**Machine-learning Techniques for Building a Diagnostic Model for Mild Cognitive Impairments**

The prevalence of dementia is increasing according to the global population ages (1). Alzheimer's disease (AD) is a neurodegenerative disorder that has devastating effects on patients and their families and the leading cause of dementia (2). Nowadays, more than 30 million people suffer from AD worldwide. The number of people suffering from AD is increasing rapidly every year (3). Mild cognitive impairment (MCI) is considered a transitional state between healthy aging and dementia. MCI patients have cognitive impairments that do not suffer significantly with daily life activities (4). Patients with MCI often more likely to progress to AD (5), and accordingly provide an important subject base for Alzheimer's research issues. A critical goal of Alzheimer's research is to improve the method of patient diagnosis. Therefore patients can be identified sooner(5). Detecting cognitive impairment is important and can help patients in obtaining greater advantages from available therapies, medication, and supporting systems and help patients and caregivers to prepare (6)(7). Thus, accurate diagnosis of AD specifically for its early stage is very important.

Eye Tracking is a non-invasive device that does not need any special coordination which makes it suitable for the patients (8). The eye-tracking test provides accurate and significant numerical variables. This quality makes eye-tracking a suitable tool in which machine learning methods can train and determine their weights to contribute as an accurate and sensitive diagnostic tool. The threshold of impaired cognitive performance has been operationalized in many ways (9). In the clinical setting, a manual diagnosis of cognitive impairment is time-consuming and can require multiple neuropsychological test scores, laboratory test results and informants reports (10). These data were assembled to create a cohesive schema of the individual`s impairments where the efficacy and accuracy are affected by the variability of cognitive tests (11), participant's level of education and expertise (10) and cross-cultural differences (12). Despite the theoretical robustness of these approaches, they are not appropriate for characterizing MCI in asymptomatic adults (13). Furthermore, the expense of medical diagnostic facilities is a primary concern leading to make a reliable alternative way instead of traditional medical routines.

The last decades witnessed a boost in the emergence of machine learning approaches applied to AD-related research, recognized as a powerful technique to improve the diagnostic approach (14). The study conducted by Chen et., al (15) indicated that several statistical and machine learning approaches, a support vector machine (SVM) and s Bayesian- network classifier were appropriate methods for discrimination mild cognitive impairment from cognitively healthy older adults. In this method automatically generated feature ??? may be attributed to categorize participants??.

In the present study, we aim to explore the relationship between eye-tracking and computerized cognitive measures along with standard cognitive tests in the individual with MCI? We extracted standard eye-tracking summary metrics and then applied machine learning algorithms to a proportion of the data to explore the possibility of automatically discrimination patients and healthy individuals based on eye-tracking metrics and other cognitive measured. Therefore, we hypothesize that machine learning classifiers can offer discriminate power for the diagnosis of MCI among healthy controls. A major goal of this study was to understand to what extent such methodology would be able to improve diagnostic accuracy using eye-tracking data and machine learning to detect early, subtle signs of cognitive impairments. In addition to classifying individuals, a secondary goal of the study was to determine a small set of attributes (neuropsychological measures, computerized cognitive tests, and eye-tracking metrics) that can be used to reliably diagnosis subtle cognitive changes. Because clinical diagnosis was originally made by considering score on neuropsychological measures we expect the machine learning algorithms to achieve higher classification when predicting them with other specified cognitive measures.

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