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Machine Learning for Alzheimer's Disease Detection and Categorization in Brain Images

[1]Dr. Mandeep Kaur, [2]Dr. Anupama Arora, [3]Dr. Sakshi Kathuria, [4]Muhammad Waqas Arshad, [5]Surya Pratap Singh

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Abstract: Alzheimer's disease (AD) is a devastating form of dementia characterised by advanced symptoms in affected individuals' later years. Significant intellectual deficiencies, memory loss, and other cognitive impairments characterise the lives of Alzheimer's patients. Diagnosing Alzheimer's disease may be difficult and time-consuming due to the multitude of mental and physical tests neurologists often use. MCI, or mild cognitive impairment, is a kind of dementia that occurs in the early stages of Alzheimer's disease. The last stage of MCI is called late-MCI, and it is sometimes mistaken for the first stages of Alzheimer's disease (EAD). Correctly classifying EAD is also crucial for preventing or delaying the start of AD. The most fundamental modification in terms of AD's physical presentation is the degeneration of brain cells. Critical biomarkers related with the illness may be uncovered by careful analysis of brain images. The use of magnetic resonance imaging, commonly referred to as an MRI, is a common diagnostic tool used in the medical imaging area during clinical investigations. A large quantity of MRI data was collected from a number of publicly available sources in order to conduct this investigation. All the photos that were taken have had the "skull stripped" effect added to them. The skull and other non-brain pixels carry very little information, hence this is necessary.

Keywords*: Alzheimer's disease, Magnetic Resonance Imaging (MRI), Mild Cognitive Impairment (MCI), skull stripping*

1. Introduction

The gradual loss of memory and other cognitive abilities over time is a hallmark of Alzheimer's disease (AD), a neurodegenerative disorder characterised by the destruction of brain cells. Dr.Alois Alzheimer is often cited as the one who gave the illness its name. Dr.Alois Alzheimer initially recognised a rare mental condition in 1906 [1]. Symptoms included memory loss, difficulty speaking, unusual conduct, etc. After her death, Dr. Alzheimer performed an autopsy on the patient's brain and discovered many anomalies. Alzheimer's disease (AD) is a progressive neurodegenerative brain illness that severely limits a person's daily functioning [2]. Beginning in the mid-60s, AD symptoms become noticeable [3]. In addition to memory loss, other symptoms of AD include:

a) Not being able to do the tasks which were once easy,

b) Finding difficulties in solving simple problems,

c) Changes in mood or personality (e.g., like to stay away from friends and family),

Alzheimer's disease is now the sixth leading cause of mortality among the elderly and is projected to rise to the third spot in the near future. [4][5]. More than 44 million individuals worldwide have some kind of dementia, including Mild Cognitive Impairment (MCI), a study by Alzheimer's and Dementia Resources found. A person with MCI has cognitive skills that are in between those of a healthy person and those of someone with AD [6]. persons with MCI have much greater memory loss than average persons their age, although the symptoms are not as severe as those of AD. The signs of Alzheimer's disease (AD), such as personality changes and difficulty to do routine tasks, are not present in people with mild cognitive impairment (MCI). Researchers found that even while not everyone with MCI progresses to AD, the risk of developing AD was much greater among those with MCI [7]. Nearly 80% of those with MCI will acquire AD within seven years, whereas just 3% of typically healthy people over the age of 65 would get AD [8]. Studies show that an individual's hereditary characteristics are a major contributor to the onset of MCI and AD [9]. The neurologist diagnoses MCI by conducting a battery of in-person examinations. Exams of cognition, memory, and communication are among

[1]*Assistant Professor, Department of Electronics and Communication Engineering, Punjabi University Patiala, Punjab, India, Email: ermandeep0@gmail.com*

[2]*Senior Resident, Department of Psychiatry, SLBS Medical College & Hospital Campus, Atal Medical and Research University, Mandi, Himachal Pradesh, India, Email: dr.aarora07@gmail.com*

[3]*Assistant Professor, School of Computer science and engineering, K.R.Mangalam University, Gurugram, Haryana, India, Email: sakshi.bhatia@gmail.com*

[4]*Ph.D. Research Scholar, Department of Computer Science and Engineering, University of Bologna, Italy, Email: Muhammad.waqas.arshad.1@gmail.com*

[5]*Research Scientist-1, Multi-disciplinary Research Unit, Uttar Pradesh University of Medical Sciences, Saifai Etawah, U.P., India, Email: spsinghadarsh@gmail.com*

these [10]. Although there are no definitive treatments for MCI or AD, patients may maintain their health and cope with everyday challenges by engaging in a number of tried-and-true routines. Normal persons also experience a cognitive deterioration as they age, albeit it is much less than that seen in those with MCI or AD [11]. Brain scans of a CN, MCI, and AD patient aged 65 (male) are shown in axial view (for a specific slice) in Figure 1.1 through Figure 1.3.

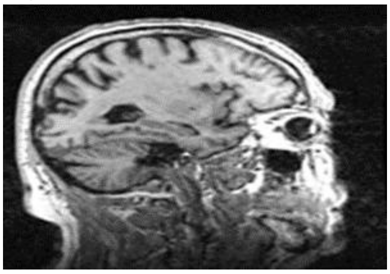


Fig 1.1: A sample MR image of a CN subject

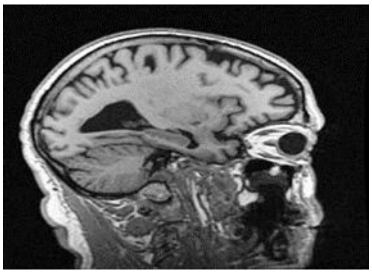


Fig 1.2: A sample MR image of a MCI subject

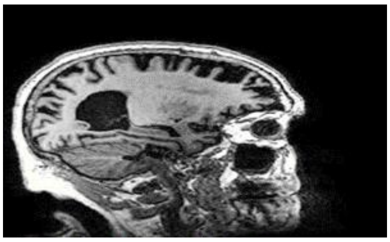


Fig 1.3: A sample MR image of a AD subject

2. Brain imaging

Alzheimer's disease structural imaging is a common aspect of the diagnostic process [12]. These exams are often done to rule out other diseases that might cause symptoms similar to Alzheimer's but have a distinct cause and therapy. Structural imaging may detect tumours, signs of small or large strokes, damage from severe head trauma, and cerebral fluid accumulation. High amounts of beta-amyloid are indicative of Alzheimer's disease, thus a doctor may use brain imaging equipment to check for this. [13]

Changes in the structure of brain in AD

Researchers are making strides towards a better understanding of the many brain alterations that occur in the onset and progression of Alzheimer's disease. The toxic change in brain tissues, the researchers say, may start long before the onset of AD's severe symptoms. As it advances, abnormal protein transfers in the brain create amyloid plaques and tau tangles. Over time, normal neuronal function declines and synaptic connections break down. The damaged areas manifest first in the hippocampus and the entorhinal cortex, two brain regions essential for memory. As a result, an increasing number of neurons inside the brain perish, leading to widespread brain atrophy. The hippocampus is a brain region essential for memory and spatial orientation. Memory loss and disorientation are hallmarks of Alzheimer's disease since the hippocampus is often the first brain region damaged. Amnesia and the inability to develop new memories result from Hippocampus injury. [14]

Diagnosing Alzheimer's disease by hand is challenging. Cognitive testing might be difficult for a psychologist to utilise to diagnose AD since significant cognitive decline is typical in normal ageing as well. Not only does this procedure take a long time, but when the psychiatrist has completed the manual examinations, they may decide to use neuro-imaging investigation as well. As a consequence, employing biomarkers found in brain cells to categorise AD is an effective technique to do so. Neuroimaging and feature extraction might be used to effectively categorise AD. Magnetic resonance imaging (MRI) is a common method for studying the brain and spinal cord in great detail. Cancer, tumours, and other diseases may frequently be diagnosed accurately by MRI. With the right image processing methods, we can tell how different people with AD, MCI, and Cognitively Normal (CN) brains really are. Researchers have shown that traditional classifiers have trouble classifying AD by analysing tissue changes because to the complex pixel patterns. One of the most popular forms of Machine Learning (ML) used to medical image processing is the Artificial Neural Network (ANN). To analyse data from the environment, ANN constructs networks of artificial neurons that mimic the organic processes of the human brain. To better absorb important properties for enhanced model training, Deep Neural Networks (DNNs) are an ANN component in which a number of hidden layers are interpreted between input and output[15].[16]. DNN is a popular machine learning technique that has shown promising results in a range of medical settings. One of DNN's selling points is its ability to process very complicated data, including brain pictures. Therefore, in this paper, DNN is predominantly used for feature extraction / classification. Prototype DNN architecture is given in Figure 1.4.

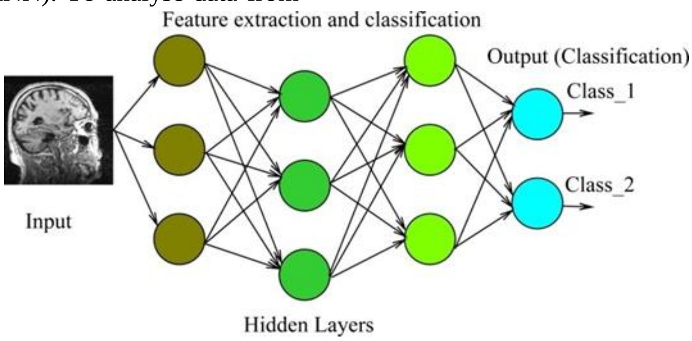


Fig 1.4: SampleDNNarchitecture

Diagnosing Alzheimer's disease is a challenging undertaking. Memory decline is common in normal ageing and might make it difficult for doctors to tell whether a patient is really developing Alzheimer's disease [17]. Therefore, identifying bio-markers in brain tissues is preferred for classifying AD. The most seriously damaged brain regions are principally important for cognitive tasks during the progression stage of AD. Accurate segmentation of brain MRIs, identification of Regions of Interest (RoI), extraction of important feature sets, and comparisons of tissues across all subject groups are some of the main challenges in identifying AD via brain imaging. A reliable feature extraction method is required for AD classification using brain images [18].

3. Literature Review

BattulaSrinivasaRao et.al (2023.The author elaborates on how ideas from convolutional neural networks might be applied to the study of brain anatomy for the purpose of identifying AD. Brain MRI segmentation for the classification of Alzheimer's disease is described, along with its advantages, recent advances, and the findings obtained on publicly available datasets. This article provides a short literature overview on Alzheimer's disease and discusses how Deep Learning might be used to enhance early detection.

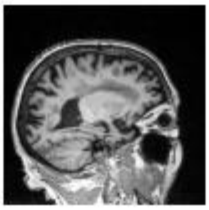
Ruchika Das et.al (2022).Our method makes use of a deep learning model that was developed using an MRI dataset. This technique appropriately classifies MRI scans into the four stages of AD based on the hippocampal volume: Mildly Demented, Moderately Demented, Non-Demented, and Severely Demented.

V. Brindha Devi et.al (2022) Using the Random Forest Algorithm for classification and the PCA (Principal Component Analysis) approach for feature extraction, the author successfully clustered MRI images. The suggested method divides the picture pixels into four groups. Among the four Alzheimer's disease classifications for which the algorithm has been applied are Mild Demented, VeryMild Demented, Non Demented, and Moderate Demeneted. Kaggle's Alzheimer's dataset is used to evaluate the effectiveness of the suggested method. The findings imply that this method is very sensitive, with an overall accuracy of 99.95%, to pinpointing the precise site of brain lesions.

Data distribution

All obtained data has had the skull removed due to the fact that it does not include any crucial information for our study. Different skull stripping methods are put to the test by collecting data and ground truth photographs to compare their results to. "NeuroImaging Tools and Resources Collaboratory" provides a large amount of useful information. For anyone interested in the field of neuroscience, there is the NeuroImaging Tools and Resources Collaboratory. Figure 2.1 and Figure 2.2

show, respectively, a representative skulled and skullless brain image.



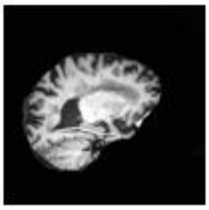


Fig 2.1: Sample input Brain MR image Figure 2.2: Sample skull stripped Brain MR image

Pre-processing

MRI is the gold standard in medical imaging because it provides more detail and accuracy than any other kind of imaging technology. Moreover, MRI is one of the safest imaging modalities for medical patients since it does not emit any hazardous radiation. For subsequent processing, visual clearing of MRI is a crucial concern. However, these pictures are contaminated at various stages by undesired pixels or noise, which might hinder further processing. Skulls are the unintentional picture artefacts that appear while sending or receiving photographs. Skulls may emerge as a result of interference and picture compression caused by utilising a flawed equipment. However, there are obstacles to eliminating skulls, such as the difficulty of removing low-frequency components, the possibility of deleting excellent pixels, etc. In order to prevent this kind of information contamination and guarantee accurate interpretation, it may be necessary to provide a reliable system for determining the location of genuine skulls. Skull stripping is the quantitative morph ometry study of separating the brain from distracting pixels. In order to diagnose brain disorders, improved segmentation to separate brain regions is required. Before using various techniques like image warping, image registration, volumetric measurement of the brain, etc., it is important to properly strip the skulls. Although there are many theoretical discussions on skull stripping techniques utilising picture segmentation, this work implements some of the most commonly employed skull stripping algorithms to help readers better grasp the idea.

Commonly used Skull stripping methodologies

The MRI of the brain generates 3D volumetric data, which is shown as a stack of 2D slices. An efficient computer-assisted tool is required for different diagnostic applications to discover the knowledge of these slices. To investigate data on a brain picture, numerous image pre-processing techniques may need to be implemented. Segmenting a picture is a crucial technique in analysing its components. There are a plethora of suggested algorithms for medical picture segmentation. You may classify them into four broad groups: methods based on pixel intensity, texture information, models for segmentation, and atlases.

Mathematical morphology-based methods

These techniques involve morphological processes like erosion and dilatation to remove skull tissue from the area of interest (ROI). Edge and threshold information is necessary for these techniques to locate the ROI. The fundamental downside of these approaches is that they are sensitive to a wide range of variables, including edge information, the thresholding information, ROI shape and size, etc. Parameter selection is difficult and may have an impact on the final outcome. In addition, these techniques are very sensitive to even little variations in input values. It might be difficult to decide on a suitable morphological size when dividing a region of interest (ROI).

Intensity based methods

These techniques divide the input image's ROI based on the pixel's intensity values. Intensity-based approaches include histograms, histogram-like distributions, edge information-based methods, and region growth. These strategies use various functions based on pixel attributes to identify and isolate the ROI from the surrounding area. In certain circumstances, such as poor contrast and low-resolution photos, images with significant noise, etc., these approaches are unable to distinguish the skulls since they rely only on pixel values.

Deformable-surface based methods

An Active Contour (AC) is often created by this process, with its parameters chosen by analysing various aspects of the photos. The picture is distorted by the AC such that it fits the brain's surface. The foundation of an AC model is the idea of a curve that, after certain restrictions are met, may be extended to the object's boundary. The processes of "shrinking" and "growing" are metaphors for the development of the curve. These techniques rely on two inputs: the position along the curve at the outset and the gradient of the picture used to terminate the curve at the desired point. Among the approaches' many benefits is their ability to pinpoint inner and outside limits at the same time. The main problem of these approaches is their susceptibility to background noise.

Region Splitting and Merging (RSM)

This is crucial in order to identify and differentiate the numerous items contained in the picture for analysis purposes. The goal of this technique is to divide the input picture into about equal halves. It's shown as a pyramid with four distinct zones on each of its square levels. The programme first assumes that there is only one area in the input picture, and then utilises a similarity criteria to determine whether this is indeed the case. If it doesn't return TRUE, the area is split into two smaller parts. When additional picture splitting is no longer required, the procedure will end. The little areas are tested, and those that return "TRUE" or "FALSE" are combined. One of the key flaws of this approach is that it may combine two neighbouring areas into one if the bigger region's similarity requirements are satisfied..

Deep Learning-based architectures for detection and classification of Alzheimer's disease

The image classification experts have been working on a model that is based on DNN. Up to this point, there have been numerous successful model advancements and innovations that have taken place. There has been a significant amount of investigation regarding the use of DNN for the classification of AD, and the findings have been fairly encouraging. The high dimensionality of the input data may be made more manageable with the use of a concept called a pooling layer when working with DNN models. MaxPooling or Average Pooling are the two types of pooling layers that are used the most often in DNN architecture. In conventional picture classifications, pixels with higher intensity levels have a tendency to play the most important roles, which is where the maximum pooling layer flourishes. However, when applied to pictures such as brain MRIs, the MaxPooling method has the important impact of discarding the element with the lowest values, which may include information that is vital to the analysis. However, when it comes to the input data components, the Average Value Pooling layer uses the mean value without question. The result of computing the average value of very high valued sections and very low valued portions does not operate as either a high valued element or a low valued element; this is a significant constraint of Average Pooling. The value that represents the operation's output is greatly impacted negatively as well when there are several components in the stride that have a value of zero. This work presents an alternate technique for identifying superior characteristics from brain images for use in the classification of Alzheimer's disease (AD) by establishing a min pooling layer and then finalising min and maximum swimming layers simultaneously. The cornerstone of this study is LeNet, and it uses LeNet as its base.

Improved LeNet model construction

One of the most efficient DNN models is LeNet, which uses very little processing power. Figure 3.1 depicts a typical LeNet model's structure.

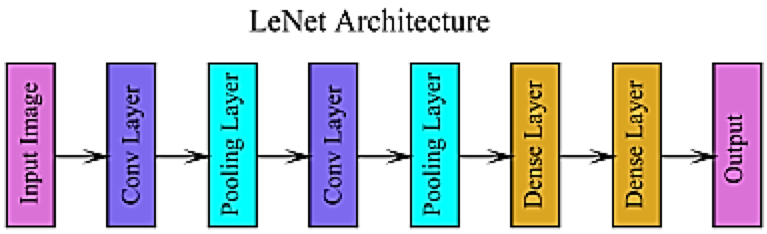


Figure 3.1: A typical LeNet model architecture

LeNet's architecture is seen in figure 3.1, and it consists of 7 levels and an output layer. The photos are processed via a size-normalization procedure at the network's input layer before being sent on to the next layer. The Convolutional layer follows, and it uses feature maps/kernels to pull out crucial feature data like edges, corners, etc. When it comes down to it, kernels and feature maps are just a collection of square matrices with the same weights. The convolution operation is the process by which kernels are slid and overlapped across all of the pixels in a picture. The suggested model's standard convolutional operations use extra memory space since they are chained together with max and min pooling layers. One common technique for speeding up computation and boosting representational efficiency is depth-wise convolution. In depth-wise convolution, each picture channels are convolved with their own unique kernels. A point-wise 1 1 convolutional operation is then used to aggregate the channel outputs. The next layer of LeNet is used for lowering the dimensionality of matrices. It's called a pooling procedure, and it involves using mathematical algorithms to eliminate irrelevant data. The layer we are on is called the Pooling layer. The Max Pooling operation is employed in the default LeNetmodel; hence this layer is often referred to as the MaxPooling layer. Max pooling selects and propagates only the highest-valued kernel items to the subsequent layer.

Architecture of the proposed DNN model

Prototype development of a deep neural network (DNN). The 19 total layers of this network (16 Convolution and

3 Dense) were inspired by the original VGG-19 model. MaxPooling layers are used in pooling operations. To simplify communication, we create forward-facing shortcut bridges linking the result of each layer of pooling to the inputs of all future convolution layers.

The next model layer is where the convolutional operations take place. Convolution layers use a consistent set of layouts to restore crucial visual components like borders, curves, etc. Parameterized quadratic arrays are what kernels are made out of. Rolling and stacking filters over a whole image's pixels is a convolution. Due to the information sharing involved in the suggested methodology, typical convolution algorithms incur large processing costs. In the following model layer, we reduce the total number of features utilised in each array. A pooling operation is the process of removing unnecessary information. In the suggested paradigm, the MaxPooling layer is used to choose and propagate just the most highly valued items in a kernel to the subsequent layer. The loss function is computed after either a complete or partial redistribution of the dataset. The loss function, in Forward Propagation, is the total number of errors in the forecasted results. Among the numerous common loss functions, the Binary Cross-Entropy (BiCE) stands out. In our model, BiCE is used. After a loss estimate has been determined, the gradients of all the key parameters can be computed, and the parameters may be optimised effectively. Since it is more fundamental in nature, the proposed model encounters difficulties such gradient vanishing and information losses. The Dense-Block idea from the DenseNet design is used to achieve this goal, since it allows for seamless inter-layer communication. DwC and pooling layers are followed by dense or fully connected ones. Neurons in these dense layers are intricately connected to one another.

When compared to other popular DNN models, LeNet is both the simplest and the oldest. LeNet is quite effective when compared to other models. LeNet uses the MaxPooling layers to reduce the dimensionality of the input data, much as the majority of other DNN models. There is a key downside to employing MaxPooling levels for AD classification when relying on brain images, and that is that it only considers the most highly rated characteristics. That is, it disregards areas of the images when the intensity is low. Dense Block, a variant of the original DenseNet architecture, mitigates this issue by connecting each output layer directly to the input layers that follow. Due to the high volume of convolutional calculations needed by such a model, however, having too many bridge connections might increase the computational burden. Better and faster results may be achieved using the depth wise convolutional process. Therefore, instead of using regular convolutional layers, the model employs depth wise convolutions. Based on the measured performance, the proposed design seems to be one of the most convincing approaches. In addition, a unique hybrid DNN model that parallels LeNet and AlexNet is shown in this chapter. The proposed model is sophisticated in its architecture and requires several iterations of convolutional processes, which increases the time required to execute it. To solve this issue and improve the model's ability to extract useful features, we replaced all of the conventional convolution layers with a series of three small parallel convolution layers equipped with 1 1, 3 3, and 5 5 filters. The proposed hybrid model is mathematically one of the lightest-weighted models given, since it extracts less convolutional parameters than the other models (with the exception of LeNet).

4. Conclusion

LeNet is a well-liked DNN-based classification model with a simple but powerful framework. Dimensionality reduction is accomplished in LeNet, as in other DNN models, thanks to the MaxPooling layer's elimination of the data associated with least valued components. It's possible that even pixels with low intensity values carry crucial information in brain scans. In order to preserve the network's minimal valued components, a dedicated layer is developed to carry out the Min-Pooling procedure. The next step is to join the MinPooling and MaxPooling layers. At long last, the concatenated layers have taken the place of all MaxPooling Layers in LeNet. The updated version of the LeNet model was found to perform better than any of the other models tested. A unique classification paradigm for early and other dementia phases of AD is offered as a contribution to the thesis. To achieve this goal, a DNN model is provided here. Denseblock is used to propagate the most relevant characteristics throughout the network, with VGG-19 serving as a benchmark.

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