

Proceedings

# System for Automatic Assessment of Alzheimer's Disease Diagnosis Based on Deep Learning Techniques <sup>†</sup>

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**Abstract:** Automatic detection of Alzheimer's disease is a very active area of research. This is due to its usefulness in starting the protocol to stop the inevitable progression of this neurodegenerative disease. This paper proposes a system for the detection of the disease by means of Deep Learning techniques in magnetic resonance imaging (MRI). As a solution, a model of neuronal networks (ANN) and two sets of reference data for training are proposed. Finally, the goodness of this system is verified within the domain of the application.

**Keywords:** Alzheimer; Deep learning; MRI; sagittal; ANN; transfer learning

## 1. Introduction

The progressive and constant aging of the population causes a higher incidence of neurodegenerative diseases associated with age. Among these diseases, the Alzheimer's has a prevalence of 5.05% in Europe as early as 2016 [1]. Early palliative diagnosis and treatment continue to be the best alternatives for improving the patient's quality of life and their environment. To make this diagnosis, various cognitive, psychological or clinical tests are used. Within the group of clinical tests, one of the most widely used is the analysis of brain images obtained by magnetic resonance imaging (MRI), as changes in brain morphology can be seen such as contraction of the hippocampus and cerebral cortex, or elongation of the ventricles [2].

The objective of this work is the use of Deep Learning techniques to support an early diagnosis of Alzheimer's disease through the analysis of conventional sagittal MRI images from two reference sets of data.

## 2. Materials and Methods

This section describes the datasets and computer models proposed in this work, each of which is described in its corresponding subsection.

### 2.1. Materials

This work makes the MRI images dataset ADNI [3]. Both sets are collections of correctly labeled MRI images of  $255 \times 255$  pixels, which are two of the most common in the literature.

### 2.2. Proposed Model

The proposed method uses the classical pipeline to solve a problem on any kind of signal, and in particular in this case images. This pipeline has a pre-established set of stages, being: pre-processing

phase, feature extraction phase and a regression or classification phase based on the features extracted from the images.

The proposed model is based on the use of a pre-trained model which, in this particular case is ResNet [4]. The idea behind this is to take advantage of features extraction phase of the model while the classification is dropped or adjusted for a new problem. This schema known under the name of transfer learning has been used many times in the related literature. In the proposed model, the classifier has been replaced by a Support Vector Machine (SVM) [5]. Thus, the speed of experimentation can be accelerated by adapting to this problem, successful models in other different problems.

### 3. Results

In this paper, the results for the ADNI dataset are presented. The results shown on Table 1 are average of 50 repetitions of a Hold-Out training strategy. The table shows the test result comparison between a reference work and two developed models, one with ResNet as base and one with MobileNet [6]. The dataset was splitted in 80% for training and 20% for testing, while a 1% of the training data set was used for validation purposes. The advantages of the ResNet approach are noticeable being the best one in precision and recall which are our main objective.

**Table 1.** Best results for ADNI.

Model	Image	Accuracy	Precision	Recall	Specificity	f1-Score	AUC
Inception [7]	PET hor.	-	63.66%	64.67%	79.00%	64.00%	76.00%
<b>ResNet</b>	<b>MRI sag.</b>	<b>81.46%±1.9%</b>	<b>82.48%±2.2%</b>	<b>93.09%±1.9%</b>	<b>55.19%±4.1%</b>	<b>87.44%±1.5%</b>	<b>74.14%±2.2%</b>
MobileNet	MRI sag.	51.08%±19.1%	37.56%±34.7%	52.4%±49.7%	47.73%±40.7%	43.16%±40.7%	50.01%±0.1%

### 4. Discussion

As a main conclusion the identification of Alzheimer’s disease in sagittal MRI images from ADNI dataset is accessible using Deep Learning techniques. These results are comparable to those proposed by the horizontal cuts in the literature. Despite the high imbalance of both data sets and the small OASIS set, the proposed model presents satisfactory results because of its simplicity.

Based on the authors’ experience in the field of Alzheimer’s disease, the sagittal plane also shows characteristic deformations of the disease. Traditionally, specialists use the horizontal plane. This opens up new ways for experimentation. New characteristics of Alzheimer’s disease can be found in them in other regions. These new features may make the diagnosis of Alzheimer’s a more precise task.

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**Conflicts of Interest:** The authors declare no conflict of interest.

### Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Network
MRI	Magnetic Resonance Imaging
AUC	Area Under Curve ROC
ROC	Receiver Operating Characteristic

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