Mediterranean Journal of Basic and Applied Sciences (MJBAS)
Volume 7, Issue 3, Pages 93-102, July-September 2023

A System for Diagnosing Alzheimer's Disease from Brain MRI Images Using Deep Learning Algorithm

Neelavathi, S.[1*], Arunkumar, P.[2] & Janani, K.[3]

[1]PG Scholar, [2,3]Assistant Professor, [1-3]Department of Electronics and Communication Engineering, Sir Issac Newton College of Engineering and Technology, Nagapattinam, Tamilnadu-611102, India.
Corresponding Author Email: neela7700@gmail.com*

DOI: https://doi.org/10.46382/MJBAS.2023.7308

Article Received: 12 July 2023 | Article Accepted: 23 September 2023 | Article Published: 29 September 2023

ABSTRACT

Disorders of the brain are one of the most difficult diseases to cure because of their fragility, the difficulty of performing procedures, and the high costs. Adults who have hypertension, one of the most common brain illnesses, may have different degrees of memory problems and forgetfulness. Depending on each patient's situation. For these reasons, it's crucial to define memory loss, determine the patient's level of decline, and determine his brain MRI scans are used to identify Alzheimer's disease. In this project, we discuss methods and approaches for diagnosing Alzheimer's disease using deep learning. The suggested approach is utilized to enhance patient care, lower expenses, and enable quick and accurate analysis in sizable investigations. Alzheimer's disease is a progressive neurodegenerative disorder that affects millions of people worldwide. In recent years, deep learning algorithms, such as convolutional neural networks (CNNs), have been increasingly used in Alzheimer's disease analysis from brain MRI scans. This paper proposes a CNN-based system for Alzheimer's disease analysis from brain MRI scans. The proposed system involves several steps, including data preprocessing, feature extraction, training the CNN model, and evaluating its performance on a test set. The results demonstrate the effectiveness of the proposed CNN-based system in accurately detecting Alzheimer's disease from brain MRI scans.

Keywords: Alzheimer's Disease; Magnetic Resonance Imaging (MRI); Deep Learning; Brain Disorder; Convolutional Neural Network (CNN).

1. Introduction

The neurological disorder. Older aged is more susceptible to Alzheimer's disease (AD), which affects around 46 million individuals globally. The first symptom of the illness is a forgetfulness of prior conversations or occurrences. As the condition worsens, it results in a substantial loss of memory and functional ability. The damage occurs years before any symptoms develop, but it first shows up in the part of the mind that regulates memory. As more parts of the brain begin to lose neurons, the brain finally becomes much smaller. Following are the stages of the illness: Mild, Severe, and Medium. Some of the more common early symptoms of Alzheimer's disease include memory loss, emotional changes, poor judgment, social withdrawal, and vision problems. This happens as a result of Alzheimer's disease harming the hippocampus, an area of the brain important for remembering. Every three seconds, a new dementia patient is found somewhere [2] [3] [5] [6] [9].

In both the hippocampus and the entorhinal, two regions of the brain essential for recall, the first consequences frequently include the death of neurons and the connections that connect them. Therefore, it is necessary to do study and analysis in order to understand the alterations in the neural network. This environment uses MRI images as input. The deviations revealed by various measures (AD) are also examined using a machine learning technique to determine whether Mild Mental Impairment (MCI) evolves into Alzheimer's disease. One could then take the necessary prescriptions if changes in such elements arise and be conscious of them. The initial phase, often known to be the mild stage, is characterized by difficulties in using the proper word or name as well as missing or misplacing priceless items. The third and longest stage is the intermediate phase, which involves losing one's own past, being unclear of one's whereabouts, and remembering what day of a week it is.

The late stage, often known as the severe stage, is characterized by changes in one's physical capacities and communication challenges. With more than 4 million people suffering from Parkinson's and various types of dementia, India has the third-highest caseload in the world, behind China and the United States. In India, there will likely be roughly 7.5 million dementia and Alzheimer's patients by the year's end of 2030. Whenever a disease can be detected in advance, the risk of death is decreased. Several methods are used for putting the illness's categorization into action.

Volumetric feature-based Alzheimer's disease [1] - Alzheimer's disease (AD), There is a mechanism in place for the seventh most frequent cause of death in the US. Research on the cause and pathology of AD, the development of animal models of AD, and the development of AD therapeutics have all made important strides. It is highly desirable to create verifiable biologically based markers that could be used to identify AD, track its progression, and determine the likelihood that AD will occur. Finding early AD markers has been done through reclined magnetic resonance (MR) scanning. Subjects in an investigation are said to be in a "resting state" if they don't perform any tasks or respond to any inputs while imaging.

Practically specialized neural networks and their linkages are revealed by new information on the connections between physically diverse brain structures in resting-state functioning magnetic resonance (MR) imaging. A novel viewpoint on network collapse in neurological disorders has been proposed. Earlier studies focused on specific hypothesis-driven evaluation, such as those on the hippocampus network, typical systems, and the tiny world network.

Automated detection of Alzheimer's disease [4] - The approach for predicting Alzheimer's disease (AD) includes the moderate cognitive impairment (MCI) stage, which may or may not progress into Alzheimer's disease (AD). MCI is the form of memory that is most prevalent. It is critical to precisely identify people at this stage because AD may or may not develop during the MCI stage. At this phase, anticipating outcomes is essential. Many investigations had thus far focused their attention on a specific biomarker method for the diagnosis of AD or MCI. According to recent research, an amalgamation of one or maybe more distinct indications may provide more details for diagnosis, but it also increases the accuracy of classification by discriminating between different groups. Using an amalgamation of four different biomarkers—CSF protein levels, systemic magnetic resonance imaging (sMRI), Fluorodeoxyglucose Positron Emission (FDG-PET), and Apolipoprotein-E (APOE) genotype—we propose an innovative machine learning-based structure in this paper to differentiate between participants with AD or MCI.

A multiclass support vector machine (SVM) classifier was used in this instance, and it was supported by a novel grid-search technique. Before passing the generated data to the classifier, we dimension-reduced high-dimensional features into lower-dimensional features using the truncate single value decomposition (Truncated SVD) method. A multi-model deep CNN [7] examined brain Segmentation of the brain tumor is crucial for therapy planning and post-treatment assessment. But it requires a long time, and there is inter- and intra-rater variability. As a result, efficient and reliable processes are favoured. However, segmenting brain tumours is a challenging task because of their inconsistent shape, appearance, and placement. In recent years, modern conclusions were established utilising CNN-based techniques. It is difficult for feature construction to detect complex patterns, such as the characteristics of brain tumours, but CNN scan can learn them with just the right amount of data.

We also look into how recalibration is implemented in FCN. All of the contextual information from the FM is collected via global average pooling in the sub block. Instead, we argue that dilated convolution is better suited for the recalculation block in FCN. As a result, this study makes three key points. First, we advise combining into lines for reduction and elongation. In the second section, we examine FM adjustment with regard to FCN. We recognise that the initial SE block is not ideal for FCN and offer a superior alternative. Third, we assess our segmentation of brain cancer proposal using data that has been easily accessible to the general population.

Single-slice Alzheimer's disease [8] - Gliomas are most prevalent and dangerous brain tumors, with a relatively short life span in their maximum grade. This method was developed to predict the many types of brain illnesses, such as brain tumours. Therefore, preparing for treatment is crucial to enhancing the quality of life for cancer patients. The amount of data produced by magnetic resonance imaging (MRI), despite being a widely used imaging technology for detecting malignant tumours, limits the application of reliable quantitative assessments in clinical practise. Due to the high anatomical and spatial heterogeneity among brain tumours, automated segmentation is difficult, necessitating the development of trustworthy techniques.

In this paper, we investigate micro 3 kernels to create a convolutional neural network (CNN)-based auto-segmentation method. Utilising smaller kernels allows for the construction of a deeper architecture while also assisting in the prevention of over-fitting because there are fewer weights in the network. Brightness Normalisation was examined as a step that happened before dividing brain tumours in MRI scans.

Residual network model [10] - When tissue delineation is required, magnetic resonance (MRI) is frequently the preferred medical imaging technique. This is especially true for any attempts to classify the brain's tissues. The suggested hybrid technique has three stages: classification, dimension reduction, and picture augmentation. We were successful in retrieving the early stage (DWT) MRI image characteristics using discrete wavelet-based processing. In the second stage, the method known as principal component analysis (PCA) was used to retrieve the most crucial components of magnetic resonance pictures. The classification process has resulted in the creation of classifiers. Both the first classifier and the second classifier use artificial neural networks (FP-ANN) that are based on feedback backward propagation.

Classifiers were initially used to categorise people in MRI images as defective or normal. In the collection's grayscale images, the foreground is always in the centre. The skull is photographed from several angles, allowing us to view the tumors' size and placement from a variety of angles. The size differences amongst the tumours make tumour diagnosis difficult. In actual practise, the knowledgeable medical professional is aware of the MRI image's direction.

Section 1 provides the introduction about domain such as machine learning and objectives for Alzheimer disease prediction with CNN algorithm. Section 2 is discussed about Literature Survey about brain imaging. Section 3 provides a system overview that has existing system, proposed system, and tools used for implementing proposed application. Section 4 provides a detailed description about proposed system that has implementation modules and algorithms involved in each module. Section 5 is about the Result and Discussion. Sections 6 and 7 is about the Conclusion and Future work.

2. Machine Learning Classifiers for Alzheimer Disease Prediction

Alzheimer's disease (AD) depends on factors associated with the diabetes sickness. It is vital to select those factors and features with an efficient manner in order to improve the precision of forecasts. Effective feature selection and categorization will increase the clinical reliability of the diagnosis as well as decrease the cost of identifying the disease. By choosing a smaller sample of relevant variables from Diabetic data, the feature selection (FS) method improves the accuracy of classification while utilising fewer features. To improve system efficiency, a significant feature of these features was selected using the technique of feature engineering. Segmenting images is the most difficult and important step in the image processing process. A picture is segmented into its distinct components or regions, and visual elements with similar characteristics are grouped together. Segment serves a number of purposes in the processing of digital pictures, include compression as well, automatic handwriting analysis, remote sensing, arthritis diagnosis from joint images, and medical image processing. The clustering algorithms may divide any image into several groups according to similarity criteria like texture or colour. The present system uses the technique of K-means clustering, which divides the image into K groups based on how similar the pixels in each cluster are.

3. Alzheimer Disease Prediction Using Deep Learning Algorithm

The chance of death of Alzheimer's disease is decreased with early detection. To either directly or through indirect means examine the pharmacology, structure, or function of the brain, scanning or brain scans is used. The brain is scanned using magnetic resonance imaging (MRI) and positron evoked potentials (PEEP). In order to measure the electrical activity in the brain, an EEG method is applied to the scalp on the head. An EEG measures the electric activity in your mind using a few electrodes that are affixed to the head. An electrical flow can enter or escape through a connection. These devices transmit data from your brain to an apparatus that gathers and stores the data. Brain tumour segmentation is the development of a simple method for determining the size and shape of a tumour in a brain MRI image.

Only a few of the layers that make up CNN and have different purposes are pooling, convolution, stimulation, and completely linked layers. The convolutional layer produces map features by convolutional resampling the input images over the kernel. The output from the previous convolution layer has been extracted at a rate using the highest number or mean of each defined neighbourhood inside the pooling layer as the value to be conveyed to the following layer. The rectified unit (ReLU) and the leaky ReLU, a variation of ReLU, are neither of the most widely used activation functions. The ReLU transforms data nonlinearly by clipping bad input values to zero and sends only the good input data as outputs.

Datasets acquisition: An MRI can be used to assess the condition of the brain and provide predictions about abnormalities and brain activity. In this study, an Automatic Diagnostic Tool (ADT) was developed with the goal of examining and categorising MRI signal patterns from the normal and Alzheimer classes. Data from MRI images can be entered using this module. A collection of MRI scans from young people with incurable Alzheimer's disorder make up this Kaggle dataset. Subjects were monitored for up to several days after stopping anti-Alzheimer medication in order to summarize the information they submitted and evaluate whether they qualified for a surgical operation.

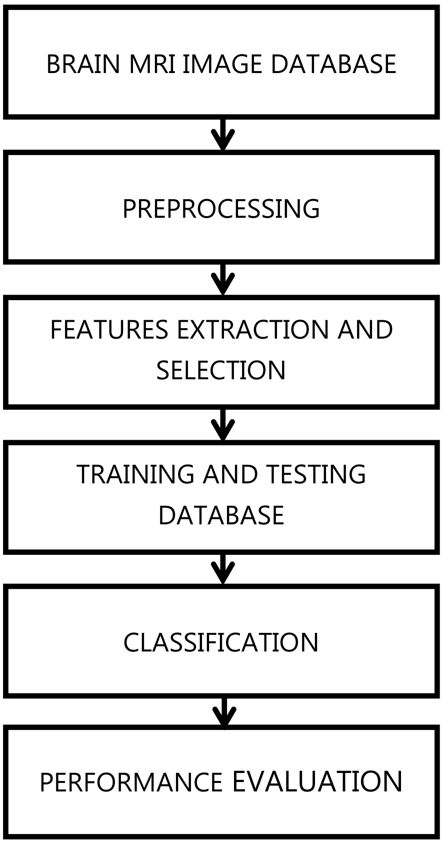

Figure 1. Proposed Framework

Preprocessing: Data preliminary processing, a crucial step in the data mining process, is the altering or wiping of data prior to usage in order to ensure or improve performance. The adage "garbage in, garbage out" is particularly relevant to initiatives using data and machine learning. The lack of proper control in data collection methods leads to anomalous data, impossible information combinations, data that's missing, etc. Inadequately checking for these issues could lead to erroneous optimistic data analysis outcomes. Therefore, an assessment of the accuracy or arrangement of the information must come before each analysis. Particularly in the field of computational biology, the single most crucial phase of a machine learning project is often preparing the information. A rolling time frame is used to first divide serial EEG recordings in earlier stages without crossing over. A wavelet transformation is then used to the EEG data to create a group of signals.

Features extraction: In this module, we can extract the temporal or frequency domain features from processed data. It includes "mean," "variety," "kurtosis," "skewness," and other characteristics that will follow identification. The average value of an N-sample signal from an EEG is what is meant by the word "mean."

Classification: A number of remark operations must be performed on the outputs of a training Deep CNN in order to obtain the offer upgraded again for test MRI scan image in the manner of diagnosing Alzheimer's disease using

MRI recordings. Input, a layer, and numerous buried layers make up a CNN. Convolution, pooling, and fully connected layers are typically seen in a CNN's layers that are concealed. The outcome of a convolutional layer's operation on the input is passed on to the next layer. The process of convolution simulates a single neuron's reaction to visual stimuli.

In convolution networks, local or global layers for pooling can be used to integrate the output of a neural cluster at one level with a nerve cell from a higher level. The mean value from each brain cell in the preceding layers is used in mean pooling. Every neuron in one layer can communicate with every other layer's neuron through fully connected layers. Conceptually, the CNN and the traditional multi-layer feed-forward neural network are identical. In comparison to conventional classifiers, CNNs are without a doubt superior for the analysis of high-dimensional data. Convolutional layers of CNNs use a parameter-sharing technique to regulate and lower.

4. Methodology

4.1. Python

Python is an interpreted high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace. It provides constructs that enable clear programming on both small and large scales. In July 2018, Van Rossum stepped down as the leader in the language community. Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library. Python interpreters are available for many operating systems. CPython, the reference implementation of Python, is open source software and has a community-based development model, as do nearly all of Python's other implementations. Python and CPython are managed by the non-profit Python Software Foundation. Rather than having all of its functionality built into its core, Python was designed to be highly extensible. This compact modularity has made it particularly popular as a means of adding programmable interfaces to existing applications.

4.2. General Algorithm

Initialize learning rate, maximum iterations, minimum errors, and training batches. training BATCHES, batch size SIZE, etc.;

Compute $n2$, $n3$, $n4$, $k1$, $k2$, according to $n1$ and $n5$;

Generate random weights θ of the CNN;

cnnModel = InitCNNModel(θ, [$n1$–5]);

iter = 0; err = +inf;

while err >ERRmin and iter<ITERmax do

err = 0;

for batch = 1 to $\text{BATCHES}_{\text{training}}$ do

Mediterranean Journal of Basic and Applied Sciences (MJBAS)
Volume 7, Issue 3, Pages 93-102, July-September 2023

$[\nabla\theta J(\theta), J(\theta)]$ = cnnModel.train (TrainingDatas, TrainingLabels),

Update θ

err = err + mean($J(\theta)$);

end for err = err/$\text{BATCHES}_{\text{training}}$;

iter++;

end while

Save parameters θ of the CNN

As a result, our suggested study uses extraction of features to overcome the separation of outliers in MRI data categorization. We can forecast both the normal and symptoms of Alzheimer's according to classification.

5. Experimental Results

Numerous performance measures, such as accuracy, sensitivity, specificity, error rate, and precision, can be established in order to analyse the system's performance.

False positives (FP) - are the number of inaccurately predicted positive outcomes.

Amount of genuine negatives - perfect forecast of a negative outcome.

Negative result (FN) - number of accurate negative predictions minus the number of actual negatives.

5.1. Error Rate Evaluation

Error rate (ERR) is computed as the fraction of total number of imperfect predictions to the total number of test data. The finest possible error rate is 0.0, whereas the very worst is 1.0. Minimization of this error rate will be the prime objective for any classifier.

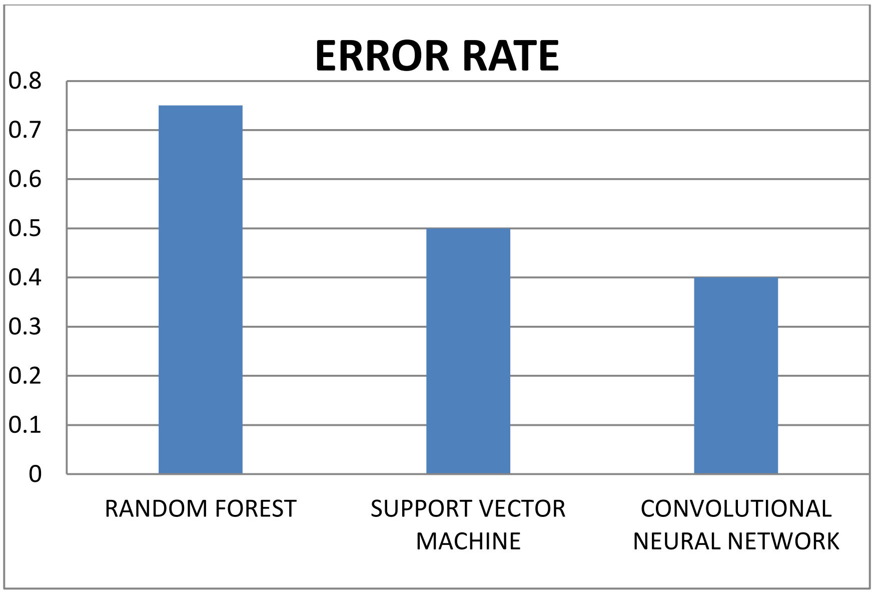

Figure 2. Error Rate

Table 1. Error rate

Algorithm	Error Rate
Random Forest	0.75
Support Vector Machine	0.5
Convolutional Neural Network	0.4

According to the aforementioned graph, the proposed CNN method offers a lower failure rate than the current technique.

5.2. Accuracy Evaluation

The percentage of overall flawless forecasts to the complete test data is known as accuracy (ACC). Additionally, it can be written as 1 - ERR. The maximum accuracy is 1.0, and the minimum accuracy is 0.0.

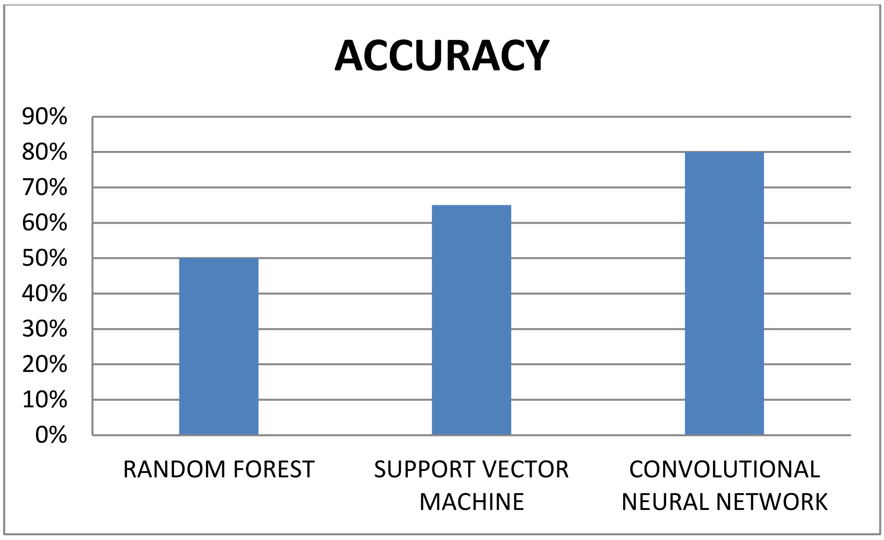

Figure 3. Accuracy rate

Table 2. Accuracy

Algorithm	Accuracy
Random Forest	50%
Support Vector Machine	65%
Convolutional Neural Network	80%

According to the graph above, the proposed CNN algorithm has a higher accuracy rate than the current approach.

6. Conclusion

Alzheimer's disease is a progressive neurodegenerative disorder that affects memory, thinking, and behaviour. The early detection and accurate diagnosis of Alzheimer's disease are crucial for timely intervention and effective management. Brain MRI (Magnetic Resonance Imaging) is a commonly used imaging modality for the diagnosis and prediction of Alzheimer's disease. MRI scans can detect structural changes in the brain, such as atrophy in specific regions, which are characteristic of Alzheimer's disease. Advanced machine learning techniques, such as deep learning, have been used to analyze MRI scans and predict Alzheimer's disease with high accuracy. These models can detect subtle changes in brain structure and identify biomarkers that are associated with the disease. While these models show promising results, further research is needed to improve their accuracy and reliability. Additionally, the use of MRI scans for Alzheimer's disease prediction should be coupled with clinical evaluation and other diagnostic tests to ensure accurate diagnosis and appropriate treatment. In conclusion, MRI scans, coupled with advanced machine learning techniques, hold promise for the early detection and prediction of Alzheimer's disease, but further research is needed to fully realize their potential.

7. Future Work

In future we can extend the framework with combination of different imaging modalities, such as MRI, PET, and CT scans, may provide more comprehensive information about the brain and improve the accuracy of Alzheimer's disease prediction. Incorporating clinical data, such as cognitive test scores and medical history, into machine learning models can improve the accuracy of Alzheimer's disease prediction and facilitate clinical decision-making.

Declarations

Source of Funding

This study has not received any funds from any organization.

Conflict of Interest

The authors declare that they have no conflict of interest.

Consent for Publication

The authors declare that they consented to the publication of this study.

Authors' Contribution

All the authors took part in literature review; research; and manuscript writing equally.

References

[1] Abol Basher et al. (2021). Volumetric feature-based Alzheimer's disease diagnosis from MRI data using a convolutional neural network and a deep neural network. IEEE Access, 9: 29870–29882.

[2] Anees Abrol et al. (2020). Deep residual learning for neuroimaging: an application to predict progression to Alzheimer's disease. Journal of Neuroscience Methods, 339: 108701.

[3] De Silva, S., Dayarathna, S., & Meedeniya, D. (2021). Alzheimer's Disease Diagnosis using Functional and Structural Neuroimaging Modalities. Enabling Technology for Neurodevelopmental Disorders, Pages 162–183.

Mediterranean Journal of Basic and Applied Sciences (MJBAS)
Volume 7, Issue 3, Pages 93-102, July-September 2023

[4] Fazal Ur Rehman Faisal & Goo-Rak Kwon (2022). Automated detection of Alzheimer’s disease and mild cognitive impairment using whole brain MRI. IEEE Access, 10: 65055–65066.

[5] Fernando Garcia-Gutierrez et al. (2022). Diagnosis of Alzheimer's disease and behavioural variant fronto temporal dementia with machine learning-aided neuropsychological assessment using feature engineering and genetic algorithms. International Journal of Geriatric Psychiatry, 37(2).

[6] Jie Zhang et al. (2021). A 3D densely connected convolution neural network with connection-wise attention mechanism for Alzheimer's disease classification. Magnetic Resonance Imaging, 78: 119–126.

[7] Manhualiu et al. (2020). A multi-model deep convolutional neural network for automatic hippocampus segmentation and classification in Alzheimer’s disease. Neuroimage, 208: 116459.

[8] Ricardo Mendoza-Léon et al. (2020). Single-slice Alzheimer's disease classification and disease regional analysis with Supervised Switching Autoencoders. Computers in Biology and Medicine, 116: 103527.

[9] Sathish Kumar, L. et al. (2022). AlexNet approach for early-stage Alzheimer’s disease detection from MRI brain images. Materials Today: Proceedings, 51: 58–65.

[10] Sreelakshmi Shaji, Nagarajan Ganapathy & Ramakrishnan Swaminathan (2021). Classification of Alzheimer condition using MR brain images and inception-residual network model. Current Directions in Biomedical Engineering, 7(2): 763–766.