**Analysis of Structural MRI Using Convolutional Neural Network for Screening Different Stages of Alzheimer’s Disease**

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**ABSTRACT:** Alzheimer’s disease is a brain disorder that slowly destroys memory and thinking skills and, eventually, the ability to carry out the simplest tasks. This paper proposes ML algorithm to detect early stages of AD using the brain MRIs. There are several stages of AD and needed to be detected in early stage for proper medication and treatment. Deep learning architectures can extract potential features of dementia disease and capture brain anatomical changes from MRI scans. The use of brain MRIs and studying different patterns of the images have helped for feature extraction. Later gaining various patterns from the set of individual subcortical regions of brain, from several different atlases, to identify subject with AD in a MRI, Convolution Neural Network (CNN) algorithm is applied, and different stages of the disease is screened. Experimental results using the proposed system are satisfactory. Several tests were carried out to verify the efficiency of the procedure and to make it more robust. The proposed procedure is general and can easily adapted to various sensors.

**KEYWORDS:** Alzheimer’s Disease, feature extraction, Magnetic Resonance imaging, Convolutional Neural Network**.**

1. **Introduction**

Alzheimer’s disease (AD) has been known as one of progressive neurodegenerative diseases and currently been ranked as the fourth most common cause of death in developed countries. AD is caused by the damage and destruction of nerve cells in brain regions which related to memory, and its most common symptoms are memory loss and cognitive decline [4]. According to Alzheimer’s Disease International (ADI) in its 2016 World Alzheimer’s Report, only 50% of people with dementia are being diagnosed, a figure that drops to 10% in less developed countries. To this day, the diagnosis of Alzheimer’s disease remains essentially clinical, meaning that it cannot be detected until the first symptoms appear, or even later, when the neuropathological damage is already significant. Alzheimer’s disease (AD) is a progressive, incurable neurodegenerative disease resulting in severe dementia. It is the sixth leading cause of death in the U.S. [1] Currently, magnetic resonance imaging (MRI) is commonly used for analysing regional volumetric atrophy, cortical thinning, shape of specific regions as well as for assessing how the disease over time affects the structural/functional connectivity maps of the different regions of the brain based on the structural MRI, the gradual progression of atrophy patterns in key brain regions such as the entorhinal cortex, Para hippocampal gyrus have been recurrently found among patients with AD [5]. The commonly used imaging modalities in dementia diagnosis include the magnetic resonance imaging (MRI), positron emission tomography (PET), and single-photon emission computed tomography (SPECT). As a result, the use of medical imaging for early diagnosis of AD has grown significantly in the last years, especially the use of MRI, given its non-invasive nature, wide availability, and relative absence of discomfort for the patient.

Recently, brain imaging is commonly considered as a source of intermediate phenotypes that augment our understanding of the subtle and complex relationship between genetics and disease phenotypes, which is termed as imaging genetics. The imaging genetics takes into consideration image-based features as a promising intermediate phenotype between genetic variants and diagnosis to discover the pathogenesis mechanisms of specific disorders. By introducing intermediate phenotypes, we can obtain closer association or even higher perceptiveness than traditional disease phenotypes[5]. There are around 47 million people effected by dementia worldwide. The overall cost of the disease is higher than the market value of both Apple and Google combined. The cost associate with providing health and social care for dementia is equivalent to the 18th largest economy in the world. This comparison helps us to comprehend the massive impact of the disease on the economy. [1] Statistics show that around 1 in 10 people over the age of 65 will be affected by Alzheimer’s. Unfortunately, there are no effective cures for this disease, and no one is immune [7].

Getting old and weak is something most people find it hard to accept. It’s a struggle that mature people over the age of 50+ are facing but the concern have doubled with the fear of losing their memory due to dementia. Elderly people who are affected by dementia are living the experience of watching themselves die slowly, fade away from their world, live in consistent confusion, and no longer able to understand their surroundings. It is a horrible experience to endure by Alzheimer's Disease victims, their careers, and their family. Having Alzheimer's Disease means losing loving memories, the ability to recognise family members, and childhood memories, or even the ability to follow simple instructions e.g. making their usual morning cup of coffee, remembering how to use the toilet, and maintain self-hygiene.

1. **RELATED WORK**

In [1] authors have used Tau stained tissue images and using these images AD is characterized by complex changes in brain tissue including the accumulation of tau-containing neurofibrillary tangles (NFTs) and dystrophic neurites (DNs) within neurons, the distribution and density of tau pathology throughout the brain is evaluated at autopsy as a component of Alzheimer’s disease diagnosis. In [2] the radiomics textural features are extracted from the structures of grey matter probability volume, using the ReliefF relevance test and using the ADNI1 database have proven the potential of some of the tested radiomic features as possible biomarkers for AD/CN differentiation. In [3] presents a completely automatic processing chain for orthorectification of optical push broom sensors. The procedure is robust and works without manual intervention from raw satellite image to orthoimage. This [4] proposes an ensemble of 3D densely connected convolutional networks (3D-DenseNets) for AD and MCI diagnosis. First, dense connections were introduced to maximize the information flow, where each layer connects with all subsequent layers directly. In [5] this study, we propose an ensemble model-based framework for firstly extracting 50 region-based image features whose values are predicted by base learners trained on raw neuroimaging morphological variables. The study in this paper [6] introduces a novel Gaussian discriminant analysis (GDA)-based computer aided diagnosis (CAD) system using structural magnetic resonance imaging (MRI) where the data is uniquely inputted for screening different stages of Alzheimer’s disease (AD) involving its prodromal stage of mild cognitive impairment (MCI) in relation to the cognitive normal control group (CN). This [7] paper discusses the importance of investigating Alzheimer’s Disease using machine learning, the need to use both behavioural and biological markers data, and a computational method to rank Alzheimer’s Disease risk factors by importance using different machine learning models on Alzheimer’s Disease clinical assessment data from ADNI. This paper [8] emphases on new features for diagnosis of Alzheimer’s disease using EEG signals with best increase in diagnostic accuracy.

1. **SYSTEM ARCHITECTURE**
2. Data gathering and pre-processing.

The Alzheimer’s Disease Neuroimaging Initiative (ADNI) database provided the neuroimaging data for this study [30]. More than 1,000 adults, including MCI patients, AD patients with a diagnosis, and healthy controls, participated in the study. Most of the people had their data obtained between two and six times, with an average gap of over a year between neighbour scans. The progression of AD has been discovered in a novel way thanks to time sequence scans.

A total of 624 subjects, including both male and female participants, and 833 T1-weighted MRIs were used. The participants' ages ranged from 70 to 90. After some time, we think that a participant's particular brain anatomy matters. Then, if the period is greater than three years, we chose two scans with the largest interval of one participant as distinct subjects. Also, it was prohibited for subjects chosen from the same participant to appear in both the training dataset and the testing dataset.

1. Proposed Algorithm

Convolutional Neural Network: - Throughout time, one specific algorithm—a Convolutional Neural Network—has been developed and optimised, largely leading to breakthroughs in computer vision with deep learning. A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning method that can take in an input picture, give various elements and objects in the image importance (learnable weights and biases), and be able to distinguish between them. Comparatively speaking, a ConvNet requires substantially less pre-processing than other classification techniques. ConvNets have the capacity to learn these filters and properties, whereas in basic techniques filters are hand-engineered. A ConvNet's architecture was influenced by how the Visual Cortex is organised and is similar to the connection network of neurons in the human brain. Only in this constrained area of the visual field, known as the Receptive Field, do individual neurons react to stimuli.

The three colour planes of the RGB image—Red, Green, and Blue—have been used to split it in the picture. Images can be found in a variety of different colour spaces, including grayscale, RGB, HSV, CMYK, etc. The Convolution Operation's goal is to take the input image's high-level characteristics, such edges, and extract them. There is no need that ConvNets have only one convolutional layer. Typically, low-level features like edges, colour, gradient orientation, etc. are captured by the first ConvLayer. With more layers, the architecture also adjusts to the High-Level characteristics, giving us a network that comprehends the dataset's pictures holistically in a way that is comparable to how we do.

There are four types of layers for a convolutional neural network: the **convolutional** layer, the **pooling** layer, the **ReLU correction** layer and the **fully connected** layer.

1. Convolutional Layer: -

Convolutional neural networks' central element, the convolutional layer, is always at least their first layer. Its objective is to find a certain collection of characteristics in the photographs supplied as input. Convolution filtering is used to do this. The basic idea is to "drag" a window representing the feature over the picture, compute the convolution product between the feature and each section of the scanned image, and then apply the result to the entire image. The two concepts are equal in this sense and a feature is thus considered as a filter.

Diagram, engineering drawing

Description automatically generated

As a result, the convolutional layer processes several pictures and computes the convolution of each image with each filter. The traits we're looking for in the photographs are precisely what the filters match.

In contrast to conventional approaches, features are acquired by the network during the training phase rather than being pre-defined according to a certain formalism (for example, SIFT). Convolution layer weights are referred to as filter kernels. Gradient descent is used in backpropagation to update them after initialization.

1. The pooling layer: -

This kind of layer, which receives many feature maps and executes the pooling operation on each of them, is frequently used between two layers of convolution.

The pooling procedure involves shrinking the size of the photos while maintaining their crucial elements. To do this, the picture is divided into regular cells, and the greatest value is then retained within each cell. To prevent too much information loss, tiny square cells are frequently utilised in practise. The most popular options are 3x3 cells separated by a step of 2 pixels, or 2x2 neighbouring cells that don't overlap (thus overlapping). The amount of feature maps we receive as output and input are same, but they are substantially smaller. The network's parameters and computations are simplified by the pooling layer. By doing this, the network becomes more effective, and overlearning is prevented. In contrast to those received as input, the feature maps obtained after pooling show the maximum values less precisely.

1. The ReLU correction layer: -

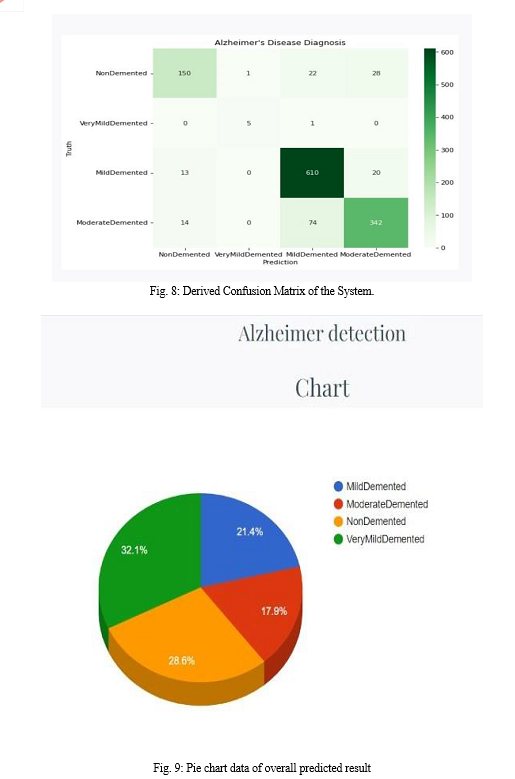
ReLu (Rectified Linear Units) refers to the real non-linear function defined by *ReLu(x)=max(0,x)*. The ReLU correction layer replaces all negative values received as inputs by zeros. It acts as an **activation function.**

1. The Fully Connected: -

It is not a feature of a CNN because the fully connected layer is always the final layer of a neural network, convolutional or not. This kind of layer takes in a vector as input and creates a fresh vector as output. To do this, it applies a linear combination to the input values received, followed optionally by an activation function.

As an input to the network, the last fully connected layer classifies the picture by returning a vector of size N, where N is the total number of classes in our image classification issue. Each component of the vector represents the likelihood that the input image belongs to a certain class. So, the fully connected layer multiplies each input element by weight, adds the results, and then applies an activation function (logistic if N=2, softmax if N>2) to determine the probabilities. This is the same as multiplying the input vector by the weight’s matrix. The phrase "fully connected" refers to the fact that each input value is connected to each output value. Similar to how it learns convolution layer filters, the convolutional neural network learns weight values by backpropagation of the gradient during the training phase. The association between the location of features in an image and a class is determined by the fully connected layer. In fact, the input table, which is the outcome of the preceding layer, corresponds to a feature map for a specific feature: the high values represent the position of this feature in the picture, which might be more or less exact depending on the pooling. A value in the table is given considerable weight if the placement of a feature at a specific point in the picture is indicative of a particular class.

1. **RESULTS AND DISCUSSION**



1. **CONCLUTION**

In this Work, the basic Convolutional Neural Network (CNN) architecture model has been used to classify Alzheimer\'s from magnetic resonance imaging (MRI) scans images. Convolutional Neural Network (CNN) architecture model is used to avoid the expensive training from scratch and to get higher efficiency with limited number of datasets. The proposed work was able to give a good accuracy where training accuracy is 86.34% and validation accuracy is 86.45% on the test data with very small misclassifications on normal and very mild demented. Future work includes using data from other modalities like PET, fMRI to improve the performance.

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