2024 10th International Conference on Advanced Computing and Communication Systems (ICACCS)

Advancing Alzheimer's Nodule Detection through a Comprehensive Multi-Scene Deep Learning Framework

C.Premkumar,
Assistant Professor,
Department of Artificial Intelligence and Data Science,
Bannari Amman Institute of Technology,
Sathyamangalam, India.
premkumar@bitsathy.ac.in

R.Rajeshwari,
Assistant Professor,
Department of Computer Science and Engineering,
CMR Institute of Technology,
Bengaluru, India
rajeshwari.r@cmirt.ac.in

R.Remya,
Associate Professor,
Department of Electronics and Communication Engineering,
Vel Tech Rangarajan Dr Sagunthala R&D institute of science and technology,
Chennai, India
drremyar@veltech.edu.in

M.S.Cholaathiraj,
Second year student,
Department of Artificial Intelligence and Machine Learning
(of Affiliation)
Bannari Amman Institute of Technology,
Sathyamangalam, India.
cholaathiraj.al22@bitsathy.ac.in

A.Reethika,
Assistant Professor,
Department of Electronics and Communication Engineering,
Sri Ramakrishna Engineering College
Coimbatore, India.
reethikaanandan@gmail.com

Dr.S.Bharathidasan,
Associate Professor,
Department of Electronics and Communication Engineering,
Erode Sengunthar Engineering College,
Erode, India.
esecbharathi@gmail.com

***Abstract*— Determining the precise location of Alzheimer's nodules is essential for estimating the risk of brain cancer. Conventional CAD modules, including MRI, PET, and CT, struggle with feature extraction and segmentation due to time limits and complexity. This study proposes an efficient brain nodule detection technique based on the Multi-Scene Deep Learning Framework (MSDLF) that makes use of the vesselness filter. A four-channel CNN model is developed using information from two image sequences to enhance radiologists' ability to recognise four-stage nodules. This adaptable model may be used in two different classes. The outcomes demonstrate how well the MSDLF performs while processing substantial volumes of image data for brain nodule recognition, improving with accuracy 98.86% and 98.45% of sensitivity by using decreasing false positives.**

Keywords— Alzheimer's nodules, Positron Emission Tomography (PET), Magnetic Resonance Imaging (MRI)- scan, and Computed Tomography (CT), Multi-Scene Deep Learning Framework (MSDLF), CNN model.

I. INTRODUCTION

A degenerative neurological disorder called Alzheimer's disease (AD) is characterised by a growing memory loss. It stands as the most prevalent cause of dementia, initiating with cognitive decline and evolving into a neurodegenerative form of dementia. The diagnostic process for Alzheimer's involves a thorough evaluation, including medical history, MMSE score, neurobiological tests, and structural and resting-state MRI, with s-MRI and rs-MRI playing crucial roles. People lie down on the MRI table and remain motionless during these imaging procedures, with their resting-state functional To prevent interfering with ongoing brain activities, data is captured using magnetic resonance imaging (rs-fMRI).[1,2,3] Notably, AD leads to shrinkage of hippocampus and cerebral cortex within the brain.

Disease's indicates its severity at given time. In more severe instances, MRI scans reveal enlargement of the ventricles, impacting an individual's cognitive functions, including thinking capacity, and planning-abilities [4]. Currently, there is no cure for AD. However, prompt therapy after a prompt diagnosis can markedly mitigate symptom severity, offering relief to the patient and minimizing their suffering. Early interventions prove highly advantageous and effective when a diagnosis is made promptly. Such early diagnoses contribute to a significant reduction in memory loss over an extended period [5].

Upon the successful diagnosis of Alzheimer's Disease (AD), prevalent anomalies were often observed in the brain scans of affected individuals. These include:

(1) the presence of a substantial layer comprising protein sediment along the boundaries of nerve cells and

(2) the occurrence of damaged nerve fibers intricately entwined within the interior nerve cells. Notably, this information has been instrumental in the diagnostic process for Alzheimer's disease [6].

Diagnosing AD necessitates a meticulous medical assessment, comprehensive patient records, the Mini-Mental State Examination (MMSE) report, and various neurobiological and physical-examinations [7]. In conjunction with structural s-MRI and rs-f-MRI, stands out as one of the predominant techniques of scrutinizing and visualizing regular changes in brain [8].

In order to help with precise and fast diagnosis, this research investigates the apps, of Deep Learning algorithms identification of AD. The research has made use of AD-

Neurological Initiative website dataset, which was pre-processed to produce synthetic [9] pictures using GAN and pre-existing libraries, increasing the dataset's informative value.

In this study, the proposed work is to identify the Alzheimer's disease through classification process by CNN and machine learning algorithm to get an exact accuracy, sensitivity and specificity. The workflow has been mentioned in figure 1

II. LITERATURE REVIEW

This section uses machine learning techniques to give an extensive evaluation of the literature on Alzheimer's disease.

Estimote Bluetooth beacons are used in a technique that employs learning algorithms to follow patient behaviour over time and find residences with an accuracy rate of over 90%. [10] 83% of observations made by researchers Sorensen, Lauge, colleagues were accurate in identifying hippocampus texture as a valuable MRI-scan based feature for early diagnosis. The characteristic greatly enhanced the categorization of MCI-to-AD converters and stable mild cognitive impairments.

The authors of Ref. [11] improved multi-class classification accuracy using weighted auto-encoders, deep learning, and softmax activation function. Their research shows that integrating many features improves classification performance, using less information and less training data.

Paper suggested a differentiation structure that makes use of the complementarity input databases and aggregates characteristics using a nonlinear graph mixing technique. [12] Between AD and NC pictures, the AUC of attribute determined as 99.1%, while between NC and MCI images, it was 85.50%.

Using methods such as Region-Based-Spatial-Statistics-(RBSS) and (ICA) Independent-Component-Analysis, authors retrieved features from MRI images, grouping pixel-wise distributions and identifying feature combinations [13].

This work uses an existing method to optimise computing cost on the ADNI dataset. Three combination techniques are applied: first, grayscale pictures are converted from 3D to 2D; second, images are cropped to minimise size and remove extraneous borders; and third, PCA reduces computational expense and temporal complexity by extracting the best features from datasets. A DL-based CNN for diagnosing Alzheimer's disease was created by Mirzaei and Adeli, [14] demonstrating the absence of a single optimal method has availability of limited huge medical images.

With a comparative comparison of prior research in Table I, this study highlights benchmark work detects and diagnosis of AD using machine learning (ML) algorithms.

TABLE I. OVERVIEW OF EXISITING LITERATURE

			Performance		
Paper year	***Source***	***Algorithm***	***Specificity (s)***	***Sensitivity (S)***	***Accuracy (A)***
2022 [14]	HMS Dataset	Variational-Mode Decomposition (VMD)	-	98.56	91.78
2022 [15]	ADNI Database	CNN	-	-	86.3+061 or 86.3-061
2021 [18]	ADNI Database	Transfer learning	-	-	98.74
2019 [16]	BRATS	Clustering and SVM	-	-	90.90
2016 [17]	Brain-tumor	Modified KNN	96.0	90.0	95.0

III. MATERIAL AND METHOD

The flowchart outlining the suggested models is supplied, as seen in figure. 1, and the dataset for the experiments was obtained from the ADNI website.

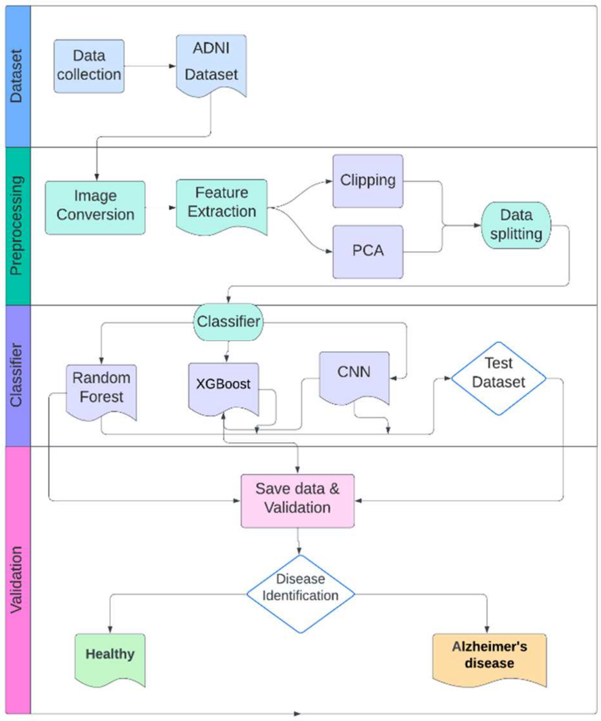

Fig.1. Proposed workflow of disease identification

A. Dataset description

4215 total images from the Alzheimer's^ Disease Neurological Initiative (ADNI)- database are divided into two groups: 2134 images from AD and 2081 images from NL, which corresponds to the average person class.

B. Pre-processing methods

A different technique has been used for pre-processing the data for the suggested method.

i. Image conversion

Image conversion is a process that converts an input image into a desired 2D format. It involves reading the input image, loading it into the Viacom library, storing the i^{th}, j^{th} and k^{th} components in vectors, and creating separate image files for individual component in the z-vector. The correlated vectors x & y are saved for every component of z-vector, generating 2D images.

ii. Parameter reduction and selective clipping

This study makes use of ADNI dataset, which contains of brain image generated by MRI that have been segmented into healthy and sick subjects. The dataset was altered by chopping sections close to the skull edge, eliminating cross-sectional scans [15] that added little value in terms of brain orientation, in order to maximise model efficiency. This change optimises the model's efficiency and guarantees a better result figure 2.

The goal of the project is to solve the information gap in skull sections by creating a model for brain edge scans. The researchers used grayscale conversion to lower the input dataset's parameters, [16] The work ensures no data loss owing to the accessibility of grayscale scans and the preservation of learning potential by using the histogram equivalency technique to modulate pixels and segment pictures from both training and testing datasets figure 3.

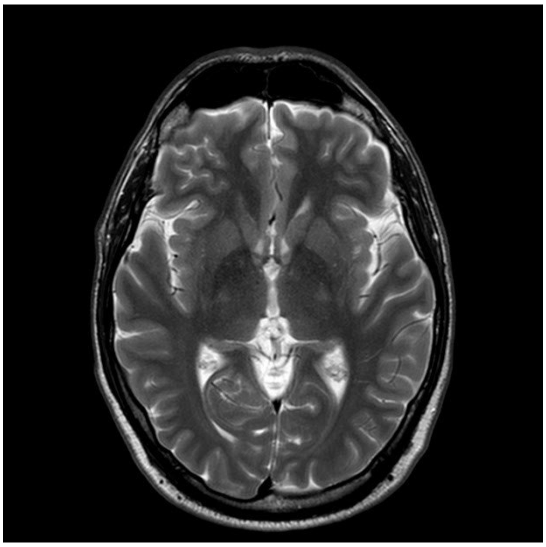

Fig 2. Human Skull image – Normal Brain

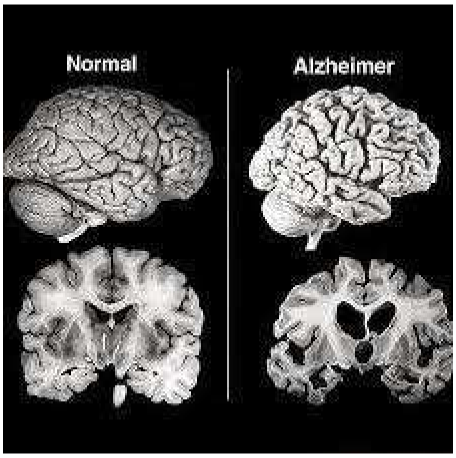

Fig 3. Image identification of normal and disease affected brain.

iii. Principal components analysis (PCA)

The PCA approach minimises average root distance between a point and a line in order to determine the line that fits the data the best in a given dimensional space. To create an orthogonal basis with uncorrelated unique data dimensions known as primary components this method applies the Gram-Schmidt process.

Implementation Process:

The associations between variables must be calculated before calculating a matrix. Next, to determine the significance of the data, divide the matrix into direction and magnitude components. Decrease the dimensionality of feature space by aligning original data with these directions. Standard classification methods such as CNN model, XGBoost classification, and random forest are then trained on the pre-processed data.

C. Deep learning classifiers

The study used a variety of techniques to divide the photos into normal and AD groups; after thorough pre-processing, Convolution Neural Networks (CNNs) proved to be the best successful classifier. Additional classification models, including XGBosst and random forest, were also utilised.

Convolution neural network.

CNN were also identified as artificial neural networks that mimic the structure of animal visual cortex by modelling brain functions. These models are made up of layers with comparable patterns of connections.

Layer-1

Filtration is carried out by the convolutional layer, sometimes referred to as the primary or main layer, by pattern analysis of the input layer. It generates an output layer, often represented by cubical blocks, with elements filtered out under particular circumstances.

Layer-2

After the convolutional and max-pooling layer uses maximum value of each block to shrink size of given input matrix. It generates greatest value found in each grid by repeatedly iterating over the original matrix using tiny grids [21].

Layer-3

The convolutional neural network (CNN)'s fully connected layer, sometimes referred to as the last layer, joins all of the nodes from the earlier design, greatly lowering the amount of spatial information. It sorts input data into output in a manner akin to ANNs. The layer is a conventional fully linked layer that links every node in the prior architecture, producing a more accurate and efficient as shown in table II.

TABLE II. CNN MODEL IMPLEMENTATION IN VARIOUS LAYERS

Layer	*Shape of brain*	*Parameter*
Layer 1	Convolutional layer (None, 103, 86, 60)	17 842
Layer 2	Maxpooling layer (None, 60, 52, 71)	0
Layer 3	Fully CNN (None,3)	254
Total trainable parameter 17 842		

D. *Classification in Machine learning*

This section describes how different machine learning algorithms are applied to a dataset and how our suggested work is used to analyse the results.

i. XGBoost

Gradient boosting is a classification approach that assembles the output of a simpler model using boosted trees to predict an outcome. Gradient descent techniques are used to minimise loss during iterative training, which involves adding new trees that forecast faults in earlier trees and combining them with earlier trees to get the final output.

ii. Random forest

An approach for natural learning called random forest is used to categorise picture collections. Like any regular forest, it is thick but incredibly sturdy. Using the input, the algorithm creates decision trees, extracts the output from each, and chooses the result that has received the most votes. Because it reduces over-fitting, this ensemble approach performs better than algorithms that use a single decision tree.

IV. EXPERIMENTAL RESULT

Convolutional Neural Network (CNN) algorithms were demonstrated a great deal of promise in recognising Alzheimer's disease pathology when applied to brain imaging data. The CNN algorithm distinguished unique patterns and structural variations in brain pictures from patients with AD and healthy persons, offering insights into neural modifications associated with the condition. The opportunity for early diagnosis and intervention presented by this accuracy and robustness might improve clinical results in Alzheimer's disease. In general, CNNs are an effective diagnostic technique for identifying and treating Alzheimer's as in figure 4.

GPUs were used to train the model on Kaggle, with different epochs being used for best outcomes. The model's correctness was assessed using accuracy and sensitivity. Using the train test split package from sklearn, the dataset was split between 76% of training and 24% of testing. Percentages by testing and training datasets is 24% and 76%, respectively.

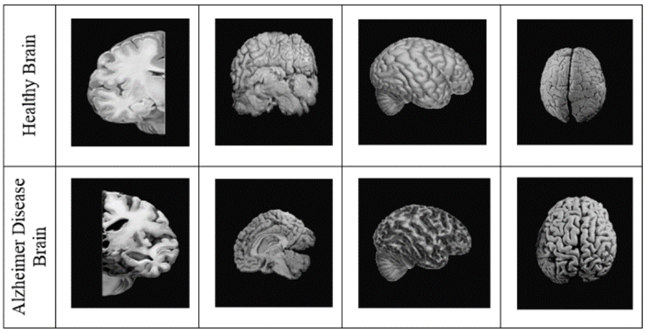

Fig.4. Result obtained from CNN algorithm

TABLE III. ACCURACY COMPARISON BY APPLYING PRE-PROCESSING

Algorithm	**Accuracy**	
	Before (%)	***After (%)***
XGBoost	91.16	93.74
Random forest	83.71	87.11
CNN model	96.05	98.60

Table III compares the classification accuracy of many models both before and after preprocessing techniques are used. Table IV compares the model's training times and table V shows that adds to dataset resulted in a considerable reduction in model training time. Table VI illustrates how we compared our results to the benchmark results already in place, demonstrating the superiority of our approaches over those of other well-known writers.

TABLE IV. COMPARISION OF TRAINED DATA USING PRE-PROCESSING

Algorithm	**Pre-processing**		
	Before training	***After training***	***% on decrease***
XGBoost	2547.10	489.75	84.75
Random forest	32.97	9.77	71.49
CNN model	237.96	94.84	45

The performance or percentage analysis has been analysed by using the equation 1, 2, 3, 4, 5 and 6.

Accuracy
$$A = \frac{TP + TN}{TP + FP + FN + TN} X\ 100\% \quad \text{.......(1)}$$

Sensitivity
$$S = \frac{TP}{TP + FN} X\ 100\% \quad \text{.......(2)}$$

Specificity
$$s = \frac{TN}{TN + FP} X\ 100\% \quad \text{.......(3)}$$

Precision
$$P = \frac{TP}{TP + FP} X\ 100\% \quad \text{.......(4)}$$

F1-score
$$F1 = 2\ X\ \frac{P + S}{P + S} X\ 100\% \quad \text{.......(5)}$$

TABLE V. ADNI DATASET PERFORMANCE BY USING PROPOSED METHOD

Algorithm	*Percentage (%)*			
	Accuracy (A)	***Precision (P)***	***Specificity (s)***	***F1-score***
XGBoost	93.48	92.86	93.47	93.16
Random forest	87.11	89.56	86.49	88.26
CNN model	97.54	99.13	97.46	98.33

The above equation are TP or TN = TruePositive or Negative, FP or FN = FalsePositive or Negative

$$\text{Computation time (decrease)} \quad \frac{TB - TA}{TB} X\ 100\% \qquad \ldots\ldots.(6)$$

Hence TB or TA = Time taken before or after pre-processing

TABLE VI. COMPARISION OF PROPOSED AND EXISTING WORK

Year	*Algorithm or Methodology*	*Accuracy (A) in %*
2019	CNN	97.95
2016	SVM	94.31
Proposed model	XGBoost, Random forest and CNN	98.63

Performance comparison of algorithms.

Following the dataset's pre-processing, the categorised results from three prediction models are shown in this section. As seen in figure. 5, we examined three models based on sensitivity, accuracy, and specificity.

The comparative analysis of planned work and recommended approach was shown in table VI. Figure 6 demonstrates how much better our suggested work performed than the current approaches.

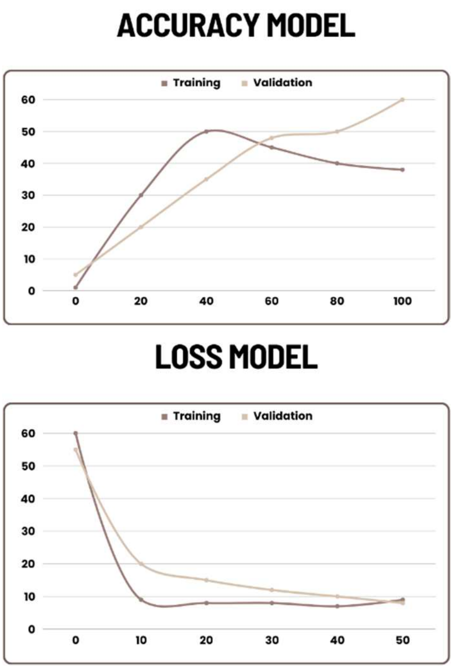

Fig.5. Graphical representation of Accuracy and Loss model

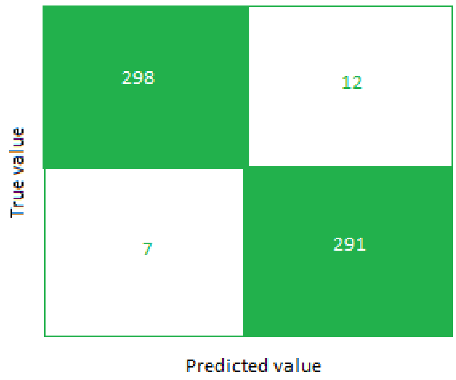

Fig.6 Matrix value of proposed CNN model

V. CONCLUSION

This study offers novel pre-processing methods that shorten training times for current learning algorithms and improve classification algorithm accuracy. The study makes use of a dataset from the ADNI that has undergone painstaking pre-processing to improve the MRI images' quality and ability to discriminate. The stages involved in this process are selective clipping, grayscale picture conversion, and histogram equalisation. Using pre-processed MRI images, three distinct learning algorithms—random forest, XGBoost, and proposed CNN model are suggested for the correct classification and diagnosis of AD.

With an astounding accuracy is 98.86% and sensitivity was 98.45%, the experimental results outperform previous studies, demonstrating the system's efficacy in precisely identifying and diagnosing AD. The results hold out hope for diagnosing brain diseases, especially when pre-processing methods are used to improve classification algorithms and shorten training times. The suggested method may greatly enhance patient treatment and results by facilitating early and precise identification of AD and additional brain disorders. In future the disease matrix value can be increased or decreased based on the size of image, performance will be improved by using CNN and machine learning algorithm.

REFERENCES”,

[1] Fujia Ren; Chenhui Yang; Qi Qiu; Nianyin Zeng, “Exploiting Discriminative Regions of Brain Slices Based on 2D CNNs for Alzheimer’s Disease Classification”, IEEE Access (Volume: 7), Page(s): 181423 – 181433, 31 May 2019.

[2] . Yang, L. Tong, M. Faraji, and A. Basu, ‘‘IVUS-Net: An intravascular ultrasound segmentation network,’’ in Proc. Int. Conf. Smart Multimedia. Cham, Switzerland: Springer, Aug. 2018, pp. 367–377

[3] Fatma El-Zahraa A. El-Gamal; Mohammed M. Elmogy,” Personalized Computer-Aided Diagnosis for Mild Cognitive Impairment in Alzheimer’s Disease Based on sMRI and ^{11}C PiB-PET Analysis”, IEEE Access (Volume: 8), Page(s): 218982 – 218996, 17 November 2020.

[4] C. Kalafatis et al., “Validity and cultural generalisability of a 5-minute AI-based, computerised cognitive assessment in mild cognitive impairment and Alzheimer’s dementia,” Frontiers Psychiatry, vol. 12, p. 1155, Jul. 2021, doi: 10.3389/fpsyt.2021.706695.

[5] Weijia Liu; Qunxi Dong; Shuting Sun; Jian Shen. “Risk Prediction of Alzheimer’s Disease Conversion in Mild Cognitive Impaired Population Based on Brain Age Estimation”, IEEE Transactions on Neural Systems and Rehabilitation Engineering (Volume: 31), Page(s): 2468 – 2476, 22 February 2023.

[6] Chima S. Eke; Emmanuel Jammeh; Xinzhong Li, “Early Detection of Alzheimer's Disease with Blood Plasma Proteins Using Support Vector Machines”, IEEE Journal of Biomedical and Health Informatics (Volume: 25, Issue: 1, January 2021), Page(s): 218 - 226.

[7] Mahmoud Seifallahi; Afsoon Hasani Mehraban; James E. Gal, “Alzheimer’s Disease Detection Using Comprehensive Analysis of Timed Up and Go Test via Kinect V.2 Camera and Machine Learning”, IEEE Transactions on Neural Systems and Rehabilitation Engineering (Volume: 30), Page(s): 1589 – 1600, 08 June 2022.

[8] Y. Chen, W. Yu, and T. Pock, “On learning optimized reaction diffusion processes for effective image restoration,” in Proc. IEEE Conf. Comput. Vis. Pattern Recognit., Jun. 2015, pp. 5261–5269.

[9] Yusera Farooq Khan; Baijnath Kaushik, “HSI-LFS-BERT: Novel Hybrid Swarm Intelligence Based Linguistics Feature Selection and Computational Intelligent Model for Alzheimer’s Prediction Using Audio Transcript”, IEEE Access (Volume: 10), Page(s): 126990 – 127004, 21 November 2022

[10] M. V. Afonsos, J.-M. Bioucaes-Dias, and M. A. T. Figueiredos, “Fastest images recovery using variables splittings and constrained optimization,” IEEE Trans. Image Process., vol. 20, no. 8, pp. 2346–2357, Sep. 2020.

[11] M. Maqsoods, F. Nazire, U. Khans, F. Aadiel, H. Jamasl, I. Mehmood, and O. -Y. Sonag, Transfer learnings assisted classifications and detections of Alzheimer’s diseases stages using 3D MRIs scans, Sensors, vol. 18, no. 10, p. 2646, 2019.

[12] Ruizhies Han; C. L. Phielip Chen; Zhuelin Liu, ” A Novels Convolutional Variations of Broad Learnings Systems for Alzheimer’s Diseases Diagnoses by Using MRI Image”, IEEE Access (Volume: 9), Page(s): 214645 – 214656, 23 November 2021

[13] V. Golkoov, A. Dosovietskiy, J. I. Spaerl, M. I. Meanzel, M. Cziasch, P. Sämaann, T. Broax, and D. Creamers, “q-spaces deep learnings: Twelvefolds shorter and model-free diffusions MRI scans,” IEEE Transs. Meds. Imag., vol. 36, no. 6, pp. 1343–1350, May 2019

[14] Kaei Lei; Jiaeng Weang; Shaenshan Li; Haiteao Yu, “Feature Extractions and Identifications of Alzheimer’s Disease based on Latent Factors of Multi-Channels EEG”, IEEE Transactions on Neural Systems and Rehabilitations Engineering (Volume: 30), Page(s): 1556 – 1568, 29 July 2022.

[15] Battulai Srinivasan Raoi; Mudiyala Aparna, “A Review on Alzheimer’s Diseases Through Analyses of MRI Image Using Deep Learnings Techniques”, IEEE Access (Volume: 11) Page(s): 71542 – 715560,: 14 July 2023.

[16] Animai Kujuri; Zahidi Razai; Arfati Ahmaid Khan, “Datas Complexit Based Evaluations of the Models Dependences of Brain MRI Images for Classifications of Brain Tumors and Alzheimer’s Diseases”, IEEE Acceess (Volume: 11), Page(s): 112116 – 112132, 22 October 2023.