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IMPLEMENTATION OF CNN FOR CLASSIFYING PATCHOULI LEAF IMAGES BASED ON ACCURACY AND EVALUATION

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Abstract — *Patchouli (Nilam leaves) holds significant potential as a high-value natural material, especially in the perfume and essential oil industries. However, the classification and quality analysis of patchouli leaves remain a challenge that requires an automated solution based on technology. This study aims to develop a Convolutional Neural Network (CNN) model capable of automatically classifying the condition of patchouli leaves. The image data of patchouli leaves were processed through several preprocessing stages and divided into training and testing data. The designed CNN model utilizes several convolutional layers, pooling, dropout, and dense layers for the training process. The evaluation results using the confusion matrix showed that the model had a very low error rate, with only 1 misprediction in the training data. For the testing data, the model achieved an accuracy of 85% with a loss value of 0.6191496. The model also demonstrated an accuracy of 98.75% with a loss of 0.443462 on the training data. However, improvements in model generalization are still needed to achieve more consistent performance on new data.*

Keywords: *accuracy, convolutional neural network, image classification, model evaluation, patchouli leaves.*

Intisari — *Patchouli (Daun Nilam) memiliki potensi besar sebagai bahan alami bernilai ekonomi tinggi, terutama dalam industri parfum dan minyak esensial. Namun, klasifikasi dan analisis kualitas daun nilam masih menjadi tantangan yang memerlukan solusi otomatis berbasis teknologi. Penelitian ini bertujuan untuk mengembangkan model Convolutional Neural Network (CNN) yang mampu mengklasifikasikan kondisi daun nilam secara otomatis. Data citra daun nilam diolah melalui serangkaian tahap preprocessing dan dipecah menjadi data pelatihan dan pengujian. Model CNN yang dirancang menggunakan beberapa lapisan konvolusi, pooling, dropout, serta dense layer untuk proses pelatihan. Hasil evaluasi menggunakan confusion matrix menunjukkan bahwa model memiliki tingkat kesalahan yang sangat rendah, dengan hanya 1 kesalahan prediksi pada data pelatihan. Pada data pengujian, model mencapai akurasi 85% dengan nilai loss 0,6191496. Model juga menunjukkan akurasi 98,75% dengan nilai loss 0,443462 pada data pelatihan. Meskipun demikian, perbaikan dalam generalisasi model masih diperlukan untuk mencapai performa yang lebih konsisten pada data baru.*

Kata Kunci: *akurasi, convolutional neural network, daun nilam, evaluasi model, klasifikasi citra.*

INTRODUCTION

Patchouli leaves (*Pogostemon cablin*) have high economic value due to their essential oil content, widely used in the cosmetics, perfume, and pharmaceutical industries [1]. Patchouli essential oil contains a primary compound called patchoulol, which offers various therapeutic benefits, including antibacterial, antifungal, and anti-inflammatory properties [2][3]. In the industry, patchouli has become a highly important commodity, serving as a key ingredient in various consumer products [4]. Therefore, quick and accurate identification and classification of patchouli leaves are crucial to support its optimal production and utilization.

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However, the manual classification process of Patchouli leaves faces significant challenges, such as morphological variations influenced by environmental factors, pests, or diseases that can affect identification results [5]. These variations often make manual classification inaccurate and time-consuming. Therefore, an automated classification system based on digital images is needed to address these variations with higher accuracy and a more efficient process [6].

Digital imaging technology, particularly through the use of Convolutional Neural Networks (CNNs), has proven effective in classifying plants and other objects [7]. CNNs can process images with high accuracy and automatically handle variations in plant leaf images without requiring manual feature extraction [8][9]. The application of CNN for classifying other plants, such as rice [10][11][12] and medicinal plants [13][14][15], It shows great potential for automatically identifying plants

Several literature reviews provide additional perspectives on the application of Convolutional Neural Networks (CNN) in image classification. First, the review titled "Identification of Plants using Deep Learning: A Review" highlights the importance of plant identification for global ecology and atmospheric health, considering that several plants possess medicinal properties.

This paper presents a literature database covering the period from 2015 to 2020, revealing that the latest generation of convolutional neural networks (CNN) exhibits outstanding performance in image recognition. Furthermore, this paper discusses various techniques and methods related to leaf recognition within the context of deep learning [16]. Second, the research titled "DeepLeaf: Automated Leaf Classification Using Convolutional Neural Networks" introduces a methodology for automatic leaf classification by utilizing Convolutional Neural Networks (CNN).

This study aims to address the limitations of traditional methods through the application of pre-processing, data augmentation, and the design of efficient model architectures. Leaf images are processed to enhance the quality and diversity of the dataset, and the model is trained using a large labeled image dataset with transfer learning techniques.

Evaluation results demonstrate the effectiveness of this approach in classifying various types of leaves, as well as the potential of this technique for applications in plant biology and agriculture [17]. Third, the study titled "Deep Learning for Plant Species Classification" emphasizes the need for biodiversity conservation and understanding of plant species. This research addresses the complexities of species identification that often rely on human-defined features, particularly for non-experts, by advocating for the use of convolutional neural networks based on deep learning to automatically extract features from leaf photos and classify plant species.

This approach has proven to be superior to existing manual techniques. However, the application of CNN for the classification of patchouli leaves remains limited, necessitating further research to tackle the challenges posed by the significant variability in patchouli leaf images [18]

However, the application of CNN in Patchouli leaf classification is still limited, and further research is needed to address the challenges of the diverse variations in Patchouli leaf images.

This research aims to develop a CNN model capable of classifying Patchouli leaves automatically and efficiently, even with considerable image variations. It is hoped that the development of this CNN-based classification system will produce a faster and more accurate model, thereby supporting the sustainability of the growing Patchouli industry.

MATERIALS AND METHODS

This study uses a dataset of 200 digital images of Patchouli leaves, which are then processed and classified into two main categories based on their condition: "Diseased" and "Healthy." The goal of this classification process is to identify visual differences between healthy leaves and those showing symptoms of disease.

Although this study only considers two classes, "Diseased" and "Healthy" Patchouli leaves, the authors implement several solutions to enhance the analysis. First, data augmentation techniques are applied to expand the dataset from the available 200 digital images, each with a resolution of 100x100 pixels. By performing transformations such as rotation, cropping, mirroring, brightness variation, and converting images to RGB format, the dataset's diversity and sample size are increased without adding new classes.

Next, more representative variables are selected to emphasize the most distinctive visual features between healthy and diseased leaves, such as color changes or visible spots on infected leaves. As part of the data analysis, Table 1 presents representative examples of Patchouli leaf images classified into both categories, along with visual descriptions that illustrate the actual condition of the leaves according to their assigned classification.

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Table 1. Patchouli Leaf Picture

Leaf Condition	Image Example
Sick	
Healthy	

Source: (Research, 2024)

In this study, the patchouli leaves are classified into two conditions: "Sick" and "Healthy." Leaves categorized as "Sick" are those infected with diseases such as fungi or pests, which typically show spots or color changes on the leaf surface, visible in the captured images. On the other hand, leaves classified as "Healthy" are patchouli leaves that show no signs of disease, are fresh green in color, and appear free from any blemishes or damage on the surface.

After all the leaf images are collected, they are placed in a local directory and resize to 100x100 pixels to ensure consistent input data size. The images are then processed by resizing them to 32x32 pixels according to the model's input requirements. The images are subsequently converted to RGB format to ensure each image has the three color channels (Red, Green, Blue) required by the model. The dataset is divided into two main subsets: the training data (80 images) and the testing data (20 images), with an 80:20 ratio to ensure optimal validation. Image normalization, which is done by converting images into a consistent format and appropriate size, ensures that the data is ready for use in training and testing the machine learning model.

The preprocessing process is carried out by resizing the image. The purpose of this preprocessing is to speed up the training process and ensure a uniform distribution of input data. The image data is then converted into an array and rearranged to match the model's input format. The CNN model designed for this research consists of several convolutional, pooling, and dense layers arranged sequentially to process images and produce accurate classifications. At the beginning, the model has two convolutional layers with 32 filters, followed by a ReLU activation function, to capture the initial features in the images. Pooling is performed through max pooling to reduce data dimensions while preserving the important features needed for classification.

To reduce the risk of overfitting, a 30% dropout technique is applied after the pooling layers. Next, the advanced convolutional layers use 64 filters, followed by additional pooling and a 40% dropout. In the final stage, a dense layer with 256 units is used to capture more complex patterns, and a 50% dropout is applied to prevent the model from learning irrelevant patterns. Finally, the output layer uses a sigmoid activation function for binary classification, generating predictions as to whether the image belongs to the "Sick" or "Healthy" category.

The next step is Model Training and Evaluation. The model is trained for 20 epochs with a batch size of 32 using the Adam optimizer. The training process includes splitting the training data into training and validation subsets with an 80:20 ratio. Evaluation is performed on the test data using accuracy, loss, and confusion matrix metrics to assess the model's performance. The final step is to evaluate the model. The evaluation is conducted using a confusion matrix, which illustrates the number of correct and incorrect predictions for both the "Sick" and "Healthy" classes.

Table 2. Confusion Matrix

Predicted/Actual	Sick	Healthy
Sick	TP	FN
Healthy	FP	TN

Source: (Research Results, 2024)

Where:
TP: True Positive, The number of sick leaves is predicted to be correct.
TN: True Negative, Number of healthy leaves predicted correctly.
FP: False Positive, Number of healthy leaves predicted to be sick.
FN: False Negative, Number of sick leaves predicted to be healthy.

In addition to the Confusion Matrix, Accuracy is also used as the main metric to measure the model's performance in classifying the Patchouli leaves as "Sick" or "Healthy." Accuracy is calculated using the following formula:

$$Accuration = \frac{Total\ Number\ of\ Test\ Data}{Number\ of\ Correct\ Predictions} \times 100 \quad (1)$$

The complete description of the stages of this research is as follows.

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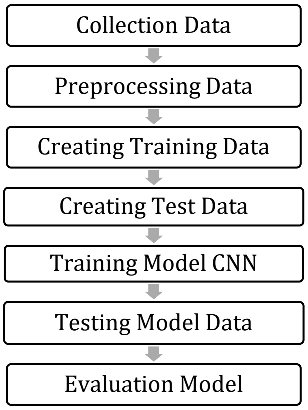

Figure 1. Research Stages
Source: (Research, 2024)

Figure 1 illustrates the research stages, outlining the steps involved in this study. The process begins with data collection, where 200 digital images of Patchouli leaves, both healthy and diseased, are gathered for analysis. Next, the data preprocessing stage is carried out to enhance image quality through size adjustment, noise removal, and color normalization. After preprocessing, the images are categorized into two groups: training data and test data, with approximately 80% of the total images allocated for training, while the remaining 20% are prepared as test data.

The Convolutional Neural Network (CNN) model is then trained using the training dataset, where model parameters and architecture are optimized to recognize key features within the images. Once training is completed, the CNN model is tested to evaluate its ability to classify Patchouli leaves, determining whether a given leaf falls into the “Diseased” or “Healthy” category.

Finally, the model evaluation stage is conducted to analyze the test results, calculating performance metrics such as accuracy to assess how effectively the model identifies leaf conditions. By following these steps, this study aims to provide in-depth insights into the application of CNN models for Patchouli leaf classification.

RESULTS AND DISCUSSION

The training process of the Convolutional Neural Network (CNN) model is carried out using processed patch images of the patchouli leaf, which have been divided into training and testing datasets.

The initial step involves image data processing. The images are resized to a specific dimension, 100x100 pixels, and saved in a new directory as preprocessed data. The image data is then divided into training and testing datasets, each consisting of a set of images for training the CNN model. Each image is resized to 32x32 pixels to meet the input requirements of the CNN model.

The designed CNN architecture consists of several layers, starting with two convolutional layers with 32 filters and ReLU activation functions, followed by a max pooling layer to reduce the data dimensions. To mitigate the risk of overfitting, a 30% dropout is applied after the first pooling layer. Further convolutional processing is performed by adding a new convolutional layer with 64 filters, followed by an additional pooling layer and a 40% dropout. The model is then followed by a dense layer with 256 units and kernel regularization, ending with a 50% dropout layer and an output layer using a sigmoid activation function for binary classification.

The model is compiled using categorical cross entropy as the loss function and Adam as the optimizer, with accuracy as the evaluation metric. A summary of the model architecture is shown in the image below, which represents the formed CNN architecture.

Layer (type)	Output Shape	Param #
conv2d_3 (Conv2D)	(None, 30, 30, 32)	896
conv2d_2 (Conv2D)	(None, 28, 28, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 14, 14, 32)	0
dropout_2 (Dropout)	(None, 14, 14, 32)	0
conv2d_1 (Conv2D)	(None, 12, 12, 64)	18496
conv2d (Conv2D)	(None, 10, 10, 64)	36928
max_pooling2d (MaxPooling2D)	(None, 5, 5, 64)	0
dropout_1 (Dropout)	(None, 5, 5, 64)	0
flatten (Flatten)	(None, 1600)	0
dense_1 (Dense)	(None, 256)	409856
dropout (Dropout)	(None, 256)	0
dense (Dense)	(None, 2)	514

Total params: 475,938
Trainable params: 475,938
Non-trainable params: 0

Source: (Research Results, 2024)

Figure 2. Model Architecture

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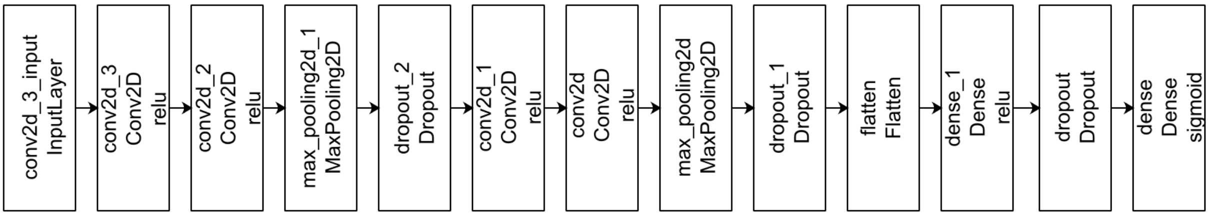


Source: (Research Results, 2024)

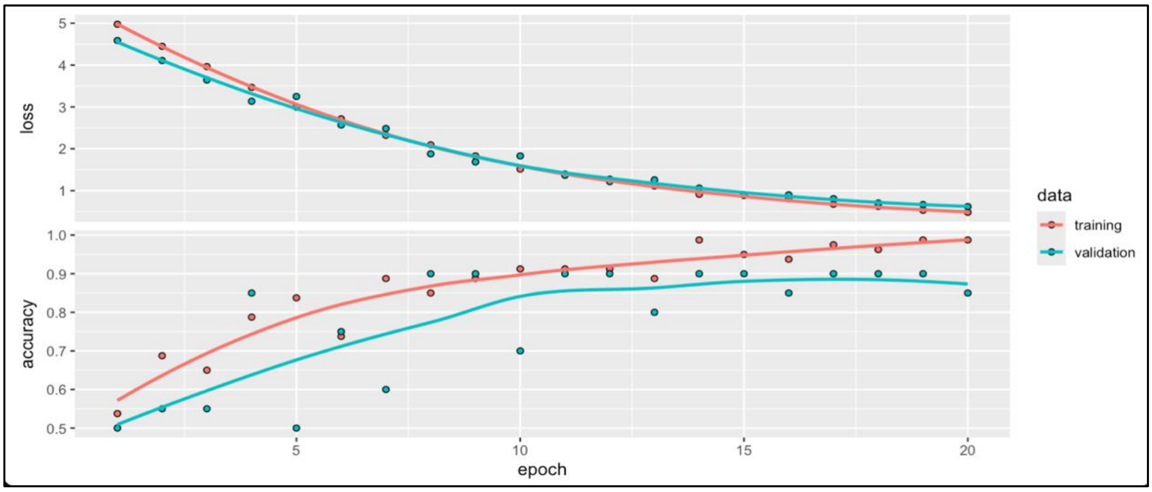
Figure 3. Layer Hierarchy Visualization on Models

The Convolutional Neural Network (CNN) model used in this study consists of several interconnected layers, each with a specific function and purpose for processing the input image. In Figure 2, a summary of the CNN model architecture is presented, showing the layers that form the model. The model begins with two convolutional layers (Conv2D), namely conv2d_3 and conv2d_2, each with output sizes of (None, 30, 30, 32) and (None, 28, 28, 32), respectively. These layers are responsible for extracting features from the input image. Following that, the max_pooling2d_1 layer performs a pooling operation to reduce the spatial dimensions of the image. This is followed by dropout layers (dropout_2 and dropout_1) that help prevent overfitting by randomly deactivating some neurons during training.

Next, the model is followed by two additional convolutional layers, conv2d_1 and conv2d, each producing outputs with dimensions (None, 12, 12, 64) and (None, 10, 10, 64), respectively. These are then followed by pooling layers to reduce the image dimensions. After that, a flatten layer is used to transform the data into a one-dimensional vector before passing it to the fully connected (Dense) layer. Here, the first layer (dense_1) contains 256 neurons, followed by the output layer (dense) with two neurons representing the two classes for classification.

This architecture summary shows that the CNN model has a total of 475,938 trainable parameters, which are used to learn features from the image data. Figure 3 illustrates the layer hierarchy in the CNN model, providing a visual representation of the relationships between layers and the overall structure of the model.

The model training process lasted for 20 epochs with a batch size of 32, accompanied by cross-validation on the test data. The plot results from the training process show the progression of accuracy and the reduction in loss over time. The image of the CNN architecture plot below illustrates the complete accuracy and loss graphs for the trained model.



Source: (Research Results, 2024)

Figure 4. Plot Accuracy and Loss

After training, the model is evaluated using the confusion matrix to measure its performance on the test data. The following confusion matrix provides a clear view of the model's performance in predicting the actual labels.

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Table 3. Training Data Confusion Matrix

Predicted/Actual	Sick	Healthy
Sick	39	0
Healthy	1	40

Source: (Research Results, 2024)

Table 3 shows the model's performance evaluation on the training data using the confusion matrix. The results reveal that the model correctly predicted the "Sick" category 39 times (True Positive), indicating a very high accuracy in recognizing the "Sick" data. There were no misclassifications of "Sick" data as "Healthy" (False Negative = 0), demonstrating perfect sensitivity on this training data. Meanwhile, there was one misclassification where "Healthy" data was classified as "Sick" (False Positive = 1), indicating a minor error in recognizing the "Healthy" category. Additionally, the model successfully identified "Healthy" data correctly 40 times (True Negative).

Overall, the evaluation results indicate that the model has a very high accuracy in classifying the training data with minimal prediction error. The model's ability to distinguish between the two categories with near-perfect precision on the training data is a positive sign. However, to ensure that the model can perform similarly on unseen data, it is important to evaluate the results on the test data to avoid overfitting or loss of generalization ability. To complete the performance analysis, the model is further evaluated based on the accuracy and loss values achieved. The following table presents the accuracy and loss results on the training and test data.

Table 4. Evaluation of Accuracy and Loss of Data Training

Dataset	Accuracy	Loss
Training	0,9875	0,443462
Testing	0,85	0,6191496

Source: (Research Results, 2024)

The evaluation results for accuracy and loss displayed in Table 4 provide an overview of the model's performance on the training and test data. The model shows a very high accuracy on the training data, with an accuracy value of 0.9875 or 98.75%. This indicates that the model is able to predict most of the training data correctly. The loss value on the training data is 0.443462, which is relatively low and indicates a small difference between the model's predictions and the actual values.

However, when evaluated on the test data, the model's accuracy decreased to 0.85 or 85%. Although this is still considered good accuracy, the difference in accuracy between the training and test data suggests that the model may be overfitting, meaning it learned too well from the training data, leading to a slight decline in performance when applied to unseen data. The loss value on the test data is 0.6191496, which is higher compared to the training data. This reflects a greater mismatch between the predictions and the actual values in the test data compared to the training data. Overall, these results indicate that the model performs very well on the training data but needs further improvement or testing to ensure consistent performance and good generalization ability on new data.

CONCLUSION

Based on the evaluation, the Convolutional Neural Network (CNN) model demonstrated excellent performance on the training data with an accuracy of 98.75% and a loss value of 0.443462. The confusion matrix indicates that the model was able to predict "Sick" and "Healthy" data very accurately, with only one misclassification where "Healthy" data was predicted as "Sick." However, the model's performance declined when tested on the test data, with an accuracy of 85% and a loss value of 0.6191496, suggesting the possibility of overfitting. The model successfully captured patterns from the training data but requires further improvement to enhance generalization and prediction accuracy on new data. Optimizations such as regularization, data augmentation, or hyperparameter tuning may be necessary steps for improvement.

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