VGG-C Transform Model to Predict Alzheimer’s Disease

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Contributor: Batzaya Tuvshinjargal, Heejoung Hwang

Alzheimer’s disease (AD) is a chronic neurobiological brain disorder that continuously kills brain cells and causes deficits in memory and thinking skills, eventually accelerating the loss of the ability to perform even the most basic tasks. Early detection and automatic AD classification have emerged, resulting in large-scale multimodal neuroimaging results. Other methods of AD research include MRI, positron emission tomography (PET), and genotype sequencing results. Analyzing different modalities to make a decision is time consuming.

Keywords: Alzheimer’s disease ; batch normalization ; CNN ; VGG-C Transform

1. Introduction

Alzheimer’s disease is the most common stage of dementia, requiring extensive medical attention. Early and precise analysis of AD prediction is required for initiation of clinical progression and effective patient treatment [1]. AD is a chronic neurobiological brain disorder that continuously kills brain cells and causes deficits in memory and thinking skills, eventually accelerating the loss of the ability to perform even the most basic tasks [2]. In the early stages of AD, doctors use neuroimaging and computer-aided diagnostic approaches to classify the disease. According to the World Alzheimer’s Association’s most recent census, more than 4.7 million people over the age of 65 in the United States have survived the disease [3]. The report also predicts that around 60 million people will be affected by AD within the next 50 years. Worldwide, AD accounts for about 60–80% of all forms of dementia, and there is a 60% chance that one dementia patient every 3 s, due to AD [4]. Alzheimer’s dementia is divided into:

- Mild cognitive impairment: while generally affected by a memory deficit in many people as they age, in others it leads to problems with dementia.

- Mild dementia: Cognitive impairment that sometimes affects their daily life is found in people with moderate dementia. Symptoms include memory deficits, uncertainty, personality changes, feelings of loss, and difficulty performing daily tasks.

- Moderate dementia: daily life becomes much more complex, and patients require special care and support. Symptoms are comparable to mild dementia but somehow get worse. People may need more help, even combing their hair. They can also show significant personality changes; for example, they become paranoid or irritable for no reason. Sleep disturbances are also likely to occur.

- Severe Dementia: At this stage, symptoms may worsen. These patients may lack communication skills and may require full-time treatment. The bladder can’t be controlled, and you can’t do small activities, such as sitting in a chair with your head raised and maintaining a normal posture. Various research paradises have been conducted to slow the abnormal degeneration of the brain, reduce medical expenses, and improve treatment. According to nih.gov’s “Alzheimer’s Disease Fact Sheet”, the failure of recent AD research studies may suggest that early intervention and diagnosis may be important for the effectiveness of treatment [5]. Various neuroimaging methods are increasingly reliant on early diagnosis of dementia, which is reflected in many new diagnostic criteria. Neuroimaging uses machine learning to increase diagnostic accuracy for various subtypes of dementia [6].

Implementing a machine learning algorithm requires specific preprocessing steps. Feature extraction and selection, feature dimension reduction, and classifier algorithms are all steps in the machine learning-based classification process [7]. These techniques require advanced knowledge and several optimization steps, which can be time consuming. Recently, early detection and automatic AD classification [8] have emerged, resulting in large-scale multimodal neuroimaging results. Other methods of AD research include MRI, positron emission tomography (PET), and genotype sequencing results. Analyzing different modalities to make a decision is time consuming. In addition, patients may experience radioactive effects with modalities, such as PET [9]. It is considered important to develop better computer-aided diagnostic systems that can interpret MRI [10] images to identify patients with AD. Existing deep learning systems use cortical surfaces to input CNNs to perform AD classification on raw MRI images [11].

2. VGG-C Transform Model with Batch Normalization to Predict Alzheimer's Disease

It is believed that deep learning focuses on its use in the diagnosis of AD. Several in-depth study methods have recently been proposed to help diagnose AD and help physicians make informed health decisions. In this section, researchers present some studies that are closely related to researchers' study. Lu nar. [12] proposed a multimodal deep neural network with a multi-step technique for identifying people with mental disabilities. The method has an accuracy of 82.4% in patients with mild cognitive impairment (MCI) and AD within three years. The model has a sensitivity of 94.23% in the AD category and an accuracy of 86.3% in the non-dementia category. Using ADNI and the National Center for Dementia Research (NRCD) data sets, Gupta nar. [13] proposed a diagnostic method for classifying ADs using cortical, subcortical, and hippocampal region features from MRI images with an accuracy of 96.42%. AD and healthy control (HC). Ahmed et al. [14] proposed a CNN model of a character extractor and a SoftMax classifier to diagnose AD. This model uses the right and left hippocampal sections on MRI to prevent overload and has an accuracy of 90.05%. Bashar nar. [15] developed a method of localization of the target region from a large MRI scale to automate the process. Based on the left and right hippocampus, this method achieves 94.82% and 94.02% accuracy, respectively.

Navaz nar. [16] proposed a pre-prepared Alexnet model to classify the stages of AD to solve the class imbalance model. The prefabricated model is used as a feature sorting device and is classified with the highest accuracy of 99.21% using support vector machine (SVM), k-nearest neighbor (KNN) and random forest (RF). Ieracitano et al. [17] proposed a data-based approach to differentiate subjects with AD, MCI, and HC by analyzing non-invasive EEG recordings. The energy spectral densities of the 19-channel EEG traces reflect their corresponding spectral profiles on a two-dimensional gray image. The CNN model is then used to classify binary classes and multi-categories from 2D images with 89.8% and 83.3% accuracy. Jain sun. [18] used the pre-prepared VGG16 model for feature unpacking, which uses "FreeSurfer" library for pre-processing, selection of MRI slices using entropy, and classification using a transfer training called PFSECTL mathematical model. Using the ADNI database, the researchers classified normal control (NC), early mci (EMCI), and late mci (LMCI) with a 95.73% accuracy. Mehmood sun. [19] used tissue segmentation to extract gray matter (GM) from each subject. This model achieves a classification accuracy of 98.73% for AD and NC and 83.72% for EMCI and LMCI patients. Shi et al. [20] proposed a deep multi-member network that works well for small and large data sets to diagnose AD. The model uses an ADNI data set with an accuracy of 55.34% in both binary and multi-class. Liu et al. [21] proposed the Siamese neural network to study the ability to differentiate all brain volume inequalities.

The team used a unique nonlinear nuclear approach to normalize features and eliminate package effects in the data set and population, while using MRI Cloud processes to create low-dimensional volume characteristics in a predetermined atlas brain structure. Networks use the ADNI data set to achieve a balanced accuracy of 92.72% in the MCI and AD categories. Van et al. [22] introduced a 3D ensemble model integration with AD and MCI using a collapsible grid method. The 3D-DenseNets were optimized using a probability-based melting method. This model uses ADNI data sets to achieve 97.52% class accuracy. Shankar nar. [23] used the wolf solution optimization method with the decision tree, KNN, and CNN models to diagnose AD with an accuracy of 96.23%. Jangel and Rator [24] proposed a pre-prepared VGG16 to extract AD features from the ADNI database. In their classification, they used clusters and decision tree algorithms meaning SVM, Linear Discriminate, and K. Their method had a 99.95% accuracy of functional MRI images and an average of 73.46% accuracy of PET images. Ge et al. [25] proposed a 3D multidimensional in-depth learning architecture to learn the features of AD. On a randomly isolated brain scanned data set of the subject, the system achieved an experimental accuracy of 93.53% and an average accuracy of 87.24%. Wang [26] introduced the Spike Convolutional Deep Boltzmann Machine model for early detection of AD with a multi-task learning technique to prevent hybrid mapping and over-tuning. Sarraf et al. [27] introduced an in-depth training line trained with multiple training drawings to perform specific classifications on scale and transition invariant processes. The model achieved 94.32% and 97.88% for functional MRI and MRI imaging. Preferred sun. [28], using data extension system, solved the problem of class imbalance in the detection of AD, achieving a classification accuracy of 98.41% in one view of the OASIS data set and 95.11% in 3D imaging.

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