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# Butterfly Image Identification Using Multilevel Thresholding Segmentation and Convolutional Neural Network Classification with Alexnet Architecture

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**Abstract:** Lepidoptera is the name for the broad group of butterflies. The ecology depends heavily on butterflies, thus it is problematic that so little is known about their many kinds. Understanding butterflies is a crucial part of education since they are a natural occurrence and may be used as teaching tools. A total of 419 butterfly photos were utilized in the data. The dataset is first input, and then it undergoes preprocessing steps like segmentation, scaling, and RGB to grayscale conversion. CNN with AlexNet architecture is used to classify the preprocessed dataset's output. The outcomes of the classification stage of the Alexnet architecture are Flatten, Danse, and ReLu (Convolution, Batch Normalization, Max_Pooling). The output data is assessed following the completion of the Alexnet CNN training process. The data's ultimate classification is based on species. High-accuracy picture classification can be achieved using the model without segmentation, however, this cannot be achieved with multilevel threshold segmentation. According to the test findings, the multilevel threshold segmentation model only attains 62% accuracy, but the segmentation-free model gets 83% accuracy. The test results demonstrate that combining AlexNet architecture with multilevel thresholding segmentation resulted in a classification model that is less accurate in identifying different species of butterflies. By comparing these test results, it is possible to draw the conclusion that the multilevel threshold segmentation model performs less well at information classification than the model without segmentation.

**Keywords:** Convolution Neural Network, Butterfly, Segmentation, Multilevel, Alexnet

## 1. Introduction (Heading 1)

Butterflies are a large group called Lepidoptera. Butterflies play an important role in the ecosystem, so the lack of knowledge about butterfly species is a problem. Other threats arrive from pests, diseases, predators, and weather transformation [1][2][3]. This research is to identify butterfly species because their populations are declining. Knowledge about butterflies is part of education because butterflies are part of the environment that can be used as learning objects. Butterflies are one of the species that have an important role in the ecosystem to be considered and studied in research. The process of identifying patterns and classifying information is an interesting discussion from time to time. Pattern recognition provides solutions to problems related to recognition or classification, such as speech recognition, document reading classification, handwriting personality classification, and batik pattern recognition.

Introduction to butterflies has the most color schemes and shapes. Computers can be used as a medium to recognize and identify butterfly species. The image segmentation stage, feature extraction stage, classification stage, and outcomes are the stages that the computer implements. The stage of picture segmentation is employed to distinguish between backgrounds and objects. Color feature extraction is used in the feature extraction stage. Convolutional Neural Networks (CNNs) are used in the classification stage to compare feature extraction with training and testing datasets of the butterfly variety. The resulting stage will provide an accuracy value or the results of the previous stages.

One of the deep learning methods capable of identifying objects in images is CNN. CNN features are considered the best approach in object detection and

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recognition [4][5]. CNN is one of the artificial intelligence algorithms that has been widely used to process images and assign weights and biases that can be learned on certain aspects of the image that can distinguish one image from another [6]. CNN has a multi-layer arrangement by pooling layers including fully connected layers. CNN layers organize neurons so that they have three dimensionsi [7][8]. There are several CNN architectures VGG-16, VGG-19, GoogLeNet, ResNet, and AlexNet that have been applied to image classification without involving or using the segmentation process [9].

This research conducted image segmentation with Multilevel Thresholding to separate objects and backgrounds in butterfly images. The type of butterfly can be determined based on the name of the species using CNN classification. Multilevel Thresholding segmentation method to get object separation with background and CNN classification to get the best accuracy results.

## 2. LITERATURE REVIEW

There are several previous studies related to the objects and methods in this study.

Andrian et al [10] using edge detection and K-Nearest Neighbor classification methods. The purpose of this research is to classify butterflies into their species in order to help developers in developing applications. Get a result of 80%.

Sowjanya & Injeti [11] utilizing a multilevel thresholding picture optimization technique. The suggested method works better than other algorithms, according to the results. Multilevel Threhsolding segmentation using the Harmony Search Algorithm was researched by Srikanth and Bikshalu. Images of the cameraman, brain, lena, and other objects were used as objects. The comparison illustrates why the suggested method's outcomes outperform those of the histogram-based approach.

Dave Jonathan et al [12] compared the location of polyps using CNN with RetinaNet architecture. The object used is a large uss image. The best model results without data extension with a value of 0.8415 and augmentation data with a matrix value of Ap25 = 0.9308.

Ibrahim et al [13] performed classification using the CNN method. The best accuracy result is 97.5% using VGGNET19 architecture. The difference from previous research is in the method and object.

Akmal Hariz [14] used the Convolutional Neural Network approach with MobileNet architecture to investigate human activity detection based on camera captures. The tool utilized is random rotation data augmentation applied to video. An ideal model with hyperparameters of 20 epochs, early termination with patience 10, learning speed 0.0001, stack size 16, and dense layer 5 was generated by the test results. After testing the confusion matrix and running the model with cross validation, the F1 final result performance was 84.52%. Using authentic COPD CT-scan images.

Zhao [15] performed multilevel threshold image segmentation study for chronic obstructive pulmonary disease using the diffusion association lender mold algorithm and entropy renyi. The experimental findings of the valuation by image quality matrix demonstrate the superior performance of the used algorithms. These findings can aid medical professionals in the qualitative and quantitative analysis of the lesion network, hence enhancing the diagnostic precision of the network.

Amalia [16] used the CNN approach with Alexnet architecture to classify brain tumor disease in MRI images. With an image size of 224 x 224 pixels, a training data ratio of 80%, validation data of 10%, and test data of 10% using the Adam optimizer, learning rate of 0.0001 utilizing batch size 8 and epoch value 50, the results obtained are the optimal parameters that determine system performance. The precision of 98.84%, recall of 97.65%, precision value of 97.65%, loss of 0.1616, and F1 score of 97.65% are the top results.

Benign and malignant skin cancer kinds were categorized by Saputra [17] using the Alexnet architectural model. The Adaptive Moment Estimation (Adam) optimization function and the AlexNet architecture are used in the construction of the model. According to the findings, the AlexNet model using the Adam Optimizer has an 81.26% classification accuracy for cancer types.

Similarities from previous research both use the Multilevel Thresholding method and butterfly objects. The similarities use CNN and Multilevel Thresholding methods.

## 3. RESEARCH METHODS

The flow of research conducted from start to finish is shown in Figure 1.

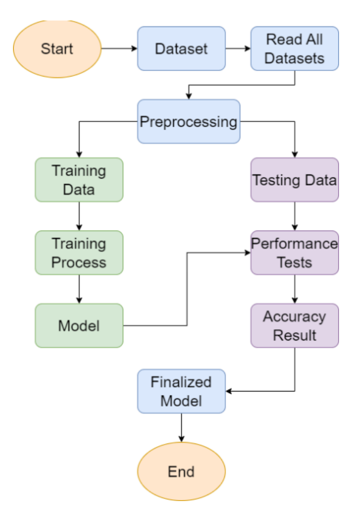



Figure 1. Research Flow

The research flow shown in Figure 1 shows that the first step is to input the dataset first, then read all the datasets. After that, data preprocessing is carried out. The results of dataset preprocessing are carried out data training, then the training process is carried out according to the AlexNet architectural CNN model. The results of the training model are then tested and the testing performance is seen. After the testing performance gets the accuracy results and the model is complete.

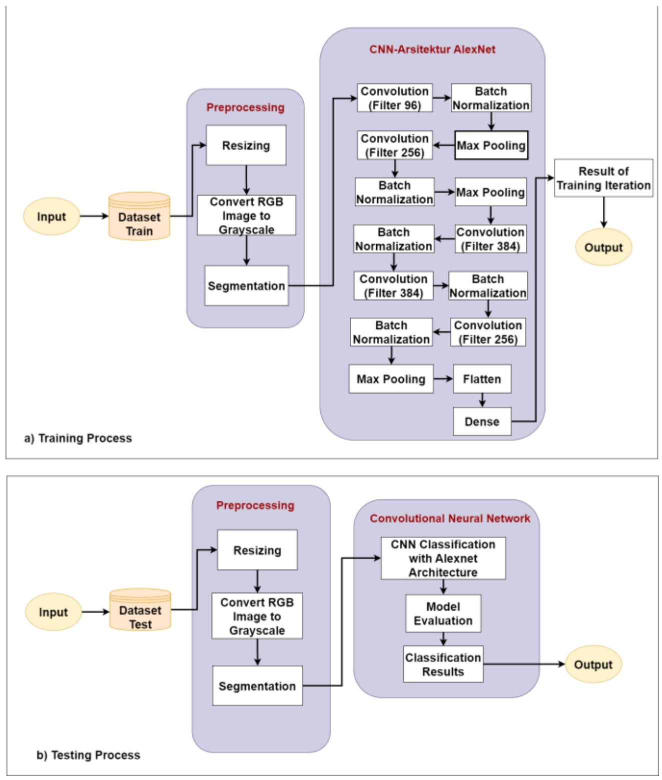



Figure 2. Training and testing process

The training and testing process shown in Figure 2 is first done by inputting the train dataset, the output of the input data is preprocessed including resize, image conversion, and segmentation. The result of preprocessing is convolution with filter 96. The convolutional output is subjected to batch normalization, i.e. ReLU, after which max_pooling is applied to the batch normalization result. The convolution, batch normalization, and max_pooling steps are performed 5 times. Then the last max_pooling result is flattened, the flatten result is dense twice. The dense results are made with a scoring model to get the best results. The results of the last stage classification results.

## A. Datasets

About 419 butterfly photos from the Kaggle website (https://www.kaggle.com/datasets/gposenka/butterfly-images40-species) are included in the dataset. The photos represent a variety of species, including common, rare, and vulnerable ones. A species is a collection of creatures with similar traits, and the term "species" refers to individuals rather than classes or groupings. The lowest rung of toxomes are species. Butterfly attributes are physical characteristics, such as color, pattern, wing form, and size, that can be seen or recognized in different species of butterflies. Building a recognition model with a big range of butterfly species will yield more valid findings when using a dataset with a sufficient number of data.

Figure 3. Butterfly image

## B. Preprocessing

Preprocessing is a step used to prepare image data before further processing [18]. Pre-processing methods to reduce these differences rely on contrast enhancement and data focusing [19][20]. The preprocessing stage where all unequal image sizes are resized to 150×150 pixels since CNNs accept the same size. After resizing, the RGB images are converted to grayscale for model processing and training [21]. A two-dimensional matrix can be used as a digital representation of a greyscale image. The table's elements each display the image's intensity (or grey level) at the associated coordinate point. An image with an 8-bit representation has 28 or 256 grey scale levels, often ranging from 0 to 255, where 0 denotes the lightest intensity and 255 the darkest. All the elements in the preceding table are referred to as image elements, or frequently, pixels. Each pixel's intensity can be altered to alter the image's overall depiction. A specific pixel in an image represented as a M x N matrix has a certain intensity. The shadow elements have distinct coordinates (x,y) and positions (i,j). Pixel counting starts from the top left corner, while the x and y coordinates are at the bottom left corner [22]. In order to assess the influence of the pre-processing on the classification outcomes of each CNN model, the images were normalized. How to use the Tensorflow Preprocessing Library to preprocess data [23].

### C. Segmentation

The process of dividing a picture into distinct areas is called image segmentation. Various segmentation techniques rely on searching inside or outside of a region. Edge detection can be used to locate region borders. The characteristics of the pixels that comprise an area define its interior. One well-liked segmentation approach is the region-based thresholding method [24].

### D. Thresholding

In image processing, thresholding procedures are frequently employed for compression, segmentation, and enhancement. Thresholding shows how important a specific level is, in terms of magnitude. In image processing, thresholding is applied in a variety of ways. The first method involves creating a binary image by applying grayscale image thresholding. Setting all gray levels with values less than or equal to T to 0 and setting the remaining gray levels to 1 establishes the threshold T > 0 [24]. Multilevel thresholding is a method that uses a set of thresholds to classify the pixels of an image into categories [25]. Color images are divided into foreground and background using more than two thresholds (tri or quad level) to separate the three components R, G, and B. This method provides good specificity [26]. Several threshold points divide the image into distinct classes, giving target region analysis possibilities.

$$O_1(x,y) = \{i\ (x,y) \in I \mid 0 \leq I\ (x,y) \leq m_1 - 1\} \quad (1)$$

$$O_2(x,y) = \{i\ (x,y) \in I \mid m_1 \leq I\ (x,y) \leq m_2 - 1\} \quad (2)$$

$$O_i(x,y) = \{i\ (x,y) \in I \mid m_i \leq I\ (x,y) \leq m_i - 1\}... \quad (3)$$

$$O_r(x,y) = \{i\ (x,y) \in I \mid m_r \leq I\ (x,y) \leq L - 1\} \quad (4)$$

Where $t_1,t_2,t_3,t_4...t_i,...t_r$ represent different thresholds. Based on the intensity value, distinct groups of gray pixels are assigned, and within the given range, each group has a separate set of pixel values [27].

### E. Classification CNN-Architecture Alexnet

Classification is a task that involves assigning class labels to input models. The class label indicates the class of a particular set of classes. Classification is performed using a model obtained using a supervised learning procedure. Depending on the type of learning used there are two classifications, one using supervised learning and one using unsupervised learning [28]. Finding an image's traits, structures, or patterns and using them to place it in a specific class is the aim of categorization. Human observers frequently complete specific classification tasks using images and visual stimuli with a high degree of accuracy [29]. CNN is a multi-layered deep education method that extends Artificial Neural Network (ANN). CNNs are processed by network arrays and create outputs of specific classes. Each level carries out training and the output of each level is used as input for the next level. Initially, CNNs create simple features such as color, brightness and edges, whereas later levels create more environmental features. CNNs consist of three fully connected layers and five convolutional layers. The first AlexNet layer is used as an input filter image for width, height and depth fields (red, green, blue) with dimensions of 227 × 227 × 3. The last composite layer combines fully 1000 composite layers, and the others. The layers serve as dividers between features. AlexNet creates a 4096-dimensional feature vector for every input image, with a hidden layer that activates immediately before the output layer. With 60 million parameters and 650,000 neurons, AlexNet is a massive architecture. A total of 1.2 million training photos and 150,000 test images from the ImageNet dataset were used to test the model. The model reduces the oversampling problem very effectively by removing and adding data [30].

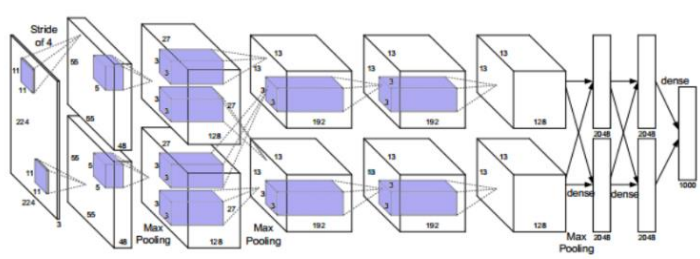



Figure 4. Alexnet Architecture

Figure 4 shows the architecture of AlexNet starting with a pre-processed input image with a result size of 150x150, then performs filtering or kerneling. kernel results using convolution which is pooled. Convolution and max-pooling are performed five times. Each is considered to have characteristics due to convolution. Then a flatten process is performed to convert the image into a one-dimensional matrix. Then it is fully connected three times. As a final step the image can be classified.

*F. Model Evaluation*

Evaluation of the Alexnet model is used to determine its effectiveness. This evaluation uses accuracy, recall, precision, and F1-score matrices which can be calculated using the following formula:

$$Accuracy(\%) = \frac{TP+TN}{total\ testing\ data} \quad (5)$$

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

$$Precision = \frac{TP}{TP+FP} \quad (7)$$

$$F1 - Score = 2 \times \frac{recall \times precission}{recall + Precission} \quad (8)$$

## 4. Results and Discussion

The results of this study use Google Colab tools using 419 butterfly image data from the Kaggle website. Image data is divided into 90% training data and 10% testing data. The first process carried out before classification to get the best results with preprocessing and segmentation thresholding stages that have been tested on butterfly image datasets. The results of the study discuss the analysis of the comparison of butterfly image classification with Alexnet architecture using multilevel threshold segmentation and without segmentation.

Figure 5. Original image of butterfly

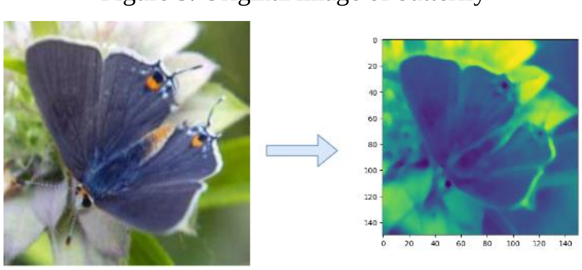


Figure 6. Resizing result

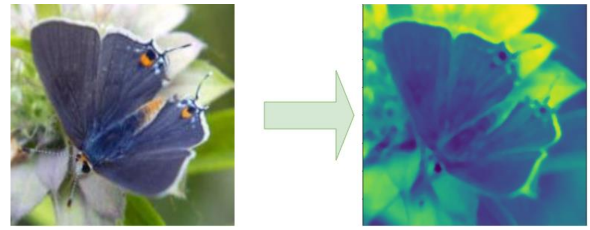
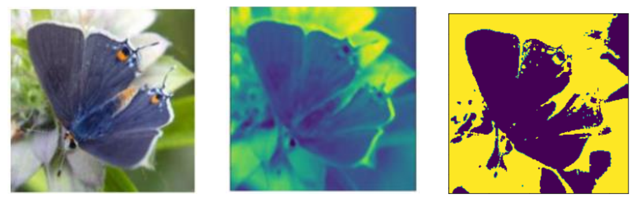


Figure 7. RGB to grayscale result



(a) (b) (c)

Figure 8. (a) Input Image (b) result without segmentation (c) thresholding segmentation result

Figure 5 is the original image that will be processed for preprocessing. at the preprocessing stage, the technique of changing the size and changing the RGB color to grayscale is carried out. The result of 150x150 resizing can be seen in Figure 6 because alexnet only accepts the same image size. The conversion of RGB to grayscale to improve the efficiency of analysis can be seen in Figure 7. After the RGB to grayscale stage, the segmentation stage is carried out using multilevel thresholding segmentation techniques. The segmentation results can be seen in Figure 8(c) and without segmentation can be seen in Figure 8(b). The results of preprocessing are used in classification using the CNN method with Alexnet architecture.

TABLE I. TRAINING EPOCH PROCESS

| **Epoch** | **No Segmentation** | | **Threshold Multilevel Segmentation** | |
|---|---|---|---|---|
| | ***Accuracy*** | ***Training Loss*** | ***Accuracy*** | ***Training Loss*** |
| *1* | *0.49* | *9.10* | *0.44* | *14.76* |
| *2* | *0.73* | *2.36* | *0.65* | *4.37* |
| *3* | *0.84* | *1.63* | *0.71* | *2.33* |
| *4* | *0.89* | *0.65* | *0.77* | *1.25* |
| *5* | *0.87* | *0.48* | *0.79* | *0.78* |
| *6* | *0.89* | *0.37* | *0.86* | *0.48* |
| *7* | *0.89* | *0.52* | *0.87* | *0.42* |
| *8* | *0.89* | *0.64* | *0.87* | *0.33* |
| *9* | *0.88* | *0.32* | *0.88* | *0.31* |
| *10* | *0.91* | *0.27* | *0.90* | *0.27* |
| *11* | *0.91* | *0.23* | *0.90* | *0.32* |
| *12* | *0.91* | *0.28* | *0.89* | *0.26* |
| *13* | *0.92* | *0.21* | *0.89* | *0.26* |
| *14* | *0.94* | *0.19* | *0.91* | *0.24* |
| *15* | *0.92* | *0.22* | *0.90* | *0.29* |
| *16* | *0.94* | *0.19* | *0.90* | *0.28* |
| *17* | *0.91* | *0.24* | *0.90* | *0.25* |
| *18* | *0.94* | *0.16* | *0.89* | *0.28* |
| *19* | *0.92* | *0.20* | *0.91* | *0.25* |
| *20* | *0.94* | *0.14* | *0.90* | *0.25* |

After 20 epochs were run, the model with no segmentation and using multilevel thresholding segmentation on the butterfly image data established satisfactory results for the simple model. Table 1 which includes the training accuracy and loss columns are the results of the epochs run, training the model using preprocessing without segmentation. Although these results are quite good, there are still some errors in butterfly image classification, especially in images with high complexity. The model training used image segmentation processed with multilevel thresholding technique. This technique is used to separate the object from the background based on the brightness of the pixels, with multilevel thresholding segmentation technique, the model cannot classify the image accurately. The epoch process results displayed from the training loss and training accuracy function values help evaluate the effectiveness of the model in classifying the train data, as well as improving each epoch process during training.

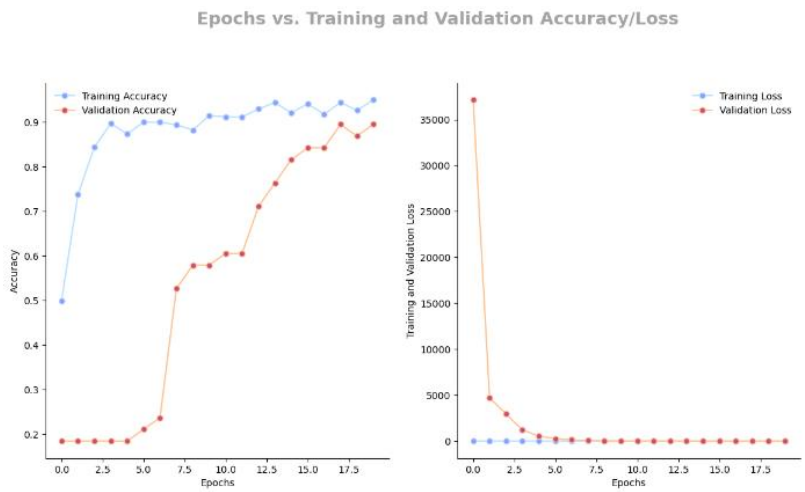



Figure 9. Accuracy graph without segmentation

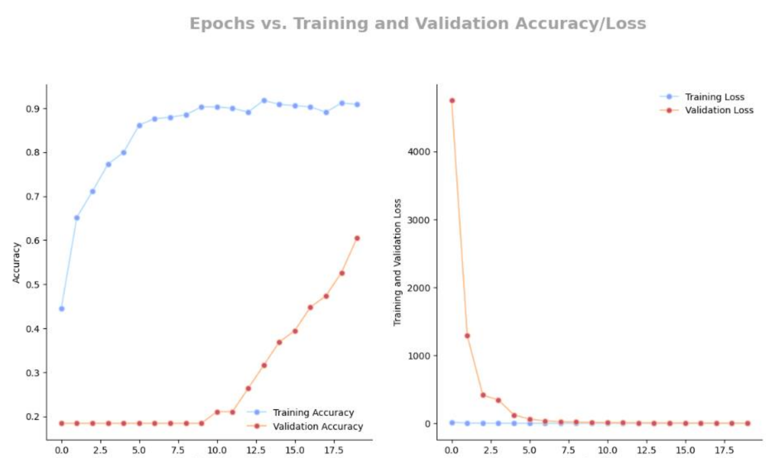



Figure 10. Accuracy graph with multilevel thresholding segmentation

Figure 9 and Figure 10 can be analyzed that the accuracy and loss graphs are generated by testing using the Alexnet architecture without segmentation and using multilevel thresholding segmentation. The accuracy and loss graphs are used to understand the performance of the model in classifying butterfly images. It can be seen from the accuracy graph that the accuracy of the model increases with the number of epochs performed. At the beginning of training, the accuracy of the model tends to be low, but over time the accuracy of the model increases significantly. This shows that the model is gradually practicing to classify the image better. At the same time, in the loss graph, it can be seen that the loss of the model decreases as the number of execution epochs increases. Loss is a measure of how far the model's prediction is from the true value, so the lower the loss value, the better the quality of the model's prediction. This study shows that the model succeeds in reducing the loss significantly over time.

Figure 11 shows the output results of the trining process.

```
              precision    recall  f1-score   support

           0       1.00      0.45      0.62        11
           1       0.78      0.47      0.58        15
           2       0.35      0.88      0.50         8
           3       0.88      0.88      0.88         8

    accuracy                           0.62        42
   macro avg       0.75      0.67      0.65        42
weighted avg       0.77      0.62      0.63        42
```

Figure 11. Alexnet training process of multilevel thresholding segmentation

The results are shown in Figure 12. The results of the confusion matrix show that 5 Adonis images could be correctly predicted from the original data. 5 images featured American snoot however, 1 photo with Adonis was recognized as an African giant swallowtail. 7 images of African giant swallowtails were judged to be good out of the raw data. AN88 is 1 of the 7 images that African Snoot should be used for. 7 of the top-rated photos of African snoot from the original information. 7 images should be considered with African giant Swallowtail. 1 image should be considered with African giant Swallowtail. 7 images of AN88 are accepted as original data. 1 image should be considered American Snoot.

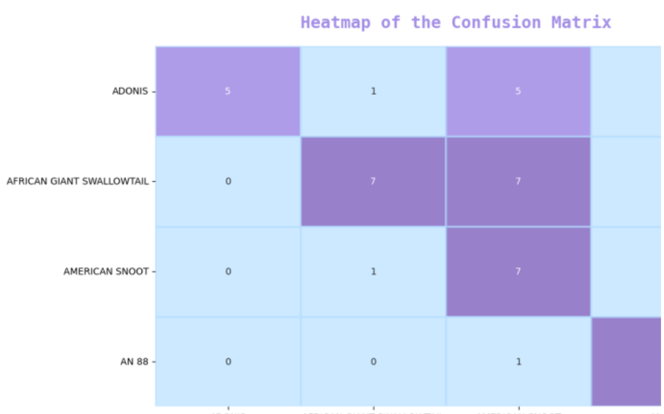



Figure 12. Alexnet's confusion matrix of multilevel thresholding segmentation images

Without segmentation, the output results of the trining process are displayed in Figure 13.

```
              precision    recall  f1-score   supp

           0       0.91      0.91      0.91
           1       0.86      0.80      0.83
           2       0.86      0.75      0.80
           3       0.80      1.00      0.89

    accuracy                           0.86
   macro avg       0.86      0.86      0.86
weighted avg       0.86      0.86      0.86
```

Figure 13. Alexnet training without segmentation

Figure 14 presents the findings. Based on the original data, 10 images of Adonis can be accurately anticipated, according to the confusion matrix result. One picture featuring Adonis was thought to be an African giant swallowtail. Out of the original data, 12 African giant swallowtail images were deemed to be good. Two AN88 photos and one American Snoot image should be taken into consideration. Six of the original information's American Snoot photos were deemed to be of high quality. One Adonis image and one African giant swallowtail image are to be taken into consideration. As raw data, 8 AN88 pictures were approved.

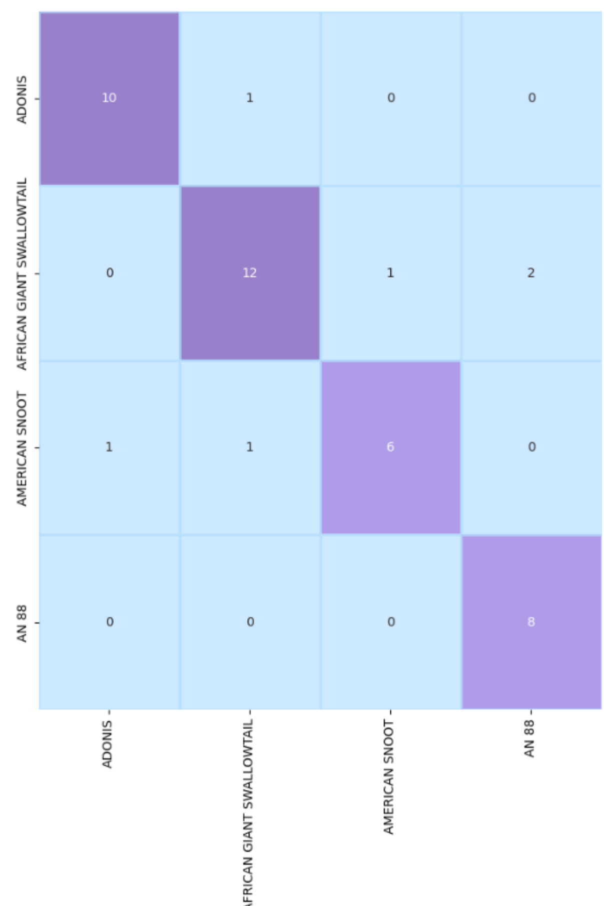



Figure 14. Alexnet confusion matrix of unsegmented image

TABLE II. BUTTERFLY IMAGE CLASSIFICATION TEST RESULTS

| Class | Amount of data | Without Segmentation | | Segmentation Multilevel Threshold | |
|---|---|---|---|---|---|
| | | ***True*** | ***False*** | ***True*** | ***False*** |
| *Adonis* | *11* | *9* | *2* | *5* | *6* |
| *African Giant Swallowtail* | *15* | *11* | *4* | *7* | *8* |
| *American Snoot* | *8* | *7* | *1* | *7* | *1* |

| | | | | | |
|---|---|---|---|---|---|
| An 88 | 8 | 8 | 0 | 7 | 1 |
| Accuracy(%) | | 83% | | 62% | |

Analyzing from Table 2 the test results of the testing data, 10% final accuracy is obtained with the Alexnet architecture without segmentation and using multilevel threshold segmentation. Table 2 shows that the model without segmentation is able to classify images with high accuracy, while using multilevel threshold segmentation cannot classify images with high accuracy. The test results show that the model without segmentation has an accuracy of 83%, while the model with multilevel threshold segmentation only achieves an accuracy of 62%.

This accuracy comparison can be caused by several factors, such as a model without segmentation can more easily identify and distinguish important features in the image, so that the model can produce more accurate predictions. At the same time, models with multilevel thresholding segmentation may have difficulty in identifying and distinguishing important features, resulting in less accurate predictions. The use of multilevel thresholding segmentation may cause the loss of important data in the image, making it difficult for the model to classify the information correctly. Meanwhile, models without segmentation can utilize the complete data in the image to create more accurate predictions.

The benefit of the AlexNet design is that the model can automatically extract hierarchical features because convolutional neural networks are used in it. AlexNet has demonstrated efficacy in resolving intricate picture categorization assignments. The requirement for vast volumes of data for ideal training, however, and increased computing complexity in comparison to simpler models are possible drawbacks.

## 5. CONLUSIONS AND FUTURE WORK

In this study, butterfly image identification using multilevel thresholding segmentation and Convolutional Neural Network (CNN) classification with AlexNet architecture was conducted. The test results show that the combination of multilevel thresholding segmentation and AlexNet architecture creates a classification model that is less accurate in recognizing butterfly species. Comparing the results of this test, it can be concluded that the model without segmentation tends to be better at classifying image data by getting an accuracy result of 83%, compared to the model using multilevel threshold segmentation getting an accuracy result of 62%. However, it should be noted that these results can vary depending on the type of dataset and the complexity of the problem. Therefore, choosing the right segmentation procedure is very important in the development of CNN classification models.

## ACKNOWLEDGMENT

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