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Lepidoptera Classification Using Convolutional Neural Network EfficientNet-B0

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ABSTRACT
Butterflies and moths are insects that have many different species. Butterflies and moths have considerable aesthetic, ecosystem, health, economic, health, and scientific values. However, because there are so many different varieties and patterns, it is vital to divide them by type for better identification. By creating a Convolutional Neural Network (CNN) algorithm that produces accurate results, a deep learning approach can be used to classify the types of butterfly and moth species. This paper offer an *Lepidoptera* including butterfly and moth classification model based on convolutional neural networks. 3390 images of 25 different butterfly and moth species were acquired with various images orientations, angles, distance, and background. Using the EfficientNet-B0 CNN architecture, different types of butterflies and moths are classified and input into the EfficientNet-B0 model. EfficientNet-B0 performs feature extraction on the image, so that it can be used to perform classification and then combined through a pooling process and connected to the final layer to produce a classification probability. The probability indicates how likely the image is to belong to a particular type or class of butterfly or moth. In comparison to earlier studies, the test results indicate an improvement in butterfly and moth classification. Increased accuracy was seen with values 97.91% of accuracy, 97% of recall, 97% of precision, and 97% of F1-Score. This paper's novelty is the enhancement of the CNN architecture EfficientNet-B0 used in image classification, which results in improved image classification accuracy.

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1. INTRODUCTION

Insects like butterflies, as well as moths, are classified as Animalia. These insects are members of the Lepidoptera order and class Insecta. Lepidoptera is a noun that derives from Greek and means "scale-winged insects" ("lepido" means scales and "ptera" means wings). Butterflies can be distinguished from moths by their colorful wings and antennae [1]. Insects in the order Lepidoptera include butterflies and moths. A recent estimate found that there are between 15,000 and 21,000 different species of butterflies in the world [2]. The classification and identification of butterflies and moths suffer from low accuracy and slow recognition because there is a great diversity of species, great similarities, and traits that make butterfly differentiation difficult[3]. For entomologists, it's crucial to have technologies that can distinguish between different kinds of moths and butterflies. This is so that studies of biodiversity and species analysis can benefit from correct butterfly and moth species recognition and classification [4].

Many researchers have used deep learning to solve a variety of picture identification problems [5]–[10]. These are some examples Jia et al. [11] offered approaches by developing an artificial neural network model for lepidoptera classification based on Single Shot Detection and Faster-RCNN. The data distribution centered on ten types of moths and twenty types of butterflies, with a total image dataset of 13.076, consisting of 3.889 moths and 9.187 butterflies. Their method's accuracy reached 95%.

Tan et al. [12] offers the Mask model approach R-CNN and FCM-KM. Instead of manual parameter adjustment, to find the ideal K grouping number FCM-KM method is used. And to classify Softmax activation in butterfly dataset are utilized in Mask R-CNN. while efficiently segmenting data. The expert literature used to reclassify the five types of butterfly images in this study totaled 1,462 images.1,187 images for training and 275 images used for testing. Their model classification result for Mask R-CNN is 80.43% and FCM-KM is 83.62% accuracy.

Arzar et al. [13] propose a method based on the GoogLeNet CNN model. The GoogLeNet model is designed to limit the number of neurons and parameters by utilizing a number of convolution kernels. One hundred and twenty butterfly photographs were gathered from an online database, and some of them were recorded with a camera with a 224 x 224 image resolution. The proposed model's accuracy was 97.5 percent.

As pointed out by the previous researchers mentioned above, classification of lepidoptera in the literature has been increase in adoption of deep learning architectures. However, there is still a gap to be filled in using deep learning architectures, especially the latest deep learning architectures, in the classification of lepidoptera. The requirement for an efficient model with less parameters, trained more quickly, and retrieved from sacrificing performance is unavoidable.

This paper offers one of the CNN model, EfficientNet [14] for lepidoptera classification. Performance of the proposed model will compared with previous CNN architecture studies such as Mask R-CNN, and Faster-RCNN. This study contributes to our understanding of Lepidoptera classification using the CNN technique to the EfficientNet50 architecture. The major contribution of this research is intended to improve the model's accuracy. Using data preparation, testing and verifying the model, and evaluating the model to achieve the optimum performance.

2. RESEARCH METHOD

In this study, 13.094 images from 100 distinct classes of Butterfly & Moths Image Classification 100 species [15] dataset were collected with resolution of the images 224 x 224. The dataset, which initially consists of 100 classes, has been reduced to 25 classes with total 3.390 images for the partition of picture data in each class in training is 3.140, as shown in the Table 1 and Figure 1 for the images samples.

Table 1. Class and number lepidopterans images in the dataset.

Classes	Images
Adonis	120
African Giant Swallowtail	100
American Snoot	100
An 88	120
Appollo	120
Arcigera Flower Moth	130
Atala	140
Atlas Moth	125
Banded Orange Heliconian	130
Banded Peacock	110
Banded Tiger Moth	130
Beckers White	110
Bird Cherry Ermine Moth	130
Black Hairstreak	120
Blue Morpho	105
Blue Spotted Crow	120
Brookes Birdwing	160
Brown Argus	165
Brown Siproeta	140
Cabbage White	125
Cairns Birdwing	115
Chalk Hill Blue	145
Checquered Skipper	130
Chestnut	120
Cinnabar Moth	130
Total	3140

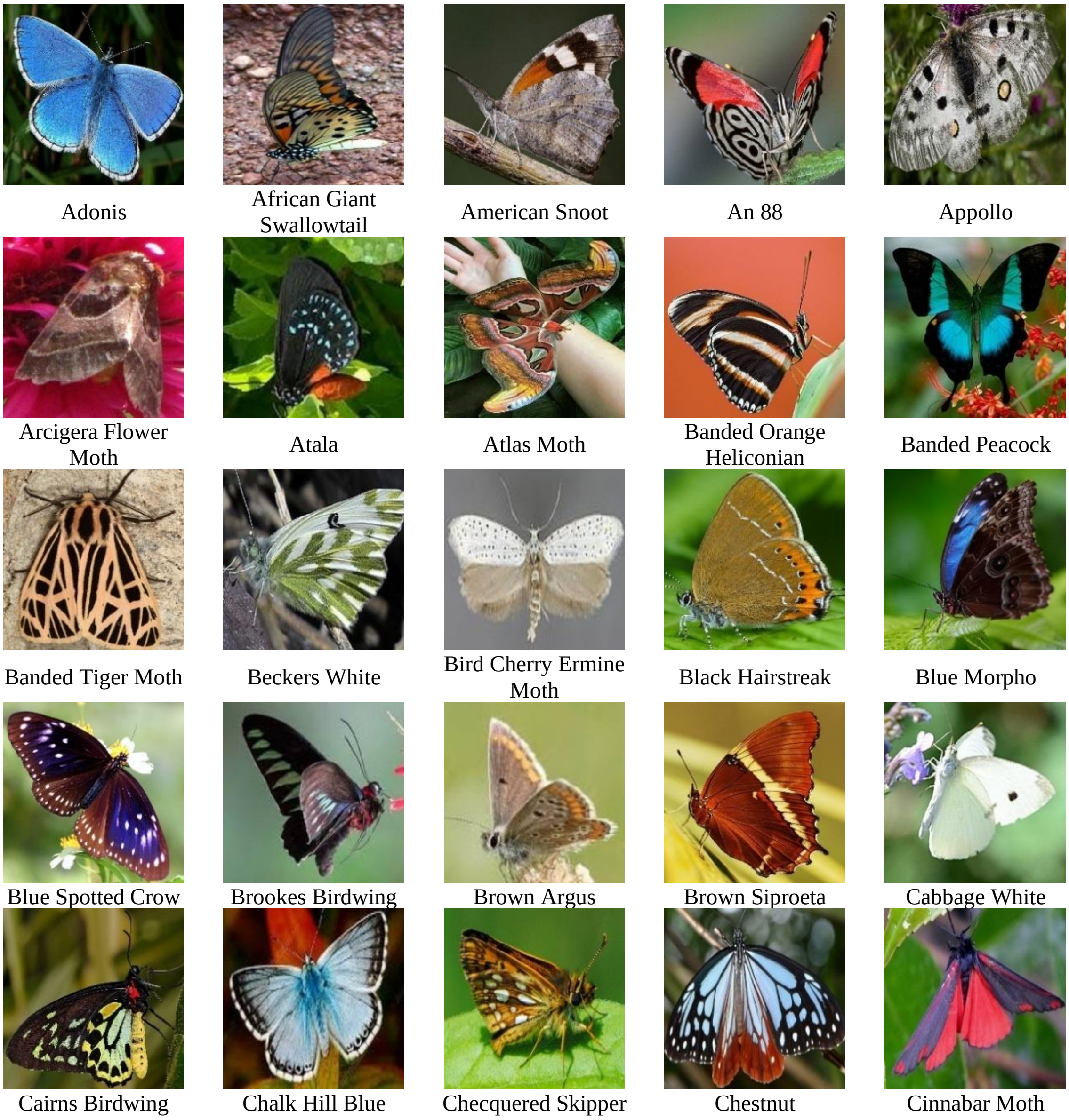

Figure 1. Sample images on the dataset

2.1 Convolutional Neural Network

A regular CNN, having similarities to an multi-layer perceptron (MLP) composed of multiple convolution layers before the pooling level, with a Fully Connected layer at the end [16]–[19]. Figure 2 show example of CNN architecture in image classification. CNN kernel represents a variety of receptors that can provide different response features, the activation function will replicate the function which only nerve electrical signals above a certain threshold can be sent to next neuron. Researchers try to develop loss functions and optimizers in an attempt to train the entire CNN system to learn what is expected [20].

In a CNN model, each layer's input x structured within three dimensions depth, width, height. Similar to NLP, convolutional layers compute dot product among input and weights, but input is a smaller portion of the native image size. Then the output of the convolutional layer applied a activation function or nonlinearity. Then feature map in subsampling layer was downsampled. This reduces parameters network, accelerate the training process, and helps address overfitting issues. Finally, similar to traditional neural networks, fully connected layers receive intermediate and lower level features and produce a high level abstraction representing the final level [18].

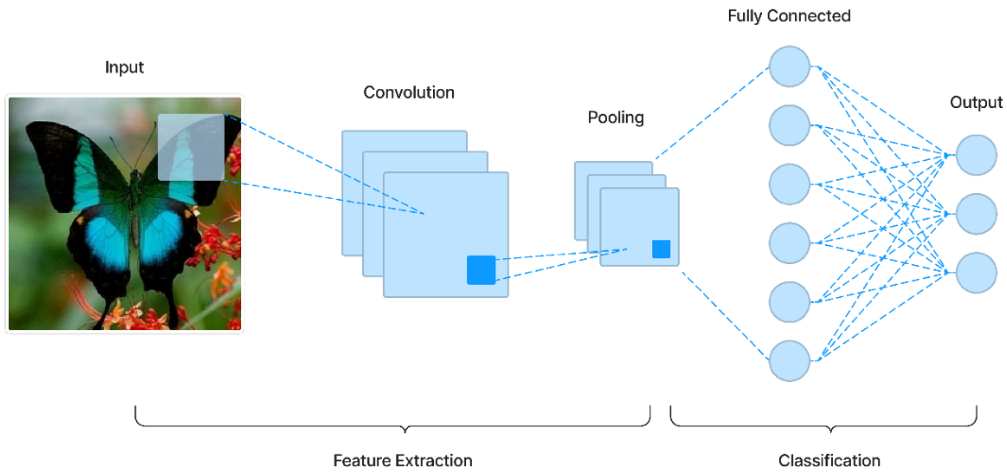

Figure 2. CNN architecture for image classifcation

2.2 EfficientNet

The EfficientNet model can be considered as a series of CNN models and one of the most sophisticated models in the situation of ImageNet classification. EfficientNet is consisting of eight models from B0 to B7, and increasing number of models does not significantly increase the number of parameters calculated, but improves accuracy. Unlike the existing CNN models, activation function called Swish was used in EfficientNet and not the Rectifier Linear Unit (ReLU) [14] activation. EfficientNet architecture can be shown in Figure 3.

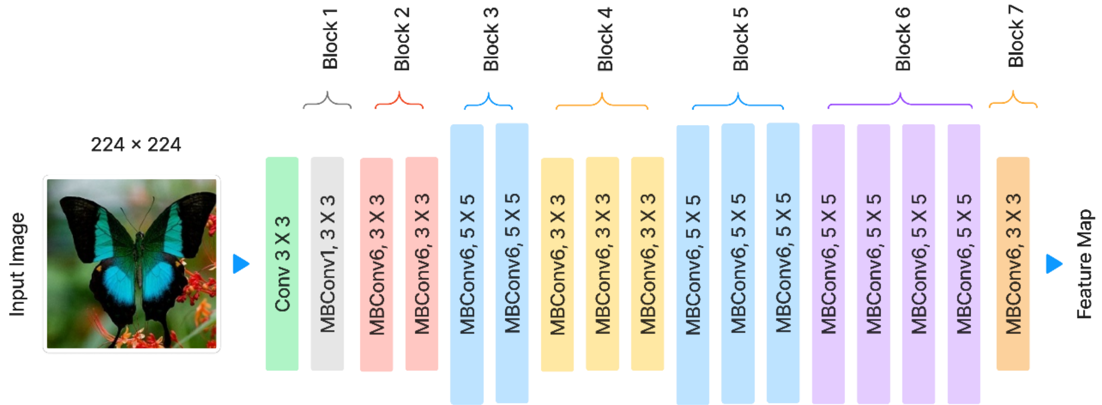

Figure 1. EfficientNet architecture

Unlike other models, by consistently scaling width, depth, and resolution EfficientNet aims more efficient results while shrinking the network. The initial stage of the scaling technique is to identify a grid that can aid in determining the relationship between the backbone network's numerous scaling dimensions with fixed resource constraints. This develops essential scaling factors in the dimensions of dimension, width, and resolution. The factor is then used to increase the size of the base network to the desired target network [14].

Reverse bottleneck MBConv was originally presented in MobileNetV2 and is the basic structure of EfficientNet [21]. Blocks in MBConv are made up of layers that expand and then compress channels, resulting in direct connections between bottlenecks and considerably less channels connected than expanded layers. Compared to common layers, our design contains deep separable convolutions for lowering complexity of computation by almost k^2, The width and height of the 2D convolution window are defined by the kernel size k [21].

EfficientNet uses a compound factor φ to scale the depth, resolution, and width of the network uniformly.

$$depth: d = \alpha^{\varphi}$$
$$width: w = \beta^{\varphi}$$
$$resolution: r = \gamma^{\varphi}$$

$$s.t.\ \alpha \cdot \beta 2 \cdot \gamma 2 \approx 2 \qquad (1)$$
$$\alpha \geq 1, \beta \geq 1, \gamma \geq 1$$

Using a small grid search constants α, β, γ can be found. Intuitively, this is a user factor that determines the amount of resources available for scaling the model, and α, β, γ determine how additional resources are allocated for network resolution, depth, and width [14].

2.3 Transfer learning

Transfer learning provides a valuable technique of machine learning in dealing with the underlying problem of inadequate data for training. It tries to transfer information from a particular field to another through decreasing the condition that training and test data be dispersed independently and uniformly. This could have a significant positive influence in many areas where improvement is difficult because of an inadequate quantity of training data [22].

During transfer learning final layer of trained network is removed and can be retrained with new layers in the target job. In terms of reducing time spent on transfer learning practices, relying on network knowledge pre-trained on vast amounts of visual data in new jobs is particularly beneficial [23].

2.4 Method

The primary objective of this research is to develop a model in classifying multi-label *lepidoptera* using the EfficientNet-B0-CNN model and the architecture shown in Figure 3. Figure 4 depicts the various phases in constructing a neural network-compliant classification model, which begin with the preprocessing phase using ImageDataGenerator and continue with the training phase using the EfficientNet-B0 CNN model. Following that, the model's precise implementation procedures will be discussed in depth.

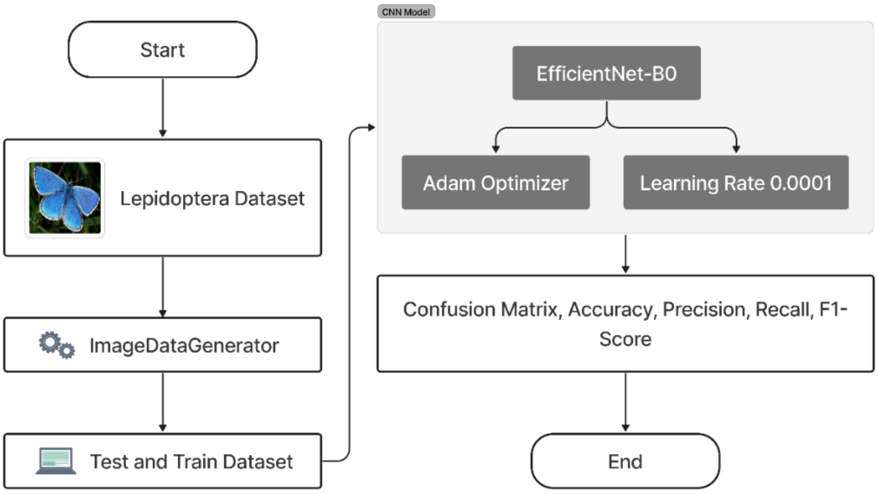

Figure 2. EfficientNet-B0 flowchart for lepidoptera classification

2.5 Experimental Setup

GPU support was built into the EfficientNet Architecture. The experiments were carried out on a Jupyter notebook provided by Google Colaboratory. The Jupyter notebook system is powered by an 2.20 GHz Intel(R) Xeon(R) CPU with 13 GB of RAM, while the GPU is NVIDIA Tesla T4 with 15 GB of memory. Code was implemented using the Keras 2.12.0 framework, a deep neural network open source library in Python.

2.6 Data Preprocessing

The image dataset has been separated into two distinct parts for training and testing. The training data composed of 3140 dataset images in total and the test data consists of 250 images in total. The data is cropped and the aspect ratio is set to 1:1 and scales the image to 244 x 244 pixels. Pre-processing prepares the input image so that the model can process it optimally and produce more accurate results [14]. The ImageDataGenerator library is used for image data augmentation. ImageDataGenerator is a Keras library. Before delivering the image data to the model, the generator will perform random alterations to each image. This ensures that the model never sees the same image during training [24]. Data augmentation techniques such as random rotation with a 90-degree range, horizontal and vertical flip, channel shift range, and cross validation were applied in ImageDataGenerator.

2.7 Training

Deep learning models were applied in this study to classify the *lepidoptera* images. EfficientNet-B0 used a CNN based on the transfer learning method. On the ImageNet dataset the model was trained and was very successful. In this study, transfer learning algorithm was used to classify *lepidoptera* dataset. The EfficientNet-B0 model's configuration such optimizer, epoch, batch size, learning rate, activation function values on the training were reported in Table 2.

Table 1. Parameter configuration.

Configuration	Value
Optimizer	Adam
Epoch	100
Batch size	64
Learning rate	0.0001
Activation function	Softmax

The EfficientNet B0 model was applied with softmax as the last layer activation function and the loss function was categorical crossentropy. Setting the learning rate is complicated since a low learning rate can inhibit convergence and a high learning rate can obstruct convergence. because the loss function fluctuates, become trapped in a local minimum, or even diverge [25], so learning rate of 1e-4 or a loss change of 0.0001 was chosen. Maximum epoch is defined as 100 epochs with 49 steps in each epoch, and adam optimizer was chosen in the training models. Table 3 shows the amount of trainable and untrainable variables (weights) for every layer, and it also shows the output form of each layer.

Table 2. Layer types, output shape and parameters of the model.

Layer	Output Shape	Parameter
EfficientNet-B0	7 x 7 x 1280	4.049.571
Global_Average_Pooling2d	1280	0
Dropout	1280	0
Dense	25	32.025
Total params	4.081.596	
Trainable params	32.025	
Non-trainable params	4.049.571	

Table 3. Confusion matrix.

		Predicted Label	
		Negative	Positive
Actual Label	Negative	TN	FP
	Positive	FN	TP

2.8 Performance Metrics

The Lepidoptera dataset contains 25 categories, therefore multiclass classification was used. The indices in Table 4 are based on confusion matrix values derived from classifications. Where TP denote the amount of adequately classified decline images in every category, and TN represent the total number of correctly classified photos in every categories except the appropriate category. FN displays the amount of inaccurately classified photographs in the associated category, whereas FP displays the number of erroneously classified photos in all categories except related ones [23].

EfficientNet-B0 performance is also measured using several measures such as Recall, F1-Score, Precision, and Accuracy. Accuracy is basic perfomance evaluation in classification, it refers to the proportion of correctly categorized samples. Precision is the possibility that a sample is positive over every sample predicted to be positive. The likelihood that an actual positive sample will be positive in comparison to the original sample is referred to as recall [26]. The harmonic mean of the precision and recall measurement functions is indicated by the F1 score.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{2}$$

$$Precision = \frac{TP}{FP+TP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

3. RESULTS AND DISCUSSION

Compare the performance of EfficientNet, to those of previous study CNN models in the literature is the main objective of this paper. The performance metrics of the EfficientNet B0 model metrics like precision, accuracy, recall, and F1 score values in the test dataset for each class are listed in the Table 5. EfficientNet-B0 model training process takes approximately two and a half hours, it indicates that transfer learning is quite beneficial in terms of time savings and excellent accuracy.

Table 4. Metrics performance in each class.

Classes	Precision	Recall	F1 Score
Adonis	0.83	1.00	0.91
African Giant Swallowtail	1.00	1.00	1.00
American Snoot	1.00	1.00	1.00
An 88	1.00	1.00	1.00
Appollo	1.00	1.00	1.00
Arcigera Flower Moth	1.00	1.00	1.00
Atala	1.00	1.00	1.00
Atlas Moth	1.00	1.00	1.00
Banded Orange Heliconian	1.00	1.00	1.00
Banded Peacock	1.00	1.00	1.00
Banded Tiger Moth	0.91	1.00	0.95
Beckers White	0.91	1.00	0.95
Bird Cherry Ermine Moth	1.00	0.70	0.82
Black Hairstreak	0.91	1.00	0.95
Blue Morpho	1.00	1.00	1.00
Blue Spotted Crow	1.00	1.00	1.00
Brookes Birdwing	1.00	1.00	1.00
Brown Argus	1.00	0.90	0.95
Brown Siproeta	1.00	1.00	1.00
Cabbage White	0.91	1.00	0.95
Cairns Birdwing	1.00	0.90	0.95
Chalk Hill Blue	0.89	0.80	0.84
Checquered Skipper	1.00	1.00	1.00
Chestnut	1.00	1.00	1.00
Cinnabar Moth	1.00	1.00	1.00
Macro Average	0.97	0.97	0.97
Accuracy	0.9791		

According to Table 5, Adonis species has the lowest value in precision performance category, with a precision value of 83%. Furthermore, the Chalk Hill Blue species has the second lowest value after Adonis, with a precision value of 83%. In the recall and F1 Score performance Bird Cherry Ermine Moth has lowest value, with a recall value of 70% recall and 82% F1 Score, this is the lowest value in overall performance category.

Figure 5 depicts the confusion matrix of the model training outcomes, where 0-10 represents the number of images in the testing session. The brighter the color exhibited, the higher the image classification result.

According to the confusion matrix, some species are still not perfect in classifying with test data, such as Bird Cherry Ermine Moth species, which can only classify 7 images correctly, Brown Argus with 9 images and 1 image is classified as Black Hairstreak species, Cairns Birdwing species, which successfully classified 9 images and the rest are classified as cabbage white, and Chalk Hill Blue, which successfully classified 8 images and the rest are classified as Adonis.

Training and Validation Learning Curves for Accuracy and Loss are shown in Figure 6. The training and validation losses are minimized to a certain point of equilibrium with a slight difference between the two ultimate loss numbers to figure out a satisfactory fit curve. The model loss on the training dataset is usually often less than the loss on the test dataset. This shows that there is a variance between the training learning curve and the validation losses. Which is referred to as the generalization gap. While model with excessive capacity may learn and fit the training dataset too well. In such instances, the model does not cause a generalization gap [27], [28].

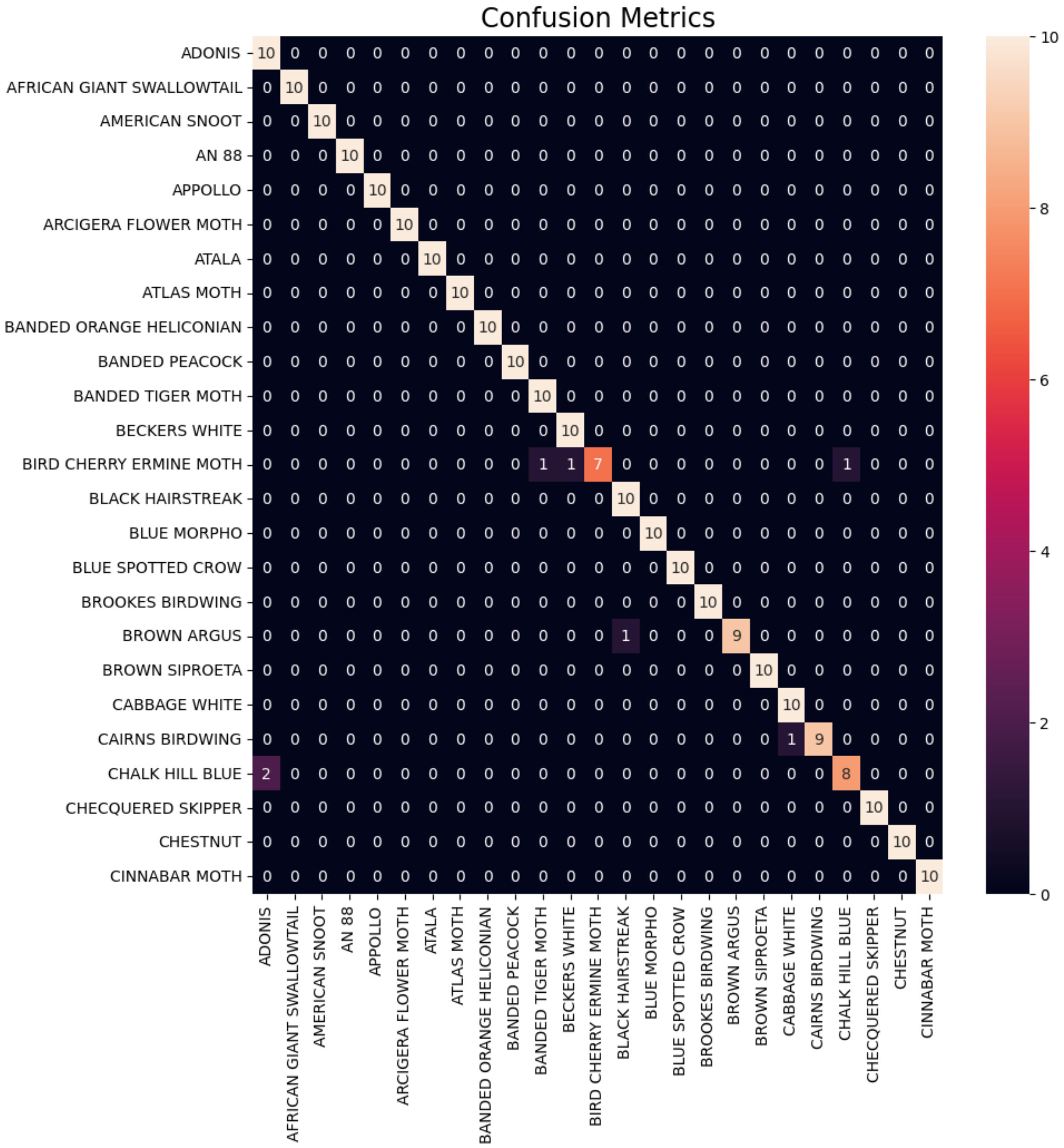

Figure 3. Confusion matrix result of EfficientNet-B0

The findings are compared to earlier research. However, because the approaches use different datasets and characteristics, the comparison is limited. Furthermore, because the majority of the publications lack software, it is unable to analyze their methodologies in order to provide a more reliable comparison. Table 6 presents a comparison with previous studies with proposed methods for classifying lepidoptera, including butterflies and moths.

Table 5. Comparison results of prevoius study for lepidoptera classification.

References	Architecture	Dataset	Accuracy
Jia [11]	Faster RCNN	13,076 images, 30 class	95%
Tan [12]	Mask - RCNN	1,462 images, 5 class	90.43%
Tan [12]	FCM-KM	1,462 images, 5 class	83.62%
Arzar [13]	GoogLeNet	120 images, 4 class	97.5%
Proposed	EfficientNet-B0	3,390 images, 25 class	97.91%

The accuracy of previous studies for lepidoptera classification, including the butterfly and moth values in Table 6, ranged from 83.62% to 97.5%. Thus, the application of the EfficientNet model provides promising results for the classification of lepidoptera with an accuracy of 97.91%.

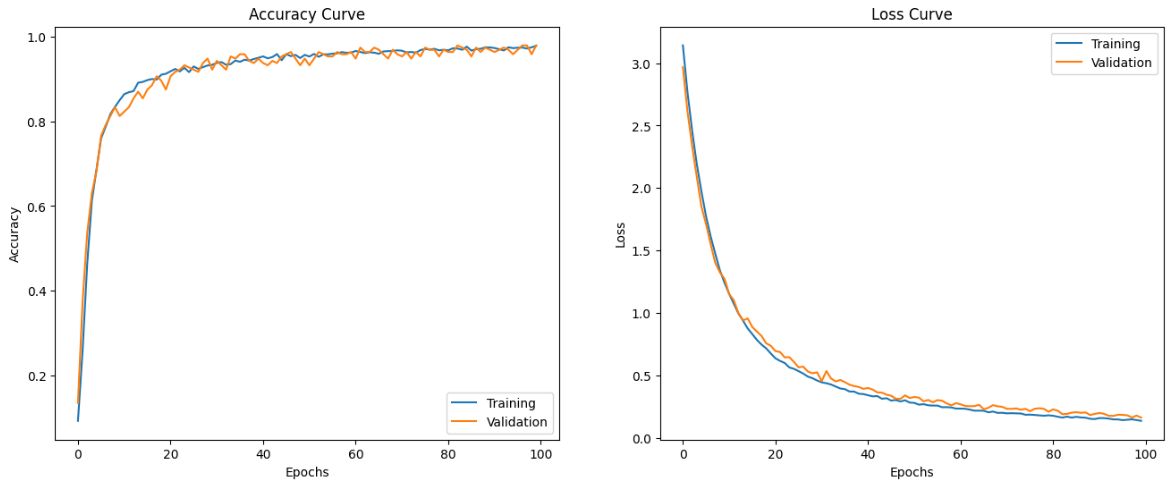

Figure 4. Accuracy and loss curve result of EfficientNet-B0

4. CONCLUSION

In this study, an CNN architecture EfficientNet is presented to classify lepidoptera from 25 classes, covering butterflies and moths. The EfficientNet-B0 model outperformed the other models in terms of accuracy, finishing the training phase in two and a half hours, proving the success of the proposed model when compared to previous study model utilized in butterfly and moth classification. The EfficientNet-B0 model had a 97% on precision, 97% on recall, and 97% on F1-score, and an accuracy of 97.91%. Establish the lepidoptera dataset in the future by increasing the diversity of butterfly and moth species as well as the number of classes. This contributes to the development of CNN architecture capable of making more accurate predictions in tough circumstances.

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