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# MRI Image Based Alzheimer's Disease Classification Using Convolutional Neural Network: EfficientNet Architecture

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***Abstract***

*Alzheimer's disease is a neurodegenerative disorder or a condition characterized by the degeneration and damage of the nervous system. This leads to a decline in cognitive abilities such as memory, thinking, and focus, which can impact daily activities. In the medical field, a technology called Magnetic Resonance Imaging (MRI) can be used for the initial diagnosis of Alzheimer's disease through image procedures-based recognition methods. The development of this detection system aims to assist medical professionals, including doctors and radiologists, in diagnosing, treating, and monitoring patients with Alzheimer's disease. This study also aims to classify different types of Alzheimer's disease into four distinct classes utilizing the Convolutional Neural Network method with the EfficientNet-B0 and EfficientNet-B3 architectures. This study utilized 6400 images that encompass four classes, namely Mild Demented, Moderate Demented, Non Demented, and Very Mild Demented. After conducting testing for both scenarios, the Exactness outcomes for scenario 1 utilizing EfficientNet-B0 reveryed 96.00%, and for scenario 2 utilizing EfficientNet-B3, the Exactness was 97.00%.*

*Keywords: alzheimer's disease; convolutional neural network; efficientnet-B0; efficientnet-B3*

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## 1. Introduction

Alzheimer's disease is a neurodegenerative disease or a condition characterized by progressive degeneration and damage to the nervous system over time [1]. This leads to a decline in cognitive function, which includes a reduction in memory, thinking ability, focus on tasks, and can impact daily activities [2]. The risk of this disease increases significantly after age 65 [3]. The triggers for this disease are attributed to the accumulation of *beta-amyloid* proteins in brain tissues, forming plaques that can damage nerve cells [4]. According to the *World Health Organization* (WHO), by the year 2050, the global population suffering from Alzheimer's disease is projected to get higher to approximately 150 million [5], with 1 in every 85 individuals affected by Alzheimer's disease. This disease ranks as the second most severe neurological disorder worldwide[6]. Diagnosing Alzheimer's disease can be quite challenging due to the gradual onset of its symptoms. Alzheimer's disease also lacks a cure or effective treatment, making initial diagnosis crucial to slow down its progression [7].

With the advancement of information technology and computers, it has become possible to identify diseases easily. Image categorization plays a crucial role in modern medical diagnosis. The utilization of large amounts of information through image data is essential for obtaining an accurate depiction of a patient's condition [8]. MRI-based images can be utilized for the initial diagnosis of Alzheimer's disease utilizing Machine Learning algorithms. One of the approaches involves image procedures and pattern recognition-based methods. This method allows for the analysis of patient brain images to identify characteristic patterns of Alzheimer's disease [9]. The development of detection systems in medical images aims to assist medical professionals, including doctors and radiologists, in diagnosing, treating, and monitoring Alzheimer's patients [10].

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The field of *Artificial Intelligence* has experienced significant growth from year to year, leading to the emergence of a new branch of knowledge known as deep learning [11]. *Convolutional Neural Network* (CNN) is one of the deep learning algorithms that play a role in image classification [12]. This method is widely used for solving highly complex problems [13]. CNNs are specifically designed to transform data into two dimensions (2D). The CNN structure consists of input layers, convolutional layers, pooling layers, fully connected layers, and output layers [14]. Currently, CNNs are reflected to have demonstrated their superiority compared to several other *Machine Learning* methods. However, one of the challenges in utilizing CNNs is the large number of parameters and high computational requirements, particularly in complex models. *EfficientNet*, which is part of the CNN architecture, is designed to address the challenges that serve as limitations in CNN models. This architecture places a strong emphasis on efficiency in terms of both time and computational capabilities. *EfficientNet* has demonstrated the ability to achieve higher Exactness with fewer parameters and faster procedures [15]. Currently, the *EfficientNet* architecture encompasses 8 models ranging from *EfficientNet-B0* to *EfficientNet-B7* [16]. These models have larger parameters and share the same layer structure, differing only in the number of layers [17]. *EfficientNet-B0* serves as the foundational model within the *EfficientNet* architecture for image procedures. It possesses relatively fewer parameters compared to other models while delivering comparable performance. This architecture was developed by studies in 2019 [18]. The *EfficientNet-B0* architecture has proven to outperform several other well-known CNN architectures in terms of Exactness and speed. Additionally, this model is more resource-efficient and requires less training time due to its fewer parameters compared to other models [19]. On the other hand, the *EfficientNet-B3* model was developed as an extension of the *EfficientNet-B0*, differing only in the number of layers with greater depth, width, and resolution, which can contribute to higher performance while maintaining computational efficiency [17].

The previous study [20] focused on Alzheimer's disease categorization utilizing 6400 MRI image data provided into four label classes: Mild Demented, Moderate Demented, Non-Demented, and Very Mild Demented. The study conducted data preprocessing, including image data rescaling and dataset splitting into training, testing, and validation sets. They also performed modifications on the Alzheimer's disease MRI images. Subsequently, models were trained to utilize the modified data, and outcomes in model evaluation based on evaluation metrics. Thus, implementing the Convolutional Neural Network model resulted in an Exactness of 75.01%. Additionally, the VGG16 and VGG19 architectures were also implemented, achieving accuracies of 80.10% for VGG16 and 80.28% for VGG19. The exact outcomes fulfilled from various image categorization models are quite good. The difference in Exactness between the VGG16 and VGG19 models is relatively small. This could be attributed to the larger VGG19 model tending to overfit the training data. Despite VGG19 having a deeper architecture compared to VGG16, it does not always guarantee a significantly higher end in Exactness.

In a subsequent study [21], a Convolutional Neural Network was also implemented for Alzheimer's disease categorization utilizing MRI images with a dataset of 6400 samples, provided into 5121 training data and 1279 test data. The Convolutional Neural Network architecture utilized in the study was InceptionV3, which achieved an Exactness of 89.00%. This exact outcome indicates that the model performed quite well and was capable of recognizing patterns within the data. These outcomes were fulfilled by reflecting various factors such as the dataset, preprocedureing, and hyperparameter tuning, all of which significantly influence the model's Exactness.

In another study [22], the categorization of Alzheimer's disease, consisting of four label classes: Mild Dementia, Moderate Dementia, Non-Dementia, and Very Mild Dementia, was conducted. The dataset comprised a total of 6400 samples, which were provided into training and test data with an 80:20 ratio, where 4079 were allocated for training data and 1024 for test data. The categorization outcomes utilizing the Convolutional Neural Network (CNN) method were then compared with other Machine Learning methods. The Exactness outcomes for the CNN method were 86.00%, the Decision Tree Classifier achieved 79.00%, the Random Forest Classifier fulfilled 84.00%, and the Support Vector Machine achieved 80.00%.

Moreover, in the study [23] Alzheimer's categorization was conducted, implementing the SqueezeNet model as a pre-trained model to extract image Equivalent attributes, which were then classified utilizing Artificial Neural Network (ANN) and Random Forest. The categorization performance indicates an Exactness of 90.00% for ANN and 65.60% for Random Forest. The SqueezeNet model with ANN achieves a high Exactness of 90.00%. This Exactness figure reflects the model's capability to effectively capture important Equivalent attributes in the data and detect complex patterns. On the other hand, the SqueezeNet model with Random Forest achieves an Exactness of 65.60%, indicating a reasonable level of Exactness. These outcomes suggest that while Random Forest can provide accurate predictions, it still lacks the ability, compared to ANN, to capture complex Equivalent attributes in addressing certain aspects.

Furthermore, the study [24] also conducted Alzheimer's categorization, achieving categorization outcomes with validation data Exactness of 80.61%, precision of 78.99%, recall of 30.55%, and an area under the curve (AUC) of 86.05%. It was found that the model achieved an Exactness of 80.67%, indicating the model's ability to correctly classify the entire sample set. Additionally, the model achieved a precision of 78.99%, Calculating the ratio of accurately predicted positive outcomes to the total number of positive predictions. Recall was relatively low, indicating the model's difficulty in identifying all true positive instances. However, the high AUC suggests that the model has a strong capability to differentiate between different classes. Therefore, it is essential to reflect balancing precision and recall when evaluating the model's performance to ensure it aligns with the desired context.

In previous research using MRI and deep learning technology for Alzheimer's detection, there has been some progress in the early identification of this disease. However, some limitations still exist in the existing literature. One of them is the large number of convolution layers and the number of parameters that cause a high computational burden, thus allowing overfitting during model training. Therefore, this study aims to overcome some of these limitations as EfficientNet is carefully designed to have good accuracy by considering lower parameter requirements and computational efficiency. This was done to obtain more effective classification result performance. The EfficientNet architecture succeeds in creating a model that can work faster because it focuses not only on accuracy but also on processing efficiency [25].

## 2. Research Methods

Figure 1 illustrates the methodology utilized in this study, which consists of several stages: dataset collection, dataset splitting, data augmentation, model training, and model evaluation.

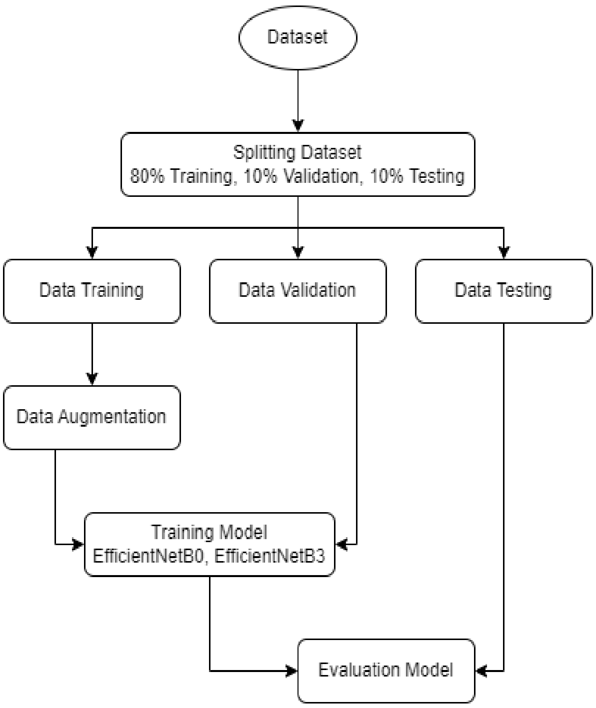


Figure 1. Study Methodology Flow

Subsequently, the data augmentation procedure is applied to the training data to generate variations of training data with slightly different versions from the original. After completing the data augmentation procedure, the model is created and trained utilizing the training and validation data. The final step involves evaluating the model utilizing the test data. In this evaluation procedure, the model will compare every sample in the test data with the actual class labels and make predictions for their categorization outcomes.

### 2.1 Dataset

The dataset for this study was derived from the Kaggle website under the title "Augmented Alzheimer MRI Dataset." The dataset used is the original dataset, consisting of 6400 data samples, every sized at 128x128 pixels. The dataset utilized in this study is divided into four classes: Mild Demented, Moderate Demented, Non Demented, and Very Mild Demented. The distribution of data for every class can be shown in Table 1.

Table 1. Number of Data per Class

| Class | Total |
|---|---|
| Mild | 896 |
| Moderate | 64 |
| Non | 3200 |
| Very Mild | 2240 |

There are a total of 6400 data points, which are further categorized into three subsets: training data comprising 80.00% of the dataset, validation data consisting of 10.00% of the dataset, and test data also accounting for 10.00% of the dataset. This division outcomes in 5120 training data points, 640 validation data points, and 640 test data points. In Figure 2, there are sample images from every class.

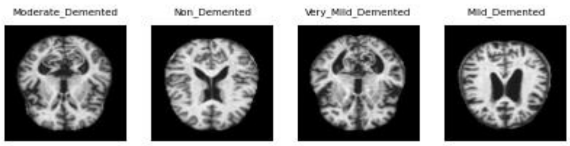


Figure 2. Images for Every Class

### 2.2 Data Augmentation

Data augmentation is utilized to get higher or enrich the variety of training data by generating slightly different versions of the original images. The purpose of applying this procedure is to decrease overfitting and enhance the categorization capability of the constructed model. The data augmentation procedure utilized in this study includes RandomRotation = -0.15, 0.15 to randomly rotate images within an angle range of -0.15 to 0.15, and RandomZoom = -0.3, -0.1 to randomly zoom in and out of images within a zoom range of -0.3 to -0.1.

Table 2. Data Augmentation

| Augmentation | Settings |
|---|---|
| Rotation | 0.15, 0.15 |
| Zoom | -0.3, -0.1 |

Detailed information about the data augmentation used can be found in Table 2, and examples of images that have undergone the data augmentation procedure can be shown in Figure 3.

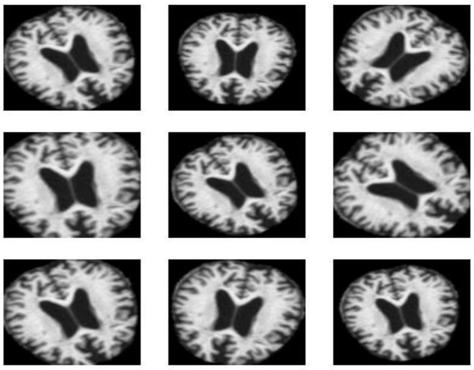

Figure 3. Image after Data Augmentation Procedure

## 2.3 EfficientNet Model Architecture

EfficientNet, as part of the Convolutional Neural Network (CNN) structure, was created to overcome the limitations that often arise in CNN models.

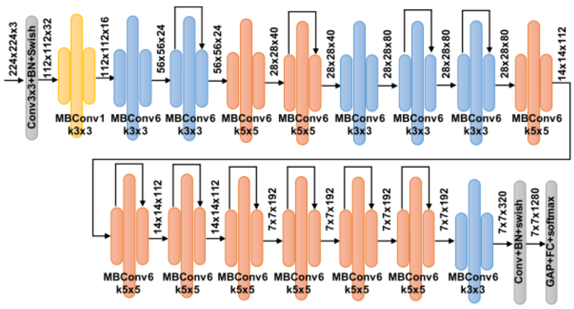


Figure 4. The EfficientNet-B0 General Architecture

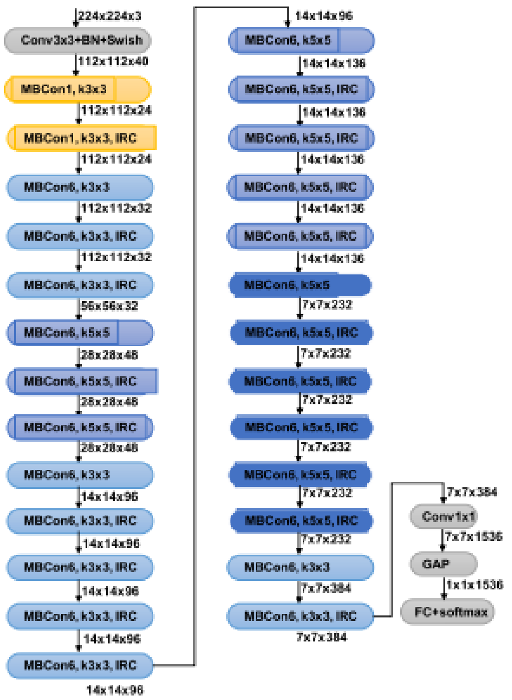


Figure 5. The EfficientNet-B3 General Architecture

Figure 4 [26] shows the architecture of EfficientNet-B0 with layers that contribute to feature extraction from images. With an efficient design, the model shows a progression of layers that adaptively increases the resolution and complexity of the feature representation. Meanwhile, Figure 5 [26] displays the more complex architecture of EfficientNet-B3 with an increased level of depth.

Table 3. Model Architecture

| Model | Layer | Shape | |
|---|---|---|---|
| B0 | Input Layer | input: | [(None, 128, 128, 3)] |
| | | output: | [(None, 128, 128, 3)] |
| | Functional | input: | (None, 128, 128, 3) |
| | | output: | (None, 4, 4, 1280) |
| | Global Average Pooling2D | input: | (None, 4, 4, 1280) |
| | | output: | (None, 1280) |
| | Dense | input: | (None, 1280) |
| | | output: | (None, 4) |
| B3 | InputLayer | input: | [(None, 128, 128, 3)] |
| | | output: | [(None, 128, 128, 3)] |
| | Functional | input: | (None, 128, 128, 3) |
| | | output: | (None, 4, 4, 1536) |
| | Global Average Pooling2D | input: | (None, 4, 4, 1536) |
| | | output: | (None, 1536) |
| | Dense | input: | (None, 1536) |
| | | output: | (None, 4) |

In its development, this architecture places significant emphasis on efficiency in terms of processing time and computational capabilities. One of its greatest achievements is its ability to achieve higher levels of accuracy by using fewer parameters and speeding up its computational process.

This study employs the transfer learning method with the EfficientNet-B0 and EfficientNet-B3 model architectures. As shown in Table 3, there is an input layer designed to receive images with a height of 128 pixels, a width of 128 pixels, and an RGB colour format, where every pixel consists of the red, green, and blue colour channels. Subsequently, the base models, EfficientNet-B0 and EfficientNet-B3, are pre-trained models with the EfficientNet-B0 architecture producing a final output of dimensions 4x4 with 1280 channels, while EfficientNet-B3 yields a final output of dimensions 4x4 with 1536 channels. Subsequently, this output is further procedureed utilizing a Global Average Pooling layer for categorization.

The Global Average Pooling layer transforms the spatial output from EfficientNet into a one-dimensional feature vector by averaging every channel across every 4x4 partial grid, ensuring that every channel contributes equally to the outcome. Furthermore, a Dense layer (fully connected layer) is utilized with units corresponding to the 4 classes to be predicted. The softmax activation function is used to map input values into probabilities within the range of 0 to 1. The higher the probability value for a class, the greater the model's confidence that the image belongs to that class or is reflected in the model's strongest or most convincing prediction.

Table 4. Model Training Parameters

| Parameter | Settings |
|---|---|
| Batch size | 32 |
| Optimizer | Adam |
| Epoch | 30 |
| Learning rate | 0.001 |
| Loss function | CategoricalCrossentropy |

As shown in Table 4, during the compilation procedure of the previously created model, several essential parameters were defined for model training. These parameters include the loss function, optimizer, and metrics. The loss function utilized is categorical cross-entropy, the optimizer is Adam with a learning rate set to 0.001, and the evaluation metrics utilized encompass Exactness, AUC (Area Under the Curve), precision, and recall. The parameter values set for the model training are by the study [27], which performed image categorization utilizing the EfficientNet architecture. These parameter values have yielded the best Exactness for the model.

This study experiment also applies callback functions during the model training. These callback functions are implemented to automatically halt the model training procedure when reversing specified parameter values [28].

Table 5. Parameters of the EarlyStopping Function

| Parameter | Settings |
|---|---|
| Monitor | val_accuracy |
| Mode | max |
| Patience | 15 |
| Verbose | 1 |

The InitialStopping function used as a callback has several parameters as indicated in Table 5. The "monitor" parameter sets "val_Exactness" as the monitored metric, and the "mode" parameter is set to "max." When the "val_Exactness" metric either starts to decrease, remains unchanged, or reverses its maximum value, the model training will be terminated initially to prevent overtraining. Additionally, the "patience" parameter is set to 15 to ensure that if, after 15 consecutive epochs, "val_Exactness" does not significantly get higher beyond a tolerance threshold, the model training will be stopped.

2.4 Evaluation

Confusion Matrix is a method used to measure the performance of a classification model. The visual representation of the confusion matrix is divided into four terms, namely True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) [29]. Based on the information found in the confusion matrix, there are metrics used to measure and evaluate the performance of classification models, namely accuracy, precision, recall, and F1-score. Accuracy, Equation 1, is to measure how often the model gives correct predictions overall. Precision, Equation 2, is to measure the model's ability to avoid giving false positive predictions. Recall, Equation 3, is to measure the model's ability to detect all relevant positive cases. While F1-Score, Equation 4, is the mean of precision and recall [30].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100\% \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \times 100\% \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \times 100\% \quad (3)$$

$$F1 - Score = \frac{FP}{TP} \times 100\% \quad (4)$$

## 3. Results and Discussions

The outcome of this study involves Alzheimer's disease categorization utilizing the EfficientNet-B0 and EfficientNet-B3 models based on an MRI image dataset. The training procedure will be conducted utilizing the EfficientNet-B0 and EfficientNet-B3 architectures. Testing for both architectures is carried out to compare their performance outcomes.

Performance outcomes encompass parameters that provide Exactness, precision, and recall values for every model scenario. Additionally, this study makes use of the confusion matrix, which furnishes information regarding the comparison of prediction outcomes from the categorization performed by the model. Before testing with the categorization model, the dataset undergoes preprocedureing to prepare it for evaluation. Subsequently, model testing is conducted, with training spanning 30 iterations (epochs).

3.1 Classification Result using EfficientNet-B0

The dataset was tested utilizing the EfficientNet-B0 model. In the training procedure conducted with the EfficientNet-B0 model, plotted graphs illustrating Exactness and loss can be shown in Figure 6 and Figure 7. Based on both of these plotted graphs, the highest Exactness value of 0.97 was achieved at epoch 29, and the lowest loss value of 0.06 was attained at epoch 24.

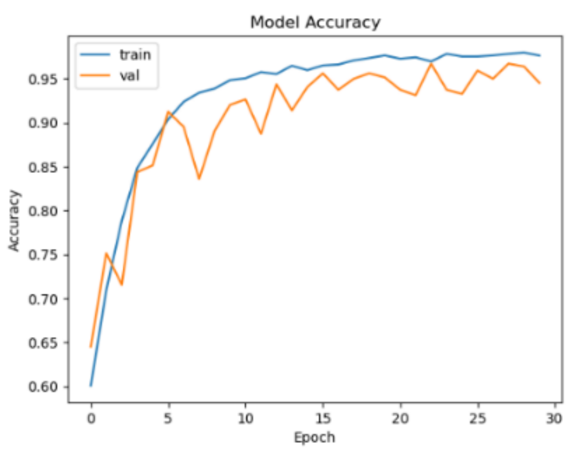


Figure 6. Exactness Graph of the EfficientNet-B0 Model

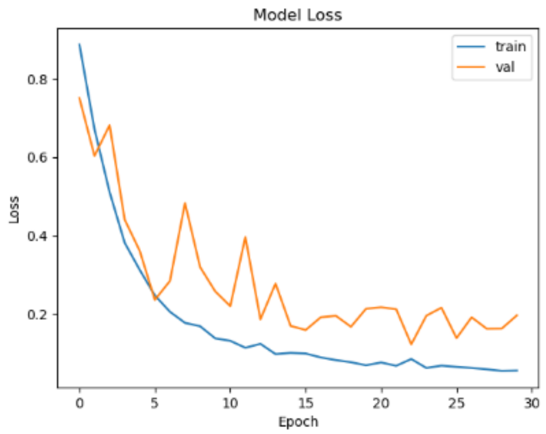


Figure 7. Loss Graph of the EfficientNet-B0 Model

After analyzing the plot graphs, the evaluation of the model proceeded by employing a confusion matrix, as depicted in Figure 8.

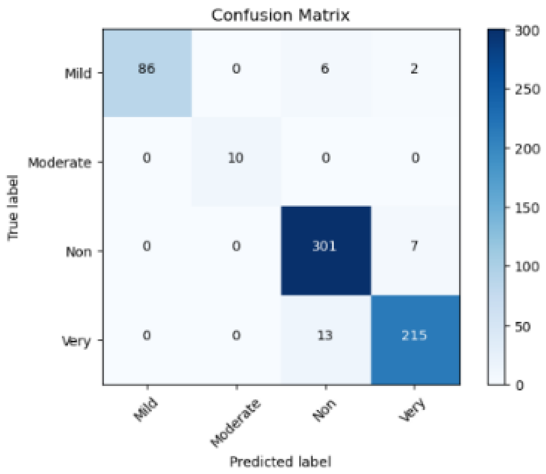


Figure 8. Confusion Matrix of the EfficientNet-B0 Model

Figure 8 represents the outcomes of the confusion matrix for the EfficientNet-B0 model. It can be observed that the "Mild" class was correctly predicted for 86 images, misclassifying 6 images as "Non" and 2 images as "Very." The "Moderate" class was correctly predicted for 10 data points. The "Non" class was accurately predicted for 301 images, with 7 images misclassified as "Very." Finally, the "Very" class achieved correct predictions for 215 images while misclassifying 13 images as "Non."

3. 2 Classification Result using EfficientNet-B3

The dataset was evaluated utilizing the EfficientNet-B3 model. During the training conducted with the EfficientNet-B3 model, the plotted graphs display the Exactness and loss as shown in Figure 9 and Figure 10. Based on both of these plotted graphs, the highest Exactness value of 0.99 was fulfilled at epoch 30, while the lowest loss value of 0.02 was achieved at epoch 30.

During the model training, fluctuations in Exactness and loss occurred due to *overfitting*. The *overfitting* was caused by the model being overly complex, primarily because EfficientNet-B3 has numerous layers and parameters. After understanding the fulfilled plot graph, the procedure is then continued with model evaluation utilizing a confusion matrix, as shown in Figure 11.

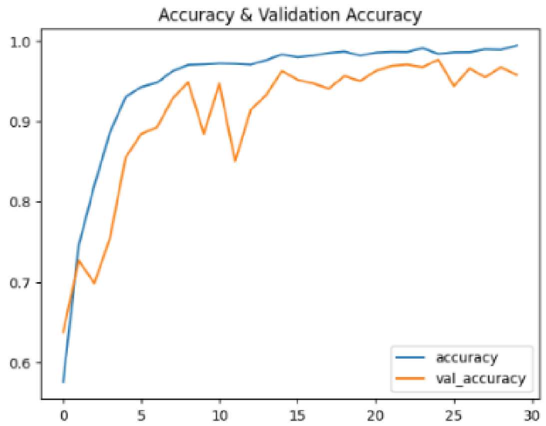


Figure 9. Exactness Graph of the EfficientNet-B3 Model

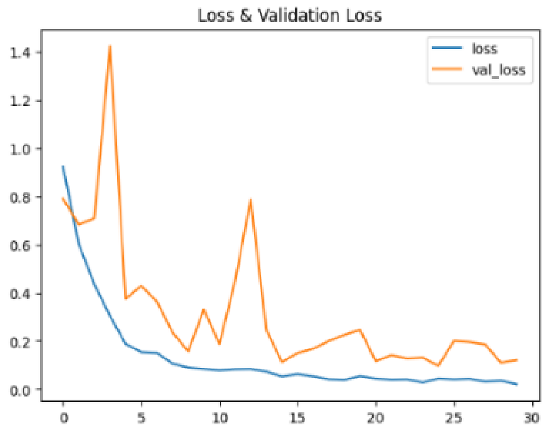


Figure 10. Loss Graph of EfficientNetB3 Model

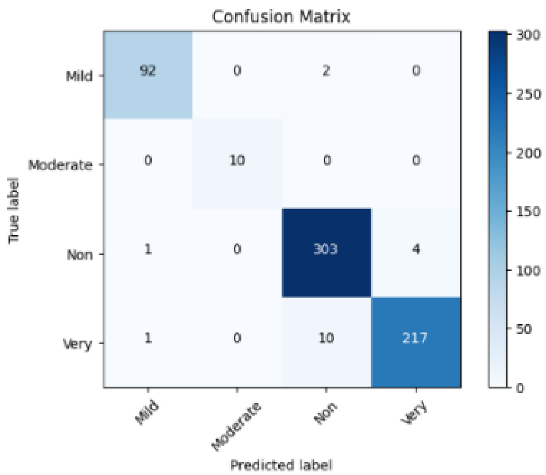


Figure 11. Confusion Matrix Model EfficientNetB3

Figure 11 represents the outcomes of the confusion matrix for the EfficientNet-B3 model. It can be observed that the Mild class successfully predicted 92 images correctly and misclassified 2 images as the Non-class. The Moderate class correctly predicted 10 data points. The Non-class correctly predicted 303 images, misclassified 1 image as Non, and misclassified 4 images as Very. The Very class accurately predicted

 

217 images, misclassified 1 image as Mild, and misclassified 10 images as Very.

3.3 Model Performance Comparison

Following the model's training, two different model scenarios were assessed for their respective performance levels, displaying categorization outcomes and confusion matrices. The following is a comparison of the two model scenarios, which can be shown in Table 6.

Table 6. Performance Results for Each Architecture

| Architecture | Class | Precision | Recall | Acc |
|---|---|---|---|---|
| EfficientNetB0 | Mild Demented | 1.00 | 0.91 | 0.96 |
| | Moderate Demented | 1.00 | 1.00 | |
| | Non Demented | 0.94 | 0.98 | |
| | VeryMild Demented | 0.96 | 0.94 | |
| EfficientNetB3 | Mild Demented | 0.98 | 0.98 | 0.97 |
| | Moderate Demented | 1.00 | 1.00 | |
| | Non Demented | 0.96 | 0.98 | |
| | Very Mild Demented | 0.98 | 0.95 | |

After evaluating the performance of the two model scenarios, EfficientNet-B0 and EfficientNet-B3, utilizing the evaluation model, it can be observed from Table 6 that the EfficientNet-B3 model achieved the best performance among the two scenarios. The Exactness fulfilled with the EfficientNet-B3 model is higher compared to the EfficientNet-B0 model. This can be attributed to several factors, including, firstly, the architectural depth; EfficientNet-B3 has 278 layers, which is significantly more than EfficientNet-B0, which has only 110 layers [31]. In other words, EfficientNet-B3 is deeper and more complex in terms of its structure, allowing it to comprehend more intricate data representations. Secondly, the architectural width of EfficientNet-B3 is greater, with more filters compared to EfficientNet-B0. A wider architecture enhances the model's capacity to capture important Equivalent attributes in the data. Thirdly, the number of parameters in the EfficientNet-B3 model is larger, approximately 12 million parameters [32] as opposed to the EfficientNet-B0 model, which has only 5 million parameters [33]. This difference in the number of parameters indicates that the EfficientNet-B3 model is larger and possesses a greater capacity for modelling data compared to the EfficientNet-B0 model. A larger capacity is capable of improving the learning of complex Equivalent attributes, thereby yielding higher Exactness. The greater number of layers and channels in the EfficientNet-B3 model can produce more accurate feature representations, consequently enhancing categorization performance. With more layers and channels, the model possesses a greater capacity to comprehend the patterns within the procedure images.

After conducting testing using two distinct model scenarios, the subsequent phase involves comparing the performance of the superior model with the results achieved in a previous study.

Table 7. Model Accuracy Comparison

| Model | Accuration |
|---|---|
| VGG16 [20] | 80.00% |
| VGG19 [20] | 80.00% |
| InceptionV3 [21] | 89.00% |
| EfficientNetB0 | 96.00% |
| EfficientNetB3 | 97.00% |

Based on Table 7, this research produces the best model in the second scenario, namely the EfficientNet-B3 model, with a fulfilled accuracy rate of 97.00%. The EfficientNet model produces the highest accuracy among the accuracies produced by previous studies. This is because in terms of architecture which can be seen in Figure 4, Figure 5, and Table 3, EfficientNet has a smaller number of parameters compared to VGG16, VGG19, and InceptionV3 so that it can prevent overfitting and increase generalization on data. The EfficientNet architecture is also designed to extract image features from simple to complex feature levels, so it can understand information at various levels of complexity of the image. In addition, hyperparameter settings such as learning rate, batch size, and optimizer can affect model performance.

## 4. Conclusions

This study utilized two model scenarios to detect Alzheimer's disease from MRI datasets. Image categorization conducted utilizing the EfficientNet-B0 and EfficientNet-B3 models yielded satisfactory outcomes. EfficientNet-B0 achieved a performance outcome with an Exactness score of 96.00%. On the other hand, EfficientNet-B3 achieved the best performance outcomes with an Exactness score of 97.00%, surpassing the VGG16 and VGG19 models in the previous study. This study outcome suggests that the performance of the model, whether good or bad, is influenced by factors such as data conditions, the ratio of data separation, the number of layers, input quantity, and data balance.

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