Machine Learning for Healthcare with Focus on Alzheimer's Disease

Rosanna Turrisi*

Istituto di Matematica Applicata e Tecnologie Informatiche, Consiglio Nazionale Delle Ricerche (CNR-IMATI), Genoa, Italy

Email address:

rosanna.turrisi@cnr.it (Rosanna Turrisi)

*Corresponding author

Abstract

Over the past few decades, Machine Learning (ML) models have demonstrated their ability to harness biomedical data to enhance the healthcare system. ML-based medical devices can serve both as support tools for patients and as aids for physicians in diagnosis, prognosis, and treatment planning. After briefly exploring various medical applications, this work turns to a central challenge in the field: the use of ML for Alzheimer's Disease (AD), the most common form of dementia, where timely diagnosis is crucial for slowing disease progression. This contribution presents a comprehensive investigation of ML techniques for AD detection using 3D brain MRI. The first part examines how modeling design choices—particularly data augmentation strategies and network complexity—affect the reliability and predictive performance of 3D Convolutional Neural Networks (CNNs). Using low-resolution 1.5T MRI scans from the ADNI dataset, fifteen models are trained by combining three affine-based augmentation strategies with five CNN architectures of increasing depth. The results show that these choices can lead to up to 10% variation in accuracy. Applying affine transformations separately consistently improves performance, and the relationship between model depth and accuracy follows a concave trend, with intermediate-complexity architectures yielding the best results. The best model reaches 87% accuracy on internal testing. However, when evaluated on an external dataset acquired with 3T scanners and different protocols, performance decreases by 16 percentage points, highlighting the significant impact of acquisition variability. The second part addresses this challenge directly by exploring Transfer Learning (TL) as strategy to mitigate data scarcity and distribution shifts caused by evolving MRI acquisition technologies. Two scenarios are considered: (A) leveraging historical 1.5T MRI data to enhance models trained on limited 3T scans, and (B) adapting 2D CNNs pre-trained on ImageNet (ResNet18/50/101) for 3D MRI processing when historical data are unavailable. In scenario (A), TL significantly boosts the baseline model's accuracy from 63% to 99%. In scenario (B), fine-tuning models pre-trained on natural images increases the baseline's accuracy by up to 12 percentage points, achieving an overall accuracy of 83%.

Keywords

Machine Learning, Transfer Learning, Healthcare, Alzheimer's Disease, Magnetic Resonance Imaging