ABILITY CONVOLUTIONAL FEATURE EXTRACTION FOR CHILI LEAF DISEASE USING SUPPORT VECTOR MACHINE CLASSIFICATION

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Abstract—*Chili plants are among the most commonly used food ingredients in various dishes in Indonesia. Leaves on chili plants are often affected by disease; if the disease is not treated immediately, it can damage the plant and cause crop failure. Early detection of chili plant diseases is important to reduce the risk of crop failure.* ***.*** *The development of technology and the application of machine-learning algorithms can automatically monitor chili plants using a computer system. Using this algorithm, the system analyzes and identifies diseases that a camera can observe and record. In this study, the proposed method for feature extraction uses a convolutional neural network (CNN) algorithm with transfer learning using VGG19. For classification using SVM for training data, accuracy generated 95%, precision 95%, recall 95%, and F1-Score 95%, and testing data accuracy generated 90%, precision 89%, recall 90%, and F1-Score 89%, proving that the convolutional process with architecture VGG19 and SVM algorithm is acceptable for classification. In future research, other architectures or extraction fusions can be used to maximize the results.*

Keywords: *leaf chilli diseases, SVM, transfer learning.*

Abstrak—*Tanaman cabai merupakan salah satu bahan makanan yang paling sering digunakan dalam berbagai masakan di Indonesia. Daun pada tanaman cabai yang sering terkena penyakit, jika penyakitnya tidak segera ditangani, maka penyakit tersebut dapat merusak tanaman dan mengakibatkan gagal panen, deteksi penyakit tanaman cabai secara dini sangat penting dilakukan, untuk mengurangi resiko gagal panen. Perkembangan teknologi dan penerapan algoritma machine learning dapat melakukan pengawasan terhadap tanaman cabai secara otomatis menggunakan sistem komputer. Dengan menggunakan algoritma ini penyakit yang dapat dilihat dan direkam oleh kamera akan dapat di analisis dan diidentifikasi kan oleh sistem. Pada penelitian ini metode yang diusulkan untuk ekstraksi fitur menggunakan konvolusi dari algoritma CNN dengan transfer learning menggunakan VGG19 dan untuk klasifikasi menggunakan SVM untuk data training Accuracy yang dihasilkan 95%, Precision 95%, Recall 95% dan F1-Score 95%, dan data testing Accuracy yang dihasilkan 90%, Precision 89%, Recall 90% dan F1-Score 89%, hal ini membuktikan bahwa proses convolutional dengan arsitektur VGG19 dan algoritma SVM sangat baik untuk proses klasifikasi.* Untuk penelitian lanjutan dapat menggunakan arsitektur lainnya atau menggunakan ekstraksi gabungan agar lebih maksimal.

Kata Kunci*: penyakit daun cabai, SVM transfer learning.*

INTRODUCTION

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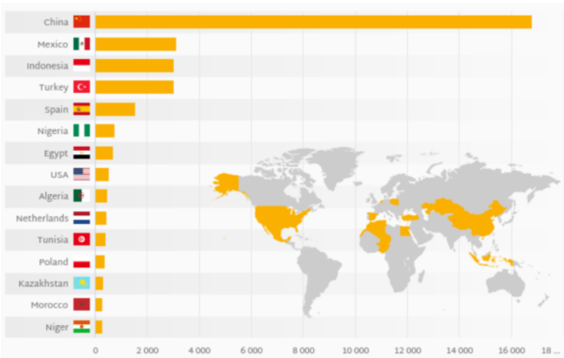
Indonesia is among the ten largest producers of chili plants in the world; nationally, chili plants are the most produced crop (Rahman et al., 2023). The need for chili in the Indonesian region continues to increase every year, in 2022 as much as 636.56 thousand tons based on horticultural statistical data, an increase of 6.78% compared to 2021 (Santika, 2023).

The chili plant is not a staple food crop but a complementary seasoning for Indonesian cuisine, with prices always fluctuating, making chili peppers a contributor to inflation in the Indonesian economy (Rosalina & Wijaya, 2020). To maintain price stability, production must be increased, and the quality of chili plants maintained (Barus et al., 2022).



Source: (Helgi Library, 2023)
Figure 1. World's Largest Chili Producing Countries in 2021

Harvest failure is one of the causes of price instability in chili crops (Polii et al., 2019), and several factors, such as pests and diseases, cause crop failure in chili plants (Firmansyah et al.,2020). Pests and diseases pose a serious threat to farmers as they can lead to a decrease in the quality and quantity of crops produced (Islam et al., 2020), so the worst impact that farmers will experience is a big loss.

Chili plants have diseases that often attack and are difficult to control when infected with leaf curl and yellow viruses (Renfiyeni et al., 2023). The disease can be visually identified by the symptoms that appear; however, visual identification has similarities, so errors can occur. This is because each person has a different assessment of the visual identification results (Rozlan & Hanafi, 2022). To solve this problem visually, computer technology that can recognize digital images has been rapidly developed (Susim & Darujati, 2021). The analysis of a digital image is a regular or random pattern (Stoilov et al., 2012), and features are the most important part of the analysis of an image. The analysis results can provide information about the structure of the surface, changes in intensity, or brightness of the color (Juandri & Anwar, 2023). features are the most important parts in the analysis of an image, where the analysis results can provide information about the structure of the surface, changes in intensity, or brightness of the color (Muzahid et al., 2020).

CNN have many architectures, one of which is VGG-19. VGG-19 is an architecture consisting of 19 layers: 16 convolutional layers, five max pooling layers, three fully connected layers, and one SoftMax layer (Mascarenhas & Agarwal, 2021). The input image size of this architecture is 224 × 224, and this architecture has been used to train more than 1 million images obtained from the ImageNet database. In addition, this architecture has a 3x3 kernel and has 5 blocks with various sizes of convolutional layers in each block, which then adds a max pooling layer as a separator for each block (Marcella et al., 2022).

Machine Learning (ML) is a type of artificial intelligence (AI) that is widely used in various fields (Suradiradja, 2021), especially in agriculture. Many studies have used these methods for automatic decision-making with computing systems (Yana & Nafi'iyah, 2021). The ML method has many models, one of which is often used and has very good accuracy in solving classification problems, namely the Support Vector Machine algorithm (Abdullah & Abdulazeez, 2021). SVMs have advantages over other ML models, such as the problem of overfitting (Nusinovici et al., 2020), the ability to work well on relatively small datasets (Rahayu et al., 2022), and the ability to overcome the problem of unbalanced or unevenly distributed data in the class (Wahab et al., 2019).

Previous research on chili leaf disease, namely: Research Araujo et al., 2019. Identification of chili leaf disease with CNN and YoloV2 algorithms. The research results were 61.49% (Das Chagas Silva Araujo et al., 2021). Wahab et al research, 2019. Detecting chili leaf disease with the K-means algorithm for segmentation and SVM for classification. The results of the study obtained an accuracy of 57.1% (Wahab et al., 2019). Karuna DKK research, 2019. Using the CNN algorithm with several architectures, the result is that the application built can classify chili leaf disease (Karuna et al., 2019). Research Windarningsih 2019, identification of viruses causing yellow leaf curl disease in chili using PCR-RFLP The results obtained by PCR can detect the disease (Windarningsih, 2019). Nuanmeesri and Sriurai 2021, using the Multi-Layer Perceptron Neural Network (MLPNN) algorithm by comparing Feature Selection Filters (IG, GR) and Wrapper Feature Selection. The results obtained by the MLPNN and Wrapper have the highest accuracy of 98.91% (Nuanmeesri & Sriurai, 2021). A study by Zikra et al.

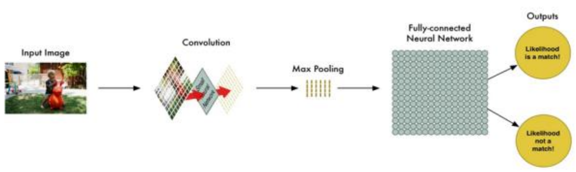
2021, using 4 angle type GLCM texture extraction and SVM Method. Their results obtained an accuracy of 95% (Zikra et al., 2021). Research by Patil and Lad 2021, using SVM and KNN algorithms using 4 GLCM texture extraction angles. The results showed that KNN had greater accuracy, namely 93% compared to the SVM algorithm of 83.33% (Patil & Lad, 2021). Dzaky, 2021. The CNN algorithm was applied using AlexNet architecture. Their results obtained an accuracy of 90%. Rozlan and Hanafi 2022, using the Deep Learning algorithm (VGG16, InceptionV3, and EfficientNetB0). The results showed that InceptionV3 had the highest accuracy of 98.83% (Rozlan & Hanafi, 2022). Kelikualiq et al. 2022. Using the CNN algorithm with AlexNet architecture on the chili plant health monitoring system based on the IOT. The results of this study obtained an accuracy of 63% (Kelikualiq et al., 2022). Research Anggraeni, Widayana, Rahayu, & Rozikin, 2022, the CNN algorithm was used for the classification of the three types of chili leaf disease. Their research obtained an accuracy of 60% (Anggraeni et al, 2022). Hafidhoh Research 2022, using GLCM feature extraction with pixel distance d = 1 to 5 and the SVM algorithm with Gaussian and polynomial kernel functions. The results showed an accuracy of 83% for the polynomial kernel (Hafidhoh, 2023).

Based on the explanation of previous research, this research will apply the SVM algorithm for classification such as research (Zikra et al., 2021; Patil & Lad, 2019; Wahab et al., 2019; Hafidhoh, 2023). However, the difference is that in this study, feature extraction uses the CNN algorithm with VGG19 transfer learning.

MATERIALS AND METHODS

1. CNN

A Convolutional Neural Network (CNN) is a type of deep learning specifically designed to recognize patterns in grid-structured data, such as images. CNN utilizes convolution operations to automatically extract image features, both low and high dimensional images (Muzahid et al., 2020).



Source: (Lina, 2019)
Figure 2. Illustration of CNN Architecture

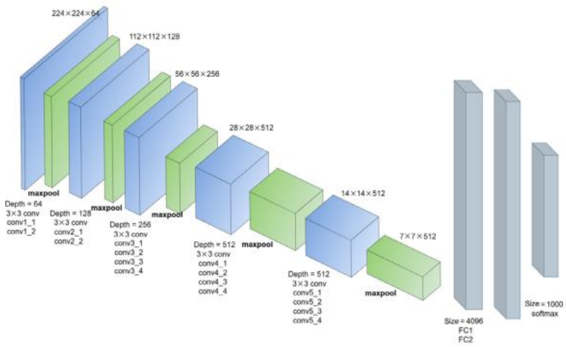
There are several layers in the CNN algorithm, one of which is the Convolutional Layers: this layer is the main operation in the CNN convolution layer. In this context, the 2D convolution between the input (image) and filter (kernel) can be explained in formula (1).

$$(I*K)\ (x, y) = \Sigma_i \Sigma_j I(x+i, y+j) \cdot K(i, j) \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where I is the input image, K is the kernel, x and y are the positions in the image, and i serta j are the indices in the kernel. The convolution result $(I*K)$ (x, y) is the value at position (x, y) in the convolved feature map.

2. VGG19

The VGG19 architecture, which is part of the VGG family of models, is known to have significant advantages in the field of image recognition. The model showed good performance in image recognition.



Source: (Mohbey et al., 2022)
Figure 3. VGG19 Architecture

3. SVM

SVM is a machine learning algorithm used for classification and regression tasks (Ibrahim & Abdulazeez, 2021). The goal is to determine the best hyperplane that separates the two data classes as much as possible with the maximum margin.

The SVM equation for multiclass classification problems depends on the approach used. In the One-Versus-Rest (OVR) approach, each class has its own SVM model. In the One-Versus-One (OVO) approach, there is a binary SVM model for each possible class pair (Setiawan et al., 2022). In this study, using the One-Versus-Rest (OVR) approach, if we have N classes in a multi-class problem, then there will be N binary SVM models. Each model separates one class from another. The general equation for prediction with the OVR approach is shown in formula (2).

$$f(x) = argma\mathcal{X}_i(\omega_i . x + b_i) \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Description: $f(x)$ is the predicted class for the test data x. ω_i is the weight vector of the SVM model for class i. b_i is the bias constant of the SVM model for class i.

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Each SVM OVR model will provide a score or value:

$$\omega_i . x + b_i \ldots\ldots\ldots\ldots (3)$$

For test data x, and the class with the highest score will be selected as the final prediction.

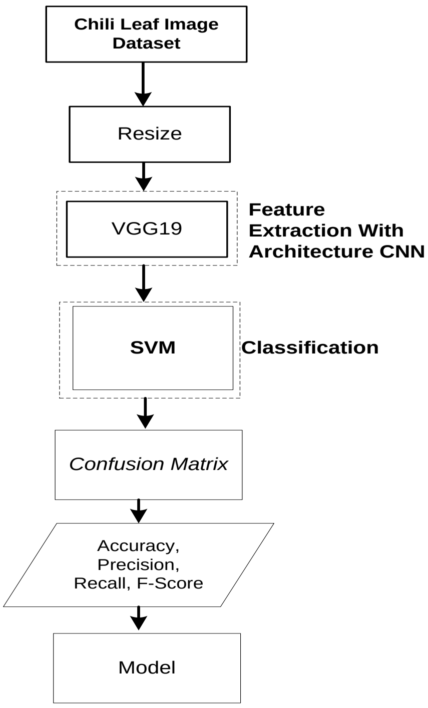
4. Confusion Matrix

The performance evaluation in this study used a Confusion Matrix. This technique is a prediction matrix measured based on the values of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) (Liyantoko, Candradewi, & Harjoko, 2019). There are 3 confusion matrices were used in this study.

Akurasi = (TP + TN) / (TP+FP+FN+TN) .... (3)
Presisi = (TP) / (TP+FP) .... (4)
Recall = (TP) / (TP + FN) .... (5)
F1 Score = 2 * (Recall*Precision) / (Recall + Precision) .... (6)

5. Research method

Figure 4 shows the stages of the research method planned in this research.



Source: (Research Results, 2024)
Figure 4. Research Method

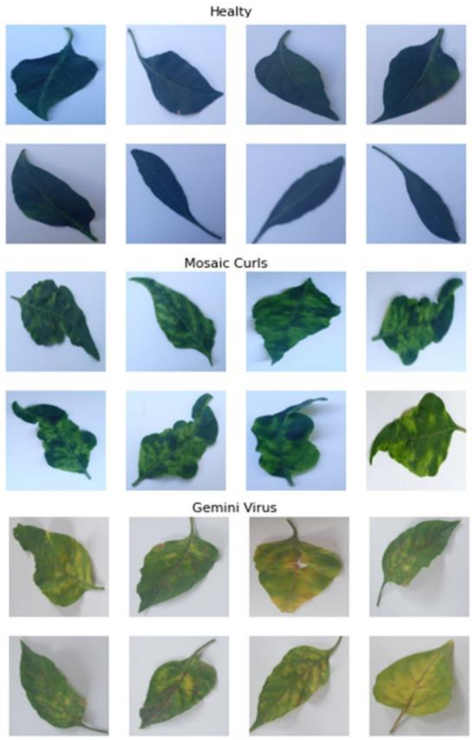
Figure 4 is the flow of the research method that will be planned, the first step is to collect image data on the types of chili leaf diseases from the farmers' gardens, after collecting all the images are resized in the python application automatically, after that step three perform feature learning using CNN architecture, namely VGG19, then the SVM algorithm classification process, then evaluate the results using a confusion matrix with the evaluation compared, namely accuracy, precision, recall and F-Score.

RESULTS AND DISCUSSION

1. Data

Image data were collected for as many as 300 data points, consisting of 100 data points on healthy leaves, 100 data points on mosaic curls, and 100 data points on gemini virus, using a smartphone, and the data were recorded one by one based on the type of disease.

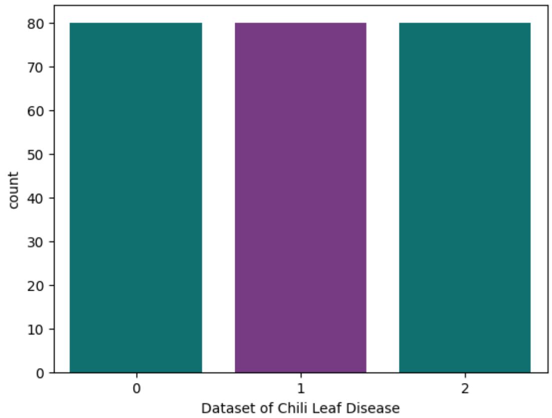
In this study, dara was processed using the Jupyter notebook with Microsoft Visual Studio Code. Figure 5 is a display of the three types of chili leaf data.



Source: (Research Results, 2024)
Figure 5. Chili Leaf Data

Of the three types of data, as much as 300 were collected, and the data were divided into 80% training data and 20% testing data. Then the data label is converted into numeric numbers 0 = Healthy Leaves, 1 = Mosaic Curls and 2 = Gemini Virus. Figure 6 is a display of the three types of chili leaves that have been converted into numeric numbers.

Figure 6 shows an even distribution of data from three types of chili leaves, as much as 80 data from one type of data.



Source: (Research Results, 2024)
Figure 6: Number of images by disease type

2. **Feature Extraction Process**

The next stage is the image resizing process carried out as an input with a size of 244 × 244 × 3. At this convolutional stage, image features are extracted using transfer learning VGG19 using the image set as. Initialize the initial weight and extractor fixed features. Process results for Jupiter notebook applying VGG19 transfer learning.

Table 1. Model "vgg19"

Layer (type)	Output Shape	Param #
input_5 (Input Layer)	[(None, 224, 224,	0
block1_conv1 (Conv2D)	3)]	1792
block1_conv2 (Conv2D)	(None, 224, 224,	36928
block1_pool	64)	0
(MaxPooling2D)	(None, 224, 224,	73856
block2_conv1 (Conv2D)	64)	147584
block2_conv2 (Conv2D)	(None, 112, 112,	0
block2_pool	64)	295168
(MaxPooling2D)	(None, 112, 112,	590080
block3_conv1 (Conv2D)	128)	590080
block3_conv2 (Conv2D)	(None, 112, 112,	590080
block3_conv3 (Conv2D)	128)	
block3_conv4 (Conv2D)	(None, 56, 56,	
……	128)	
Total params: 20,024,384	(None, 56, 56,	
Trainable params: 0	256)	
Non-trainable params:	(None, 56, 56,	
20,024,384	256)	
	(None, 56, 56,	
	256)	
	(None, 56, 56,	
	256)	

Source: (Research Results, 2024)

3. **Process Evaluation**

After the resize process and feature extraction process, then the next classification process uses a machine learning algorithm, namely SVM. Table 2 presents the results of the training and testing processes.

Table 2. Training and Testing Data Results

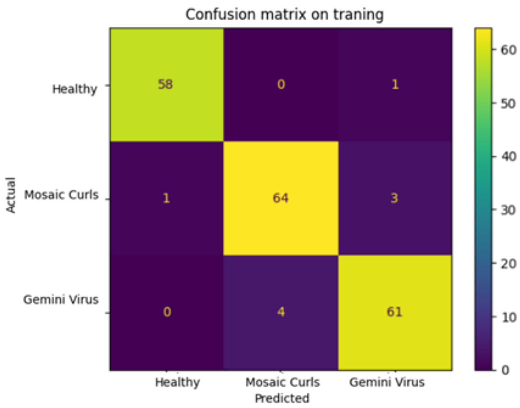
No	Algorithm CSVM	Accuracy	Precision	Recall	F1-Score
1	Training	95%	95%	95%	95%
2	Testing	90%	89%	90%	89%

Source: (Research Results, 2024)

In Table 2, it can be explained that by applying transfer learning VGG19 and classification using SVM for training data, the resulting accuracy is 95%, precision 95%, recall 95% and F1-Score 95%, and the resulting testing data accuracy is 90%, precision 89%, recall 90% and F1-Score 89%.

4. **Confusion Matrix**

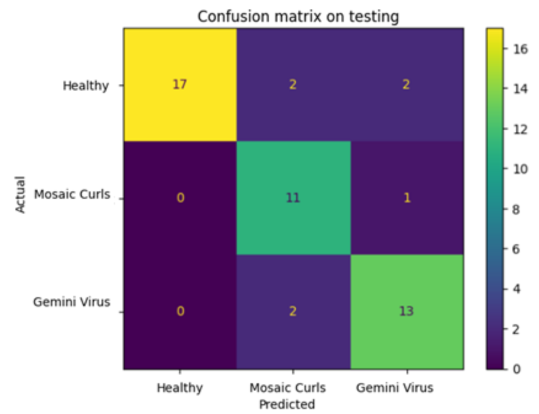
The confusion matrix is a step to evaluate the performance of a classification model. The confusion matrix provides information about the correct and incorrect predictions made by the model compared to the actual label or class. In this confusion matrix, three classes are considered: Healthy Leaf, Mosaic Curl and Gemini Virus. The confusion matrix results of the training process are shown in Figure 7.



Source: (Research Results, 2024)
Figure 7. Confusion Matrix of Training

Figure 7 shows the Confusion Matrix of the training results, where the vertical axis (y-axis) shows the true class (True Labels), and the horizontal axis (x-axis) shows the predictions made by the model (Predicted Labels).

The classification results show that for 'Healthy Leaf', the model has successfully identified 60 cases correctly, and only one of the 'Healthy Leaf' cases was mistakenly classified as 'Gemini Virus'. In the 'Mosaic Curly' category, one case was misclassified as 'Healthy Leaf' and 64 cases were correctly classified, while the other three cases were misclassified as 'Gemini Virus.' For 'Gemini Virus, the model made the mistake of not recognizing four cases as 'Mosaic Curl, but managed to classify 61 cases correctly. The Confusion Matrix of the training results showed a fairly good performance, with the majority of cases correctly classified in each category. However, there were some misclassifications that occurred, particularly in the recognition of 'Gemini Virus,' which may require further investigation to determine the cause of the errors and improve the accuracy of the model.



Source: (Research Results, 2024)

Figure 8. Confusion Matrix Testing

Figure 8 shows the confusion matrix of the test results of the model identifying the 'Healthy Leaf' class with a total of four errors, although the majority of 'Healthy Leaf' cases 15 out of 21 were correctly classified. In the case of 'Mosaic Curly,' the model performed better, correctly identifying 11 out of 12 cases. Only one 'Mosaic Curly' case was misclassified as 'Gemini Virus. For 'Gemini Virus,' the model accurately classified 13 out of 15 cases, with two cases misclassified as 'Mosaic Curls.'

Overall, the confusion matrix shows that the model has a good ability to classify the three categories, but there is still room for improvement, especially in terms of minimizing misclassification between categories. These errors can come from a variety of factors, such as features that are not sufficiently discriminative and class imbalance in the training data.

CONCLUSION

This research successfully demonstrated the applicability of convolutional feature extraction techniques using the transfer learning architecture VGG19 for image classification tasks. By combining the features extracted by VGG19 and using SVM as a classifier, the model achieved very high performance on the training data, with Accuracy, Precision, Recall, and F1-Score values all reaching 95%. In the testing data process, there was a decrease in performance, and the results showed a good accuracy of 90%, precision of 89%, recall of 90%, and F1-Score of 89%. This decrease in performance is common, considering that models tend to perform better on training data than on testing data. The use of VGG19 transfer learning for feature extraction with SVM classification proved to be an excellent combination for image classification. Although there were errors, they need to be further analyzed to understand the basis of each misclassification. Future research can apply improvement strategies, such as collecting more training data, applying data augmentation techniques, exploring different architectural models, or using fusion extraction.

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