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Multi-Class Classification of Dementia from MRI Images Using Transfer Learning

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***Abstract*— The term dementia is used to describe a number of different conditions affecting the brain. Dementia interferes with a person's daily life and activities as the patient has difficulty remembering events or conversations. A deep learning (DL) framework can be used to detect dementia using MRI scans. But a paucity of MRI scans that are needed to train the deep learning model is the main challenge in DL-based dementia detection. To address this issue, we use the transfer learning technique with fine tuning to detect and classify the severity of dementia using MRI scan images. The dataset used in this paper is obtained from open-source platform which consists of different severity levels of MRI images. The data imbalance is managed with data augmentation techniques to avoid the overfitting of the model. The model performance is assessed on the accuracy, precision, recall, F-1 score, and confusion matrix. The proposed technique achieved an overall accuracy of 97.66%.**

Keywords—Dementia Detection, Transfer Learning, Deep Learning, Convolutional Neural Networks, Alzheimer's Disease, MRI images

I. INTRODUCTION

Dementia is a broad term used to describe a group of symptoms of illness affecting the brain. [1]. There are different kinds of dementia and Alzheimer's Disease (AD) is the most common kind and accounts for 60-70% of the cases worldwide. Dementia mainly affects people older than 65 years and a family history of the disease increases the risk by 30% [1]. According to World Health Organization (WHO) [2], currently, dementia is the seventh leading cause of death. Although AD currently has no effective cure, there are medications available to cope with the symptoms and delay its progress and protect the brain. Therefore, in the management of dementia, a timely diagnosis in an early stage is crucial.

The diagnosis of dementia is based on physical examination, Mini-Mental State Examination (MMSE), laboratory tests such as Magnetic Resonance Imaging (MRI) scan, and Positron Emission Tomography (PET) [3]. MRI is a non-invasive test that delivers multi-mode information from the brain structure and function. MRI scans assist physicians to distinguish AD patients from healthy people. Although the diagnosis of dementia using MRI scans requires the expertise of a neurologist, computer-aided deep learning technology can assist and or automate dementia detection.

Deep learning techniques, especially convolutional neural networks (CNNs) are highly suitable for image recognition or object detection. This makes them desirable for medical applications such as the automatic detection and segmentation of oncological lesions. Since CNNs are data-driven, a large amount of training data is needed to achieve high inference accuracy. In medical image applications where large, labeled training data sets are not available transfer learning can be successfully applied. In transfer learning, the knowledge of an already trained machine learning model is applied to a different but related problem. In this paper, the transfer learning technique is implemented using a pre-trained network for the multi-class classification of AD. The model classifies healthy individuals (*Non-Demented*) and patients with dementia based on severity levels such as *Mild Demented, Moderate Demented,* and *Very Mild Demented*.

The remainder of the paper is structured as follows: Section II presents the Literature review. Section III describes the methodology and implementation used in the research. Section IV illustrates the results and section V concludes the research.

II. LITERATURE REVIEW

Deep learning and machine learning research in health care have gained considerable attention recently as they emerge as reliable techniques for the classification of various medical images and data. This section presents various existing techniques in the literature to predict AD or dementia. Ebrahimi-Ghahnavieh et al. [4] present a combination of transfer learning on various 2D Convolution Neural Networks (CNNs) and Long-Short memory (LSTM) networks. *The Alzheimer's Disease Neuroimaging Imitative (ADNI)* [16] data is used to train and test the model. This method achieved 90.62% accuracy on multi-view classification using *SqueezeNet* and LSTM. In Ref [5], the CNN method is employed to extract features with a tailored DEMNET model which is suitable for training the model on a small dataset. SMOTE is implemented to address the data imbalance and the DEMNET model achieves 95.23% accuracy on Alzheimer's dataset.

In Ref [6], a deep learning-based method is proposed to detect AD. A 6-layered Neural Network is trained and tested on the *Open Access Series of Imaging Studies (OASIS)* [17] dataset. The proposed model achieves 80.25% accuracy. Basheer et al. [7], proposed a modified capsule network that performs matrix

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decomposition using Singular Vector Decomposition (SVD) and propagates it across the network. The proposed methodology achieved 92.39% accuracy on the OASIS dataset.

Raeper et al. [8], proposed a correlational method such as *canonical correlation analysis (CCA)* and a discriminative method such as *linear discriminative analysis (LDA)* to devise the *shallow convolutional brain multiplex (SCBM)* and to encode *region-to-region* and *network-to-network* relationships. Then they represent each brain using a set of SCBMs, that is used to train the CCA-SVM and LDA-based classifier on the ADNI dataset. This method achieved 80.95% accuracy. Ref [9], proposed a stacking technique using a gradient boosting machine and artificial neural network to predict dementia using a longitudinal collection of OASIS datasets. This approach achieved weighted accuracy of 89%.

Ref [10], proposed the EfficientNet Transfer Learning model to address the issue of uneven adjustments of network parameters such as depth, width, and resolution using the composite coefficient. The ADNI dataset is used to train and test the model and the proposed model achieved 91.06% accuracy. Ref [11], used the Transfer Learning technique using existing models such as VGG19, Inception-ResNetv2, ResNet152v2, EfficientNetB5, EfficnetNetB6 and one custom CNN. The paper proposed an ensemble method in order to increase the predictive performance. The proposed classifier consists of a weighted average ensemble of all six models. The OASIS dataset is used to train and test the model. The proposed method achieved 96% accuracy. Ref [12], proposed a novel end-to-end deep learning approach with the EfficientNet model. The data augmentation technique, Two-stage Random RandAugment (TRRA), is used to address the overfitting issue and Grad-CAM++ is used for heatmap visualization. The proposed approach is evaluated on two datasets and the model achieved 93.2% accuracy on ADNI and 92% accuracy on the Australian Imaging Biomarkers and Lifestyle (AIBL) [18] dataset.

From the literature, it can be observed that various machine learning (ML) and DL techniques and/or a combination of both are used for AD classification with varying degrees of detection accuracy.

III. METHODOLOGY AND IMPLEMENTATION

Transfer learning with fine tuning is used in this research to address the issue of paucity of labeled data for training. In this paper, we use the pre-trained *EfficientNetB7* [13] network for dementia detection using transfer learning, The *EfficientNetB7* is trained on a large ImageNet dataset [14] that helps to extract the low-level features or patterns

A. Dataset

The dataset used in this paper is Alzheimer's dataset obtained from the open-source platform Kaggle [15] which is used for training and testing the proposed network. The size of MRI images of the dataset is 176 x 208. It consists of a total of 6400 MRI images. The MRI images are categorized into four classes such as *Mild Demented, Moderate Demented, Non-Demented*, and *Very Mild Demented*. Table 1 gives the data distribution of images from each class. Fig 1 shows the sample image of each class from the dataset.

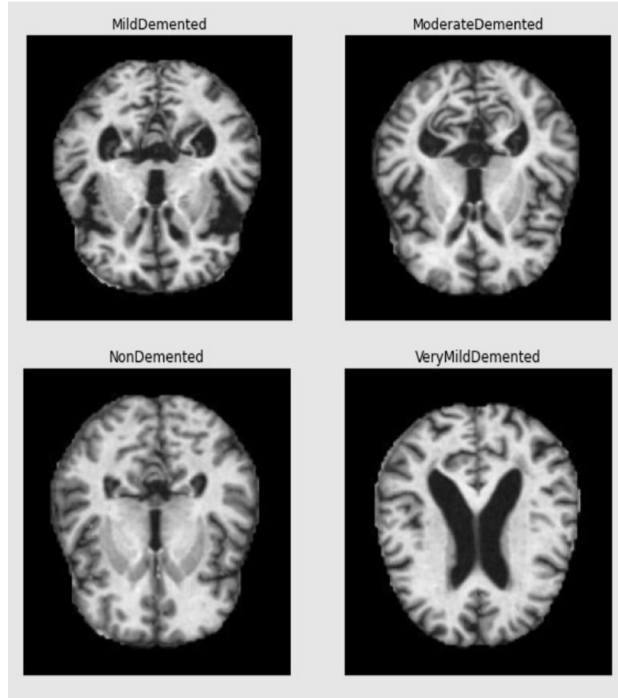

Fig. 1. Sample images from each class from the data set used.

TABLE I. MRI DATASET DISTRIBUTION

Class	*Number of Images*
Mild Demented	896
Moderate Demented	64
Non-Demented	3200
Very Mild Demented	2240

B. Data Processing

The disparity in the dataset may lead to an unfair prediction of the data with more samples and affect the reliability of the classification results. To overcome this drawback data processing techniques are utilized. Data processing is a method of formulating unprocessed data and making it appropriate for deep learning.

In this paper, the dataset images are resized to 175 x 175 greyscale images. The dataset is divided into two categories: 80% for training and 20% for validation. Table II presents the number of MRI images divided into training and testing datasets. After resizing, data augmentation techniques are applied using *ImageDataGenerator* from TensorFlow Keras functionality on the training dataset. The data augmentation is leveraged with the following parameters: horizontal flip, rotation range, zoom, and wide shift. One hot encoding is also implemented for converting the categorical data variables to achieve enhanced prediction and classification accuracy of the model.

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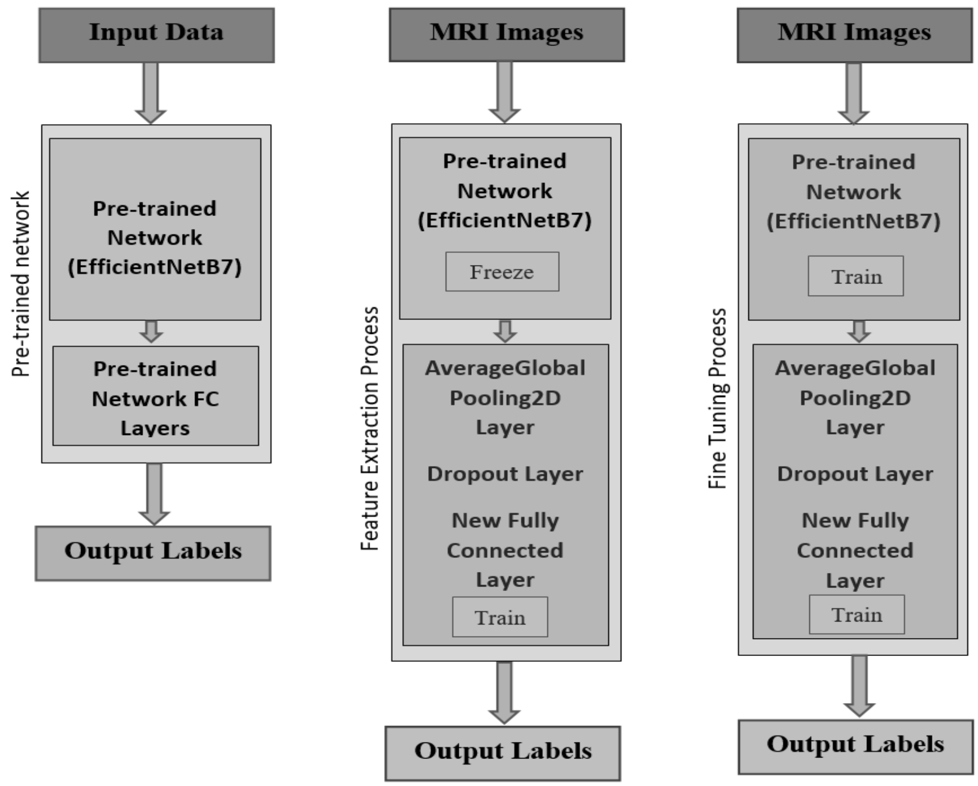

Fig. 2. The proposed step-by-step process of transfer learning using fine-tuning with EfficientNetB7

TABLE II. MRI DATASET DISTRIBUTION FOR TRAININGAND TESTING OF PROPOSED MODEL

Class	*Number of Images for training*	*Number of Images for testing*
Mild Demented	698	198
Moderate Demented	50	14
Non-Demented	2576	624
Very Mild Demented	1796	444

C. Methodology

It is a challenge to train a CNN from scratch on a small dataset without overfitting. To overcome this challenge, we implemented transfer learning with fine-tuning technique. The motivation behind transfer learning is that the feature learned on a problem can be leveraged on a related problem. This technique is helpful when a dataset is too small to train a CNN model from scratch without conceding the performance.

Fig 2 depicts the proposed stepwise process of transfer learning with fine tuning for *EffcientNetB7* network model. These steps are explained below.

Initially, we instantiate *EfficinetNetB7* as a base model and load 'ImageNet' weights into it. Then we substitute the fully connected layer or head with a new set of layers consisting of GlobalAveragePooling2D layer, a dropout layer with a dropout rate of 0.2, and finally a fully connected layer with the desired number of classes and activation function. The dropout is a regularization technique used to reduce overfitting and the best dropout value ranges between 0.2 to 0.5. We set the new fully connected layer with 4 neurons as we are performing a 4-class classification and the activation function is set as *softmax.* Equation (1) denotes the mathematical formula for the *softmax* activation function where z is the vector for the output layer and j indexes the output.

$$\sigma(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad for\ j = 1, \dots, K \tag{1}$$

In the next step, we freeze the convolution layers of the base model below the fully connected layers of the model to avoid changes in weights. The significance of this step is to avoid the gradient from backpropagating through the backward pass to block them from reaching the deep layers. Therefore, stopping the backpropagation after the fully connected layer helps to learn the patterns from the discriminative filters of convolution layers. The next step is to add a trainable layer on top of the frozen layers. This stage helps to modify old features to learn new patterns and perform predictions on another dataset. The new layers are now trained on the Alzheimer's dataset. This step is also known as feature extraction. Now, the model is converged on a new dataset which is the MRI image dataset. In the subsequent stage, we unfreeze the convolution layers of the base model and retrain the entire model with a small learning rate. There are two reasons to keep a very small learning rate: first, to

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prevent the risk of overfitting as we are training a large model on a small dataset and second is readjust the pretrained weight incrementally. Fine-tuning helps to achieve significant improvement in accuracy on a small dataset.

D. Experimental Setup

The *EffifientNetB7* model is used as a base model for transfer learning with fine-tuning for MRI image classification. In the initial training phase, the following hyperparameters are used: number of epochs 10, optimizer is set as *Adam* with learning rate 0.001, batch size of 32, and loss function is set as *categorical cross-entropy*. A callback function is used to perform actions at different stages of training such as saving the weights and reducing the learning rate. The *factor* is the value by which the learning rate is reduced. The new learning rate is the product of existing learning rate and the *factor*. The *patience* is the value by which learning rate is reduced when no improvement is observed after consecutive number of epochs. The *factor* is set as 0.3 and *patience* is set as 2.

In the retraining phase, when the remaining layers of the pre-trained model are unfrozen, we keep all the hyperparameters the same except the learning rate and the number of epochs. A very small learning rate of 0.0001 and 20 epochs are used to retrain the network. The very small learning rate will adopt the change in weights gradually and avoid overfitting.

E. Evaluation Criteria

For a fair evaluation of the transfer learning model using *EffifientNetB7*, we used different performance metrics such as *precision, recall, F-1 score, accuracy*, and *confusion matrix*. The performance metrics are governed by True-Positive (TP), True-Negative (TN), False-Positive (FP), and False-Negative (FN) values.

- True-Positive signifies that the actual value is true and the model is predicted true.
- True-Negative signifies that the actual value is false and the model is predicted as false.
- False-Positive signifies that the actual value is false and the model is predicted as true.
- False-Negative signifies that the actual value is true, and the model is predicted as false.

Accuracy is defined as the ratio between the number of accurate predictions to the total number of predictions.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP+TN+FN+FP)} \tag{2}$$

Precision is the ratio of positive prediction to the total positive prediction. For a good classifier, precision should be high.

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

The *recall* is also known as true positive rate or sensitivity. It is defined as follows:

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

F-1 score is the Harmonic mean of precision and recall.

$$\text{F1-score} = 2* \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

IV. RESULTS

The transfer learning technique developed in this research using *EffifientNetB7* model for dementia classification using MRI images is evaluated in terms of accuracy, precision, recall, F-1 score, and confusion matrix. The transfer learning model is trained to classify dementia into four categories *Mild Demented, Moderate Demented, Non-Demented*, and *Very Mild Demented*. The main goal of the research is to maximize the accuracy and minimize the loss. The model achieves 99.99% training accuracy and 97.66% validation accuracy, and training loss is 0.00001 and validation loss is 0.1203. Table III shows the precision, recall, and F-1 score for each class. Fig 3 represents the confusion matrix. It is observed from the confusion matrix that the model predicts the labels accurately despite of data imbalance. The model predicts the *Moderate Demented* labels correctly even though it consists only of a smaller number of MRI images as compared to other types of dementia used for classification. The proposed model achieved high precision, recall, and F-1 score for Moderate Demented. The accuracy along with other evaluation parameters indicates the model reliability for the classification of MRI images.

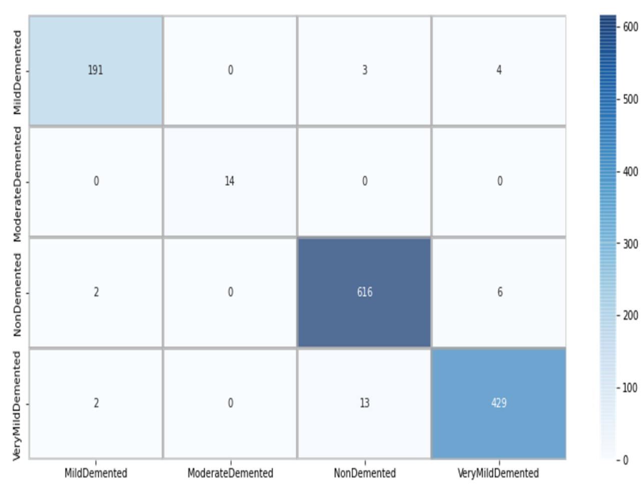

Fig. 3. Confusion Matrix for Multi Class Classification

TABLE III. CLASSWISE PRECISION, RECALL AND F-1 SCORE

Class	*Precision*	*Recall*	*F1-score*
Mild Demented	0.98	0.96	0.97
Moderate Demented	1.00	1.00	1.00
Non Demented	0.97	0.99	0.98
Moderate Demented	0.98	0.97	0.97

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TABLE IV. PERFORMANCE COMPARISON ANALYSIS OF OUR APPROACH WITH DIFFERENT MODELS

Model	*Dataset Source*	*Model Details*	*Accuracy*
Ebrahimi-Ghahnavieh et al. [4]	ADNI	A combination of transfer learning on various 2D Convolution Neural Networks (CNNs) and Long-Short memory (LSTM) networks	90.62%
Murugan et al. [5]	Alzheimer's dataset	A CNN to extract features with a tailored DEMNET model along with SMOTE to address the data imbalance	95.23%
Ullah et al. [6]	OASIS	A deep learning-based method consisting of a 6-layered Neural Network	80.25%
Basheer et al. [7]	OASIS	A modified capsule network that performs matrix decomposition using Singular Vector Decomposition (SVD) and propagates it across the network	92.39%
Raeper et al. [8]	ADNI	A correlational method such as *canonical correlation analysis (CCA)* and a discriminative method such as *linear discriminative analysis (LDA)* to devise the *shallow convolutional brain multiplex (SCBM)* and encode *region-to-region* and *network-to-network* relationships	80.95%
Rawat et al. [9]	OASIS	A stacking technique using a gradient boosting machine and artificial neural network	89%
Sethi et al. [10]	ADNI	the EfficientNet Transfer Learning model is proposed along with the adjustments of network parameters such as depth, width, and resolution using the composite coefficient	91.06%
Sadat et al. [11]	OASIS	The Transfer Learning technique with an ensemble combination of VGG19, Inception-ResNetv2, ResNet152v2, EfficientNetB5, EfficnetNetB6, and one custom CNN	96%
Zhang et al. [12]	ADNI ABIL	The end-to-end deep learning approach with the EfficientNet model. Two-stage Random RandAugment (TRRA) data augmentation and Grad-CAM++ is used for heatmap visualization	93.2% 92%
Proposed Model	**Alzheimer's dataset**	**Transfer Learning with EfficientNetB7**	**97.66%**

We compared our model with existing state-of-art methods from the literature. Table IV gives the accuracy comparison of our model with the existing models. Ref [4] [10-12] also utilized the transfer learning technique. The transfer learning technique proposed in this paper using EfficientNetB7 achieved the highest accuracy of 97.66%. It can be observed that our approach outperforms all the existing models mentioned in the literature review.

V. CONCLUSION

In this paper, we developed a stepwise process of transfer learning via fine-tuning to implement a deep convolutional neural network model for classifying dementia. Pre-trained *EffcientNetB7* model was selected to fine-tune the layers to perform multi-class classification using MRI scan images. The advantage of using EfficientNetB7 model network is that it can be adjusted in depth, width, and resolution which helps with the accurate prediction of AD. The precision, recall, and F-1 score provide insight into model performance. The fine-tuning methodology enhances the performance of the model and results in high accuracy for classifying the four classes of dementia. The proposed model achieved an overall accuracy of 97.66% for the four-class classification. Higher precision values suggest the reliability of the correct classification of the model. The proposed model can assist physicians and or automate dementia detection to accurately predict the severity of dementia using MRI scans.

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