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CNN-Driven Detection of Alzheimer's Disease: A Deep Learning Approach with MRI Data from the Kaggle Dataset

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Abstract

The neurological system is impacted by Alzheimer's disease (AD). As of right present, neither a medication nor a cure for Alzheimer's disease exist. An accurate diagnosis is critical for the early treatment of Alzheimer's disease (AD) because it allows patients to begin preventative medications prior to the development of permanent brain damage. This is due to the fact that the illness is currently in a very advanced stage. People with Alzheimer's disease can benefit from early diagnosis and effective treatment. The identification of Alzheimer's disease (AD) has been the subject of several research that have employed statistical and machine learning methods. A number of uses have allowed deep learning algorithms to demonstrate competence on par with humans in a number of fields. It is possible to detect Alzheimer's disease using magnetic resonance imaging (MRI) data and Deep Learning technologies for disease classification. Using deep learning algorithms for Alzheimer's disease classification has demonstrated encouraging outcomes. The combination of high precision, rapid processing, and generalisability over a wide variety of demographics is necessary for these techniques to be used in clinical settings. Using images from MRI scans that were trained with the Kaggle dataset, this study builds a system that can diagnose Alzheimer's disease using a fully convolutional network (CNN) architecture. It is feasible to assess the efficacy of each model by training them on the identical dataset.

Keywords: *Convolutional neural network (CNN), magnetic resonance imaging (MRI) Alzheimer's disease (AD), and Bayesian classifiers.*

1. INTRODUCTION

The world's most common neurodegenerative disease is Alzheimer's disease (AD). There are 12.17 cases per 1,000 person-years, and it affects more than 6% of Europe's population. It is still unclear what causes Alzheimer's disease, so doctors often use a patient's medical history in conjunction with results from comprehensive neuropsychological tests like the Mini-Mental State Examination (MMSE) to make a diagnosis. There is some evidence from recent studies [2, 3] that these tests might add uncertainty to diagnoses.Therefore, it is crucial to understand the development of illness and to research and develop new disease markers [4]. Determination of Alzheimer's disease often takes a long time after symptoms first appear. People who are just starting to show signs of Alzheimer's disease are known as having mild cognitive impairment (MCI). Unfortunately, only 25-35% of people who initially experience Mild Cognitive Impairment (MCI) could progress to Alzheimer's Disease (AD). Alterations in the brain induced by Alzheimer's disease commence far in advance of cognitive deterioration in an individual, encompassing initial lateral ventricle enlargement and noticeable atrophy of the hippocampus and amygdala. Certain brain regions

have begun to atrophy, as indicated by studies on biomarkers associated with Alzheimer's disease. Consequently, it is imperative to recognise AD at the earliest opportunity.

Prominent indicators encompass inadequate communication abilities, increased susceptibility to infections, suboptimal decision-making, impaired spatial orientation, short-term memory deficits, and visual impairments. A recent poll estimates that there are 50 million Alzheimer's patients worldwide. The cognitive symptoms of patients are often ascribed to ageing, posing a considerable challenge for scientists and physicians, as the condition is typically diagnosed only in its advanced stages. The danger presented by this sickness will endure until improved treatment is administered. The disease poses a considerable risk to the older population. Unfortunately, there is presently no treatment or cure available for dementia; Nevertheless, if taken action promptly, the disease's advancement can be slowed. A reduced risk of Alzheimer's disease is linked to a healthy diet, frequent exercise, social engagement, avoiding head trauma, reading, learning an instrument, and participating in intellectual activities. Beyond the obvious benefits to general brain health and cognitive performance, this is an added bonus. You can see each of the signs of Alzheimer's disease in Figure 1.

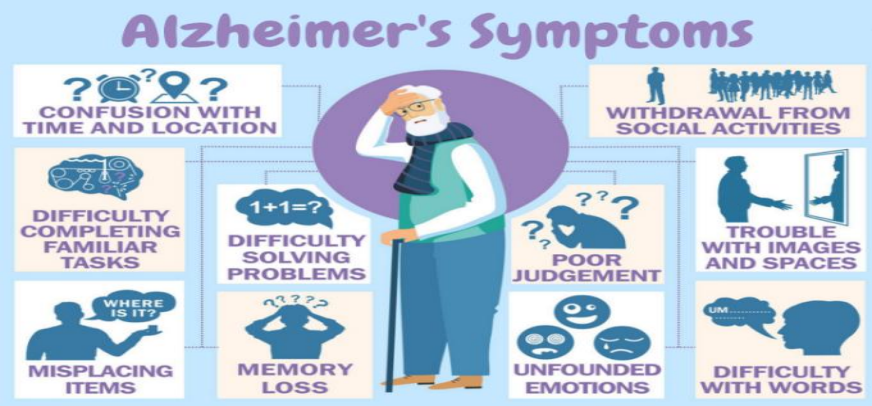

Fig.1: Symptoms of Alzheimer's disease

The transformative impact of Deep Learning (DL) architectures and advancements in computational technology has been pivotal in biomedical image processing, evidenced by various methodologies employing dense networks [8], two- and multi-convolutional neural networks [9], [10], residual networks [11], and numerous examples [12], [13].

2. LITERATURE SURVEY

A thorough evaluation of prior research on a certain subject is what a "literature review" is all about. The analysis of pertinent scholarly publications is known as a literature review, and it is often required as part of research projects. Each piece of pertinent earlier research must be described, summarised, and included in this review along with an objective assessment and any necessary clarifications.

In their ground breaking work on AD classification utilising the OASIS dataset and image augmentation-based methods, Afzal et al. [14] presented a new methodology. They achieved a performance accuracy of 98.2% while doing each experiment using transfer learning. Juergen Dukartet al.[15] used SVM to combine MRI and FDG-PET to improve AD identification. They irresponsibly removed the FDG PET and MRI scans from two different databases: the ADNI and the Leipzing Cohorts. They were 85.7% accurate with ADNI datasets.

Seixas et al. [16] offer Bayesian classifiers, sometimes referred to as based on Bayesian decision models (NCs), to help diagnose Alzheimer's disease, moderate cognitive impairment (MCI), and policy will apply. These classifiers performed better than several popular solutions, including Ada boost-enhanced choice based systems, multilayer perceptual ANNs, decision tables, Naive Bayes, and Logit Classification (LRC). Although Liu et al.'s Bayesian kernelization technique in [17] increased the accuracy of differentiating between Alzheimer's disease and normal controls, it fell short when it came to identifying MCI-converter (MCI) and MCI non-converter (MCI).

A better method than decision boundary criterion, location preservation projections (LLP), or principle component analysis was proposed by Zhao et al. [18] to address TR-LDA in dementia investigations; this method is known as improved iterative tracing ratio (iITR). P. Padilla et al. propose a new CAD for first-pass AD analysis that makes use of support vector machines and the non-negative technique. They used PET and SPECT datasets that included both AD patients and healthy controls. They recommended NMF-SVM, which is 91% accurate [19].

Papakostas et al. [20] discovered that VBM and KNN had 89.25% accuracy, 79.25% sensitivity, and 69.52% specificity, respectively, when comparing MRI scans of individuals with and without MC. The value of using pre-trained networks as a basis for building more networks was demonstrated by T. D. Phong et al. [21]. Two further research models, Google Net and Res Net, are pre-trained on Image Net thanks to Python's Tensor Flow framework. This gives them more competency in distinguishing between many different kinds of real-world images. Starting with training on partially connected networks, the models in this research could only be trained on fully connected networks going forward[35–38].

To improve the reliability of MRI for the detection of mild cognitive impairment, larger samples are required. Augmentation and TL approaches are employed by S. Wang et al. [22]. With OASIS2, they achieved a 90.6% success rate when comparing MCI to the Normal Control. Diffusion Tensor Images maps are typically used to understand the upright modularity for AD Identification. By applying what is known about MRI scans to DTI images, K. Aderghal et al. proposed transfer learning in [23]. Before moving the data from the ADNI dataset repository for Normal subject categorisation, AD, and MCI to the DTI dataset, they trained the model using MRI employing major unique augmentation procedures [27-29].

By utilising Free Surfer with Support Vector Machine on MRI data, Schmitt et al. [24] achieved a sensitivity of 82.80% and a specificity of 88.08% in differentiating between normal volunteers and patients with MC. With an accuracy of 78.0%, sensitivity of 75.0%, and specificity of 82.52%, Horn et al.[37] used support vector machines to identify between Alzheimer's disease patients and those with other types of front temporal dementia (FTD).pp. 30-34 Table 1 shows the total survey results.

Table 1.Literature Survey on Alzheimer's Disease Prediction Mechanisms

S.No	**Author**	**Year Of Publication**	**Technique**
1	Horn[25]	2009	Support vector machine Partial least squares and K-NN Partial least squares And Latent Dirichlet Allocation
2	P. Padilla et al.[19]	2012	Support Vector Machine & Non-negative Matrix Factorization
3	Dukart[15]	2013	Meta-Analysis, Support vector Machine
4	Liu[17]	2013	Multifold Bayesian kernelization
5	Zhao[18]	2013	Kernel Principal Component Analysis Trace Ratio , Linear Discriminate Analysis
6	Seixas et al.[16]	2014	Bayesian network
7	Papakostas[20]	2015	Value-Based Methods, K-NN
8	Schmitter[24]	2015	Free Surfer, Support Vector Machine
9	T.D. Phong et al.[21]	2017	Transfer learning
10	S. Wang et al.[22]	2017	Transfer learning
11	K.Aderghal et al.[23]	2018	Transfer learning, MRI to DTI
12	Afzal et al.[14]	2019	Transfer learning
13	Mehmood A	2021	Transfer learning

3. METHODOLOGY

Convolution neural networks are used to identify Alzheimer's disease. Dataset, data preparation, picture processing, and model training are all part of the methodology.

3.1 Dataset:

On Kaggle, the dataset is accessible. Essentially, test data and train data make up the two categories of data. 5121 images made up the training set, whereas 1279 were in the testing set. The majority of the pictures in were exceptionally clear and well-formatted.

There are four labels for which we need to provide forecasts.

1. Mild Dementia
2. Moderate Dementia
3. Non Dementia
4. Very Mild Dementia

3.2 Data Preparation:

In the dataset, you might find both the test and training sets. The validation set, however, was missing. Since there is a need to divide the training data set in half, an 80:20 ratio can be achieved by using 4079 for training and 1024 for validation.

3.3 Image Processing:

In order to improve or extract useful information from images, a technique known as "image processing" is applied. photo processing involves taking an input (a photo) and producing an output (another picture, a subset of the input picture, or some attribute of the input picture).

3.4 Rescaling:

Since the image size has a maximum pixel count of 255, or a range of [0,255], we must rescale the image before feeding it to the model because this makes it difficult for the model to process such high pixels.

3.5 Model building and training:

We utilise convolutional neural networks for the purpose of training the models. A deep learning network design known as a convolutional neural network learns from data in a very direct fashion. Objects, classifications, and categories in photos can be located using CNNs by examining picture patterns. In addition, they are masters in signal, time-series, and audio data classification.

3.6 Working of Convolution Neural Networks (CNN):

Even though a convolution neural networks may have hundreds of layers, each layer can be trained to identify certain features in an image. In order to train a neural network, each trained image is passed through a succession of filters of varying granularity, with the resulting distorted image serving as input for the network's subsequent layers. The filters can begin with very basic criteria, such as how bright a picture ought to be and where the boundaries ought to be, and then progress to more complex rules that are specific to the object being filtered. Between its input and output layers, a convolutional neural network (CNN) consists of numerous hidden layers. By manipulating the data in different ways, these layers can isolate its distinctive features. Triggering, or ReLU layers, pooling layers, & pooling are the most popular types of layers. To bring out specific details in an image, convolution employs successive convolution layers.

- **Rectified linear unit (ReLU)** which keeps positive values but maps negative values to zero, allowing quicker and more effective training. It's called "activation" because only the "on" features are passed on to the following "layer".
- **Pooling** Pooling reduces the complexity of the network's training by performing nonlinear up sampling on the output.

In deep learning, the same actions are repeated across hundreds of layers, with each layer learning to identify a new set of characteristics.

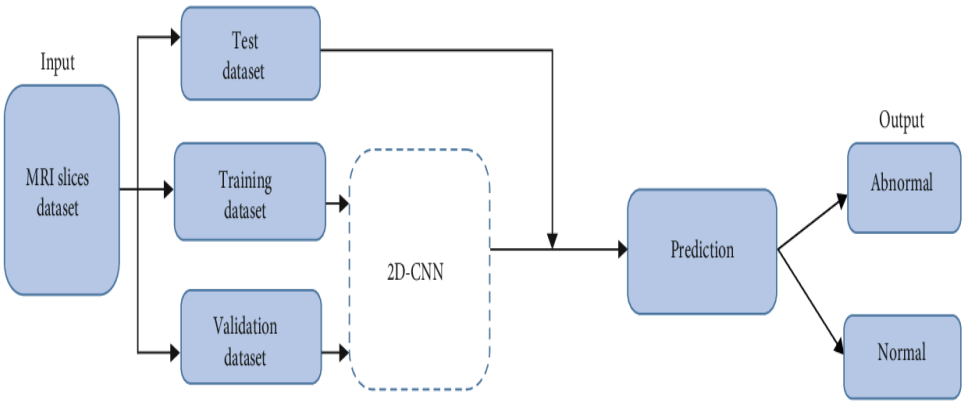

Fig.2: process for prediction of Alzheimer's disease

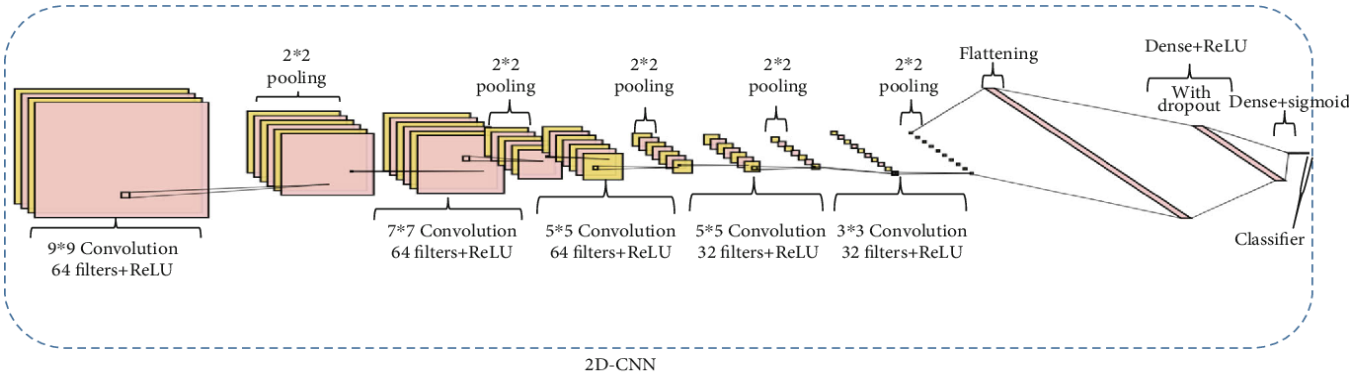

Fig.3: Working of CNN

CNNs differ from traditional neural networks in that all of the hidden neurons in a particular layer share the same weights and bias values. This indicates that all of the unseen neurons are picking up the exact same feature, such an edge or a blob, wherever in the image. Therefore, the network recognizes the validity of object translation in photographs. A CNN's design transitions to classification when it has learned data across many layers. A fully connected layer, the second-to-last layer, produces a K-dimensional vector containing the probability for each category that a classification model can assign to a picture, where K is the maximum number of classifications that may be predicted. Ultimately, the classification result is generated by a classification layer located in the final stage of the CNN design. Following is a summary of the entire method and technique for making predictions.

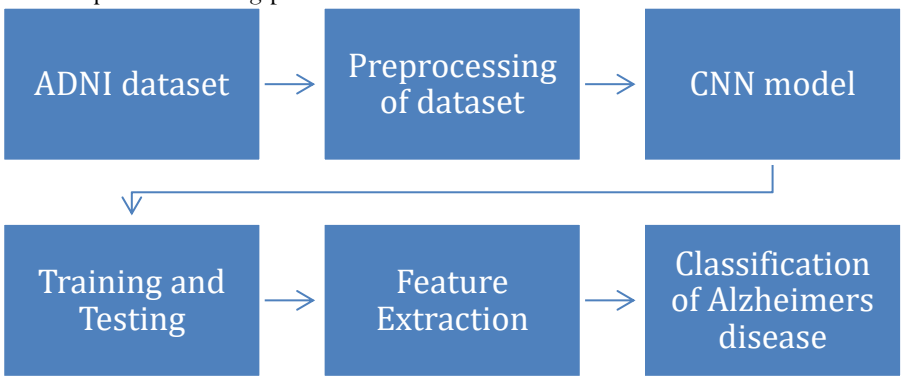

Fig.4: Block diagram for detection of Alzheimer 's disease

CNN Algorithm:

Input: ADNI dataset containing MRI Images of the brain.
Output: Classification of brain Alzheimer's disease.

1. Collect the ADNI dataset.
2. Perform preprocessing Operations on the ADNI dataset.
3. Build the Convolution Neural Networks (CNN) model.
4. Train and Test the CNN model.
5. Feature extraction using the CNN model.
6. Classify Alzheimer's disease into different stages.

4. EVALUATION:

We evaluate the effectiveness of the model based on several metrics, such as the F1 score, recall, accuracy, or precision. Overfitting and improper tuning of parameters were discovered using a number of different metrics and techniques after the model was created. Performance evaluations can be either binary and multiclass in nature, and the confusion matrix is employed to illustrate these differences. It was determined that a Convolutional Network could accurately predict and distinguish between healthy and Alzheimer's disease-affected members of a given population, and so a learning model was developed to single out those with the disease.

4.1 Accuracy: It is a measurement of the percentage of locally occurring findings that are accurately classified. Here accuracy is calculated on a 10 point scale

$$\text{Accuracy (in percentage)} = \frac{TN+TP}{TP+TN+FP+FN} \times 100 \quad (1)$$

4.2 Precision: By dividing the total predicted positive rate by the total expected positive rate, this method determines the accuracy of the prediction. The classifier is successful if and only if the precision is 1.

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

4.3 Recall: A true positive rate is recall. Recall of 1 is intended to be a good classifier.

$$\text{Recall (in percentage)} = \frac{TP}{TP+FN} \quad (3)$$

4.4 F1 Score: It's a scale that evaluates performance based on both recall and precision. When both recall and precision are 1, the F1 score also equals 1.

$$\text{F1Score (in percentage)} = 2 \times \frac{Recall \times precision}{Recall + Precision} \quad (4)$$

The following table 1 is a comparison of CNN with Machine Learning models.

Table2.Evaluated Results of the CNN with remaining ML Models

Prediction Mechanism	Accuracy	Precision	Recall	F1-Score
CNN	0.86	0.89	0.87	0.88
Decision Tree Classifier	0.79	0.72	0.72	0.71
Random Forest Classifier	0.84	0.81	0.84	0.84
Support Vector Machine	0.80	0.73	0.68	0.75

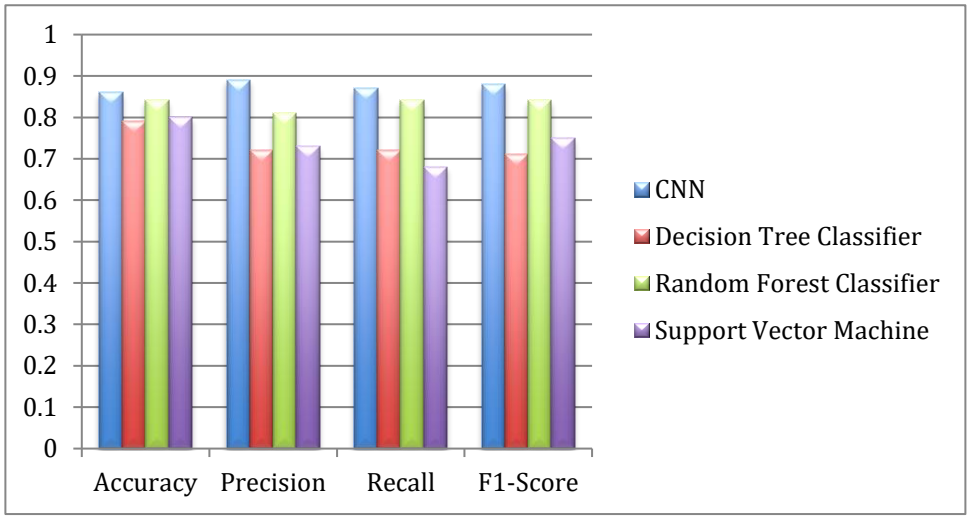

Fig.5: Evaluated Results of Various Predictions Mechanisms

5. CONCLUSION

In this work, we use the Convolution Neural Networks model of deep learning to diagnose Alzheimer's illness. It makes use of brain MRI scans that may be found in the ADNI dataset.The proposed procedure comprises mostly of two parts. One is feature extraction and the second is classification of Alzheimer disease into stages. The model doesn't need any manual feature extraction and it is a fast and simple process for Alzheimer disease detection. It aims at early detection of Alzheimer disease as it has no cure one can take precautions at it's early stage and helps to maintain good health. Comparing the proposed model to machine learning models reveals that it performs well and is more accurate.

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