



Diagnosis of Alzheimer Disease Using Deep Learning

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ABSTRACT

The most common form of dementia, Alzheimer's disease (AD), can significantly limit a person's ability to perform day-to-day activities. AD may be the third leading cause of death among older adults, after heart disease and cancer, according to the findings. Before treatment options can be tried, people at risk for AD need to be identified. The study's objective is to use segmented MRI to thoroughly examine tissue structures, allowing for a more precise diagnosis of certain brain diseases. For the purpose of identifying AD, a number of complex segmentation methods have been developed. Due to their ability to provide precise results across a large amount of data, DL algorithms for brain structure segmentation and AD classification have attracted a lot of attention. As a result, more and more people are choosing DL strategies over cutting-edge Machine Learning (ML) methods. You will find an overview of the most popular deep learning-based segmentation algorithms for analyzing brain magnetic resonance imaging for the treatment of Alzheimer's disease in this study. In the end, a discussion about the advantages and disadvantages of the methods, as well as future directions, was held. This may help researchers better understand the current algorithms and methods in this field and eventually design new algorithms that are more successful

Keywords: Alzheimer's disease, deep learning, First stage detection and diagnosis.

1.1 INTRODUCTION

The most common form of dementia is Alzheimer's disease (AD). In developed nations, the prevalence of Alzheimer's disease is estimated to be around 5% after the age of 65 and staggering 30% for those over 85. Around 0.64 billion people will be diagnosed with Alzheimer's disease by 2050, according to estimates. People with Alzheimer's disease lose their memory, mental functions, and capacity to carry on with day-to-day activities as a result of the destruction of brain cells. Alzheimer's disease initially affects the part of the brain that controls memory and language. Alzheimer's disease patients, on the other hand, experience memory loss, confusion, and difficulty speaking, writing, or reading. They may not recognize their family members and frequently forget about their life. They struggle to perform everyday tasks like brushing their teeth and hair. Patients with Alzheimer's disease become anxious, aggressive, or impulsive as a result of all of these factors. In the end, Alzheimer's disease kills people by destroying the part of the brain that controls breathing and heart function. Alzheimer's disease has three major stages: very mild, mild, and moderate. Until a patient reaches the moderate Alzheimer's disease stage, it is still not possible to accurately diagnose Alzheimer's disease (AD). Physical and neurobiological examinations, the Mini-Mental State Examination (MMSE), and the patient's detailed history are all required for an accurate medical assessment of Alzheimer's disease. Brain Cancer is the 10th most commonly diagnosed cancer in men and the 9th in women, but the 4th leading cancer death for both men and women in the United States. Brain Cancer is only the major cancer with a five-year relative survival rate in the single digits. A recent report issued by brain cancer action in 2020, brain cancer is expected to become the second largest leading cancer cause of cancer death in the united states. A major cause of this ,is the late detection of the brain tumor because there are no effective early detection methods available. Also most of the symptoms of brain tumor are vague and could be contributed to many other abdominal conditions. Also if the cancer has spread to the other organs the treatment becomes very difficult. So there is an urgent need of method that will help radiologists in diagnosis of the brain tumor at an early stage. There is not much work done on brain tumor detection. It is found from the literature survey that brain tumor detection is done by using the symptoms of the disease and taking patient history but not using image processing.

1.2 Deep Learning

Deep learning is a branch of [machine learning](#) which is completely based on [artificial neural networks](#), as neural network is going to mimic the human brain so deep learning is also a kind of mimic of human brain. and it is a particular kind of machine learning that achieves great power and flexibility by learning to represent the world as a nested hierarchy of concepts, with each concept defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones.

While deep learning algorithms feature self-learning representations, they depend upon ANNs that mirror the way the brain computes information. During the training process, algorithms use unknown elements in the input distribution to extract features, group objects, and discover useful data patterns. Much like training machines for self-learning, this occurs at multiple levels, using the algorithms to build the models. Deep learning models

make use of several algorithms. While no one network is considered perfect, some algorithms are better suited to perform specific tasks. To choose the right ones, it's good to gain a solid understanding of all primary algorithms Here is the list of most popular deep learning algorithms:

- i. Convolutions Neural Networks(CNNS)
- ii. Long Short Term Memory Networks(LSTMs)
- iii. Recurrent Neural Networks(RNNS)
- iv. Generative Adversarial Networks(GANs)
- v. Radial Basics Function Networks(RBFs)
- vi. Deep Belief Networks(DBNs)

1.3 Convolutional Neural Networks

In [deep learning](#), a **convolutional neural network (CNN/ConvNet)** is a class of [deep neural networks](#), most commonly applied to analyze visual imagery. Now when we think of a neural network we think about matrix multiplications but that is not the case with ConvNet. It uses a special technique called Convolution. Now in mathematics **convolution** is a mathematical operation on two functions that produces a third function that expresses how the shape of one is modified by the other. Convolutional neural networks are composed of multiple layers of artificial neurons. Artificial neurons, a rough imitation of their biological counterparts, are mathematical functions that calculate the weighted sum of multiple inputs and outputs an activation value. When you input an image in a ConvNet, each layer generates several activation functions that are passed on to the next layer.

The first layer usually extracts basic features such as horizontal or diagonal edges. This output is passed on to the next layer which detects more complex features such as corners or combinational edges. As we move deeper into the network it can identify even more complex features such as objects, faces, etc. Based on the activation map of the final convolution layer, the classification layer outputs a set of confidence scores (values between 0 and 1) that specify how likely the image is to belong to a "class." For instance, if you have a ConvNet that detects images containing tumors, the output of the final layer is the possibility that the input image contains any of those tumors.

2. LITERATURE SURVEY

1) Projecting cancer incidence and deaths to 2030: the unexpected burden of thyroid, liver, and pancreas cancers in the United States

AUTHORS: Rahib L, Smith BD, Aizenberg R, Rosenzweig AB, Fleshman JM,

Matrisian LM.

Cancer incidence and deaths in the United States were projected for the most common cancer types for the years 2020 and 2030 based on changing demographics and the average annual percentage changes in incidence and death rates. Breast, prostate, and lung cancers will remain the top cancer diagnoses throughout this time, but thyroid cancer will replace colorectal cancer as the fourth leading cancer diagnosis by 2030, and melanoma and uterine cancer will become the fifth and sixth most common cancers, respectively. Lung cancer is projected to remain the top cancer killer throughout this time period. However, pancreas and liver cancers are projected to surpass breast, prostate, and colorectal cancers to become the second and third leading causes of cancer-related death by 2030, respectively. Advances in screening, prevention, and treatment can change cancer incidence and/or death rates, but it will require a concerted effort by the research and healthcare communities now to effect a substantial change

2) Brain Ductal Adenocarcinoma Radiology Reporting Template: Consensus Statement of the Society of Abdominal Radiology and the American Brain Association

AUTHORS: Al-Hawary MM, Francis IR, Chari ST, et al

Brain ductal adenocarcinoma is an aggressive malignancy with a high mortality rate. Proper determination of the extent of disease on imaging studies at the time of staging is one of the most important steps in optimal patient management. Given the variability in expertise and definition of disease extent among different practitioners as well as frequent lack of complete reporting of pertinent imaging findings at radiologic examinations, adoption of a standardized template for radiology reporting, using universally accepted and agreed on terminology for solid brain neoplasms, is needed. A consensus statement describing a standardized reporting template authored by a multi-institutional group of experts in brain ductal adenocarcinoma that included radiologists, gastroenterologists, and hepato-pancreato-biliary surgeons was developed under the joint sponsorship of the Society of Abdominal Radiologists and the American Brain Association. Adoption of this standardized imaging reporting template should improve the decision-making process for the management of patients with brain ductal adenocarcinoma by providing a complete, pertinent, and accurate reporting of disease staging to optimize treatment recommendations that can be offered to the patient. Standardization can also help to facilitate research and clinical trial design by using appropriate and consistent staging by means of resectability status, thus allowing for comparison of results among different institutions

3) Deep learning and artificial intelligence in radiology: current applications and future directions

AUTHORS: Yasaka K, Abe O.

Radiological imaging diagnosis plays important roles in clinical patient management. Deep learning with convolutional neural networks (CNNs) is recently gaining wide attention for its high performance in recognizing images. If CNNs realize their promise in the context of radiology, they are anticipated to help radiologists achieve diagnostic excellence and to enhance patient healthcare. Here, we discuss very recent developments in the field, including studies published in the current PLOS Medicine Special Issue on Machine Learning in Health and Biomedicine, with comment on expectations and planning for artificial intelligence (AI) in the radiology clinic

3. REQUIREMENTS SPECIFICATION

3.1 Hardware Requirements:

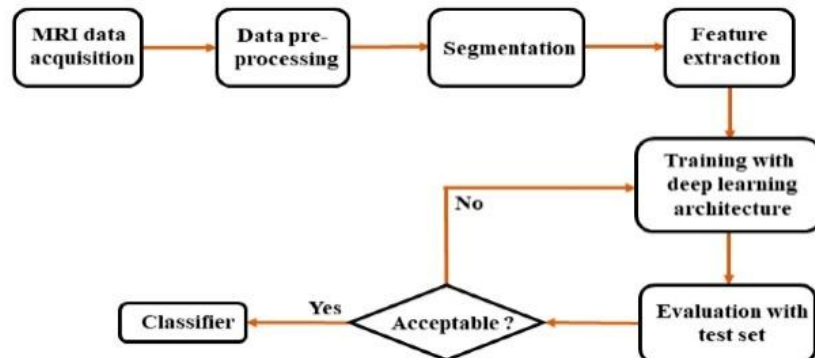
System	:	Intel core i5 Processor.
Hard Disk	:	1000 GB.
Monitor	:	15'' LED
Input Devices	:	Keyboard, Mouse
Ram	:	8 GB

3.2 Software Requirements

Operating system	:	Windows 8,10
Coding Language	:	Matlab
Web Framework	:	SQL

Matlab and related libraries. Dataset is obtained fromKaggle. The data consists of 48x48 pixel grayscale imagesof Alzheimer Disease.

4. SYSTEM ARCHITECTURE



4.1 Proposed Architecture

It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.

It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the systemat the cost of more computational power.

4.2 INPUT DESIGN

The input design is the link between the information system and the user. It comprises the developing specification and procedures for data preparation and those steps are necessary to put transaction data in to a usable form for processing can be achieved by inspecting the computer to read data from a written or printed document or it can occur by having people keying the data directly into the system. The design of input focuses on controlling the amount of input required, controlling the errors, avoiding delay, avoiding extra steps and keeping the process simple. The input is designed in such a way so that it provides security and ease of use with retaining the privacy.

4.3 OUTPUT DESIGN

A quality output is one, which meets the requirements of the end user and presents the information clearly. In any system results of processing are communicated to the users and to other system through outputs. In output design it is determined how the information is to be displaced for immediate need and also the hard copy output. It is the most important and direct source information to the user. Efficient and intelligent output design improves the system's relationship to help user decision-making.

The output form of an information system should accomplish one or more of the following objectives.

- Convey information about past activities, current status or projections of the
- Future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action.
- Confirm an action.

5.IMPLEMENTATION

5.1 IMAGE PROCESSING

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects

of a business. Image Processing forms core research area within engineering and computer science disciplines too.

Image processing basically includes the following three steps.

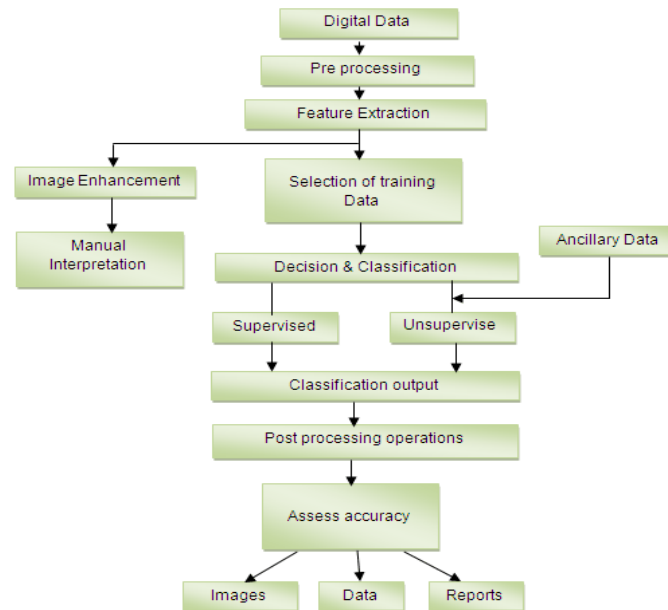
- 1) Importing the image with optical scanner or by digital photography.
- 2) Analyzing and manipulating the image which includes data compression and image enhancement and spotting patterns that are not to human eyes like satellite photographs.
- 3)Output is the last stage in which result can be altered image or report that is based on image analysis.

Purpose of Image processing

The purpose of image processing is divided into 5 groups. They are:

1. Visualization - Observe the objects that are not visible.
2. Image sharpening and restoration - To create a better image.
3. Image retrieval - Seek for the image of interest.
4. Measurement of pattern – Measures various objects in an image.
5. Image Recognition – Distinguish the objects in an image.

The two types of methods used for Image Processing are Analog and Digital Image Processing. Analog or visual techniques of image processing can be used for the hard copies like printouts and photographs. Image analysts use various fundamentals of interpretation while using these visual techniques. The image processing is not just confined to area that has to be studied but on knowledge of analyst. Association is another important tool in image processing through visual techniques. So analysts apply a combination of personal knowledge and collateral data to image processing. Digital Processing techniques help in manipulation of the digital images by using computers. As raw data from imaging sensors from satellite platform contains deficiencies. To get over such flaws and to get originality of information, it has to undergo various phases of processing. The three general phases that all types of data have to undergo while using digital technique are Pre- processing, enhancement and display, information extraction



5.2 IMAGE PROCESSING CONCEPTS

5.2.1 Binary Images

Binary images are images whose [pixels](#) have only two possible [intensity values](#). They are normally displayed as black and white. Numerically, the two values are often 0 for black, and either 1 or 255 for white.

Binary images are often produced by [thresholding](#) a [grayscale](#) or [color image](#), in order to separate an object in the image from the background. The color of the object (usually white) is referred to as the foreground color. The rest (usually black) is referred to as the background color. However, depending on the image which is to be thresholded, this polarity might be inverted, in which case the object is displayed with 0 and the background is with a non-zero value.

Some [morphological](#) operators assume a certain polarity of the binary input image so that if we process an image with inverse polarity the operator will have the opposite effect. For example, if we apply a [closing](#) operator to a black text on white background, the text will be [opened](#)

5.2.2 Color Images

It is possible to construct (almost) all visible colors by combining the three [primary colors](#) red, green and blue, because the human eye has only three different color receptors, each of them sensible to one of the three colors. Different combinations in the stimulation of the receptors enable the human eye to distinguish approximately 350000 colors. A [RGB](#) color image is a [multi-spectral](#) image with one band for each color red, green and blue, thus producing a weighted combination of the three primary colors for each pixel.

A full [24-bit color](#) image contains one 8-bit value for each color, thus being able to $2^{24} = 16777216$ display different colors.

However, it is computationally expensive and often not necessary to use the full 24-bit image to store the color for each pixel. Therefore, the color for each pixel is often encoded in a single byte, resulting in an [8-bit color](#) image. The process of reducing the color representation from 24-bits to 8-bits, known as [color quantization](#), restricts the number of possible colors to 256. However, there is normally no visible difference between a 24-color image and the same image displayed with 8 bits. An 8-bit color images are based on [colormaps](#), which are look-up tables taking the 8-bit pixel value as index and providing an output value for each color.

5.2.3 8-bit Color Images

Full [RGB](#) color requires that the intensities of three color components be specified for each and every pixel. It is common for each component intensity to be stored as an 8-bit integer, and so each pixel requires 24 bits to completely and accurately specify its color. If this is done, then the image is known as a [24-bit color image](#). However there are two problems with this approach:

- Storing 24 bits for every pixel leads to very large image files that with current technology are cumbersome to store and manipulate. For instance a 24-bit 512×512 image takes up 750KB in uncompressed form.

- Many monitor displays use [colormaps](#) with 8-bit index numbers, meaning that they can only display 256 different colors at any one time. Thus it is often wasteful to store more than 256 different colors in an image anyway, since it will not be possible to display them all on screen.

Because of this, many image formats (e.g. 8-bit GIF and TIFF) use 8-bit [colormaps](#) to restrict the maximum number of different colors to 256. Using this method, it is only necessary to store an 8-bit index into the colormap for each pixel, rather than the full 24-bit color value. Thus 8-bit image formats consist of two parts: a colormap describing what colors

Another problem occurs when the output image from an image processing operation contains different colors to the input image or images. This can occur very easily, as for instance when two color images are [added together](#) pixel-by-pixel. Since the output image contains different colors from the input images, it ideally needs a new colormap, different from those of the input images, and this involves further color quantization which will degrade the image quality. Hence the resulting output is usually only an approximation of the desired output. Repeated image processing operations will continually degrade the image colors. And of course we still have the problem that it is not possible to display the images simultaneously with each other on the same 8-bit display.

Because of these problems it is to be expected that as computer storage and processing power become cheaper, there will be a shift away from 8-bit images and towards full 24-bit image processing.

5.2.4 Color Quantization

Color quantization is applied when the color information of an image is to be reduced. The most common case is when a [24-bit color](#) image is transformed into an [8-bit color](#) image.

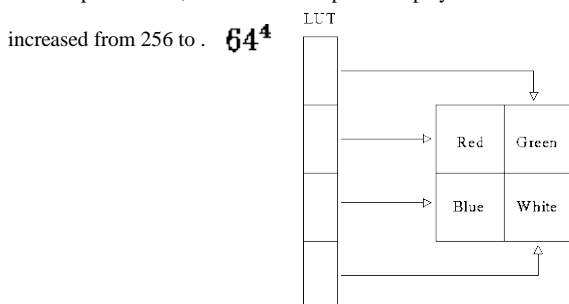
Two decisions have to be made:

1. which colors of the larger color set remain in the new image, and
2. how are the discarded colors mapped to the remaining ones.

The simplest way to transform a 24-bit color image into 8 bits is to assign 3 bits to red and green and 2 bits to blue (blue has only 2 bits, because of the eye's lower sensitivity to this color). This enables us to display 8 different shades of red and green and 4 of blue. However, this method can yield only poor results. For example, an image might contain different shades of blue which are all clustered around a certain value such that only one shade of blue is used in the 8-bit image and the remaining three blues are not used.

Alternatively, since 8-bit color images are displayed using a [colormap](#), we can assign any arbitrary color to each of the 256 8-bit values and we can define a separate colormap for each image. This enables us perform a color quantization adjusted to the data contained in the image. One common approach is the popularity algorithm, which creates a [histogram](#) of all colors and retains the 256 most frequent ones. Another approach, known as the median-cut algorithm, yields even better results but also needs more computation time. This technique recursively fits a box around all colors used in the [RGB colorspace](#) which it splits at the median value of its longest side. The algorithm stops after 255 recursions. All colors in one box are mapped to the centroid of this box.

All above techniques restrict the number of displayed colors to 256. A technique of achieving additional colors is to apply a variation of half-toning used for [gray scale](#) images, thus increasing the color resolution at the cost of spatial resolution. The 256 values of the colormap are divided into four sections containing 64 different values of red, green, blue and white. As can be seen in Figure 1, a 2x2 pixel area is grouped together to represent one composite color, each of the four pixels displays either one of the [primary colors](#) or white. In this way, the number of possible colors is



5.2.5 Convolution

Convolution is a simple mathematical operation which is fundamental to many common image processing operators. Convolution provides a way of 'multiplying together' two arrays of numbers, generally of different sizes, but of the same dimensionality, to produce a third array of numbers of the same dimensionality. This can be used in image processing to implement operators whose output pixel values are simple linear combinations of certain input pixel values.

In an image processing context, one of the input arrays is normally just a graylevel image. The second array is usually much smaller, and is also two-dimensional (although it may be just a single pixel thick), and is known as the [kernel](#). Figure 1 shows an example image and kernel that we will use to illustrate convolution.

I₁₁	I₁₂	I₁₃	I₁₄	I₁₅	I₁₆	I₁₇	I₁₈	I₁₉
I₂₁	I₂₂	I₂₃	I₂₄	I₂₅	I₂₆	I₂₇	I₂₈	I₂₉
I₃₁	I₃₂	I₃₃	I₃₄	I₃₅	I₃₆	I₃₇	I₃₈	I₃₉
I₄₁	I₄₂	I₄₃	I₄₄	I₄₅	I₄₆	I₄₇	I₄₈	I₄₉
I₅₁	I₅₂	I₅₃	I₅₄	I₅₅	I₅₆	I₅₇	I₅₈	I₅₉
I₆₁	I₆₂	I₆₃	I₆₄	I₆₅	I₆₆	I₆₇	I₆₈	I₆₉

K₁₁	K₁₂	K₁₃
K₂₁	K₂₂	K₂₃

Figure 1 An example small image (left) and kernel (right) to illustrate convolution. The labels within each grid square are used to identify each square.

The convolution is performed by sliding the kernel over the image, generally starting at the top left corner, so as to move the kernel through all the positions where the kernel fits entirely within the boundaries of the image. (Note that implementations differ in what they do at the edges of images, as explained below.) Each kernel position corresponds to a single output pixel, the value of which is calculated by multiplying together the kernel value and the underlying image pixel value for each of the cells in the kernel, and then adding all these numbers together.

So, in our example, the value of the bottom right pixel in the output image will be given by:

$$O_{57} = I_{57}K_{11} + I_{58}K_{12} + I_{59}K_{13} + I_{67}K_{21} + I_{68}K_{22} + I_{69}K_{23}$$

If the image has M rows and N columns, and the kernel has m rows and n columns, then the size of the output image will have $M - m + 1$ rows, and $N - n + 1$ columns.

Mathematically we can write the convolution as:

$$O(i, j) = \sum_{k=1}^m \sum_{l=1}^n I(i + k - 1, j + l - 1)K(k, l)$$

where i runs from 1 to $M - m + 1$ and j runs from 1 to $N - n + 1$.

5.3 Preprocessing

Pre-processing is a common name for operations with images at the lowest level of abstraction of both input and output are intensity images. The aim of pre-processing is an improvement of the image data that suppresses unwanted distortion. Some of the point processing techniques include: contrast stretching, global thresholding, histogram equalization, log transformations and power law transformations. Some mask processing techniques include averaging filters, sharpening filters, local thresholding... etc

Different techniques: Data preprocessing is a data mining technique that involves transforming raw data into an understandable format. ... Data preprocessing is a proven method of resolving such issues. Data preprocessing prepares raw data for further processing, or enhances some image features important for further processing

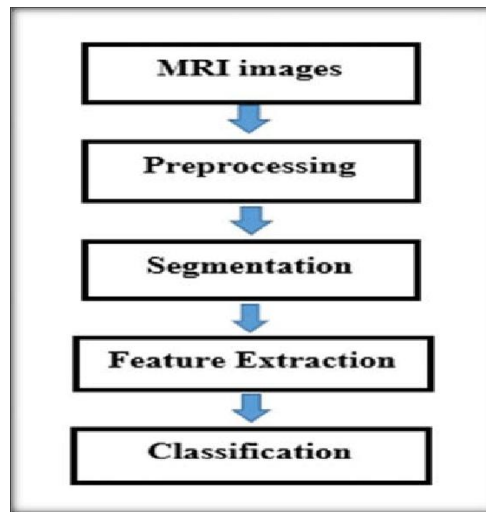
5.4 Feature Extraction

Feature extraction is a part of the dimensionality reduction process, in which, an initial set of the raw data is divided and reduced to more manageable groups. ... These features are easy to process, but still able to describe the actual data set with the accuracy and originality. Feature Extraction uses an object-based approach to classify imagery, where an object (also called segment) is a group of pixels with similar spectral, spatial, and/or texture attributes. Traditional classification methods are pixel-based, meaning that spectral information in each pixel is used to classify imagery

5.5 Segmentation

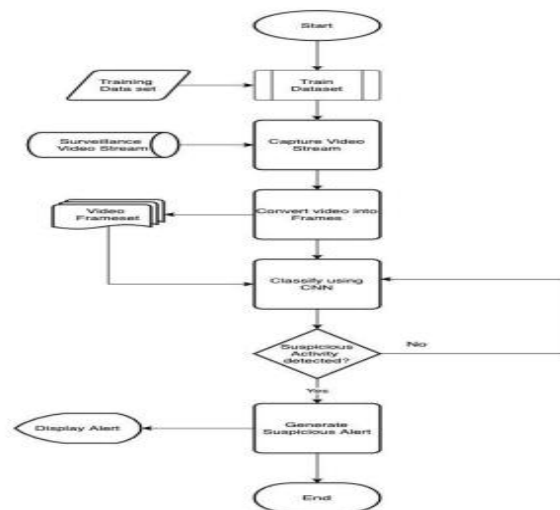
Image Segmentation is the process by which a digital image is partitioned into various subgroups (of pixels) called Image Objects, which can reduce the complexity of the image, and thus analysing the image becomes simpler. We use various image segmentation algorithms to split and group a certain set of pixels together from the image. By doing so, we are actually assigning labels to pixels and the pixels with the same label fall under a category

where they have some or the other thing common in them. Using these labels, we can specify boundaries, draw lines, and separate the most required objects in an image from the rest of the not-so-important ones. In the below example, from a main image on the left, we try to get the major components, e.g. chair, table etc. and hence all the chairs are colored uniformly. In the next tab, we have detected instances, which talk about individual objects, and hence all the chairs have different colors



6. RESULTS AND DISCUSSION

We trained our Convolutional Neural Network model using Kaggle database which includes Brain Tumor MRI Scan database. The detected Alzheimer Disease are resized to 48x48 pixels, and converted to grayscale images then were used for inputs to the CNN model. We achieved an accuracy rate of 70-90% for the first stage of Alzheimer Disease recognition

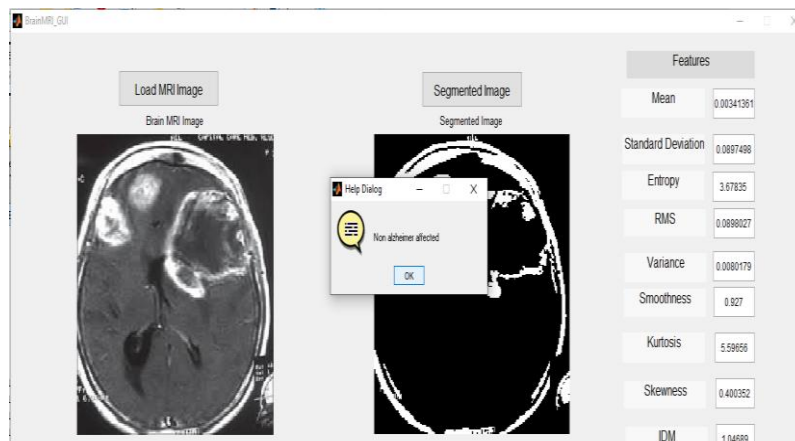


1) Execution of Alzheimer Disease Using Matlab

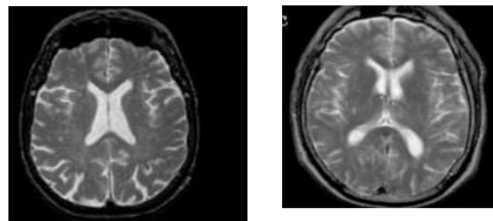
```

1
2
3 function varargout = BrainMRI_002(varargin)
4
5
6 % Begin initialization code - DO NOT EDIT
7
8 gui_singleton = 1;
9 gui_State = struct('gui_Name',       mfilename, ...
10                  'gui_OpeningFcn', @BrainMRI_002_OpeningFcn, ...
11                  'gui_OutputFcn',  @BrainMRI_002_OutputFcn, ...
12                  'gui_LayoutFcn',  [] , ...
13                  'gui_Callback',    []);
14
15 if nargin <= 2 && ischar(varargin{1})
16     gui_State.gui_Callback = str2func(varargin{1});
17 end
18
19 if nargout
20     [varargout{1:nargout}] = gui_mainfcn(gui_State, varargin{:});
21 else
    
```


2) Execution of Alzheimer Disease



3) Normal MRI image & Alzheimer Disease MRI image



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