ALZHEIMER DISEASE DETECTION BY COMPUTER AIDED BRAIN DIAGNOSIS USING BRAIN MRI IMAGES BASED ON DECOMPOSITION TECHNIQUES AND CONVOLUTIONAL NEURAL NETWORK

DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
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OF

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CANDIDATE'S DECLARATION

Vanshika Asthana student of Master of Technology (Signal Processing and Digital Design), hereby declare that the project Dissertation titled "**Alzheimer Disease Detection by Computer Aided Brain Diagnosis using Brain MRI Images based on Decomposition Techniques and Convolutional Neural Network**" which is submitted by me to the Department of Electronics and Communication Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

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Date: 31-05-2022

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CERTIFICATE

I hereby certify that the Project Report titled "**Alzheimer Disease Detection by Computer Aided Brain Diagnosis (CABD) using Brain MRI Images based on Decomposition Techniques and Convolutional Neural Network**" which is submitted by **Vanshika Asthana**, **2K20/SPD/15** of Electronics and Communication Department, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: Delhi | **Dr. Anukul Pandey**
Date: 31-05-2022 | **SUPERVISOR**

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Vanshika Asthana

ABSTRACT

The main goal of this thesis is to create a system which can determine whether the patient is Alzheimer affected or not and that system we call it as a CABD (System Computer Aided Brain Diagnosis). T2 weighted MRI have been taken as an input. In this thesis, series of quantitative techniques have been taken such as filtering, feature extraction and KNN classifier.

The motive of this research work is to develop an interface which can classify normal and Alzheimer Disease cases. Firstly, we collect the 2D test images of Brain MRI. Now after collecting these 2D test images, we implement a preprocessing technique on these images, the result of which is the enhancement of test pictures and removal of the noise. The preprocessing employs a median filtering algorithm which automatically separate noise from the test images. Then from those median filtered Brain MRI, features were collected using various transforms which are describe further.

Now, at the final stage we implement KNN classifier which then classifies that whether the person is Alzheimer affected or not.

CONTENTS

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREVIATIONS

- **AD** - Alzheimer's disease
- **ANN** - Artificial neural network
- **CNN** - Convolutional neural network. A type of ANN.
- **MCI** - Mild cognitive impairment
- **MRI** - Magnetic resonance (imaging). A form of neuroimaging.
- **CAD** - Computer assisted diagnosis
- **PET** - Positron emission tomography. A form of neuroimaging.
- **SVM** - Support Vector Machine. A classification method based on separating hyper-planes.
- **UDS** - Uniform data set. A standardized set of forms used in diagnosis of Alzheimer's disease.

CHAPTER 1

INTRODUCTION

1.1 Overview

In this chapter a brief introduction about MRI and Alzheimer Disease is provided. Types of MRI and Why we consider MRI for extracting useful information . So in this chapter we are going to explore some details about MRI.MRI is a non-invasive imaging technology, non-invasive means which is not spreadable. MRI produces three dimensional anatomical images in detailed manner. Anatomic images means the images of physical structure of human body. It is oftenly used for the detection of diseases, diagnosis and treatment monitoring. It is based on technology that exites and detects the change in the direction of the rotational axis of protons which are found in water and makes up the living tissues.How does MRI work is MRI consist of powerful magnets which produces magnetic field that forces the protons in the body to go and align with that field. When a radiofrequency current is passed through the patient, the protons are stimulated, getting out of equillibirium straining the pull of the magnetic field. When this radiofrequency current has been turned off, then the sensors in the MRI detect the energy released as the proton gets realign with the magnetic field. The time it takes for the protons to realign with the magnetic field changes depending upon the environment and chemical nature of the molecules[1].

MRI is used to display the soft tissues of the body. Brain, spinal cord nerves , muscles and ligaments are seen much more clearly with MRI than with regular X-rays and CT Scan and that is why MRI are used to see the images of knee and shoulder injuries

1.2 Alzheimer disease

Alzheimer's disease is a neurological illness that is quickly spreading among the elderly. According to the findings of a recent survey, while cancer and heart disease have traditionally been the top priority in healthcare, Alzheimer's disease has risen to the top. Alzheimer's disease (AD), the most common cause of dementia in the elderly, is a chronic degenerative disease characterised by progressive loss of cognitive function. The progressive disappearance of healthy nerve cells in the cerebral cortex, particularly in the frontal and medial temporal regions of the brain, characterises cognitive decline. AD is also a significant cause of morbidity, ranking fifth among causes of death according to the World Health Organization[2].

Memory problems, disorientation, a lack of self-care, behavioural changes, depression, anxiety, and language difficulties Alzheimer's disease is widely assumed to progress gradually and irreversibly. In the final stages of the disease, the patient may lose the ability to perceive, think, speak, or move, eventually leading to loss of bodily functions and, eventually, death. The disease can progress over a period of 3 to 9 years or even longer.

Pre-dementia, early stage, middle stage, and advanced stage are the stages of Alzheimer's disease. The symptoms of pre-dementia mimic the natural ageing process, including forgetfulness and mild cognitive impairment. Impaired learning, executive function, and memory are more prominent in the early stages, often resulting in some language difficulty[4]. Speech difficulties become more noticeable in the middle stage, reading and writing skills deteriorate, and long-term memory is compromised. Alzheimer's patients in the advanced stage may exhibit apathy, and simpler tasks cannot be completed independently; the afflicted individual eventually becomes bedridden, and death occurs .The phrase "neurodegenerative disorders" refers to medical problems that affect the brain's neurons directly. Parkinson's disease, Alzheimer's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis are only a few of them. Patients with these diseases have a long-term cognitive decline with symptoms such as gait irregularities, speech issues, and memory loss due to increasing cognitive deterioration[4]. Because people are living longer, neurological disorders have become more common in developed countries, putting a significant financial strain on health-care facilities[5].

1.3 Structural MRI

As the T1 relaxation rates differ, structural MRI uses tiny changes between voxels to discriminate bad tissue, resulting in the eventual resolution of unique voxel intensities. Examining the varied relaxation rates of nuclei in each of three habitats often encountered in a scan of a neuroscience subject: bone, brain, and cerebral-spinal fluid (CSF)[6] is illustrative in the case of a T1 picture. Because of the scarcity of spin-lattice interactions in the stiff material, the surrounding lattice in bone is a solid with few protons to begin with, and those that are there have a long T1 relaxation time. The mobility and molecular absorption frequencies of the tissue in the brain now allow for such relaxing episodes, resulting in a reduction in anxiety.The chance of an adequate transfer event falls as suitable absorption frequencies are thinly distributed throughout a broad range, lengthening T1 relaxation time[7]. CSF has the same low image intensity as bone as a result of this connection. While T1 susceptibility 4 imaging of tissue is typical in anatomical research, it is not uncommon to obtain a T2 image as well, because certain types of disease are more easily detectable in a T2 image. Anatomical study acquisition duration is usually limited solely by the patient's tiredness within the bore or clinical concerns. Although scans are frequently repeated for signal averaging, there is only one measurement of each voxel volume required. The phrase "neurodegenerative disorders" refers to medical problems that affect the brain's neurons directly. Parkinson's disease, Alzheimer's disease, Huntington's disease, and Amyotrophic Lateral Sclerosis are only a few of them. Patients with these diseases have a long-term cognitive decline with symptoms such as gait irregularities, speech issues, and memory loss due to increasing cognitive deterioration[8]. Because people are living longer, neurological disorders have become more common in developed countries, putting a significant financial strain on health-care facilities.

Because the degenerative mechanism reverses the process of neuron growth, the patient begins to act like a kid as the disease develops, resulting in functional abnormalities, behavioural changes, impairments, cognitive and behavioural problems

1.4 Functional MRI

Functional imaging, unlike anatomical imaging, necessitates capture speed and sensitivity at the sacrifice of resolution[9]. The signal acquired in a functional imaging scan is not fundamentally different from that recorded in any other type of anatomical imaging procedure; nonetheless, the essential interest is not anatomical discriminability, but change in tissue characteristics over time. Because of the fluctuating local magnetic field caused by diverse effects emerging from functional activation, T2 weighted pictures are virtually commonly used. The cornerstone of functional MRI is based on the discovery that active brain tissue undergoes a vascular change), which is still a hotly discussed topic. The volume and flow of blood to an activated area of the cortex can fluctuate dynamically, along with the amount of oxygen used.

Multiple low-resolution photos of the area of interest are captured in rapid succession, with a volume often finished in less than two seconds. After that, the images can be compared in order to create a time series of intensities for each voxel. The nature of the signal produced is determined by the kind of study utilised, which varies primarily in the contrast approach used, as detailed below[10]. This time series can then be utilised in either a block design or an event-related paradigm to test reaction to an applied stimulus. The participant in a block design experiment does two or more different tasks, one after the other, for an extended period of time. During each task, the relative levels of activation are calculated.

1.5 MR Based neuroimaging

MR based neuroimaging can provide qualitative and quantitative information regarding brain structure and function. The advances in the MR imaging technology over the past decade have opened new avenues for mental health research utilizing neuroimaging data. In typical use, MR techniques are used for imaging soft tissue that allows researchers to investigate structural and functional characteristics of the human brain. MR image acquisition is a non-invasive, safe for humans, process that produces three dimensional detailed anatomical images without the use of harmful radiation. Neuroimaging processing pipelines consist of multiple sequential tasks prior to statistical analysis. The pipeline begins with the acquisition of MR images comprising biases and artifacts induced by the hardware and acquisition protocol itself. These artifacts are subsequently corrected for using appropriate image processing techniques. Images are also cropped to remove areas beyond region of interest. After these pre-processing steps, images are used towards subsequent statistical analyses. Structural MR images form the basis of this thesis. As a result, these steps are described in detail in following sections.

1.6 MR Acquisition

An MR imaging scanner consists of a main magnet, which generates a strong primary magnetic field, a radiofrequency (RF) coil, which transmits and receives radiofrequency energy to and from the tissue), which are used to generate field gradients to enable frequency and spatial encoding used for signal source localization. The primary magnetic field, denoted as B0, causes protons from the abundantly present water molecules in a human body to align with the field. Conventionally this field defines the

coordinate frame of reference with B0 oriented along z-axis. B0 causes protons to process at a frequency, known as Larmor frequency, that is proportional to the field strength:

$$\omega_L = \gamma B_0 \tag{1.1}$$

where the gyromagnetic ratio γ is characteristic of the nuclei under consideration. The alignment along the z-axis is perturbed out of equilibrium by an application of a radio frequency (RF) pulse perpendicular to this axis. Once the RF field is turned off, the sensors can detect the energy released by the protons as they undergo realignment to the primary magnetic field. The amplitude of this signal is maximal immediately following the RF pulse, and decays with time. By employing magnetic field gradients, signal source can be spatial localized by inducing differential Larmor frequencies along the z-axis. Additionally gradient induced phase encoding is used to resolve signal location in the xy plane. The sampling of this frequency and phase encoded signal generates a complex-valued 3-dimensional array in a spatial frequency domain. Several parameters of the acquisition protocol influence the quality of the image (i.e., signal to noise ratio, resolution, field of view, etc.) But typically, image quality is improved with higher B0, which is commonly set to be 1.5T or 3T; although 7T scanners have become commercially available. The signal is quantified using a time constant characterizing signal decay. The excited protons generate magnetization components along z-axis (longitudinal) as well as, xy (transverse) plane. A set of macroscopic equations to calculate nuclear magnetization (M) as a function of time, and are written in matrix form as follows.

$$\frac{dy}{dx}\begin{pmatrix} M_x \\ M_y \\ M_z \end{pmatrix} = \begin{pmatrix} \frac{-1}{T_2} & \gamma B_z & -\gamma B_y \\ -\gamma B_z & \frac{-1}{T_2} & \gamma B_x \\ \gamma B_y & -\gamma B_x & \frac{-1}{T_1} \end{pmatrix}\begin{pmatrix} M_x \\ M_y \\ M_z \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ \frac{M_0}{T_1} \end{pmatrix} \tag{1.2}$$

Where γ is the gyromagnetic ratio, and T1 and T2 are the time constants associated with the decay of the signal corresponding to the longitudinal and transverse components, respectively. The recovery of longitudinal magnetisation as the protons align with B0 is known as spin-lattice (T1) relaxation

$$M_z(t) = M(\Theta)\left(1 - e^{\frac{-t}{T_1}}\right) \tag{1.3}$$

Decay of transverse magnetization during realignment is known as spin-spin (T2) relaxation

$$M_{xy}(t) = M(\Theta)e^{\frac{-t}{T_2}} \tag{1.4}$$

Where M is nuclear spin magnetization vector parallel to the external magnetic field B0. These time constants are dependent on the surrounding environment i.e., biological tissue. Thus, the resultant MR contrast is dependent on these time constants as well as the proton density of each tissue type. A basic MR acquisition sequence, referred to as spin-echo, comprises a two RF pulses. First, a 90 degree pulse tips the net magnetization into transverse plane. Once the RF transmitters is turned off, transverse magnetization decays, and longitudinal magnetization is recovered as the protons align themselves to B0. Protons themselves re-radiate the absorbed energy which can be detected by the receiver coils. The signal received in the transverse plane decays faster than T2 would predict. This is modelled by a modified time constant T2 comprising pure T2 decay as well as the static inhomogeneities in the magnetic field which accelerate the dephasing process. The 90 degree pulse is followed by a 180

degree pulse in order to rephase the spins in the transverse plane and reverse the static field inhomogeneities. The signal is measured after the phase coherence is achieved. This time epoch is called echo time, which is the time between the 90 degree pulse and MR signal sampling. The 180 degree pulse is applied at time TE/2. This process is repeated several times, and the time between two 90 degree pulses is referred to as the repetition time (TR). Due to different T1 and T2 values for each tissue, MR contrast can be modified with different configurations of TE and TR. With short TR and TE, contrast depends primarily on the tissue specific differences in the longitudinal magnetization recovery, i.e., T1. This is referred to as T1-weighted sequence. Relatively, with longer TR and TE, T1 differences diminish, and tissue contrast results mainly from the T2 properties of the
tissue. This is referred to as T2-weighted sequence. Configuration of long TR and short TE produces a proton density image, in which the contrast is a function of the differences in the proton density of the tissues, as neither longitudinal or transverse signal is allowed to recover by sampling at high rate. Tissues with longer T1 and T2 appears dark in T1-weighted image and bright in the T2-weighted image. Conversely, tissue with short T1 and a long T2 appears bright in the T1-weighted image and dark in the T2-weighted image.

1.7 MR Image pre-processing

The raw image acquisition usually comprises noise and artifacts that need to be accounted for prior to downstream computational analysis. In addition, it is also important to extract brain-tissue from the raw image and discard background, skull and other regions irrelevant to the computational analysis of interest. These pre-processing steps alter signal-to-noise and contrast-to-noise ratios (SNR, CNR) of the image and thus influence the subsequent image analysis. Therefore, it is crucial to carefully design pre-processing pipelines to achieve accurate as well as reproducible results\.

1.8 MR Image denoising

The noise in the MR signal are resultant of thermal vibrations of ions and electrons in the receiving coil and the tissue manifested as intensity fluctuations. The noise in magnitude MR images generally follows a Rician distribution. In theory, the SNR can be improved by averaging multiple repeatedly acquired images. However, this requires substantially more acquisition time that is not feasible in practice. Another simple approach to mitigate high-frequency noise is to use low-pass Gaussian filter which essentially averages neighbouring pixels. However, this results in blurred images diminishing high-frequency spatial information such as structural boundaries. Several advanced denoising methods have been proposed and applied that include anisotropic diffusion filter , wavelet-based filters and adaptive non-local means . We note that based on our assessment of the quality of publicly available, standardized datasets utilized in this thesis, we did not include denoising step in our pre-processing pipeline for any of the three projects.

1.9 Image registration

Image registration is an alignment problem that deals with transforming raw data into a common frame of reference. In medical imaging, registration is crucial for establishing comparability across different individuals, time points, and modalities. For structural MR images, this typically implies estimating a one-to-one mapping between two image spaces to have anatomical correspondence. Registration approaches can be divided by degrees of freedom, and similarity metrics (i.e. cross-correlation, mutual information) . Mathematically, the registration of image J into the space of image I can be formulated as an optimization problem with the goal of finding transformation as follows.

$$T^{*} = argmax_{M_e} S(I, J, M) \qquad (1.5)$$

where, I = reference image

J = image to be transformed

M = transformation

S = similarity measure

T* = optimal transformation

1.10 Image segmentation

The process of image segmentation refers to parcellating pixels or voxels into labelled salient regions. Segmentation provides meaningful representation of an image that facilitates quantitative analysis. In MR imaging, segmentation is commonly performed at different levels of granularity as well as anatomical categories. Several classes of segmentation methods exist, including manual segmentation, auto segmentation.

1.11 Manual Segmentation

The gold standard for the anatomical segmentation identifying various cortical and subcortical structures is defined the experts through a manual delineation process. This manual delineation is a tedious and time-consuming process, and also introduces inter- and intra- variabilities into segmentations.

1.12 Automatic segmentation

In the last two decades, rapid progress has been made in automatic techniques to improve the performance and efficiency of cortical and subcortical segmentations. The earlier approaches classified healthy brain tissue into grey matter (GM), white matter (WM) and cerebrospinal fluid (CSF) broadly based on the differential intensity profiles of each tissue types. Alternatively, several region growing, classification, and clustering approaches have been proposed for intensity-based segmentation. Region growing requires selection of seed points (voxels) that belong to a region of interest. Region growing methods are suitable for structures with large connected regions, such as brain vessels, tumours, etc. The classification methods make use of a training set of labelled images to automatically learn the mapping between intensity profile and corresponding categorical label. One of the simplest non parametric classifiers used towards segmentation is k-nearest neighbour, where voxels are classified according to majority vote of the closest training data . Another commonly used parametric approach includes a Bayesian classifier. During training, a Bayesian classifier models the probabilistic relationship between the image intensities and the class labels. Then a new image gets assigned labels using an inference technique, such as the maximum a posterior estimation, based on Bayes' rule. These types of classifiers are commonly implemented in expectation-maximization framework in several MR segmentation software packages such as SPM ,FAST ,Free Surfer, and 3DSlicer . In contrast with classification methods, clustering methods belong to unsupervised learning paradigm that segment images into voxel clusters with similar intensities. Some of the commonly used clustering methods include k-means , fuzzy C-means , and expectation-maximization methods. Similar to classification methods, clustering methods typically do not incorporate spatial neighbourhood information making them vulnerable to noise and intensity inhomogeneities. Although several extensions have been proposed to mitigate this issue, atlas-based alternative approaches have become more popular choice for leveraging prior anatomical knowledge for localization and identification of several brain regions. The atlas-based approaches are extremely powerful in their ability to transfer a prior spatial anatomical information to the new image during segmentation. Traditionally, atlas based techniques use a single template derived from manual segmentation that would serve as a reference atlas for automated techniques. An image to be segmented is aligned to this atlas via affine and then nonlinear registration techniques. Once the new image and atlas are in the same reference frame, all the label information can be propagated from the atlas to the new image via transform information from the registration step. Several methods have been proposed to refine the post registration segmentation quality via unifying these two processes.

1.13 Cortical surface estimation

Cortical thickness and surface area are commonly used metrics for examining neuroanatomical properties and alterations of cerebral cortex as captured by MR images. Cortical thickness and surface area are known to reflect differential neurobiological processes as well as genetic influences. The layered organization of cortex can be parsed into columnar units . Then in this arrangement, cortical thickness and surface area are postulated to reflect the number of cells within a cortical column and the number of columns themselves, respectively . Furthermore, cortical thickness is thought to include dendritic arborisation and pruning and surface area is thought to include cortical folding and gyrification. Thus, investigation of these two measures and how they separately contribute to cortical architecture can provide important information about neuroanatomical development and the potential underlying cellular mechanisms, as well as about the neuroanatomical correlates of various diseases and neuropsychiatric conditions . Cortical thickness estimates are derived by classifying the brain into grey matter, white matter and CSF, and defining the boundaries of the white matter and pial surfaces. Inner and outer surfaces are then extracted, and the distance between these two surfaces at a given point is calculated, which represents the cortical thickness at this vertex. Two of the most widely used tools for estimating cortical thickness values are CIVET and Free surfer . These tools differ in the manner in which the cortical surfaces are reconstructed.

1.14 Masking

Masking of non-brain tissue, such as skull, fat and neck regions is another common pre-processing step. Such cropping of region of interest improves subsequent image analysis. Masking involves binary classification of each voxel from the raw scan as brain or non-brain tissue, where the brain comprises grey matter, white matter and cerebrospinal fluid (CSF) . A common method for is Masking uses a deformable model of a sphere's surface, which expands one vertex at a time until the boundary of the brain's surface is reached.

1.15 Objective

The vital aim and the objective of the projected thesis is to create and innovate a model or the classifier which will be efficient enough to detect any sort of tumor in the medical images that will be fed to the classifier as an input and simultaneously find some properties related to that tumor. The first and the foremost step of the Alzheimer disease detection is to acquire the data as this is the main and one of the hardest task as the data set for the brain images is rarely available and very much complicated for acquiring this data and then feeding in the classifier. Many researchers studied and focused on the defined work and methods like filtering, segmentation and feature selection. In our present work we focused on building or innovating a method or the system which can fulfill all the basic and the vital tasks to detect the tumor or the lesions and its features. We in the presented work formulated a model which is very effective and accurate and the model helps in the process of segmentation and the finding of the Alzheimer disease detection without the indulgence of the human and the manpower is also saved. Depending upon the traditional classifiers, we came out with the result which will give the best results and the performance of the model is also the best in terms of ROC Curve and Scatter Plot.

1.16 Dissertation Organization

This Dissertation work that is being proposed is formulated in the form of seven different section. In an upcoming section we will be briefly describing the chapters of the Dissertation in detail.

• **Chapter 1:- Introduction**

This is the first and the foremost important chapter of the Dissertation which includes the objective or the aim , the goal and the contribution related to our Dissertation. Herein we will describe the Alzheimer Disease detection and classification .

• **Chapter 2:- Methodology**

The chapter 3 of our thesis describes the methodology that is being employed in innovating the model to segment the brain MRI image containing tumor with the help of the image processing techniques and methods along with the traditional machine learning classifiers to detect the tumor in brain MRI image which is causing in the Alzheimer Disease.

• **Chapter 3:- Machine Learning Tools**

This chapter of our presented work describes about all the prerequisites that are needed for this thesis work in this chapter I have described the basics of the image processing methods and techniques and the various traditional and new machine learning algorithms and classifiers in detail.

• **Chapter 4:- Results and Discussions**

In this chapter five, we have explained the performance of the model that is being designed and along with the results that are obtained based on the proposed methodology are discussed in detail in this chapter.

• **Chapter 5:- Conclusion and Future Scope**

In this chapter six the main aim of this chapter is to discuss the conclusion that is being taken from the proposed algorithm. IN this proposed work we will list the limitations that are resulted from our proposed work and future scope and further innovations that we can add onto our proposed work.

CHAPTER 2
METHODOLOGY

This section will present the concepts that are used throughout the thesis. It will also present a list of abbreviations that can be used as a reference.

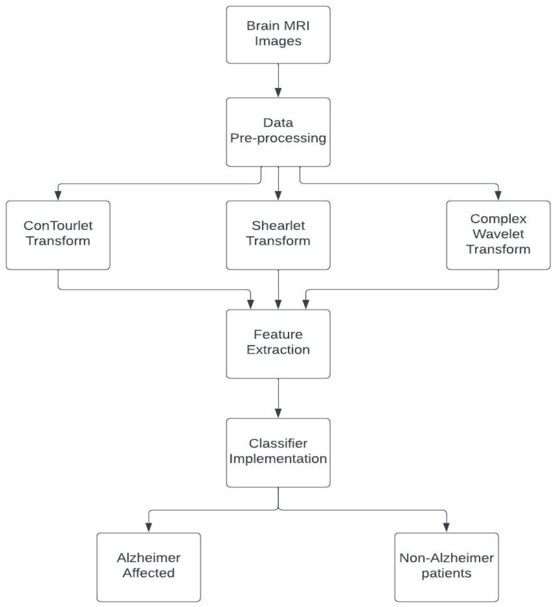

Figure 2.1 Structure of CABD System

2.1 Data preprocessing

This method refers to clean the data and convert it into a form which we can extract some useful information. Here what pre-processing doing is it enhances the test pictures and removes the unwanted data or noise. The pre-processing tools include filtering, interpolation, frequency domain processing, time domain processing. Why we are doing pre-processing is for the accurate, efficient and meaningful analysis of data[9].

2.2 Contourlet transform

Let us first discuss about contours, Contours are defined as a line that connects all points with the same intensity along the image's boundaries. Contours are basically the imaginary lines which connects the similar points. They represent the lines which is a function of the variables, forming a curve and along that curve the function represent a constant value. CoT is a 2D transform method for image representation. In this, the contour of original images which are the dominant features in natural images, are captured effectively with new coefficients using CoT[10].

The basic features of CoT are multiscale and multidimensional. The properties of CoT are:

1. Multiresolution
2. Localization
3. Directionality
4. Critical Sampling

2.3 Step towards contourlet transform

ConTourlet Transform, a formal approach for the better representations of an image in two dimensions. This transform is not limited to 2D but it has overcome the properties of critical sampling, localization, multiresolution. However, it’s basic properties are still remains the same that is multidimensional and multiscale. The features which are dominant in natural image are basically the contours and these dominant features are captured easily with the help of ConTourlet Transform.

2.4 Discrete Wavelet Transform:

Discrete wavelet transform is a kind of the wavelet which is used for analyzing various frequencies that are present in an image with the help of the different scales that are present. In this proposed wok we are employing the technique the discrete wavelet transform (DWT) which is a very powerful method or tool used for extracting the features. This technique is used for extracting the coefficients of wavelets from the brain MRI image. The wavelet used here is used to localize the information in the form of frequency of the signal function that played a crucial rule in classification. The main principal on which this discrete wavelet transform actually works is that in this the images that are of interest are taken and are decomposed into different spatial frequency components those are extracted from the low level (LL) sub-bands although the high- low (HL) sub-bands have higher accuracy in comparison with (LL) lo-level, for better results both the techniques HL and LL are been employed which accurately defines the text features [11].

2.5 Shearlet transform

Shearlets are used in image processing applications such as denoising, compression, restoration, feature extraction and are widely used because of their optimal sparse approximation properties in medical image analysis. Shearlets are associated to multiresolution analysis. To accurately analyse signals and images with abrupt changes, we need to use a new class of functions that are well localised in time and frequency.here shearlets are used. Shearlets are defined as a framework which is done on multiscale level to allow significant encoding of eluotropic features in huge number of statistical variables. Shearlets are well known for the approximation of functions like sparse array or a sparse matrix, in which the number of elements are mostly zero. Shearlets are advanced version of wavelets. A wavelet is nothing but a wave which produces the oscillations and which is having an amplitude that initiates with zero. Now, shearlets combine multiple operations like scaling and translation which is applied to the infinite succession of number by making them as a coefficient of power series.

2.6 From wavelet to Shearlet

We all know that wavelet transform is limited by only dimension i.e., they do well perform only up to one dimension. For example – Let us take an example of approximating a function, containing two variables forming a discontinuity along a curve. Now, as the discontinuity is spatially spread out, therefore it extensive interacts with the elements of wavelets. And, as a result, the representation of variables is not dispersed, that means a large number of wavelet coefficients are required to precisely present this discontinuous function[12].

2.7 Overfitting

Overfitting is the phenomenon where by a machine learning model overly adapts to the training data and thus performs on that data it has not seen before. In the context of neural networks, one way of combating overfitting is a method called dropout. It works by reducing the model's complexity by making a random selection of neurons. This way, the network is less likely to overfit to the noise in the training data . Another method for combatting overfitting is called batch normalization and works by normalizing the input in each batch of data in the training process. This can both make the training process faster and help combat overfitting .

2.8 NACC Uniform Data Set

In order to standardize data collection in studies of Alzheimer's disease, the National Alzheimer's Coordinating Centre (NACC) defined the Uniform Data Set(UDS) . The UDS contains three different sets of forms: one to be filled during the patient's initial visit, one to be filled during follow-up visits and one to be filled during telephone follow-ups. The information contained within the forms include the patient's demographics, medical history, family's medical history, physical evaluation, various mental tests and clinician's diagnosis[13]. This set of information can then be used to diagnose the patient.

CHAPTER 3
MACHINE LEARNING TOOLS

In order to determine whether supplementing the raw image data with clinical data features helps improve the accuracy of a classifier based on ANNs, two models were created: one taking only image data as input and one taking both images and numerical features as input. Aside from this difference, the two models were made as similar to one another as possible. Since the goal was to compare two different approaches rather than to design a powerful classifier, the models were not made any more complex than necessary. Making the networks more complex and optimized was deemed outside the scope of this project. In order to simplify the design and construction of the networks, the machine learning framework was used along with the programming language Python to perform the experiments The two neural networks were then trained and validated on an 80%-20% split of data set chosen randomly with a fixed seed for reproducibility. Since the dataset used in the study was unbalanced, the samples were weighted so that samples belonging to the less common class were given proportionately more importance.The design of the neural networks is described in more detail.

3.1 Artificial neural network

Artificial neural networks (ANNs) are a computational tool commonly used in supervised machine learning that are based on a simplified model of networks. Although, invented as early as 1946, there has recently been a resurgence in the use of ANNs, owing to the fact that modern computers have become powerful enough that large ANNs can be trained in a feasibly short amount of time. A single artificial neuron consists of the following parts: a vector valued input, the neuron's body where the input is combined with weights by means of a scalar product, and finally some activation function which introduces a non-linearity to the model and thus allows it to model non-linear relationships. Several of these artificial neurons can be stacked on top of each other in a single layer, and a network can consist of several layers so that all outputs of one layer are connected to the inputs of the next layer. Such a network is called a fully connected feed- forward network and a network consisting of three or more layers is considered as *deep* neural network. The function of an artificial neuron can thus be summarized with the following formula:

$$E\sigma\sum(xiwi \qquad (4.1)$$

where σ is the activation function, $\vec{x}$ is the neuron's input and w mean weights. Training an ANN model involves finding appropriate weights in each layer. This is accomplished by computing the loss of the model, that is some measure of how the model's prediction differs from the correct answer in the training data. The loss is a function of the model's parameters (in this case the weights) and training the model involves feeding the loss to an optimization algorithm so that the loss is minimized . A commonly used method for minimizing the loss is gradient descent. This method consists of computing the gradient of the loss function with respect to the weights and then adjusting the weights in the opposite direction to this gradient vector. This process is then repeated until the loss is sufficiently small.Sometimes, for the sake of training speed, the gradient is not computed on the whole data set. When performing gradient descent on a neural network, the entire training data set is iterated through multiple times.

3.2 Convolutional neural networks

Convolutional neural networks (CNNs) are a type of neural network that was created to analyse data using a grid-like architecture.. [Examples of such data are images, which can be thought of a 2D grids of pixels. CNNs differ from regular feed-forward networks described above in that they contain one or more so-called convolutional layers. The main principle behind the Conolutional neural networks is that it is pre-assumed that the input to the ConvNets architecture are images in nature , which certainly allows the users to encode specific properties and characteristics in the architecture or the model. The model then subsequently allows the forward function to take place easily and effectively and this certainly reduces the abstraction of the parameters used in the network. The Convolutional neural networks are basically build from the neurons which comprises of some weights and the biases. The main ideology behind this is that every neuron present exactly receives an input in the form of an image and simultaneously performs the dot product.

In this algorithms firstly all the layers are arranged in manner that they appear in three different dimensions that are height, width and depth. In this neurons that are present in single level they does not get connected to these neurons those are present in the succeeding level but only gets connected to the smaller area of it. To sum up this algorithm procedure the final output that is obtained will get reduced in the manner and will be represented to a individual vectors of probable scores which are arranged depending upon the depth dimension. In addition the Convolutional Neural Network the also performs the conolutional operations in the case of the matrix multiplication.

3.3 Decision Tree

Decision tree algorithm is supervised learning algorithm which is used for the classification as well as regression problems. Decision tree is one of the predictive modelling approaches used in statistics, data mining and machine learning. Decision tree classifier, the input is split into sub-spaces based upon certain functions. It helps in reaching a conclusion based upon conditional control statement. In decision tree, there are two nodes, which are the decision node and leaf node.

3.4 SVM

Support vector machine (SVM) is a popular classification technique. Support vector machine (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challengers Its high generalization ability makes it to be used in many fields of classification successful.

The SVM support vector machine algorithm is the algorithm which is used for the formation of model which is used to assign the new examples to a specific category and to the other , keeping it to be non - probabilistic binary linear classifier [17]. The SVM classifier is generally used to represent the instances represented as the points in space which are certainly lined in the manner that the instances of the other categories are separated in such a manner that the gap between the two categories is as wide as possible. The algorithm works in the manner that the instances are being mapped onto the similar space and then the prediction is done on the basis of the category they belong to and onto which of the side of gap they exactly fall. For performing the linear classification the SVM algorithm can be accurately used to execute a non linear classification as well which is given by the name of kernel trick which generally maps down the inputs present onto the high dimensional features space.

3.5 Naive Bayes

Naive Bayes is the artificial machine learning algorithms which is used for the classification purposes and to solve the classification problems. This algorithm is fundamentally dependent on the on the Bayes's probability theorem which is used to predict the group of unknown data - sets. This algorithm is used to predict the probabilities of each group like the probability that is being given and recorded and the data sets or the points that is belonged to a certain class of the data. The class is the main class only when the probability of that class is the highest. The machine learning algorithm such as the Naive Baye's artificial classification machine learning algorithm have multiple and many important features and particular classes.

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 Scatter Plot

Scatter Plot is referred to as a set of points which are plotted on horizontal and vertical axis. Scatter plot shows the extent of correlation (Correlation is a statistical measure that defines how the two variables are related with each other. Correlation is generally expressed by correlation coefficient. The value of correlation coefficient ranges from -1.0 to 1.0. Despite of giving the extent of correlation, scatter plot gives the sense of correlation. There are two types of Correlation.

1.Positive Correlation

2.Negative Correlation

If the vertical variable increases with the horizontal variable, then the correlation is said to be positive. By knowing the above definition, the graph of positive correlation is going to be linear and if the vertical variable decreases while the horizontal variable increases, then the correlation is said to be negative. By knowing the above definition, the graph of negative correlation is going to be nonlinear. Now in order to know how much one variable is affected by another variable, the scatter plots are used.

4.2 Receiver Operating Characteristics (ROC)

ROC is a graph which shows the performance of a classification model at all classification thresholds. The curve plots the two parameters that are True Positive Rate (TPR) , False Positive Rate (FPR).

$$TPR = \frac{TP}{TP+FN} \tag{4.1}$$

$$FPR = \frac{FP}{FP+TN} \tag{4.2}$$

ROC Curve plots TPR versus FPR at the different classification thresholds points. Minimizing the classification thresholds determines the items as positive which in turn maximizes the False Positives and True Positives.

Area Under ROC Curve (AUC)

The AUC calculates the two-dimensional (2D) area under the ROC Curve. AUC gives the aggregate measure of performances of all classification thresholds.

4.3 Data Collection and Pre-Processing

Once the dataset is in CSV format, many features of it should be examined in order to determine whether it is ready to be used as input data for the neural network. The first component that has been handled, as stated in Section 4.3, is a simple statistical exploration of each of the fields. The CSV file was loaded into a data frame to accomplish this.

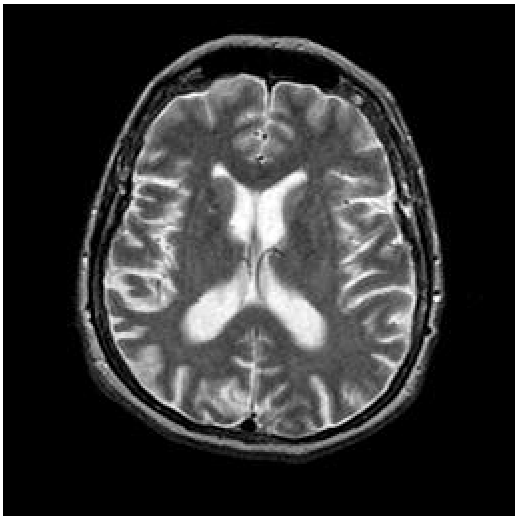

Figure 4.1 test image

Figure 4.2 pre-processed image

4.4 Training & Analysis of The Model

4.4.1 Decision tree

(a) Scatter plot

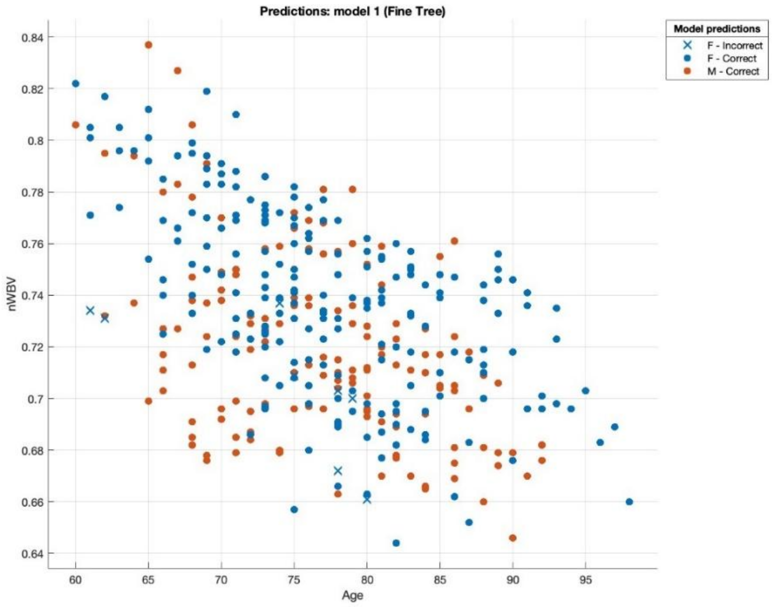

Figure 4.3 Scatter plot of decision tree model

The graph shows the plot between age (on -x axis) and nWBV (on y-axis). nWBV means normalize whole brain volume which determines the volume scaling factor for Brain size. The graph determines the correlation between age and nWBV. As the age of a person varies the volume scaling factor for Brain size for that person also varies. In the middle region of scatter plot the data points are closely associated that means that region consist of strongly bonded data and at the outer side the data points are far way that means that region consist of weakly associated data.

(b) Receiver Operating Characteristics (ROC)

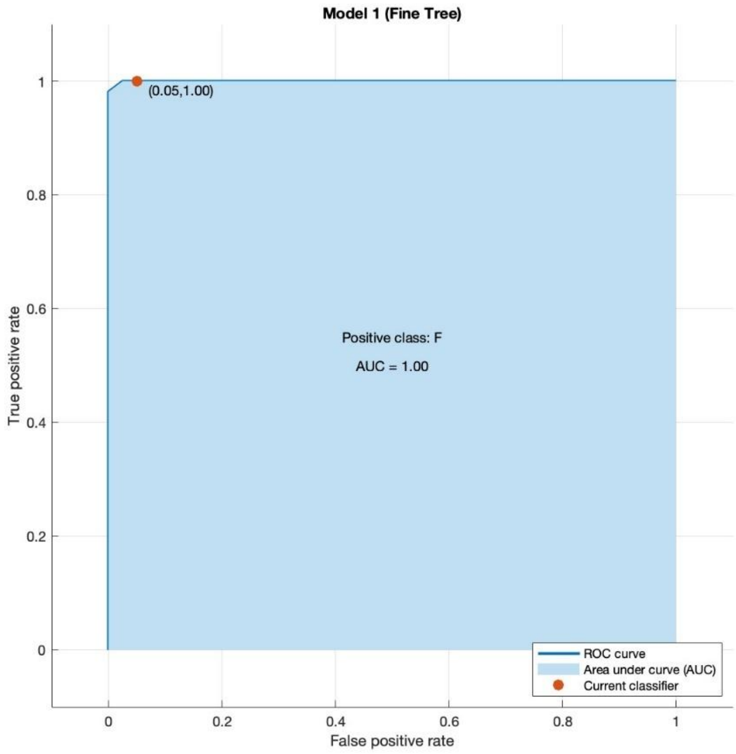

Figure 4.4 ROC curve of decision tree

ROC Curves are used to measure the performance of binary classifiers. These ROC curves are usually tradeoff between True Positive Rates (TPR) and False Positive Rates (FPR). TPR is the fraction of positive examples currently classified. FPR is the fraction of negative examples currently classified. TPR is known as Sensitivity. FPR is known as Fallout. We have some points on this curve and these points denotes classifier or the model which is induced by classifier. There are some critical points on this ROC Curve which conveys some special meaning. If both TPR and FPR are equal to zero that means the classifier predicts all the instances to be of negative class. If both TPR and FPR are equal to 1 that means our classifier predicts all the instances to be of positive class and if TPR is 1 and FPR is 0 that means it is an ideal class. AUC is the area under curve and is used to depict the performance of classifier. If AUC is 0.5 then that would be a random classifier. The range of AUC is [0, 1]. Here in this ROC, AUC is 1 that means all positive examples comes after negative examples.

4.4.2 SVM

(a) Scatter Plot

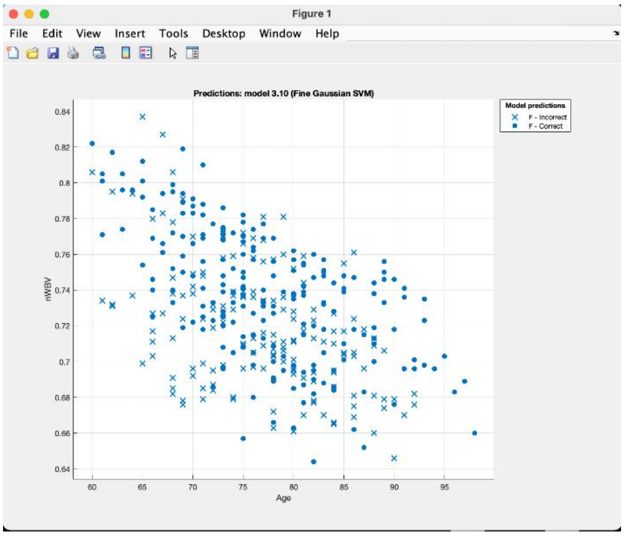

Figure 4.5 Scatter Plot of SVM Classifier

Here the graph is plotted between age and nWBV parameter on y-axis. Here in the graph as the age of the person increases the nWBV factor decreases that means this denotes the negative correlation and as the data points are closely associated in the middle that means these data are forming a strongly bonded cluster.

(b) Receiver Operating Characteristics (ROC)

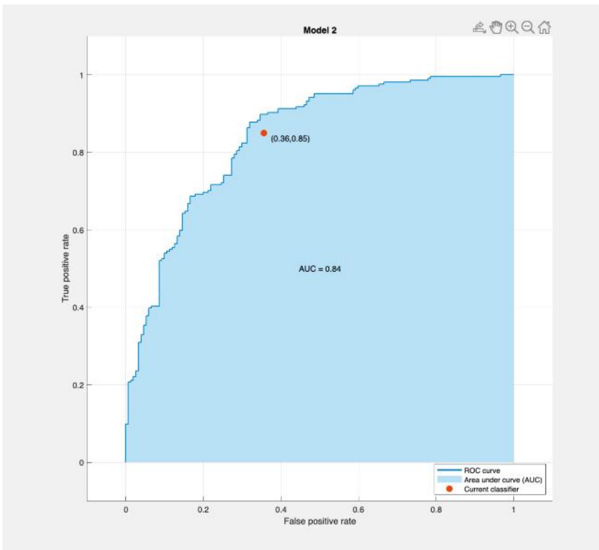

Figure 4.6 ROC curve of SVM Classifier

In this ROC curve of SVM, the classifier is inside the are under curve whereas in Tree the classifier was at the boundary line and here the AUC is 0.84 that is nearer to 1 which means all the positive examples comes after the negative examples.

CHAPTER 5

CONCLUSIONS AND FUTURE SCOPE

An investigation of the axial images of T2-weighted brain MRI, with and without Alzheimer's disease (AD), was compared in this study. The study's main goal was to create an efficient CABD system for assessing the severity of brain abnormalities caused by AD without relying on manual techniques, which are slower to implement and may be cost prohibitive when providing supportive care. A detailed evaluation of the existing feature extraction procedures is also provided. The findings of this study confirm that the decision tree technique produces better results than SVM. n comparison to alternatives Furthermore, when compared to other techniques, the decision tree requires fewer features . On the brain MRI obtained from the medical clinic and the benchmark AD dataset, the proposed paradigm produced better results. This system's performance can be improved with other classifiers. In future work, instead of using Decision Tree and SVM, other classification techniques such as neural-networks, random forest, and AdaBoost will be implemented to improve the performance of the CABD system. A suitable deep learning model can also be proposed to improve classification accuracy.

FUTURE SCOPE

- There are some more possibilities for the betterment or more deep investigation can be done on the proposed work in the future.
- Firstly the data that has been worked upon should contain more number of parameters in order to get the model trained easily and efficiently.
- Secondly , more work should be done on Brain MRI so as to get clear information .
- Thirdly , some many traditional classifiers should be applied in order to get the enhanced accuracy.
- Fourth, the instrument from which we get the MRI should work precisely and efficiently.
- To conclude the last work that can be done is to employ more deep learning approaches so that the model can be more automated and efficient.

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