IMPLEMENTATION OF CONVOLUTIONAL NEURAL NETWORKS FOR DETECTION OF ALZHEIMER'S DISEASE

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Abstract

A neurological condition called Alzheimer's disease (AD). There is no specific treatment for AD. Treatment of Alzheimer's disease (AD) patients in the early stages of the disease depends on an accurate diagnosis. because it enables patients to take preventative measures before irreversible brain damage happens. Alzheimer's sufferers can benefit from early diagnosis and appropriate therapy. To diagnose AD, many research use statistical and machine learning methods. In numerous fields, the effectiveness of Deep Learning algorithms has been demonstrated at the human level. In the suggested methodology, AD is detected using MRI data, and the current disease is classified using Deep Learning technology. Deep learning techniques have produced encouraging findings for the classification of Alzheimer's disease, and its implementation in clinical settings necessitates a blend of high accuracy, speedy processing, and generalizability to varied populations. In this workutilizing images from magnetic resonance imaging (MRI) scans that were trained using the Kaggle dataset, Using fully convolution network (CNN) architecture, we built a system to identify Alzheimer's illness. To evaluate the models' performances in this study, the same dataset is used to train all of the models.

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

1.Introduction

Alzheimer's disease (AD) is the world's most common neurodegenerative disease in the world. It affects and over 6 % of the population of Europe [1] and has an incidence rate of 12.17 for every 1000 person-years. The cause of AD hasn't been found, so doctors often use the patient's medical history and the results of long neuropsychological tests such as the Mini-Mental State Exam (MMSE) to make a diagnosis. However, recent studies [2, 3] show that these tests may add confusing data to the diagnostic process..Understanding disease progression and researching and developing novel disease indicators are therefore crucial [4]. The delay between the onset of AD and the final diagnosis is extensive. Mild cognitive impairment (MCI) is the term used to describe patients who are in the early stages of Alzheimer's disease (AD)[5]. However, only about 25–35% of MCI patients will eventually progress to AD. Changes in the brain caused by AD begin long before the onset of cognitive decline in a patient, including early lateral ventricle extension and evident hippocampal and amygdala atrophy[6],[7]. Some brain areas have started to diminish, according to studies on biomarkers linked to AD. Therefore, it is crucial to identify AD as soon as possible.

The most noticeable signs include poor communication skills, a higher risk of infections, poor decision-making, a bad sense of direction, short-term memory loss, and visual issues. According to a recent poll, there are estimated to be 50 million Alzheimer's patients globally. Due to the fact that patients' cognitive symptoms are commonly attributed to ageing, this ailment presents scientists and doctors with a significant issue today because it is frequently not discovered until patients are in the latter stages of the disease. The threat posed by this illness will persist until better care is given. As a result, the disease has a significant risk of affecting the elderly.There is currently no treatment for this illness, however early intervention can decrease the progression of dementia. A balanced diet, regular exercise, social interaction, avoiding head injuries, reading, learning an instrument, and engaging in intellectual pursuits have all been linked to a lower risk of Alzheimer's disease; these activities can improve overall brain health and cognitive function.Various Symptoms' of Alzheimer's disease is as shown in figure 1

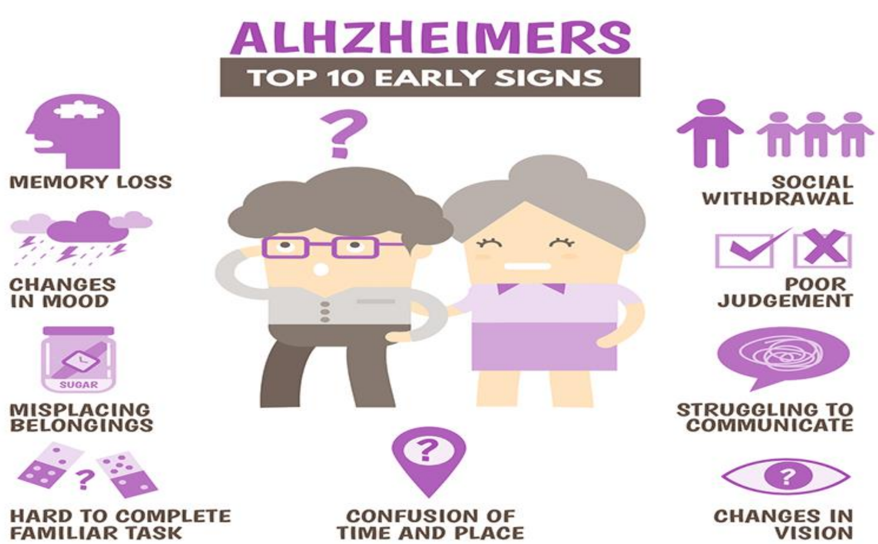

Fig.1: Symptoms of Alzheimer's disease

The revolutionary predefined by Deep Learning (DL) architectures and the technical advances in computation have been key to biomedical image processing, as shown by different approaches using dense networks [8], two- and multi convolution neural networks [9], [10], residual nets [11], and a variety of examples [12], [13].

2.Literature survey

The term "literature review" refers to a comprehensive analysis of previous research on a certain topic. As part of a research project, you may be asked to do a literature review in which you analyze relevant academic works. This review has to provide a list, description, summary, objective evaluation, and clarification of the relevant prior research.

Afzal et al. introduced a novel method in [14] for classifying AD using the OASIS dataset and image augmentation-based approaches. They used transfer learning to carry out each experiment, and their performance accuracy was 98.2%.In order to improve AD identification, Juergen Dukartet al.[15] combined magnetic resonance imaging (MRI) and FDG-PET using SVM. They carelessly deleted the FDG PET and magnetic resonance images from the ADNI and Leipzing Cohorts databases, two separate repositories. For ADNI datasets, they attained an accuracy of 85.7%.

To aid in the diagnosis of Alzheimer's disease, moderate cognitive impairment (MCI), and policy will apply, Seixas et al. [16] provide a Bayesian classifier, i.e. a Based on bayesian decision model (NC). They outperformed numerous popular classifiers, including Naive Bayes, Logit Classification (LRC), multilayer perceptual Artificial Neural Network (ANN), decision table, and Adaboost-enhanced choice based. Although Liu et almulti fold's Bayesian kernelization strategy in [17] could more accurately distinguish between Alzheimer's disease and normal controls, it produced subpar results when detecting MCI-converter (MCI) and MCI non-converter (MCI).

To solve the problem of TR-LDA in dementia analyses, Zhao et al. [18] suggested an improved iterative tracing ratio (iITR) approach, which outperformed the principle component analysis , locality preservation projections (LLP), and decision boundary criterion.When it comes to first-pass AD analysis, P. Padilla et al. suggest a novel CAD that utilizes non-negative method and support vector machines. They made use of two databases with AD patients and healthy controls (PET and SPECT). They suggested the 91% accurate NMF-SVM [19].

When comparing MRI scans of patients with and without MC, Papakostas et al. [20] found that VBM and KNN had an accuracy of 89.25%, sensitivity of 79.25%, and specificity of 69.52%, respectively. T. D. Phong et al. [21] shown the usefulness of leveraging pre-trained networks as a foundation for constructing supplementary networks. Google Net and ResNet are two additional research models that are enhanced by Python's TensorFlow library2 and thus are pre-trained on ImageNet, resulting in superior competency to distinguish between many various types of real-world images. After initial training on partially connected networks, the models in this analysis were restricted to training on completely connected networks[35-38].

In order to detect moderate cognitive impairment on MRI, we need to increase the sample sizes so that we can do so with more confidence, S. Wang, et al. [22] use TL methods and Augmentation. Their performance accuracy for MCI vs. Normal Control was 90.6% using OASIS2. The upright modularity for AD Identification is usually understood from the Diffusion Tensor Images maps.Transfer learning was suggested by K. Aderghal et al. in [23] by transferring the knowledge from MRI data to DTI pictures. They used substantial unique augmentation approaches to train the model using MRI before transferring the data to the DTI dataset using the ADNI dataset repository for Normal subject categorization, AD, and MCI [27-29].

By applying FreeSurfer with Support Vector Machine to MRI data, Schmitt ret al.[24] were able to distinguish between patients with MC and normal participants with a sensitivity of 82.80% and a specificity of 88.08%. Using SVM, Horn et al.[37] successfully distinguished between patients with Alzheimer's disease and those with other kinds of Frontotemporal Dementia (FTD), with an accuracy of 78.0%, a sensitivity of 75.0%, and a specificity of 82.52%..[30-34] The overall Survey is as shown in Table 1.

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	FreeSurfer,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:

Both the training and test sets were included in the dataset. But the validation set wasn't there. The training data set has to be split in half, with 4079 used for training and 1024 used for validation as a result (an 80:20 ratio).

3.3 Image Processing:

Image processing is a method of using different techniques on an image to make it better or get helpful info from it. It is a form of signal processing where a picture is used as the input and another picture, parts of the input picture, or characteristics of the picture are used as the output.

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:

For model training, we use convolutional neural networks. Convolutional neural networks are a type of deep learning network architecture that directly learns from data. By analysing patterns in the images, CNNs may identify items, classes, and categories in photographs. They can also classify audio, time-series, and signal data extremely effectively.

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

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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.

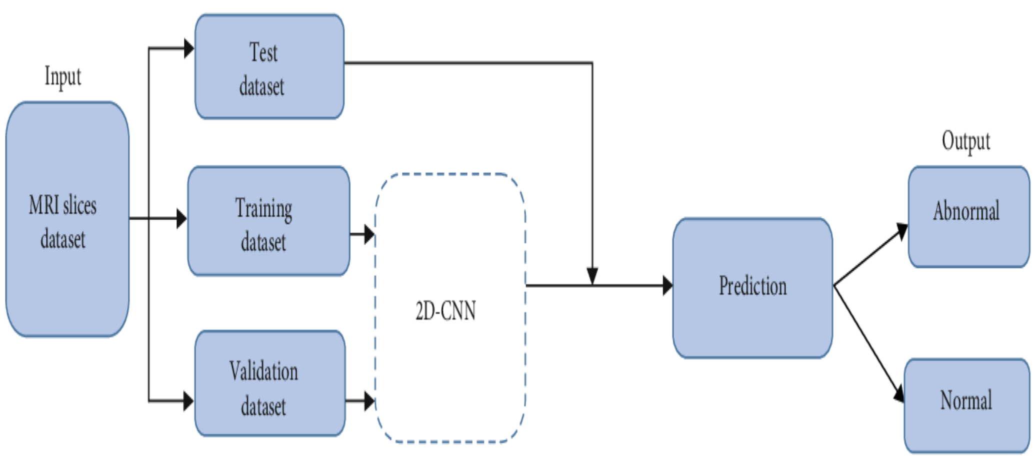

Fig.2: process for prediction of Alzheimer’s disease

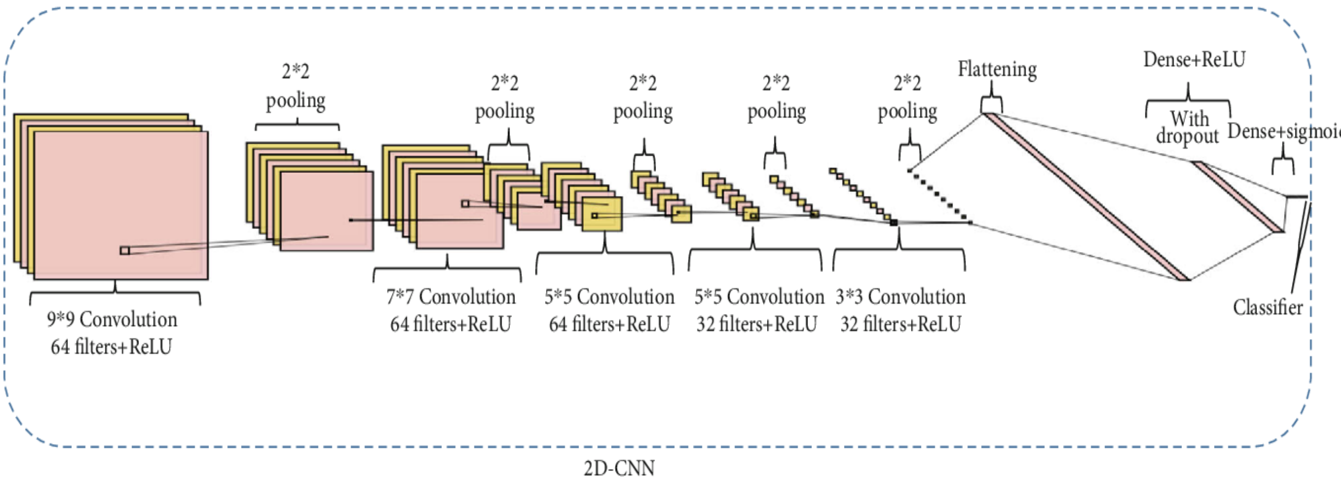

Fig.3: Working of CNN

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.

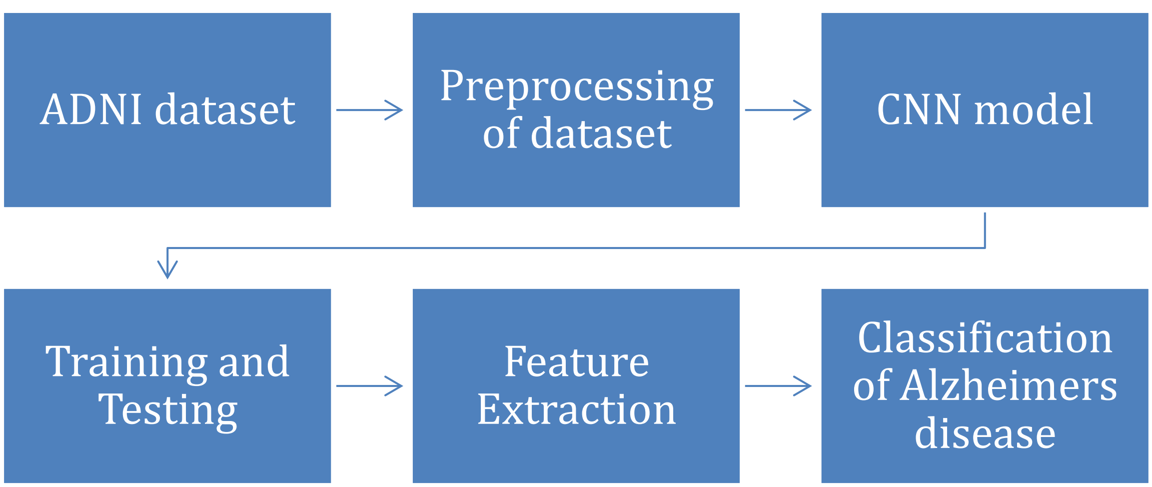

Fig.4: Block diagram for detection of Alzheimer 's disease

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

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

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.

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

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

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

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.

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

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

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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

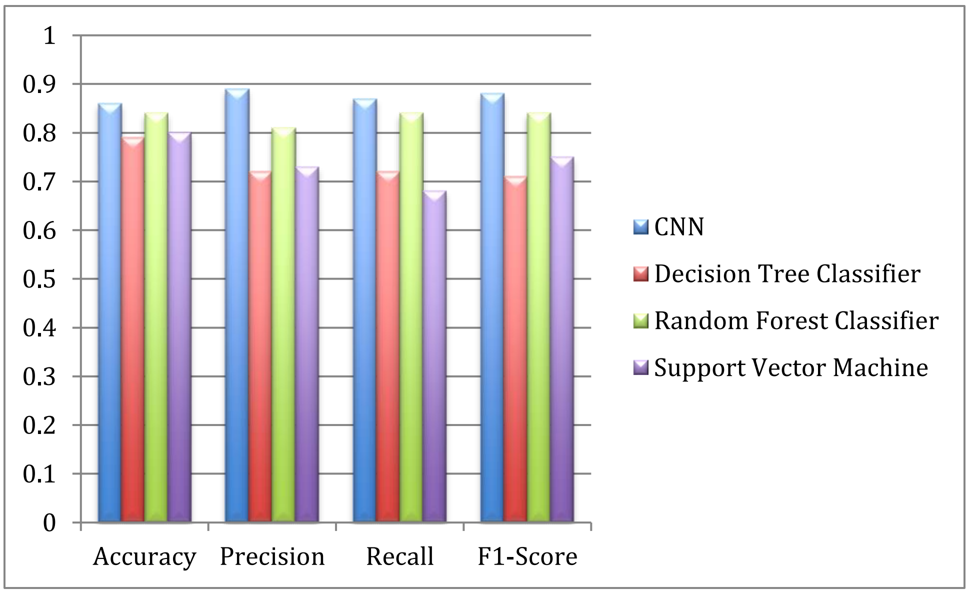

Fig.5:Evaluated Results of Various Predictions Mechanisms

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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