Deep Learning in Mild Cognitive Impairment Diagnosis using Eye Movements and Image Content in Visual Memory Tasks

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INTRODUCTION

The WHO's "Global Status Report on the Public Health Response to dementia" [10] highlights dementia as a growing global health issue, affecting over 55 million people, projected to rise to 139 million by 2050, with a disproportionate impact expected in middle-income countries. This emphasizes the urgent need for diagnostic tools and interventions, particularly as populations age. Dementia is characterized by cognitive decline that interferes with daily life, including memory loss and impaired thinking. Alzheimer's disease is the most common form, though other types include vascular, frontotemporal, and Lewy body dementia [2]. Before developing dementia, patients go through a stage called Mild Cognitive Impairment (MCI), experiencing mild cognitive changes that do not significantly interfere with daily life activities, *e.g.* impacts on memory function. Early detection of MCI provides a critical window for interventions that may delay progression to dementia [11].

RESEARCH PROBLEM

MCI is influenced by age, genetics (*e.g.* APOE $\varepsilon 4$ allele), lifestyle, and cardiovascular health and is associated with biomarkers such as hippocampal atrophy and amyloid-beta accumulation [6, 8]. However, diagnosing it in a timely manner remains challenging, as the limited availability of specialists restricts the widespread use of diagnosing tools, such as standard cognitive tests like MMSE and MoCA or neuroimaging tools. When combined with delayed symptom recognition, this often results in MCI being detected only when cognitive decline is noticeable, limiting early intervention opportunities [1, 3].

THEORETICAL FRAMEWORK

To tackle these challenges, digital assessments on computers, tablets, and smartphones are emerging as practical and cost-effective alternatives [13]. When integrated with wearable sensors, cameras, or eye-tracking devices, these tools capture many relevant data without adding time costs, enhancing their diagnostic potential [7].

Eye-tracking integration in MCI diagnosis has gained attention, with studies suggesting that eye movement patterns could serve as early indicators of cognitive decline [19].

Eye-movements: A window to the memories

Eye movements, essential for visual perception, offer insight into cognitive processing and memory. Key movements include saccades, rapid gaze shifts between points, and fixations, where the eyes pause to process information. Saccades allow quick repositioning but temporarily suppress visual intake, while fixations enable detailed analysis, with durations varying by task [12]. Fixations are particularly useful, as their longer periods allow for easier detection. Eye movements significantly impact memory mechanisms, aiding encoding and retrieval. Increased fixations and shifts in gaze while encoding a scene improve memory recall, as eye movements facilitate scene exploration [5]. During encoding, eye movement patterns differ notably between MCIs and healthy individuals. MCI patients often have delayed saccadic responses and less accurate saccade targeting, leading to inefficient visual exploration. Their fixations are longer but fewer, possibly indicating attention and visual processing difficulties. This reduced fixation frequency and longer saccadic latency contribute to limited scene exploration, impacting their ability to recognize and remember visual details [19]. In the literature, we also see that image content influences eye movements by engaging in a process where our eyes selectively focus on elements perceived as necessary, consequently influencing the memory processes [15].

Deep Learning and MCI

To enhance the digital tools deep learning algorithms are being employed, improving diagnostic accuracy and scalability, thus making the timely detection of MCI a possibility [19].

Algorithms based on various methods have been employed, such as Recursive Neural Networks (RNN), Convolutional Neural Networks (CNN), autoencoders, transformers, and others [14]. The transformer based architectures usually perform better than the others, however they require large amounts of data to be properly trained [9, 14]. One problem with recent studies is the fact that, typically there is no differentiation between MCI patients and patients with more advanced dementias, such as Alzheimer's, which can bring biases to the results obtained [14].

RESEARCH OBJECTIVES

Building upon recent advancements, this study explores deep learning models that use eye-tracking data collected from MCI patients and Healthy Controls (HCs). The participants perform a visual long-term active memory task to predict MCI, which have been shown to have better diagnostic accuracy [17, 19]. Additionally, this research investigates incorporating image content, a topic that has not been extensively researched, and memory performance to try to enhance the diagnostic process further.

PROPOSED METHODOLOGY

The models will use the data from MCI patients and Healthy Controls (HCs) collected by us and also the data available in Coco *et al.* [4] performing a similar task (44 participants: 24 MCI patients — 71.92 ± 9.06 years old, 9.83 ± 4.50 schooling years; 20 HCs — 68.50 ± 8.79 years old, 11.05 ± 5.10 schooling years).

The tasks is a visual long-term active memory task divided in two sections: an encoding phase, where, in both studies, the participants are displayed a series of images that they are asked to try to remember; and a recognition phase, where in our task the participants are shown again a series of images, however, this time, they are asked to say whether they remember seeing the image. In Coco *et al.* [4] they are presented with two images at the same time, and they have to choose which of the images they remember seeing before.

While this task is being performed, the eye movements of the participants are being recorded. The data from the encoding phase will then be used to train variations of the VTNet, a model that as already shown to have the capability of predicting if a person as Alzheimer's[16]. This model receives two inputs: a visual representation of the eye-movements, which is then processed via a CNN; and a time-series representation of the eye-movements, which is processed via a RNN.

Method	Sensitivity	Specificity
Sriram *et al.* [16]	70 ± 0.02	73 ± 0.02
Ours	68.42 ± 27.26	76.47 ± 27.64

Table 1: Models sensitivity and specificity (mean ± standard deviation) for Sriram *et al.* [16], using Alzheimer's disease patients and Scanpaths, and our results using MCI patients and gaze heatmaps.

WORK PLAN

In the first part of the project we started by training various models with on the data collected from Coco *et al.* [4]. For each model we experimented with various types of visual inputs: scanpaths, gaze heatmaps, image content (*i.e.* image seen) and a combination of the gaze heatmaps and the image content. We observed that gaze heatmaps lead to better performing models, having been able to reach comparable results to Sriram *et al.* [16], while performing under more challenging conditions, as Alzheimer's patients are easier to differentiate than MCI patients (Tab. 1).

After our first experiment we proved that this architecture can be used to predict if a person as MCI. We are now continuing to collect more data, having already collected data from 21 participants (9 HCs and 12 MCI patients). The participants need to be between 50 and 85 years old and have at least 4 years of schooling in order to account for cognitive biases related to both age and education. Also, the patients need to be clinically diagnosed with neurodegenerative MCI and not any more severe condition. We will then combine the two datasets to have a more significant sample size and a more robust model. Also, to address the significant standard deviation we are looking into methods such as bootstrap aggregation[18].

EXPECTED CONTRIBUTIONS

With this study, we pretend to create a diagnosis test capable of doing an initial triage of people with MCI. We also believe that it has the capability of being adapted to work on laptops using their respective built-in cameras increasing the scalability and availability of the diagnosis.

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