Deep Learning Methods to Detect Alzheimer's Disease from MRI

Mariana Filipa Macedo Coelho*, João Manuel R. S. Tavares †

***Abstract*—Alzheimer's disease (AD) is a progressive and irreversible neurodegenerative condition in the brain that affects memory, thinking, and behaviour. To overcome this problem, which according to the WHO is on the rise, the creation of strategies is essential to identify and predict the disease in its early stages before clinical manifestation. In addition to cognitive and mental tests, neuroimaging plays a promising role in this field, especially in the assessment of brain matter loss. Therefore, computer-aided diagnosis (CAD) systems have been imposed as fundamental tools to help imaging technicians, as the diagnosis becomes less subjective and time consuming. In recent years, articles addressing the topic of Alzheimer's diagnosis by means of deep learning models have become increasingly popular, with an exponential increase from year to year, with increasingly higher accuracy values. However, the disease classification remains a challenging and progressing issue. This document presents a deep learning-based transfer learning methodology to diagnose AD, performing the following classifications, is also added: binary classification (CN vs. AD; CN vs. EMCI; EMCI vs. LMCI; LMCI vs. AD) and multiclasification (CN vs. EMCI vs. LMCI vs. AD), where CN stands for cognitively normal, EMCI for early Mild Cognitive Impairment, and for LMCI late MCI. The proposed model is a fine-tuned 80-layer SEResNet152 with the Elastic Transformation data augmentation technique, whose inputs are skull-stripped MR images. The effectiveness of the presented tests is evaluated through the ADNI dataset with multiple metrics. The results show promising performance, having reached a value of 92.98% in terms of accuracy in the CN vs. AD classification.**

***Index Terms*—Alzheimer's disease, 3D MRI brain image, Deep Learning, CAD, Transfer Learning.**

I. Introduction

ALZHEIMER'S disease is a progressive neurodegenerative disorder marked by behaviour and cognitive impairment that eventually interferes with daily functional living activities. The pathology is incurable, and its rate of progression varies [1]. Additionally, there are no specific laboratory or imaging tests to confirm the diagnosis of AD in the early stages, making the disease difficult to diagnose [1]. The medications available to treat the condition only work for the mild disease but also have a number of undesirable side effects [1]. Magnetic resonance imaging (MRI) is one of the most well-established procedures for detecting and tracking AD [2]. This non-invasive imaging technique generates accurate three-dimensional anatomical images that are frequently used for disease detection, diagnosis, and therapy monitoring [2].

In many medical applications, Deep Learning is currently the most successful machine learning technique [3]. These artificial neural networks with multiple layers can have different architectures, including CNNs for image and video, RNNs for sequential data, and transformers for natural language processing [3]. Deep learning models have some requirements regarding hardware and data, i.e., they must be trained using large datasets and significant computational power (using GPUs) [4]. However, in the medical field, it is common to have a small amount of images, so some problems arise like overfitting [4]. There are some techniques and strategies that help prevent overfitting and improve model performance, like training with more data, data augmentation, and more [4]. Another good tool for small datasets is transfer learning, which is a technique that uses pre-trained models as a starting point for a new task [4]. This way, the knowledge and features learned by the pre-trained model on a large dataset are leveraged to solve a new, related problem with a smaller dataset [4].

II. Methodology

The objective of this experimental study is to develop a computational platform for AD diagnosis based on deep recurrent networks. In this sense, the development of a CAD system that incorporates the steps of data acquisition, preprocessing, and classification was analysed and developed based on MR images, as depicted in Figure 1.

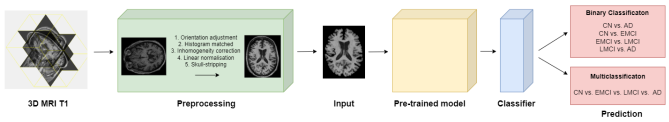

Fig. 1. Proposed CAD system for AD diagnosis. It is divided into 3 steps: definition of the image type - 3D MRI T1; pre-processing, which encompasses the 5 techniques represented; classification process, which is characterized by the compilation of the pre-trained network plus the classification block.

A. Image Acquisition

The dataset adopted in the project was gather from the Alzheimer's Disease Neuroimaging Initiative (ADNI) [5]. From the phase ADNI2, 1140 T1-weighted MR images were acquired, including 286 CNs, 283 EMCIs, 287 LMCIs, and 284 ADs.

B. Image Preprocessing

All the images acquired were processed and parcellated by MRICloud [6]. In the pipeline, the raw images were automatically preprocessed using five techniques: (1) orientation adjustment, (2) histogram matched, (3) inhomogeneity

*up202103368@up.pt
†Supervisor, DMEC, tavares@fe.up.pt

correction, (4) linear normalisation in the MNI space, and (5) skull-stripping. After this, the images were further normalised in the range [0, 1] and resized to 96x128x128. Finally, the MR images were converted from one to three channels to fit the pre-trained 3D architectures.

1) Data Augmentation: In order to reduce the general issue of the small dataset, which is overfitting during training, the data augmentation technique was applied. Thus, the Elastic Transformation technique was apllied. This technique focuses on random elastic deformations in the shape, geometry, and size of an object. Here the deformation parameters were set between 0 and 0.25 with an interpolation of 1.

C. Prediction Model

A whole deep-learning architecture from scratch could not be trained due to the very little amount of data provided in this study compared to the number of samples required to train a CNN model that is stable, unbiased, and not overfitted. So, transfer learning can be used to combat this problem. Pre-trained 2D models in the ImageNet dataset have previously been demonstrated in several studies to have great potential for transfer learning to different domains with higher accuracy and/or faster convergence, including applications for medical image analysis. However, the problem addressed in this paper requires 3D inputs, so the study developed by R. Solovyev et al. was adopted, which took advantage of pre-training on large-scale 2D image datasets for 3D image analysis [7]. From several possible models, the best model chosen was a fine-tuned 80-layer SEResNet152.

III. Resuls and Discussion

Table I demonstrates the results obtained for the various tasks described.

TABLE I
PERFORMANCE OF THE PROPOSED MODEL FOR THE DIFFERENT TASKS.

Task	ACC (%)	Loss	AUC (%)
AD vs. CN	**92.98**	**0.3840**	**94.33**
CN vs. EMCI	75.43	1.3839	80.43
EMCI vs. LMCI	78.94	1.0007	84.23
LMCI vs. AD	85.08	0.5212	90.60
CN vs. EMCI vs. LMCI vs. AD	67.98	1.091	-

As expected, and since it is the least complex task, the binary classification CN vs. AD obtained better results with an ACC of 92.98%. The results also show that it was easier for the model to classify LMCI vs. AD than EMCI vs. LMCI or CN vs. EMCI, this may be linked to the progression of the disease, where the more advanced the stage, the more manifestations are visible. Also, as one would expect given the complexity, multiclassification was the most complicated task for the model. Even though SEResNEt152 performed well in learning the representations, it nevertheless experienced the standard overfitting issue due to the short dataset used. This is true even with the application of various regularisation methods, such as dropout, data augmentation, early stopping, and even the transfer learning technique itself. This might be a result of the classification task's high level of complexity. The subtle discrepancies between the CN, EMCI, and LMCI images require a lot of data to learn the differences and perform the correct classification. Another reason might be that the dataset being used in this project differs significantly from the ImageNet dataset. The SEResNet was pretrained on common images from the ImageNet without including medical images. Therefore, the high-level features picked up by the model's higher layers are insufficient to distinguish the classes in this study.

IV. Conclusion

The central theme of this article was the development of a CAD system based on 3D magnetic resonance images to identify different stages of AD. Emphasising the complexity of the disease, the distinction between normal cognition, mild cognitive impairment (and its intermediate phases, EMCI and LMCI), and an AD subject is not easy, and it is even harder in the early stages of the disease when the structural changes are less obvious. Pre-trained networks have grown in popularity across a variety of applications because they make training quicker thanks to early learning about basic features that can be used in multiple tasks, like edges, shapes, corners, and intensities. Hence, this work explored a network with the application of ImageNet weights, followed by fine-tuning regarding the task. The experimental work was executed on the publicly available dataset, the ADNI. The pipeline is composed of three main stages: preprocessing, pre-trained models, and the classification task. The best project results were obtained through the CN vs. AD task, as expected, where an accuracy of 93% in the test set was achieved. The proposed method still has some drawbacks, though. The first limitation of this study is that, despite using the ADNI dataset, which is the largest worldwide regarding AD, the sample size was still quite small. Second, the model settings may not be fully optimised, such as batch size and dropout value. The overall outcomes were encouraging and show that computed methods can help medical professionals.

References

[1] G. e. a. Lee, "Predicting Alzheimer's disease progression using multi-modal deep learning approach," *Scientific Reports 2019 9:1*, vol. 9, no. 1, pp. 1–12, feb 2019. [Online]. Available: https://www.nature.com/articles/s41598-018-37769-z

[2] E. M. Reiman and W. J. Jagust, "BRAIN IMAGING IN THE STUDY OF ALZHEIMER'S DISEASE," *Neuroimage*, vol. 61, no. 2, p. 505, jun 2012. [Online]. Available: /pmc/articles/PMC3351556//pmc/articles/PMC3351556/?report=abstracthttps://www.ncbi.nlm.nih.gov/pmc/articles/PMC3351556/

[3] M. I. Razzak, S. Naz, and A. Zaib, "Deep Learning for Medical Image Processing: Overview, Challenges and the Future BT - Classification in BioApps: Automation of Decision Making," *Springer*, vol. 26, pp. 323–350, 2018. [Online]. Available: https://doi.org/10.1007/978-3-319-65981-7{_}12

[4] F. Chollet, *Deep Learning with Python*. Manning Publications Co., 2017.

[5] "ADNI | Alzheimer's Disease Neuroimaging Initiative." [Online]. Available: https://adni.loni.usc.edu/

[6] S. Mori, D. Wu, C. Ceritoglu, Y. Li, A. Kolasny, M. A. Vaillant, A. V. Faria, K. Oishi, and M. I. Miller, "MRICloud: Delivering high-throughput MRI neuroinformatics as cloud-based software as a service," *Computing in Science and Engineering*, vol. 18, no. 5, pp. 21–35, sep 2016.

[7] R. Solovyev, A. A. Kalinin, and T. Gabruseva, "3D convolutional neural networks for stalled brain capillary detection," *Computers in Biology and Medicine*, vol. 141, p. 105089, feb 2022.