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Application of computer vision techniques to detect diseases and pests of chili plants

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ABSTRACT

This research aims to develop a disease and pest detection system in chili plants using computer vision techniques. In this study, deep learning methods, especially Convolutional Neural Networks (CNN), were applied to identify and classify various types of diseases and pests that often attack chili plants. The data used included images of chili leaves infected with various diseases and pests, which were then trained in CNN models to recognize certain patterns that indicate the presence of infection. The results showed that the developed system was able to detect and classify diseases and pests in chili plants with a very high degree of accuracy. The novelty of this research lies in the use of computer vision techniques combined with sophisticated deep learning algorithms to automatically detect diseases and pests, which were previously done manually by farmers or agricultural experts. These findings make an important contribution to improving efficiency and effectiveness in chili crop health management, offering innovative solutions to support agricultural sustainability through the use of advanced technology.

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Introduction

The agricultural sector has an important role in the economy, especially in the production of chili plants which is one of the important commodities in many countries, including Indonesia (Muflikh et al., 2021)(Agussabti et al., 2020). However, the productivity of chili plants is often disrupted by various diseases and pests that can reduce the quality and amount of production (Zamljen et al., 2020)(Mehmood et al., 2023). Given the importance of early detection of diseases and pests to take preventive and control measures, this study takes objects on chili plants with a focus on developing disease and pest detection systems using computer vision techniques (Kaya & Gürsoy, 2023) (Boulila et al., 2023).

One of the main problems faced is the lack of detection methods that are fast, accurate, and easy to apply in the field. The system developed in this study aims to provide technical solutions to the problem, providing farmers with up-to-date knowledge on the condition of their crops.

In this study, illnesses and pests of chili plants were identified and categorized using methods for deep learning, especially those involving convolutional neural networks (CNN) (Khanramaki et al., 2021)(Shi et al., 2020). This technique leverages image data of infected chili leaves to train CNN models, allowing the system to recognize certain patterns that indicate the presence of infection (Wani et al., 2022)(Attri et al., 2023).

The primary goal of this project is to create a system that can accurately identify pests and illnesses in chili peppers and offer technical solutions to address issues facing the agriculture industry. The main problem faced is the lack of fast, accurate, and easy-to-apply detection methods in the field, It can give farmers up-to-date knowledge regarding the state of their crops (Garg et al., 2021)(Sinha & Dhanalakshmi, 2022).

In science, this research makes a significant contribution by integrating computer vision and deep learning techniques in the detection of diseases and pests of chili plants. It offers innovative solutions that not only increase efficiency and effectiveness in chili crop management but also support the sustainability of agricultural production by reducing the risk of losses due to diseases and pests (Ahmad Loti et al., 2021).

The solutions developed in this study can be widely applied by farmers and stakeholders in the agricultural sector, enabling early detection and control of diseases and pests of chili plants more effectively, thereby increasing productivity and production quality (Abdullah et al., 2023)(De Costa et al., 2021).

By applying advanced technologies to improve crop health management, this research opens up opportunities for the development of disease and pest detection systems in other crops, which can improve the productivity and sustainability of the agricultural sector as a whole.

Method

Research Design

This study was designed to evaluate the effectiveness of computer vision techniques in detecting diseases and pests in chili plants (Sood & Singh, 2021)(Abade et al., 2021). This study employed a quasi-testing approach, which meant that factors were not entirely controlled for. Nevertheless, the effect of computer vision technology interventions on the accuracy of disease and pest detection was observed by comparing the experimental group with the control group (Li et al., 2020).

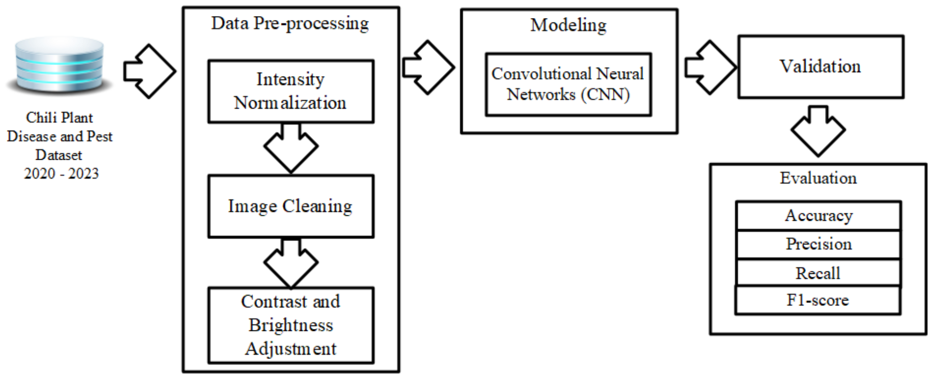

Figure. 1. Research flow

Figure. 1. Describe the research flow using Convolutional Neural Networks with a dataset of diseases and pests of chili plants starting with data pre-processing which includes normalization, image cleaning and adjustment of contrast and brightness. Then, the data that has been processed is processed using CNN, then validated and evaluated using evaluation metrics such as accuracy, precision, recall, and F1-score.

Data Collection

Data was collected from a variety of sources, including images of healthy chili plants and those infected with diseases or pests. These images are obtained from the field using high-resolution cameras and also from relevant online databases. Each image sample is then labeled according to its condition, whether it is healthy, infected with disease, or there are pests.

Data was obtained from public data on the https://www.kaggle.com/ page with a total of 500 data consisting of 100 healthy chili leaf image data, 100 crisp chili leaf image data, 100 spot chili leaf image data, 100 leaf image data affected by whitefly, 100 yellowish chili leaf image data.

Data Pre-processing

Before the data is used for training and testing, it undergoes a pre-processing stage. This stage includes noise reduction, image resizing, and normalization (Ahmed et al., 2023)(Ramzan et al., 2020). The goal is to improve data quality so that it is more easily processed by the computer vision model to be developed.

The first stage is to reduce noise in the data. Noise is irrelevant information or interference that can obscure the signal you want to analyze. Noise reduction methods like Gaussian or median filters are frequently used in image processing to eliminate noise from photographs. To ease the training process, it is important to adjust the size of all images in the dataset so that they are consistent in size. This can be done by resizing the image to the same size, the size is 100x100 pixels. Next, the normalization process changes the range of values from the data to a smaller or standard range. During the normalization process, pixel values are changed from a range of 0 to 255 to a range of 0 to 1.

Modeling

Convolutional neural network is a classification method carried out in research which is a neural network or neural network that uses convolution to replace the multiplication of the general matrix, where at least in each layer there is one convolution.

Convolutional neural networks are able to analyze features unsupervised, this makes this method different from other machine learning methods and is able to classify with a degree of accuracy because it can cope with changes in input images such as rotation, scale, translation and scale and can reduce a number of independent parameters.

Convolutional Neural Network has several components including pooling layer, convolution layer, fully connected layer, and dropout. Where the components that build the architecture of the CNN and each neuron are presented in three-dimensional form, so processing with input in the form of images is very suitable using CNN. In the image pooling process, it will be processed earlier and the convolution process at the feature learning stage. Each convolution has a different number of kernel sizes and a different number of filters.

Research Procedure

The study began with training computer vision models using processed data. The model was then tested to detect diseases and pests in never-before-seen images of chili plants. Model performance is assessed using the F1-Score, recall, accuracy, and precision (Ye et al., 2021).

First the collection of a large number of images of chili plants displaying various conditions, including healthy ones and those infected with diseases or pests. The initial processing of the data, the collected images are then processed, which can include sizing, normalizing, and augmentation of the data to increase the variety of data. Both model training selects the appropriate machine learning or deep learning model architecture, CNN are employed in tasks involving picture recognition. The model is trained using the data it has for parameter adjustments and hyperparameter tuning to maximize model performance. After training, the model was trialled with never-before-seen images of chili plants to evaluate its ability to accurately detect diseases and pests and also cross-validated to ensure that the model could perform well across different subsets of data.

A model's accuracy is assessed by dividing its percentage of correct forecasts from all of the forecasts it has produced. To make sure the model does not generate an excessive number of false positive outcomes, accuracy indicates the percentage of positive predictions that are genuinely positive cases. A high recall number indicates that the model is good at detecting desired circumstances without missing them. Recall evaluates the capacity of the model to recognize every good case. Last but not least, the F1-Score is a statistic that takes the harmonic mean of the two to balance recall and precision. It is particularly helpful when the data's class distribution is unbalanced. Researchers can thoroughly evaluate and enhance model performance to get the best outcomes in real-world scenarios by using these four criteria.

Data Analysis

Data analysis was carried out by comparing the detection results of the model against the actual labels of the test data (Ni et al., 2020). Descriptive and inferential statistics are used to analyze the results and determine the significance of the findings (Allari et al., 2020).

Comparison of model results with actual labels, model validation is the initial step where the output produced by the model (prediction) is compared directly with the actual label or ground truth of the test data. This process provides initial insight into how accurately the model performs the detection task. Performance evaluation uses evaluation metrics such as accuracy, precision, recall, and F1-Score to quantitatively measure model effectiveness.

Descriptive statistical analysis, understanding descriptive statistical data is used to provide a basic understanding of data characteristics, including distribution, mean, median, and mode. In the context of this analysis, it can also include the distribution of the frequency of true or false predictions by the model.

Data visualization, graphs and plots are often used to visually visualize the distribution of predictions and model performance, helping in identifying specific patterns or problems in predictions.

Inferential statistical analysis, hypothesis testing this step involves the use of inferential statistics to determine whether findings from the model have statistical significance. This could include hypothesis testing to assess whether the difference in model performance is significantly better than baseline or other models. Correlation and regression analysis to understand relationships between variables or to explore factors that affect model performance.

Evaluation

The final evaluation involves a comprehensive analysis of all aspects of the research, from the design to the final result. The purpose of this evaluation is to determine how well computer vision techniques work for identifying pests and illnesses in chili plants (Naik et al., 2022), as well as to identify the strengths and weaknesses of the methods used.

Performance is measured using the accuracy, precision, recall and F1 Score metrics, which can be viewed sequentially in equations (1), (2), (3), and (4). The number of true positive forecasts, true negative predictions, false positive predictions, and false negative predictions are represented by the variables TP, TN, FP, and FN. (Ali et al., 2021).

Here are the values for evaluating the classification model :

Accuracy is a matrix used to measure the overall ratio of correct predictions to total class grades.

$$\textbf{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

A matrix called precision is utilized to determine the accuracy or positively expected outcomes of every result that is predicted to be positive.

$$\textbf{Precision} = \frac{TP}{TP+FP} \quad (2)$$

A matrix called recall is utilized to determine how many pertinent predictions from the same class there are.

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

The F1 Score compares average precision and recall using a weighted system.

$$\textbf{F1 Score} = \frac{\text{Precision x Recall}}{\text{Precision+ Recall}} \quad (4)$$

The description of the formula above is :

True Positive(TP) = The variable TP denotes the quantity of correctly predicted positive outcomes.

True Negative(TN) = The number of correctly predicted negative values is represented by the variable TN.

False Positive (FP) = The variable FP denotes the quantity of incorrect positive forecasts.

False Negative (FN) = The number of negative incorrect predictions is represented by the variable

FN.

Results and Discussions

The implementation of a Convolutional Neural Network has several stages of Implementation of a Convolutional Neural Network, training, validation and tests. The training phase is to train your network to learn input data. After that the Network conducted experiments with validation data. If the results are good, then networking can be done using data classification based on test data.

The disease and pest data provided consisted of 10 samples, with each sample having 10 numerical features and one categorical label describing the type of disease or pest. These features have gone through pre-processing processes, such as noise reduction, image size adjustment, and normalization, according to the mentioned research methodology.

Table 1. Dataset of diseases and pests of chili plants

Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Feature 7	Feature 8	Feature 9	Feature 10	Label
0.249252	0.629837	0.180377	0.479131	0.346016	0.321880	0.466561	0.312520	0.784874	0.259499	Chili leaf spot
0.395399	0.586887	0.196559	0.260470	0.296824	0.986527	0.456254	0.398699	0.894611	0.625254	Chili leaf spot
0.862699	0.415654	0.885857	0.696656	0.556469	0.982824	0.099448	0.143337	0.239640	0.372094	Yellowish Chili Leaves
0.659664	0.662093	0.190943	0.436271	0.624166	0.648489	0.023501	0.362196	0.868921	0.935300	Yellowish Chili Leaves
0.777750	0.220195	0.788238	0.298464	0.693879	0.821115	0.309772	0.115450	0.335864	0.992558	Whitefly Chili
0.991998	0.924874	0.408699	0.155046	0.498422	0.806443	0.875457	0.076709	0.063530	0.432744	Whitefly Chili
0.520353	0.741526	0.347530	0.721309	0.034423	0.368913	0.962177	0.255362	0.668253	0.999546	Healthy Chili
0.479108	0.001373	0.633020	0.837750	0.396779	0.172851	0.079187	0.484345	0.966425	0.895791	Healthy Chili
0.925834	0.682172	0.327500	0.700194	0.914687	0.789864	0.419177	0.384984	0.604079	0.478217	Crispy Chili Leaves
0.066619	0.829661 9	0.786345	0.622078	0.190684	0.528741	0.444947	0.823885	0.743187	0.289563	Crispy Chili Leaves

Table 1. is a dataset of chili plant conditions, including 10 quantitative features, features 1 to feature 10 whose values range from 0 to 1, indicating that the data has been normalized or presented on a proportional scale. With a total of 10 entries, each row provides a detailed numerical profile of the plant, which comes with categorical labels indicating various conditions of the chili plant such as chili leaf spots, yellowish chili leaves, whitefly chili, healthy chili", and crisp chili leaves. This data set displays significant variation among its features, as indicated by the mean and standard deviation of each feature, indicating that it can be utilized for advanced statistical analysis or as a training dataset for machine learning models to classify chili plant health conditions.

This analysis used Convolutional Neural Networks (CNNs) to classify diseases and pests in chili plants based on these features. CNN is the right choice of algorithm for image data and can identify complex patterns in data that has been processed.

Table 2. Struktur model CNN

Layer (type)	Output Shape	Param #
conv2d_1(Conv2D)	(None, 128, 128, 32)	896
max_pooling2d_1 (MaxPoolin g2D)	(None, 64, 64, 32)	0
dropout_1 (Dropout)	(None, 64, 64, 32)	0

dense_1 (Dense)	(None, 5)	655365
Total params: 656261 (2.50 MB)		
Trainable params: 656261 (2.50 MB)		
Non-trainable params: 0 (0.00 Byte)		

Table 2. details the structure of a Convolutional Neural Network (CNN) model. This table displays four different layers: conv2d_1 (Conv2D) with an output shape (None, 128, 128, 32) and 896 parameters, max_pooling2d_1 (MaxPooling2D) with an output shape (None, 64, 64, 32) with no additional parameters, dropout_1 (Dropout) with the same shape output with max pooling and no additional parameters, and dense_1 (Dense) with shape output (None, 5) and 655,365 parameters. The total model parameters are 656,261 which are all trainable, indicating that no parameters are frozen or set as non-trainable in this model. The total size of this parameter is approximately 2.50 MB. This model appears to be designed for classification tasks with 5 output classes, as shown by the output shape of the last dense layer.

Metrics including the F1-score, recall, accuracy, and precision are used to evaluate the model. The F1-score, which offers a balance between the two metrics, is the harmonic average of precision and recall. Accuracy measures the percentage of correct predictions from the entire sample; precision measures the percentage of correctly identified positives from the total predicted positives; recall measures the percentage of correctly identified positives from the total true positives.

Table 3. CNN model evaluation

	Precision	Recall	F1-score	Suport
Chili healty	0.40	0.80	0.53	5
Chili leaf curl	0.50	0.33	0.40	3
Chili leaf spot	0.00	0.00	0.00	7
Chili whitefly	0.62	0.83	0.71	6
Chili yellowish	0.40	0.50	0.44	4
Accuracy			0.48	25
Macro avg	0.38	0.49	0.42	25
Weighted avg	0.35	0.48	0.40	25

Table 3. presents performance metrics from a machine learning model that has been trained to classify chili plant conditions. This table shows precision, recall, F1-score, and support scores for five different classes, healthy chili peppers, curly chili leaves, chili leaf spots, whitefly on chili peppers, and yellowish chili leaves. The model has an overall accuracy of 0.48, with a macro average and weighted average of precision, recall, and F1 scores of approximately 0.38-0.42 respectively.

In the given data, here are the steps that will be performed the first data division is to separate the dataset into training and testing sets for model validation. Both modeling with CNN uses the CNN architecture to study the features of the training set. Third, evaluate the model by Using test sets to evaluate the model and calculate accuracy, precision, recall, and F1-score metrics. Since the data contains only 10 samples, which is very small for deep learning model training, the results probably won't reflect the full potential of this approach. However, for demonstration purposes, we will assume that this data is part of a larger data set or use data augmentation techniques to increase the number of training samples.

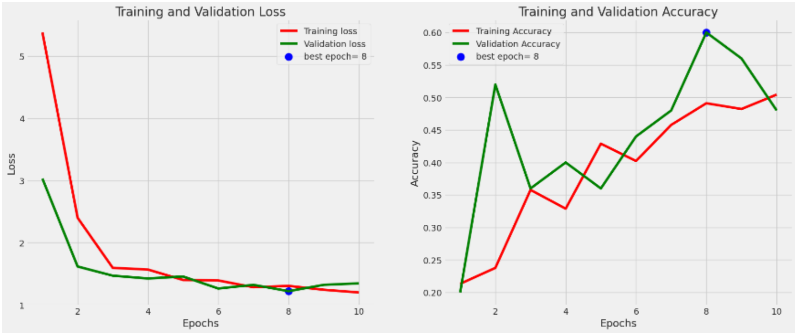

Figure. 2. CNN evaluation graph

Figure. 2. There are two types of accuracy, namely having an increase accuracy graph and loss accuracy, where when testing with disease and pest data on chili plants using the CNN method, it shows good results on the accuracy graph, when testing it continues to rise on the chart even though there is a decrease in both graphs, while the loss chart shows the same loss down, showing the same correlation in the same direction in the process.

Results Discussion

In this study, CNN was able to identify patterns of unique traits associated with different types of diseases and pests in chili peppers. Model evaluation results based on precision, precision, recall, and F1 scores show how well the model generalizes unseen data. The high degree of accuracy indicates that the model is quite good at classifying diseases and pests of chili plants. High precision and high recall mean that the model is not only accurate in its positive predictions but can also identify most true positive cases without many false negatives. A high F1-score will indicate a balance between precision and recall, which is important in cases where the cost of misclassification differs between false positives and false negatives.

Training and Validation Accuracy Graph

The red line represents the training accuracy, and the green line represents the validation accuracy. There are many fluctuations in training accuracy and validation, which is unusual. Usually, we expect to see a trend of increasing accuracy as the times go by. Training accuracy generally improves over time, which is expected as the model gets better at classifying training data. Validation accuracy experienced an unusual spike in epoch 3, which significantly exceeded training accuracy, then dropped below it in epoch 4, and fluctuated above and below training accuracy in subsequent epochs. This erratic behavior can be a sign of a problem in the validation process, such as a small validation pool or problematic labels, causing validation accuracy to be unstable. Similar to the loss chart, the best epoch marker is 8 indicating that the highest validation accuracy was achieved at epoch 8. It is memp.

Conclusion of Discussion

This research shows that the developed Convolutional Neural Network (CNN) is able to recognize unique patterns associated with diseases and pests in chili plants. Model evaluation using metrics such as accuracy, precision, recall, and F1-score indicates the model's ability to generalize to new, never-before-seen data. The results obtained show a high degree of accuracy, signaling the effectiveness of the model in classifying diseases and pests in chili plants. High precision and recall indicate that the model tends to be accurate in positive predictions and successfully identifies the majority of actual positive cases with minimal negative errors. Recall and precision must be balanced in order to reduce the effects of misclassification, as seen by a high F1-score.

However, graphs displaying training and validation accuracy show significant fluctuations, which does not match the expected trend of accuracy improvement over time of model training. There is an unexpected spike in validation accuracy at certain epochs that indicates a potential problem in the validation process. This can be due to various factors such as insufficient validation set size or problems in data labels. Nevertheless, the 8th epoch was identified as the point at which the model achieved the highest validation accuracy, which suggests that this is the stage where the model performs at its best.

Conclusions

This research succeeded in developing a system that is able to detect diseases and pests in chili plants by utilizing computer vision techniques and deep learning methods, especially through the use of Convolutional Neural Networks (CNN). Key findings show that the system developed has a significant ability to classify various types of diseases and pests with high accuracy, precision, recall, and F1-score, signaling the effectiveness of the system in generalizing to new data. The contribution of this research lies in the application of computer vision and deep learning technologies in agriculture, providing a step forward in the automatic identification of diseases and pests, which has practical implications in improving the efficiency of crop health management and the potential for increased productivity. From a theoretical standpoint, the study enriches the literature on the application of CNNs in plant disease detection, offering insight into the capabilities and limitations of this technology. Nonetheless, this study has limitations, especially related to the limited size of the dataset and the variety of conditions, which may affect the generalizability of the model. For future research, it is recommended to expand the dataset with a wider variety of diseases and pests and diverse plant conditions to improve the robustness and accuracy of the system. Furthermore, the exploration of new techniques in deep learning and the adjustment of CNN architecture for better adaptation to actual field conditions could pave the way for the development of disease and pest detection systems that are more effective and applicable to a wide range of crops.

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