The International Joint
Conference on Neural Networks
2020

**Shounak Roychowdhury**

# A Modular Framework to Predict Alzheimer's Disease Progression Using Conditional Generative Adversarial Networks

Shoumik Roychowdhury
Westwood High School
12400 Mellow Meadow Drive,
Austin, Texas 78750, USA
Email: shoumikitu@gmail.com

Shounak Roychowdhury
Department of Computer Science
Texas State University
San Marcos, TX
Email: s_r546@txstate.edu

***Abstract*—Alzheimer's disease (AD) is a chronic neurodegenerative disease that worsens over time. The number of AD cases is growing, around 3 million new US cases each year. Although state-of-the-art research shows promise, predicting the disease's rate of progression for a case by case basis remains a challenging problem. Current methods of predicting the progression of AD can delay treatment and lead to misdiagnosis. We propose a novel approach to simulate the rate of progression of AD and the atrophy of the brain over time. We seek to achieve this by generating synthetic magnetic resonance (MR) images via a series of Conditional Deep Convolutional Generative Adversarial Neural Networks (CDCGANs) and then analyze them by computing the fractal dimensionality of the cortical brain ribbons. This paper shows the feasibility of this proposal by cascading CDCGANs that simulate different stages of AD. It is possible to extend by a tandem of CDCGANs that would simulate the different stages of the disease. MR images used here are from ADNI(Alzheimer's Disease Neuroimaging Initiative). The atrophy is measure using fractal dimension (box-counting method)of the cortical ribbon(CR). A decreasing fractal dimension is a confirmation that the disease progress over time.**

## I. Introduction

Alzheimer's disease (AD) is an irreversible neurodegenerative disease that progresses with time. Its main characteristics are the accumulation of a large number of amyloid plaques and neurofibrillary tangles in the brain. These plaques and tangles destroy the neurons that cause a loss of neurological faculties. Thus, cognitively, it affects memory, thinking, and social behavior. AD is the most common form of dementia. Approximately 5.7 million Americans are living with AD in 2018 [1]. The projection is that this number will rise to nearly 14 million. Unfortunately, there is no cure for this disease at the moment. Current treatments only can decelerate the progression of AD. Therefore, it is of utmost importance for timely treatment so that it possible to delay the progression. It has become clear that it is imperative to develop strategies for the detection of AD at an early stage. During its early stages, it is quite challenging to detect because cognitive faculties do not reveal the effects of subtle neural degeneration that is already underway. Over the years, researchers have identified a few categories in the AD spectrum, starting from not having the disease to the last stages of AD. This mid-range category is called Mild Cognitive Impairment (MCI), where the various degrees of cognitive impairments become noticeable. There are two main categories: NC-MCI (non-convertors) and c-MCI (converters). The c-MCI group is most at risk of transit to AD in later stages of the lives. Early detection at the MCI stages, through macro biomarkers such as isolate systolic hypertension [7], can delay the onset of the disease, before irreversible damage develops. Thus, the detection of this disease early on is an essential step towards prevention. Various studies report that MCI patients progress to AD at a rate of 10% to 15% per year, and 80% of these MCI patients will have converted to AD after approximately six years of follow-up [19].

Many studies have different types of machine learning techniques have used in the classification of AD and MCI. In the traditional machine learning setup, before the popularity of deep neural networks, Support vector machine (SVM) is a primary tool that dominated AD research for addressing the classification/regression problem. Typically, these methods use MRI, FDG-PET, and CSF data and perform a multi-task feature selection and, after that, perform regression or classification using SVM. A study reported by Zhang et al. shows 73.9% classification accuracy [23].

In a domain transfer learning technique, for MCI conversion prediction, use data from both the target domain (i.e., MCI) and other non-target domains such as AD and NC from different imaging modalities to separate MCI-C and MCI-NC patients. The results show the classification of MCI-C patients from MCI-NC patients with an accuracy of 79.4% [4]. Zhang et al. used Bayesian methods to multimodal classifying AD and MCI [22].

Cho et al. use cortex thickness as a discriminatory feature for classification. Their method uses eigenfunctions of the Laplace–Beltrami operator, which are derived from the graphical geometry of a cortical surface [5]. Cortical surface thickness is also used in the fractal analysis of cortical ribbons CR to discriminate different degrees of cerebral atrophy that occurs in Alzheimer's disease [12].

Roychowdhury, S., & Roychowdhury, S. (2020). A modular framework to predict Alzheimer's disease progression using conditional generative adversarial networks. 2020 International Joint Conference on Neural Networks (IJCNN), 1–8.
https://doi.org/10.1109/ijcnn48605.2020.9206875