# COMPARATIVE ANALYSIS OF EFFICIENTNET AND RESNET MODELS IN THE CLASSIFICATION OF SKIN CANCER

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## ABSTRACT

*Skin cancer get classified as one of the most common types of cancer cause to death. There are some types of skin cancer as: basal cell carcinoma (BCC), melanoma (MEL), and others. This cancer may have different symptoms depending on the type of skin cancer, but the most common signs include changes in the size, shape, or color of a mole or skin. The progress in machine learning has been increasing, mainly on deep learning and artificial intelegenct. In the recent past deep learning has been developed for medical research. In the latest papers, algorithms that have been applied for medical research are pre-trained models. In this research, the author compares the pre-trained EffecientNet and ResNet-50 for classification of skin cancer on the HAM10000 dataset to find out which is the best for classifying skin cancer and what is the best pre-trained model for skin cancer classification. This study aims to find the pre-trained EffecientNet and ResNet-50 models for accurate and efficient  for skin cancer classification. In this experiment the results obtained were: that the highest accuracy on test was achieved by EfficientNet B7 on 88.41% accuracy and the lowest accuracy on test was achieved by ResNet 50 on 83.42% accuracy.*

**Keywords:** skin cancer, Pre-trained, EfficientNet, ResNet-50

## INTRODUCTION

Skin cancer is one of the most common cancers that cause death. Skin cancer can be categorized into several types like basal cell carcinoma (BCC), melanoma (MEL), and many others. Symptoms of skin cancer can vary depending on the type of cancer, but the most common signs include changes in the size, shape, or color of a mole or skin. Skin cancer is a serious health concern that needs to be prevented from the beginning and treated with proper awareness and care.

In recent, the progress of machine learning mainly in deep learning and artificial intelligence has been increasing especially in medical research. Two algorithms that have recently been applied for medical research are the pre-trained CNN. Pre-trained CNN is an algorithm that uses a CNN that has been trained on a large dataset. Overall, the progress of machine learning, especially in deep learning and artificial intelligence, has greatly contributed to improving medical research.

In this study, the author HAM10000 dataset contains about 7 types of pigmented lesions. The author compares pre-trained CNN EffecientNet and ResNet-50 to predict and classify skin cancer on the HAM10000 dataset to find the best accuracy. By evaluating and comparing the performance of different algorithms, the author can determine which algorithm is best used for skin cancer classification.

## LITERATURE STUDY

Several studies have been done into the classification of skin cancer. Huang et al.[1] developing binary and multiclass classification models using EfficientNet and DenseNet on The Kaohsiung Chang Gung Memorial Hospital (KCGMH) and HAM10000 dataset. DenseNet-121 has a remarkable performance in binary classification on the KCGMH dataset with 89,5% accuracy. Still, EfficientNet B-4 has 85,8% accuracy for the seven-class classification HAM10000. Ali et al.[2] was also using HAM10000 dataset to classify skin cancer. the study removing the noise and balancing the dataset. The best performance on EfficientNets B4 and B5 is 88% on precision, 88% on recall, 87% on F1 score, Specificity of 88 percent, and the area under the receiver operating characteristics (Roc Auc) Score of 97.5 percent. Islam et al.[3] also using HAM10000 dataset to classify skin cancer into 2 class which are benign and malignant cancer. by sing enhancing and resizing images proposed model the accuracy is 96.10% in training and 90.63% in testing. Tahir et al.[4] using ISIC 2020, HAM10000, DermIS dataset and using a deep learning-based skin cancer classification network (DSCC_Net) and got 99.43% AUC, 94.17% accuracy, 93.76% recall, 94.28% precision, and 93.93% F1 score. Ali et al.[5] is using a proposed deep convolutional neural network (DCNN) method and using HAM10000 dataset to classify benign and malignant skin. The processes that were used were removing the noise, normalizing input, and augmenting the image. From the proposed DCNN get 93,16% of training and 91,93 testing accuracy. Popescu et al.[6] also using the HAM10000 dataset with combined nine type of model which are AlexNet, GoogLeNet, GoogLeNet-Places365, MobileNet-V2, Xception, ResNet-50, ResNet-101, InceptionResNet-V2, and DenseNet201 and got 86.71%. Khamparia et al.[7] using a framework using pre-trained CNN architectures such as Inception V3, VGG19, SqueezeNet, and Resnet50 from the International Skin Imaging Collaboration (ISIC) image archive dataset from the International Skin Imaging Collaboration (ISIC) image archive dataset and got The average accuracy from the framework that was created is 99,2% for 80%-20% data splitting and 99,6% for 70%-30% data splitting and the highest score after the proposed framework is ResNet50. Mohapatra et al.[8] comparing ResNet50 and MobileNet on HAM10000 dataset and concluding that MobileNet performs better than ResNet50 when performing binary classification for cancerous and non-cancerous images specifically while ResNet50 performs better than MobileNet when it is classifying an image into more than two classes. Abuared et al.[9] using HAM10000 to classify only two cancer types and one non-cancer type and got the result 0.985 on training accuracy, and 0.975 on test accuracy. Tajerian et al.[10] using HAM10000 dataset then was preprocessed including resizing, augmentation, and labeling and achieved 84.3% on accuracy. Based on previous research about skin cancer classification that has been done before. Huang et al.[1] said that the best method for multiclass classification is EfficientNet and Mohapatra et al.[8] said that the best method for multiclass classification is ResNet-50. The dataset was used by Mohapatra et al.[8] which is the HAM10000 dataset. In this research, the author wants to compare pre-trained CNN using EfficientNet and Resnet-50 on the HAM10000 dataset.

## RESEARCH METHODOLOGY

To achieve similar results in this research study, it is important to clearly define the structured research methods clearly. If the research method is not explained in detail, the output will vary differently compared to this research because even when using the same method and the same dataset, the result can be very different. The following steps to increasing the probability of achieving similar results between studies demand implementation of these steps:

1. Literature study related to the topic in the project.
2. Collecting datasets, learning the algorithm used.
3. Preprocessing dataset and augmenting the data.
4. Implementation using EfficientNet and ResNet50
5. Analyze results of implementation and make conclusion.

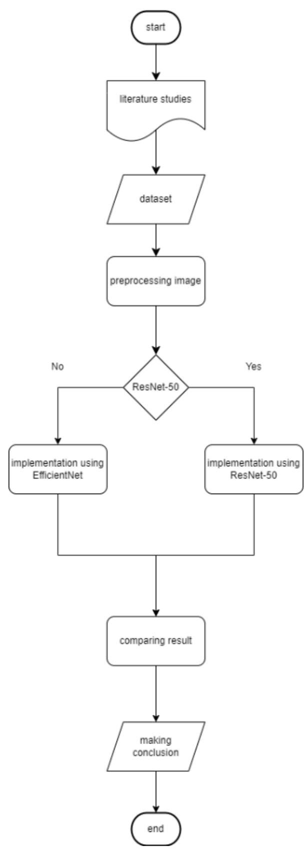


**Figure 1.** Research Methodology

### Dataset Collection

In this research the dataset that will be used was taken from Kaggle, namely Skin Cancer: HAM10000 with a total size of 3 GB. The dataset contains one CSV file, 10015 images, and its mask. The CSV file contains the image name and the ground truth of its class. The images are contained 1113 images of melanoma (MEL), 6705 images of melanocytic nevi (NV), 514 images of basal cell carcinoma (BCC), 327 images of Actinic keratoses and intraepithelial carcinoma / Bowen's disease (AKIEC), 1099 images of benign keratosis-like lesions (BKL), 115 images of dermatofibroma (DF), and 142 images of vascular lesions (VASC).

### Data Preprocessing

To get the best result, it is important to clean the data before into the model. Because models such as ResNet50 and EfficientNetB0 need an image of the size 224x224 pixels but the image itself is 600x450 pixels the author needs to resize it into 224x224 pixels. And on the image dataset namely HAM10000 there is an image of skin cancer but inside the image, there is some noise that covers the image which is hair. So, the author wants to remove the hair from the image.

### Models

In this project, after preprocessing the data, splitting the data was important because training data are things that will be trained with the model to predict so it will be accurate. In this project, the author split the data into 3 which are training, validation, and testing with 80% training data, 10% validation data, and 10% testing data. After splitting the data, the training data can be used to model classifications. In this project a pretrained model was used. The difference between pretrained and without pretrained is the model on pretrained are already trained with a large number of data but the model without pretrained is not trained with data so it need a large of data to train the model. Because there are not enough skin cancer image for several classes pretrained model was used because HAM 10000 dataset doesn’t have enough dataset for several classes like dermatofibroma (DF) only contain 115 images . In this project, author use two different models namely EfficientNet and ResNet-50.

#### *EfficientNet*

The EfficientNet is a type of convolutional neural network architecture that employs a scaling method to uniformly scale its depth, width, and resolution dimensions using compound scaling. Compound scaling means if the input image is bigger it means that the network also needs more layers. This stands in contrast to conventional practices that can arbitrarily scale these factors, utilizing specific scaling coefficients instead ensures the scaling across network width, depth, and resolution remains consistent and uniform. There are some types of EfficientNet which are EfficientNet B0, EfficientNet B1, EfficientNet B2, EfficientNet B3, EfficientNet B4, EfficientNet B5, EfficientNet B6, and EfficientNet B7.

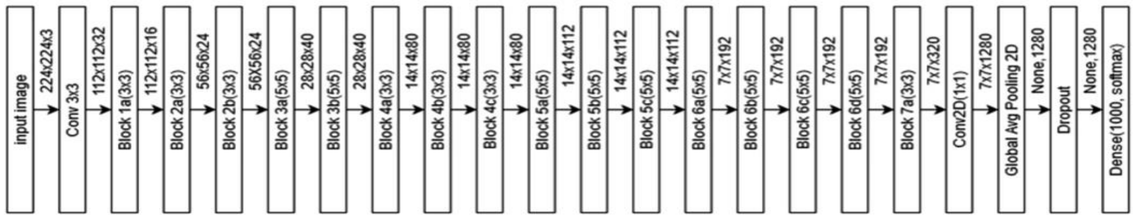


**Figure 2.** EfficientNet B0 Block Diagram[2]

### *ResNet-50*

A residual Network usually called ResNet is one of the deep-learning models used for image recognition. ResNet is a Convolutional Neural Network (CNN) that supports up to a hundred layers. This method is known for its skip connection with residual block. With residual block, ResNet can skip layers about 2-3 layers at one time. ResNet has a lot of types of architecture by its layer such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-150. This experiment uses ResNet 50 as its model. Resnet 50 contains one MaxPool layer, one average pool layer, and forty-eight convolutional layers.

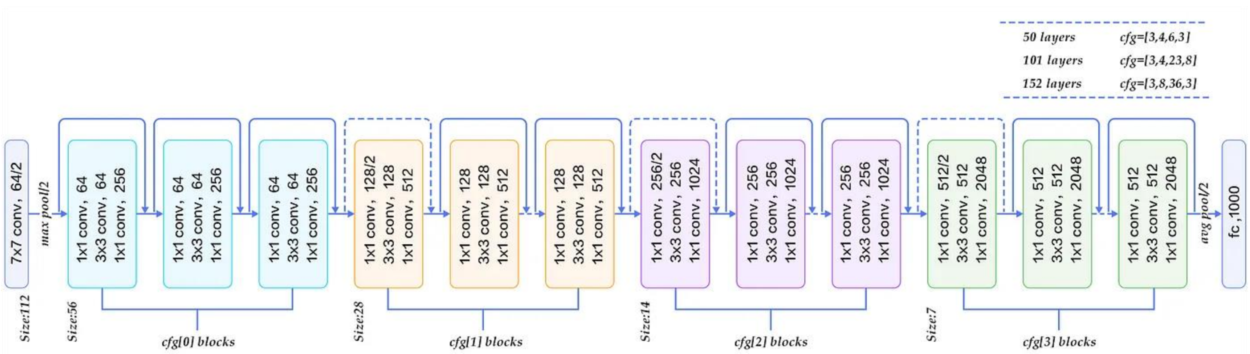


**Figure 3.** ResNet-50 Architecture[11]

### *Result Analysis*

This study will compare the Resnet50 and EfficientNet B0-B7 with the accuracy of it The author will record the result of training accuracy, validation accuracy, and test accuracy using EfficientNet and ResNet-50. After all results have been recorded comparing the result between EfficientNet and ResNet-50 the author will be made to be able to see the comparative value between the two algorithm models between EfficientNet and ResNet-50. By comparing between two algorithm models EfficientNet and ResNet-50 it can understand which model is better and more efficient in classifying skin cancer.

## IMPLEMENTATION AND RESULTS

Because the output from model like ResNet50 cannot have the output of exact number of classes, the author using additional layer so it can have the exact output that same to the number of classes. In this experiment, the author also compared additional models with different additional layers. For the first additional model, the author uses Flatten and Drop 0.2 as an additional layer. For the next additional model, the author uses Flatten and Drop 0.5 as an additional layer. After that the author uses GlobalAveragePooling2D and Drop 0.2 as an additional layer. Next one the author uses GlobalAveragePooling2D and Drop 0.5 as an additional layer. The author also uses GlobalAveragePooling2D, BatchNormalization and Drop 0.5 as an additional layer for the next additional model. Next, the author uses GlobalAveragePooling2D, BatchNormalization, Drop 0.5, Dense (256), and Drop 0.5 as an additional layer for the next additional model. And lastly, the author uses GlobalAveragePooling2D, BatchNormalization, Drop 0.5, Dense (512), and Drop 0.5 as an additional layer for the next additional model.

All the results that have been acquired are using almost the same parameter for each model. The only difference is only happening to EfficientNet B7 because when the author tries to train the model there are some issues. To fix the issue the author reduced the batch size from 32 to 16 only for the EfficientNet B7. The result from the first additional model the author uses Flatten and Drop 0.2 as an additional layer.

**Table 1.** Accuracy Table Flatten – Drop 0.2

| Model | Train | Validation | Test |
|---|---|---|---|
| ResNet50 | 94.56% | 78.56% | 80.72% |
| EfficientNet B0 | 98.73% | 86.43% | 84.12% |
| EfficientNet B1 | 98.36% | 85.73% | 86.41% |
| EfficientNet B2 | 99.04% | 87.92% | 87.01% |
| EfficientNet B3 | 97.64% | 85.53% | 84.62% |
| EfficientNet B4 | 98.98% | 84.93% | 85.01% |
| EfficientNet B5 | 98.03% | 85.93% | 84.52% |
| EfficientNet B6 | 99.45% | 85.93% | 85.51% |
| EfficientNet B7 | 98.94% | 85.93% | 86.91% |

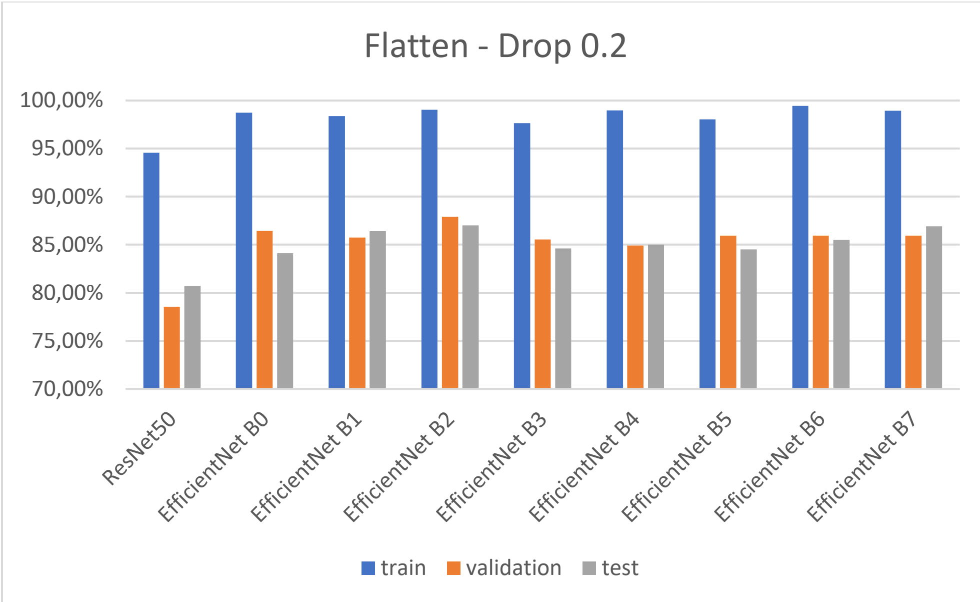


**Figure 4.** Graph Flatten – Drop 0.2

From the first additional model, which is Flatten – Drop 0.2 the Table 1 and Figure 4, it reveals that the training accuracy is a lot higher than the validation and test accuracy. The lowest validation and test accuracy acquired by ResNet50 achieved 94.56% on train accuracy, 78.56% on validation accuracy and 80.72% on test accuracy. The highest validation accuracy, and test accuracy acquired by EfficientNet B2 achieved 99.04% on train accuracy, 87.92% on validation accuracy, and 87.01% on test accuracy.

**Table 2.** Accuracy Table Flatten – Drop 0.5

| Model | Train | Validation | Test |
|---|---|---|---|
| ResNet50 | 97.54% | 82.24% | 80.54% |
| EfficientNet B0 | 98.90% | 86.03% | 84.62% |
| EfficientNet B1 | 98.69% | 85.93% | 85.21% |
| EfficientNet B2 | 98.83% | 85.73% | 86.71% |
| EfficientNet B3 | 99.13% | 87.33% | 86.31% |
| EfficientNet B4 | 98.68% | 86.33% | 87.01% |
| EfficientNet B5 | 98.75% | 83.33% | 84.72% |
| EfficientNet B6 | 99.06% | 84.13% | 84.92% |
| EfficientNet B7 | 99.08% | 86.33% | 86.11% |

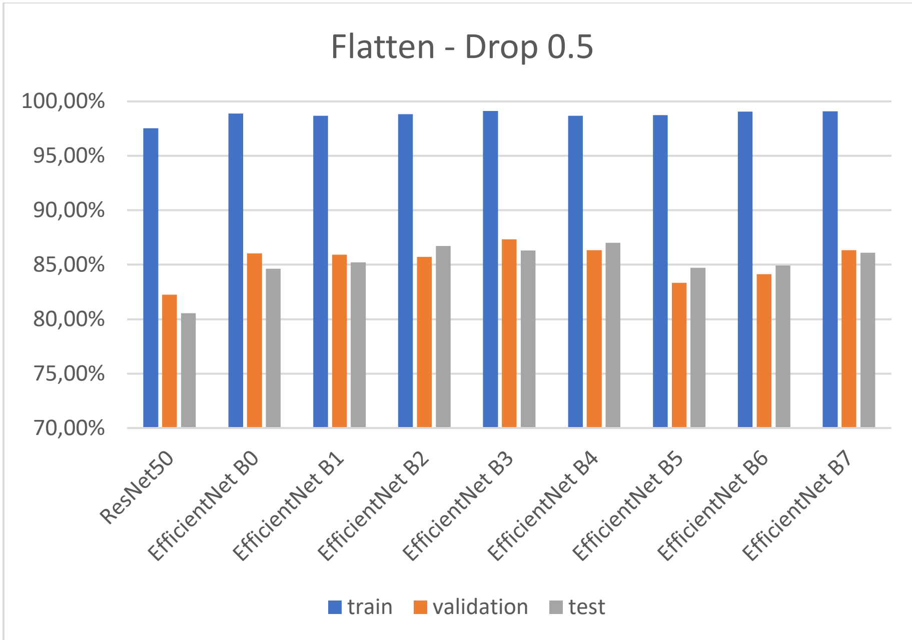


**Figure 5.** Graph Flatten – Drop 0.5

The second additional layers model is Flatten – Drop 0.5 on Table 2 and Figure 5 can be seen that training accuracy is way higher than validation accuracy and test accuracy. The lowest validation accuracy and test accuracy was achieved by ResNet 50 which got 97.54% on train accuracy, 82.24% on validation accuracy and 80.54% on test accuracy. The highest test accuracy was achieved by EfficientNet B4 which got 98.68% on train accuracy. 86.33% on validation accuracy, and 87.01% on test accuracy.

**Table 3.** Accuracy Table GlobalAveragePooling2D – Drop 0.2

| Model | Train | Validation | Test |
|---|---|---|---|
| ResNet50 | 97.90% | 82.44% | 79.52% |
| EfficientNet B0 | 98.34% | 86.73% | 85.51% |
| EfficientNet B1 | 98.60% | 85.63% | 85.91% |
| EfficientNet B2 | 98.61% | 88.02% | 87.91% |
| EfficientNet B3 | 99.13% | 88.52% | 86.41% |
| EfficientNet B4 | 99.20% | 86.93% | 85.51% |
| EfficientNet B5 | 98.88% | 83.33% | 85.51% |
| EfficientNet B6 | 99.20% | 85.43% | 88.21% |

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|---|---|---|---|
| EfficientNet B7 | 98.83% | 86.43% | 87.81% |

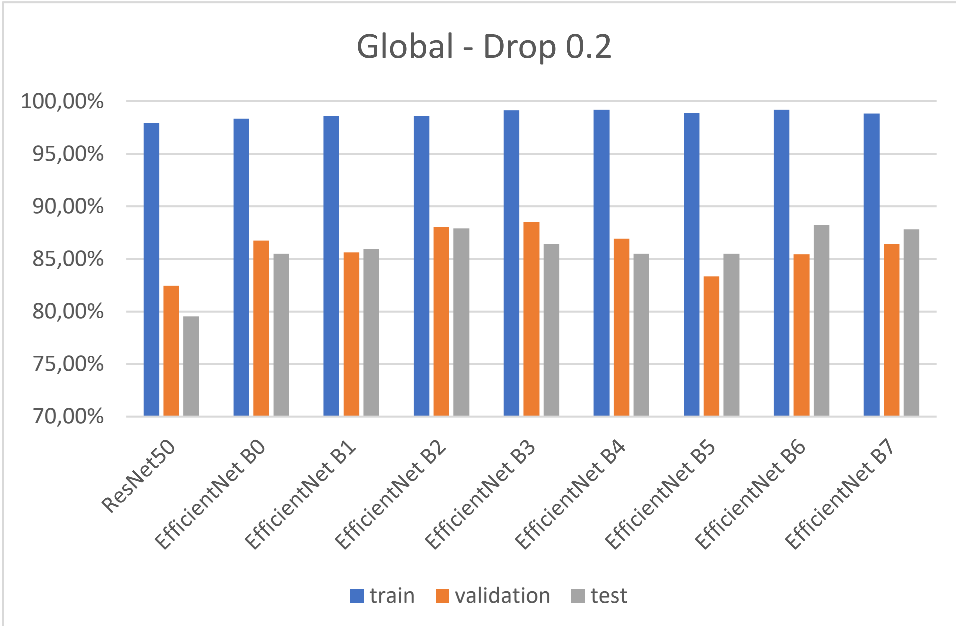


**Figure 6.** Graph GlobalAveragePooling2D – Drop 0.2

The next additional layers model is GlobalAveragePooling2D – Drop 0.2 on Table 3 and Figure 6 showing that training accuracy is way higher than validation accuracy and test accuracy. The lowest validation accuracy and test accuracy was achieved by ResNet50 which got 97.90% on train accuracy, 82.44% on validation accuracy, and 79.52% on test accuracy. The highest test accuracy was achieved by EfficientNet B6 which got 99.20% on train accuracy. 85.43% on validation accuracy, and 88.21% on test accuracy.

**Table 4.** Accuracy Table GlobalAveragePooling2D – Drop 0.5

| Model | Train | Validation | Test |
|---|---|---|---|
| ResNet50 | 90.66% | 83.33% | 81.52% |
| EfficientNet B0 | 98.19% | 86.43% | 84.42% |
| EfficientNet B1 | 98.65% | 87.43% | 87.81% |
| EfficientNet B2 | 96.83% | 86.73% | 87.91% |
| EfficientNet B3 | 98.90% | 85.43% | 86.91% |
| EfficientNet B4 | 99.38% | 87.33% | 87.01% |
| EfficientNet B5 | 98.86% | 86.03% | 84.32% |
| EfficientNet B6 | 99.14% | 85.33% | 84.72% |
| EfficientNet B7 | 98.90% | 86.13% | 85.21% |

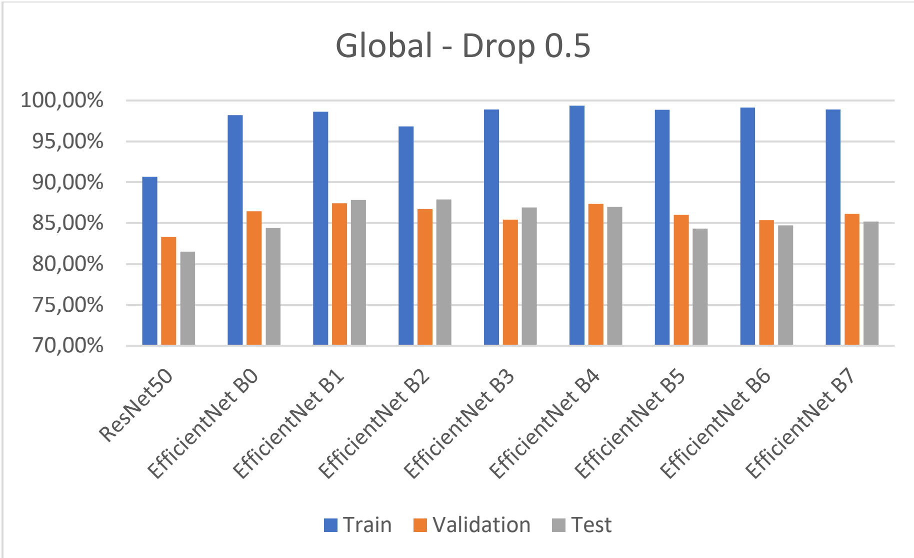


**Figure 7.** Graph GlobalAveragePooling2D – Drop 0.5

On Table 4 and Figure 7 with additional layer model GlobalAveragePooling2D – Drop 0.5 the highest validation accuracy acquired by EfficientNet B1 acquire 98.65% on train accuracy, 87.43% on validation accuracy, and 87.81% on test accuracy. However the highest test accuracy was acquired by EfficientNet B2 with 0.1% difference accuracy that acquired 96.83% on train accuracy, 86.73% on validation accuracy, and 87.91% on test accuracy. The worst validation accuracy and test accuracy was acquired by ResNet50 that have 90.66% on train accuracy, 83.33% on validation accuracy, and 81.52% on test accuracy.

**Table 5.** Accuracy Table GlobalAveragePooling2D – BatchNormalization – Drop 0.5

| Model | Train | Validation | Test |
|---|---|---|---|
| ResNet50 | 96.83% | 81.34% | 78.62% |
| EfficientNet B0 | 98.56% | 85.93% | 83.32% |
| EfficientNet B1 | 98.73% | 85.63% | 85.01% |
| EfficientNet B2 | 98.75% | 87.92% | 84.92% |
| EfficientNet B3 | 98.44% | 86.93% | 87.51% |
| EfficientNet B4 | 99.19% | 85.43% | 86.11% |
| EfficientNet B5 | 98.86% | 85.43% | 84.02% |
| EfficientNet B6 | 98.54% | 85.23% | 84.52% |
| EfficientNet B7 | 98.74% | 86.33% | 84.72% |

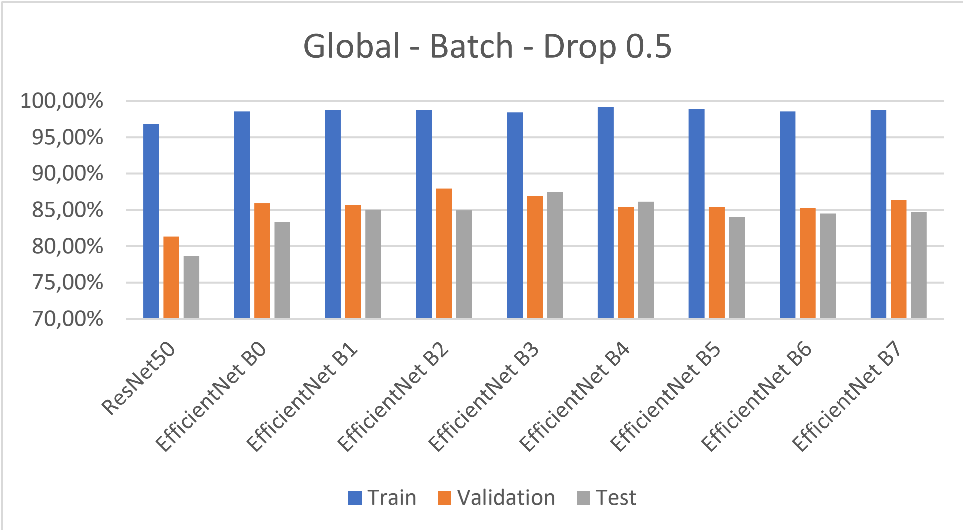


**Figure 8.** Graph GlobalAveragePooling2D – BatchNormalization – Drop 0.5

The fifth additional layers model is GlobalAveragePooling2D –- BatchNormalization - Drop 0.5 on Table 5 and Figure 8 can be seen that training accuracy is way higher than validation accuracy and test accuracy. The lowest validation accuracy and test accuracy was achieved by ResNet50 which got 96.83% on train accuracy, 81.34% on validation accuracy, and 78.62% on test accuracy. The highest validation accuracy acquired by EfficientNet B2 was 98.75% on train accuracy, 87.92% on validation accuracy, and 84.92% on test accuracy. But the highest test accuracy was acquired by EfficientNet B3 with a 2.59 % difference accuracy with EfficientNet B2 which acquired 98.44% in train accuracy, 86.93% in validation accuracy, and 87.51% in test accuracy.

**Table 6.** Accuracy Table Global – Batch – Drop 0.5 – Dense 256 – Drop 0.5

| Model | Train | Validation | Test |
|---|---|---|---|
| ResNet50 | 97.79% | 83.83% | 83.42% |
| EfficientNet B0 | 97.68% | 85.63% | 84.82% |
| EfficientNet B1 | 98.45% | 85.03% | 85.21% |
| EfficientNet B2 | 98.13% | 88.02% | 84.12% |
| EfficientNet B3 | 98.68% | 85.83% | 85.61% |
| EfficientNet B4 | 98.66% | 85.53% | 86.71% |
| EfficientNet B5 | 98.70% | 84.63% | 84.72% |

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|---|---|---|---|
| EfficientNet B6 | 98.79% | 84.03% | 85.81% |
| EfficientNet B7 | 97.14% | 86.23% | 88.41% |

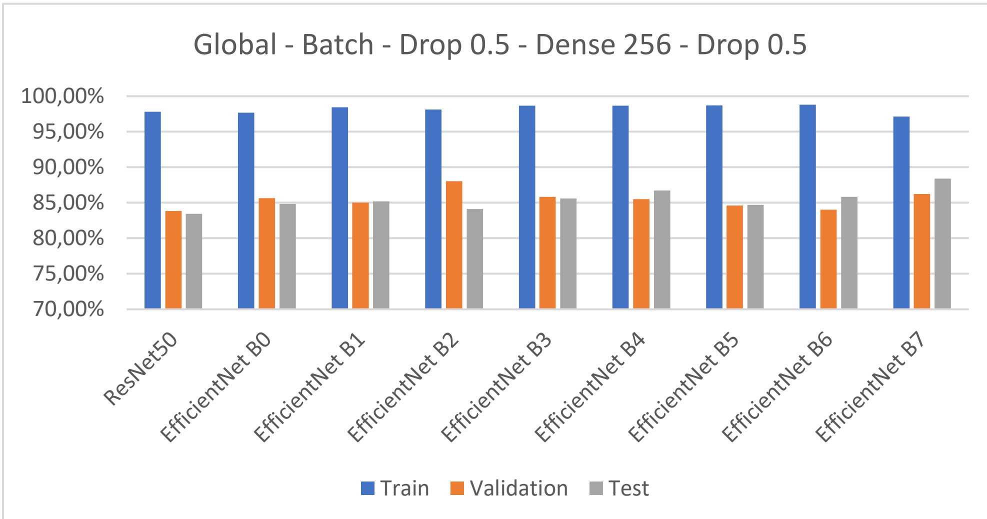


**Figure 9.** Graph Global – Batch – Drop 0.5 – Dense 256 – Drop 0.5

The next additional layers model is GlobalAveragePooling2D –- BatchNormalization - Drop 0.5 – Dense 256 – Drop 0.5 on the Table 6 and Figure 9 showing that training accuracy is way higher than validation accuracy and test accuracy. The lowest validation accuracy and test accuracy was achieved by ResNet50 which got 97.79% on train accuracy, 83.83% on validation accuracy, and 83.42% on test accuracy. The highest validation accuracy acquired by EfficientNet B2 was 98.13% on train accuracy, 88.02% on validation accuracy, and 84.12% on test accuracy. But the highest test accuracy was acquired by EfficientNet B7 with 4.29 % difference accuracy with EfficientNet B2 which acquired 97.14% on train accuracy, 86.23% on validation accuracy, and 88.41%on test accuracy.

**Table 7.** Accuracy Table Global – Batch – Drop 0.5 – Dense 512 – Drop 0.5

| Model | Train | Validation | Test |
|---|---|---|---|
| ResNet50 | 96.69% | 79.54% | 78.82% |
| EfficientNet B0 | 97.77% | 86.13% | 86.11% |
| EfficientNet B1 | 98.02% | 86.03% | 85.01% |
| EfficientNet B2 | 98.29% | 86.13% | 85.31% |
| EfficientNet B3 | 98.54% | 86.63% | 85.91% |

| | | | |
|---|---|---|---|
| EfficientNet B4 | 98.85% | 84.03% | 86.41% |
| EfficientNet B5 | 98.84% | 85.23% | 83.32% |
| EfficientNet B6 | 98.79% | 84.23% | 85.31% |
| EfficientNet B7 | 97.70% | 84.43% | 85.81% |

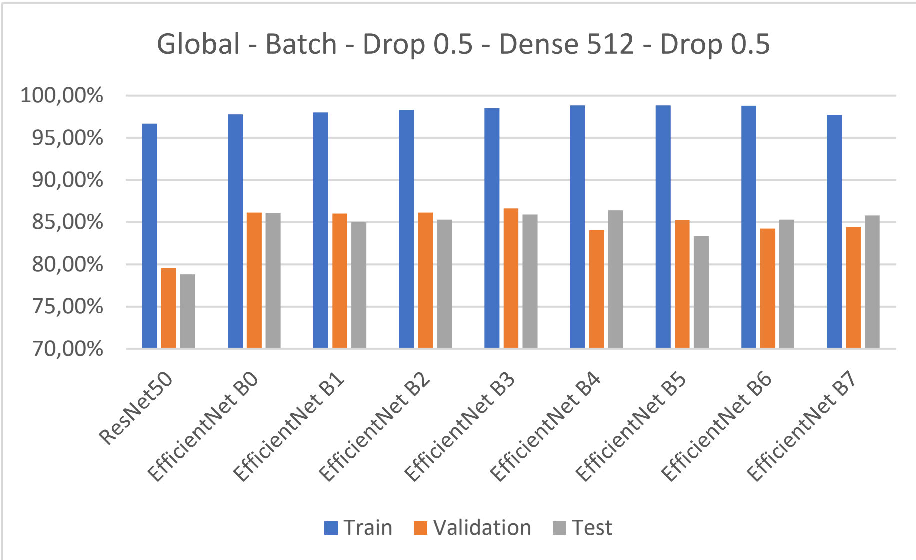


**Figure 10.** Graph Global – Batch – Drop 0.5 – Dense 512 – Drop 0.5

The last additional layers model is GlobalAveragePooling2D –- BatchNormalization - Drop 0.5 – Dense 512 – Drop 0.5 on the Table 7 and Figure 10 showing the highest validation accuracy acquired by EfficientNet B3 acquired 98.54% on train accuracy, 86.63% on validation accuracy, and 85.91% on test accuracy. But the highest test accuracy was acquired by EfficientNet B4 with a 0.5% difference accuracy with EfficientNet B3 which acquired 98.85% in train accuracy, 84.03% in validation accuracy, and 86.41% in test accuracy. The lowest validation accuracy and test accuracy was achieved by ResNet50 which got 96.69% on train accuracy, 79.54% on validation accuracy, and 78.82% on test accuracy.

From the accuracy obtained from before that has been acquired is showing that the training accuracy was so much higher than the validation accuracy and test accuracy. It also shows that the validation accuracy and test accuracy never surpass 90% accuracy. It might happen because the dataset that has a different amount of data for each class like the class melanocytic nevi has 6705 images of it but class dermatofibroma only has 115 images of it. What make it worse is because the number of that before splitting the data into 80% training, 10% validation, and 10% test.

**Table 8.** Best Test Accuracy

| **Model** | **Test** | **Additional Layer** |
|---|---|---|
| ResNet50 | 83.42% | Global - Batch - Drop 0.5 - Dense 256 - Drop 0.5 |
| EfficientNet B0 | 86.11% | Global - Batch - Drop 0.5 - Dense 512 - Drop 0.5 |

| | | |
|---|---|---|
| EfficientNet B1 | 87.81% | Global - Batch - Drop 0.5 |
| EfficientNet B2 | 87.91% | Global - Drop 0.2 |
| EfficientNet B3 | 87.51% | Global - Batch - Drop 0.5 |
| EfficientNet B4 | 87.01% | Global - Drop 0.5 |
| EfficientNet B5 | 85.51% | Global - Drop 0.2 |
| EfficientNet B6 | 88.21% | Global - Drop 0.2 |
| EfficientNet B7 | 88.41% | Global - Batch - Drop 0.5 - Dense 256 - Drop 0.5 |

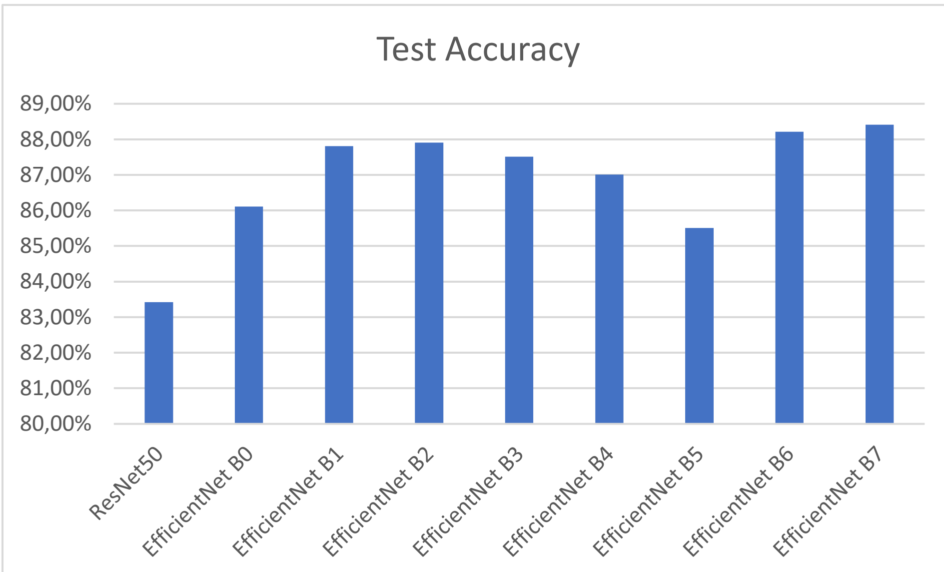


**Figure 11.** Graph Best Test Accuracy

These are the best results of the test accuracy. It shows that the lowest test accuracy is from ResNet50 with 83.42% accuracy and the highest accuracy obtained from EfficientNet B7 with 88.41% accuracy. it shows that the ResNet 50 is not very good at classifying skin cancer. It also shows that when using additional layers like Flatten - Drop 0.5 or Flatten – Drop 0.2 the accuracy obtained cannot be maximized.

## CONCLUSION

In this research, the author compares between ResNet50 and EfficientNet B0-B7 on the classification of skin cancer. From the result, it can be concluded that both ResNet and EfficientNet can be used to classify skin cancer. but on the test and validation EfficientNet Outperforms ResNet 50. When on the best additional layer model that this experiment does the EfficientNet got the highest score on test accuracy that was acquired by EfficientNet B7 on 88.41% accuracy. But when the ResNet50 on the best additional layer model, this experiment only acquired 83.42% accuracy. From that, the author can conclude that EfficientNet was better at the classification of skin cancer.

This research can be enhanced more by changing the dataset or adding the dataset because this dataset that used for the experiment is very unbalanced like the class melanocytic nevi have 6705 images of it but class dermatofibroma only has 115 images of it. Using other pre-trained algorithms can also be used to compare the accuracy of the EfficientNet like DenseNet and many others. It can be also compared between using pre-processing or not or using other pre-processing methods.

## DAFTAR PUSTAKA


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