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Classification of Chili Fruit Diseases Using Deep Convolutional Neural Network Transfer Learning

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ABSTRACT

Chili peppers are among the highest-value agricultural commodities, often experiencing significant price fluctuations due to supply constraints. The rainy season frequently leads to crop failures caused by diseases affecting chili plants. Existing methods often struggle to accurately differentiate between similar symptoms on leaves and fruits, leading to misdiagnosis and ineffective disease management strategies. Early detection of these diseases, which manifest as symptoms on the leaves and fruits, is crucial for effective pest management. Common diseases include anthracnose, characterized by dry brown spots on the fruit, and fruit rot, where the interior of the fruit decays while the skin remains intact. Identifying these diseases promptly is essential for applying appropriate treatments to ensure optimal yields.In this study, a comprehensive approach is taken to classify diseases in chili pepper plants (Capsicum annuum L.) by incorporating both leaf and fruit segmentation. The research employs Deep Convolutional Neural Networks with Transfer Learning (DCNN) to enhance detection capabilities. The findings reveal that for leaf disease classification, fewer neurons in additional layers yield better accuracy and reduced loss, while for fruit disease classification, a more complex model with additional neurons is necessary. This underscores the need for balancing model complexity to achieve optimal performance and prevent overfitting, particularly in distinguishing between leaf and fruit diseases.

Keywords: Deep Convolutional Neural Network, Chilie Fruit Disease, Transfer Learning

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INTRODUCTION

Chili peppers are one of the highest-value agricultural commodities or vegetable crops compared to other vegetables (Nauly, 2020). Currently, the price of chili peppers often fluctuates and experiences significant increases in the market due to limited supply (Farid & Subekti, 2012). For chili farmers, the rainy season often leads to crop failure due to the prevalence of diseases attacking chili plants. However, these diseases can be detected early by observing the symptoms or changes that appear on the leaves and fruits of the chili peppers (Zikra et al., 2021), (Anwar, 2023).

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Diseases or pests that attack chili plants can vary greatly within a single plant. Here are some common diseases or pests that affect chili plants: (1) Anthracnose disease, which is characterized by dry brown spots resembling burns on chili fruits, and (2) Fruit rot disease, where the inside of the fruit becomes rotten and black, while the skin remains fresh (Meilin, 2014). These diseases must be identified quickly so that farmers can apply pesticides to ensure optimal yields from chili plants. Understanding chili plant diseases is not easy, and many farmers do not fully understand chili plants and the diseases or pests that attack them. As a result, symptoms often go undetected early on.

In the application of Computer Vision in agriculture, several previous studies have classified diseases on plant leaves using Convolutional Neural Networks (CNN). These studies have improved the model and utilized various types of plant leaves for disease identification, with a total of 10 types of leaves used (Hang et al., 2019). Additionally, in research combining YOLO and CNN, leukocyte identification in leukemia was conducted. YOLO is used for detecting leukocyte objects in leukemia, while CNN functions to classify leukocytes into the classes Lymph, Mono, and Neutro (Abas et al., 2022).

In a study focused on detecting diseases in chili plants, the Gray Level Co-Occurrence Matrix method was used to extract features from images of chili leaves, followed by multiclass classification using a Support Vector Machine (Zikra et al., 2021), (Anwar, 2023). The study achieved an accuracy of 95% with a computation time of 3 to 3.7 seconds for detecting disease in a single leaf image. Previous research related to disease detection in chili plants has been helpful but lacks fast computation time. Additionally, disease detection has primarily focused on leaf images and has not extended to detecting diseases in chili fruit images (Meilin, 2014). Based on the above explanation, the researcher will conduct a study focusing on the classification of diseases in chili pepper plants (Capsicum annuum L.), which will include segmentation of both leaves and fruits. In this study, images of chili fruits will be classified to detect diseases using Deep Convolutional Neural Network with Transfer Learning (DCNN).

METHOD

A. Analysis and Design

The analysis and design of the program will outline the input and output of the developed program and determine the required model. Specifically, the analysis will focus on identifying the types of data (such as images of chili fruits) that will serve as input, and the expected output (such as the classification of specific diseases). In the design depicted through the flowchart, one optimal DCNN model is needed for detecting diseases in chili fruits. The design process involves experimenting with different configurations, where the best model is obtained by comparing performance metrics like accuracy and loss while systematically adding layers during fine-tuning using the base model EfficientNetV2. The chosen model will be validated to ensure it generalizes well to new, unseen data, thus ensuring its effectiveness in real-world applications.

B. Building Dataset

The dataset used in this study was obtained from chili farms in Malang City, with the chili peppers ranging in age from 2 to 5 months, or ripe for harvest. A total of 1,200 chili plant disease images were collected, categorized into three classes: normal chili, chili with leaf spot disease, and chili with fruit rot diseaseas, shown in Table 1. We have published the dataset on Roboflow, which can be accessed through the following link https://app.roboflow.com/tesis-ttvii/chili-t51wv/overview .

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Table 1. Dataset

Class	Informant	Quantity	Picture
fruit rot diseases	Having black spots or being black in color.	502	
chili spot disease	Having parts of the chili that appear dry and scorched	401	
normal chili	Having green or red color and without any black or brown spots.	603	

Course : Roboflow

C. Implementation and Testing
For the DCNN model using transfer learning on chili leaves and fruits, fine-tuning is applied. Fine-tuning involves unfreezing several top layers that were previously frozen and training new classifiers that are added, along with the layers of the model that remain unfrozen. This technique aims to optimize the weights of the new classifiers as well as the weights of some or all of the base layers of the pre-trained model, with the goal of improving the accuracy of disease detection in chili plants. Fine-tuning allows the model to better adapt to new data while leveraging the existing knowledge from the pre-trained model.

To evaluate the performance of the DCNN model, accuracy and precision are commonly calculated. Accuracy is determined by dividing the number of correctly predicted instances by the total number of instances in the dataset. It is expressed as:

$$accuracy = \frac{Number\ of\ correct\ Prediction}{Total\ Number\ of\ Predictions}$$

Precision, on the other hand, measures the proportion of true positive predictions out of all positive predictions made by the model. It is calculated as:

$$Precision = \frac{True\ Positif}{True\ Positif + False\ Positif}$$

Both metrics are crucial for assessing the model's performance in detecting diseases in chili plants, with accuracy providing a general measure of performance and precision indicating the reliability of positive predictions.

Additionally, the performance of the model can be assessed using a confusion matrix. A confusion matrix is a table used to describe the performance of a classification model by comparing the predicted labels to the true labels. It consists of four components:

- True Positives (TP): The number of instances correctly predicted as positive.
- False Positives (FP): The number of instances incorrectly predicted as positive.
- True Negatives (TN): The number of instances correctly predicted as negative.
- False Negatives (FN): The number of instances incorrectly predicted as negative.

RESULTS AND DISCUSSION
The DCNN model in this study uses EfficientNetV2, which is then applied with transfer learning through fine-tuning techniques. EfficientNetV2 offers advantages such as improved training speed and enhanced parameter efficiency compared to previous models. The EfficientNetV2 architecture includes several developments, such as: (1) adding MBCov and fusedMBCov to the early layers, (2)

using a smaller expansion ratio for MBConv, as smaller expansion ratios tend to reduce memory access overhead, (3) selecting a smaller 3x3 kernel with additional layers to compensate for the reduced receptive field due to the smaller kernel size, and (4) removing the final stride-1 stage in the original EfficientNet to decrease parameter size and memory access overhead (Tan & Le, 2021), (Anwar, 2023). The EfficientNetV2 method is implemented in three versions: S, M, and L, initialized according to the size of the model.

The DCNN model developed in this study requires a single classification dataset with image dimensions of 224 x 224 pixels, which aligns with the input specifications for the EfficientNetV2 model. For this research, the EfficientNetV2 model chosen is the medium (M) version. This version offers a balanced model size that is neither too large nor too small, and it provides a higher base model accuracy compared to earlier versions. The EfficientNetV2 model is enhanced through fine-tuning in this study. During the fine-tuning process, the model's early layers are frozen, up to the block7e_dwcov2 layer, to retain the learned features from pre-training while adapting to the specific needs of the dataset. This approach aims to optimize the model's performance by preserving useful features from the initial training while focusing the learning process on the later layers to improve accuracy for the specific classification task.

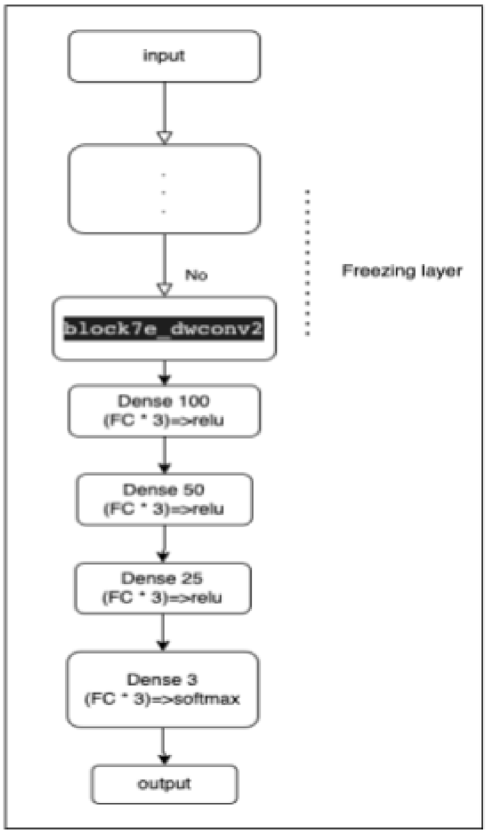

Figure 1. Architecture Model DCNN
Source : Tan & Le (2021)

In the detection models for chili leaf and fruit diseases, additional layers with ReLU activation functions were incorporated, as outlined in Table 2, to identify the optimal model accuracy. Following this, a final layer consisting of three dense layers was added, aligned with the number of output classes and using a softmax activation function, since this study focuses on single classification tasks. This configuration allows the model to classify each input into one of the

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predefined categories. Figure 1 illustrates the architecture of the model, highlighting the parts where layers were frozen and where additional layers were integrated. By enhancing the model with these modifications, the goal is to improve its performance in accurately detecting and classifying diseases in chili plants. The combination of ReLU activations for intermediate layers and softmax for the final classification layer aims to optimize the model's ability to differentiate between various disease states and ensure robust and reliable predictions.

Table 2. Architecture Model DCNN

Layer	Model1	Model2	Model3
1	Dense 32 (FC*3)=>relu	Dense 64(FC*3)=>relu	Dense 128(FC*3)=>relu
2	Batch normalitation	Batch normalitation	Batch normalitation
3	Dropout	Dropout	Dropout
4	Dense 16 (FC*3)=>relu	Dense 32 (FC*3)=>relu	Dense 64 (FC*3)=>relu
5	Dropout	Dropout	Dropout
6	Dense 6 (FC*3)=>relu	Dense 16 (FC*3)=>relu	Dense 32 (FC*3)=>relu
7	Dense 16 (FC*3)=>relu	Dense 16 (FC*3)=>relu	Dense 16 (FC*3)=>relu

Source : Data Processing, 2024

For both model configurations, adjustments, additions, and modifications were made to specific layers in order to optimize accuracy and minimize loss, aiming to prevent issues of overfitting or underfitting. Table 2 presents various model configurations that have been adjusted using the fine-tuning method. These configurations will undergo training and testing phases to evaluate their performance. The goal is to refine the model's parameters to achieve the best possible results, ensuring it generalizes well to new data and performs effectively in real-world scenarios.

Table 3. Accuracy Testing

Model	accuracy	loss	accurarcy validate	loss validate
Model1	0.993	0.03	0.826	0.815
Model2	0.998	0.01	0.810	0.639
Model3	0.994	0.04	0.89	0.410

Source : Data Processing, 2024

The training process for each model involved 50 epochs and a batch size of 10. The training was performed using GPU processing, although the specific training duration for each model was not included in the results. The outcomes, including the accuracy and loss values for each trained model, are presented in Table 3. This table provides a summary of the performance metrics obtained after completing the training process for the models. Table 3 presents the accuracy and loss values for the trained models, with Model3 achieving the best results for chili fruit image detection. The comparative graphs of validation accuracy versus accuracy and validation loss versus loss, shown in Figure 2, indicate that the model does not exhibit significant overfitting or underfitting. These visualizations demonstrate that the model maintains a well-balanced performance across different evaluation metrics, ensuring reliable detection of diseases in chili fruits.

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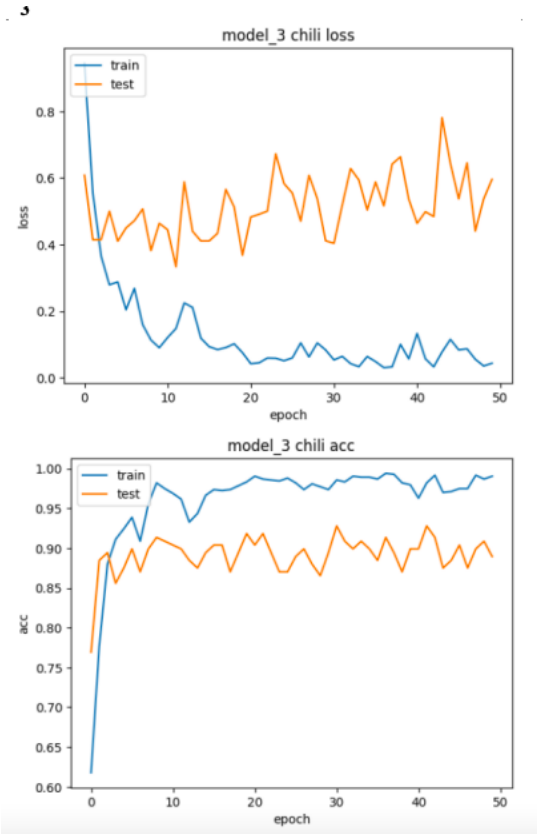

Figure 2. Accuracy and loss
Source : Data Processing, 2024

CONCLUSION

Based on the implementation of the methods used in developing the program for detecting diseases in chili plants, the researcher draws the following conclusions: For the classification of chili leaf diseases using transfer learning with the EfficientNetV2M base model, it was observed that adding a large number of neurons to the additional layers during training is not necessary. In fact, fewer neurons often result in better accuracy and lower loss values. Increasing the number of neurons beyond a certain point can lead to overfitting, which is characterized by an increasing gap between the training loss and actual loss. Conversely, when constructing the classification model for chili fruit diseases, a larger number of neurons was required compared to the model for chili leaf disease classification. This indicates that the complexity of detecting diseases in chili fruits necessitates a more intricate model setup with additional neurons to achieve optimal performance. The findings suggest that while fewer neurons can be advantageous for leaf disease classification, the complexity of fruit disease classification demands a more substantial network. This balance is crucial for achieving accurate and reliable detection while avoiding overfitting in both scenarios. For future research, it is recommended to explore alternative methods for mitigating overfitting, such as implementing advanced regularization techniques or data augmentation strategies. Further investigation into the optimal number of neurons for different types of diseases across various plant species could also provide more generalizable guidelines. Additionally, examining the impact of different architectures or combining multiple models through ensemble learning may enhance classification accuracy. Researchers should also consider testing the models in real-world environments to validate their robustness and effectiveness. Finally, expanding the dataset to include more diverse samples could help improve model generalization and reduce the risk of overfitting.

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