Chapter 13
Diagnostic Categorization and Neurocognitive Prediction Employing Neuroimaging Data Using Deep Learning in Alzheimer's Illness

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ABSTRACT

Traditional analytic strategies for investigating neuroimaging biomarkers for neuropsychiatric illnesses have relied on mass univariate statistics, assuming that various brain areas function separately. Machine learning (ML) methods that take into account intercorrelation across areas have recently become a popular and important part of computer-assisted analytical procedures and are now frequently used for the automated diagnosis and analysis of neuropsychiatric illnesses. The goal of this chapter is to provide a detailed overview of CNN and RNN applications in medical image comprehension. The overarching goal is to encourage medical image understanding experts to use CNNs extensively in their research and diagnosis. This chapter describes the development of various novel DL-based approaches and models as well as advancements in high-speed computing techniques, which provide a once-in-a-lifetime chance to anticipate and control Alzheimer's disease.

INTRODUCTION

Alzheimer's disease is a type of dementia marked by memory, cognitive, and behavioral issues. AD affects an estimated 5.5 million people aged 65 and more, and it is the sixth largest cause of mortality in

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the United States. Improved neuroimaging techniques including as magnetic resonance imaging (MRI) and positron emission tomography (PET) have been developed and implemented to uncover AD-related structural and molecular biomarkers. Due to fast developments in neuroimaging techniques, integrating large-scale, high-dimensional multimodal neuroimaging data has become problematic. As a result, there has been a surge in interest in computer-assisted machine learning approaches for integrative analysis. Linear discriminant analysis (LDA), linear programme boosting method (LPBM), and logistic regression are examples of well-known pattern analysis approaches (LR), Support vector machines (SVM) and support vector machine recursive feature elimination (SVM-RFE) have been utilized and show promise in detecting Alzheimer's disease early and predicting its progression. Appropriate architectural design or pre-processing processes must be pre-defined in order to employ such machine learning algorithms. Feature extraction, feature selection, dimensionality reduction, and feature-based classification method selection are the four processes in the process (Scheltens, 2016). These processes necessitate specialized knowledge as well as many optimization steps, which can be time-consuming. Deep learning, a developing branch of machine learning research that uses raw neuroimaging data to build features using "on-the-fly" learning, is gaining traction in the field of large-scale, high-dimensional medical imaging analysis to address these issues. (Hwang, 2019).

We reviewed various publications where deep learning algorithms and neuroimaging data were utilized to detect Alzheimer's disease early and forecast its progression.

OVERVIEW OF DEEP LEARNING TECHNIQUES

Deep learning is a type of machine learning that learns features through a hierarchical learning process. Methods of deep learning for a variety of domains, categorization and prediction have been used. Including natural language processing and computer vision both of which are show performance breakthroughs. DL is a branch of machine learning that can be used to create models that extract high-dimensional characteristics from data. It has gotten a lot of attention in recent years, notably in the field of image analysis. A number of deep learning architectures have been published in the literature, including CNN, DNN, RNN, AE, Deep Belief Network (DBN), and Probabilistic Neural Network (PNN) (Gulshan, 2016).

Convolutional Neural Network (CNN):

A CNN, also known as a ConvNet, uses learnable weights and biases to apply to distinct regions of an input image, allowing one image to be distinguished from another.

CNN employs convolution instead of basic matrix multiplication in at least one of their layers. It's most commonly used in unstructured datasets. 2D-CNN predicts segmentation maps for a single slice using 2D-convolutional kernels.

Only spatial dimensions such as height and width can be used by 2D-CNN. Context information from adjacent slices cannot be recovered since 2D-CNN only accepts one slice as input. In terms of utility, voxel data from neighboring slices may be sufficient for categorization tasks. By predicting the volumetric patch of neuroimaging data, 3D-CNN, on the other hand, can retain temporal dimensions. Although the capacity of 3D-CNNs to anchor interslice context information improves performance, it comes at a cost in terms of computation time and the number of parameters that 3D-CNNs must utilize. Figure 1 shows CNN Architecture

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