International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Computational Modeling of Dementia Prediction Using Deep Neural Network:Analysis on OASIS Dataset

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ABSTRACT

Alzheimer is a progressivedisease and it is the most prevalent neurodegenerative disorder. It is believed that the people with mild cognitive impairment are at high risk of developing this disease. Alzheimer is the sixth leading cause of death in the United States. Thus, there is a need of educating people about this disease, reducing the risks by militating the necessary precautions to disseminate its affect by diagnosing it at early stages. It is also important to propose some recent advancement in this research which can help in early prediction of the disease using machine learning techniques. This paper intends to develop the novel algorithm by proposing changes in the designing of capsule network for best prediction results and making the model computationally efficient. The research is conducted on the Open Access Series of Imaging Studies (OASIS) dataset with dimensions (373 X 15) to diagnose the labels into two groups, as demented and non-demented. The novelty lies in conducting the in-depth research in identifying the importance of features, correlation study between factors and density of data showing status of factors by studying hierarchical examination of all the data points available using exploratory data analysis.

Keywords: Feature extraction, Deeplearning, Magnetic resonance imaging,Machine learning, Predictive models, Neuroimaging, Prediction algorithms.

I. INTRODUCTION

Dementia, a devastating illness that results in gradual loss of memory and other cognitive ability which is mostly identified in people more than 60 age groups. Alzheimer is a progressive disease that destroys memory and other important functions. Brain cell connections and the cells themselves degenerate and die, eventually destroying memory and other important mental functions. An Alzheimer diagnosed person lives for four to eight years only. Few people live for twenty years as well because it completely depends on different factors. Various biological and neuropsychological studies discover that AD can be predicted at its early stage and useful to take treatment in an efficient direction. It starts from a specific subcortical region and increases to the cortical mantle with the passage of time. The most common effect of AD is memory loss and slows down the abilityto do any task. It is found that MCI, a highly heterogeneous phenotypic spectrum, has very less considerable memory deficits than AD. These MCI may convert to AD in a study it was discovered that 10%-15% MCI patientsconverted to AD within a short span of time.

The development of AD can be predicted several years before which are helpful in controlling the progress of AD. Biomarkers, magnetic resonance imaging(MRI), genetic data, cerebrospinal fluid, Positron emission tomography (PET) have attracted interest in identifying the early symptoms of AD dementia. MRIs do not involve ionizing radiation and are economical than PET and minimal invasive than cerebrospinal fluid (CSF). MRI provides multi-mode information for the brain's structure and function. MRI works successfully in distinguishing healthy people with AD survivors. MRI results can identify the sMCI (stable MCI) and pMCI (progressive MCI). These clinical and neuroimaging data have been used to extract feature information voxels, classify different groups and use it with several cognitive measures to produce support vector machine (SVM) based predictions, obtaining an area under Receiver operating characteristics (ROC)and authentication curve (AUC).

Neuroimaging techniques are progressing very fast that makes it difficult to integrate large scale high dimensional multimodal neuroimaging data. Thus computer aided machine learning approaches are adopted forintegrative analysis.

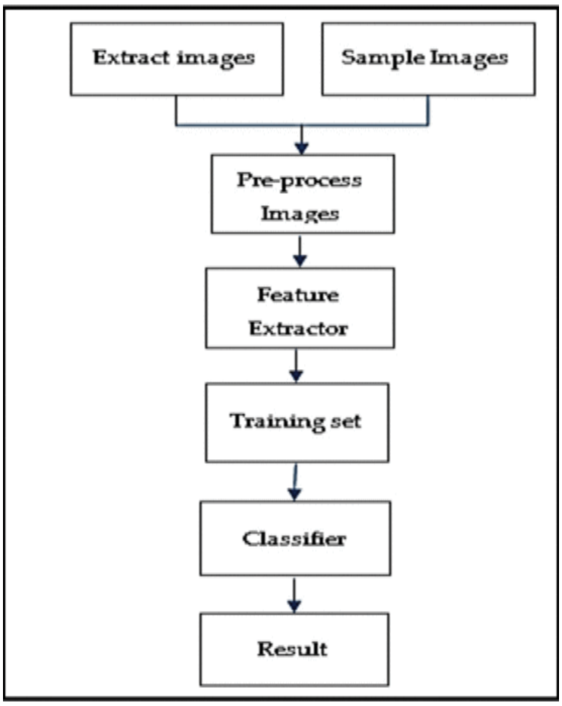
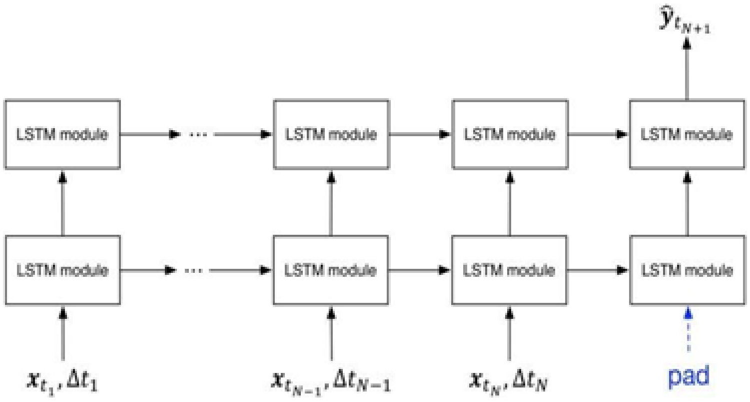


FIGURE 1. BLOCK DIAGRAM



II. EXISTING SYSTEM

The proposed method uses modified capsule network, which takes the data as an input, makes the parent vector by considering the various features available inthe OASIS dataset. The CNN with RELU activation function is that in which the data is fed which gives the transformation vector w. This w along the output from various capsules is used using the logic of dynamic routing for us to get the feature. The KPCA is used to do a feature extraction before passing the memory from one capsule to another. Squash is a special type of activation function used in Capsule Networks to normalize the magnitude of vectors, instead of the scalar elementsthemselves.

DATA PREPARATION

The data used for preparation of the paper is taken from OASIS database. The dataset consists of MRI and PET images of clinical patients collected over the period of 15 years. The study was done on longitudinalMRI dataset consisting of 150 subjects for exploratory data analysis. The details on the dataset is given in the experimental results sections. The feature extraction techniques are applied for extracting patches from the image and thereafter, mathematical transformation is done for generating feature vectors. Finally the model is trained and built. For all the weights and the bias from labelled cases, training a model means determining good values. We further observed that the data is hierarchical in nature and therefore, Capsule Networks (CapNets) were used for the task of prediction.

DESIGNING OF CAPNET

CNN works on image data anddetects features of an image to recognize objects with information. In CNN, the layers detect only edges of an object and layers that are deeper can detect complex features of an object. The CNN based deeplearning model basically uses all thelearned features to make final predictions. The major flaws of CNN are absence of spatial information and pooling function. In max pooling operation, only important information found from the most active neurons are to be gathered to the next layer. Due to this, some important spatial information gets lost between the layers. Therefore, to handle the above issues of CNN, we use a more refined form of CovNets called CapNet or Capsule Networks. Capsule Network is just a variant of a CNN. CapNets were devised to handle hierarchical modeling problems and are the most suitable for thisresearch problem. CapNets does not resembles the Pooling layers used in CovNets. Because of pooling in CovNets, it is used to reduce the details and increase the speed of algorithmic runtime. However in CapNets, pooling layer considers the minor details into account which is based on CapNet (concept of inverse rendering). The beauty of CapNet lies in the structure represented by nesting of convolutional layers. The two important functions of CapNet are Routing algorithm and Squashing. The routing is referred to as coupling between capsules and squashing is done on the DigitCaps layers. During training, the activation vector of the correct digit is masked out and thisactivity vector is used to reconstruct the input image using fully connected decoder.

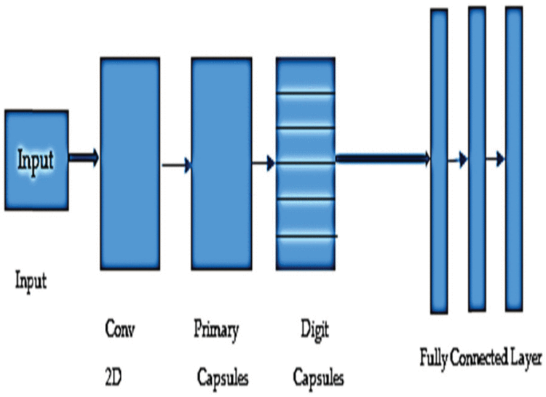


FIGURE 2. Basic Architecture of CapNet model.

A number of deep learning based research articles for AD have been studied and elaborated in related work. None of the previous researches claimed and emphasized on the use of a high performance modified capsule network for prediction of dementia on Open Access Series of Imaging Studies (OASIS) dataset. To develop an early prediction model of dementia based on the longitudinal data on OASIS dataset,1 we did exploratory analysis of the dataset to find that the data has dimensions: 373 X 15. All these 15 factors are considered while analyzing and implementing various machine learning models. Exploratory data analysis (EDA) results and graphs are in OASIS EDA file. Analysis is done using various algorithms 1 and their accuracy and other factors are considered. From the analysis, we see that none of the traditional methods give us accuracies up to 92.39%. We further observed that the data is hierarchical in nature and therefore, Capsule Networks (CapNets) were used for the task of prediction. However, due to the large number of features, we use a modified capsule network that does some optimization in the variables (W, K) and feature selection to make the model faster and more accurate. The results claim to achieve a considerable accuracy of 92.39% as compared with the other state-of-theart machine learning and deep learning classifiers. The motivation of the paper lies in early detection by extracting the complete visual features from the image. Second is to categorize all the images into proper labels. Finally to index these collection of MRI images and transforming into the series of text documents. In the recent scenario, many convolutional neural networks (CNN) works best with the images and has been used over a decade for labelling the images with achievable performance. But these methods onlywork well with large set of scaled dataset in order to develop the classifier for prediction tasks like in AD and works well in MRI images. The CNN can be trained on large image datasets where ConvNet can be used as a featureex-tractor. There are drawbacks where CNN method is not applicable and so, CapNet known as highly structured machine learning designs can be used for image classification using deep learning technique. The faith of CapNet is because of its robust structure, it is able to access and fit in different data augmentation techniques and needs less dataset for training purposes. This paper aims to find the features by using CapNet which has capsules defined inits structure instead of neurons in neuralnetwork.
Justification of proposed work :

The objective of proposed model is to early predict AD, so that proper care and treatment can be given to the patient. The proposed model is modified capsule networks or Modified CapsNets (M- CapNets) which is more efficient than CNN. To authenticate the validity of proposed model and to train the model, OASIS data set is used. M-CapsNets overcome the issues of CNN and provide promising results for medical image analysis. This novel model will benefit the people living inside the kingdom and research in the medical community to take better decisions in early stages of dementia. The related work study discovers that most of the work on AD is done under CNN networks. But there are various limitations of CNN, such as lack of spatial information and pooling function. The basic Capsule network has certain limitations as far as computational factors are compared with respect to time and space complexity. It works by extracting images or taking some sample images. The image preprocessing techniques are applied such as filtering, restoration, removing background noise,segmentation.

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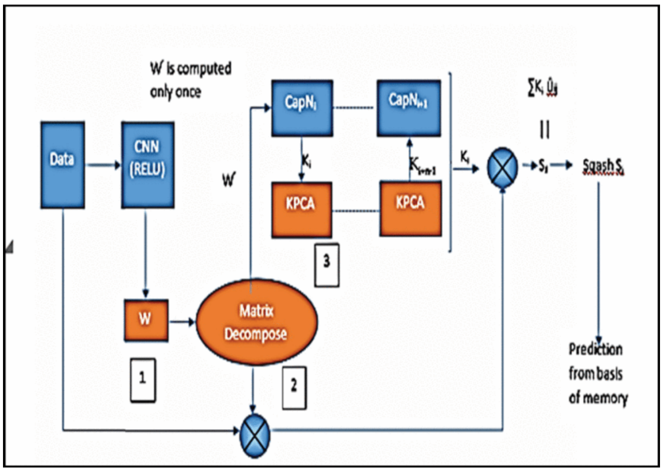

OASIS dataset consists of a longitudinal collection of 150 subjects aging from 60 to 96 years old. Each subject was scanned on two or more visits, separated by at least one year for a total of 373 imaging sessions. For each subject, 3 or 4 individual T1-weighted MRI scans obtained in single scan sessions are included. The subjects are all right-handedand include both men and women. In this analysis, 72 of the subjects were characterized as non-demented throughoutthe study.

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