Alzheimer's Disease Classification Using MRI Images and Convolutional Neural Networks

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***Abstract*—This study presents a method for classifying Alzheimer's disease using MRI images and Convolutional Neural Networks (CNNs). Alzheimer's disease is a significant neurodegenerative disorder that requires early diagnosis in order to improve patients quality of life. Firstly, an overview of relevant researches is presented underlying the different aims, approaches and results. Then, the proposed methodology is thoroughly described followed by the conducted experiments and the results.The proposed CNN architecture effectively distinguishes between healthy individuals and those with dementia by analyzing RGB brain MRI scans. The network, consisting of multiple convolutional and fully connected layers, was trained and tested on relatively large dataset consisted of 6.411 MRI images. The model achieved an accuracy of 75.5%, demonstrating its potential in early diagnosis of Alzheimer's disease.**

I. INTRODUCTION

Alzheimer's disease is a progressive, unremitting, neurodegenerative disorder that affects wide areas of the cerebral cortex and hippocampus[1] resulting in memory loss, difficulties on completing daily tasks, increased anxiety while in advanced stages it can cause hallucinations, delusions, paranoia, inability to communicate and problems recognizing family and friends [2]. It is estimated that 6.7 million Americans age 65 and older are living with Alzheimer's dementia today, making it the sixth-leading cause of death in the United States[3]. While the first Alzheimer's disease incident was described in 1906 by Alois Alzheimer, still today, over a century later, the early diagnosis and treatment of the disease are major challenges. According to [4], receiving the appropriate treatment on early stages of the disease can significantly improve the patients quality of life, increase the life expectancy and also decrease the rate of institutionalisation by 20%, facts that indicate the importance of an early diagnosis.

Convolutional Neural Networks(CNN) are powerful neural networks that their applications include image classification, object detection, facial recognition, natural language processing and medical imaging. Researchers have proposed CNN in order to classify the language of origin on text that appears on images[5], identify the writer of a text[6], recommend relevant movies to users [7] and recommend relevant products on e-commerce site users[8]. Also, they have been used on predicting heart diseases [9], skin diseases [10] and many other clinical applications. Overall, CNN are widely used neural networks that can provide solutions on a variety of different domains.

The present work proposes a solution on classifying patients with dementia by using MRI scans and convolutional neural networks. The neural network consists of several convolutional layers followed by fully connected layers. The input of the model is an RGB brain MRI scan and the output is whether the patient has signs of dementia or not. The proposed architecture is the best performing one after experimenting with different configurations and layers.

II. RELATED WORK

There is a plethora of related work done by researchers that attempt to predict Alzheimer's disease in early stages, as a successful approach could improve the life of millions of people each year. All these approaches differ on the data used, the number of patients, the architecture and the technologies. To evaluate the literature, we will focus on the works that use artificial intelligence to solve the problem, and split them into two categories, the attempts that use machine learning and the attempts that use deep learning. The main difference between the two is that machine learning methods mainly use tabular data to classify the patients while in deep learning the input data could vary from tabular data, images, videos or a combination of them.

A. Classification using Machine Learning techniques

[11] Is an approach that uses demographic data like age and education along with longitudinal MRI data as input in machine learning algorithms. While the results seem promising, the number of patients were relatively small and it is not stated if the patients were sampled from different areas and countries or if they were all part of the same community which indicates forms of bias. [12] Is a work that uses the oasis dataset [13] and attempts to predict Alzheimer's disease by applying machine learning algorithms on tabular data. This approach also has a relatively small dataset size, but the main issue is that the proposed models seem to be overfitting as they achieved 100% accuracy on the training data and around 80% on the test data.A similar approach is [14], where the researchers attempted to identify Alzheimer's disease by collecting demographic and MRI data and then using machine learning algorithms, like Random Forest Classifier, for the

classification. While again the final results were promising, all the algorithms had very low specificity rates, less than 35%, when classifying patients that were cognitive normal(CN) and patients with early mild cognitive impairment(EMCI), which is a very early stage of dementia and Alzheimer's disease[15], so consequently the models weren't very efficient on identifying the disease on early stages.

B. Classification using Deep Learning techniques

There are plenty of researches that use deep learning techniques to achieve an accurate prediction of Alzheimer's disease, with some of them using simple fully connected neural networks, some of them using custom CNN while others use pre-trained networks. [16] is an example of a successful identification of Alzheimer's disease using neural networks. The network used is a variation of LeNet-5[17], that achieved 96.85% accuracy on classifying healthy people and people with Alzheimer's disease. While the results indicate that the proposed method was very successful, its is not clearly stated if the patients that the network was tested on were on early or very progressed stages of the disease. [18]Attempts to solve the problem by using transfer learning, where pre-trained convolutional networks are used to construct the convolutional layers of the network and the training data are used to train only the fully connected layers. The pre-trained networks used were VGG16[19] and Inception V4[20] and the proposed method achieved 96.25% on classifying people with Alzheimer's disease.

III. Data

The data used for the experiments are MRI brain scans of people with and without dementia. The source of the dataset is a Kaggle repository [21]. The original dataset is split into train and test subsets and four categories {Mild Demented, Moderate Demented, Non Demented, Very Mild Demented}, with a total of 5.121 train and 1.279 test examples.The data are very unbalanced as the Moderate Demented class has only 52 examples in the training data. Probably, the images have undergone some processing because all of them have the same dimensions(208x176) and the same orientation.

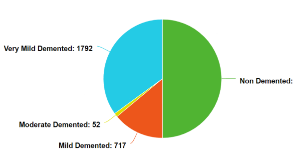

Fig. 1. Distribution of training subset

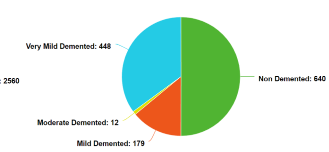

Fig. 2. Distribution of test subset

A. Data processing

Before training the neural network, data processing is necessary to make sure that the used dataset is fully aligned with the purpose of the work. Because the proposed method aims to classify demented and non-demented people, the examples of the 3 classes{ Mild Demented, Moderate Demented, Very Mild Demented } were merged into one class named 'Demented'. In order to validate the performance of the neural network, a validation subset was created that has a size of (0,2*size of train set) or 1024 examples. Also, before feeding them into the model the images were resized to (128x128).

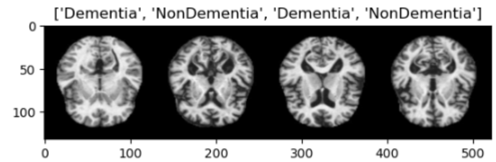

Fig. 3. A sample of the data

IV. Methodology

A. Convolutional Networks

The proposed architecture for the classification problem is a Convolutional Neural Network that consists of 5 convolutional layers followed by 3 fully connected layers that receives as input an (3x128x128) RGB image.

Usually, a convolution network consists of convolution layers, pooling layers and activation functions. The convolution layer receives as input an image that has been transformed into an tensor, usually a 2D image with dimensions (3 x height x width), and by sliding across the image a second smaller array called kernel it constructs a feature map that is very useful for feature extraction. To construct the feature map, the values of the tensor and the values of the kernel are multiplied and then summed resulting in the values of the feature map. The size of the kernel is decided by the designer of the network while its values are set by the optimisation method. This whole procedure helps on reducing the size of the images without losing much information while at the same time, different features are extracted from different areas of the image.

Pooling is a method that down samples the feature maps in order to reduce their size while making them more robust to changes in the position of the feature in the image. The pooling layer gets as input the output of the convolutional layer, a feature map, and by sliding across it a small kernel it constructs a smaller feature map by selecting either the max value of the area that the kernel lies every moment, Max Pooling, or the average value of that area, Average Pooling. Average and Max pooling are two of the most common types of pooling, but other more complex methods like tree[22] and stochastic[23] pooling are also widely used.

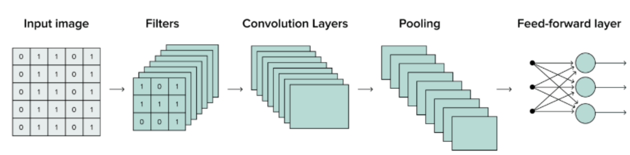

Fig. 4. Visualisation of a simple CNN [24]

Activation functions are specific mathematical functions that add non-linearity to the network. They are very useful because without them the output of each layer of the network would be a linear function, making it impossible for the network to perform complex tasks. Activation functions are usually positioned between the convolution and pooling layer in convolutional networks and after every layer in fully connected layers. One of the most common activation functions, and the one used for the proposed architecture, is Rectified Linear Unit(ReLU) function. ReLU function takes as input a number(x) and outputs zero if x is negative or x if x is positive. ReLU formula is:

$$f(x) = max(0, x) = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

Other widely used activation functions are Sigmoid, Tanh, SoftMax and ReLU variations.

B. Proposed Architecture

As mentioned above, the proposed architecture consists of 5 convolution layers and 5 MaxPooling layers, using ReLU activation function after each layer, followed by 3 fully connected layers with ReLU activation function after each layer and Sigmoid activation function after the last layer because its a binary classification problem. The first convolution layer has 32 output channels, the second 64, the third 128, the fourth 256, the fifth 512 with a kernel size of (3x3). The kernel size for the pooling layer was set to (2x2). Figures 5 and 6 visualise the architecture of the network

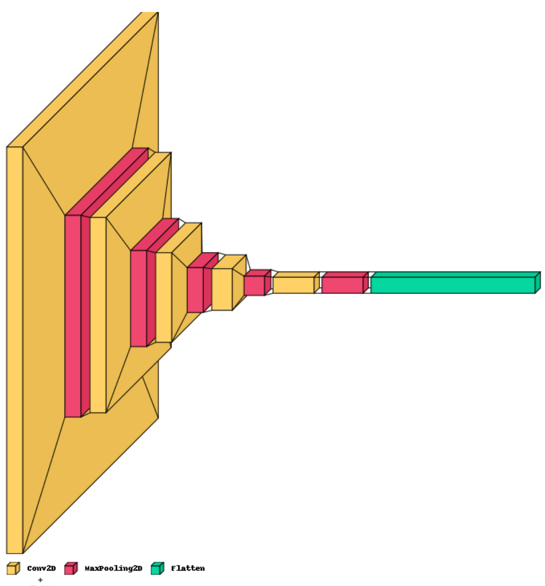

Fig. 5. A visualisation of the convolutional layers

C. Training

In order to train a neural network, a loss function and an optimiser are required. The loss function calculates the error rate of the network between the prediction and the ground truth. The loss function basically indicates how well

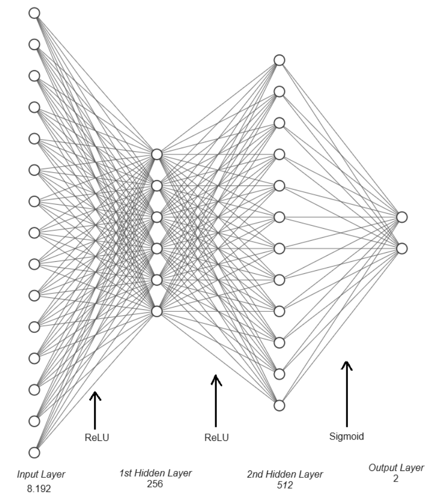

Fig. 6. A visualisation of the fully connected layers

the network is performing, with a high loss indicating that the predictions are far from the true value and a low loss indicating that the predictions are close to the actual value. The optimizer is a method that changes the parameters of the network(e.g weights, bias) in order to reduce the value of the loss. On each training session with a batch of the dataset, the loss of the network is calculated and the optimizer adjusts the parameters accordingly in order to reduce the loss.There is a plethora of different loss functions and optimizer algorithms, but for the proposed network the selected loss functions is Cross Entropy Loss and the selected optimiser is Adam with 0.0001 learning rate. The training set was split to batches, with each batch containing 64 images, while the training was conducted in 50 epochs.

V. MODEL EVALUATION AND RESULTS

A. Evaluation Metrics

Section 'IV' describes in detail the proposed architecture and the training process of the neural network. In order to conclude whether the proposed methodology achieves the goals of the study, the performance of the model on unseen data must be evaluated using appropriate metrics. The unseen data used for the evaluation is the test subset that was described in section 'III'. The final trained network was given as input the test subset and made its predictions. The metrics used to evaluate the quality of the predictions, are the accuracy of the model, the confusion matrix, the sensitivity and the specificity.

Confusion matrix is a (3x3) array that is widely used to evaluate models performance. It represents a summarisation of the predictions made by the classifier and the actual class of the examples.'Table I' is an example of a binary classification confusion matrix.

Predicted

Actual	**1**	**0**
1	True Positive	False Negative
0	False Positive	True Negative

TABLE I
EXAMPLE OF CONFUSION MATRIX

- True positive(TP) is the number of examples that are ‘class 1’ and were predicted as ‘class 1’.
- False Negative(FN) is the number of examples that are ‘class 1’ but were wrongly predicted as ‘class 0’.
- False Positive(FP) is the number of examples that are ‘class 0’ but were wrongly predicted as ‘class 1’
- True Negative(TN) is the number of examples that are ‘class 0’ and were predicted as ‘class 0’

Given the above, we define:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

$$Sensitivity = \frac{TP}{TP + FN}$$

$$Specificity = \frac{TN}{TN + FP}$$

By matching ‘Table I’ to our example, ‘1’ is ‘Dementia’ and ‘0’ is ‘No Dementia’. Accuracy indicates how good is the overall performance of the model, sensitivity indicates how well the model performs on identifying dementia and specificity indicates the performance of the model on classifying non demented people.

B. Results

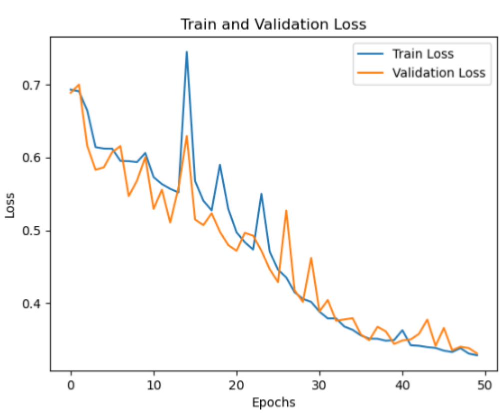

Fig. 7. Train and Validation Loss During Training

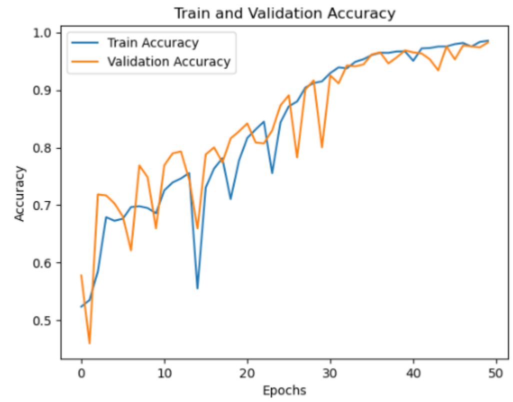

Fig. 8. Train and Validation Accuracy During Training

Figures 7 and 8 visualise the fluctuation of accuracy and loss for the training data during the 50 epochs of the training process. The loss for both training and test subsets is less than 10% after 50 epochs, while the accuracy peaks at around 98%. After the 25 epochs, the validation subset has slighter less accuracy and slightly greater loss than the test subset. Overall, the model seems to be having a good performance during the training process, as its slightly improved after every epoch and peaks at acceptable levels.

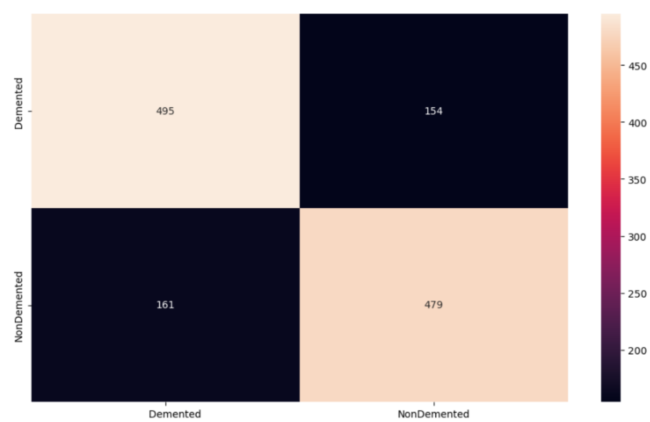

Fig. 9. Confusion Matrix for test data

Metrics	**CNN**
Accuracy	75.5%
Sensitivity	76.2%
Specificity	74.8%

TABLE II
PERFORMANCE OF CNN

Figure 9 is the confusion matrix of the model on the test data. The overall accuracy of the model is 75.5%, with sensitivity of 76.2% and specificity of 74.8%. The network performs slightly better on identifying demented patients and correctly classifies 3/4 people.

While at first glance it might seem that the performance of the model is not ideal, it needs to be considered that the vast majority of the demented people on the test subset, as described on section III, are people categorised as very mild demented which means that are potentially at the early stages of Alzheimer's disease. Considering the importance of an early diagnosis, and the difference that it could make on people's life, the results could be promising but there is definitely a lot of space for improvement.

VI. Future work

The neural network used for the implementation is a simple but efficient convolutional network. The specific task could be approached using more complex or cutting edge architectures that would behave differently and presumably better or by using pre-trained convolutional networks that have been trained on similar tasks with very large datasets. As the medical approaches on the disease progress and different treatments are discovered and will be discovered, the prediction of the stage of the disease (e.g Moderate,very early) could potentially be very useful, as doctors might follow different treatments according to the stage. Lastly, the implementation of a research that would collect more MRI data from patients at different stages of the disease from different areas and countries could benefit dramatically the future researchers.

VII. Conclusion

The present work, is a proposed methodology that attempts to identify people with Alzheimer's disease using a neural network that receives as input an MRI brain scan image. The neural network used for the experiments is a convolutional neural network, which is an architecture that is proven it performs well on tasks that involve images. The obtained results are promising, and confirm that its a problem that could be solved up to a point using deep learning, as long as the data used are suitable and the network architecture appropriate. Deep learning is a domain with a lot of possibilities that is evolving at a rapid pace and it could help humanity in different ways, but the researchers should always be aware of the challenges and the responsibilities that come with its applications.

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One Drive link for the code: https://stummuac-my.sharepoint.com/:u:/g/personal/22538128_stu_mmu_ac_uk/EUGjUkaIu-dMvpcQCnMtEeEBPQdIxCxqVxVhP8bjtSeagQ?e=sLKdyz