2D/3D Convolutional Neural Networks for Alzheimer's Disease Prediction using Brain MRI Image

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ABSTRACT
The symptoms of Alzheimer's disease (AD) include significant memory loss and cognitive decline. It is linked to major alterations in brain structure that can be seen by magnetic resonance imaging (MRI) scans. Utilizing image classification technologies like convolutional neural networks, the visible preclinical structural alterations offer a chance for AD early identification (CNN). The sample size of the majority of AD-related studies, however, is currently a limitation. It is crucial to find a productive technique to train an image classifier with little data. In our project, we investigated various CNN-based transfer-learning techniques for MRI brain structure AD prediction. We discover that the prediction performance was enhanced when compared to a deep CNN trained from scratch by both pretrained 2D AlexNet with a 2D-representation approach and simple neural networks with a pre-trained 3D autoencoder.The pretrained 2D AlexNet performed even better (86%) than the 3D CNN with autoencoder (77%).

General Terms
Alzheimer’s disease, Machine Learning

Keywords
Alzheimer’s disease, Machine Learning Models, CNN, Accuracy

1. INTRODUCTION
Clinical studies and patient care for Alzheimer's patients both greatly benefit from early diagnosis of the condition. In this paper, we provide a novel method to discriminate mild Alzheimer's disease dementia from mild cognitive impairment and cognitively normal persons using structural MRIs. Our method is based on 3D deep convolutional neural networks. We created a reference model for comparison using the sizes and thicknesses of previously described brain areas that have been linked to the course of known diseases. Our internal held-out cohort from The Alzheimer's Disease Neuroimaging Initiative (ADNI) and an independent, external cohort from The National Alzheimer's Coordinating Center serve as the basis for the validation of both models (NACC).The volume/thickness model is substantially slower and less accurate than the deep learning approach. The model can also be used to predict how a subject will progress; for example, subjects with moderate cognitive impairment who were incorrectly labelled as having mild Alzheimer's disease dementia over time developed dementia more quickly. An examination of the proposed model's features learnt reveals that it uses a variety of locations linked to Alzheimer's disease. According to these results, deep neural networks may be able to automatically learn which imaging biomarkers are indicative of Alzheimer's disease and exploit them for precise early disease detection.

2. RELATED WORK
The most prevalent form of dementia, Alzheimer's disease (AD), is named after the German psychiatrist Alois Alzheimer and is characterised by neuritic plaques and neurofibrillary tangles a result of amyloid-beta peptide (A) buildup in the brain's most affected region, the medial temporal lobe and neocortical structures [1]. When Alois Alzheimer examined the brain of his first patient, who experienced memory loss and a change in personality before passing away, he found the presence of amyloid plaques and a significant loss of neurons. He defined the illness as a terrible disease of the cerebral cortex. In his psychiatric handbook's eighth edition, Emil Kraepelin for the first time referred to this illness as Alzheimer's disease [2,3].Alzheimer's disease (AD) and other brain disorders, infections, abnormalities in the pulmonary and circulatory systems that reduce the amount of oxygen delivered to the brain, nutritional deficiencies, vitamin B12 deficiencies, tumours, and other conditions can all contribute to the progressive loss of cognitive abilities [4,5].There are currently about 50 million AD sufferers globally, and it is predicted that this number will double every five years to reach 152 million by 2050. Individuals, their families, and the economy are all impacted by the burden of AD, which is thought to cost $1 trillion USD yearly globally. Alzheimer's disease currently has no known cure, however there are therapies that can help with the symptoms [6,7]. This review's objectives are to provide a brief overview of the diagnosis, pathology, causes, and current therapies for Alzheimer's disease (AD) and to draw attention to recently developed drugs that may be able to prevent or treat AD by focusing on a

number of pathogenic mechanisms, including A- and tau aggregation and misfolding, inflammation, oxidative damage, and others.A patient who is suspected of having AD should undergo a number of tests, including a neurological examination, MRI for the neurons, blood tests like vitamin B12, and other testing in addition to the patient's medical and family histories [8]. According to certain research, vitamin (vit.) B12 insufficiency has long been known to be linked to neurologic issues and an increased risk of AD. Elevated homocysteine levels are a unique indicator of vitamin B12 deficiency and can lead to brain damage through oxidative stress, increased calcium influx, and apoptosis. Measurement of serum vitamin B12 levels together with tests for serum homocysteine levels and full blood counts can be used to diagnose vitamin B12 insufficiency [9,10].The NINCDS-ADRDA criteria were modified in 2011 by The National Institute on Aging—Association Alzheimer's for increased specificity and sensitivity in the diagnosis of Alzheimer's disease. Along with clinical biomarkers, the newly recommended criteria now include probable and possible AD dementia for use in clinical contexts as well as probable or possible AD dementia with pathophysiological evidence for research reasons. There are two types of biomarkers for Alzheimer's disease: (a) those that measure brain amyloid, such as positron emission tomography (PET) and cerebrospinal fluid (CSF), and (b) those that measure neuronal injury, such as cerebrospinal fluid tau, fluorodeoxyglucose (FDG) for metabolic activity, and magnetic resonance imaging (MRI) for atrophy measurement [11,12,13].

3. PROPOSED ALZHEIMER'S DISEASEPREDICTION SYSTEM

Block diagram of the Proposed Alzheimer's Disease Prediction system, as depicted in Figure 1.

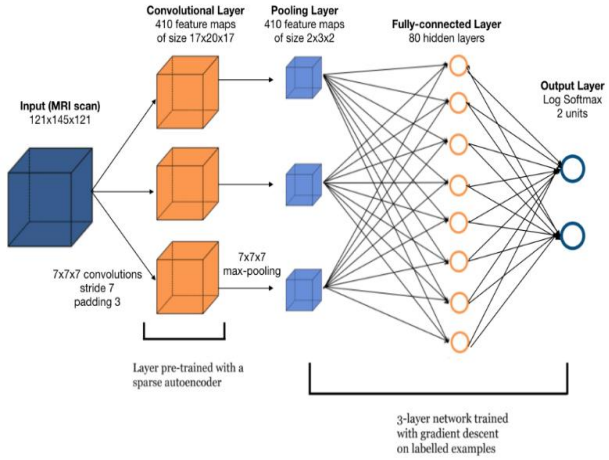


Figure 1: Block diagram of proposed Heart Disease Prediction system

3.1 Sparse Auto encoder

A 3-layer neural network called an autoencoder is used to extract features from an input like an image. By revealing the hidden structure in the data, sparse representations can offer a straightforward interpretation of the input data in terms of a manageable amount of pieces. The input and output layers of the autoencoder each have the same amount of units, whereas the hidden layer has additional units for a sparse and overcomplete representation. The decoder function converts the representation h to the output x, while the encoder function converts the input x to the representation h.In our issue, we use 3D patches that we extract from scans as the network's input. With the help of the hidden representation h.t, the decoder function attempts to reconstruct the input.

3.2 Image Processing

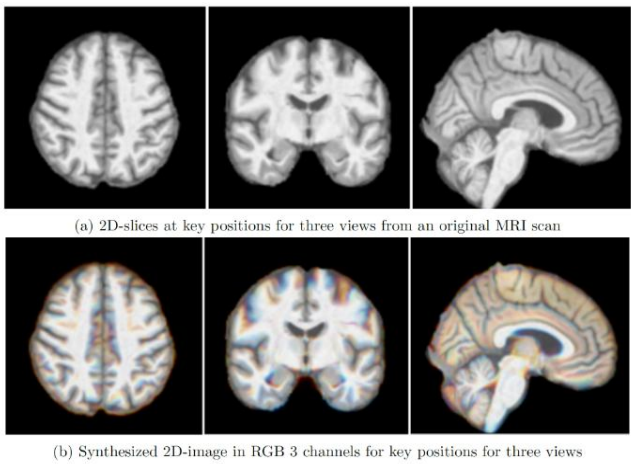
Utilizing version 12 of the Statistical Parametric Mapping (SPM) programme, images were preprocessed. The original MRI scans were first stripped of the skull and segmented using a 6-tissue probability mapping segmentation technique. Next, using affine registration, the scans were normalised to the International Consortium for Brain Mapping template of European brains. Bias, noise, and global intensity normalisation are other configurations. The typical preparation procedure generates 3D picture files that are consistently 121x145x121 in size. By converting the original brain image into a standard image space, skull-stripping and normalising ensured the comparability between images by allowing the same brain substructures to be aligned at the same image coordinates for various participants. The changes in structure were compensated for by using diluted or augmented intensity. the In our experiment, we utilised both of the full brain's

3.2 Convolutional Neural Network

The second stage involves training the 3D convolutional neural network (CNN). The CNN we employ in this project consists of a log softmax layer, two linear layers, a pooling layer, and one convolutional layer. After training the sparse autoencoder, we employ the encoder's weights and biases in a 3D convolutional layer of the 1-layer convolutional neural network's 3D filter. The network design is depicted in Figure 1.

4. EXPERIMENTS

We employed 2D-image slices from 3D MRI scans as inputs to a 2D neural network classifier. Axial, coronal, and sagittal views are three perspectives that are perpendicular to the three typical image coordinate axes that can be used to view a 3D MRI picture. With the use of observations, we were able to pinpoint specific areas in a 3D MRI whose corresponding 2D image might show a more distinct morphological structure between AD cases and healthy controls in terms of the degree of brain atrophy. (We'll refer to the point we just specified as the "key position"). The key position has the same position index on all images because of the standard image space: position index 78 for axial views, 79 for coronal views, and 57 for sagittal views. Image 2a.During the training phase, a slice index was randomly extracted between pm10 and pm20 for each of the three views (slices). The key position slice, one slice one index before the key position, and one slice one index after the key position are concatenated into R, G, and B channels, respectively, to create an RGB colour image (Figure 2b). We expect that by doing this, the synthesised image will be more robust and integrate more spatial information. For the sake of testing and validation, we created the 2D-slice photos at the precise essential locations mentioned above for each of the three viewpoints. Three 2D-slice pictures (from the three viewpoints) were consecutively fed into the trained network for each testing MRI image.



(a) 2D-slices at key positions for three views from an original MRI scan

(b) Synthesized 2D-image in RGB 3 channels for key positions for three views

Figure 2: Results of Proposed system

Network Layer	Validation Accuracy
Last convolution layer	55%
The first linear fully-connected Layer	80%
The second linear fully-connected layer	79%

Table 1: The comparison of performance using different layers feature output

5. CONCLUSION

Our findings indicated that a potential appropriate method for training a CNN classifier on a small training dataset for AD prediction based on structural brain MRI scans is transfer learning. Convolutional layers that were pretrained on ImageNet and were able to extract general image features, like those in AlexNet, could give useful input features for a subsequent neural network for AD classification.

6. REFERENCES

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