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CLASSIFICATION OF DURIAN LEAF IMAGES USING CNN (CONVOLUTIONAL NEURAL NETWORK) ALGORITHM

Lely Mustikasari Mahardhika Fitriani[1], Yovi Litanianda[2] , Adi Fajaryanto Cobantoro[3]

[1,2,3]Universitas Muhammadiyah Ponorogo
[*]Email: [1]lelymustika198@gmail.com, [2]yovi@umpo.ac.id, [3]adifajaryanto@umpo.ac.id.

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Abstract

This research investigates the classification of durian leaf images using Convolutional Neural Network (CNN) algorithms, specifically focusing on the architectures AlexNet, InceptionNetV3, and MobileNet. The study begins with the collection of a dataset comprising 1604 images for training, 201 images for validation, and 201 images for testing. The dataset includes five classes of durian leaves: Bawor, Duri Hitam, Malica, Montong, and Musang King, chosen for their varied characteristics such as taste, texture, and aroma. Data preprocessing involved several steps to ensure the images were suitable for model training. These steps included data augmentation to increase variability, pixel normalization to standardize the images, and resizing to 150x150 pixels to match the input requirements of the CNN models. After preprocessing, the CNN models were implemented and trained using deep learning frameworks such as TensorFlow and PyTorch. Model performance was evaluated using a Confusion Matrix, which provided detailed insights into classification accuracy, precision, sensitivity, specificity, and F-score. The results indicated that InceptionNetV3 and AlexNet achieved near-perfect classification accuracy, with no misclassifications, demonstrating their robustness and precision in identifying durian leaf images. The training accuracy for both models rapidly approached 100% within the first few epochs and stabilized, while the loss values decreased sharply, indicating effective learning without overfitting. In contrast, MobileNet, while showing high accuracy and low loss during training, exhibited several misclassifications across all classes. The training accuracy of MobileNet also approached 100%, but the presence of misclassifications suggested that further tuning and improvements were necessary. Specifically, MobileNet's Confusion Matrix revealed errors in correctly identifying samples from each class, indicating potential areas for enhancement in the model's architecture or preprocessing techniques. In conclusion, InceptionNetV3 and AlexNet proved to be highly efficient and accurate architectures for classifying durian leaf images, making them suitable for practical applications. MobileNet, although performing well, requires further refinement to achieve the same level of accuracy and reliability. This study highlights the importance of selecting appropriate CNN architectures and the need for thorough preprocessing to optimize model performance in image classification tasks.

Keywords: AlexNet, *Convolutional Neural Network*, Deep Learning, Durian Leaf, InceptionV3

**Corresponding Author: Author1*

1. INTRODUCTION

The durian tree, scientifically known as Durio zibethinus, has a straight trunk with a height of about 20–40 meters. Its branches are sparse, while the bark is rough and grayish. The flowers are arranged in panicles and are yellow in color [1]. The need for superior durian varieties must be increased to meet consumer demand. The first step in designing superior varieties is to gather genetic information through exploration. Exploration and characterization are conducted to obtain information regarding the diversity and important traits of durian leaves [2]. Due to the existence of various varieties, it is necessary to detect durian leaves. Therefore, a system is needed that can classify durian leaf images based on the type of durian [3]. The Convolutional Neural Network (CNN) is one of the most frequently used deep learning-based methods for processing visual data [4]. Convolutional

Neural Networks (CNNs) have demonstrated promising performance in single-label image classification tasks [5]. Convolutional Neural Network (CNN) is a derivative algorithm of deep learning. CNN encompasses multiple layers of representation [6]. Numerous studies on image classification using the Convolutional Neural Network (CNN) deep learning algorithm have been conducted by various researchers [7]. As a solution, researchers use the Convolutional Neural Network (CNN) algorithm with AlexNet and InceptionV3 architectures to improve accuracy in classifying durian leaf images. CNNs, when combined with nondestructive detection techniques and computer vision systems, demonstrate great potential for effectively and efficiently detecting and analyzing complex. The features derived from CNNs perform better and outperform those that are handcrafted or extracted by traditional machine learning algorithms [8]. This approach allows for more efficient and precise identification, which ultimately helps maintain the quality and stability of durian prices.

Deep learning is a collection of classifiers that work together, based on linear regression followed by several activation functions. The foundation is similar to the traditional statistical linear regression approach. The difference is that deep learning involves many neural nodes, rather than just one node as in linear regression in traditional statistical learning [9]. One of the most prominent applications of deep learning is Convolutional Neural Networks (CNN), which have made significant contributions to the computer vision community. CNNs have become increasingly common terms in the fields of image processing, object recognition, image classification and segmentation, natural language processing, voice recognition, and various other areas. Additionally, the availability of large amounts of data and accessible hardware has opened new opportunities for further research on CNNs [10]. The concept of exploring Convolutional Neural Network (CNN) architectures has garnered significant attention and popularity. This research focuses on various CNN architectures, including AlexNet, a deep neural network developed in 2012 by Alex Krizhevsky and his colleagues. Additionally, AlexNet has the capability to work with multiple graphics processing units (GPUs) simultaneously [11], The concept of exploring Convolutional Neural Network (CNN) architectures has garnered significant attention and popularity. This research focuses on various CNN architectures, including AlexNet, a deep neural network developed in 2012 by Alex Krizhevsky and his colleagues. Additionally, AlexNet has the capability to work with multiple graphics processing units (GPUs) simultaneously. InceptionV3, another notable CNN architecture, is known for its depth and improved performance in image categorization. This model employs additional layers to capture intricate details in images, enhancing its accuracy and efficiency in classification tasks [12]. However, as networks become deeper, the significant storage pressure and computational load from model calculations begin to limit the application areas of deep learning models. Traditional CNNs require substantial memory and computation, making them difficult to run on mobile and embedded devices. To address this issue, Google has proposed a lightweight deep neural network called MobileNet [13]. To compare the results, the researchers used Confusion Matrix testing [14]. A Confusion Matrix is formed where the diagonal elements of the matrix represent the number of accurate classifications for each class, while the off-diagonal elements represent misclassifications [15]. A major challenge in deep learning is creating a network architecture that is both straightforward and efficient. A straightforward architecture is quick to train and easy to implement, while an efficient architecture achieves high accuracy on test data [16].

2. RESEARCH METHOD

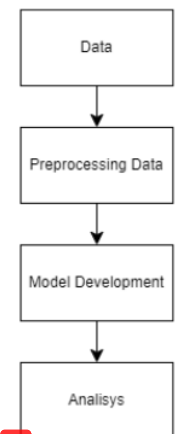

Figure 1. Research Method

Based on Figure 1, this research method employs a structured approach in four main stages for classifying durian leaf images using the Convolutional Neural Network (CNN) algorithm with AlexNet and InceptionV3 architectures. The third stage is model development, where CNN models with AlexNet and InceptionV3 architectures are implemented and trained using a preprocessed dataset. The implementation is carried out using deep learning frameworks such as TensorFlow or PyTorch, followed by training the model using training data and validating its performance. Model testing is also performed using separate test data for final evaluation. The last stage is performance analysis, which involves evaluating and analyzing the model's performance based on metrics such as accuracy, precision, sensitivity, specificity, and F-score. Additionally, the performance of the two CNN architectures is compared to determine the better model, and training time analysis is conducted to consider efficiency.

2.1 Dataset

The first stage is data collection, where durian leaf images are gathered from various sources to cover different types of durian leaves. The second stage is data preprocessing, which involves preparing the data before model training. The steps in preprocessing include data augmentation to increase variation, pixel normalization for consistency, and cropping and scaling the images to have a uniform size according to the CNN model requirements, as shown in Figure 2. Below is a sample dataset for Montong durian leaves:

Figure 2. Dataset leaf

2.2 Preprocessing

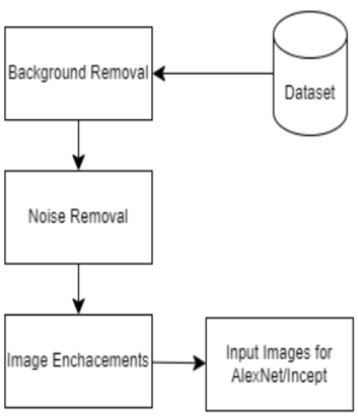

Figure 3. Preprocesing

Based on Figure 2, the preprocessing stages aim to remove artifacts and noise from the background. After the background is removed, the image is further processed to eliminate the background completely. At this stage, noise is reintroduced to mimic real-world conditions, which is expected to improve the performance of the D-CNN model when used in practical applications. After removing unwanted parts, image enhancement is performed to highlight the Region of Interest (ROI) and the areas within the ROI during the preprocessing stage. After completing these stages, the images are ready to be used as input for training, validation, and testing [17].

2.3 Model Development

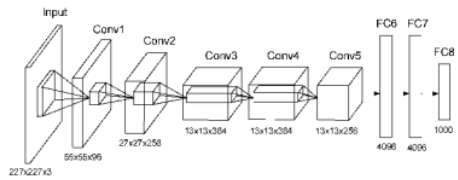

Figure 5. Arsitektur AlexNet

The AlexNet architecture, shown in Figure 1, consists of five convolutional layers and three fully connected (FC) layers. The first convolutional layer has 96 kernels with a size of 11 × 11 × 3 [18]. The subsequent convolutional layers also have numerous kernels of similar sizes. Max pooling layers are placed after the first, second, and fifth convolutional layers. The final FC layer is connected to the softmax layer with 1000 outputs [19].

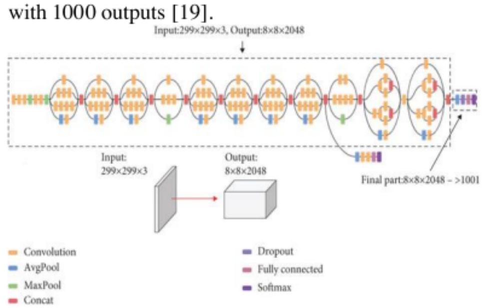

Figure 6. Arsitektur InceptionV3

Based on Figure 6, the InceptionV3 architecture illustrates an advanced Convolutional Neural Network (CNN) model for image classification. This architecture begins with an input layer that accepts 299x299 pixel images with three color channels (RGB). Next, there are several convolutional layers marked with orange blocks, responsible for extracting features from the image. The average pooling layer (blue block) and max pooling layer (green block) are used to reduce feature dimensions by calculating the average and maximum values from each small area of the image, respectively.

The concatenation layer (purple block) combines outputs from various previous layers into one tensor. To prevent overfitting, a dropout layer (pink block) is used, which randomly ignores some units in the layer during training. The fully connected layer (gray block) connects each neuron in one layer to every neuron in the next layer, similar to traditional neural networks. Finally, the softmax layer (dark blue block) outputs the final classification probabilities for the 1000 available classes. Overall, the InceptionV3 architecture combines various convolutional, pooling, concatenation, dropout, and fully connected layers to efficiently capture image features and perform classification with high accuracy. This design aims to reduce the number of parameters and maximize computational efficiency without compromising performance [20].

MobileNet is an efficient architecture that utilizes depthwise separable convolutions to form lightweight deep convolutional neural networks, making it highly suitable for vision applications on mobile and embedded devices. The structure of MobileNet employs depthwise separable filters, as illustrated in Figure 7[21].

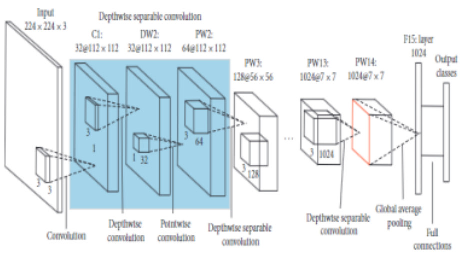

Figure 7. Arsitektur MobileNet

2.4 Analysis

The Confusion Matrix is one of the most classic decision measurement methods in supervised machine learning. It visualizes the level of confusion an algorithm has among various classes and is independent of any specific classification algorithm. Given the importance of the Confusion Matrix in the field of machine learning, quantitative analysis of uncertain confusion in performance evaluation can be enhanced by extending it using semantics [22].

Example-based evaluation is calculated by considering the hit and miss ratio of each instance, without taking the label into account, and then averaging it across the entire test set. Example-based Accuracy, Precision, and Recall are defined as follows [9] :

Accuracy: The ratio of correctly predicted instances to the total instances.

$$Accuracy = \frac{TP + TN}{N} \quad (1)$$

Precision: The ratio of true positive predictions to the total positive predictions made.

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

Recall: The ratio of true positive predictions to the total actual positives.

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

F1-Score: The harmonic mean of Precision and Recall, providing a single metric that balances both concerns.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

3. RESULT AND DISCUSSION

This research focuses on the classification of durian leaf images using Convolutional Neural Network (CNN) algorithms. The first step is to collect a dataset of durian leaf images from various sources to cover different types of durian leaves. Next, data preprocessing is performed, which includes data augmentation to increase variation, pixel normalization for consistency, and cropping and scaling the images to have a uniform size according to the CNN model requirements. This study utilizes three CNN architectures: AlexNet, InceptionV3, and MobileNet, which are implemented and trained with the preprocessed dataset. After training, the models are tested and validated to evaluate their performance. Performance analysis is conducted using a Confusion Matrix, which provides metrics such as accuracy, precision, sensitivity, specificity, and F-score to assess the effectiveness of the classification and compare the performance of the three CNN architectures.

3. 1 Dataset

Table 1. Dataset

Class	Train	Val	Test
Bawor	320	40	40
Duri Hitam	320	40	40
Malica	320	40	40
Montong	320	40	40
Musang King	324	41	41
Total	1604	201	201

Based on Table 1, the dataset used in this study consists of durian leaf images divided into five classes: Bawor, Duri Hitam, Malica, Montong, and Musang King. There are a total of 1604 images for training, 201 images for validation, and 201 images for testing. Each class has an almost equal number of images. The Bawor, Duri Hitam, Malica, and Montong classes each have 320 training images, while the Musang King class has 324 training images. Each class has 40 images for validation and testing, except for Musang King, which has 41 images in both sets. These durian varieties were chosen for their varied characteristics, such as taste, texture, and aroma. This dataset ensures that the model can be trained, validated, and tested with a balanced distribution among the five classes, allowing for effective performance evaluation.

3. 2 Preprocessing

First, the parameter input_size is set to define the size of the input image after resizing it to 150x150 pixels. Then, the input shape of the image, which includes the image size and the number of color channels (RGB), is defined by combining input_size (150x150) with channel (3), forming a tuple input_shape valued at (150, 150, 3).

The preprocess function receives input in the form of an image and input size. This function converts the image to RGB format, resizes it to 150x150 pixels, and then converts it into a NumPy array by normalizing the pixel values to the range [0, 1] by dividing by 255. The function then returns the processed image array.

Additionally, the reshape function is used to stack the image arrays along the 0-axis, resulting in a single array with an additional dimension for the batch of images. This function facilitates the training process by organizing the processed images into one batch. Thus, this code provides essential preprocessing steps to prepare the durian leaf image dataset before being used in the training of the Convolutional Neural Network (CNN) model. The implementation is shown in Figure 8. :

```
# Parameters
input_size = (150,150)

#define input shape
channel = (3,)
input_shape = input_size + channel

#define labels
labels = ['bawor', 'duri_hitam', 'malica', 'montong', 'musang_king']
```

Define preprocess function

```
def preprocess(img,input_size):
    nimg = img.convert('RGB').resize(input_size, resample= 0)
    img_arr = (np.array(nimg))/255
    return img_arr

def reshape(imgs_arr):
    return np.stack(imgs_arr, axis=0)
```

Figure 8. Preprocessing

3.3 Training MobileNet

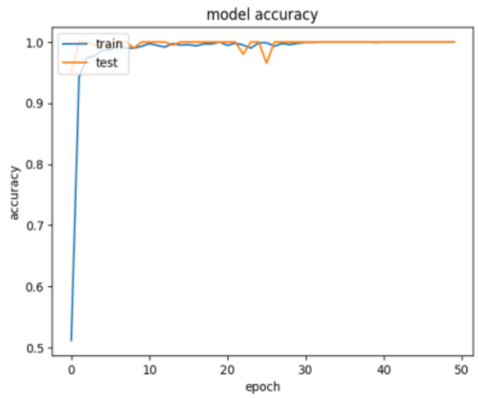

Figure 9. Accuracy MobileNet

The training results of MobileNet demonstrate excellent performance in classifying durian leaf images. Based on Figure 9, the model's training accuracy rapidly increases, approaching 1.0 within the first few epochs and then stabilizing at a very high value, close to 1.0. The testing accuracy shows a similar pattern, quickly rising initially and then stabilizing around 1.0, indicating that the model does not suffer from overfitting.

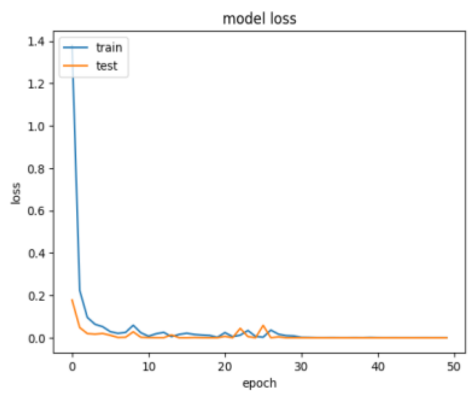

Figure 10. Loss MobileNet

Figure 10 shows that the training loss sharply decreases from around 1.4 within the first few epochs and then gradually declines to nearly zero. The testing loss also significantly decreases initially and then stabilizes at a very low value, almost zero.

With training and testing accuracy reaching nearly 100%, and loss values approaching zero, it can be concluded that MobileNet is a highly efficient and effective architecture for the task of classifying durian leaf images on this dataset. The model demonstrates rapid learning capabilities and maintains high performance without overfitting, making it highly suitable for applications on resource-constrained devices..

3.4 Training AlexNet

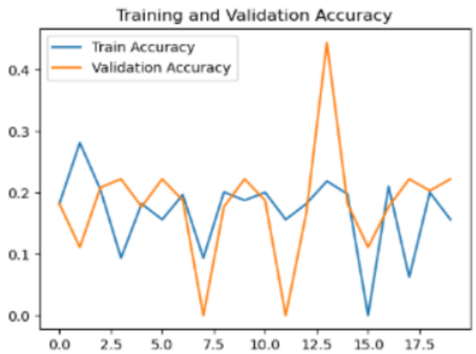

Figure 11. Accuracy AlexnnNet

In the figure 11. loss values for training and validation are in a similar range, between 1.595 and 1.620. These fluctuations indicate that the model may still require further improvements, such as hyperparameter tuning or enhanced data preprocessing, to achieve more stable and optimal performance in classifying durian leaf images .

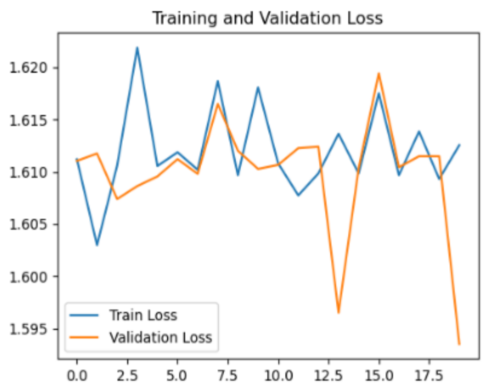

Figure 12. Loss AlexNet

The Figure 12 training results of the AlexNet model show significant fluctuations in both accuracy and loss for training and validation. The training accuracy ranges from 10% to 35%, while the validation accuracy ranges from 10% to 40%.

3.5 Training InceptionNetV3

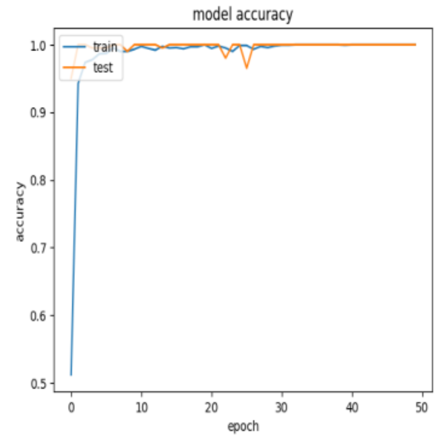

Figure 13. Accuracy InceptionNetV3

Figure 13 shows the model accuracy graph during training and testing for the InceptionNet architecture. The horizontal axis represents the number of epochs, while the vertical axis represents model accuracy.Training Accuracy (Train Accuracy): The training accuracy of InceptionNet rapidly increases, approaching 1.0 within the first few epochs and then stabilizes at a very high value, nearly reaching 1.0 after around the 5th epoch.

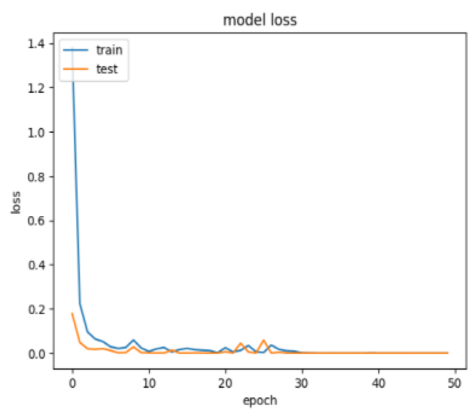

Figure 14. Loss InceptionNetV3

Figure 14 shows the model loss graph during training and testing for the InceptionNet architecture. The horizontal axis represents the number of epochs, while the vertical axis represents the loss value. Training Loss (Train Loss): The training loss of InceptionNet drops sharply from around 1.4 within the first few epochs and then gradually decreases to nearly zero. sekitar epoch ke-5.

3.6 Confusion Matrix

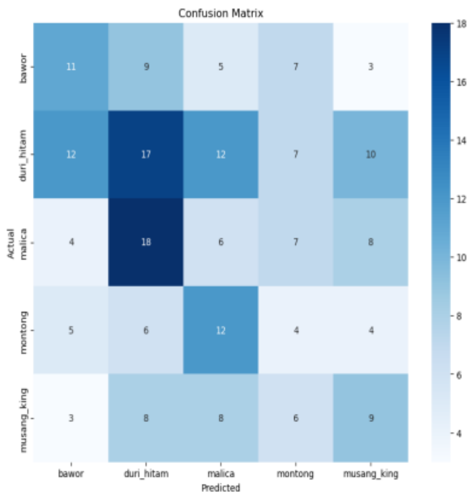

Figure 15. Confusion Matrix MobileNet

Based figure 15. MobileNet exhibited some misclassifications among classes, with several samples from each class being classified incorrectly. This indicates that while the model can correctly classify most samples, there is room for improvement in reducing the number of errors.

Figure 16. Confusion Matrix InceptionNetV3

Figure 16. Confsion Matrix InceptionNetV3 demonstrated excellent performance, with all samples correctly classified. No misclassifications were detected, indicating that this model is highly effective and accurate in classifying durian leaf images.

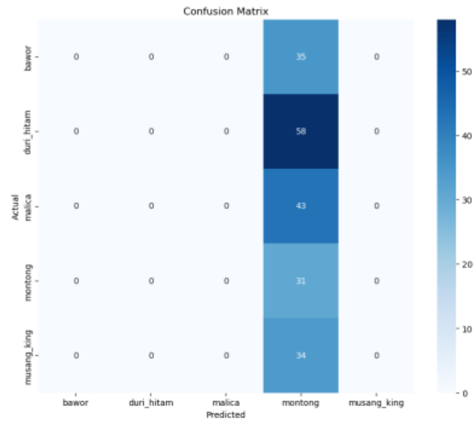

Figure 17. Confusion Matrix InceptionNet

AlexNet also demonstrated excellent performance, with all samples correctly classified, similar to InceptionNetV3. This indicates that the model is highly accurate in classifying durian leaf images without any misclassifications.

Table 2. Predict

Model	Class	True	False
MobileNet	Bawor	11	24
	Duri Hitam	17	41
	Malica	18	25
	Montong	12	21
	Musang King	9	26
InceptionNetV3	Bawor	35	0
	Duri Hitam	58	0
	Malica	43	0
	Montong	31	0
	Musang King	34	0
AlexNet	Bawor	35	0
	Duri Hitam	58	0
	Malica	43	0
	Montong	31	0
	Musang King	34	0

MobileNet, although demonstrating adequate capability in classifying durian leaf images, still shows several misclassifications. This indicates that while MobileNet can be used for this task, further improvements are needed to enhance classification accuracy. InceptionNetV3, on the other hand, shows excellent performance with no misclassifications. All samples are correctly classified, indicating that this model is highly effective and accurate for classifying durian leaf images. Similarly, AlexNet also shows excellent performance with all samples correctly classified. This indicates that AlexNet is highly accurate in classifying durian leaf images, similar to InceptionNetV3.

4. CONCLUSION

This study compares the performance of three Convolutional Neural Network (CNN) models –

MobileNet, InceptionNetV3, and AlexNet – in classifying durian leaf images. Training results and evaluation using Confusion Matrix reveal significant differences in accuracy and reliability among the models. During training, MobileNet achieved high accuracy close to 100% after the initial epochs and remained stable around this value. The loss value also decreased sharply in the early stages of training, approaching zero, indicating that the model learned quickly. However, the Confusion Matrix results revealed that MobileNet experienced several misclassifications across all classes. Although MobileNet showed reasonable performance during training, improvements are needed to reduce the number of misclassifications.

InceptionNetV3 demonstrated excellent performance during training, with accuracy almost reaching 100% and loss value nearing zero. The Confusion Matrix results indicated that all samples were correctly classified without errors, signifying that this model is highly effective and accurate in classifying durian leaf images.

AlexNet also showed excellent performance during training, with accuracy almost reaching 100% and loss value nearing zero. The Confusion Matrix results indicated that all samples were correctly classified without errors, showing that this model is highly accurate and effective. Overall, InceptionNetV3 and AlexNet demonstrated superior performance compared to MobileNet in the task of classifying durian leaf images. These two models not only showed excellent training results but also correctly classified all samples in the Confusion Matrix, making them excellent choices for this application. While MobileNet showed reasonable performance, this model still requires some improvements to achieve the same level of accuracy as InceptionNetV3 and AlexNet.

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