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An optimum hyperparameters of restnet-50 for orchid classification based on convolutional neural network

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ABSTRACT

There are many types of orchids in Indonesia, such as Phalaenopsis Amabilis (Moon Orchid), Cattleya, etc. Because the shape and color of each orchid flower looks the same, a system is needed that can classify orchid flowers. In this research, we will use a system using a Convolutional Neural Network with ResNet50 architecture to classify orchid species. There are 4 types of orchids that will be used, namely Moon Orchids, xDoritaenopsis Orchids, Cattleya Orchids, and Coelogyne Pandurata Orchids (1000 datasets for each type). The aim of this research is to implement deep learning using the Convolutional Neural Network method combined with the ResNet50 architecture and identifying the types of orchid flowers and calculating accuracy when identifying orchid flower types. This research uses 4000 orchid image datasets, with a data split of 80:20 so that 800 images are used as training data and 200 as test data. ResNet50 uses a confusion matrix evaluation, namely Accuracy, Precision, Recall, Specificity and F1-score with epochs 10, 20, 30, 40. From the research that has been carried out, it produces the highest accuracy on Test Data with the 30th epoch, reaching 98.87%. and the lowest accuracy on Test Data with the 10th epochs which produces an accuracy of 97.75%.

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1. INTRODUCTION

Indonesia is a country that is rich in natural resources and has various types of plants. One of them is ornamental plants, ornamental plants in Indonesia have their own charm because various groups of people keep ornamental plants in their homes. Therefore, Indonesia is one of the countries that has a diversity of flora and fauna and Indonesia's tropical clim ate is one of the factors that has a big influence on the diversity of flora and fauna [1]. The richness of flora or plants in Indonesia is a privilege, because various types of plants can be found and it is not uncommon for there to be plants that are rare and can only grow in Indonesia. For this reason, many Indonesian people are very interested in keeping ornamental plants, not infrequently because the beauty and uniqueness of flowers in Indonesia makes these flowers become ornamental plants [2]. One of the ornamental plants that is very popular with the public is orchids.

Orchids are a type of ornamental plant and belong to the Orchidacae family, which is the largest family of flowering plants. This orchid is also divided into two types, namely Species Orchids and Hybrid Orchids. Species Orchids are orchid plants that grow naturally and develop in forests and have not been crossed with other types of orchids. Meanwhile, hybrid orchids are orchid plants that have been crossed with other orchids to provide the opportunity to have the best offspring that are capable of having a high level of adaptation in various regions. This plant is able to survive from minus to high temperatures such as in the desert. This ability to adapt and grow can make orchid plants live in tropical areas even in polar regions. This tropical area itself is an area that has a diversity of orchid types. The uniqueness of orchids in adapting and their unique beauty which lies in the color and shape of these flowers, makes orchids an attraction for ornamental plant fans from within and outside the country and provides a high selling value as well as an opportunity for cultivation and cross-breeding to create new species [2], [3]. Because the results of cultivation in cross-breeding continue to grow, it has led to high public interest in various things such as keeping orchids for use as decoration, such as home decorations, greeting flowers, and religious events.

Orchids have more than 25,000 species that have spread throughout the world, especially in tropical areas [4], [5]. This plant has beautiful flowers and very diverse shapes, colors and aromas. Several types of orchids also have high economic value because of their beauty, such as black orchids and moon orchids. Orchids are usually grown and used as ornamental plants, for important events, and are also used as raw materials in the perfume and cosmetics industry [6]–[8]. Phalaenopsis Amabilis or commonly called the Moon Orchid [9] is a type of orchid that originates from Southeast Asia. This species has large and beautiful flowers, and is often used as decoration in pots or planted on tree trunks. Phalaenopsis Amabilis has white flowers with light purple or pink veins in the center of the flower. This flower grows on a long stalk and stands straight upwards, usually this flower blooms for several weeks. Apart from that, this orchid also has wide, bluish-green leaves and well-maintained roots. This orchid is also an epiphytic orchid, which means they grow on tree trunks or on rocks. Therefore, Phalaenopsis Amabilis can grow well in pots or in hydroponic conditions (medium without soil for the body). Phalaenopsis Amabilis also has several varieties, each of which has its own characteristics and uniqueness. The Doritaenopsis orchid is a type of hybrid orchid that comes from a cross between the moon orchid (Phalaenopsis) and the Doritis orchid. If a layman looks at the Doritaenopsis orchid, it will be difficult to differentiate between the Doritaenopsis orchid and the Moon orchid because they both look very similar. Doritaenopsis tend to have larger, bolder flowers than moon orchids, and the flowers themselves often have more colors or patterns than moon orchids. Apart from that, Doritaenopsis also has a tendency for leaves to be longer and wider than moon orchids. Cattleya [3] is a species of orchid which is a genus of epiphytic orchid which is famous for its large, colorful and fragrant flowers. The Cattleya genus belongs to the Orchidaceae family and consists of many different species and hybrids. The characteristic of the Cattleya orchid is its large, symmetrical flowers with curved petals. The flowers usually have striking colors, such as red, yellow, purple and white. Some species also have interesting patterns or spots on their flower petals. Cattleya is often bred through crossing to produce new hybrids with various color variations and flower shapes. Coelogyne pandurate's common name is "Black Orchid" or "Black Orchid." This orchid is characterized by large, shiny leaves and attractive flowers with dark colors such as dark purple and striking black, so it is often nicknamed the "Black Orchid". They grow in their natural habitat as epiphytes, namely attached to trees or other objects, in lowland to highland forests. Coelogyne pandurata is a species of orchid that is classified as rare and protected. Its beauty has made it popular among orchid collectors.

Due to the many experiments on each type of orchid species that were created, this plant has several similarities in the pattern, texture, shape and color of each type of orchid and makes ordinary people who see the orchid flower think that the orchid is 1 of the same type [4]. Therefore, machine learning technology is needed that can classify images of orchids to differentiate orchid species [10], [11]. The development of technology provides various conveniences for various life problems [12]. The digital representation of flowers, characterized by their vivid chromatic attributes, establishes them as viable candidates for deployment as input imagery within the object recognition paradigm [13]. Recently machine learning has become widespread research in various aspects, such as spam detection, video recommendation, multimedia concept retrieval, and image classification [5], [14]. Among these algorithms, Deep Learning is often implemented in research [5]. Because the deep learning process uses Artificial Neural Networks or artificial reasoning networks which include many layers to explore hierarchical data representation and also complete tasks such as segmentation, regression and classification. The emergence of Convolutional Neural Networks has made the application of deep learning to image recognition faster and more accurate. The 2DCOS method used and combined with residual Convolutional Neural Networks with ResNet can differentiate 20 species of orchids. During processing, it shows that the 1800-450cm and 2400 - 1900cm band features display 100% accuracy in both the training and testing data sets. Therefore, it is concluded from this research [15] that the combination of 2DCOS with ResNet can be an effective and accurate method for classifying different species of Dendrobium orchid flowers.

Another research conducted by Seeland et. al [16] had been implemented Convolutional Neural Network (CNN) to classify images. According to Marco Seeland, CNN is the deepest class of neural networks with many layers, namely the steps in each information processing. Each successive layer changes the output of the previous layer. Starting from a raw pixel-based image as input to the first layer, according to CNN, it also learns which filters best translate the input data into a suitable representation and selection for classification. Researchers explain that 1000 training data images per genus are sufficient to achieve an average accuracy of 60%, while accuracy in family classification with 1000 training data images produces an average of less than 50%. This classification accuracy varies, especially between different groupings. And researchers have carried out a series of systematic image classification experiments and studied the accuracy achieved on 1000 plant species belonging to 516 genera and 124 families. Using images of plants taken from natural habitats with large variations in viewpoint, scale and extent to which the plants are depicted. In a first series of trials, researchers learned how classifying by abstracting this visual variability can improve when identifying groupings at the more general genus and family levels. And the researchers found that the classification technique using Convolutional Neural Network was able to carry out classification groups at the genus and family levels.

There has been a lot of research conducted regarding the classification or identification of orchid flower types. Like research conducted by Xiao et. al [9] where the researchers explained that one of the most common orchid varieties, namely phalaenopsis, is often found on the ornamental flower market with different growth phases. As the cultivation develops, market demand has increased recently, and the scale of phalaenopsis planting continues to grow. In 2018, phalaenopsis became the most productive potted plant, with a yield of up to 60 million. And in the process of producing and selling in large quantities, it makes a manual classification process necessary to classify phalaenopsis of different growth phases. However, the industrialization level of phalaenopsis cultivation is relatively low, and the production efficiency in manual classification is quite low, so it is urgent to apply information technology in the form of image processing and deep learning to automatically classify phalaenopsis according to their growth phases.

Analyzing problems is meant to be able to master the problems that have been defined within the scope or boundaries [17]. From the previous studies that have been described, it is known that the convolutional neural network method has good performance in image classification. Therefore, this research developed a lightweight Convolutional Neural Network system to classify phalaenopsis according to their growth phases to help production in the agricultural sector. Collecting a dataset of phalaenopsis images taken manually in a greenhouse, then using data augmentation techniques to increase the number of images, in building a classification model for the Convolutional Neural Network model.

The aim of this research is to implement deep learning using the Convolutional Neural Network method combined with the ResNet50 architecture and identifying the types of orchid flowers and calculating accuracy when identifying orchid flower types. In this article, we focus on implementing deep learning using the Convolutional Neural Network method combined with the ResNet50 architecture and identifying the types of orchid flowers and calculating accuracy when identifying orchid flower types. Deep Learning development using the Convolutional Neural Networks algorithm and ResNet50 architecture. There are 4 types of orchids used, namely Phalaenopsis Amabilis, xDoritaeopsis, Cattleya and Coelogyne Pandurata, with 1000 images of each type.

2. METHOD

Image Classification

Classification is a process of grouping objects or data into certain categories or classes based on the characteristics or features they have. In machine learning models, classification is a type of task or problem that can be solved using machine learning techniques [18]. Classification aims to predict the class or category of an object or data based on the features or attributes it has. The classification process in a machine learning model involves several stages, including [19]–[21]:

1. Feature selection: Selecting the features or attributes that are most relevant and influence the class or category to be predicted.
2. Data preprocessing: Preparing data that will be used as input in building a classification model. At this stage, the data will go through a resizing process to equalize the size of the dataset so that the model can understand the data more optimally.

3. Model building: Building a classification model using machine learning algorithms such as naïve Bayes, k-nearest neighbors decision tree, neural networks, or support vector machine. The performance of these algorithms will later be compared to find the model with the best performance.
4. Model evaluation: measuring the performance of a classification model using matrices such as accuracy, precision, recall, specificity, or F1-score.
5. Model usage: Using a classification model to predict the class or category of a new object.

RestNet-50 Architecture

Convolutional Neural Network (CNN) [20], [22] is a type of neural network that is often used to process image data. Convolutional Neural Network is used to classify data that has been labeled using a supervised learning method. In the supervised learning method, the expected target of the input that can be accepted by the network is previously known. Convolutional Neural Networks is an architecture that can be trained and consists of several stages [23]. The input to a Convolutional Neural Network is an image, and the process of describing the image into a feature that can be understood by the network is what makes a Convolutional Neural Network different from other neural networks [24], [25].

ResNet [15] is designed to overcome a problem that often arises in very deep artificial neural network architectures, namely the vanishing gradient problem. This problem often occurs when the gradient error passed to the back layers is very small, making the learning process difficult and increasing the risk of overfitting. ResNet50 is a variant of ResNet which has 50 layers in its architecture. In this architecture, Resnet has 48 Convolution Layers, 1 Average Pool Layer, and 1 Maxpool Layer. The ResNet-50 architecture is also one of the architectures that is often applied when compared with other versions of ResNet. ResNet50, which is one of the architectures of Convolutional Neural Networks, also introduces a new concept, namely "shortcut connections". The emergence of the concept of shortcut connections in the ResNet50 architecture is due to its connection to the vanishing gradient problem or exploding gradient problem which occurs where the gradient (change in weight value) becomes very small or very large when passing through many layers or deepening. structure of a neural network. However, when deepening a network with the aim of improving its performance, this cannot be done simply by stacking layers. The deeper the network, the more problems it can create, namely vanishing gradients, which can cause the gradients to become very small and pose a risk of decreasing performance or accuracy. A RestNet-50 architecture can be seen in Figure 1.

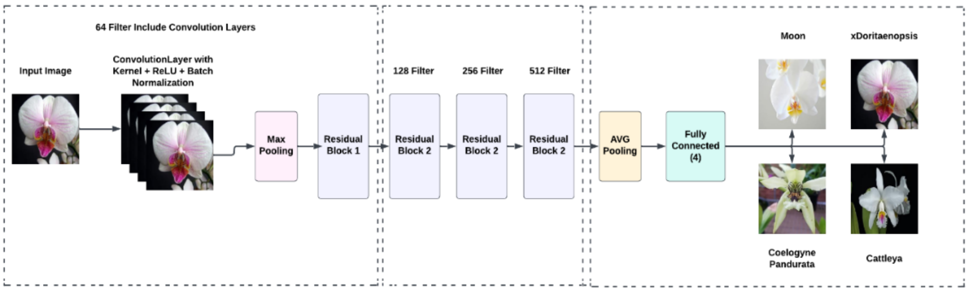


Figure 1. A RestNet-50 architecture

Image Dataset

Here, the total dataset that has been collected is 4000 image datasets on the 4 types of orchids used. The image dataset is collected into an orchid folder where each type of orchid has the same number of datasets, namely Phalaenopsis Amabilis (Moon Orchid) 1000 datasets, xDoritaenopsis 1000 datasets, Cattleya 1000 datasets, Coelogyne Pandurata 1000 datasets. The image of each orchid is a public source obtained via social media and from the internet at the link https://id.pinterest.com/. Where each dataset obtained from public sources is downloaded one by one, and each image has a different size resolution and in a different format such as JPG, PNG. The image that has been obtained is resized to a size of 250x250 and changed to JPG format. Next, the dataset that has been resized and collected worth 4000 is then divided into 4 subfolders with 1000 images each. Then split the testing data with training data of 80:20. Based on 1000 images, 800 images were taken to be used as training data and 200 images were used as testing data. The sample of the dataset used in this research can be seen in Figure 2.

Phalaenopsis Amabilis xDoritaenopsis Cattleya Coelogyne Pandurata

Figure 2. Sample dataset

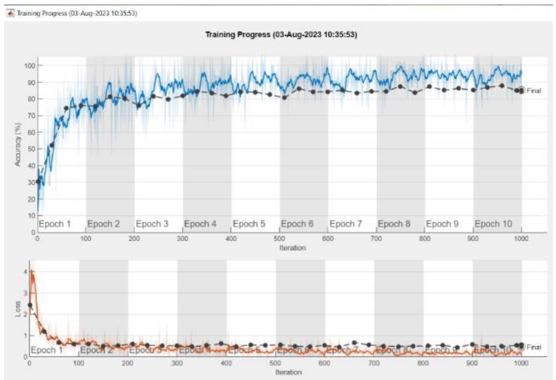
After the dataset is obtained, the next process in this research is preprocessing, the aim of the image preprocessing process before processing is to improve the image quality to obtain maximum results. In initial image preprocessing there are still different sizes and to make things easier and obtain maximum accuracy results, all image sizes must be the same, namely by using an image size of 250x250. When resizing an image, a function from Matlab is used, namely (imresize). The preprocessing stages can be described:

1. Define a variable f to store the complete address of the "Moon" folder using fullfile().
2. Get a list of files in the "Moon" folder using ls(f). This list will be stored in variable d.
2. Delete the first two lines of list d to remove entries for directories ".." and "." generated by ls().
3. Create a new folder with the name "Moon Class1" using mkdir().
4. Open a loop from 1 to size d (i.e. the number of files in the "Moon" folder).
5. In each loop iteration, read the image from directory f using imread() by utilizing the variable d(i,:) for the file name.
6. Change the image size to 250x250 pixels using imresize().
7. Give a new name to the file by adding the iteration number using strcat() and num2str().
8. Save the resized image to a new folder "Moon Class1" with the new name created using imwrite().

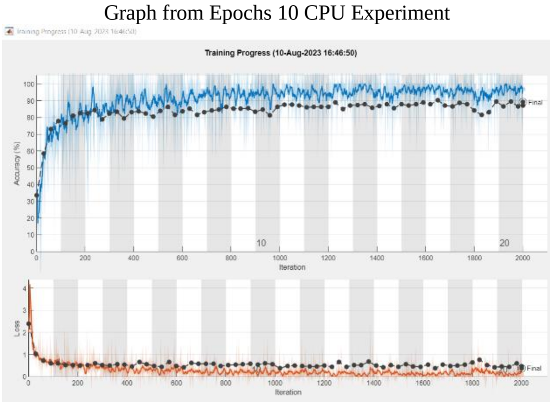
3. RESULTS AND DISCUSSIONS

Recognizing types and classifying orchid flowers based on the pattern, shape and color of the flower uses the Convolutional Neural Networks (CNN) algorithm and to further clarify the gradient during processing in Convolutional Neural Networks, the additional ResNet50 architecture is used. The training and testing had been yielded a high score as visualized in Figure 3 based on 10, 20, 30, 40 epochs. Graph visualization based on variation epochs can be seen in Figure 3.

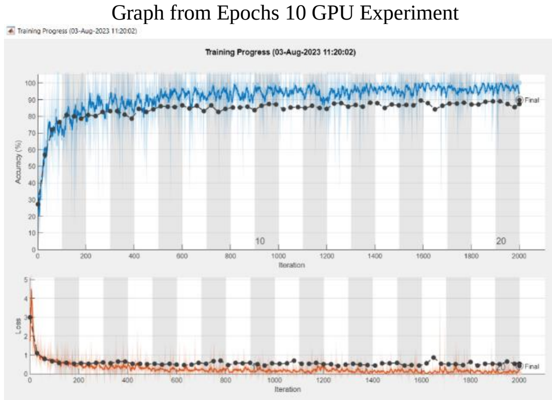
Graph from Epochs 10 CPU Experiment



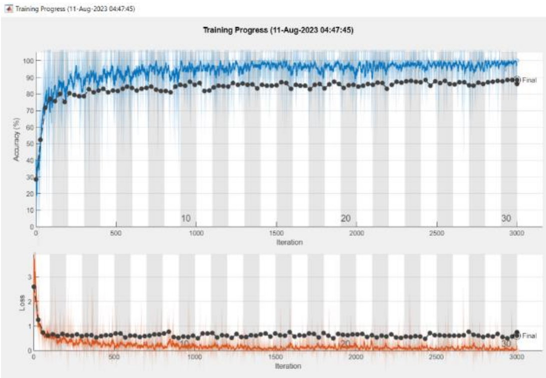
Graph from Epochs 10 GPU Experiment



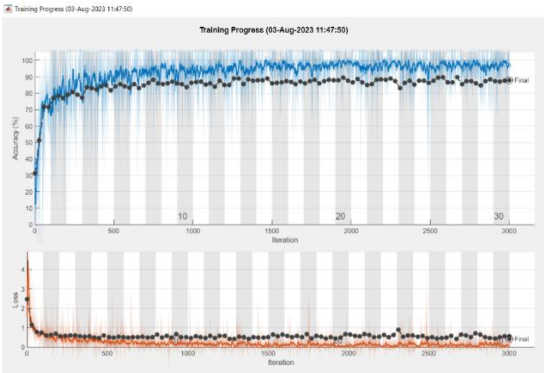
Graph from Epochs 20 CPU Experiment



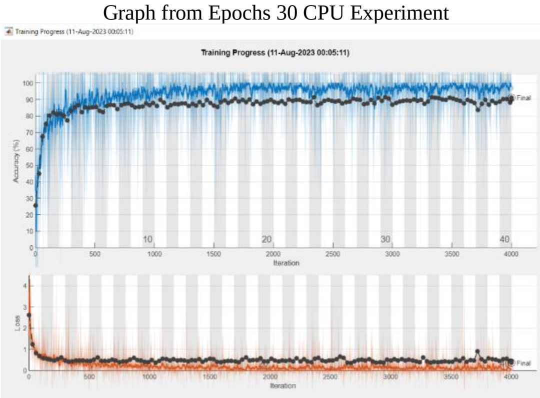
Graph from Epochs 20 GPU Experiment



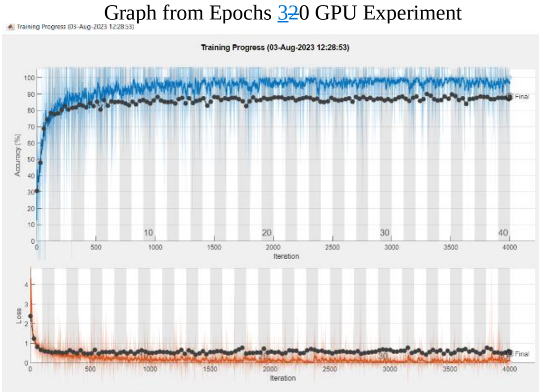
Graph from Epochs 30 CPU Experiment



Graph from Epochs 3~~2~~0 GPU Experiment



Graph from Epochs 40 CPU Experiment



Graph from Epochs 4~~2~~0 GPU Experiment

Figure 3. Graph visualization based on variation

The process begins with preprocessing the image, then data training is carried out to determine the results of the confusion matrix values starting from Accuracy, Sensitivity or Recall, Precision, Specificity, and F1-Score. The result od fata preprocessing can be seen in Figure 4.

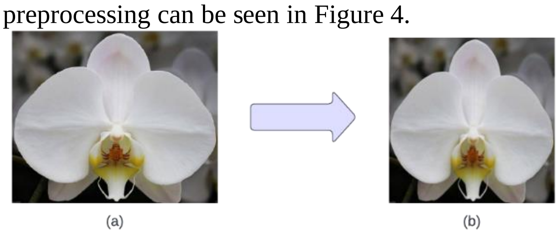


Figure 4. Sample of image pre-processing

Model evaluation process will be carried out to get the results of Accuracy, Precision, Recall, Specificity, and F1-score which will be used as image classification from the Convolutional Neural Network with 2 parameters used with differences in CPU and GPU as follows in Table 1.

Table 1. Results based on hyperparameters using adam optimizer

No	Hyperparameter						
	Execution Environment	Max Epochs	Mini Batchsize	Validation Data	Validation Frequency	Verbose	ElapsedTime
1	CPU	10	32	imdsValidation	30	False	85 Minutes 50 Seconds
	GPU						9 Minutes 5 Seconds
2	CPU	20	32				143 Minutes 15 Seconds
	GPU						20 Minutes 13 Seconds
3	CPU	30	32				209 Minutes 12 Seconds
	GPU						29 Minutes 23 Seconds
4	CPU	40	32				271 Minutes 51 Seconds
	GPU						39 Minutes 5 Seconds

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Based on the result in Table 1, the first parameter using Optimizer Adam, ExecutionEnvironment CPU, MaxEpochs 10, MiniBatchsize 32, ValidationData imds Validation, ValidationFrequency 30 and ElapsedTime, namely 85 Minutes 50 Seconds. By using Adam Optimizer, GPU ExecutionEnvirontment, MaxEpochs 10, MiniBatchsize 32, ValidationData imds Validation, ValidationFrequency 30, ElapsedTime which is 9 Minutes 5 Seconds. Experiment with the first parameter using Optimizer Adam, ExecutionEnvironment CPU, MaxEpochs 20, MiniBatchsize 32, ValidationData imds Validation, ValidationFrequency 30 and ElapsedTime, namely 143 Minutes 15 Seconds. Experiment with the second parameter using Optimizer Adam, ExecutionEnvirontment GPU, MaxEpochs 20, MiniBatchsize 32, ValidationData imds Validation, ValidationFrequency 30, ElapsedTime which is 20 Minutes 3 Seconds. By using Adam Optimizer, ExecutionEnvironment CPU, MaxEpochs 30, MiniBatchsize 32, ValidationData imds Validation, ValidationFrequency 30 and ElapsedTime which is 209 Minutes 12 Seconds. Experiment with the third parameter using Optimizer adam, ExecutionEnvirontment GPU, MaxEpochs 30, MiniBatchsize 32, ValidationData imds Validation, ValidationFrequency 30, ElapsedTime which is 29 Minutes 23 Seconds. By using Adam Optimizer, ExecutionEnvironment CPU, MaxEpochs 40, MiniBatchsize 32, ValidationData imds Validation, ValidationFrequency 30 and ElapsedTime which is 271 Minutes 51 Seconds. Experiment with the fourth parameter using Optimizer adam, ExecutionEnvirontment GPU, MaxEpochs 40, MiniBatchsize 32, ValidationData imds Validation, ValidationFrequency 30, ElapsedTime which is 39 Minutes 5 Seconds.

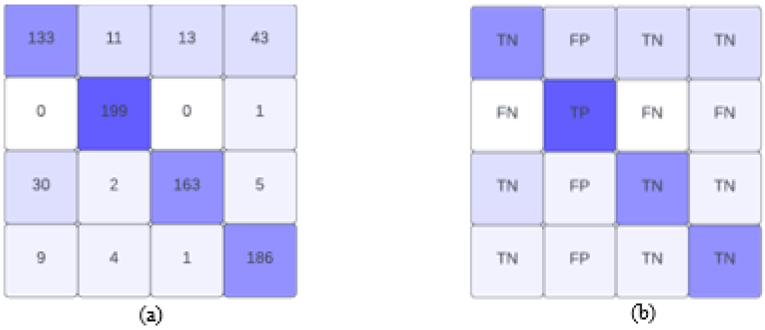

Figure 5. Confusion matrix table with 10 epochs experiment: (a) Confusion matrix results, (b) Original label and prediction results

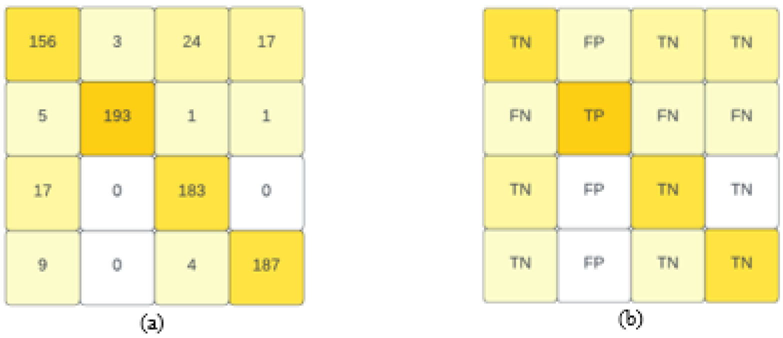

Figure 6. Confusion matrix table with 20 epochs experiment: (a) Confusion matrix results, (b) Original label and prediction results

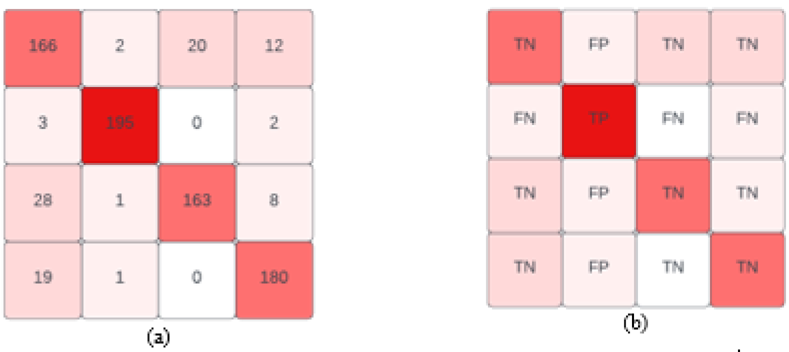

Figure 7. Confusion matrix table with 30 epochs experiment: (a) Confusion matrix results, (b) Original label and prediction results

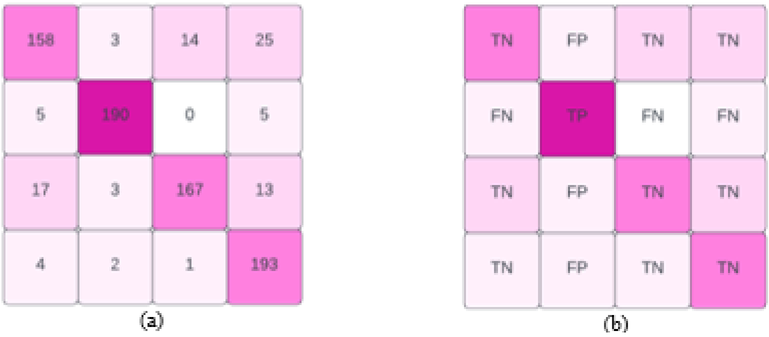

Figure 8. Confusion matrix table with 40 epochs experiment: (a) Confusion matrix results, (b) Original label and prediction results

Table 2. Sample results for moon orchid classification (phalaenopsis amabilis)

Image File (.jpg)	Classification Name		
	Actual Class	Identification Class	True Positive or True Negative
Moon (4).jpg	Moon	Moon	TP
Moon (11).jpg	Moon	Moon	TP
Moon (612).jpg	Moon	Moon	TP
Moon (444).jpg	Moon	Moon	TP
Moon (357).jpg	Moon	Moon	TP
Moon (787).jpg	Moon	Moon	TP
Moon (696).jpg	Moon	Moon	TP
Moon (200).jpg	Moon	Moon	TP
Moon (123).jpg	Moon	Moon	TP
Moon (987).jpg	Moon	Moon	TP
Moon (753).jpg	Moon	Moon	TP
Moon (812).jpg	Moon	Moon	TP
Moon (700).jpg	Moon	Moon	TP
Moon (195).jpg	Moon	Moon	TP
Moon (519).jpg	Moon	Moon	TP
Moon (619).jpg	Moon	Moon	TP
Moon (21).jpg	Moon	Moon	TP
Moon (80).jpg	Moon	Moon	TP
Moon (64).jpg	Moon	Moon	TP
Moon (800).jpg	Moon	Moon	TP

Table 3. Sample results for xdoritaenopsis orchid classification

Image File (.jpg)	Classification Name		
	Actual Class	Identification Class	True Positive or True Negative
xDori(7).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(53).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(772).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(421).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(145).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(800).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(13).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(555).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(1).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(699).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(421).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(216).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(709).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(811).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(307).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(465).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(189).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(911).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(199).jpg	Doritaenopsis	Doritaenopsis	TP
xDori(512).jpg	Doritaenopsis	Doritaenopsis	TP

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Based on Figure 5, the results of the first experiment using MaxEpochs 10 produced an accuracy of 97.6%, Precision 92.1%, Recall 99.5%, Specificity 97% and finally an F1-score of 95.6%. Based on Figure 6, the results of the second experiment using MaxEpochs 20 produced an accuracy of 98.7%, Precision 98.4%, Recall 96.5%, Specificity 99.4% and finally an F1-score of 97.4%. Based on Figure 7, the results of the third experiment using MaxEpochs 30 produced an accuracy of 98.8%, Precision 97.9%, Recall 97.5%, Specificity 99.3% and finally an F1-score of 97.7%. Based on Figure 8, the results of the fourth experiment using MaxEpochs 40 produced an accuracy of 97.7%, Precision 95.9%, Recall 95%, Specificity 98.6% and finally an F1-score of 95.4%. Here, we can see that the optimum parameter is using Adam based on 20 epoch and minimum MiniBatchsize is 32. Based on Table 2 is result of the Moon Orchid Classification experiment used 20 random images and the output results were classified according to the category of orchid type. Table 3 is result of the xDoritaenopsis Orchid Classification experiment, 20 random images were used and the output results were classified according to the category of orchid type. Table 4 is result of the Cattleya Orchid Classification experiment used 20 random images and the output results were classified according to the category of orchid type. Table 5 is result of the Coelogyne Pandurata Orchid Classification experiment used 20 random images and the output results were classified according to the category of orchid type.

Table 4. Sample results for cattleya orchid classification

Image File (.jpg)	Classification Name		
	Actual Class	Identification Class	True Positive or True Negative
Cattleya(69).jpg	Cattleya	Cattleya	TP
Cattleya(3).jpg	Cattleya	Cattleya	TP
Cattleya(12).jpg	Cattleya	Cattleya	TP
Cattleya(30).jpg	Cattleya	Cattleya	TP
Cattleya(215).jpg	Cattleya	Cattleya	TP
Cattleya(525).jpg	Cattleya	Cattleya	TP
Cattleya(700).jpg	Cattleya	Cattleya	TP
Cattleya(373).jpg	Cattleya	Cattleya	TP
Cattleya(111).jpg	Cattleya	Cattleya	TP
Cattleya(999).jpg	Cattleya	Cattleya	TP
Cattleya(663).jpg	Cattleya	Cattleya	TP
Cattleya(90).jpg	Cattleya	Cattleya	TP
Cattleya(806).jpg	Cattleya	Cattleya	TP
Cattleya(769).jpg	Cattleya	Cattleya	TP
Cattleya(416).jpg	Cattleya	Cattleya	TP
Cattleya(591).jpg	Cattleya	Cattleya	TP
Cattleya(9).jpg	Cattleya	Cattleya	TP
Cattleya(167).jpg	Cattleya	Cattleya	TP
Cattleya(876).jpg	Cattleya	Cattleya	TP
Cattleya(468).jpg	Cattleya	Cattleya	TP

Table 5. Sample results for coelogyne pandurata orchid classification

Image File (.jpg)	Classification Name		
	Actual Class	Identification Class	True Positive or True Negative
Coelogyne(1).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(900).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(555).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(667).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(718).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(911).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(125).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(101).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(439).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(854).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(15).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(299).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(153).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(61).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(9).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(1000).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(500).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(72).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(955).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP
Coelogyne(888).jpg	Coelogyne Pandurata	Coelogyne Pandurata	TP

Based on CPU tested, the hardware specifications in this research are the computer device specifications used to run the CPU accuracy program without VGA, with an AMD Ryzen 7 5700G processor, 16 GB RAM and 1024 GB SSD. On the other hand, testing using a GPU using an AMD Ryzen 7 4800H processor, 8 GB RAM, 1024 GB SSD, and NVIDIA GeForce GTX 1650 Ti. The Code Editor software in the experiment using CPU and GPU both uses Matlab R2021a because it can test programs directly with the

Windows 10 64-bit Operating System. Based on Figure 6, testing with this CPU can be seen that all of the 4 epoch configurations produce an accuracy of above 97%. Increasing the number of epochs starting from the 10th, 20th, 30th and 40th epochs, the classification accuracy that has been produced in this system tends to increase significantly, but it is important to note that calculating this accuracy takes quite a long time. Up to 271 Minutes 51 Seconds around 4.5 hours at epochs 40 if calculate the whole 1 epoch takes around 6.5 – 7 minutes. On the other side we also tested using GPU as in Figure 7, the test can be seen that all of the 4 epoch configurations produce an accuracy of above 95%. Increasing the number of epochs starting from the 10th, 20th, 30th and 40th epochs, the classification accuracy produced by this system tends to increase significantly. It only takes a fairly short time, namely 39 minutes 5 seconds at epochs 40 where if you calculate the whole 1 epoch it only takes 54 seconds.

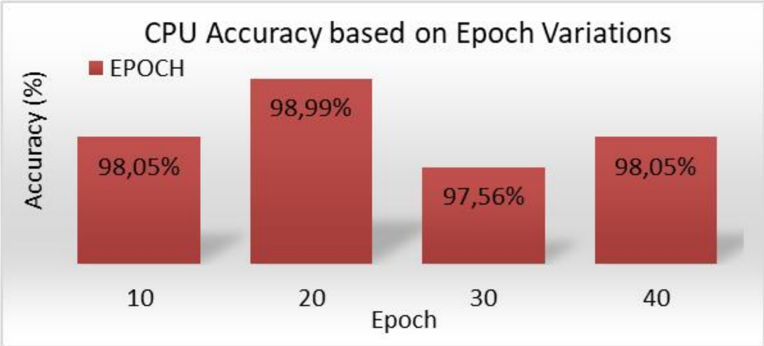

Figure 9. CPU accuracy based on epoch variations

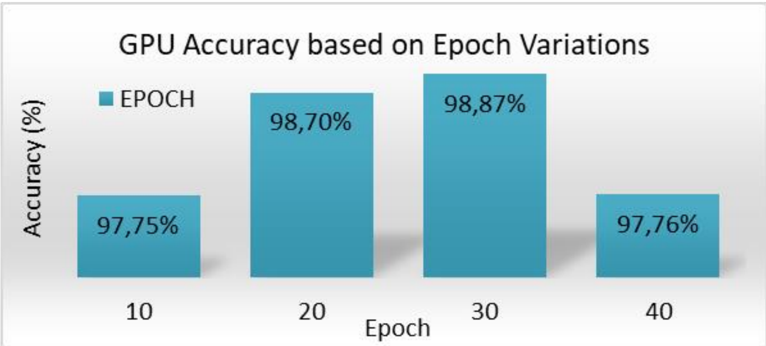

Figure 10. GPU accuracy based on epoch variations

Based on Figure 10, starting from 97.75% at epochs 10, 98.70% at epochs 20, 98.87% at epochs 30. When the configuration of the number of epochs is added from the last 30 to 40, the accuracy of this model suffers slightly an increase of 97.76% compared to the accuracy in the 30th epoch, namely 98.87%. From all the results obtained from the trials, the best accuracy was achieved in the epochs 30 configuration with a result of 98.87% and the worst was in epochs 10 with a result of 97.75%. It can be seen that the epoch 30 graph has high accuracy, because when testing training progress on graph Figure 5, the hyperparameter used requires MinibatchSize where the parameter used is Randomize, which means randomizing 1 folder containing 32 images. From this parameter function, it produces a different graph for each epoch which marks the end point of the accuracy point in the training progress graph. The end point of each main epoch is based on the point where the accuracy results will be displayed. At epochs 10, 20, 30, and 40 it produces accuracy where the epochs have not yet converged to the convergent point. Here, 80 images are used with 20 images of each type (Phalaenopsis Amabilis, xDoritaenopsis, Cattleya, and Coelogyne Pandurata) by taking images randomly in each sub-dataset to carry out classification experiments, and produce an output that is True Positive that the classification of the image is according to its type.

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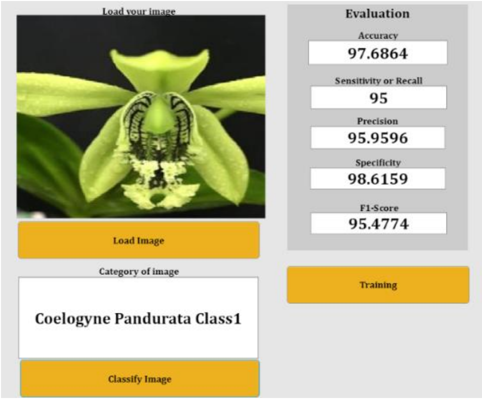

Figure 11. Example classification testing using GUI

Figure 11 is a visualization of the classification results for orchids of the Coleogyne Pandurata (Black Orchid) type, and displayed on the right of the image is the calculation result of the confusion matrix and obtained an accuracy result of 97.6% at epoch 40. The classification of the Coelogyne Pandurata orchid can be in accordance with the label The type is because when carrying out evaluation calculations, the system takes 32 images for each label until the 1000 images are used up and placed in each subfolder according to their type, and when classifying images, the system looks for similarities and the results of the most prediction iterations from the input images.

4. CONCLUSION

Based on research on Classification of Orchid Flower Types Using a Convolutional Neural Network with a combination of Resnet50 Architecture, it can produce high enough accuracy so that it can be used as a system for classifying orchid flower types. Based on research that has been carried out, it shows that using ResNet50 at the 30th epoch produces the highest accuracy on test data, namely reaching 98.8% and using ResNet50 at the 10th epoch produces the lowest accuracy on test data, namely reaching 97.75%. And the image classification of the orchid produced a True Positive with no errors. It can be seen that using certain hardware specifications also affects the classification of the Convolutional Neural Network algorithm with the ResNet50 architecture on time efficiency because using this algorithm and architecture requires a minimum of medium to high specifications by adjusting the number of filters that are suitable for classification. To improve the results and refine the research that has been carried out, there are several suggestions that can be used in further research are using a combination of other architectures such as GoogleNet, Densenet, etc., and can use ResNet with the highest layer from ResNet50 to get maximum accuracy results; it is recommended to try to use more datasets to maximize the classification process and increase accuracy; using the ResNet50 architecture requires medium to high specifications, especially on the GPU.

CREDIT AUTHORSHIP CONTRIBUTION STATEMENT

Author1, Author1, and Author3: Conceptualization, Methodology, Software, Project administration. **Author4, Author5, and Author6**: Software, Writting – original draft. **Author1 and Author3**: Writing – review & editing. **Author5**: Validation**. Author2**: Supervision.

DECLARATION OF COMPETING INTERESTS

The authors declare there are no conflict interest in this paper.

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