Classification of Dementia using MRI images: A deep learning approach

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Abstract— Dementia is a disease found in the elderly due to damage in brain cells overtime. The damage that is caused often tends to hinder cognitive abilities in an individual. When neurons are not able to transmit signals called neurotransmitters, it can impact cognitive abilities like thinking, reasoning and memory function. Additionally, Dementia is quite often diagnosed by employing a sequence of imaging tests, associated by evaluating an individual's anamnesis. Brain imaging helped doctors perceive the depth of the disease so it could be treated efficiently. This paper contains an automated computer aided system to diagnose the depth of the disease by using a type of brain imaging test called MRI scan. This paper suggests a computer aided method to detect early dementia using MRI images. This method consists of three sub-processes: First Pre-processing, Segmentation then classification. Noise removal, Skull Stripping and Edge enhancement is applied as the pre-processing methods. The pre-processed MRI images are classified based on 4 diagnosis groups: MD, ND, Mod-D, VMD. In our paper classification is done using Inception v3 CNN architecture. And segmentation of the WM (White matter) region is done. The suggested dementia detection obtains an average classification accuracy rate of 92.26 %, with a loss of 0.2117, precision of 97.6%, F1-Score of 92.30 percent, and recall of 95.5 percent.
Keywords— Brain MRI, deep learning, CNN, segmentation, dementia, Inception v3

I. INTRODUCTION

Medical issues are increasing in number. Experts and numerous organizations are trying to achieve a conclusion for the diagnosis and detection of the issues of their patients. Among these, one includes the Dementia which is growing numerously in the elderly.

Dementia is a term that expresses cognitive impairment and leads to symptoms related to loss in thinking ability, attention, memory, and logical reasoning. Dementia is quite often not a disease but is a collection of symptoms that leads to mild to severe cognitive impairment in daily life. The quick detection of dementia using MRI images would supply a threshold to treat these symptoms in no time. Dementia exists in many forms it incorporates many diseases one of them is vascular dementia. Our use case here is classification of demented brain MRI images of the Alzheimer's disease. CAD/CAMs are being implemented in order to detect different conditions in imaging of medical data and changing accuracy of diagnosis by using state-of-the-art pattern recognition as well as image processing. [1].

This condition commonly affects people aged 65 and over with only 10% of cases transpiring in young adults. That is why we diagnose this early. The changes in brain cells caused by this disease is not irreversible although it can be paused by medication provided by a verified neurologist. Classifying images is a very essential step in recognizing the pattern and getting insights of images. Earlier. Deep learning has been used in many types of image classification. Mainly Convolutional neural network has the best results for this image classification. [2]

First in the section, we present the Kaggle dataset which was attained through medical image acquisition and contains both healthy and diseased brains. Signal or Image de-noising is an essential task when working with MRI images. All MRI images have a range of noises. The pre-processing is done using data augmentation, noise removal and edge enhancement [3]. For noise removal, the bilateral filter is being employed, and as for edge enhancement the histogram equalization method is implemented.

Finally, the result of learning classification model and performance of the system under consideration are calculated. This includes values of Recall, Precision, F1-score, Accuracy etc.

II. LITERATURE REVIEW

Hierarchical extreme learning machine turned in 2020 [4], through Huizu Gu et al for computer-Aided Dementia analysis. using multilayer feature representation. DCADx, a CADx framework primarily based on H-ELM, is provided. due to the fact CSP and BFN were proven to have higher redundancy effects on brain facts, the DCADx incorporates exclusive information redundancy discount techniques: (1) CSP-primarily based DCADx (this is, DCADxCSP model) and (2) BFN-based totally DCADx. On Alzheimer's disease, the DCADx-CSP model scored 83.2 percentage.

In 2019 [5], Fubao Zhu et al .proposed a multiclass deepL used , precision, accuracy, let us not forget Recall, and F1-rating to assess every diagnostic version in the check set. This model of DNN suggests better balance and got the fine accuracy of 0.88%.

In 2021, Suriya Murugan et al [6]. proposed deep gaining knowledge of version for early analysis of alzheimer illnesses and dementia From MRI images. The Convolutional Neural network (CNN) is used to assemble a framework for detecting particular Alzheimer's ailment symptoms from MRI snap shots. To come across dementia stages thru MRI, a Dementia network (DEMNET) has been proposed. The DEMNET has a ninety three 93% accuracy.

In 2016, slice optimization was proposed by Yin Zhang et al [7]. OASISi dataseti wasi usedi andi i evolvedi ai versioni whichi showsi thei diseasesi byi combiningi Waveleti Entropyi (WE),i Multi-Layeri Perceptroni (MLP)i andi Biogeographyi Basedi Optimizationi (BBO).i Byi usingi thisi approach,i ani accuracyi ofi 92.40%i wasi achieved.i Thei statisticali resultsi ofi theiri methodi obtainedi ani accuracyi ofi 92.40i ±i 0.83percent,i ai specificityi ofi 92.47i ±i 1.23i %i andi ai sensitivityi ofi 92.14i ±i 4.39%,.

In 2018, Gang Li et al [8] usedi Longitudinali analysisi fori Alzheimer'si diseasei diagnosisi andi usedi RNNi withi thei OASISi Dataset.i RNNi isi ai typei ofi loopingi networki isi usedi toi detecti thei diseasesi ofi Alzheimer's.i Thei partsi ofi thei datai giveni isi vectorized.i Thei layeri isi furtheri usedi toi extracti temporali columnsi thati givei detailsi abouti thei comparisonsi thati havei beeni made.i Ini thesei twoi layersi therei existsi ai binaryi layeri fori classesi andi fullyi connectedi layer.i Trainingi andi testingi andi theni validatingi thei accuracyi wasi foundi toi bei eightyi six.89%i buti thei accuracyi ofi MLP+BGRUi isi foundi toi bei 89.69i percent.

In 2018, Riashat et al [9]. Implemented a Deep Convolutional Neural Networks for Alzheimer's Disease and detection of demented images using 3D slices. In CNN, the 3D data is pre-processed such that 2D input data is obtained. After training and testing the model using the proposed approach, an accuracy of 80.5% was achieved. This paper has an alternative approach , that is fast, cheap and more reliable. Convolution Neural Networks inspired Multilayer perceptron specifically capable of image
processing.

In 2020, Zhao Fan et al [11]. hired an powerful type of MRI snap shots of Alzheimer's ailment with the aid of making use of the ADNI dataset. On this observation a characteristic class version for Alzheimer's disorder primarily based on KPCA algorithm and AdaBoost algorithm changed into constructed, and decided on 21 patients with Alzheimer's disease (advert). those outcomes display that the KPCA set of rules is getting used in the article to acquire the very best class accuracy of the 2 groups: 94.seventy seven%, the single function distinguishing capability is the node level, and the accuracy of 90.ninety four% can be performed in the imaging analysis of AD.

So, in this paper we are using noise removal, data augmentation and edge enhancement for data pre-processing. For noise removal we are using Bilateral Filter and for edge enhancement Histogram Equalization (HE). White matter slicing is done using segmentation. We referred to a paper Convolutional neural networks for multi-class brain ailment identification by MRI.In this AlexNet, Vgg-16, ResNet-18, ResNet-34, ResNet-50 And Inception v3 models are used. That said, comparing their classification performance with pre-trained models are done the accuracy of 92.15% was got. We have used Inception v3 Architecture for the classification of images from the Kaggle dataset. The ideal image size for Inception v3 model is '224 X 224' pixels.

The processes are highlighted in the further sections of this article. Before the images were loaded for pre-processing, we converted the image resolution of the training and testing set to 224 x 224 pixels.

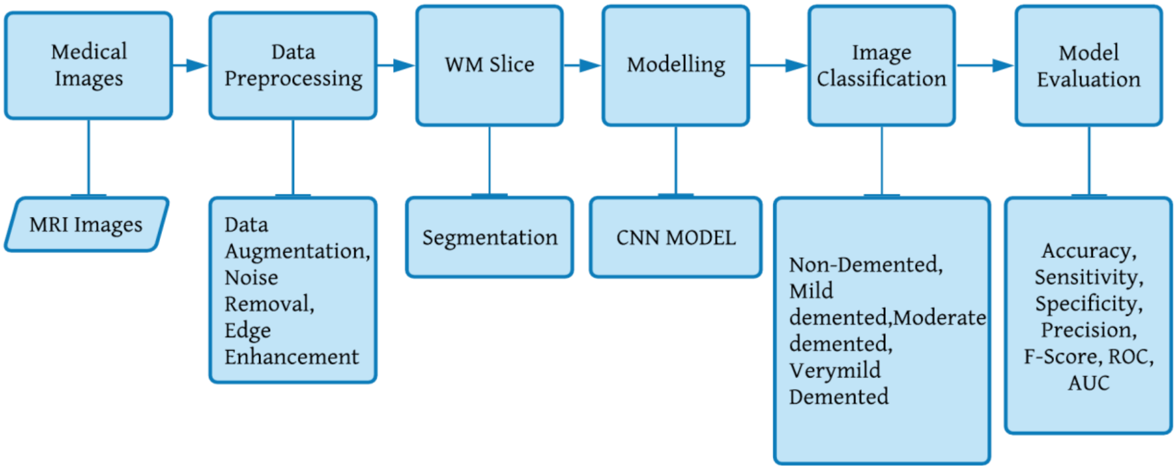


Figure 1 : Proposed methodology

III. METHODOLOGY

In our project we introduced the method of deep learning model as shown in figure 1. The step are: (2) Segmentation, (3) Image classification. This paper proposes an efficient method to establish and diagnose one of the most prevailing brain diseases, Dementia. We have made a diagram for the method we want to implement in Figure 1. First, we start by acquiring the dataset from Kaggle. A sample of the dataset is shown in figure 2. This data is mapped in a table format which is shown in table 1. We have reshaped our images to the size 224x224 before image processing.
The processes are highlighted in the further sections of this article. Before the images were loaded for

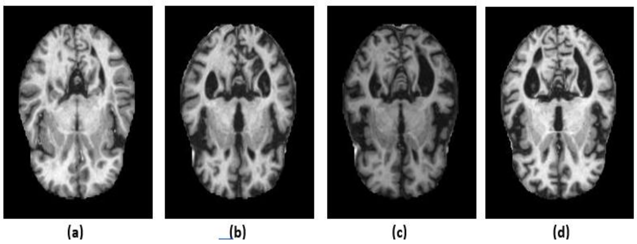


Figure 2 : (a) ND (b) VMD (c) MD (d) MODD

pre-processing, we converted the image resolution of the training and testing set to 224 x 224 pixels.

A. *Data pre-processing*

Images we acquired first undergo image pre-processing. Noise removal and Edge enhancement. First Data Augmentation was done as there was a class imbalance. Noise removal for test and train images is done using: The bilateral filter, this filter has proven its efficacy in MRI images in the past and thus the bilateral filter is our first approach. After this edge enhancement is done using Histogram Equalization..

a) Data Augmentation

Data augmentation is a pre-processing technique used to handle class imbalance and to establish a balanced dataset in each of its classes. In this article, we have implemented data augmentation to balance out two classes: Mild and Very Mild. Before augmentation it had 717 and 52 images in the train dataset respectively for each of the classes. This is depicted in table 2 with values of specific classes of the test and train dataset.

b) Noise Removal

Table 1 : Data Before and after augmentation

	Test Data	Train Data	
		Before Augmentation	After Augmentation
Non-Demented	640	2560	2560
Mild Demented	179	52	2548
Moderate Demented	12	1792	1792
Very Mild Demented	448	717	2151

We have implemented the bilateral filter for noise removal. It is called the edge preserving filter which is non-linear and it utilizes the gaussian convolutional phase. The bilateral filter is given by:

$$I^{\text{filtered}}(x) = \frac{1}{W_p} \sum_{x_i \in \Omega} I(x_i) f_r(\|I(x_i) - I(x)\|) g_s(\|x_i -$$

Here, the normalization term Wp is represented by,

$$W_p = \sum_{x_i \in \Omega} f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

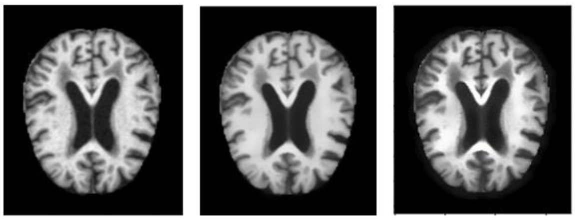
'f(r)' is the range kernel and 'g(s) ' is the special.

c) Edge Enhancement

Our project uses Histogram Equalization (H.E) for edge enhancement. A histogram of an image is the graphical representations of intensity distribution of an image. It represents the pixel numbers in each colour component. H.E depends on the use of cumulative probability function(cdf), it is defined by [16]

$$cdf(x) = \sum_{k=-\infty}^{x} P(k)$$

To change the contrast of the edges or the image in general it shows the most frequent intensity values or stretches out the intensity range of the image, this would lead to the image's area of low contrast to have higher contrast.



(a) (b) (c)

Figure 3: (B) First image (B) After pre-processing (C) Edge enhancement done

B. *Segmentation*

After the dataset undergoes data pre-processing, we have used the "os" package in python to store the images. These images after pre-processing have to undergo segmentation. Firstly, we need segmentation in our project as it helps in acquiring the required white matter (WM) of the brain MRI. Brain tissue segmentation is a very challenging task due to heterogeneity in intensities, noise and different structures of the dataset. Tissues in the brain are CSF, WM, and GM they stand for cerebrospinal fluid(csf), white Matter(WM) and Grey Matter(CM).

a. K-Means Clustering

K-means set up for clustering is an unsupervised machine learning algorithm.

number of clusters number of cases

case i centroid for cluster j

$$\text{objective function} \leftarrow J = \sum_{j=1}^{k} \sum_{i=1}^{n} \underbrace{\left\| x_i^{(j)} - c_j \right\|^2}_{\text{Distance function}}$$

It is very efficient in computing and gives satisfactory results if the clusters are compact and well separated. The classification is performed by minimizing the distances between the data and the corresponding cluster centre. In K-means, all image values are used to initialize the random centres and to calculate the Euclidian distance with the clustering centre. The algorithm is characterized by ability to segment image faster. Moreover, it reduces the computational complexity and improves the performances of K-means algorithm [19]

The results show that K-Means algorithm has good time complexity and accuracy. K-clusters are formed after partitioning the data based on the K-centroids..

b. K-means clustering steps:

1. Select the number of clusters.

2. Then we take k as random points, and its centroids

3. Next we assign data to nearest centroid value, which in turn forms K-clusters.

4. After forming Clusters we compute new centroids of each new cluster.

5. The last step is to assign each datapoints closer to the centroids, if any reassignment occurs, go to step 4. Else, the model is said to be ready.

In our project, k-means clustering is used with the help of "Add packages" in python. In order to get the white matter (WM) and pass it into our model.

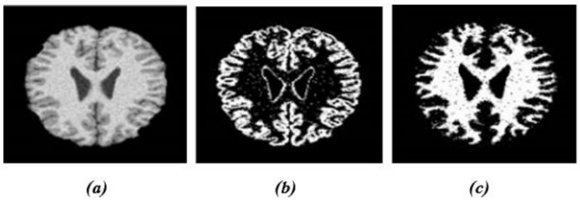


Figure 5 : (a). Original image (b). Gray matter (c). White matter

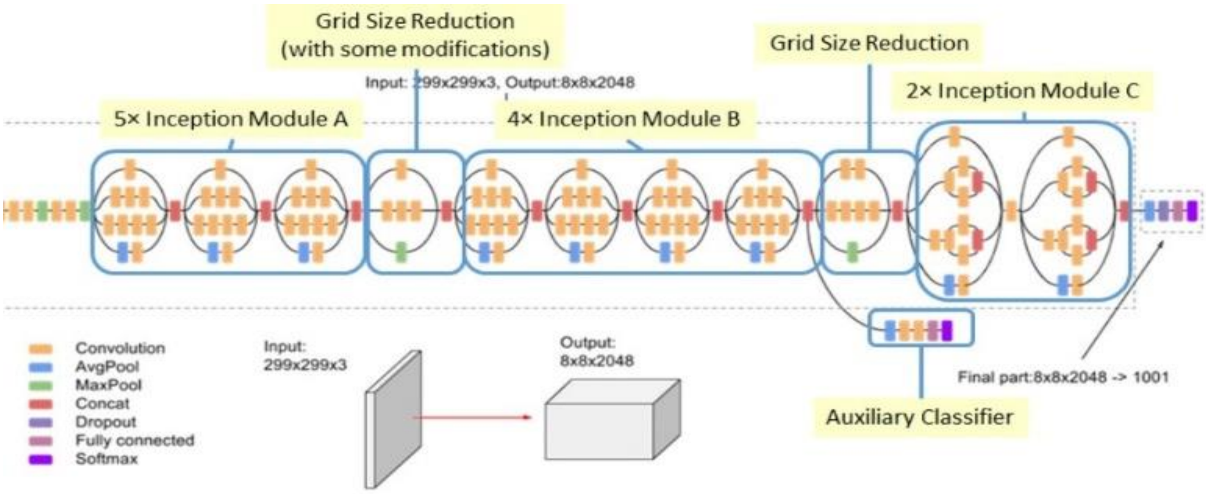


Figure 4: Architecture of Inception v3

C. Modelling

This project uses CNN model in order to classify the image from one class to a different. CNNs are regularized variations of multilayer perceptron. Multilayer perceptron's commonly suggest completely related networks, this is, each neuron in one layer is attached to any or all neurons within the subsequent layer. The "full connectivity" of those networks causes them to be in danger of overfitting records. Regular methods of regularization, or preventing overfitting, consist of: penalizing parameters for the duration of education (consisting of weight decay) or trimming connectivity (skipped connections, dropout, and lots of others.

In our problem statement we used Inception v3 because the architecture that classifies the test set into 4 classes. Inception v3 consists of 48 layers. It uses an input image size of 224X224 for best results. It uses 23 million trainable parameters and is an existing model of CNN architecture.

The Inception v3 model may be a resilient model because it can train hundreds and thousands of layers and still achieve great performance. The matter of exploding gradients was rectified by taking a shallow model and adding identity layers to it. This would provide a deep learning model that essentially must not produce higher training error than its counterpart because the layers added were only identity layers.The gradient exploding and training error problem was solved using this residual neural network where shortcut connections are used to perform identity mappings. This shortcut connection was needed because it helped in not having additional parameters being sent into the model and the computational time being very less.

D. IMAGE CLASSIFICATION

Our problem statement has images present in 4 classes. They are:
1. ND(non-demented)
2. VMD(Very mild-demented)
3. MD(mild demented)
4. MOdD(moderate demented)

The first class is the non – demented. It consists of 2560 images in training and 640 images in testing. The non-demented brain images provide a benchmark for other images to get classified.

The second class is the Very mild – demented. This class consists of 2151 images in training and 448 images in testing. The characteristics of a very mild demented brain is a small decline in hippocampal region. The 3rd class is mild – demented. This class consists of 2548 images in the training set and 179 images in testing set. The characteristics of this class is little to small decline in hippocampal regions. The 4th category is the Moderate- demented. This class consists of 1792 jpeg files in the train set and 12 jpeg files in the test set.

IV. RESULT

The Inception v3 model is used to classify the demented images. The standard preciseness and assessments are used in detecting the performance of categorization of models in this plot. About six evaluation metrics were used to evaluate the model performance for the particular research, namely;

- Accuracy rate
- F1- Score
- Precision
- Recall
- AUC-ROC curve

A confusion matrix was generated based on the performance of this particular approach. [11]

It figured that, every confusion matrix contains the following four situations.

- **True positive (TP)**: In this condition includes those patients who had the one in all 3 kinds of Alzheimer's or healthy brain. This also predicted that he is the one with the same situation.

- **True Negative (TN)**: This involves those who didn't have one in all 3 kinds of Alzheimer's .This predicts that patient is not having the same situation.

- **False positive (FP):** This condition includes those who didn't have one in all the 3 kinds of Alzheimer's .Nevertheless the prediction showed that patients had that scenario.

- **False Negative (FN)**: It involves those patients who were one amongst the 3 styles of Alzheimer's or healthy brain. It conjointly expected without identical scenario.

$$\text{Accuracy (ACC)} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{precision (PREC)} = \frac{TP}{TP + FP}$$

$$\text{recall (Sensitivity)} = \frac{TP}{TP + FN}$$

$$\text{f1 score} = \frac{2TP}{2TP + FP + FN}$$

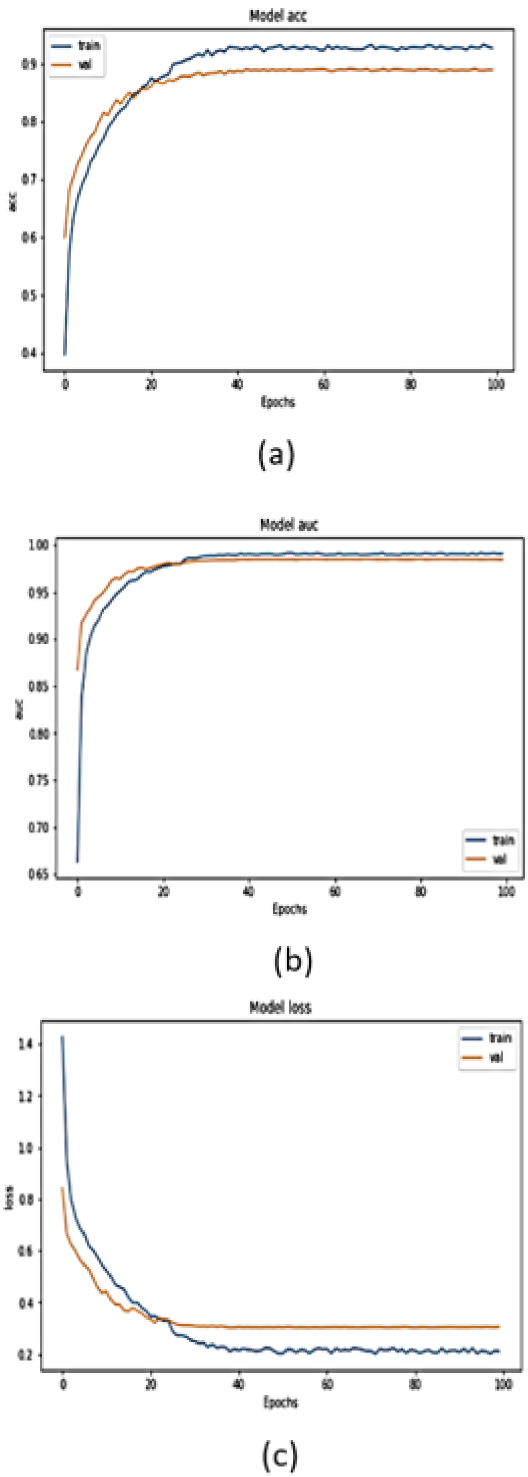


Figure 6 : Evaluation plots (a) Accuracy (b) AUC (c) loss

In our paper 9051 brain MRI images are categorized as about 2548 as mild demented, 2560 non-demented, moderate demented about 1792 and very mild demented 2151. The proposed diagnosed system stated in this paper correctly classifies and obtains 92.1% of accuracy. We also find out other factors like precision, F1-score and Recall.

Table 2 : Model comparison

Ref	Dataset	Modality	ACC	PR	REC	F1-Score
MLP[21]	ADNI	MRI	89	85	87	89
CBLSTM[21]	ADNI	MRI	82	79	82	82
CBLSTM +SMOTE [21]	ADNI	MRI	82	78	88	82
DEMNET[22]	Kaggle	MRI	85	80	88	83
H-ELM [22]	Kaggle	MRI	82	79	81	82
Proposed Method	Kaggle	MRI	92.26	94.6	95.5	92.5

In our paper our proposed model is compared with different types of deep learning techniques , CNN and classical machine learning models. The Inception v3 's performance is compared to that of several approach with the results which is presented in the composition publication. Our article uses Precision, accuracy, recall, F1-score and AUC of previous models which are then compared with proposed model. The method considered to acquire insights on the performance on both types of classification can be used. Our model antiquated on the MRI images which is our dataset. These are equated with the others, such as Hierarchical Extreme Learning Machine, multiclass deep learning method based on the Keras framework, Dementia Network (DEMNET). and results are provided in Table 3. The Inception v3 definitely performs better than all other models when we are comparing in terms of accuracy, recall and accuracy and we also see those results by classifying 4 different classes.

V. CONCLUSIONS

In this framework, the Inception v3 architecture is presented to identify Alzheimer’s affected images. Convolutional layers and pooling layers with CNN are used in the Inception v3 architecture. The neural network method generates a pattern that can be classified as demented, mild demented, moderately demented, or non-demented. Following that, the k means segmentation process is performed to find the alzheimer's impacted pixels. The suggested method is validated using brain MRI images from an open-access dataset. The suggested method's performance metrics used are accuracy, precision, F1-score, and recall. The suggested alzheimer's detection obtains an accuracy rate of 92.26 %, with a loss of 0.2117, precision of 94.6%, F1-Score of 92.1 percent, and recall of 95.5 percent.

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