Deep Learning Type Convolution Neural Network Architecture for Multiclass Classification of Alzheimer's Disease

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Abstract: Alzheimer's disease (AD) is one of the common medical issues that the world is facing today. This disease has a high prevalence of memory loss and cognitive decline primarily in the elderly. At present, there is no specific treatment for this disease, but it is thought that identification of it at an early stage can help to manage it in a better way. Several studies used machine learning (ML) approaches for AD diagnosis and classification. In this study, we considered the Open Access Series of Imaging Studies-3 (OASIS-3) dataset with 2,168 Magnetic Resonance Imaging (MRI) images of patients with very mild to different stages of cognitive decline. We applied deep learning-based convolution neural networks (CNN) which are well-known approaches for diagnosis-based studies. The model training was done by 70% of images and applied 10-fold cross-validation to validate the model. The developed architecture model has successfully classified the different stages of dementia images and achieved 83.3% accuracy which is higher than other traditional classification techniques like support vectors and logistic regression.

1 INTRODUCTION

Alzheimer's Disease (AD) is the most well-known and largely diffused neurodegenerative disorder occurring in the elderly. AD negatively affects patients' everyday lives, causing an advanced decline of cognitive capabilities such as memory, language, behaviour, and critical thinking (Alzheimer's Disease International (ADI) 2010). Changes in cognitive impairment of AD patients start slowly and evolve rapidly over the long run.

Similar to other body parts, brain can change as people get older. Some people lost thinking and incidental issues with recollecting certain things. Excessive cognitive decline, and other significant changes in the manner in which brain function is impaired (Jaussent et al. 2012). The first symptoms of AD are trouble recalling recently learned data because Alzheimer's progressions regularly start in the brain areas involved in learning and memory. As Alzheimer's progresses progressively severe symptoms like confusion, mood changes, disorientation, unwarranted doubts about family and companions, and trouble talking appear. Individuals with cognitive decline or other potential indications [1]of AD may think that it's difficult to remember they have an issue.

AD is a type of dementia with several implications on the cognitive domain, affecting primarily thinking and memory. Specialists and different parental figures screen the movement of AD in patients by assessing the level of decrease in the patients' psychological capacities that are often classified into three stages: very mild (normal cognitive), mild cognitive impairment (MCI), and demented (Gaugler et al. 2016). Figure 1 presents the magnetic resonance image (MRI) images of different AD conditions. Although the MCI and dementia patients both are experiencing a reduction of cognitive abilities, dementia patients would suffer from more pronounced difficulties with thinking or hampered judgment.

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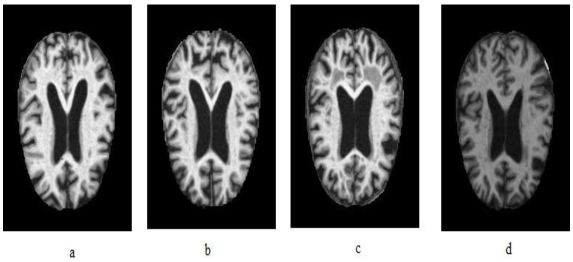

Figure 1: AD presented by MRI images (a) mild dementia; (b) moderate demented; (c) nondemented; and (d) very mild demented.

In clinical practice, the capacity to accurately forecast the patient diagnosis can help by adding appropriate medical decisions on treatment approaches. Recently, machine learning (ML) algorithms are largely applying to forecast and predict diseases and helping in quick decision making (Battineni, Sagaro, et al., 2020). Pattern-related approaches like logistic regression (Johnson et al., 2014), support vector machines (Battineni, Chintalapudi, en Amenta 2019), and linear discriminant analysis (Rathore et al. 2017) are giving promising results in the prediction of AD development and early AD detection.

Deep learning models were used unlabeled data during preprocessing. These are well suited for imbalanced datasets and achieve a knowledge base (Mittal et al. 2019). At present these are largely involved in all other problems that are not able to be addressed by traditional artificial intelligence (AI) techniques. Neural networks are the latest deep learning algorithms that have discovered the functionality of different situations. Convolutional neural networks (CNN) are characterized contributions to profits through a complex composition of layers that presents building blocks including nonlinear functions and transformations.

Medical experts feel that deep learning could be a promising solution in AD identification and stage detection (Khan et al., 2020). For instance, (Basheera en Sai Ram, 2019) applied CNN modeling for AD diagnosis based on T2 weighted magnetic resonance imaging (MRI) and achieved 90.47% accuracy. A Siamese CNN can also help to categorize the AD and studies reported 99.05% of accuracy (Mehmood et al. 2020). It is also reported that AD prediction from MCI using the CNN model reported 79.9% of accuracy(Lin et al., 2018). Therefore, it is assumed that an effective and comprehensive deep learning model can help to identify early AD prediction and ultimately provide timely treatment to the suffered patients. In this work, we proposed convolutional neural networks (CNN) model of deep learning type for detection of early-stage AD and successfully classify the MRI images on four different dementia stages presented in Figure 2.

Experiments were conducted on longitudinal neuroimages of the OASIS-3 database that include MR scans of T1-weighted, T2 weighted, ASL, SWI, DTI sequences, FLAIR, time of flight, and resting-state BOLD. The rest of the paper is structured according to the following outline: Section 2 presents the dataset and proposed model architecture; section 3 presents the experimental results, and section 4 makes a discussion which is followed by the conclusion in section 5.

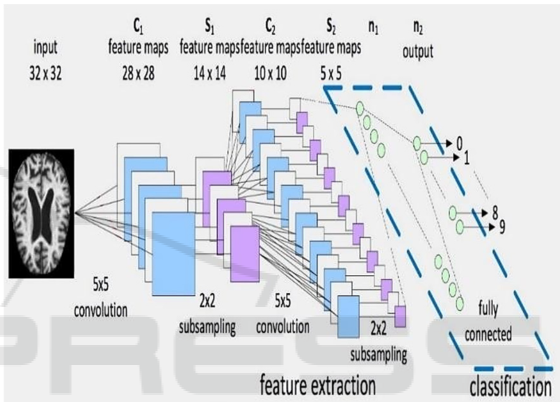

Figure 2: Brain image classification with the CNN model framework.

2 METHODS

2.1 Dataset

The Open Access Series of Imaging Studies (OASIS) contains MR scanning information that is openly accessible to scientific communities. They released OASIS-1 (cross-sectional) and OASIS-2 (longitudinal) MRI datasets among different subjects and these datasets are widely used in many studies (Sweeney et al. 2013; Palumbo et al. 2019). OASIS-3 is the extension of previous datasets. It includes 1,098 patients aging from 42 to 95 years. Among participants, 609 are associated with normal cognitive decline (very mild), and 489 were associated with different cognitive decline stages. OASIS-3 dataset incorporated both functional and structural features of more than 2,000 MRI images. The dataset outcome of four categories of MR images has presented in Figure 3.

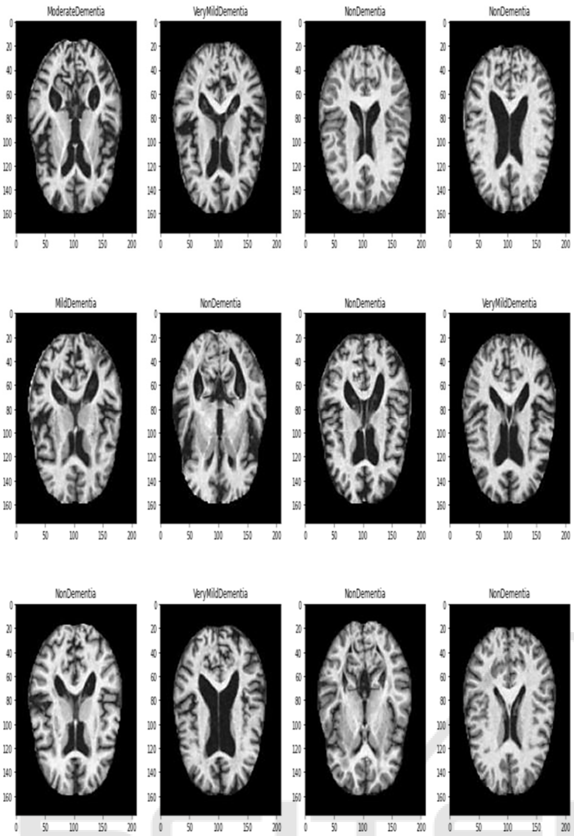

Figure 3: Dataset outcome of different dementia stages (3*4 image matrix).

2.2 CNN Model Architecture

A convolutional neural network (ConvNet) is deep learning type algorithms that take images as input, assign features based on their importance (biases and learnable weights) to different image objects, and also be able to separate one from the other (Krizhevsky, Sutskever, en Hinton 2017). When compared with other classification models, ConvNet possesses low complex pre-processing steps. In CNN, each input image is gone through sequence convolution layers namely pooling layers, filtering layers (kernels), and fully connected layers (FCs).

To make the proposed model easier for understanding, we created a dense layer block and convolution block. The architecture of the CNN model is inspired by the article (Pan et al. 2020). We built the CNN model by using five convolutional slabs covered with convolution layers, feature engineering, max pooling, and classification. We have used cross-entropy as a loss function and Adam as an optimizer. SoftMax has been used to classify the multiclass AD stages since it is associated with a mutually exclusive relationship. The feature representation (f_k) works as an input to the SoftMax layer and interprets output brain stages. A probability score P (k) for each class as defined as

$P_k=\frac{\exp(fk)}{\sum_{k=1}^{k} exp\ (fk)}$;where fi feature representation, and Cross entropy loss function as

(L)= $\sum_{k=1}^{k} tk.\log(pk)$; where t_k ground truth of MRimage then $\frac{\partial L}{\partial fk}=P_k-t_k$.

2.3 Experimental Setup

Figure 4 presents the most relevant procedures followed to construct the feature data of brain images and extraction of AD images developed in this paper. After pre-processing steps, the given image dataset has been divided into training and validation files with standard (80:20) division.

The procedures indicated red line are MR images that fed to the CNN model for training purposes. The model extracts the input image features of trained images under present parameters and supplies them to the SoftMax classifier for testing. The SoftMax function calculates the loss and model accuracy. For avoiding high loss, network parameters are adjusted by the back-propagation algorithm. After applying several iterations (epochs) the better-trained parameters have been achieved. The model visualization metrics like loss and receiver operating characteristic area under the curve (ROC AUC) have been taken as the performance parameter for AD classification since it has been considered one of the key metrics in multi-image classification techniques. The experimental setup and AD detection and classification have been done through TensorFlow and python language.

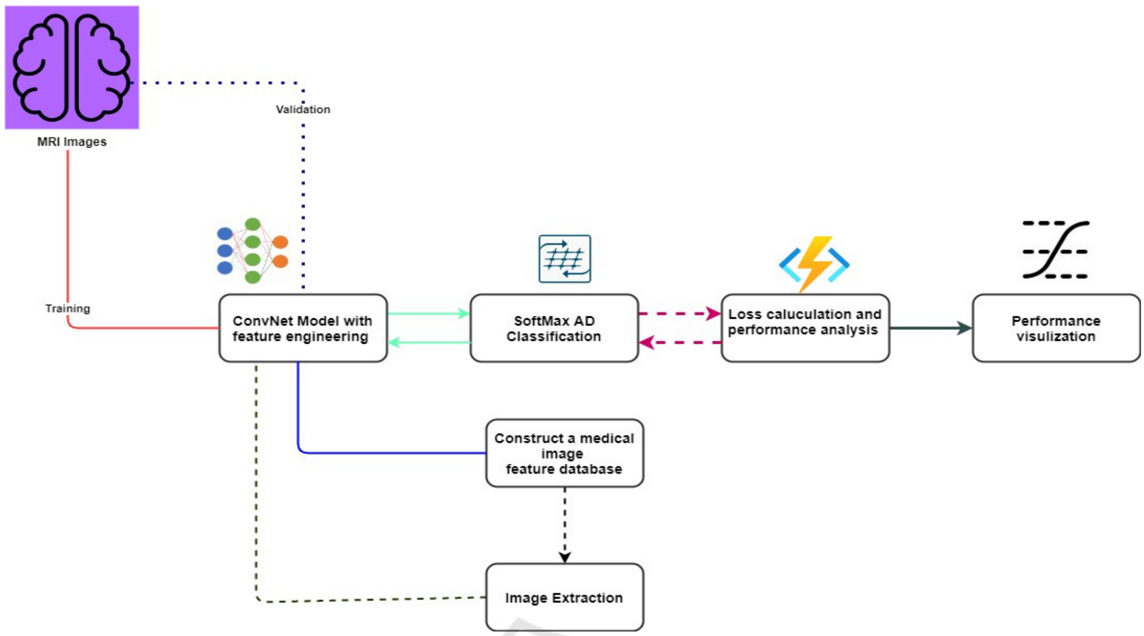

Figure 4: Experimental setup of the work.

3 RESULTS

To do efficient training on our CNN model, a back-propagation algorithm is set to adjust the rate of learning and stop the model automatically once it reaches maximum accuracy. Since the learning rate is one of the hyperparameters that decides model accuracy and time to process the model. OASIS-3 dataset consisted of 2168 independent MRI scanners. Among the given images, 1,734 are used for training and 434 were used for validation purposes. Because of the large image dataset, 10-fold cross-validation has been used and we have used each fold 70% as training, 10% as validation, and 20% images are used testing. The distribution of the dataset is presented in Table 1.

Table 1: Total image distribution.

Total Images: 2168	
Type	***Percentage***
Trained images	1517 (70%)
Testing images	434 (20%)
Validation images	217 (10%)

The model-fitting has to be done on a sample of 100 epochs and to prevent model overfitting we stop the model early at the 80th iteration. The model took a run time of 138 min to process the trained images. Figure 5 presents a graphical representation of ROC. AUC and loss metrics after each iteration on both training and validation image data.

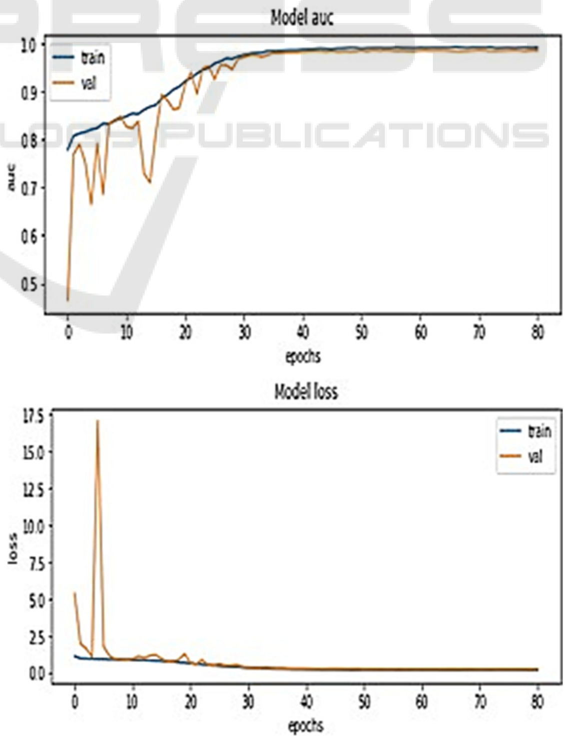

Figure 5: Model AUC and loss metric outcomes.

Though the model evaluation has been done on the validation dataset, we also perform the experiments on the testing dataset. The testing dataset model AUC curve outcome has presented in Figure 6 and the model achieved a ROC of 83.3% which is considered as an optimal classifier for AD image detection and this value is significantly higher than traditional ML approaches (Battineni, Chintalapudi, en Amenta 2019; A. Khan en Zubair 2020).

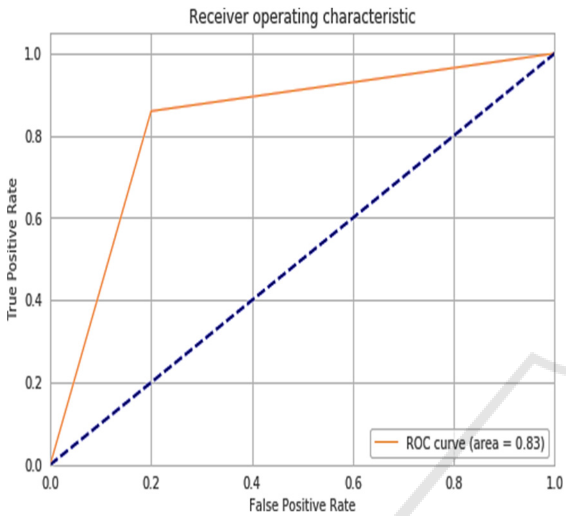

Figure 6: The ROC curve of test data.

4 DISCUSSION

In this work, we presented a novel deep learning type CNN model for the classification of AD subjects. As mentioned above, AD is the most common adult-onset dementia and contributes about 60-70% of worldwide dementia cases (A. Khan en Zubair 2020). Unfortunately, there is no proper medication or cure for AD, and advancements in AD cure have been getting slow. Screening among people of AD risk given electronic health records (EHR) in preclinical stages may prompt early identification of AD pathology and suggest better approaches for complying with the AD beginning. Current biomarkers of AD have required specimen collection (like serum or liquid), MRI image data, or more sophisticated markers that at the present can be identified just in highly specialized centres (Mantzavinos en Alexiou 2017; Hadjichrysanthou et al. 2020).

On the other hand, the EHRs for example medical records in clinical settings, or administrative health information don't require extra time or effort for data collection. Likewise, with the coming of digitalization, the measures of such information have drastically increased (Shao et al. 2019). Since it is omnipresent, enormous, and cost-effective, the digitized medical database might be a significant asset for testing different AD predictive models. Nonetheless, despite its enormous possible value, somehow thought about the degrees to which the enormous scope of EHR data can help in risk of AD prediction (Shao et al. 2019; Mayer et al. 2015). The possible prediction of future AD progression is incredibly significant in clinical practice also, in healthcare research. Advanced neuroimaging techniques like MRI, positron emission tomography (PET) is developed and presented to identify AD-related molecular and structural biomarkers (Hadjichrysanthou et al. 2020).

Computer scientists are recommending applying sophisticated computing techniques like machine learning and deep learning. It is reported that 99.1% of accuracy has been achieved through the application of ensemble learning models for late-life AD detection among 150 patients (Battineni, Chintalapudi, et al. 2020). AD prediction among 123 subjects with Pre-MCI and MCI was done by clinically transmittable ML algorithms and results reported the whole sample accuracy of 96.2% (Grassi et al. 2018). However, most of the outcomes proposed by these algorithms are based on demographic magnetic resonance image (MRI) information. Because of this, researchers believed that deep learning algorithms are the best approaches if brain images were included (Choi en Jin 2018). Most of the works associated with Machine learning in the early prediction of AD occurred with high success. For instance, it is reported that 94.1% of accuracy by 3D convolutional neural networks (CNN) (Esmaeilzadeh et al. 2018).

This work presented a deep CNN with 10-fold cross-validation and achieved more than 80% accuracy. While applying computing methods for diagnosis, a small portion of datasets are presented. Therefore, our model maintained a random image selection of train, test, and validation datasets. The proposed model produced promising results in AD image classification. The most notable outcome for this study is the progressions among predictiveness of AD diseases.

5 CONCLUSIONS

An autonomous AD detection classifier based deep ConvNet framework is presented. We adopted the latest release of the OASIS-3 dataset that contains different categories of AD datasets. For training, more than 1,500 images model took a bit longer process than expected, but it is faster than mankind process. Deep ConvNets do not need any handcrafted feature selection approach because of having autonomous feature tuning. The main limitation of the study is to adopt only a single classifier for the brain MRI data classification and there are other possibilities to do better improvements in the proposed model architecture. Although attained results of higher 80% accuracy while compared over traditional ML classifiers, many advancements are proposed to enhance the model quality.

CONFLICTS OF INTEREST

No author has produced any conflicts of interest.

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