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Comparative study of classification of eye disease types using DenseNet and EfficientNetB3

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Abstract

The purpose of this research is to build a classification model that can perform the eye disease identification process so that the diagnosis of eye disease can be known and medical action can be taken as early as possible. This research used a dataset which has a total of 4217 eye image data and had 4 main classes namely cataract, diabetic retinopathy, glaucoma, and normal. With the data distribution of 1038 cataract images, 1098 diabetic retinopathy images, 1007 glaucoma images, and 1074 normal images, which of this data will be divided with a data percentage scheme of 50:10:40, 60:10:30, and 70:10:20, to see the results of which dataset division can produce optimal accuracy. In this study, the classification process will use 2 CNN transfer learning architectures, namely DenseNet, and efficientnetb3, which are both trained using the ImagiNet dataset. The results obtained after completing the testing process on the model built using the DenseNet architecture get optimal accuracy when using data division as much as 60:10:30, which is 78.59% while using the efficientnetb3 architecture optimal accuracy results when using the data division of 70:10:20, which is 95.66%. In research on the classification that had previously been done, it is very rare to find a classification process for eye disease types, therefore, in this study, the classification process will be carried out and provide an overview of the eye disease classification process with the CNN transfer learning method with more optimal accuracy results.

1. Introduction

The eye is an important sense in the human body that allows us to be able to carry out daily activities smoothly [1]. Therefore, we should always be able to maintain the health of our eyes by consuming foods or drinks that contain vitamin A, such as carrots [2]. Eye disease is one type of disease that is dangerous and becomes one of the frightening diseases because it threatens the human visual sense [3], [4]. Types of eye diseases that can occur in humans include cataracts, diabetic retinopathy, and glaucoma. Cataract is a type of eye disease that can trigger blindness and can affect parents with a prevalence of 40 years and over reached approximately 11.8% to 18.8% [5]. Diabetic retinopathy is a type of eye disease caused by high blood sugar content that can damage blood vessels in the retina of the eye [6]. Meanwhile, Glaucoma is a condition where there is a loss of retinal ganglion cells and thinning of the retinal nerve fiber layer, which can also cause loss of vision [7]. Therefore, we must be able to always maintain the health of our eyes with a good lifestyle, so that they can stay healthy and can move well [8].

Machine learning is an integral component of artificial intelligence (AI) [9]. In the context of machine learning, a model is built based on a collection of sample data commonly referred to as training data [10]. The model was able to read patterns from the data and automatically make predictions based on previously learned information. Classification is a method used to predict or identify data classes by comparing input data with values obtained from the model training process [11], the model can distinguish data based on its class. Deep learning, is part of the concept of machine learning, which involves artificial neural networks that function similarly to the human brain [12]. Convolutional Neural Network (CNN) is a deep learning technique that can be effectively applied in predicting data [13]. The application of CNN techniques was chosen due to its ability to automatically extract information [14]. Therefore, models that utilize CNN techniques are capable of handling real-time data classification [15].

In this research, the classification process of eye disease types will be carried out using the CNN Transfer Learning method. The purpose of this research is to carry out the process of building a classification model and comparing the best model that can be used to classify eye disease types so that it can help in the diagnosis process and can be used to take preventive action as early as possible. The purpose of using CNN in this study is because CNN has excellent performance in performing the image classification process [16]. Meanwhile, the purpose of using the transfer learning process compared to the usual CNN method is that the transfer learning model can perform the classification process well because it can perform the training process faster when compared to building a model from scratch and can be optimal if used to build models with small datasets [17]. In this research, two transfer learning models will be used, namely DenseNet and Efficient Net. The purpose of using DenseNet is because this model has a strong interrelationship between layers so that all layers can be well connected [18]. Meanwhile, the purpose of using Efficient Net is because this architecture conducts training with relatively few parameters compared to other architectures, but still has good classification performance [19]. In this study, the data division process will also be carried out in 3 variations, namely 50:10:40 (50% training, 10% validation, and 40% testing), 60:10:30 (60% training, 10% validation, and 30% testing), and 70:10:20 (70% training, 10% validation and 20% testing). The purpose of this data division is to determine the method and data division scheme, so the testing accuracy can be optimized.

In 2021, a study by K. Thaiyalnayak [20] discusses diabetes management methods using a combination of MLP deep learning methods and conventional machine learning, namely SVM. The purpose of this research is to combine deep learning approaches, namely MultiLayer Perceptron (MLP) and Support Vector Machine (SVM) to complete the diabetes classification system. The results obtained after this research was conducted found that the classification system using MLP SVM achieved a test accuracy of 77.474%. Previous research conducted by Qadamboyevich et al. [21] in 2023 discussed the process of automatic classification of eye diseases using the CNN transfer learning method, namely MobileNet, and EfficientNetB0. The purpose of this research is to build a model and make comparisons on the classification process of eye disease types. The results obtained in this study after the testing process was carried out showed that the classification process using EfficienNetB0 getting a testing accuracy of 94.00% and classification with the MobileNet model getting an accuracy of 73.00%.

2. Research Method

In this research, the classification process will use the Convolutional Neural Network (CNN) transfer learning method. CNN is a deep learning method that can automatically perform the learning process and pattern recognition from data [22], [23]. The CNN process uses layers, where the layers are connected so that they can perform recognition, feature extraction, and the classification process of the data. Layers that usually exist in CNN are the input layer, hidden layer, and output layer [24]. The hidden layer is usually divided into several layers, namely the convolution layer or layer that is used to perform the feature extraction process from the data [25], the pooling layer that is used to perform the dimensional reduction process so that the next training process is not too heavy [26] and fully connected layer that is used to perform the classification process based on data or information from the previous layer [27]. The calculation formulas for convolution, pooling, and fully connected layers are given in Equation 1, where Z is the input texture, P is the kernel used, o and q are the coordinate points of the results of Z and P, N and M are height and width, and x and y are matrix iteration variables. Where i and j denote the results of the max pooling process, Z is the input variable, and N and M are the dimensions of the pooling process as in Equation 2. Where N is the number of neurons of the previous layer, W(x,y) is the weight connected from the previous layer to the current layer, Actv(o) is the activation function of the previous layer and B(q) is the bias of the current layer as in Equation 3.

$$(\mathrm{Z} * \mathrm{P})(o,q) = \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} Z(o+i, q+j) * P(i,j) \tag{1}$$

$$(Pool_{max})(o,q) = max_{i=0}^{N-1} max_{j=0}^{M-1} Z(o+i, q+j) \tag{2}$$

$$X_q = \sum_{o=1}^{N} \left(W_{o,q} * Actv_o\right) + B_q \tag{3}$$

In this research, the CNN method that will be used is transfer learning, or a process where using a model that has previously been trained to perform new tasks optimally by being able to use a small number of datasets [28]–[31]. Thus, by using the CNN transfer learning method, it can perform the classification process optimally even with a limited dataset [17]. Transfer learning used in this research is the DenseNet architecture and also Efficient Net. The reason for using the DenseNet architecture is that it performs the process with a strong connection between layers in a neural network, by combining the output of each layer to the next layer, optimizing parameter usage, improving feature representation learning, and overcoming the problem of missing gradients in training neural network models [18]. Meanwhile, the reason for using the Efficient Net architecture is that it can achieve a high level of accuracy with a smaller number of parameters than other architectures, making it efficient in the use of computational resources. With a careful scaling approach to depth, width, and resolution, EfficientNet provides an optimal balance between model performance and computational efficiency [19]. In this research, we used a dataset which is obtained and downloaded from the kaggle.com website. The dataset used is an eye disease image dataset which has a total of 4217 image data and has 4 classes, namely cataract, diabetic retinopathy, glaucoma, and normal. With data distribution in each class, namely 1038 cataract images, 1098 diabetic retinopathy images, 1007 glaucoma images, and 1074 normal images. The visualization of the dataset used is given in Figure 1.

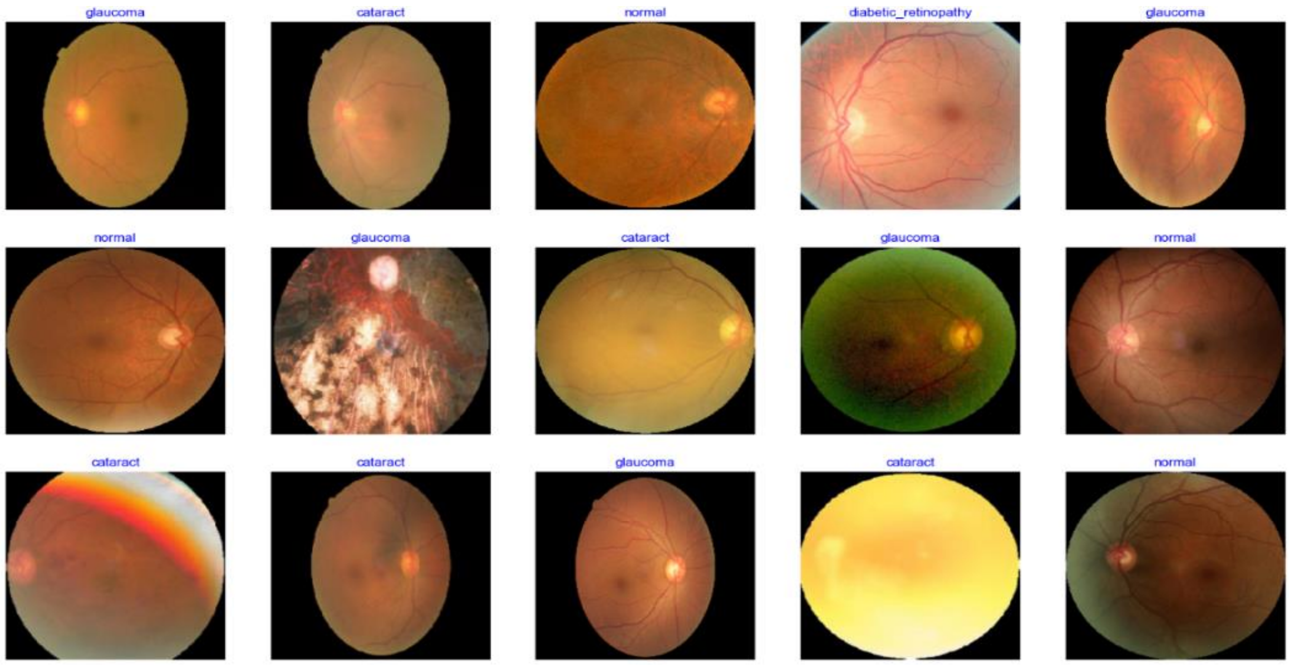


Figure 1. Dataset Visualization

Figure 1 shows the visualization of the dataset used. Of the total 4217 data, in this study, we will divide it into 3 variations with the first division being 50% training data, 10% validation data, and 40% testing data, the second division being 60% training data, 10% validation data and 30% testing data, and the third division being 70% training data, 10% validation data and 20% testing data. The purpose of dividing the data into 3 variations is so that later comparisons can be made and see which division scheme is more effective to get optimal accuracy. Validation data in this study is used to ensure that the model built does not experience overfitting and can run well. The flow of the classification process in this research is given in Figure 2. Figure 2 shows the classification process carried out in this study. It can be seen in Figure 2 that the first thing done in this research is to read the image data that will be used for the training, validation, and model testing processes.

Furthermore, after the image data is read, a data augmentation process will be carried out, which is a process to change the shape, position, and pixel intensity therefore as to produce an augmented image [32]. The purpose of this process is to help so that the model built does not experience overfitting. The data augmentation process that will be carried out is a rotation by 40, length expansion by 0.25, width expansion by 0.2, shear by 0.2, and zoom by 0.1. After the data augmentation process is carried out, the next step is to split the data. In this study, the data division will be divided into 3 schemes, namely 50:10:40 (50% training, 10% validation, and 40% testing), 60:10:30 (60% training, 10% validation, and 30% testing) and 70:10:20 (70% training, 10% validation and 20% testing). The purpose of doing the data division process with these 3 schemes is to determine which data division process performed best for the model to get maximum accuracy.

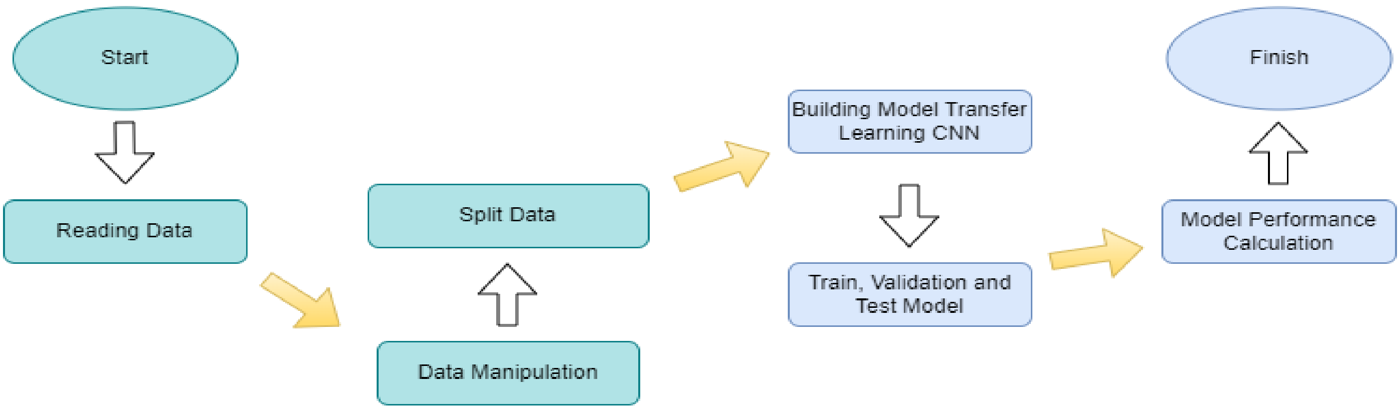


Figure 2. Classification Process

Furthermore, after the data division process is carried out as presented in Figure 2, the model and layer development process of the transfer learning model used will be carried out. The transfer learning code used and the layers used in this research are given below.

```
pretrained_model = load("DenseNet")
# pretrained_model = load("EfficientNetB3")
for layer in pretrained_model.layers:
   layer.trainable = False
# Create a new layer for the classification task
model = layer shown in table 1
model.compile(optimizer="adam",loss="categorical_crossentropy",
metrics=["accuracy"])
```

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 densenet121 (Functional)    (None, 7, 7, 1024)        7037504

 global_average_pooling2d (  (None, 1024)              0
 GlobalAveragePooling2D)

 flatten (Flatten)           (None, 1024)              0

 dense (Dense)               (None, 256)               262400

 dense_1 (Dense)             (None, 512)               131584

 dense_2 (Dense)             (None, 512)               262656

 dense_3 (Dense)             (None, 4)                 2052

=================================================================
Total params: 7696196 (29.36 MB)
Trainable params: 658692 (2.51 MB)
Non-trainable params: 7037504 (26.85 MB)
```

(a) Layer for DenseNet

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb3 (Functional  (None, 1536)              10783535
 )

 batch_normalization (Batch  (None, 1536)              6144
 Normalization)

 dense (Dense)               (None, 256)               393472

 dropout (Dropout)           (None, 256)               0

 dense_1 (Dense)             (None, 4)                 1028

=================================================================
Total params: 11184179 (42.66 MB)
Trainable params: 11093804 (42.32 MB)
Non-trainable params: 90375 (353.03 KB)
```

(b) Layer for EfficientNetB3

Figure 3. Layer for Transfer Learning Model

After the process of building a classification model, it will then carry out the process of training, validating, and testing the model that has been built using a variety of data schemes that were previously determined as presented in Figure 3. Then, after the process of training, validating, and testing the model, it can carry out the process of calculating the performance of the model with the confusion matrix by using the precision value (model accuracy), recall (the ability of the model to guess correctly in each class) and F1-Score (harmonic value/balance of precision and recall). The purpose of calculating the value of the confusion matrix is to determine the performance of the classification results of the model built based on the previously determined research scheme using Equation 4, Equation 5, and Equation 6.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{4}$$

$$\mathrm{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{5}$$

$$\mathrm{F1-Score} = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{6}$$

3. Results and Discussion

After the dataset that has been read is processed, the next step is to carry out the model training and validation process. In this study, the process of training and validating the model will use an epoch value of 30 using the Adam optimizer and calculate the loss value using categorical cross-entropy. Table 1 shows the results of the training and validation process on models using the DenseNet and EfficientNetB3 architectures. It can be seen in Table 1, there was overfitting in DenseNet model because, for the graph of training and validation results of the model, there were data gaps that occurred during the training and validation process of the model. Meanwhile, for the classification process using Efficient Net B3, there was less overfitting because when the training and validation process was carried out, the curves did not show any discrepancy.

In EfficientNetB3 architecture, when using the split data method of 70% training, 10% validation, and 20% testing, the best validation result is 93.847%. Meanwhile, in DenseNet architecture, when using the data division scheme of 50% training, 10% validation and 40% testing, the best validation result is 77.08%. These scores show that the EfficientNet and DenseNet architectures built are good enough to perform the pattern recognition process on new data other than training data. After the training and validation process of the model, a testing process will be carried out on the classification model that has been trained and validated. The results of the model testing process that has been carried out are given in Table 2.

Table 1. Training Result

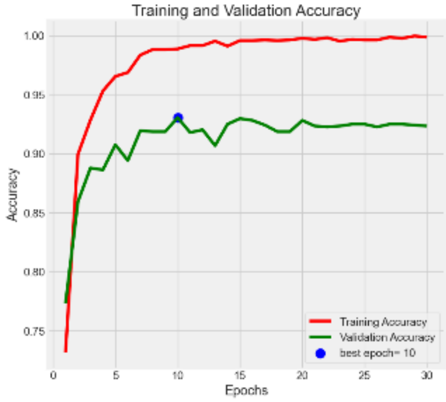
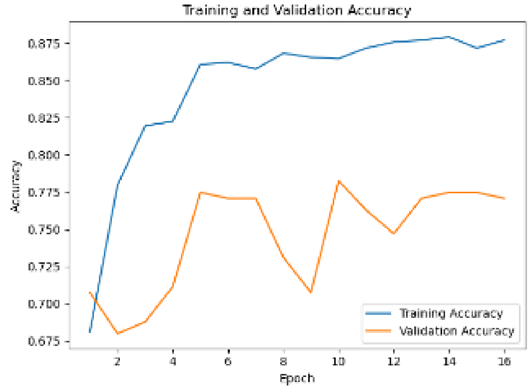
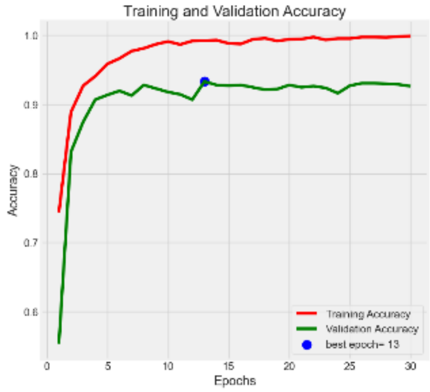
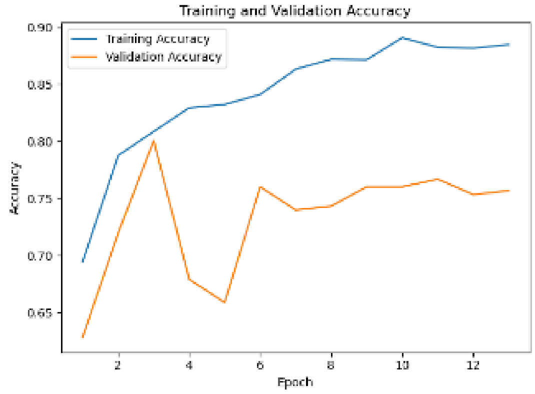
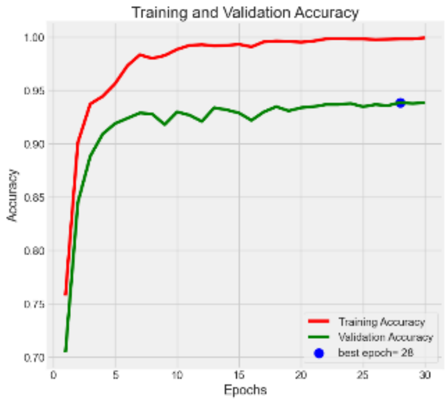
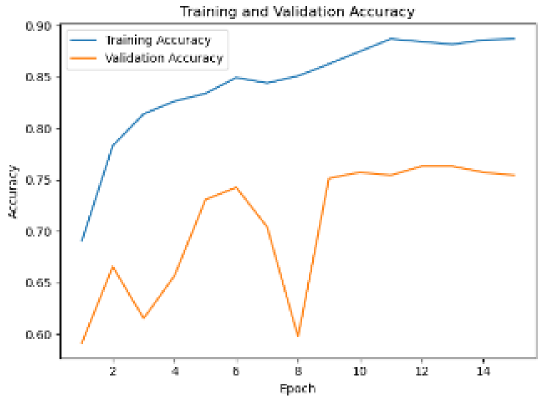
<table>
<tr><th>Split data (training : validation: testing)</th><th>EfficientNetB3</th><th>DenseNet</th></tr>
<tr><td>Accuracy Data 50:10:40</td><td>
</td><td>
</td></tr>
<tr><td>Accuracy Data 60:10:30</td><td>
</td><td>
</td></tr>
<tr><td>Accuracy Data 70:10:20</td><td>
</td><td>
</td></tr>
</table>

Table 2. Classification Report Result

Data Split	EfficientNetB3				DenseNet			
	precision	recall	f1-score	support	precision	recall	f1-score	support
50:10:40	93.00%	93.00%	93.00%	844	78.00%	74.00%	73.00%	844
60:10:30	94.00%	94.00%	94.00%	507	81.00%	79.00%	78.00%	507
70:10:20	96.00%	96.00%	96.00%	254	82.00%	79.00%	78.00%	254

Table 1 shows the results of the classification process of EfficientNetB3 and DenseNet models that have been trained and validated previously. Based on Table 1, it has been seen that the precision, recall, and f1-score performance results generated from the EfficientNet model have better performance when compared to the DenseNet model. It can be seen from the table, that the average performance value resulting from the confusion matrix of EfficientNet is more than or equal to 94.33%, while for the average performance of the DenseNet model, the results are more than or equal to 77.99%. With a data difference of 16.34%, it can be seen that the EfficientNet model perform the prediction and classification process more accurately compared to the DenseNet model.

The best precision, recall, and f1-score performance results on the EfficientNet architecture were obtained when the classification process was carried out with a data-sharing scheme of 70% training, 10% validation, and 20% testing, which amounted to 96.00%, recall of 96.00% and f1-score of 96.00%. Meanwhile, the best precision, recall, and f1-score performance results on EfficientNet architecture are obtained when using a data sharing scheme of 70% training, 10% validation, and 20% testing, namely with a precision value of 82.00%, recall of 79.00% and f1-score of 78.00%. From these values, it can be seen that the DenseNet model has good prediction accuracy, has good performance for guessing existing classes, and has a good balance value between recall and precision. Meanwhile, the support value for each model is the same because the support value is the value of the data used for the model testing process. The comparison of the accuracy results of the test model is given in Table 3.

Table 3 shows the accuracy of the classification process results after the testing process. It can be seen in Table 3 that the classification results using EfficientNetB3 get maximum accuracy when the classification process is carried out with a data division scheme of 70% training, 10% validation, and 30% testing, namely 95.66%. Meanwhile, for the DenseNet architecture, it obtains the most optimal testing accuracy when using a data sharing scheme of 60% training, 10% validation, and 30% testing is 78.59%. In this study, the testing process did not get the maximum accuracy of 100% because this study used mixed data in the form of real data and data on eye disease images, so the datasets used may have data that was similar to each other in different classes. Therefore, it can affect the accuracy obtained.

Table 3. Accuracy Performance from Model

Split Data	EfficientNetB3	DenseNet
50:10:90	93.24%	73.32%
60:10:30	94.28%	78.59%
70:10:20	95.66%	78.43%

An eye disease classification was processed by Prasher et, al [21] in 2023 using the CNN transfer learning method, namely MobileNet, and EfficientNetB0. The results obtained in this study after the testing process was carried out shows that the classification process using EfficienNetB0 had a testing accuracy of 94.00% and classification with the MobileNet model had an accuracy of 73%. Between this research and the present research, there are differences in terms of the architecture used. This study uses DenseNet architecture, while previous study used MobileNet architecture. Both of this study and the previous study used the same EfficientNet architecture, but this study used the EfficientNetB3 architecture, while the previous study used the EfficientNetB0 architecture. The comparison results is given in Table 4.

Table 4. Comparison with Previous Research

Previous research by	Model	Result
[21]	MobileNet and EfficientNetB0	MobileNet accuracy: 73.00% EfficientNetB0 accuracy: 93.00%
Our proposed	DenseNet and EfficientNetB3	DenseNet accuracy: 78.59% EfficientNetB3 accuracy: 95.66%

Table 4 shows a comparison of the test results between the previous research and the current research. It can be seen in Table 4 that the model built in this study has better accuracy when compared to the previous study. Therefore, it can be said that this research succeeds in being able to improve accuracy in the eye disease classification process and build models that can have more accurate performance

4. Conclusion

After the process of training, validation, and testing the DenseNet and EfficientNetB3 models in this study, the best classification results of DenseNet obtained when using the split data method of 60% training, 10% validation, and 30% testing were 78.59%. The best classification results of the EfficientNetB3 model get the best test results with a data split scheme of 70% training, 10% validation, and 20% testing, which is 95.66%. From these results, it can be concluded that the EfficientNetB3 model is the best model that can perform the eye disease classification process when compared to the DenseNet architecture or in previous tests. For further research, it is expected to be able to carry out the classification process with other architectures and also add a hyperparameter tuning process so that the model built can have optimal parameters. Future research is also expected to be able to improve the accuracy of the classification process carried out.

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