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Ealdtl: Early Alzheimer Disease Diagnosis Using Transfer Learning

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Abstract

Early detection of moderate cognitive impairment using magnetic resonance imaging (MRI) is critical for dementia therapy. Deep learning architecture produces good results in such studies. Algorithms need a huge number of annotated datasets to train a model. We avoid this obstacle in our study by employing layer-wise transfer learning and tissue segmentation of brain images to detect Alzheimer's disease in its early stages (AD). For layer-wise transfer learning, the VGG architecture family with pre-trained weights was employed. The proposed model distinguishes between normal control (NC), early mild cognitive impairment (EMCI), late mild cognitive impairment (LMCI), and Alzheimer's disease (AD). The Alzheimer's Disease Neuroimaging Initiative (ADNI) database was accessible by 85 patients with NC, 70 patients with EMCI, 70 patients with LMCI, and 75 patients with AD in this research. Each patient's grey matter (GM) tissue was removed utilising tissue segmentation. Preprocessing data are utilised to assess the proposed technique, which obtains the highest rates of classification accuracy on AD vs. NC (98.73%) and EMCI vs. LMCI patients (83.72%), while remaining classes accuracy is more than 80%. A comparison with earlier studies revealed that the proposed model beat the state-of-the-art models in terms of testing precision.

Keywords: Transfer learning, Alzheimer’s disease, Image classification, early diagnosis.

I Introduction

Alzheimer's disease (AD) is a kind of dementia that mostly affects the elderly. It is thought to start 15 to 20 years before symptoms appear. Syndromes are caused by the removal of neurons involved in memory, cognition, and learning. Symptoms tend to grow over time and interfere with daily chores such as family event planning, walking, and skill loss [1]. Cognitive impairment is now related to Alzheimer's disease and is referred to as dementia. The brain changes that go from normal cognitive function (NC) to moderate cognitive impairment (MCI) and, finally, the last stage of Alzheimer's disease (AD). With 121,404 deaths documented in 2017, Alzheimer's disease is the sixth leading cause of death in the United States [2]. Alzheimer's disease is expected to affect 60 million people over the next 20 years. According to the World Alzheimer's Report, the number of people suffering from the disease will rise to 152 million by 2050. Long-term care for dementia patients is expected to cost roughly $290 billion in total. Researchers are attempting to detect Alzheimer's disease early in order to reduce the abnormal loss of brain neurons [3]. It also provided emotional and monetary advantages to the patient's relatives. Alzheimer's disease is diagnosed by functional magnetic resonance imaging (fMRI), magnetic resonance imaging (MRI), single-photon emission computed tomography (SPECT), positron emission tomography (PET), and computed tomography (CT) [4].

These modes are contrasted. MRI images are often available in a standard format for clinical usage. The researcher developed functional connectivity modelling for Alzheimer's disease diagnosis using sparse representation methods, graphical techniques, and partial correlation-based methodology [5]. Cortical thickness, grey matter density, ventricular enlargements, and brain atrophy are all used by researchers. White matter (WM), grey matter (GM), and cerebrospinal fluid (CSF) in brain images, on the other hand, are critical. In contrast, researchers identified a stronger link between GM atrophy and cognitive decline in MCI [6].

Mild cognitive impairment (MCI) is a stage in the evolution of Alzheimer's disease dementia (AD). The six-year MCI to AD conversion rate investigated is 80%. Identifying MCI patients who may be further classified into two stages, such as early mild cognitive impairment (EMCI) and late mild cognitive impairment (LMCI), is a continuing problem for AD-related research (LMCI). The early detection of NC and MCI provides clinicians with crucial information for treatment and decision making. It was also beneficial to save costs while providing long-term care [7]. The support vector machine has shown early success in AD classification (SVM). Deep learning-based technologies such as sparse autoencoder and convolutional neural network (CNN) have recently provided optimal classification solutions in a range of fields such as computer vision, voice identification, and natural language processing [8]. Deep learning algorithms, on the other hand, have limitations when training a model on scratch data since the model needs a significant number of medical photographs with annotations [9]. The availability of a large amount of labelled data complicates a solution to this issue, which may be avoided by classifying medical scans utilising transfer learning techniques [10].

In this study, we look at a transfer learning framework based on the most sophisticated CNN architecture for categorising Alzheimer's disease images into four categories: NC, EMCI, LMCI, and AD. The fundamental goal of transfer learning is to transfer features from nature photography to Alzheimer's images and suggest a novel strategy for categorising AD that may help novice physicians establish objective judgements and make correct diagnoses. Our main goal is to get cutting-edge results with a smaller dataset while avoiding overfitting [11]. To achieve this aim, we applied the data augmentation strategy, which enables us to avoid overfitting and get the desired results [12]. We rebuild the final fully connected and classifier layers using layer-wise transfer learning on a deep CNN architecture. The proposed model is divided into two groups, with some layers being gradually trained while the others are frozen. Using transfer learning in this way, we estimate the best results for binary categories such as NC, EMCI, LMCI, and AD Overcoming the problem of inadequate training data, measuring the robustness of transfer learning, and avoiding overfitting were key challenges in previous studies [13-15].

Ii Background Study

Acharya, H. et al. [1] This study looked at possible learning techniques for predicting the stage of Alzheimer's disease. Proposed model work for data testing at the Kaggle warehouse, in which the MRI image was classified as demented (VMD), demented (MD), moderate AD (MAD), and demented (ND) to pick the model's highest accuracy as 95.70%. The analysis looked at how lowering congestion and changing the model affected the performance of these author application. To do this, the researchers employed familiarity and then compared recommended strategies to the three existing advanced networks CNN, VGG16, and RESNET50; the new model outperformed the others significantly.

Cilia, N. et al. [2] As a preliminary observation, the author observe that the nonhandcrafted characteristics seem to be more promising than the handmade ones, with the Random Forest classifier obtaining the best accuracy. The results obtained with handmade features were, on average, poorer to those obtained with non-handcrafted features, according to the comparison table (see V). Indeed, for every task and classification scheme, there was a CNN model whose properties allow us to get better results than with handcrafted models.

Ebrahimi, A. et al. [7] The author successfully moved data from the ImageNet dataset to the ADNI dataset. ADNI has hundreds of MRI scans from Alzheimer's disease patients, whereas ImageNet includes millions of nature photographs. The framework of 2D ResNet-18 was extended to properly accomplish this transition. ResNet was a well-known and capable CNN that performed well on the ImageNet dataset. 3D filters were applied to 2D filters to turn the basic 2D ResNet-18 model into a 3D model. Any extra layers received the updated filters. The learnable parameters were transferred from a 2D ResNet-18 model pre-trained on ImageNet to a 3D ResNet-18 model by replicating (copying twice) the 2D filters across the third dimension.

Gonzalez, H. et al. [8] This study's proposed subject semi-independent training for EEG-based emotion recognition involves rating selection, subject selection, and two rounds of unsupervised learning. Unsupervised learning was used first to cluster stimuli for data selection, followed by clustering of similar EEG responses.

Zaabi, M., et al. [15] The author identified AD using two separate techniques: CNN and Transfer Learning. The proposed method was divided into two stages (extraction of region of interest and classification). The first step divides the image into blocks to identify the region of the brain containing the hippocampus. CNN and Transfer Learning algorithms were examined in the second stage. The results show that image classification using Transfer Learning produces better accurate results than CNN. High classification rates have been attained utilising the two relevant techniques, outperforming state-of-the-art algorithms employing the same methodology.

Iii Material And Methods

3.1 Dataset preprocessing operations

In this study, a thorough preparation strategy was used to the T1-weighted images from the ADNI database. All data was prepared using the neuroimaging informatics technology initiative (NIFTI) format and statistical parameter mapping. Since grey matter (GM) segmentation in the brain has the potential to be useful in revealing early abnormalities in sporadic Alzheimer's disease, this is where our study is primarily focused. Data from the brain's white matter (WM), grey matter (GM), and cerebrospinal fluid (CSF) are segmented during preprocessing. We apply the ICBM space template to all datasets for a fine regularisation, with the bias regularisation set to extremely light (0.0001), the bias full width at half maximum (FWHM) set to 60mm cuto_. We used the MNI reference space to achieve the desired normalisation. The voxel size in this study image is (2 2 2), and a Gaussian kernel smooths the pictures. The segmentation results in a 256-by-240-pixel sample size. The proposed model requires all images to be reduced in size to 224 by 224 before being used for training and testing.

3.2 Convolutional neural networks and transfer learning

The architecture of convolutional neural networks (CNNs) is hierarchical and clustered. A convolution layer, a pooling layer, many sequential completely connected layers, and a softmax layer round out these multilayer architectures. CNNs typically use convolution layers to extract neighbourhood information from data at the input. These basic features are extracted and then used in pattern recognition tasks by way of intermediate layers to build more complex features. Over-weighted connections connect each artificial neuron to the layer above it. CNN's method might help widen and deepen photos with complex compositions. The pooling layer is an important CNN parameter for minimising computation time, and it is often implemented using nonlinear functions in the form of max and min pooling. By lowering the need for computation and parameters, the pooling layer provides an additional benefit in the fight against model overfitting. Max-pooling layers that include an activation function are used in a variety of studies. We used the RELU activation function, which converts negative feature values to zero and speeds up CNN convergence, in this study.

The current CNN-based model, consisting of many different layers and optimization algorithms, was developed by hand by researchers. Throughout the ImageNet dataset, we experimented with different training parameters for our models, including as learning rate, batch size, and weight decay. CNN's lower layers may give broad feature extraction capabilities, while the higher levels can provide more specific information vital to the classification task. Using transfer learning to classify precancerous diseases, cardiac imaging, and lung diseases has shown promising results. Using convolutional neural networks and transfer learning, the scientist developed a system to categorise medical images. These results demonstrate that transfer learning produced good accuracy for classification in medical domains and achieved maximum results on AD classification with a lower quantity of information.

3.3 Proposed transfer learning model

As a result of CNN's encouraging results, several well-established models have been developed by academics to tackle binary and multi-class classification problems. Improvements in object identification have been made thanks in large part to the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). The biggest challenge is figuring out how to organise the many different items. For this task, we analyse the winning object classification schemes from the competition. In this study, we extended the VGG family architecture to create a transfer learning model. VGG-19 was used because it provided better results from computer-aided diagnostics. Specifically, the VGG-19 network consists of 16 convolutional layers, 5 max-pooling layers with stride 2, 3 fully-connected layers, and a softmax layer as its final layer. We make changes to the last two categorization levels and the final fully connected layer to address our problem. These 1000 and 512 layers are linked and use binary categorization. Second, we "freeze" the convolutional layers by using transfer learning. It is common practise to employ just the fully connected layer that was learnt from the training data for the whole transfer learning process, leaving the convolutional layers unchanged. Our suggested strategy, on the other hand, splits the model in half and progressively freezes the layer blocks while training on augmented and unaugmented datasets.

IV RESULTS AND DISCUSSION

The suggested model was built using Python programming using version 3.8. The experimental results are shown in this chapter.

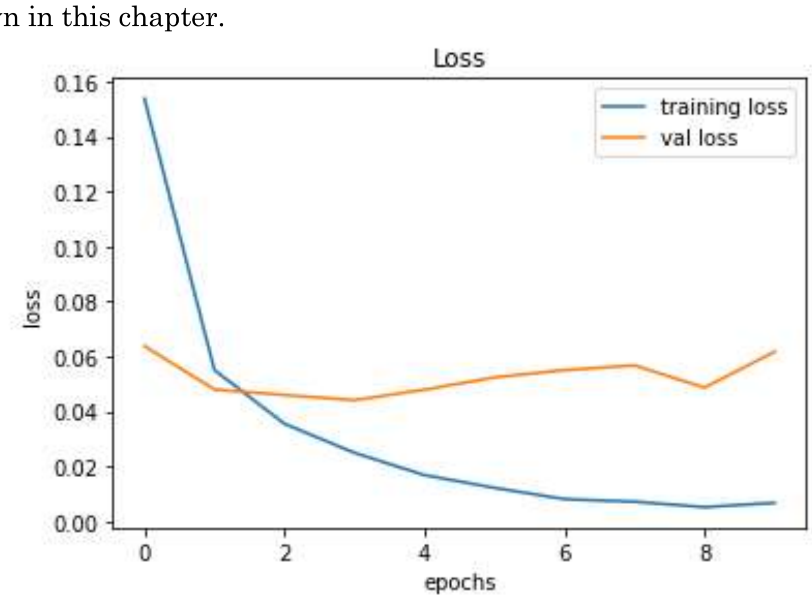

Figure 1: Training and testing loss

As illustrated in Figure 1, the suggested model is trained using loss values. The X-axis represents the Epoch, and the Y-axis represents the lost value.

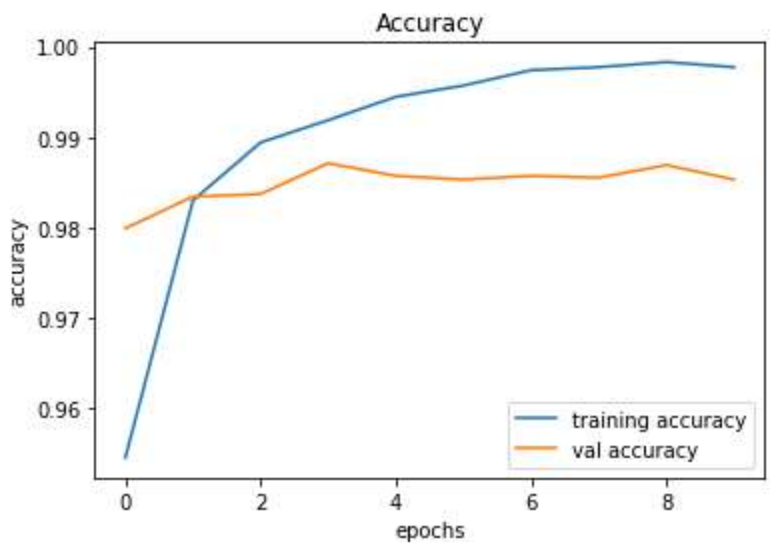

Fig 2: Training and testing Accuracy.

The CNN-ResNet has been trained using 2 Training Epochs, and Figure 7 displays the testing accuracy. The Y-axis reflects the accuracy, while the X-axis represents the Epoch number.

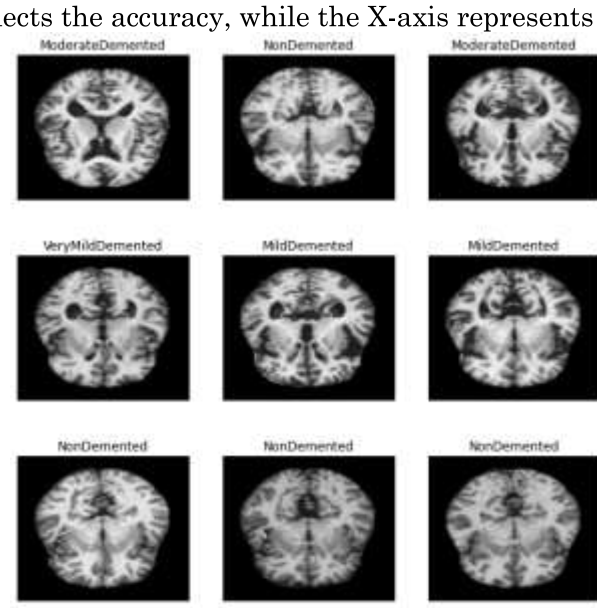

Figure 3: CNN Image Classification

The proposed model achieves 98% accuracy. And the CNN has classified the MRI image as multi-class classification, as shown in figure 3.

V Conclusion

This study reported the identification of Alzheimer's disease (AD) using a transfer learning model that assists clinicians in the diagnosing process. This paper presents an EALDTL framework for the early identification of Alzheimer's disease. Vascular dilatation and shrinking of the brain Image segmentation is used in the detection of bigger vascular/tumor masses. The degree of enlargement reflects whether a patient is healthy, in the initial stage of Alzheimer's disease, in the second stage, or has considerable cognitive impairment. Another important element in determining Alzheimer's disease is brain shrinkage. This research offered a methodology for detecting Alzheimer's disease early. CNN was used to remove noise from the MRI image, and the image was segmented using watershed segmentation. Resnet50 with Alexnet architecture was used for training. Transfer learning was used to categorise the data. According to the findings, utilising improves classification precision. This approach solves the issue of early detection without causing brain injury, and it has a 99% success rate. This will aid in the advancement of medical imaging research; the long-term goal of this effort is to merge mobile applications into authentic MRI images.

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