Classification method of applying types of rice fertilizers using Resnet50 architecture

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Abstract: The Indonesian government has implemented various strategies to increase rice production and productivity. However, until now, the results have not met expectations, and the sustainability of rice farming practices in Indonesia is still poor. One of the important problems that needs to be addressed is the imbalance of fertilizer use, as it can cause various problems in rice cultivation that lead to non-optimal productivity of rice plants, such as reduced yields and decreased quality of rice grains. Various techniques have been developed to determine the appropriate fertilizer for rice plants based on leaf color of their leaves. However, using specific algorithms to solve the illumination problem increases the computational process and still leaves the possibility of inaccurate image representation. In addition, the use of Unmanned Aerial Vehicles (UAV) is very expensive, making their implementation difficult for farmers. Beside that, previous studies generally only classify Nitrogen status into low or high, fertile or infertile classes, whereas each fertilizer has different characteristics. Therefore, this study proposes a classification method of applying types of rice fertilizers based on vegetative microscopic images of rice leaves using the ResNet50 architecture. The proposed method uses Resnet50 architecture of Convolutional Neural Network to analyze microscopic rice leaf images and classify three types of rice fertilizers accurately, quickly and non-destructively.
Keywords: classification, cnn, microscopic, resnet, rice leaves

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1 Introduction

Economic growth in Indonesia in the agricultural sector is driven by rice production, one of the rural population's primary income sources and the staple food of almost all Indonesians (Salam et al., 2019). However, rice production in Indonesia still needs to overcome several obstacles such as limited water supply, suboptimal productivity levels, poor-quality seeds, and imprecise fertilization (Effendy et al., 2022). In addition the projected demand for rice in Indonesia increases yearly as the population increases (Sahardi et al., 2021). The government has implemented various policies to increase rice production and productivity to overcome these problems. However, until now, the results have not met expectations, and the sustainability of rice farming practices in Indonesia is still poor (Purba et al., 2021; Mucharam et al., 2020). Therefore, proper management of rice farming practices in Indonesia is needed to ensure optimal rice production with minimal environmental impacts.

One of the critical problems that needs to be addressed is the imbalance of fertilizer use because it cause various problems in rice cultivation that lead to

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suboptimal productivity of rice plants, such as reduced yields and rice grains that decrease in quality. Many factors influence these problems (Alim, 2012). For example, there is a need for a better understanding of the impact of fertilizer use. Inorganic fertilizers can degrade soil quality and nutrient balance and can even lead to environmental pollution (Maru et al., 2021). On the other hand, using organic fertilizers alone cannot provide adequate nutrients for rice plant growth (Daquiado, 2019).

Application of too much fertilizer also harms the growth of rice plant. For example, overapplication of nitrogen fertilizers can decrease nitrogen use efficiency and reduce crop yield (Qian et al., 2014). In addition, excessive fertilizer use can contribute to the emission of greenhouse gases such as methane and nitrous dioxide, which are the main causes of climate change (Wang et al., 2020; Wang et al., 2019). This changing climate will harm agriculture. Furthermore, excessive use of chemical fertilizers results in soil damage and makes the soil infertile (Jayalakshmi et al., 2021).

Therefore, it is necessary to use fertilizers in a balanced and sustainable manner in rice cultivation. The use of balanced organic and inorganic fertilizers is vital for achieving optimal rice production while minimizing environmental impact (Alim, 2012). To determine whether the rice plant has received adequate nutrition, farmers in Indonesia usually do so by observing at the green color of the rice leaves. The green color of rice leaves indicates their nitrogen content is in rice leaves. Rice can be considered fertile when the green color of the leaves or nitrogen content exceeds a specific intensity value.

Nitrogen is an essential nutrient for the growth and development of rice plants, especially during the vegetative phase, and affects the physical appearance of the leaves. Nitrogen content acts as the main component of chlorophyll, which gives rice leaves a green color. This is supported by the results of research showing that the chlorophyll content in leaves is positively correlated with the greenness of rice leaves. Even during leaf aging, chloroplast proteins, including RuBisCO, are rapidly degraded, and the released nitrogen is remobilized and reused in newly growing tissues (Wada et al., 2015). Therefore, farmers can use the greenness of rice leaves as a critical indicator of Nitrogen content, which can help them optimize fertilizer use and increase crop yields.

Various techniques have been developed to determine the appropriate fertilization for rice plants based on leaf color of their leaves. One conventional technique that farmers often use is rice leaf color charts to determine nitrogen requirements (Saleh et al., 2023). Unlike in developed countries, remote sensing technology is widely used. This technology is considered more effective for measuring the nitrogen content of rice plants (Adzima et al., 2022). Drone-based vegetation index analysis has also proven effective in evaluating the nitrogen content in rice plants (Adzima et al., 2022). In addition, the soil plant analysis development (SPAD) method has also been used to measure the nitrogen content in rice leaves (Adzima et al., 2022). Based on the explanation above, the green color of the leaves, which is positively correlated with nitrogen content, can be used as the primary reference to determine the fertilizer needs of rice plants.

This information has led to rapid research on nitrogen measurement techniques for rice plants, based on digital image processing and computer vision. This technique is not only applied to measure the fertility level of rice plants, but also to detect rice plant diseases. Saberioon et al. (2014) developed a new method to determine nitrogen and chlorophyll content in rice leaves. The method involves analyzing all visible bands in the images of rice leaves captured using a regular digital camera. Using Principal Component Analysis, the essential variables of the image can be retained so that this method can effectively determine the nitrogen and chlorophyll content.

Sharma et al. (2022) proposed a deep learning-based approach to diagnose plant diseases and classify plant images into healthy and diseased classes. Leaf images were analyzed by looking at several parameters, one of which was the green color of the leaves. A convolutional neural network (CNN) method was used, and it achieved high accuracy in diagnosing the disease. Yuan et al. (2021) used hyperspectral imaging technology to detect and distinguish between blast disease in rice leaves and rice leaves that lack nutrients. Based on these results, this method effectively diagnosed blast disease in rice leaves at an early stage. Sun et al. (2018) proposed a dynamic image analysis method to diagnose nitrogen deficiency in rice leaves. This method utilizes dynamic leaf shape and color features to distinguish between different nitrogen supplements. This study found that this method effectively diagnosed nitrogen deficiency in rice leaves.

Chen and Wang (2014) applied static scanning technology to acquire images of rice leaves and extract spectral and shape information to detect nitrogen stress. The results showed that computer vision technology could quickly and non-destructively recognize the nitrogen status of rice plants. Zhao et al. (2021) developed a method to detect and monitor nitrogen content in rice leaves and whole plants using an RGB color index. The results showed that the color change of rice leaves after anthesis could be used to effectively and efficiently monitor the nitrogen content of rice leaves and whole plants.

Wu et al. (2022) propose a hybrid radial basis function neural network model with a partial least-squares regression model to predict Nitrogen content in rice leaves during growth and maturation phases. In this study, images of rice leaves were captured several stages. The image was processed to extract the feature value using digital image processing for prediction purposes. The results show that digital image processing or computer vision technology can be applied to detect the nitrogen content in rice leaves. However, there is a problem of illumination inconsistency that needs to be overcome to make this method more accurate and efficient for diagnosing nitrogen deficiency in rice plants.

Uneven and inconsistent illumination, including detecting nitrogen content in rice plant leaves, is critical problem in computer vision (Chen and Wang, 2014). Although computer vision technology can help identify the nitrogen status of rice in a non-destructive and fast manner, images acquired through digital cameras, including drones, are greatly affected by environmental conditions and often lead to degraded quality and inaccurate representation of the resulting images (Chen and Wang, 2014).

Static scanning technology can improve image quality by capturing images of the top three leaves of fully developed rice plants during four growth periods (Chen and Wang, 2014). However, image quality is still highly dependent on external factors, such as lighting. The retinex theory can be utilized to explain how the human visual system perceives colors under different lighting conditions (Ng and Wang, 2011). The total variation model for retinex can be utilized to assume the spatial smoothness of illumination and reflection continuity (Ng and Wang, 2011). In addition, hyperspectral remote sensing data collected by unmanned aerial vehicles (UAVs) can be used to quantitatively measure the nitrogen content in rice (Du et al., 2018). This method can provide a noninvasive method to measure it. However, using specific algorithms to solve the illumination problem increases the computational process and still leaves the possibility of inaccurate image representation. In addition, using UAVs is very expensive, making it difficult for farmers to implement. Besides that, the studies discussed above generally only classify nitrogen status into low or high, fertile or infertile classes, whereas each fertilizer has different characteristics.

Therefore, this study proposes a classification method of applying types of rice fertilizers based on vegetative microscopic images of rice leaves using ResNet50 architecture. The proposed method uses Resnet50 architecture of Convolutional Neural

Network to analyze microscopic rice leaf images and classify 3 types of rice fertilizers accurately, quickly and non-destructively.

2 Method

2.1 Dataset

The object of this research is the image of rice leaves which is divided into three types. The first was unfertilized rice that is not fertilized and was named class "K". Second, rice is provided with an artificial fertilizer named "U". This fertilizer was made from a mixture of UPK, Zeolite and Agricultural Lime. Third, rice that is given control release fertilizer (CRF) which is then named class "F".

Images of the three classes of rice leaves were acquired using a smartphone camera equipped with a microscope lens. The overall dataset was divided into three classes: K, U, and F. Furthermore, 80% of the dataset was used as training data and 20% as test/validation data.

2.2 Resnet

ResNet, short for Residual Network, is a CNN architecture that has gained popularity in recent years due to its ability to train very deep neural networks. It is a deep learning model that is widely used in various machine vision tasks, including image classification, object detection, and semantic segmentation (Chen, 2023). For example, in medical image processing, ResNet50 has been used for chest X-ray imaging diagnosis of COVID-19 (Sun, 2023). In vehicle classification, ResNet50 has been used to classify vehicle types using surveillance images (Qian et al., 2022). In fire image detection, ResNet50 has been used for intelligent fire image detection based on FPGA (Guo et al., 2023).

The ResNet architecture was introduced in 2015 by Microsoft Research and won the ImageNet 2015 competition (Bai and Yang, 2022). The ResNet architecture uses skip connections to allow the network to learn residual functions, which helps avoid the vanishing gradient problem that can occur in very deep neural networks. Table 1 presents an overview of the various ResNet architectures (ResNet50, ResNet101, ResNet152) (Bai and Yang, 2022; Sarwinda et al., 2021).

The ResNet50 model is a variant of ResNet architecture with 50 layers. It uses a bottleneck structure as the input block type, which is convenient for model storage and calculation; the number of input blocks is (Bai and Yang, 2022). The ResNet50 architecture consists of several components, including convolutional blocks, identity blocks, and a fully connected layer. Convolutional blocks are used to extract features from the input image, whereas identity blocks are used to propagate the features through the network. A fully connected layer was used to classify the images based on the extracted features.

The ResNet50 architecture contains the following elements.

(1) A convolution with a kernel size of 7 × 7 and 64 different kernels, all with a stride of size two (one layer);

(2) Max pooling with also a stride size of 2.

Table 1 Resnet architecture

Layer Name	Output Size	50-layer	101-layer	152-layer
conv1	112 × 112		7 × 7, 64, stride 2	
			3 × 3 max pool, stride 2	
conv2_x	56 × 56	$\begin{bmatrix} 1\times1, & 64 \\ 3\times3, & 64 \\ 1\times1, & 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, & 64 \\ 3\times3, & 64 \\ 1\times1, & 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, & 64 \\ 3\times3, & 64 \\ 1\times1, & 256 \end{bmatrix}\times3$
conv3_x	28 × 28	$\begin{bmatrix} 1\times1, & 128 \\ 3\times3, & 128 \\ 1\times1, & 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, & 128 \\ 3\times3, & 128 \\ 1\times1, & 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, & 128 \\ 3\times3, & 128 \\ 1\times1, & 512 \end{bmatrix}\times8$
conv4_x	14 × 14	$\begin{bmatrix} 1\times1, & 256 \\ 3\times3, & 256 \\ 1\times1, & 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, & 256 \\ 3\times3, & 256 \\ 1\times1, & 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, & 256 \\ 3\times3, & 256 \\ 1\times1, & 1024 \end{bmatrix}\times36$

In the subsequent convolution, there is a 1 × 1, 64 kernel, followed by a 3 × 3, 64 kernel, and finally, a 1 × 1, 256 kernel; these three layers are repeated three times (nine layers).

(1) Next, kernel of 1 × 1, 128. Subsequently, a kernel of 3 × 3,128 and a kernel of 1 × 1, 512 were used. This step was repeated 4 times (12 layers).

(2) After that, there is a kernel of 1 × 1, 256 and two more kernels with 3 × 3, 256 and 1 × 1, 1024, and this is repeated 6 times (18 layers).

(3) And then again, a 1 × 1, 512 kernel with two more of 3 × 3, 512 and 1 × 1, 2048 was repeated 3 times (9 layers).

(4) After that, we do an average pool and end it with a fully connected layer containing 1000 nodes and, in the end, a softmax function (1 layer).

2.3 A non destructive method

In this study, a non-destructive method is proposed to detect the type of fertilizer applied to rice plants based on the microscopic images of the leaves, as shown in Figure 1. The first stage of the proposed method is the image acquisition process. Image acquisition was performed using a smartphone equipped with a microscope lens. The smartphone used has a camera resolution of 12 MP with settings of WB Daylight, Auto Focus, shutter speed of 1/30, and ISO 200. The additional microscope lens was used as the APL-MS002 200x Phone Microscope. This additional lens is accompanied by six leds that can provide consistent lighting during the image capture.

Next, the rice leaf image dataset was acquired in 5 stages. First, the microscope lens was mounted on Redmi 8 smartphone camera lens. Second, the microscope lens led is turned on. Third, the microscope lens attached to the camera is pressed against the rice leaves until the camera lens reached the right focus. The microscope lens led provides consistent light when pressed against rice leaves. Fourth, to ensure the consistency of the color of the leaves, the backs of the rice leaves were covered with white cardboard that was not translucent. Fifth, ensure that the image on the screen is in focus and, press the capture button. Thus, a microscopic image of rice leaves can be obtained that is consistent in terms of lighting without damaging the rice leaves.

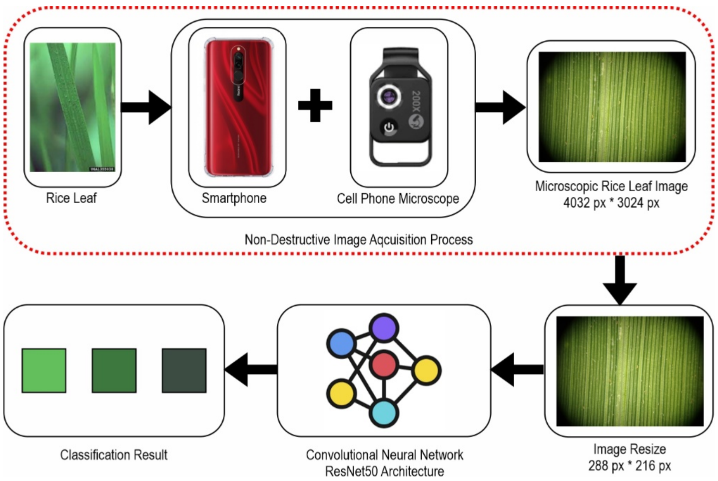

Figure 1 A non-destructive rice fertility classification method

Furthermore, in the second stage, preprocessing is carried out in the form of image resizing to reduce the size of the image that has been obtained so that it can facilitate the computational process when training the CNN model. The image that has been reduced is then used as the training data for the CNN model. At this stage the architecture used was Resnet50. After the model was trained, it classified the new input image.

3 Results and discussion

In this study, examples of the acquired images based on their classes are shown in Figure 2. The dataset images resulting from the image acquisition process were RGB images with the JPG extension measuring 4032 px × 3024 px and divided into three classes: F, K, and U. Based on the results of image acquisition using the Redmi 8 Smartphone equipped with a 200x magnification micro lens, it can be seen that the details of the rice leaves can be seen quite clearly at a resolution of 4032 px × 3024 px as shown in Figure 3.

Figure 3 shows that the image obtained through the image acquisition process using a 200x magnification micro lens can produce an image that is quite detailed in describing the texture and areas containing green substances in rice leaves. Additionally, the resulting image was confirmed to be consistent in terms of illumination. This is because when the image is taken, the camera tip is tight to the rice leaves, so that no outside light escapes. In addition, when the image was captured, the rice leaves were covered with opaque cardboard. This ensured that light from behind the rice leaves did not affect the resulting image. This is an advantage of this method in which images are easily obtained with consistent lighting without damaging the rice leaves.

(a) Class F (b) Class K (c) Class U

Figure 2 Example of micro-image of rice leaves based on their classes

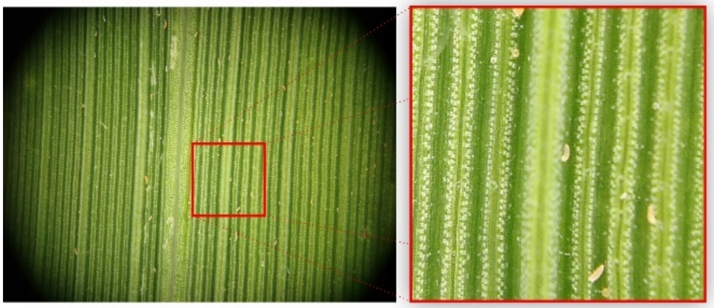

Figure 3 Image acquisition results with 100% magnification

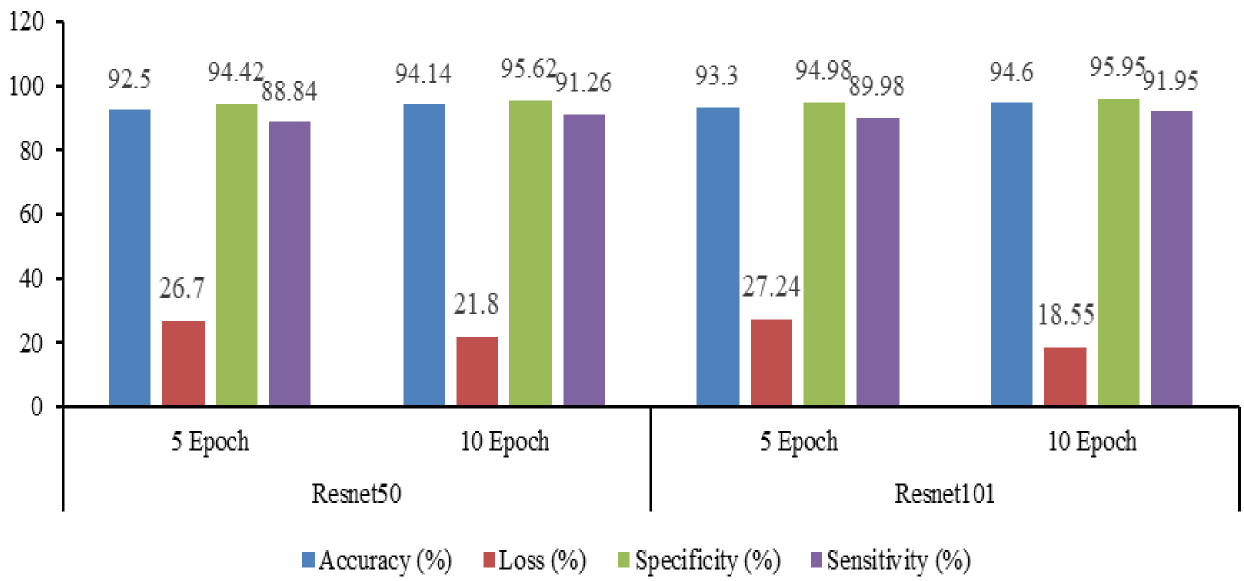

Figure 4 Performance comparison of ResNet architecture

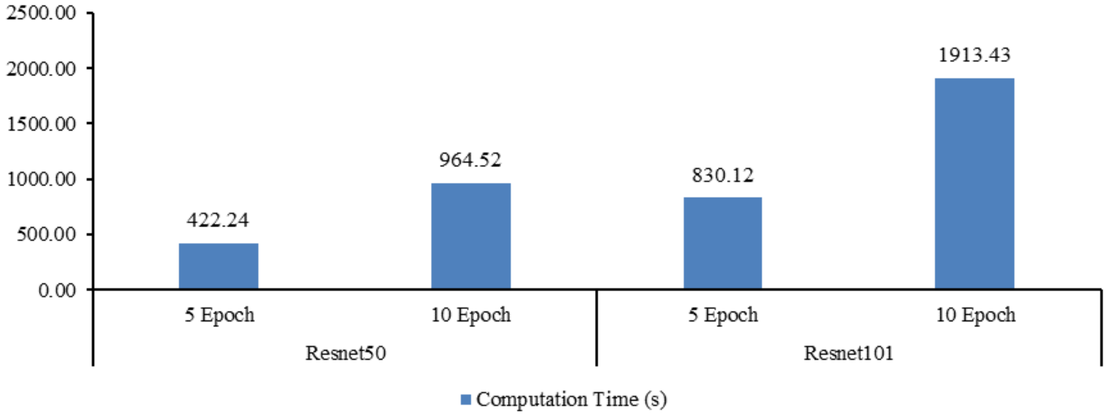

Figure 5 Time computation comparison of ResNet architecture

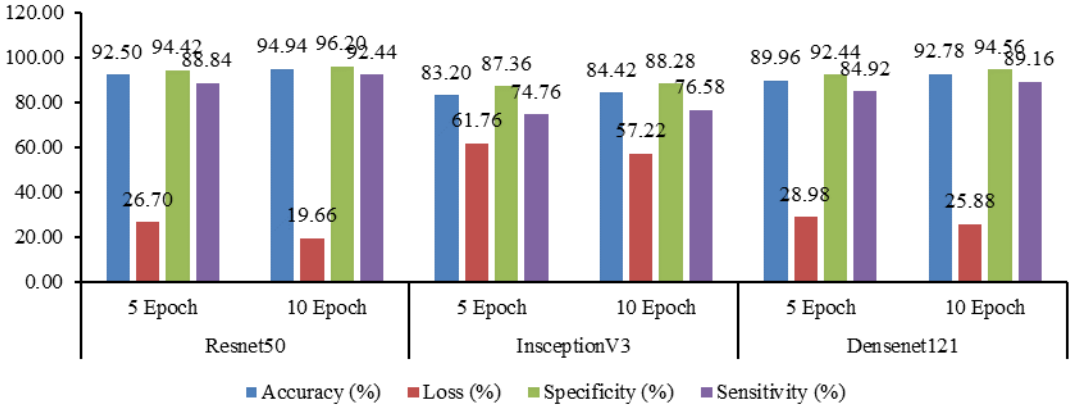

Figure 6 Performance comparison of ResNet, InsceptionV3, and DenseNet architecture

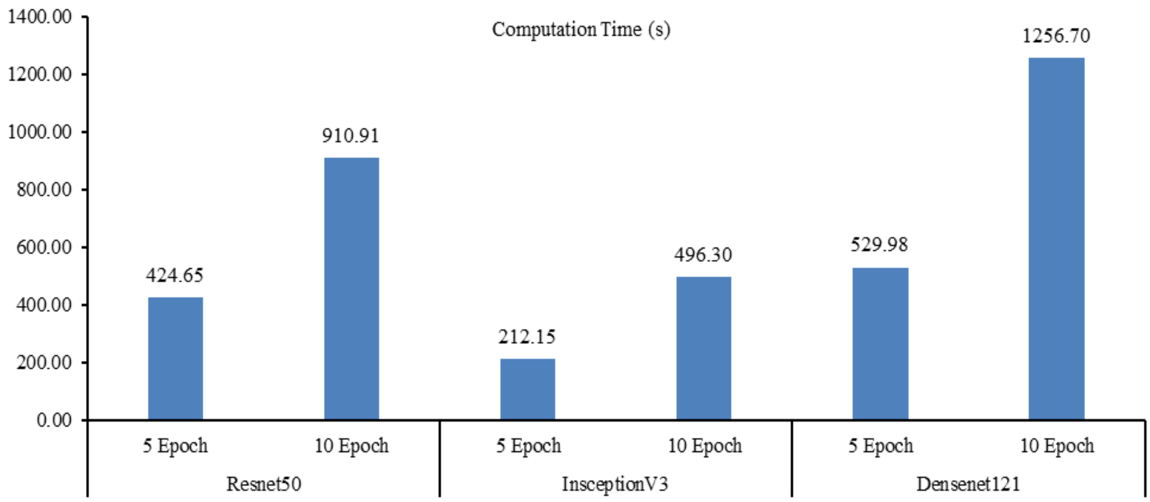

Figure 7 Time computation comparison of ResNet, inseceptionV3, and Densenet121 architecture

After obtaining all the images that need to be used as a dataset, they are then used as training and test data for the ResNet architecture. In the first part of the experiment, testing was performed using two ResNet variants: ResNet50 and ResNet101. The devices used for testing have the following specifications:1) 11th Gen Intel(R) Core(TM) i7-11800H @ 2.30 GHz 2.30 GHz; 2) 8 GB DDR4-3200 installed RAM; 3) 64-bit Windows Operating System; 4) 512 GB M.2 NVMe™ PCIe® 3.0 SSD Storage. The test results in Turbo mode with Intel®UHD Graphics GPU support are shown in Table 2.

In terms of accuracy, from the experiments for each architecture and number of epochs, the Resnet50 architecture with 5 epochs yielded, gave the lowest accuracy of 90.60%, while the highest accuracy was achieved by the Resnet101 architecture with 10 epochs at 96.20%.Furthermore, in terms of loss value, the Resnet50 architecture provides the highest loss of 32.20% while ResNet101 provides the lowest loss of 17.50%. In terms of specificity and sensitivity, Resnet50 again provided the lowest values of 93.00% and 86.00%, respectively. On the other hand, Resnet101 provides the highest values, 97.10% and 94.30%, respectively. As shown in Figure 4, although the ResNet101 architecture was able to provide the best value in the various aspects evaluated, Resnet50 with 10 epochs was able to provide a better average accuracy. Resnet50 provides an average accuracy of 94.94%, which is 0.02% greater than ResNet101.

Based on the test data shown in Table 2 and the average computation time in Figure 5, it can be seen that the greater the number of epochs and the greater the number of layers, the longer the time required in the computation process. This can be observed from the computation time of each tested ResNet variant. The computation time increases to 2 times directly proportional to the number of epochs and the number of layers used. Therefore, in this case, it can be seen that the ResNet50 architecture with a low number of epochs can perform the computation process aster than other ResNet architectures and a larger number of epochs. Based on the test results that have been carried out above, it can be seen that the ResNet50 Architecture with the number of epochs 10 provides the best performance.

Furthermore, the ResNet50 architecture was compared with other architectures such as InsceptionV3, and Densenet121. The comparison results can be seen in Figure 6. Based on these figures, it can be seen that the accuracy performance of the ResNet50 classification results with epoch 5 is still better than that of other architectures. The lowest average accuracy is produced by the InsecptionV3 architecture with the number of epochs 5 of 83.20%. In terms of loss, ResNet50 with 10 epochs also provides the smallest average loss value of 19.66%. In contrast, the InsceptionV3 architecture with a number of epochs of 5 provides an average loss value of 61.76%.

In terms of specificity and sensitivity, the Resnet50 architecture with 10 epochs again provided the best performance. The comparison results can be seen in Figure 7. The architecture gives an average value of specificity and sensitivity of 96.20% and 92.44%, respectively. In contrast, the InsceptionV3 architecture with 5 epochs again showed the lowest performance of 87.36% for specificity and 74.76% for sensitivity.

Although InsceptionV3 performed well in terms of accuracy, loss, specificity and sensitivity, it showed the fastest computation time with five epochs at 212.15 seconds. The longest computation time is achieved by Densenet121 architecture with the number of epochs 10 at 1256.70 seconds. Resnet50 with 10 epochs requires an average computation time of 910.91 seconds.

Based on the results obtained from the comparison of the three types of CNN architectures above, it can be concluded that the ResNet50 architecture with epoch 10 is the best architecture to be applied in detecting the type of fertilizer applied to rice plants based on the microscope image of the leaves.

4 Conclusions

This research successfully produced an RGB image dataset measuring 4032 px × 3024 px and divided it into three classes namely F, K, and U. By using a 200x magnification micro lens on a Redmi 8 smartphone, the details of the rice leaves can be seen quite clearly at that resolution. The resulting image is consistent in terms of illumination, making it a superior method for obtaining images easily and without damaging rice leaves.

Based on the results of the experiments conducted, it can be concluded that the ResNet50 CNN architecture with 10 epochs provides the best performance in detecting the type of fertilizer applied to rice plants based on microscopic images of their leaves. This is indicated by better accuracy, loss, and specificity and sensitivity values compared with other architectures. Although the InceptionV3 architecture shows the best performance in terms of computation time, its performance in terms of accuracy, loss, and specificity and sensitivity is much lower than that of ResNet50. Therefore, ResNet50 with 10 epochs can be used as a more precise and accurate architecture for detecting the type of fertilizer applied to rice plants based on the microscope image of the leaves.

However, in terms of computation time, the ResNet50 architecture requires a considerable amount of time for the computation process. Therefore, a suggestion for further development is to reduce the computation time of The ResNet architecture.

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