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Transfer Learning for Alzheimer's Disease Diagnosis Using EfficientNet-B0 Convolutional Neural Network

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ABSTRACT

Alzheimer's disease (AD) is an irreversible neurological disorder that causes the gradual decline of one's cognitive abilities, and thus, early detection is significant to slow down its deterioration. Magnetic resonance imaging (MRI) images have been commonly used to diagnose AD. Furthermore, deep learning techniques such as the Convolutional Neural Network (CNN) are utilized to assist the diagnosis due to the complexity of MRI's analysis. However, CNN models require large datasets for training and have a challenging nature for model optimization. Thus, Transfer Learning, an emerging method that can improve the performance of the deep learning model by eliminating the need for training from scratch, is introduced. This paper will propose a Transfer Learning-based EfficientNet-B0 model to classify MRI brain images for AD diagnosis. The MRI images are obtained from Alzheimer's Disease Neuroimaging Initiative (ADNI) database; only axial-plane images are used in this study. As a result, the multi-class classification of MRI images into AD, MCI, and NC classes using a Transfer Learning-based model resulted in a training accuracy of 98.93% and a validation accuracy of 87.17%. These results evidenced the significance of Transfer Learning in improving model performance.

1. Introduction

Alzheimer's Disease (AD) is a chronic neurological disease associated with the deterioration of the brain's cognitive abilities, which could be ultimately fatal. AD patients experience memory loss, progressive decline in daily living abilities, and unusual personality changes. Currently, there is no definitive treatment for curing AD. Medical attention can just delay its progression. The World Alzheimer's Disease 2018 report [1] stated that approximately 50 million people worldwide live with AD, projected to rise to 152 million by 2050. Therefore, it is imperative to predict and detect AD in a patient so that healthcare professionals can take appropriate countermeasures to slow the disease's progression [2].

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A medical imaging process named Medical Resonance Imaging (MRI) has been frequently used to detect and diagnose the existence of AD in a patient. Strong magnetic fields and radio waves are used in MRI scans to provide precise images of the inside of the body, including the brain [3]. By examining the anatomical components of the brain, the cause of the disease can be identified, enabling medical practitioners to develop treatment strategies. MRI is widely utilized due to its perceived safety in comparison with other techniques, such as Computed Tomography (CT) and Positron Emission Tomography (PET) [4]. Moreover, significant advancements in MRI-based brain anatomy research and brain injury evaluation, including detecting multiple sclerosis [5], further contribute to the MRI's pervasive usage. AD is typically diagnosed by using MRI to observe tissue shrinkage of the brain's hippocampus region, which is responsible for controlling memory and learning [6]. Xu *et al.,* [7,8] classified MRI images into different classes to diagnose AD.

Nevertheless, the delicate and massive amount of MRI images poses a challenge for data analysis to diagnose AD. Moreover, it is challenging to detect a prodromal stage of AD known as Mild Cognitive Impairment (MCI) due to its subtle symptoms [9]. Therefore, it is necessary to apply automated computerized systems to analyze MRI brain images and produce precise results for diagnosing AD [10]. Deep learning, a popularly emerging method subset of artificial intelligence (AI), has gained attention due to its potential in the medical field [11,12]. It can learn predictive features directly from the original datasets [13]; thus, it is now widely used in AD applications. Convolutional Neural Networks (CNN), one of the most popular types of deep learning, are frequently used to analyze images due to their high accuracy and efficiency [14]. Several studies [15-17] have shown the application of CNN models in classifying MRI images with high accuracies to diagnose AD.

However, deep learning models encounter their constraints, including the necessity of possessing vast data for training and the challenging nature of model optimization. Very limited MRI images are publicly available due to patients' privacy, resulting in a scarcity of data for training. Data insufficiency significantly hinders the optimization of the parameters and weights of CNN models. Hence, Transfer Learning (TL), an enhancement technique that can boost a deep learning model's performance, is gaining popularity in AD diagnosis applications [15]. It eliminates the need to train a model from scratch, where a pre-trained model can be utilized directly for AD detection with only minor adjustments. TL will serve as the basis for this study, and in this paper, a TL-based EfficientNet-B0 model is proposed to classify MRI brain images for AD diagnosis. The significance of this study is to highlight the improvements in model performance by applying TL. At the same time, the novelty of this research stands in the unique usage of axial-plane MRI brain images for multi-class classification with the EfficientNet model.

2. Methodology

The main components of training deep learning models include the data used, network design, and parameters set. A balance of these three components can ensure an effective training process to produce good results. Usually, numerous trials will be needed to train a model from scratch, as the training parameters must be adjusted according to the performance levels achieved. However, this research employed pre-trained networks that already contain optimized parameters. Thus, only minimal fine-tuning will be needed to attain maximum performance range. The sections below will discuss the principles and concepts of TL and the methodology used in this study. Next, the following subsections will cover the experimental dataset and proposed model used for this research.

2.1 Transfer Learning

Transfer learning (TL) is the transfer of knowledge or the method of modifying a pre-trained network for another task [18]. The concept was born from the notion that human being can utilize their skills to accomplish various tasks in diverse fields. A deep learning model created for one task can be efficiently reused for another by fine-tuning an existing model, where only necessary adjustments are made. In TL, the new dataset often resembles the original dataset in many ways; for instance, both are image datasets. Thus, the type of fine-tuning applied to a pre-trained model is usually determined by the new dataset used to train the network.

Based on domain and tasks, the mathematical component of TL can be described as follows [19]. *T* indicates the task to be completed, while *D* represents the domain. Each domain is enclosed by the feature space *X*, and *P*(*x*) represents the probability distribution, where $x = \{x_1, x_1, \dots, x_1\} \in X$.

A certain domain can be represented in terms of feature space as

$$D = \{X, P(x)\} \tag{1}$$

The task with two (2) components, objective function *f*(*x*) and label space *Y*, is represented as

$$T = \{Y, f(x)\} \tag{2}$$

The predictive function learns from the training data that consist of feature-label pairs, $\{x_i, y_i\}$, where

$$x_i \in X \text{ and } y_i \in Y \tag{3}$$

For a given source domain, D_S, source learning task T_S, target domain D_T, and target learning task T_T, T_L improves the predictive function $f(x)$ in D_T, with knowledge D_S and T_S with the condition:

$$D_S \neq D_T \text{ or } T_S \neq T_T \tag{4}$$

A study in [16] described the benefits of employing TL for training a deep learning model. Generally, it saves time in designing a model for a new task, as pre-trained models can be utilized with some fine-tuning. Besides, in cases with insufficient training data, the pre-trained networks which have been trained with a large amount of data can be used to achieve superior outcomes. TL can provide a network model with a higher start value, asymptote, and slope in the training process [20].

Hence, TL is now one of the most extensively used learning strategies for various tasks. Pre-trained networks have been designed using numerous deep learning frameworks, like CNN, and users can readily use them for their corresponding tasks. For example, some pre-trained networks include GoogleNet, DenseNet, EfficientNet, VGG-16, VGG-19, ResNet, AlexNet, and SqueezeNet. These networks were all previously trained using the ImageNet dataset, which has 1000 different classes of images. Aside from being trained using millions of images, these pre-trained networks also addressed numerous challenges.

This study will examine and justify the benefits of TL by fine-tuning a pre-trained model to perform the brain image classification task. The performance of the pre-trained network will be evaluated by testing it on a test set after the model has been trained using MRI images for AD detection. The network's performance is evaluated by its ability to classify MRI images into different AD classes.

2.2 Dataset

MRI images used in this research are obtained from the open-access database: Alzheimer's Disease Neuroimaging Initiative (ADNI). The ADNI is a study conducted for clinical trials to treat AD [21]. Its main goal is to develop biomarkers so that clinical trials can be performed in the early phases of AD to forecast a cognitive decline. Various imaging modalities, including MRI and PET, have been used to create medical images in ADNI. Since 2004, a few phases of ADNI data have been published, starting with ADNI 1, a study that spanned over five years. The following version, ADNI GO, was created after an additional 2-year extension and ultimately evolved into ADNI 2 and ADNI 3 today. In the current state, ADNI has accumulated thousands of data points, including brain scans, genetic profiles, and biomarkers in cerebrospinal fluid.

In this study, structural MRI data will be used to classify the presence of AD with TL. Around 199 subjects have been chosen, and their MRI images will be extracted from ADNI to be used as the dataset in this research [22]. The dataset will consist of 3 classes, i.e., AD (Alzheimer's Disease), MCI (Mild Cognitive Impairment), and NC (Normal Control) subjects, respectively. They will be divided into three (3) parts, i.e., training set, validation set, and test set. Table 1 shows the distribution of MRI images among classes for training and validation. Moreover, all the MRI images obtained are axial-plane images.

Table 1
MRI image distribution for the ADNI dataset

	AD	MCI	NC	Total
Training	924	1260	1240	3424
Validation	200	200	200	600

Generally, the human brain can be divided into three (3) anatomical planes: the axial, coronal, and sagittal planes [23]. However, in this study, only the axial plane is involved in MRI scans, which slice across the brain from top to bottom. Figure 1 and 2 show examples of axial-plane MRI images extracted from the ADNI database.

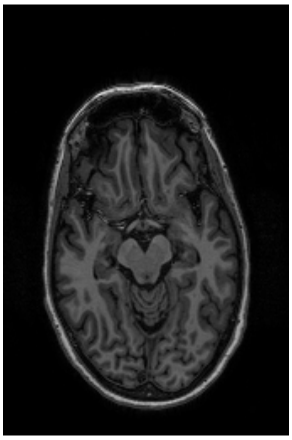

Fig. 1. Example of MRI image for AD subject on axial-plane [22]

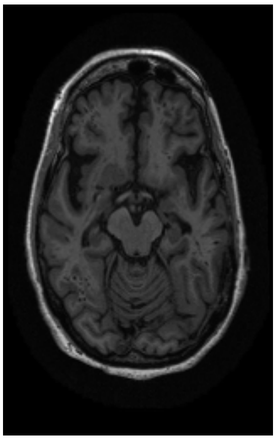

Fig. 2. Example of MRI image for MCI subject on axial-plane [22]

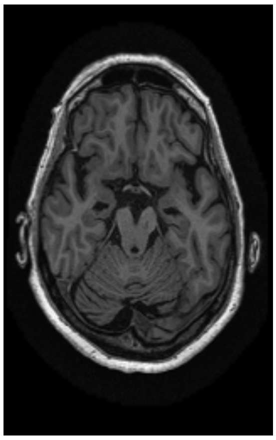

Fig. 3. Example of MRI image for NC subject on axial-plane [22]

2.3 Proposed Model

A typical CNN model performs a classification task by first taking an image as an input, assigning biases and learnable weights to various image elements before distinguishing them. However, the primary issue of CNN is the randomness in adjusting model parameters, such as the number of layers and neurons in each layer [24]. The EfficientNet model can overcome this issue by evenly modifying the network's parameters by employing a composite coefficient. The EfficientNet is a type of pre-trained CNN model using TL. The network's feature representations are comprehensive due to its training with a dataset of over one million images from ImageNet. In the EfficientNet model, the input size of images is set at a dimension of 224 x 224.

As shown in the EfficientNet model architecture [25] in Figure 4, the 2D depth-wise convolutional units form the foundation of the EfficientNet model design. In addition, it is made up of several inverted mobile bottleneck convolutions (MBConv) in its architecture. Generally, the EfficientNet model is characterized by the optimized benchmark design that results in quicker training and the scaling technique that ensures the network's depth while retaining accuracy.

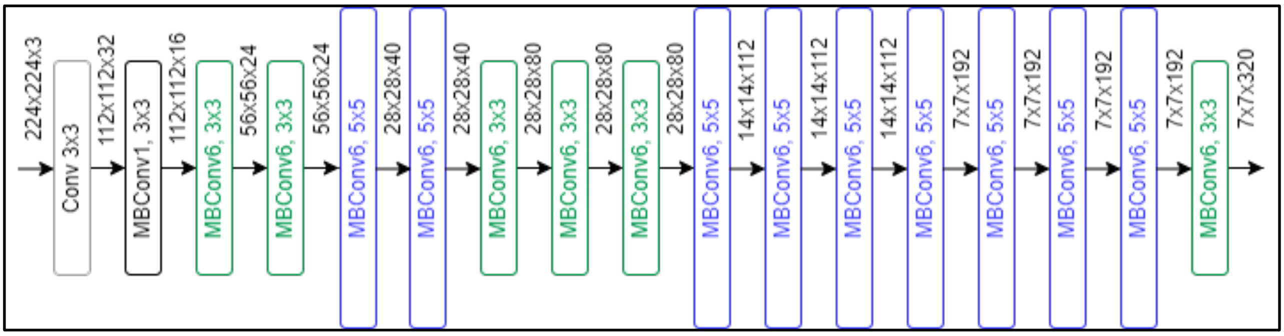

Fig. 4. EfficientNet model architecture [25]

Figure 5 shows the block diagram of how the EfficientNet model with TL classifies brain MRI images. Firstly, the model will be pre-trained using substantial data from ImageNet. Then, the dataset containing the MRI images will be fed into the pre-trained EfficientNet model for training. Here, the computing resources and training time can be significantly reduced as only the last classification layers of the pre-trained model will be fine-tuned. Lastly, after fine-tuning, the model will be ready for training using the inputted MRI dataset to classify brain images in detecting AD

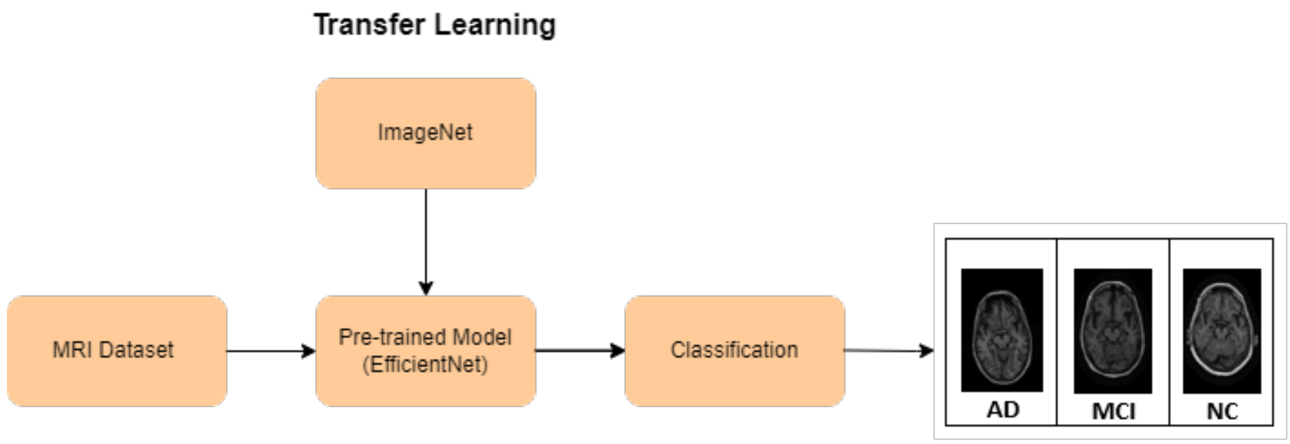

Fig. 5. Block diagram of proposed model application in AD diagnosis

3. Results and Discussion

In this study, TL is performed using the pre-trained network, EfficientNet-B0 for a multi-class classification task to diagnose AD. The network model is developed using the Python-based deep learning framework known as Pytorch. The Pytorch is an open-source machine learning library based on the Torch library that focuses on tensor computations, automated differentiation, and GPU acceleration, mainly used for research prototyping and deployment [26].

3.1 Experimental Setup

The hyperparameters assigned for training the EfficientNet-B0 model to classify MRI images are listed in Table 2. The MRI images are resized into a dimension of 224 pixels x 224 pixels with three (3) channels to accommodate them in the EfficientNet model. A total of 4024 slices of axial-plane MRI images from three classes, namely AD, MCI, and NC, are split into training and validation sets with a ratio of around 8:2, respectively. Several unseen MRI images are also set aside to be used as the test set to validate the performance of the trained model. The model training dataset consists of 3424 images from the three classes, while the validation dataset has 600 MRI images. The number of data allocated for each of the three classes is also balanced.

After the classification layers of the pre-trained EfficientNet-B0 model are fine-tuned, the model is trained to classify MRI images. The network is trained for 20 epochs with a batch size of 32 and a learning rate of 0.0001. The momentum is set to 0.9, with Adam optimizer as the optimization algorithm. Moreover, categorical cross entropy, a loss function for multi-class classification tasks, is utilized in this computation. The performance of the TL-based EfficientNet-B0 model will be evaluated by applying these hyperparameters for training and validation of the network model, followed by testing it on a test set.

Table 2
Hyperparameters used for model training and validation

Hyperparameters	Training	Validation
MRI Image Size	224 x 224 x 3	224 x 224 x 3
Number of MRI Slices	3424	600
Epoch	20	20
Batch Size	32	32
Learning Rate	0.0001	0.0001
Momentum	0.9	0.9
Optimizer	Adam optimizer	Adam optimizer
Loss Function	Categorical Cross Entropy	Categorical Cross Entropy

3.2 Experimental Results and Discussion

The figures below show the result of the experiment using a pre-trained EfficientNet-B0 model for multi-class classification of axial-plane MRI brain images. Figure 6 illustrates the performance of the Efficientnet-B0 model in terms of its training and validation accuracies.

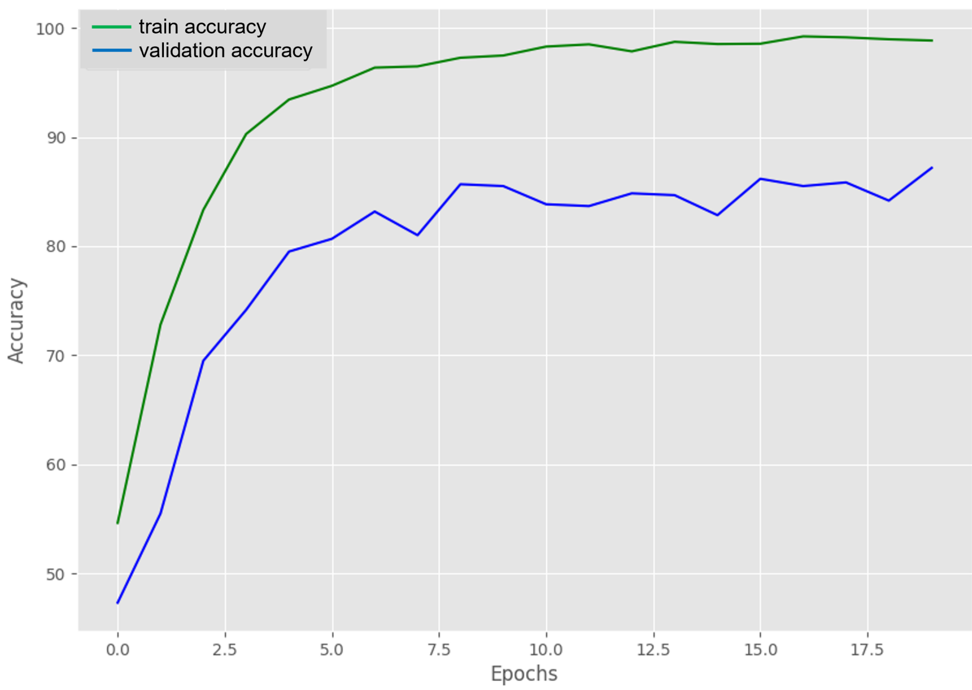

Fig. 6. Performance of network model in terms of accuracy

While Figure 7 depicts the training and validation losses.

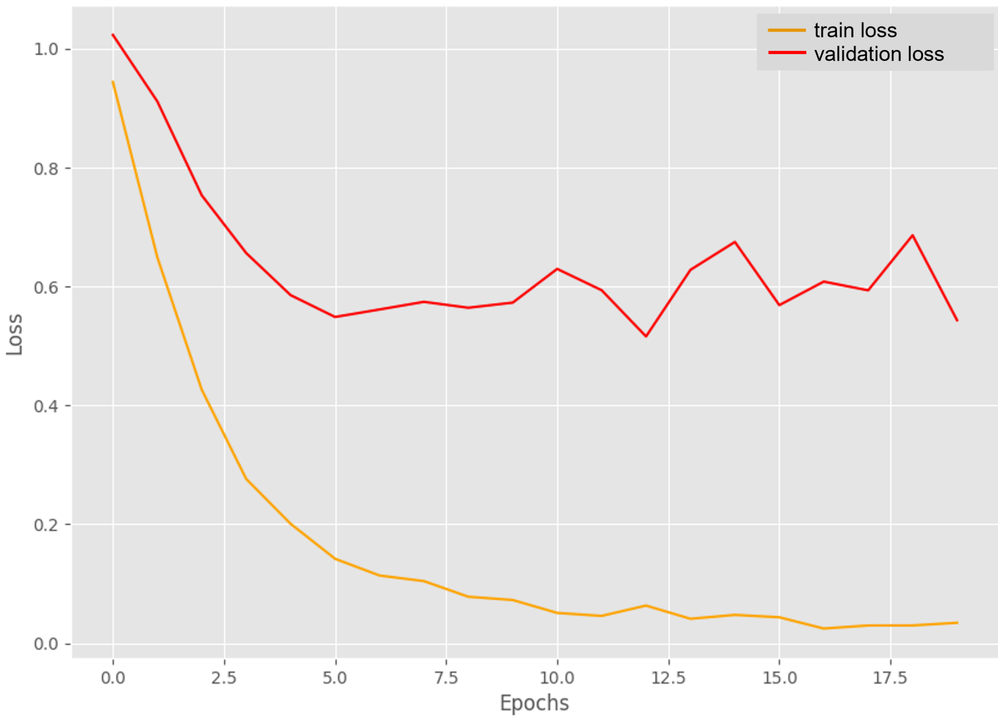

Fig. 7. Performance of network model in terms of loss

On the other hand, Figure 8 shows the model's performance when tested on a test set. For training purposes, 924 (AD), 1260 (MCI), and 1240 (NC) slices of axial-plane MRI images have been fed into the model. The pre-trained model will then learn the different features of images from the three (3) classes. After completing the training, the model will be used to classify 600 images from the validation dataset. Finally, the trained model will perform a multi-class classification of the MRI brain images on a test set consisting of unseen data using the knowledge learned from the training process. The images that show severe symptoms of Alzheimer's disease will be classified into AD class, those with minor or initial signs will be in the MCI class, and MRI scans that show a healthy brain with no signs of Alzheimer's will be classified into NC class.

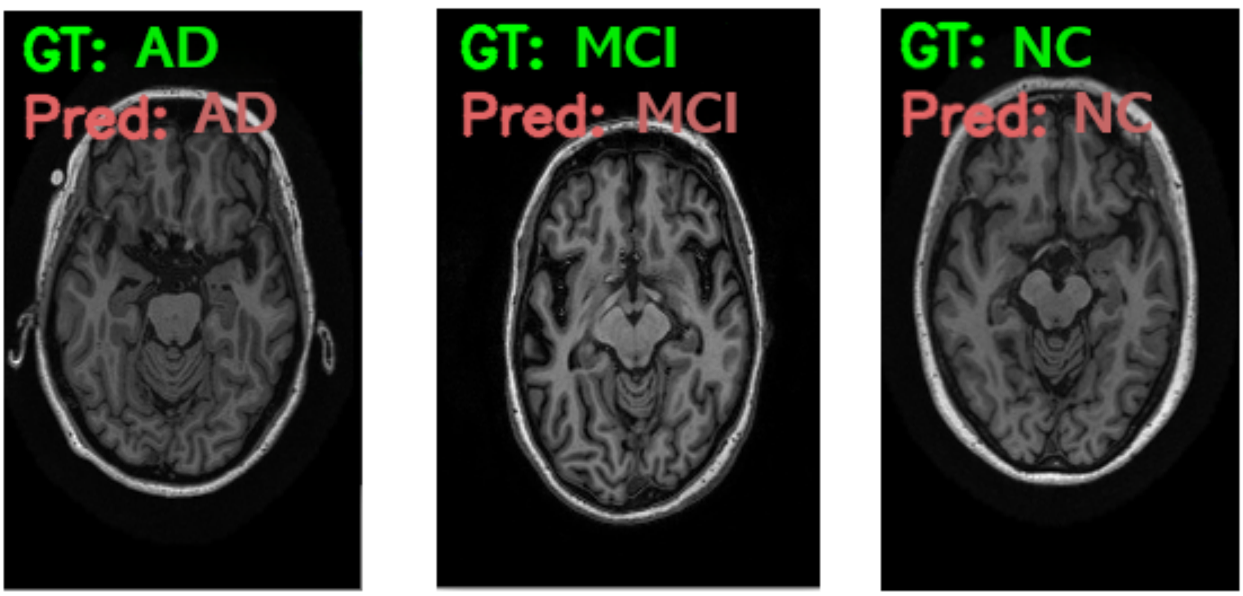

Fig. 8. Testing performance of network model

Based on the graph in Figure 6, it can be observed that training and validation accuracy increases sustainably with the number of epochs. On the other hand, the loss decreases steadily after every epoch, as observed in Figure 7. The model has achieved an accuracy of 98.93% for training, and a validation accuracy of 87.17%, while for the losses, a 0.034% training loss and 0.541% validation loss can be observed. The trained model is then tested on a test set to measure further its performance on unseen MRI data from different classes, resulting in the observation in Figure 8. On the output images, both the trained model's original class names and the predicted class of the MRI images will be displayed with different colours. The "ground truth" labelled GT will represent the MRI images' original class, while the trained model's predicted class will be represented by "Pred". As observed in Figure 8, the predicted results match the original results of the test images for all three classes, depicting that the trained model has correctly classified the test images into their respective classes. Thus, it can be inferred that the EfficientNet-B0 model could accurately classify the axial-plane MRI images into their multi-classes with few losses.

In Table 3, a comparison with other models that did not apply TL in classifying AD is made. With the same dataset used, the methods that did not utilize TL in training their model had lower accuracy than the TL-based EfficientNet model used in this study. Therefore, the TL-based model improved AD classification precision, even with a small input dataset. However, one of the drawbacks observed in this study is the presence of some overfitting in the outputs. As a result, the validation accuracy is less precise than the training accuracy, which was almost 100%. The same applies to the validation loss with higher values than the small amount of training loss obtained. This issue can be overcome by expanding the dataset, adding dropout, or reducing the neural network layers to increase the model's generalization ability.

Table 3
Literature comparison with related works

Reference	Model	Modality	Problem Solved	Transfer Learning	Accuracy
[27]	Inception-v4, ResNet	MRI	Multi-stage Classification	No	93.18%
[28]	KNN	MRI	Multi-stage classification	No	96%
[29]	SVM, KNN, LDA, QDA, DT	MRI	Multi-stage classification	No	91.3%
[30]	Alexnet, Resnet50, Densenet201, Vgg16	MRI	Multi-stage Classification	No	90%
This paper	EfficientNet	MRI	Multi-stage Classification	Yes	98%

4. Conclusion

This study demonstrated the significance of applying transfer learning in deep learning models for MRI classification to diagnose AD. The TL-based CNN model: EfficientNet-B0, had successfully classified axial-plane MRI brain images into three (3) classes, namely AD, MCI, and NC, with high accuracy. A more efficient and exact model can be developed using pre-trained CNN models, aside from minimizing the computational resources and time needed for training. Further improvements may include improving the model generalization to prevent overfitting and exploring the usage of hybrid learning and enhancement modules.

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