.9375	0.9356	81
Weighted avg	0.9418	0.9383	0.9386	81

The outcomes of the predictions derived from the confusion matrix and the classification model encompass all 17 leaf spot classes, 21 gemini classes, 22 curly classes, and 16 healthy classes. Refer to Figure 2 below.

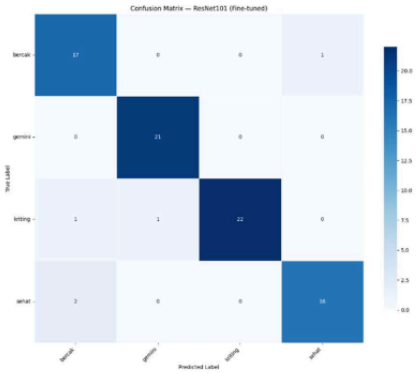


Figure 10. Confusion matrix – ResNet101 (fine-tuned)

The normalized confusion matrix revealed that the classification model exhibited outstanding performance, with the Gemini and Curly classes attaining flawless accuracy of 1.0, signifying that all predictions for these classes were accurate.

This is depicted in the graphic below.

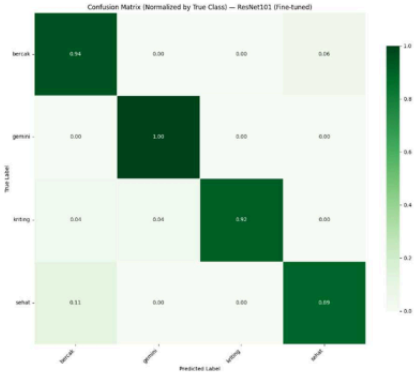


Figure 11. Confusion matrix (normalized by true class) – ResNet 101 (fine-tuned)

The table below displays the accuracy for each evaluated class as assessed by the model.

Table 3. Accuracy per class

	Class	Accuracy
0	Spots	0.944
1	Gemini	1.000
2	Curly	0.917
3	Healthy	0.917

Classification Test

Testing simulations for each class: {'spotted', 'gemini', 'curly', and 'healthy'}. Classification assessment for chili leaf photos.

Submit a single image of a chili leaf (.jpg/.png):



Top-1 Prediction: curly (p = 0.9954)

Table 4. Probability classes

	Class	**Probability**
0	Curly	0.995368
1	Healthy	0.003248
2	Spots	0.001058
3	Gemini	0.000326

Attached is a probability diagram of the detection results for the curly prediction class.

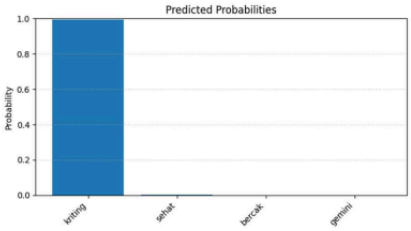


Figure 12. Predicated probabilities

Implementation of models in information systems

The deployment of the ResNet 101 architectural model is the outcome of training the model for each class: {'leaf spot', 'gemini', 'curly', and healthy}. The phases for delineating the detection model are categorized into two approaches: the initial approach permits users to contribute photographs, whereas the subsequent approach employs a camera stream scanning functionality.

Object of the spot class

The diagnostic outcomes for the leaf spot category encompass treatment methodologies, beginning with the symptoms of leaf spot disease, control strategies, and field treatment protocols. Figure 13 below illustrates the object for the leaf spot class during the model implementation phase.

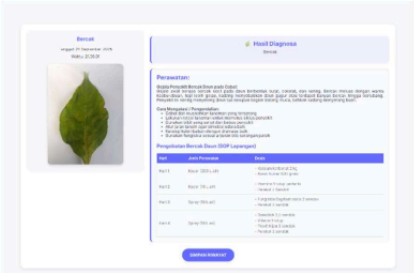


Figure 13. Scan of the spot class

Gemini class objects

The diagnostic findings for the Gemini class encompass treatment modalities, commencing with the symptoms of Gemini sickness, control strategies, and field management for the Gemini virus. Standard Operating Procedure, Figure 14 below illustrates the object for the Gemini class during the implementation phase.

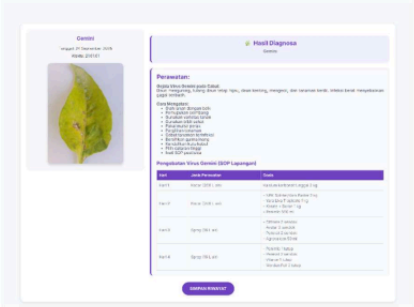


Figure 14. Gemini class scan

Object of class curly

The diagnostic results for curly leaf illness include treatment methods, symptoms, management strategies, and remedies for field leaf curl. Figure 15 below illustrates the class objects of the curly leaf disease during the implementation stage.

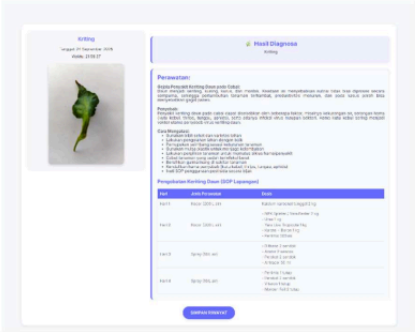


Figure 15. Scan of the curly class

Healthy class object

The diagnostic results for the healthy class include attached chili plant care strategies for optimal circumstances and plant maintenance in compliance with field operational standards. The healthy class object at the implementation phase is seen in Figure 16 below.

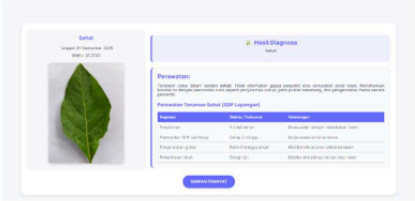


Figure 16. Healthy class scan

The findings of implementing the detection model with ResNet 101 within the information system indicate that each class {'leaf spot', 'gemini', 'curly', 'healthy'} corresponds with the training data model evaluated in the preceding modeling phase. The detection simulation utilizing the ResNet 101 model, derived from the training data, can be accessed at the following link: https://bit.ly/leaf-detection

CONCLUSION

The research findings indicate that the application of the ResNet 101 architecture within the Convolutional Neural Network (CNN) algorithm has demonstrated efficacy in identifying illnesses in chili plant leaves using image processing, achieving an overall accuracy of 0.9383. The ResNet 101 model effectively utilizes substantial network depth to extract intricate features from the leaf image dataset categorized into predefined classes: leaf spot, gemini, curly, and healthy, hence enhancing the accuracy of disease type recognition. Through the application of data augmentation approaches and fine-tuning, the model demonstrates enhanced classification accuracy, attaining scores of 0.944 for leaf spot, 1.00 for gemini, 0.917 for curly, and 0.917 for healthy, thereby diminishing the probability of diagnostic errors. This research highlights the significant potential of utilizing technology in agriculture, enabling farmers to make faster, more precise, and more effective decisions regarding plant health management. Additional research and testing on more extensive datasets and other disease types are anticipated to improve the system's reliability.

REFERENCES

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