

## Efficient Image Classification for Alzheimer's Disease Prediction Using Capsule Network

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**Abstract** — Alzheimer's disease is a kind of brain disorder that affects older adults. People with this disease tend to lose their memory capacity completely, eventually ending up with an inability to carry out even the simple day to day tasks. This is a permanent brain disorder that leads to Demnatia. Though there is no cure for this disease, the early prediction of this disease, at its onset could help reduce the adverse effects of the disease. Machine learning algorithms have been excelling in many fields especially in medical diagnosis for early predictions of various diseases. Psychological parameters like age, sex, urine protein level, family illness etc., have been used so far for the prediction of the disease. This paper focuses on the prediction of the disease using the MRI images of the brain. The detection of plaques and tangles in the brain is considered to be the major feature for the prediction of this disease. Convolutional Neural Network has made successful predictions in images. Hence, a variant of CNN, which is Faster R-CNN using Capsule Networkarchitecture is used in this paper for detecting and localizing the plaques and tangles present in the brain. The model is compared with the other prediction techniques and it has yielded an average prediction of 93.5% with kaggle dataset.

**Keywords** —Convolution neural networks, Logistic Regression, Random Forest, K-Nearest Neighbors, Multilayer Perceptron, Capsule Network.

### 1. INTRODUCTION

Various revolutionary computing technologies have come up today that have begun to make medical diagnosis easier. Especially, imaging technologies like image recognition, classification etc., using machine and deep learning techniques have ploughed their way into medical science thereby greatly benefiting and encouraging physicians, researchers and scholars for further research and analysis. The importance of imaging technology in the industry is very well understood, which has led to development and technical alterations through the purpose of analyzing the parameters in the medicinal images and by delivering a contiguous understanding of the subsequent symptoms. Numerous medical imaging modal techniques such as advanced x-ray technique Digital Radiography, Mammogram (MG), MRI, Ultra sonographs, CBIR, cross sectional images from Computed Tomography (CT) are used today in order to obtain medical images for diagnosis. Datasets are developed with the collection of brain images obtained through MRI scans are of immense significance. The benefit of scanned MRI images is that it produces high three-dimensional resolutions as well as gives a detailed view of the images for thorough diagnosis of disease [1,2].

One of the most common neurodegenerative diseases include Alzheimer's Disease which is a health condition commonly viewed in elderly and aging population, revealed by slow memory loss and reduced cognitive functions [3,4]. Worldwide, AD cases are

estimated to grow suggestively over the next 40 years because of the aging population and increasing life expectancy rate posturing a massive challenge to the society [5]. Alzheimer's disease regards with brain proteins which functions abnormally, interrupt the function of nerve cells and leads to a sequence of noxious actions. The nerve cells get harmed, misplace networks among themselves and ultimately get deceased. Generally, a part of the brain that pedals memory is where the damage starts. But the procedure of degeneration commences years before the initial symptoms. The brain contracts significantly by the time the later stages of the disease are reached. Researchers and medical professionals suggest that there could be a predictable pattern in which the neuron degeneration proliferates to the remaining parts of the brain. The brain shrinks significantly by the time the later stages of the disease are reached. Our purpose in this paper is to study and observe the performance of various models using an image dataset and conclude on the best model for the Alzheimer's disease prediction.

## 2. RELATED WORK

AD is an accelerating illness that causes cells of brain to degenerate and pass out. One of the most communal causes of dementia is Alzheimer's Disease which causes nonstop weakening of thought processes, behavioural and social aids which upsets a man's skill to perform individually. Medications currently available for AD might momentarily recover indications or decrease the degree of deterioration. These medications might occasionally benefit individuals having AD exploit function and continue individuality for a period. Utilization of radical computer aided diagnosis methods along side Content Based Image Retrieval (CBIR) [6] have opened up new abilities in the field Magnetic Resonance imaging (MRI) in similar image revival and recognition training of Alzheimer's disease movement during the initial phases. CapsNet model appears as a favourable recent system for image classifying, for researches and experimental work that need additional vigorous computational assets and polished CapsNet model architecture may deliver even healthier results.[7]

There are different techniques that currently being used today to diagnose AD at early stages. Several studies for the recovery of pictures of brain via MRI databases linked through collections of data of images of brain have been done already. Brain imaging techniques have been benefiting the diagnosis of a large number of diseases [8-10]. Brain images now are widely used in pinpointing evident anomalies associated with constraints apart from AD like strokes, tumours, or trauma that might cause intellectual modification. New imaging implementations, presently used mainly in chief medical hubs or in medical trials might permit medics to sense precise brain variations triggered through Alzheimer's.

Brain design images contain MRI and Computerized tomography (CT). MRI releases comprehensive images of brain by means of radio waves and a strong magnetic field. To exclude other conditions, MRI scans are used [11-13]. Though it might demonstrate brain reduction, evidence does not presently add any notable value in making of a diagnosis. A Computerized Tomography scan and a very specialized X-Ray technology, processes cross-sectioned pictures of the brain and is presently utilized for removing strokes, tumors, and other brain wounds. Tomography of illness procedures can be accomplished using positron emission tomography (PET). When a low-level radioactive tracer is inserted into the blood to expose a particular characteristic in the brain, it is called as a PET scan [14].

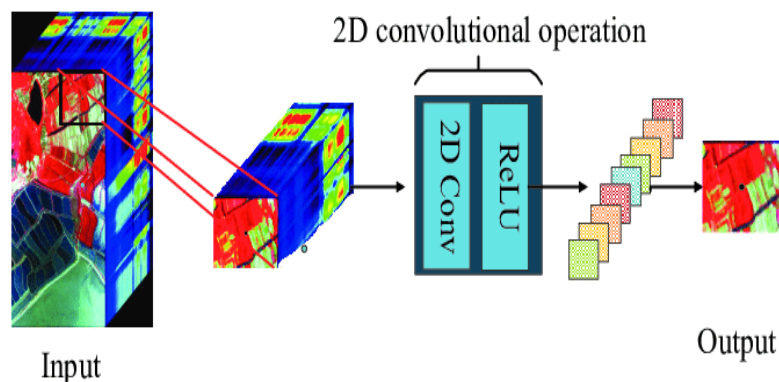
The most significant trait of AD anatomy is nerve cell drop trailed by brain atrophy developing in AD chief areas (e.g. amygdala and hippocampus) to the whole cortical area which could also be recognized through MRI scan. Those recognizable layout variations have occurred well in advance perceptible deterioration in perception and hence offers a chance to AD initial recognition through an image tool. For this purpose, CBIR, one of the most powerful image reclamation tool and it might as well be used for handling huge datasets effectively. CBIR schemes are systems which empower effective image recovery grounded in the picture information. The working of a CBIR can be defined as the discovery of key visual fundamentals within a group of images. The visual characteristics which may refer to colour, shape or texture can form visual words, which describes an area in a data image which is utilized in a pictorial record which designates the entire image. [15-18]

Multiple researches have been carried out to optimize the existing methods using techniques such as SVM and multi-tier technologies that provide flexibility in terms of experimentation with classification, representation, feedback and ranking [19]. Their accuracies were found to be about 90.65% and 82.45% respectively. Deep learning methods are proficient in knowledging such depictions using data, specifically with CNN [20]. Yet additional modern work analysed use of heavy CNN to difficulties and making computer aided detection (CAD) usage within the medicinal division.

Capsule Network is powerful for retrieval of information rotations, variations and involves lesser datasets in model training with a lesser learning curve [21, 22]. Several other techniques projected to identify AD with various unique auto-encoders or Three Dimensional CNNs [23, 24]. The paper sightsees structure recovery by intermixing dual transfer training techniques, a 3D pre - trained autoencoder with shallow neural networks, 3D CapsNet to categorize Alzheimer's disease sufferer through steady controller built on structures of brain scanned images using MRI. "Routing by Agreement" is one the most notable features of CapsNet. This enables the lower layers of the CapsNetto anticipate the outcomes for the results of upper-layer capsules. Hence, the initiation of capsules to upper layers matches with the harmony of little such estimation. In addition to learning good weights for characteristic extraction, CapsNet architecturealso finds a way to deduce parameters like three-dimensional pose within an image. For instance, a capsule model acquires to decide not only if an airplane is in the picture, but also the orientation (to the right or to the left or whether at all it is rotated). This property is called the equivariance.

### 3 PROPOSED WORK

We have aimed at implementing different models for prediction of Alzheimer's disease using Logistic Regression, Random Forest, K-Nearest Neighbours, Multilayer Perceptron and Convolution neural networks. As CNN is considered to be a better suited model for prediction, we are also using CNN to obtain a better result of accuracy using this model. CNN and its variants are the most efficient architectures in classifying data, especially when it comes to images.



**Figure 1.2D Convolutional Network Model**

The datasets are taken from the ADNI website ((ADNI\_Training\_Q3\_APOE\_CollectionADNI1Complete 1 1Yr 1.5T\_July22.2014.csv) and kaggle. Images from Kaggle consists of two files – Training and Testing. Based on the severity of the diseases, the images are classified into different sections in training and testing set. The severity of Alzheimer’s falls under following categories

1. MildDemented
2. VeryMildDemented
3. NonDemented
4. ModerateDemented

The models used for the prediction based on the images and their comparison of their results is displayed below:

### 3.1 Logistic Regression

It is a technique of Machine Learning for binary classification problems. The technique is good at mapping any real-valued number to a value between 0 and 1 based on the datasets. The technique results in a ‘S’ shaped curve for the expression given by

$$1 / (1 + e^{-\text{value}}) \quad (1)$$

Where e is the base of the natural logarithms and value is the actual numerical value that you want to transform. Multi Class Logistic regression is used in case of checking the probabilities for classification problems having more than two classes. The model with finest coefficients would predict a value more close to one for the positive class (Images with Alzheimer’s symptoms) and close to zero for the negative class. On training the model for ADNI dataset, it yielded a validation Accuracy of 69.25% and 74.2 % for kaggle dataset.

### 3.2 Random forest

It is a versatile classifier with multiple trees. Each tree is developed with some randomization with the internal nodes possessing a test that best splits the classes of data. The estimation of the posterior distribution is used to label the external nodes of the tree (leaf nodes). Subsampling of training data is done to develop each tree with a different subset.

Randomness is injected in this process of subsampling and also in the selection of node tests. The final prediction is obtained by combining the predictions of the individual trees.

Let the ROI  $R_i$  in image  $I$  and the subset of  $S$  other images  $X$  that have “corresponding” object instances amongst the set of training images for that class. Then we could determine the corresponding ROIs  $R_x$  of images  $X$  by optimizing the following cost function:

$$F_i = \max \{R_x\} \sum_{X=1}^K K(E(R_i), E(R_j)) \quad (2)$$

where  $E(R_i)$  and  $E(R_j)$  the descriptors for the ROIs  $R_i$  and  $R_j$  respectively, and their similarity is measured using the kernel defined by

$$K(EI, EJ) = \exp\left\{\frac{1}{\beta} \sum \alpha |e_l(EI, EJ)|\right\} \quad (3)$$

For the test images a “sliding window” over a range of translations and scales is applied. A new sub-image  $WI$  classified by considering the average of the probabilities  $Q_{t,l}(Y(I) = A)$ :

$$Y^*(I) = \operatorname{argmax}_l \frac{1}{T} \sum_{t=1}^T Q_{t,l}(Y(I) = A) \quad (4)$$

where  $l$  is the positive class. We classify an image  $I$  as the class  $C_k$  provided by the ROI which gives highest probability. An average Validation Accuracy of 65.88% is obtained on kaggle and ADNI datasets.

### 3.3 K-Nearest Neighbours

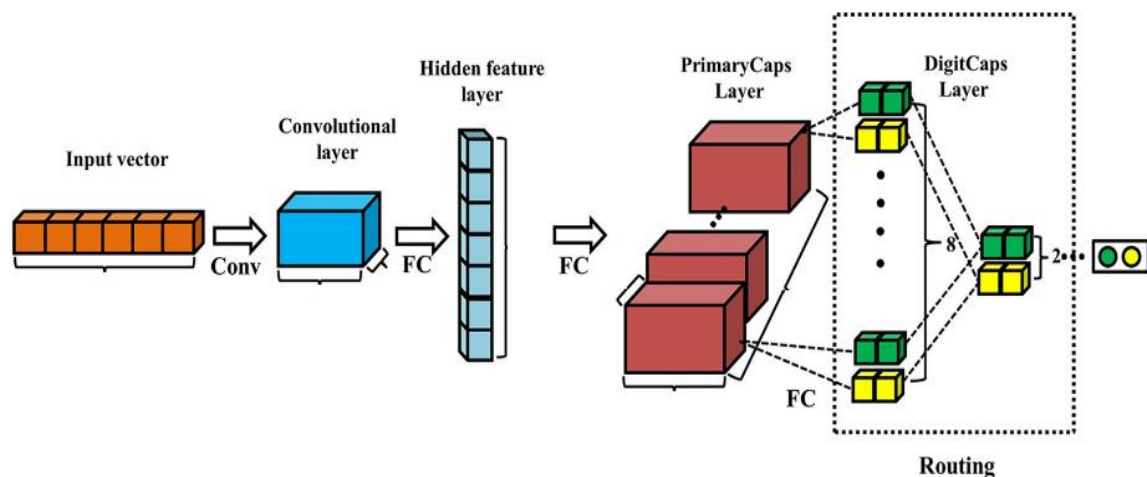
K-Nearest Neighbours (k-NN) is a supervised machine learning algorithm. The model makes predictions based on the distance metric. It tries to calculate the distance between the objects that are lying close to “K” and based on the majority of the neighbours, the model predicts the output finally. The distance metric used to calculate distances may differ, such as either a L1 distance function which is the summation of the differences between the pixels of the images.

$$D1(I1, I2) = \sum A |IP1 - IP2| \quad (5)$$

The KNN model classifies Alzheimer’s data points based on the points that are most similar to it using an “educated guess” on test data by which it yields a validation Accuracy of 69.46%

### 3.4 Convolutional Neural Network

Convolutional Neural Network (CNN) is an algorithm that can take an input image then allocate learnable weights and biases to various objects in the image and be able to differentiate one-another. The model does not require abundant pre-processing as feature extraction is done by the layers of CNN itself. But the model demands Image annotation which is done using Labelmg [25 – 28]. The concept of transfer learning is used in this process for the CapsNet architecture to classify the datasets. Transfer learning is the process of using a pre-trained model for any dataset of similar type. These models have proved to make significant predictions and hence it reduces the burden of developing a model from the scratch [29]. Also the knowledge acquired by the model while developing and training numerous datasets, elevates the performance of the model for Alzheimer’s prediction and hence it is used in our system.



**Figure 2 CapsNet Architecture**

As the pooling operation loses lot of vital information in the images, the concept of pooling is ignored in this model using routing by agreement concept, in which even the low level feature descriptors will be considered for further detection process. The dynamic routing process, weighs the input vectors every time thereby the selection of the subsequent higher level capsule will be decided and the outputs will be routed to that capsule. The average validation Accuracy obtained for both the datasets is 95.44% for the validation set while 94.3% for the test set.

#### 4 RESULTS AND DISCUSSIONS

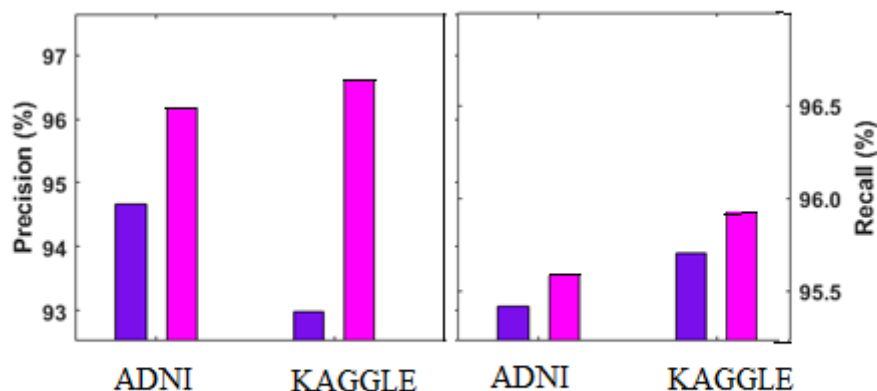
The results of the CapsNet model for the prediction of Alzheimer's disease in terms of F-Score are given in Table 1.

**Table 1 Prediction results of the model**

Dataset	Classes	Precision	Recall	F-score
ANDI	Positive	91.67	90.42	94.89
	Negative	93.87	92.78	95.98
KAGGLE	Positive	92.99	95.70	94.21
	Negative	96.86	96.09	96.18

The Precision and Recall graphs for both the datasets using CapsNet model is given below in Figure 3.





**Figure 3 graphical representation of the Prediction Results**

From the results, it is highly evident that CapsNet architecture is highly efficient in classifying the images for Alzheimer's disease prediction when compared to other techniques of Machine Learning.

## 5 CONCLUSION AND FUTURE WORK

We have found that the image dataset used along with CNN model provides more discrete information. It has shown better results of accuracy compared to the other models discussed in the paper. Although even now presently there are no treatments that can lower down the disease progression, management and organization to the intellectual and behavioral indications of AD can remarkably advance the life of medical patients and guardians. It is known that Alzheimer's disease pathology consists of phospho-tau neurofibrillary tangles and  $\beta$ -amyloid plaques. To curb the insufficiency and disadvantages in Convolutional Neural Networks, using recently announced machine learning operational model proposals called Capsule Network (also called CapsNet) that's appropriate for fast and profound learning of information image data. Capsule Network is powerful for information retrieval transformation and rotations, while requiring less data for model training and with a lower learning curve. One of the utmost significant feature of CapsNets is called as "routing by agreement", denoting that the junior-level capsules can predict the outcomes or results of capsules in upper-levels. Hence, the initiation of capsules within the upper layers depends on the lower layers.

In lower-level capsules, position data [28] is "position-coded" through the current active capsule because grading stays elevated, further more position based data is "rate-coded"[29] within the actual data module of the capsule output vector. All those infer that as we climb up the ladder, the size of capsule sits essentially rise. Nevertheless, CapsNets gives permit to require complete benefit of characteristic three-dimensional relation and imitate the flexibility of grasping data image variations to higher recapitulate which we observe. Alongside these noted features, we are employing CBIR architecture scheme for categorization for Alzheimer's Disease while acting with huge datasets. With 3-D Convolutional Neural Networks and CapsNet from scrape with query-based techniques and CBIR for determining the F1 score. Ultimate outcome is equated with the introductory experimental results to AD estimations.

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