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A Study on Deep Learning Networks for Detecting Alzheimer's Disease

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Abstract: Alzheimer's disease (AD) is a most prevalent form of dementia which cause severe memory loss and decline in other cognitive functions. The early diagnosis of Alzheimer's disease is essential in order to avoid severity in the disease. The early stage of AD called as Mild cognitive impairment should be diagnose early for better timely treatment. The combination of neuroimaging modalities such as positron emission tomography (PET) and Magnetic resonance imaging (MRI) shows effective way for the diagnosis of Alzheimer's disease. The deep learning techniques can be effectively used for the better diagnosis of Alzheimer's as early as possible. The main objective of this study is based on the different networks that are used to detect the Alzheimer's disease and its optimization.

Keywords: Deep learning, multimodal neuroimaging, transfer learning, AlexNet, CNN

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I. INTRODUCTION

Alzheimer's disease, which is a usual form of dementia, is a degenerative brain disorder which ends up with gradual memory loss. In US, it is the seventh leading reason behind the death and also it affects 5.3 million Americans. The familial AD affects the individuals with age less than 65, if we account within the United States over 500000 AD cases. Other classification is termed as isolated AD which occurs in adults having age greater than 65 and older. The classification of AD will vary according to many other reasons including age, genetics, education level and co-morbidities. For the effective diagnosis of Alzheimer's disease, the most definite way is to do an autopsy. There is no complete cure for Alzheimer's disease. But hopefully promising researches, analysis, and development for early detection is underway. Over some past decades MRI, Functional MRI, PET, CT has been used with the advancement in neuroimaging. Biomarkers have been used for diagnosing of Alzheimer's disease since it have capabilities of visualization, functional information of the brain (Jack CR.et al., 2008).In some recent years, Computer Aided Diagnosis (CAD) have considerable achievements in neuroimaging system(Liu SQ et al., 2015).

Also the different brain imaging modalities and multimodal analysis improves the diagnostic performance to a better step. The main aim in all diagnosis framework are to detect, analyze and classify the AD (Brookmeyer et al., 2007.In the case of CAD, since it needs feature representation, feature extraction will be a crucial step. In recent terms Deep Learning provides many applications by achieving great success. It was first introduced in 2006 by Hinton. By considering the conventional learning architectures, Deep learning provides better data representation of high level features with layered and hierarchical architecture (Zhang WL et al., 2015). In recent years deep learning forms a good domain in medical field with great applications in detection, segmentation and classification .Also it can be used for the diagnosis of other brain disorders. Suk et al. have proposed a multimodal deep Restricted Boltman machine for learning features from neuro images having 3D huge patches (Szegedy C et al., 2015). Brosch et al. have used a Deep Belief Network for the effective diagnosis of AD. Gupta et al. have used a Stacked Auto Encoder (SAE) followed by the application of a Convolution network. Liu et al. proposes a stacked auto encoder network with the help of multimodal neuroimaging for Region of Interest (ROI)based feature learning.ROI based approach is using widely since it covers the whole brain. But the features extracted using ROI cannot be reflected with small changes involved in the disease. Payan et al. involved with AD prediction using local patches. However here creates a new space for feature learning with the help of learning algorithms (Sarraf S et al., 2016).

In this study involves the advantages of Convolutional Neural Network for the effective diagnosis of Alzheimer's Disease. The networks in CNN are discussed with transfer learning.

The rest of the paper is organized as follows. Section II deals with Diagnosing Criteria which are used for detecting Alzheimer's disease. Section III provides Deep Learning Architecture followed by Section IV explain about the AlexNet and Section V gives the Conclusion.

II. DIAGNOSING CRITERIA

The methodology for uniquely diagnosing Alzheimer's disease could be an autopsy of brain. But for physicians the diagnosis cannot do effectively up to 90% because of some physical, mental and behavioral conditions. There exists some criterion for the diagnosis of disease which is given in DSM-III (Diagnostic And Statistical Manual of Mental Disorders) by the psychiatric association in America. Here in the manual, Alzheimer's disease is classified under the class of chronic degenerative dementia.

a. Multimodal Neuroimaging

As discussed, dementia can be identified by the impairment of memory and muscles, loss of ability to speak, walk and show difficulties in social interaction. The doctors can identify the severity of the disease and there by the stage at the present. They can analyze the symptoms and how long it will persist and how it changes further more. Along with autopsy and physical examination they can also do a blood or urine culture for better analysis and estimation. The dementia can further cause hormone imbalance, vitamin deficiency and urinary tract infections. The problem involves with the brain scan in which they have to perform additionally to remove the brain tumors, other cognitive accidents, brain injury in order to distinct features of the tangles and plaques which are found within the brain. The neuro imaging system together with magnetic resonance imaging and computed tomography offers information based on the shape and volume of the brain region. Along with the MRI and CT scan, a functional MRI or Positron Emission Tomography (PET) offers better information regarding the cognitive features and symptoms based on the disease. Far better way doctors use an Alzheimer's Disease Assessment Scale (ADAS) which ranges from 0 to 70. According to the severity of Alzheimer's disease the scale will indicate better value representing higher level of cognitive disorder and feature impairment.

b. Positron Emission Tomography (PET)

Positron emission tomography is used to make a three dimensional color image of the body using radiation signals. For the procedure the patient is first injected by a radiotracer which is contained with a hot radioactive medicine which has a natural chemical bounding. For experiments the naturally producing chemical is glucose. The positrons are emitted since the compound is metabolized and the radiotracer will travel through the organ that used the molecule. Then the energy formed from these positrons is identified by the PET and converts the given input to an image. The color image is produced with respect to the quantity of positrons emitted. There exists a range of intensities and color which gives the details of brain activity. PET scan also enables us to detect the abnormality in the rate of glucose and also in blood flow process within the brain .Addition to diagnosis; a PET image may even enforced in determining the effectiveness of Alzheimer 's disease treatment.

c. Computed Tomography(CT)

The computed tomography (CT) is another neuroimaging technique in which takes the number of cross sectional images of the brain. Further with the help of a pc these individual scans are correlated into one single image with information about the density of various tissues within the body. In order to get differentiate between similar tissues; a distinction dye can be injected.

d. Magnetic Resonance Imaging (MRI)

Magnetic Resonance Imaging (MRI) is first used in 1977 for diagnosing injury and diseases by producing 2D OR 3D images of the body. The system which produces the MRI scan consists with a super conducting magnet that produces a large and stable magnetic field. Human body is consisting with billions of atoms. Moreover its hydrogen atom will highly get altered by the magnetic field and flux. Under the influence of magnetic field, the molecules get lined up in the direction of field since the hydrogen atoms are spinning around the definite axis. Here half of the atoms are pointing towards the head and other half is pointing towards the feet in such a way that they cancel each other. Some of the atoms do not cancelled out. Then the machine will emit a radio frequency signal which causes the protons present in the atoms to spin in another direction. When the spinning gets stopped, then the protons will release some energy which is absorbed by the system. We can differentiate between the tissues by using a dye or otherwise the image will seem to be in grey color. By considering the working of the system, effective diagnosis and also the structural changes that is analyzed by the doctors. The formation of atrophy hippocampus, which is usually seen in AD before the appearance of other early symptoms can be effectively detected by using MRI as an indicator of AD disease. Thus it will make easier to slower down the further progression in future and make the treatment better in order to take revenge against the severe symptoms.

III. DEEP LEARNING ARCHITECTURE

Deep Learning is a machine learning algorithm. It is also termed as Hierarchical learning since it produce a hierarchical concept. It makes use of serially connected multiple layers which can be used for feature extraction. It will learn the features with the help of supervised or unsupervised learning manner. Each layer which is a nonlinear processing unit will use the output from previous layer as input. It has greater application on a wide range in medical fields, image recognition, speech recognition etc. More precisely Deep Learning refers to the transformation of data through a number of layers. If we consider an example of image recognition, in turn exists many layers for the recognition of different image structures. However deep learning technique will be able to process each features effectively on corresponding level by its own.

a. Neural Networks

A Neural Network is a computational model in which the layered structure resembles like the structure of brain neurons with connected nodes. The neural networks are trained to recognize the data for classification and for other future events. For performing desired tasks, specified learning rules are involved to adjusts the weights of individual elements during training. Shallow Neural Networks are Neural Network which can operate on two or three layers of connected neurons. Deep Learning Network also can have hundreds of layers. These are machine learning techniques which can learn data directly from the input.

In the learning procedure the deep learning is baked with supervised and unsupervised learning. Considering supervised learning we have Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) etc. Under unsupervised learning we have Deep Belief Network, Sparse Auto Encoder etc. An Artificial Neural Network (ANN) can be used with supervised as well as unsupervised learning. Among these networks Convolutional Neural Network (CNN) provides a better accuracy with different layers of operation.

b. Convolutional Neural Network (CNN)

Artificial intelligence has a great growth in filling the gap between the abilities of machine and human beings. One of such area is Computer Vision (CV). It makes the world in such a way that machines can behave and perceive like humans. It has great applications in analyzing and classifying image, video recognition, language processing etc. The advancement in CV with Deep Learning paid the way for Convolutional Neural Network. So CNN is a deep learning technique which can be used in an input image to assign specific weights and biases and thus differentiating one with the other. The ConvNet have the ability to learn the filter characteristics to provide spatial and temporal features of images and thus the preprocessing is much lowered when compared to other classification networks. The main role of CNN is to predict the things without losing the features. Since the numbers of parameters involved are less it gives better fitting to the image dataset.

(i). Convolutional layer

The convolution operation involves the edge detection as a high level feature. The network consists of many layers with a first layer which helps in extracting low level features and then added layers which help to adapt with high level features.

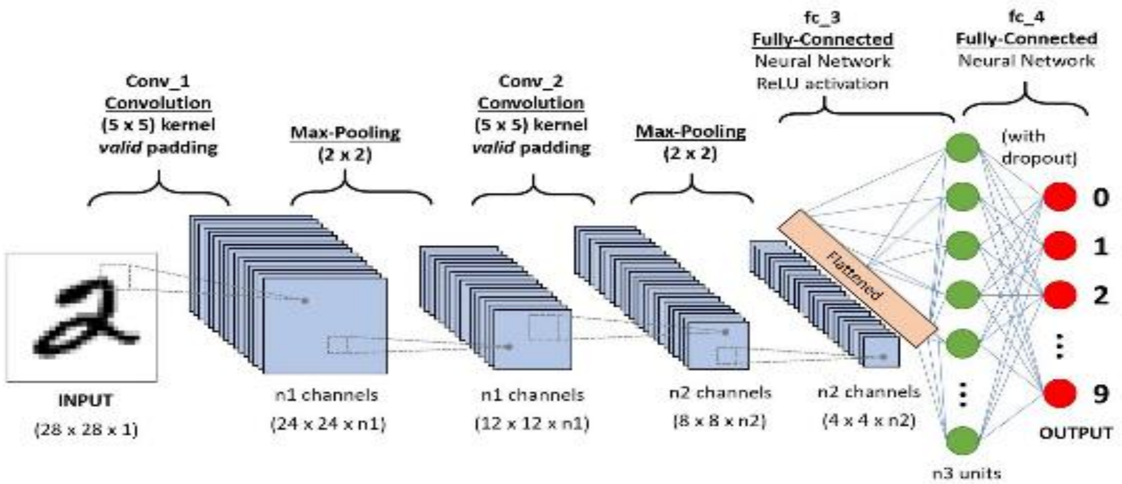

Figure 1: A CNN sequence used to classify a handwritten digit

(ii). ReLU Layer

ReLU layer stands for Rectified Linear Unit. It helps in increasing the nonlinearity properties of decision function by applying the non saturating activation function for removing the negative values and set them to zero values. The main difference between the rectified and non rectified version of the image is that the advancement of the colors.

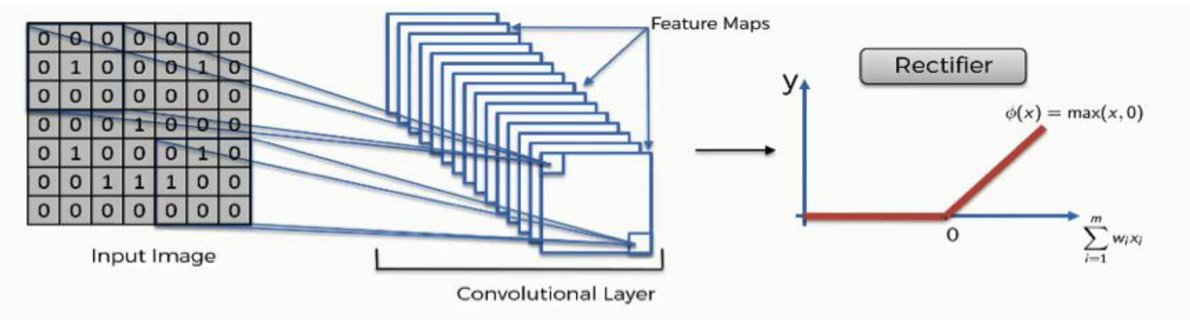

Figure 2: Rectifier Function

*(*iii). Pooling layer

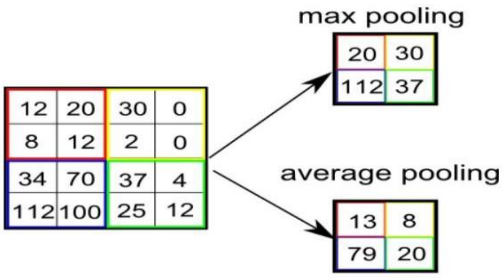

Figure 3: Maximum and Average Pooling

The main objective of pooling layer is to reduce the computational power for data processing. This layer is responsible for the reduction in spatial size of the convolved image. Furthermore it will help to extract dominant features for the effective training of the model. Mainly there exists two types of pooling maximum pooling and average pooling. Maximum pooling which returns the maximum value of the image which is covered with kernel(The element used to carry out convolution operation for the first part of image Convolutional layer). And average pooling which give average of all the values of the covered by the kernel. Max Pooling is also helps to suppress the noise by denoising along with the dimensional reduction. The max pooling layer along with the Convolutional layer creates a i-th layer of CNN. There will be changes in number of such layers with respect to the complexity of given images with minimum computational power.

(iv). Classification- Fully Connected layer (F C layer)

For learning the sequences of nonlinear combinations given by the output of convolutional layer, we are adding a Fully Connected Layer. This stage is given to fully connected regions.

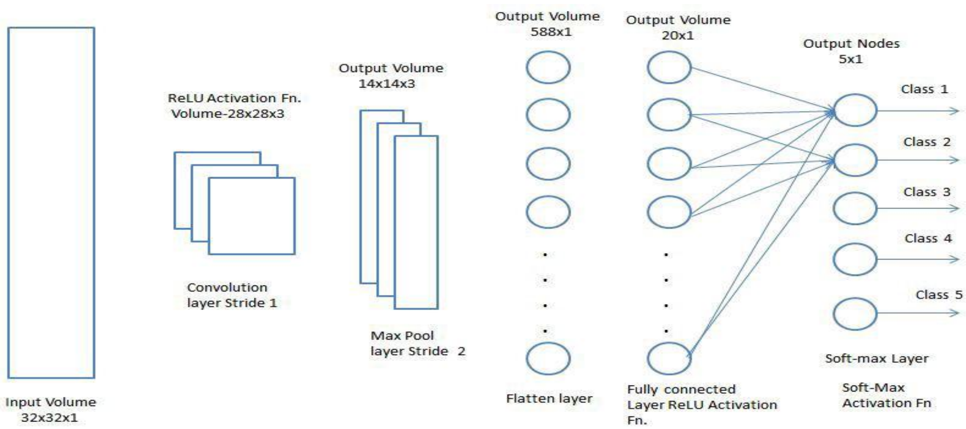

Figure 4: A CNN model with different layers

For learning the sequences of nonlinear combinations given by the output of convolutional layer, we are adding a Fully Connected Layer. Now we have to convert the input image to the multilevel perceptron. Before that we have to flatten the input image into a column vector so that can given this flatten image to a feed forward network. Back propagation is done to each iteration. After a series of epochs, the model can distinguish between high level and low level features and classify them according to the given parameters using Softmax Classification. There exists various types of CNN architecture which will make featured changes in AI. Some of them are AlexNet, VGGNet, LeNet, GoogLeNet, ResNet, ZFNet

IV. Alex Net

Alexnet consists with 8 layers having 5 convolutional layers and 3 fully connected layers. Have multiple convolutional kernels to extract important features of an image. For each convolutional layer, there have many kernels of same size. The first 2 convolutional layers are followed by overlapping max pooling layers. The third fourth and fifth convolutional layers are directly connected. Fifth layer then correspondingly followed by overlapping max pool layer. The output from The second FC layer get feeds into a Softmax classifier with 1000 class labels.

a. Transfer learning using alexnet

Transfer learning have commonly used in applications of Deep learning. Here we can reuse the pretrained network. If we have a pretrained network we can use it to learn a new task by making it as a starting point. That is we can model the second task in an improved version by incorporating the model which have been trained on first task. Maximum information about the problem or data is transferring from previous task to next. We can use the transfer learning for fine tuning of a network in order to make the training more easier than randomizing the initial weights. Also requires smaller number of training data for a new task.

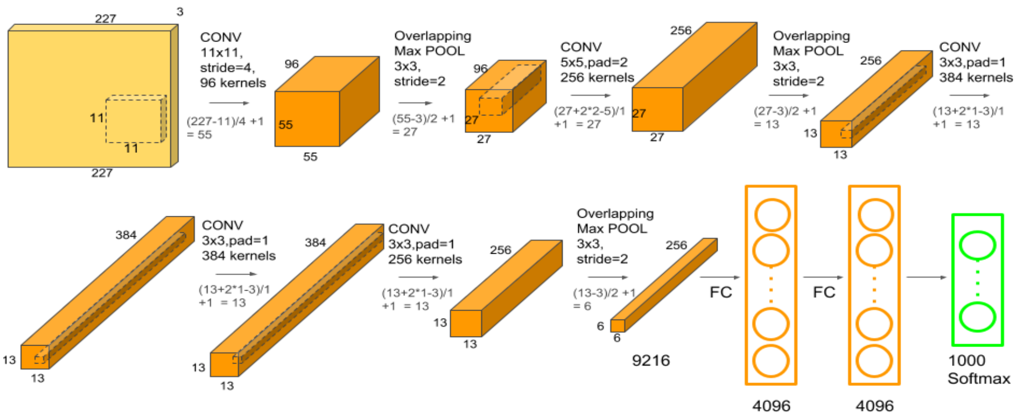

Figure 5: AlexNet model structure.

AlexNet have been trained over millions of image and can be classify images into 1000 categories. For example we can classify the given image data into various categories like keyboard, coffee, car, bus and like many. The network will compute the probability for each category of object and in the output the network takes a label for the object with the object together. Here detection can be performed via classification by modifying the AlexNet classifier to classify the given data in two classes.

The steps involved in the AlexNet is as follows.

- Load data: unzip and load the new image data as image data store.
- Divide the given data into training and validation
- Load pretrained AlexNet neural network
- Replace the final layers: replacing with a fully connected layer, Softmax layer and a classification output layer
- Train the network
- Classification of validation images

The input image layer need input image size as 227x227x3 where 3 is used as the number of color channels. The trained network is having with higher accuracy.

IV CONCLUSION

The dataset for the study is taken from ADNI (Alzheimer's disease Neuroimaging Initiative). Through this work, we are intended to do detection via classification with the help of transfer learning using AlexNet in order to classify into two classes with and without Alzheimer's. We can also use other classification networks by incorporating transfer learning.

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