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Research Paper

Nudibranch Suborders Classification based on Densely Connected Convolutional Networks

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A B S T R A C T

Nudibranchs, often called sea slugs, are a group of soft-bodied marine gastropod mollusks that shed their shells after their larval stage. With their body structure that is very similar between one suborder and another, sometimes it is hard to tell apart the suborder of a nudibranch. In this work, we make an Image Classification model for determining the suborder of a nudibranch using deep learning algorithms DenseNet and EfficientNet. The experiment is conducted using Google Colaboratory environment. For DenseNet, we use 121, 169, and 201 layers; meanwhile, we only use the baseline algorithm for EfficientNet. The dataset for research is randomly taken from marine fauna forums on the internet. DenseNet with 201 layers shows a better generalization than other classifiers (accuracy of DenseNet 121, 169, 201, and baseline EfficientNet, respectively 53%, 41%, 73%, and 47%). The research produces a decent system for classifying the suborder of the Nudibranch. Usage of image recognition or background blurring systems in future research can improve the system's accuracy.

INTRODUCTION

Marine is the largest ecosystem on the Earth and covers two-thirds of our planet's surface [1]. It makes the research on marine ecosystems one of the most important to understand our world and how we might have affected them. Research on the marine ecosystem cannot be separated from research on the biota that lives in it. Changes in behavioral patterns, diet, and physical characteristics of marine life can give us a clue to help us understand what is happening to the marine ecosystems. One such marine creature is called Nudibranch. Scientists, divers, and photographers have all been intrigued by nudibranchs, also known as sea slugs, a colorful and diverse group of marine gastropod mollusks. They are from the family of Opisthobranchs (common sea slug) and phylum Mollusca. There are mainly four suborders of nudibranchs, namely the dorids, aeolids (also known as eolids), dendronotus, and arminids, and over three thousand currently known species [2]. Therefore, the classification of nudibranchs not only lists colorful and curious animals. More profoundly, it is the basis for the knowledge of marine biodiversity, ecosystem functioning, and relations, as well as the field of evolutionary biology, and it is a promising source for the opening of new scientific exploration and potential pharmaceutical discoveries. It can be widely used for conservation purposes and in monitoring the marine environment to preserve its health. Thus, the classification of nudibranchs is fundamentally crucial in marine science.

Even though classified as different suborders, many nudibranchs have a similar body structure to one another, namely the difference between nudibranchs from one suborder to another can be as small as the shape of gills, size, and number of appendages [3]. It makes it difficult for researchers or divers to classify Nudibranch in the field, namely it is impractical to bring books or other data storage media underwater. Animal classification systems are usually only trained using data of animals from different orders or animals that have a noticeable difference, namely animals that are not similar to each other. [4] use a Multi-Layer Perceptron and Support Vector Machine for creating predatory animal classification models with 82% and 72% accuracy. In research [5], the animal species classification model was created using a Support Vector Machine with 86.4% accuracy when tested using three animals (dog, cat, and tiger). It is more challenging for animals in the same order to get a high accuracy because animals in the same order tend to have similar features.

This issue can be solved nicely using the more advanced image classification method. The usage of deep learning algorithms such as Convolutional Neural Networks (CNN) [6]–[8] and Residual Neural Networks (ResNet) [9] has shown promising results in making Image Classification models for many different fields, such as differentiating between animal and vehicle or furniture [10], detecting cancer [11], to seeing the defect in train railway [12]. Choosing the dataset for learning is also very important in classification tasks. A dataset with an imbalanced class or insufficient data will cause the resulting model not thoroughly to learn the characteristics of each class. Deep learning algorithms such as EfficientNet [13] and DenseNet [14] have been shown to give a result with accuracy similar to or better than both CNN and ResNet while using a smaller or unbalanced dataset. The denseNet algorithm has also shown a good effect for classifying animals in the same species, such as parrots [15].

In this research, we will make an image classification model using DenseNet, EfficientNet deep learning algorithms for classifying suborders of Nudibranch (case of classifying animals in the same order but different suborders) based on its image. This research will not only help show the effectiveness of using the EfficientNet and DenseNet algorithms for the animal's classification system but also help the research on Nudibranch itself, namely provide faster field classification for experts. The research will be carried out in a Google Colaboratory environment and using data that consists of 4 classes of Nudibranch suborders, namely the dorids, aeolids, dendronotus, and arminids. Lastly, we will evaluate the finished model using a confusion matrix. The contributions to this research are 1) evaluating the use of DenseNet and EfficientNet transfer learning on imbalanced data. 2) Exploring the DenseNet model 121, 169, and 201 layers.

METHOD

Collecting the dataset is the first step in making the Nudibranch suborder classification model. The dataset consists of four classes of Nudibranch's Suborder, namely the dorids, aeolids (also known as eolids), dendronotus, and arminids [2]. Next, we read the dataset image into an RGB matrix and then resize it so all the images in the dataset have a size of 224 x 224. The preprocessed dataset is trained to baseline EfficientNet and DenseNet models with 121, 169, and 201 layers, respectively. Lastly, all the models will be compared, and the best one is the result of the research. The process for Nudibranch suborder classification can be seen in Figure. 1.

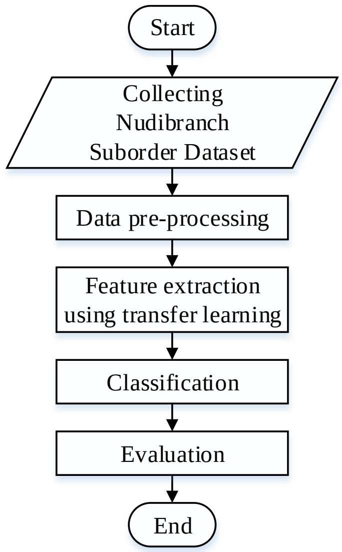

Figure 1. Architecture of Nudibranch Suborders classification system

Nudibranch Dataset

Two datasets that consist of a thousand and a hundred pictures of Nudibranch from four different suborders are used for this research. The picture is collected manually from [14] and [16]. Each image has another resolution from one. The class of the dataset is the four suborders of Nudibranch, which consists of aeolidiae, dendronotids or dendronotus, doridae, and arminids [2], can be seen in Figure 2.

Figure 2. Example of Nudibranch dataset

Table 1. Nudibranch Datasets

Dendronotids	Doridiae	Aeolidiodea	Arminids
Tethys Fimbria	Doris Chysoderma	Shag-rug Nudibranch (Aeolidia papillosa)	Striped Nudibranch (Armina California)
Doughnut Doto	Glossodoris symmetricus	Aeolidia campbellii	Dermatobranchus rubidus
Hancock's Nudibranch	Hypselodoris bullocki	Aeolidia filomenae	Dermatobranchus fortunatus
Hooded Nudibranch	California Blue Dorid	Aeolidia loui (Warty Shag-rug Nudibranch)	Dermatobranchus Gardineri
Threaded Nudibranch	Nembrotha Chamberlaini	Aeolidiella alderi	Dermatobranchus caeruleomaculatus
Seal Doto	Goniobranchus splendidus	Aeolidiella Drusilla	Armina Occulta
White Dendronotus	Anna Chromodoris	Aeolidiella glauca	Dermatobranchus Ornatus
Melibe Engeli	Acanthodoris Nanaimoensis	Aeolidiella sanguinea	Armina tigrine
Eel Bornella	Jorunna funebris	Anteaeolidiella chromosoma (Colorful Aeolid)	Armina scotti
Dendronotus Iris	Tambja morosa	Anteaeolidiella oliviae (Olive's Aeolid)	

In this research, the number of datasets was imbalanced: 274 aeolidiodea, 175 arminids, 250 dendronotids, and 250 doridoidea. This dataset is used for the creation of the Nudibranch suborder classification model. The list of Nudibranch species used for the dataset is in Table 1. The second dataset is used for evaluation purposes and has 25 images for each class. Each image is random but not the same Nudibranch species as the image in the dataset for making the model.

Preprocessing Nudibranch Dataset

For this research, all the pictures in the dataset are resized into 224 x 224 resolution. That's because the pictures in Nudibranch don't yet have the same resolution size, as seen in Figure 3 (some images are bigger than others. Meanwhile, some are smaller). OpenCV library is used for the resolution resizing process.

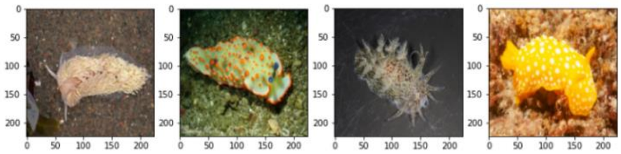

Figure 3. Example of Resized Nudibranch dataset

Feature Extraction

The RGB value of each nudibranch image in the preprocessed dataset is extracted and used as a dataset for making the model. We chose the RGB value because each suborder of Nudibranch tends to have a distinct color (not just black and white), making it essential for the finished model to differentiate between colors. OpenCV library extracts RGB values from the pictures, resulting in a thousand RGB values for 224 x 224 pixels. The result then changed, so it ranged from 0 to 1 by dividing the RGB value in each pixel by 255.

Classification using DenseNet and EfficientNet

Two types of convolutional neural networks, DenseNet and EfficientNet, are used for this research.

DenseNet

The Densely Connected Convolutional Neural Network (DenseNet for short) is a convolutional neural network with dense connections between each layer. DenseNet connects all layers with matching feature map sizes using a Dense Block module [17]. Meanwhile, Figure 4 shows a Dense Block with a layer count of five and a growth rate of k. The feature maps from the layers above each are sent to the next.

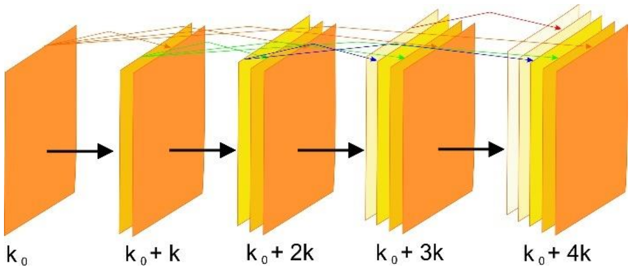

Figure 4. Structure of Dense Block

DenseNet architecture is a collection of Dense Blocks, where each block can have different layers. The first layer in DenseNet architecture is the Convolutional Layer. The convolution operation is applied to the RGB value of input training data, then reducing the feature using the Pooling layer. Then, each Dense Block will calculate the representations, which will be down sampled in the Transition layer (combination of convolution and pooling layer). Lastly, the Classification layer will change the number of channels to equal the number of classes, namely aeolidiae, dendronotids, doridae, and arminids, by computing the cross entropy loss and weight [18]. Figure 5 is an illustration of image classification using DenseNet. For this research, we use three DenseNet architectures of 4 Dense Blocks each, namely DenseNet with 121, 169, and 201 layers [17]. Table 2 shows the architecture of each DenseNet.

EfficientNet

The EfficientNet is a Convolutional Neural Network (CNN) that uses a scaling method where all input images' depth, width, and resolution dimensions are uniformly scaled using a compound coefficient rather than an arbitrary scaling on one or multiple dimensions [13].

Figure 6. shows a scaling model using only width, depth, or resolution and the compound scaling, namely complex scaling that combines width, depth, and resolution scaling. Compound scaling deals with a common problem when using only a single scaling method: the reduced accuracy gains for bigger models. Compound scaling work by uniformly scaling the depth, width, and resolution using a compound coefficient (ϕ). This formula is shown in equation (1).

$$\begin{aligned} &depth: d = \alpha^{\phi} \\ &width: w = \beta^{\phi} \\ &resolution: r = \gamma^{\phi} \\ &s.t.\ \alpha.\beta^2.\gamma^2 \approx 2, \alpha \geq 1, \beta \geq 1, \gamma \geq 1 \end{aligned} \tag{1}$$

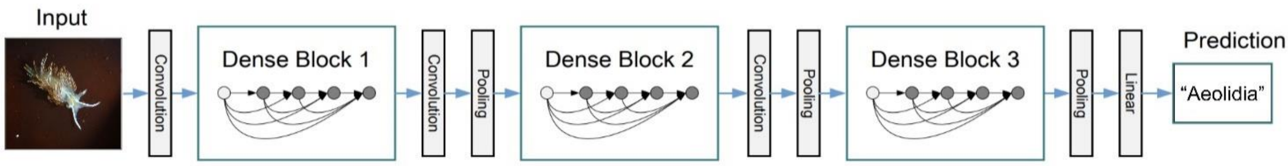

Figure 5. Image Classification by DenseNet

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Table 2. Architecture of DenseNet with 121, 169, and 201 layers

Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201
Convolution	112 x 112	7 x 7 conv, stride 2	7 x 7 conv, stride 2	7 x 7 conv, stride 2
Pooling	56 x 56	3 x 3 max pool, stride 2	3 x 3 max pool, stride 2	3 x 3 max pool, stride 2
Dense Block (1)	56 x 56	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 6$	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 6$	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 6$
Transition Layer (1)	56 x 56	1 x 1 conv	1 x 1 conv	1 x 1 conv
	28 x 28	2 x 2 average pool, stride 2	2 x 2 average pool, stride 2	2 x 2 average pool, stride 2
Dense Block (2)	28 x 28	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 12$	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 12$	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 12$
Transition Layer (2)	28 x 28	1 x 1 conv	1 x 1 conv	1 x 1 conv
	14 x 14	2 x 2 average pool, stride 2	2 x 2 average pool, stride 2	2 x 2 average pool, stride 2
Dense Block (3)	14 x 14	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 24$	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 32$	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 48$
Transition Layer (3)	14 x 14	1 x 1 conv	1 x 1 conv	1 x 1 conv
	7 x 7	2 x 2 average pool, stride 2	2 x 2 average pool, stride 2	2 x 2 average pool, stride 2
Dense Block (4)	7 x 7	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 16$	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 32$	$\begin{bmatrix} 1\ x\ 1\ conv \\ 3\ x\ 3\ conv \end{bmatrix} x\ 32$
Classification Layer	1 x 1	7 x 7 global average pool	7 x 7 global average pool	7 x 7 global average pool
		1000D fully connected, softmax	1000D fully connected, softmax	1000D fully connected, softmax

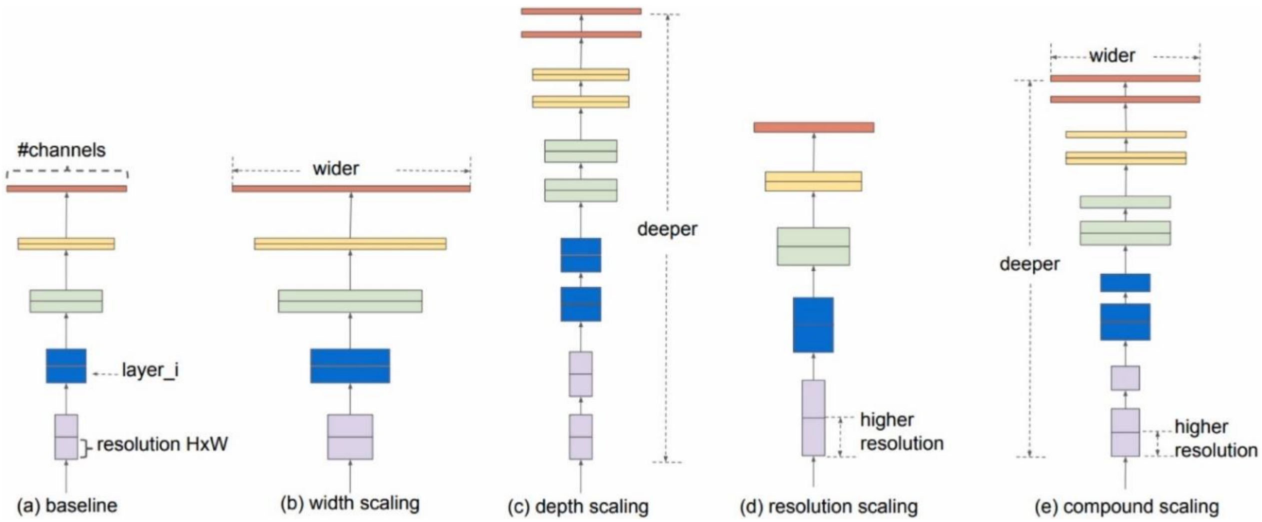


Figure 6. Scaling Model; (a) baseline scaling, (b) width scaling, (c) depth scaling, (d) resolution scaling, and (e) compound scaling.

The provided formula represents one of the key ideas behind the compound scaling method for the EfficientNet architecture, which is a family of models developed for transfer learning. More specifically, the EfficientNet scaling method systematically progresses performance improvements through depth, width, and resolution networks. Moreover, α, β, γ refer to coefficients used to scale each aspect, that is, the depth, width, and resolution of a network, with the compound coefficient, which is represented by ϕ. Depth means the number of layers in the network, the width refers to the number of channels in each layer, while resolution relates to the size of an input image. Thus, the formula demonstrates how much the computational costs change as ϕ doubles for the depth being cubed, width squared, and resolution squared.

In this research we only use the baseline EfficientNet model (EfficientNet B0), mainly for comparison purposes with the DenseNet model. The EfficientNet-BO used MBConv (mobile inverted bottleneck) as its main block [19] and optimized it using squeeze and excitation [20]. The architecture of this model can be seen in Figure 7.

Evaluation

The model is evaluated by comparing the classification result with the actual result. From this, we can find how well the model predicts the correct class from all predictions for that class (precision), from all basic values of that class (recall), and simply how many predictions the model makes are correct (accuracy). To do this, we use a confusion matrix for evaluation [21]. The recall, precision, F-score, and accuracy formulas are shown in equations (2), (3), (4), and (5).

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

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

$$F - score = 2\ x \frac{recall\ x\ precision}{recall+precision} \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{5}$$

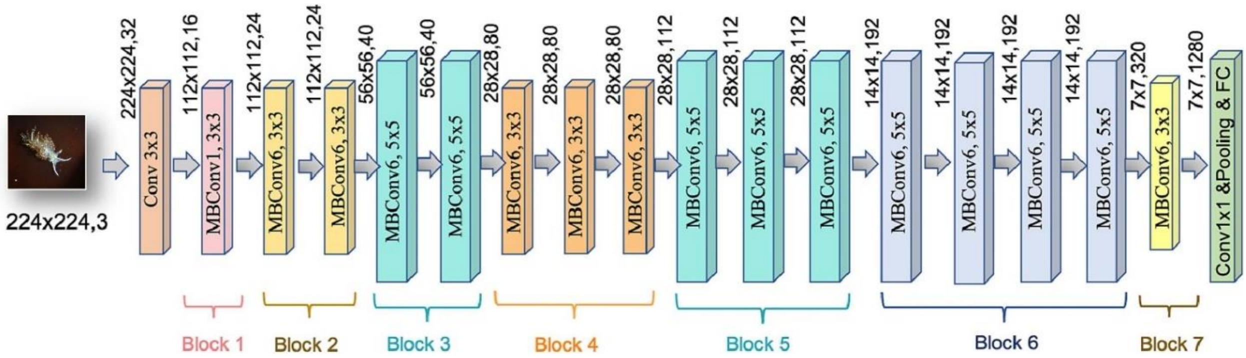


Figure 7. Architecture of EfficientNetB0

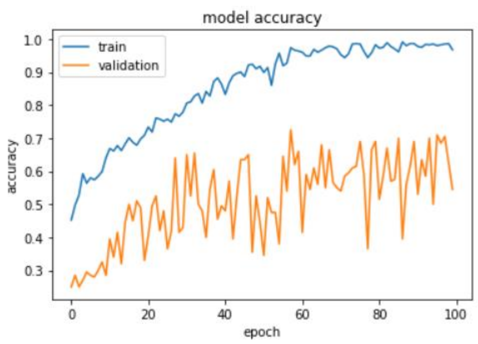
RESULTS AND DISCUSSION

The nudibranch image classification is run on google Collaboratory with an Intel(R) Xeon(R) CPU 2.30GHz, 12GB of RAM, and Nvidia K80 GPU with 12GB of Memory.

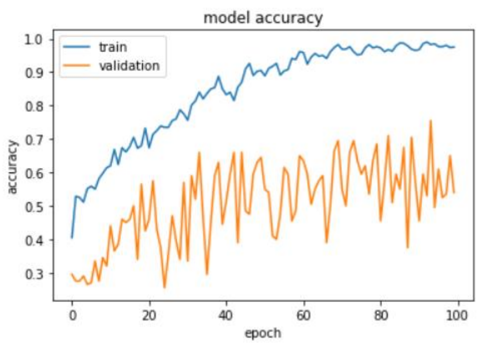
Learning results using DenseNet and EfficientNet

DenseNet architecture with 121, 169, and 201 layers; a baseline model of EfficientNet is used to make the classification model. Eight hundred random images from the first dataset will be used to train the model. Meanwhile, the last 200 images will be used for testing the learning result. Each model is trained for 100 epochs. Figure 9 shows the accuracy progression for each epoch in the learning experiment.

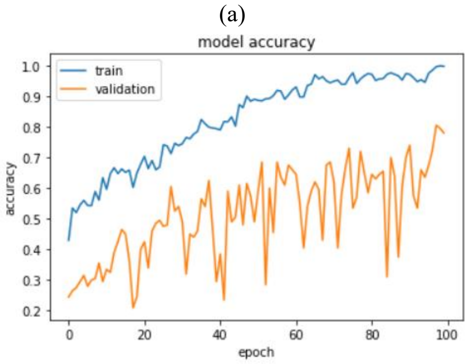
From Figure 9, the more layers used for DenseNet architecture, the better the model's accuracy is. Because the training data preprocessing step doesn't include an image detection system, the model must learn how to differentiate the nudibranch image from the background image in the training data. Increasing the layer gives the model more room to learn from the training data, hence the better accuracy result. Fluctuations also happen in the accuracy result of the DenseNet model, unlike the EfficientNet baseline model. The change is because of the lack of training data. The EfficientNet baseline model doesn't fluctuate because of compound scaling, which uniformly scales for depth, width, and resolution. While no underfitting was found in the learning result, the enormous distance between the validation and training accuracy in the DenseNet model with 121 and 169 layers and the EfficientNet baseline model clearly indicates overfitting. In the learning process, those models fail to differentiate the nudibranch image from the background image.



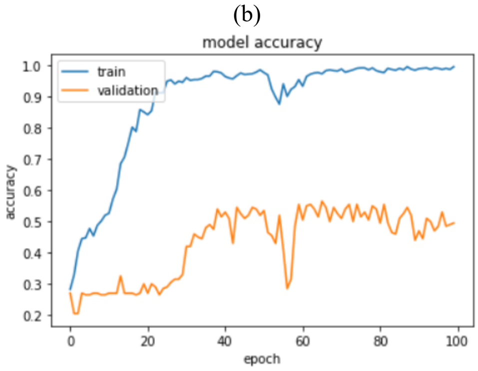
(a)



(b)



(c)



(d)

Figure 9. Accuracy and validation accuracy in learning for: (a) DenseNet-121; (b) DenseNet-169; (c) DenseNet-201; (d) EfficientNet-B0

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Table 3. Learning result for every 20 epochs in an experiment with 100 epoch.

Methods	Validation Accuracy at Epoch					Best Result	
	20	40	60	80	100	Val Acc	Epoch
DenseNet 121	33	49.5	66	69	54.5	72.5	58
DenseNet 169	42.5	44.5	65	68.5	54	75.5	94
DenseNet 201	40	29.5	66	58.5	78	80.5	98
EfficientNet B0	30	51.5	55.5	54	49.5	56.5	66

For this experiment, the model with the best accuracy result is the DenseNet with 201 layers. The highest validation accuracy for the DenseNet model and 100 learning epoch with 201 layers is 80.5% at 98 epochs. With 169 layers, the highest validation accuracy is 75.5% at 94 epochs, and with 121 layers, the highest validation accuracy is 72.5% at 58 epochs. The training accuracy result for DenseNet is decreasing as the layer decreases. The highest validation accuracy for the EfficientNet baseline model is 56.5% at 66 epochs. The detailed learning process for every 20 epochs can be seen in Table 3.

Based on data from Table. 3, the EfficientNet baseline model, while the only one that doesn't fluctuate, has the worst validation accuracy compared with all the DenseNet. The EfficientNet baseline model also stopped learning as early as 60 epochs, while DenseNet still learned until 80 to 100. It shows that compound scaling in EfficientNet is not as good as DenseNet for Figureuring out the pattern in an image with background noise, namely EfficientNet includes the background color in the learning process. Even though the EfficientNet baseline has the worst validation accuracy, the EfficientNet and DenseNet are only trained on ten species of Nudibranch. Therefore, to see how well these models generalize for all species of Nudibranch, experiments on a new dataset that consists of different nudibranch species will be conducted.

Research on marine biota is one of the most important to understand the ecosystem and how we might have affected them. Nudibranch is one of those creatures that can help researchers understand the ecosystem's change. Many nudibranchs have a similar body structure to one another, even though they are in different suborders. It makes it difficult for researchers to classify Nudibranchs immediately in the field. For that reason, we propose a nudibranch classifying system based on an image in this research.

The resulting model for the nudibranch suborder classification that we got was then tested using the testing dataset with different species than the dataset for training the model. This experiment intends to see how well the model generalizes for any nudibranch species. Table. 4 shows the accuracy and average for precision, recall, and f1-score for the experiment using the new dataset.

The nudibranch suborder classification system classifies pictures of Nudibranchs based on similar characteristics in each suborder, namely color, body shape, and size. Environment or background is another characteristic that the system will try to learn, even though it will not help the system by any means, namely it will cause overfitting. A good system must be able to ignore the background environment in the learning process as much as possible. Figure 10 is an example of predicting the dorid nudibranch using each classification system. Under the progress bars, the predictions of all models are presented in arrays that show the probabilities of four classes. Every array consists of four elements, reflecting the model's confidence that an image belongs to one of the classes it was trained to recognize. In this case, the models make the exact prediction, as all estimates are equal to 1 in the third position of the arrays and 0 in the other four positions. Thus, it is possible to suggest that all models agree that the described organism is a nudibranch with a high degree of certainty.

Table 4 shows that the only classification model that can learn from the dataset correctly is the DenseNet model with 201 layers. The accuracy of DenseNet in layers 121 and 169 and the EfficientNet baseline for the new dataset are not that much different from each other. It could mean all models aside DenseNet with 201 layers get into a similar problem, namely include the not necessary background in the learning process. This result still has many weaknesses, the apparent one being accuracy. While only having a decent effect (only 0.73 accuracies for the new dataset), the DenseNet with 201 layers can still generalize the nudibranch suborder correctly (not focus too much on the background image), which other models can't do. DenseNet with 201 layers can give a more generalized result because it has more layers than other models, which also means it learns the dataset deeper. By including image detection or background remover for future works, it will fix these problems by helping the algorithm to focus learning on the Nudibranch. Figure 11 is the result of Nudibranch classification using DenseNet 201.

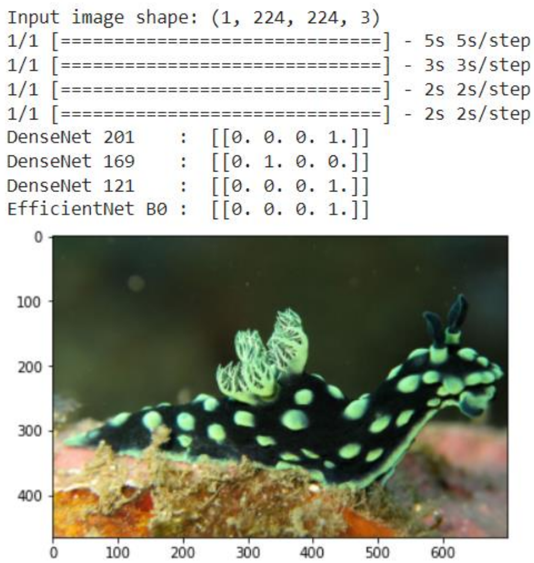

Figure 10. Example of predicting doridae Nudibranch; index: (0) arminids, (1) aeolid, (2) dendronotids, (3) doridae

Table 4. Experiment result of precision, recall, f1-score, and accuracy for new dataset.

Methods	Avg			Accuracy
	Precision	Recall	F1-Score	
DenseNet 121	0.53	0.61	0.53	0.53
DenseNet 169	0.41	0.5	0.4	0.41
DenseNet 201	0.73	0.78	0.74	0.73
EfficientNet B0	0.47	0.47	0.47	0.47

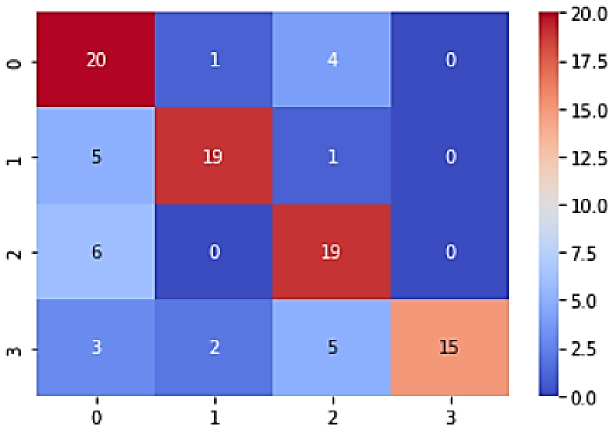

Figure 11. Confusion Matrix of the result with DenseNet 201 layers.

Discussion

As for the results, it is noticeable that the DenseNet-201 substantially outperforms its DenseNet analogs across all metrics. It can be assumed that the extra layers in denseNet-201 provided a substantial advantage in learning the features that distinguish nudibranchs. As a result, DenseNet-201 has the most significant average accuracy values, followed by the highest precision. Additionally, it has the highest recall and f1-score. It shows that it is the most capable of correctly identifying all the relevant instances for each class.

DenseNet-121, the one with the fewest layers in the study, performs relatively well. It is essential to consider that this model, which, with some margin, achieved the lowest number of layers among the DenseNet models, can still correctly classify nudibranchs at a moderate level. For instance, it has a reasonable level of precision, average accuracy, and the F1-score. However, its recall is worse than the DenseNet-201. As a result, this type of neural network might have difficulty correctly classifying all the relevant instances while being deeper than some of its analogs.

The DenseNet-169 design underperformed this type of model because it had the worst average accuracy and other values on the included metrics. Additionally, it is interesting to mention that it has fewer layers than DenseNet-201, so it might not be the case that more layers always facilitate a better outcome for neural networks. Instead, the task's complexity and the amount of training data should be used to determine the optimal network depth.

Next, the EfficientNet-B0, a unique type of neural network belonging to a family of models, is tailored to scale up in a more structured manner than merely adding more layers. It is supposed to use a compound scaling that uniformly scales the network width, depth, and input resolution according to a set of fixed scaling coefficients. It should be the primary member of that model family since the name suggests it is smaller than other effects, such as EfficientNet-B5, EfficientNet-B1, and EfficientNet-B2. However, this study reaches the same results as a DenseNet model. Although the balanced performance suggests that this type of neural network could be presumably more accurate than its dense analogs, they were not as effective. It could result from not scaling the model's complexity in a way that allowed meeting the study's requirements.

These results show several limitations when using these deep learning models to classify nudibranch species. First, while DenseNet-201 was found to be much better at distinguishing these categories, its average accuracy of 0.73 means that 27% of the nudibranch images will be misclassified, assuming the model provides unbiased performance. Such accuracy is likely too low for applications where precision is a high priority, such as scientific work that revolves around the accurate identification of species. The average accuracy of the other two models, 0.53 for DenseNet-121 and 0.47 for EfficientNet-B0, indicates that either the models are not complex enough or have not been optimized well enough for this task, causing many misclassifications. The model DenseNet-169 performed even worse across all categories, narrowing down the issue to either the model not being optimized for such a task or the overall architecture not being suitable for accurately recognizing images.

CONCLUSIONS

The nudibranch suborder classification models are created using four algorithm types (DenseNet in 121, 169, 201 layers, and EfficientNet), using only RGB value for its feature extraction. Models created using the algorithm DenseNet with 201 layers give the best result with a validation accuracy of 80.5%. The four models were then tested again on a new dataset containing images from different species of Nudibranch. Once again, the DenseNet algorithm with 201 layers gives the best result with 73% accuracy. The lack of an image detection system or small training data may be the reason for the drop in accuracy. In future work, using image detection to extract features will help the model focus on nudibranch image (ignoring background noise) and increase the overall accuracy. Increasing the number of nudibranch images in the dataset (adding more species) may also give the model more examples to understand each nudibranch suborder's characteristics better. Future research can apply other deep learning models or modify deep learning to improve accuracy results.

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