

DESIGN THINKING APPROACH FOR CLASSIFICATION OF ALZHEIMER'S DISEASE USING DEEP LEARNING AND REGION-BASED CONVOLUTIONAL NEURAL NETWORKS (RCNN)

Dr.M.PRAVEENA¹, Associate Professor,
praveenamaramannan@gmail.com,
RAVINThER. V², RUBESHWAR², SAMMUNDI. N²
Department of Computer Science,

Dr.SNS Rajalakshmi College of Arts and Science (Autonomous), Coimbatore - 49.

Abstract—Deep learning methods used in modern machine learning have particularly excelled at detecting complex structures in high-dimensional, complex data. The use of deep learning in early identification and automatic categorization of Alzheimer's disease has garnered significant interest, thanks to sophisticated neuroimaging methods that generate multimodal neuroimaging data. This has enabled researchers to develop more precise tools for diagnosis and monitoring. Alzheimer's disease typically affects those 60 years or older. But doctors are now diagnosing more middle-aged cases, specifically those aged 45-65. Research shows that this group is at greater risk. Early diagnosis and treatment can slow progression and improve quality of life. We advise adopting the Region-based Convolutional Neural Network (RCNN) approach to categorize features from intricate medical images. It is frequently used in medical image analysis and increases feature extraction accuracy. We examine the efficacy of feature extraction and feature selection in enhancing performance and producing accurate results, which are crucial components in classification. The strategy achieves comparable results to analyzing all data at once but reduces the number and cost of biomarkers needed for diagnosis. This is done by selectively identifying and using relevant biomarkers, simplifying the diagnostic process, and reducing costs. As a result, it might help with the accurate and personalized detection of AD and be useful in clinical situations.

Keywords— Region-based Convolutional Neural Network, design thinking, empathize, ideate, prototype, deep learning.

I. INTRODUCTION

The capturing of enormous amounts of information is now possible thanks to ongoing innovations. Deep learning strategies have been put forth to assist in interpreting this data for clinically independent guidance and finding. The most well-known neurological disease in older people is Alzheimer's disease (AD), and there is often a significant delay between the onset of AD and the clinical diagnosis of AD dementia, which requires confirmation through dissection. Because it is so difficult to accurately and early diagnose AD, there is a need for clever methods to aid clinicians in their individualized diagnosis of this condition. Both inherited and natural variables, which have an effect on a person's cerebrum over time, contribute to Alzheimer's disease. The hereditary changes ensure an individual will foster this sickness.

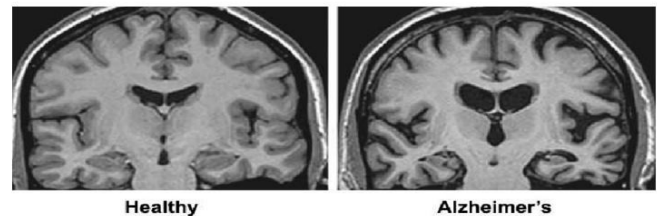


Figure 1: Comparison

Over time, this condition weakens the tissue of the brain. People over 65 experience it. Regardless, people with this illness have it for an average of 9 years, and 1 in 8 people 65 and older have it. The Mini-Mental State Examination (MMSE) score is used to estimate the probability of cognitive impairment. A person's MMSE score will steadily drop if they have diseases like Alzheimer's or dementia. A real risk exists for dementia to develop in people with mild cognitive impairment (MCI). The situation is intended to lead to dementia as a result of this type of illness when the primary MCI results in memory loss. There is no cure for the disease of Alzheimer's. In the most advanced stages of the sickness, complications such as thirst, hunger, or contamination occur, which causes passing. The MCI stage analysis will assist the client in concentrating on a positive life philosophy and a strong desire to control cognitive decline. The relationship between the heart and brain is crucial, as the heart pumps blood through a complex network of veins that support the brain and cerebrum. To reduce the risk of developing conditions such as diabetes, heart disease, and stroke, people should maintain appropriate levels of weight, blood pressure, cholesterol, and glucose. These are key risk factors for these conditions, and managing them can help prevent or delay the onset of these diseases. Eating an eating regimen low in immersed fats and wealthy in foods grown from the ground, practicing consistently, and remaining intellectually and socially dynamic may all assist with safeguarding the cerebrum.

II. LITERATURE SURVEY

1. Alzheimer disease classify by Machine learning- VascoSaDiogo

We chose these algorithms for their capacity to identify important features and generate probabilities. The tree-based techniques (DT, RF, ET) relied on impurity, while the other

techniques determined feature importance based on feature weights. We estimated the average feature value of each classifier's vote in the binary decision to determine the overall feature importance for the binary classifier.

2. Alzheimer's Disease measured with Neuroimaging- Sarita, Saurabh Mukherjee

Neuroimaging is a method for measuring the fundamental pathological alterations connected to Alzheimer's disease (AD). Classification frameworks that facilitate diagnosis and prognosis have quickly integrated these indicators as key features of Alzheimer's disease (AD).

3. using artificial intelligence, Diana Prata and Hugu Alexandre have developed a multi-diagnostic, generic approach to early Alzheimer's disease diagnosis.

Clinical professionals refer to the subsequent early symptomatic stage as having "mild cognitive impairment due to AD" when they think that the cognitive loss is caused by the prodromal stage of AD. (herein referred to as MCI). (As opposed to other types of dementia, medication, depression, or other causes).

4. Alzheimer's Disease using Convolution Neural Networks – T. Choudhury

The ability of a Convolution Neural Network (CNN) to simulate the non-linear cognitive process and record its complexity has greatly expanded the applications of a CNN.

5. AI-Enhanced multi model sensor-on-a-chip for Alzheimer's Disease Detection – Fenglong Huang

The program will pioneer a novel Multimodal Optical, Mechanical, Electrochemical Nano sensor with Two-dimensional material Amplification (MOMENTA) platform for sensitive and selective detection of AD biomarkers.

6. Alzheimer's Disease using amyloids – Heidi Agerbo, Anders

We intend to administer the working memory, executive planning, and visuomotor tasks used in the AD detection method to a total of 60 senior APOE4 gene-carrying subjects. (40 amyloid negatives and 20 amyloid positive healthy controls without overt cognitive decline along with diagnosed AD patients). The presence/quantity of amyloid and tau proteins, as well as a pathological decrease in hippocampal volume, in the preclinical Alzheimer group, are predicted to positively correlate with covertly impaired cognitive functions, as measured by the AD Detect & Prevent detection tool.

III. SYSTEM OVERVIEW

A. Components

1.1 HARDWARE REQUIREMENTS

1. Processor: core i3 processor
2. RAM size: 8 GB
3. Hard disk capacity: 500 GB
4. Keyboard type: Internet Keyboard

COMPUTER SOFTWARE REQUIREMENTS

1. Windows 10 as the operating system
2. Front End: Mat lab

B. System Working

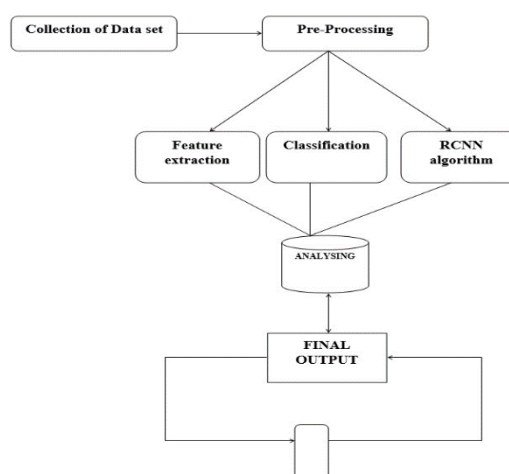


Figure 2: Working Flow

c. Related Work

2.1 Validation of a Regression Approach to White Matter Hyperforce Segmentation in Alzheimer's

Mahsa Dadar et al. (2017) assert that segmentation and volumetric measurement of white matter hyper forces is crucial for calculating and monitoring the vascular weight in aging and Alzheimer's disease. (AD), particularly when taking into account their impact on perception. Due to time and precision constraints, physically dividing WMHs into large parts is impractical. Automated systems that can accurately and efficiently distinguish WMHs are necessary. We propose a fully automated approach for volumetric measurement and segmentation of mature and Alzheimer's disease (AD) white matter hyperintensities (WMHs). Our method integrates physical markers from post-mortem data and intensity values from multiple magnetic resonance imaging (MRI) contrasts, utilizing a linear classifier for swift and accurate segmentation.

2.2 Deep Learning's Convolutional Autoencoder for Structure Analysis of Alzheimer's Disease

Fernando J. Martinez-Murcia and colleagues (2019): The field of Alzheimer's disease (AD) research has historically employed outdated AI methods, which include techniques such as principal component analysis for image degradation, as well as more complex non-linear decomposition calculations. Because MRI pictures internally display the information flow in low-layered manifolds, the profound learning paradigm has made it possible to currently differentiate undeniable level conceptual highlights straight from these images. The effects of the numerous directions within the autoencoder architecture on cognitive function are subsequently evaluated by breaking down and visually representing how the extracted features are distributed across various combinations.

2.3 Alzheimer's Disease Case Study: Modeling Disease Progression Using Multisource Multitask Learners

According to Liqiang Nie et al. (2016), knowing how an infection spreads can help victims take preventative

action. To anticipate the illness status later on time focuses, different AI approaches have been proposed. Be that as it may, a couple of them mutually think about the double heterogeneities of ongoing infection movement. The assignments given at each time point are designed to build upon one another in a sequential order, drawing on information from various sources. Each assignment requires students to synthesize information from multiple sources to demonstrate their understanding of the material.

2.4 Diagnosing Alzheimer's Infection with Latent Representation Learning and Data on Genetics and incomplete multimodal neuroimaging

According to Tao Zhou et al. (2019), the integration of critical data from numerous approaches [The advancement diagnostic of automated Alzheimer's disease (AD) has evolved thanks to elements such as genetic information, positron emission tomography (PET), and magnetic resonance imaging] (MRI). However, because not all the individuals have all of the multi-methodology data, multi-methodology-based AD symptomatic models are frequently prevented from being fully developed. Many previous investigators have used the fundamental strategy of discarding tests that have missing modalities. In any instance, this considerably lowers the quantity of practise exams, leading to an inadequate characterization model.

2.5 Alzheimer's Disease Longitudinal Data Analysis Using Temporally Constrained Group Sparse Learning

According to Biao Jie et al. (2016), sparse learning has been thoroughly studied for the evaluation of brain pictures in order to aid in the identification of mild cognitive impairment, often known as the prodromal stage of Alzheimer's disease, and both. However, the majority of existing machine learning studies only use cross-sectional assessment approaches, and the resulting models are typically constructed using data from a single time point. This limited approach can hinder the accuracy and usefulness of the model for predicting disease progression over time. All things considered, different in general, brain imaging apps provide time points of data that can be used in some longitudinal studies. examination procedures to reveal the infection movement designs more. Provide a creative temporary forced bunch clustering learning technique that concentrates on the longitudinal study using several informational time points, if appropriate.

3. PROPOSED METHODOLOGY

Deep Learning techniques used in conjunction with radiological imaging can not only improve the accurate detection of Alzheimer's disease but also help address the issue of a shortage of qualified medical professionals in rural areas. RCNN is an advanced convolutional neural network algorithm designed to locate and segment objects in the field of oral pathology. Although initially developed to detect infections and segment objects in standard images, it has

since been adapted for use in oral pathology. This test enables the use of RCNN in specialized fields such as oral pathology. Researchers have suggested a better Radiation therapy for the esophagus uses the R-CNN (region-based convolutional neural network) model for multi-organ segmentation. R-CNN represents the latest cutting-edge technology in object segmentation. The shapes of organs can vary depending on the method used to observe their limitations. While a single R-CNN performs well when analyzing a single image, it struggles when analyzing multiple organs. Furthermore, extensive tests on the acquired dataset have shown that the proposed technique can accurately and effectively segment the clinical target volume (CTV) and identify Alzheimer's disease (AD). The test findings demonstrated the system's substantial potential for real-world clinical applications, with only 5% of the instances having missed recognition or inaccurate identification.

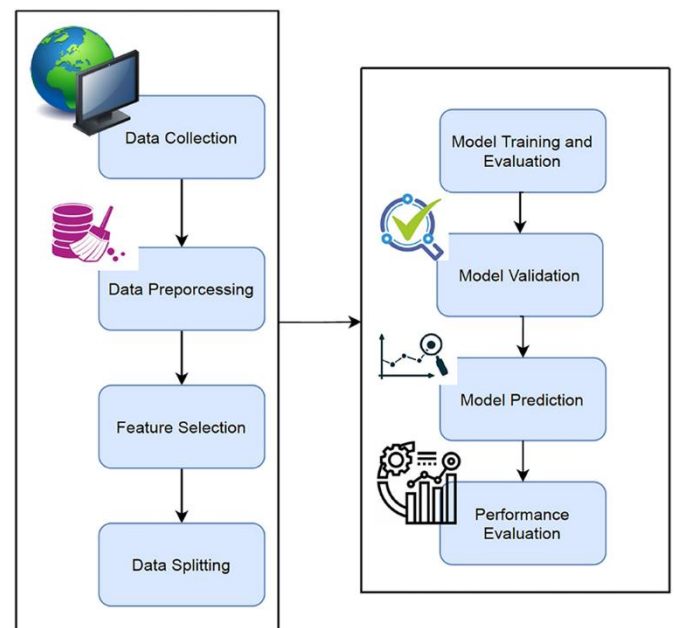


Figure 3: The Flowchart Contains the process of Dataset Processing

3.1 Pre-Processing

The collection of primary EEG reports in the ADNI includes data from individuals diagnosed with Alzheimer's disease (AD) as well as from healthy controls. To prepare the data for analysis, we performed preprocessing and ensured that the ADNI-EEG dataset was properly organized.

3.2 Extraction of Features

Element vectors for normal Alzheimer's cases will typically exhibit uniform properties, resulting in a conservative subspace. When learning the subspace, these

component vectors are used instead of regular information.**3.3 Classification**

Every information collecting point's objective class is determined by the order procedure. By dissecting patients' examples of illnesses, a gamble component can relate to patients with the use of the arrangement technique.

3.4 Pre-Processing

The ADNI data collection had an information design that provided the basic information for underlying EEG reports on both AD and gathering. We performed preprocessing on the ADNI-EEG dataset to prepare it for our investigation, ensuring that the data was properly organized.

3.5 Include Extraction

A typical Alzheimer's will contain component vectors with somewhat homogeneous properties, leading to a smaller typical subspace. The subspace related to common information is learned using these element vectors.

3.6 Arrangement

Every information collecting point's objective class is predicted by the arrangement process. A gamble aspect can be associated with patients with the aid of the arrangement technique by looking at their examples of infections.

3.7 RCNN calculation

The researchers presented a robust learning-based approach and tested the region-based convolutional neural network (RCNN) model using various picture division techniques and datasets. Finally, the most efficient image division procedure produced a result with a high exactness of 96% (Precision: 96%, Accuracy: 98%). The CNN model also left some dataset elements alone. The studies indicate that information processing and deep learning strategies are essential for the early diagnosis of Alzheimer's disease.

IV. CONCLUSION

This computerized framework detects Brain X-ray pictures that can accurately diagnose Alzheimer's disease 97.36% of the time. It executes parallel arrangements without manual element extraction, enabling efficient diagnosis and treatment. The model is versatile and can be used to test larger datasets and interact with existing frameworks. It also proves helpful in areas where the test unit falls short. There hasn't been any acknowledgment from the research locality of clinical professionals for AD sure case recognition from radiology photographs using deep learning structure up until recently. By demonstrating the improved R-CNN system's ability to detect Alzheimer's disease and clarify the esophageal cancer dataset, we can validate its suggested structure. Due to the time-consuming and challenging process of annotating clinical images, we plan to explore semi-supervised and weakly supervised techniques for brain and organ segmentation.

V. RESULT

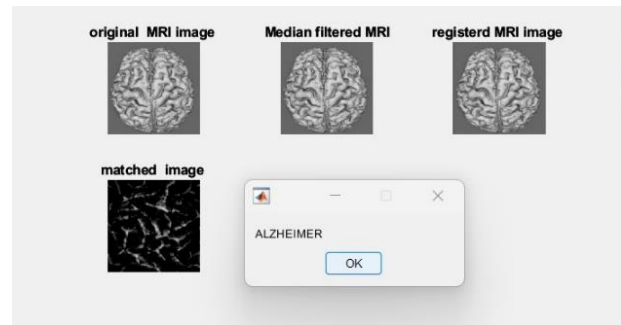


Figure 4 : Final output

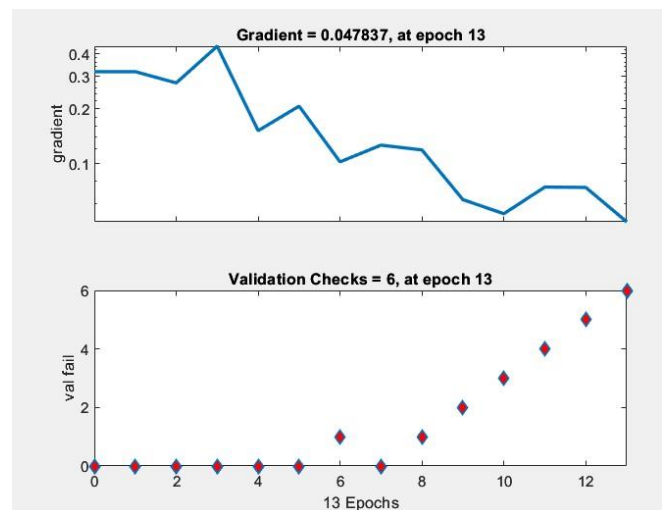


Figure 5 :Epoch Validation

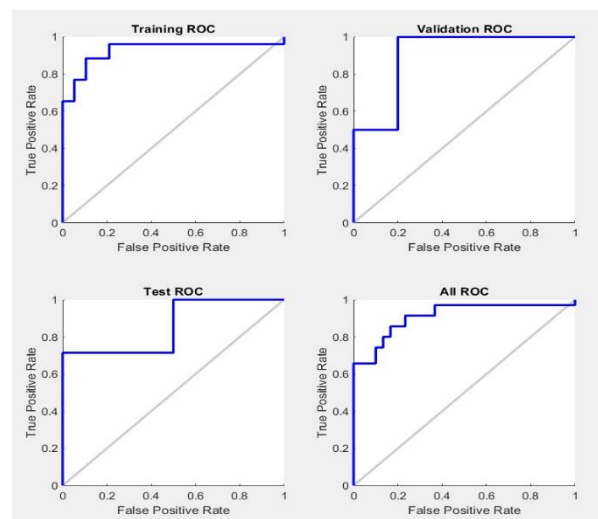


Figure 6: True False Rate

ACKNOWLEDGMENT

To complete this research, the authors would like to thank all of the academic members of our information technology department for their insightful comments, gracious cooperation, and ongoing encouragement.

REFERENCES

- [1] M. Dadar et al., "Approval of a Regression Technique for Segmentation of White Matter Hyperintensities in Alzheimer's Disease," in IEEE Transactions on Medical Imaging, vol. 36, no. 8, pp. 1758-1768, Aug. 2017, doi: 10.1109/TMI.2017.2693978.
- [2] F. J. Martinez-Murcia, A. Ortiz, J. - M. Gorriz, J. Ramirez and D. Castillo-Barnes, "Concentrating on the Manifold Structure of Alzheimer's Disease: A Deep Learning Approach Using Convolutional Autoencoders," in IEEE Journal of Biomedical and Health Informatics, vol. 24, no. 1, pp. 17-26, Jan. 2020, doi: 10.1109/JBHI.2019.2914970.
- [3] L. Nie, L. Zhang, L. Meng, X. Tune, X. Chang and X. Li, "Displaying Disease Progression through Multisource Multitask Learners: A Case Study With Alzheimer's Disease," in IEEE Transactions on Neural Networks and Learning Systems, vol. 28, no. 7, pp. 1508-1519, July 2017, doi: 10.1109/TNNLS.2016.2520964.
- [4] T. Zhou, M. Liu, K. - H. Thung and D. Shen, "Idle Representation Learning for Alzheimer's Disease Diagnosis With Incomplete Multi-Modality Neuroimaging and Genetic Data," in IEEE Transactions on Medical Imaging, vol. 38, no. 10, pp. 2411-2422, Oct. 2019, doi: 10.1109/TMI.2019.2913158.
- [5] B. Jie, M. Liu, J. Liu, D. Zhang and D. Shen, "Transiently Constrained Group Sparse Learning for Longitudinal Data Analysis in Alzheimer's Disease," in IEEE Transactions on Biomedical Engineering, vol. 64, no. 1, pp. 238-249, Jan. 2017, doi: 10.1109/TBME.2016.2553663.
- [6] P. Jiang, X. Wang, Q. Li, L. Jin and S. Li, "Relationship Aware Sparse and Low-Rank Constrained Multi-Task Learning for Longitudinal Analysis of Alzheimer's Disease," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 4, pp. 1450-1456, July 2019, doi: 10.1109/JBHI.2018.2885331.
- [7] S. Minhas, A. Khanum, F. Riaz, S. A. Khan and A. Alvi, "Anticipating Progression From Mild Cognitive Impairment to Alzheimer's Disease Using Autoregressive Modeling of Longitudinal and Multimodal Biomarkers," in IEEE Journal of Biomedical and Health Informatics, vol. 22, no. 3, pp. 818-825, May 2018, doi: 10.1109/JBHI.2017.2703918.
- [8] B. Lei et al., "Neuroimaging Retrieval through Adaptive Ensemble Manifold Learning for Brain Disease Diagnosis," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 4, pp. 1661-1673, July 2019, doi: 10.1109/JBHI.2018.2872581.
- [9] R. Cui and M. Liu, "Hippocampus Analysis by Combination of three dimensional DenseNet and Shapes for Alzheimer's Disease Diagnosis," in IEEE Journal of Biomedical and Health Informatics, vol. 23, no. 5, pp. 2099-2107, Sept. 2019, doi: 10.1109/JBHI.2018.2882392.
- [10] L. Brand, K. Nichols, H. Wang, L. Shen and H. Huang, "Joint Multi-Modal Longitudinal Regression and Classification for Alzheimer's Disease Prediction," in IEEE Transactions on Medical Imaging, vol. 39, no. 6, pp. 1845-1855, June 2020, doi: 10.1109/TMI.2019.2958943.