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# Detection and Classification of Alzheimer's Disease Using Deep Learning Technique

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***Abstract***

*It is crucial that people with Alzheimer's disease (AD) receive a proper diagnosis to begin preventative action before irreparable brain damage develops. Most people who suffer from Alzheimer's disease (AD), a neurological condition that progresses, are older than 65 years. The area of interest (ROI) in the hippocampus has been extensively studied for several purposes, including neurological illness research, stress development monitoring, and memory function analysis. Moreover, a connection between Alzheimer's disease and hippocampus volume shrinkage is shown. On the other hand, several biomarkers are used in the diagnosis of AD, such as tau, phosphorylated tau, amyloid beta (aβ42) protein, and hippocampus volume atrophy. Even though much recent research has used computers to diagnose AD, congenital findings with most of the machine learning strategies with information such as MRI and PET imaging, we aim to improve diagnostic reliability. The model's effectiveness had been assessed using standard metrics, and it achieved a high accuracy of 94.7% in classifying individuals into healthy, mild cognitive impairment (MCI), and Alzheimer's sections. These findings highlight the possibility of deep learning as a tool for programmed and reliable Alzheimer's recognition, offering significant advantages for clinical diagnostics. Alzheimer's disease (AD) is a progressive neurodegenerative disease that primarily affects memory, cognition, and behavior. Early and accurate detection of AD is essential for effective management and treatment planning. Deep learning, one of the most recent developments in artificial intelligence (AI), has the potential to completely transform medical diagnosis.*

**Keywords:** Alzheimer's disease, deep learning, Initial-stage detection and diagnosis, sensor research, biomarkers, machine learning, magnetic resonance imaging

## INTRODUCTION

Senior citizens are the main population affected by Alzheimer's disease (AD), a serious brain illness. After heart disease, cancer, and brain hemorrhage, it is the fourth most typical cause of death worldwide [1]. Almost 60% of the 50 million people who suffer from dementia globally live in low- and middle-income countries. At any given time, 5–8% of adults 60 years and older suffer from dementia. By 2030, 82 million people will be affected by dementia; by 2050, that number will have reached 152 million. A large amount of this increase is explained by the rise in dementia patients living in low- and middle-income countries. Approximately 10 million new cases are recorded annually. In terms of neurology, AD is a chronic neurodegenerative disease that results in the death of nerve and tissue cells. Senile dementia is the term used to describe the progressive loss of memory and cognitive abilities in the patient because of this. Alzheimer's disease also impairs a patient leading to a gradual decline in the patient's memory and cognitive function, which

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is commonly known as senile dementia. Alzheimer's disease also impairs a patient, and leads to a gradual decline in the patient's memory and cognitive function, which is commonly known as senile dementia. Alzheimer's disease impairs a patient's capacity to carry out daily tasks, such as writing, speaking, and attempting to read, and it can cause problems recognizing friends and family. There are three phases in the progression of AD: early, moderate cognitive, and late. Individuals in the late stage experience heart failure and potentially fatal respiratory system malfunctions, while those in the intermediate cognitive stage react violently [2]. Diagnosing dementia is typically a challenging process [3]. Three distinct phases of routine clinical diagnosis are required for AD disease follow-up, and these can be completed by (i) speaking with (ii) conducting logical neuropsychiatric evaluations, and (iii) obtaining magnetic resonance imaging (MRI) or PET scans, or positron emission tomography. Based on AD statistics, it was discovered that 66% of dementia patients also had AD, of whom only 10% had an early diagnosis and 90% did not receive one. Hence, early detection of AD is advantageous to humanity since it creates the conditions for early intervention, the creation of health care programs, preventative measures, and reasonably priced interventions. Conversely, patients with late diagnosis are frequently found too late to benefit from conventional therapy, and the high rate of misdiagnosis in current therapeutic approaches makes late diagnosis problematic. Furthermore, treating amyloid fibrils late in the diagnosis process makes it more difficult to cure the disease.

## RELATED WORK

A significant amount of research has been done recently for the diagnosis or prognosis of early AD. This idea has received support from recent advances in machine learning (ML) and deep learning (DL) methodologies. Zhang *et al*. suggested, for instance, using DL-based classification to distinguish between healthy and Alzheimer's disease brains [4]. To develop a trained and predictive model, they utilized a Convolutional Neural Network (CNN), a deep learning architecture known for its effectiveness in pattern recognition and feature extraction [5]. For the diagnosis of AD, MCI, and its early stages, they recommended employing stacked auto-encoded minimally labelled learning samples, a SoftMax regression layer, and therefore less experience [6]. 311 ADNI subjects: 65 AD individuals, 67 converter MCI subjects, 102 non-converter MCI (ncMCI) patients, and 77 normal control (NC) subjects, submitted neuroimaging data to assess the methodology. Using both MRI and Positron Emission Tomography (PET) images, the results showed that the 4-class classification accuracy was 47.4% and the binary classification accuracy was 88.58%. A Dementia Network (DEMNET) has been proposed by Murugan *et al*. to aid in the MRI-based assessment of dementia stages, to construct a framework in MRI pictures for the prediction of Alzheimer's disease features [7]. Through the analysis of distinct dementia phases and a given diagnosis, the suggested framework produces a high disease probability that maps to a multilayer perceptron from the local brain framework. This allows for the accurate and easily recognizable visualization of individual Alzheimer's disease risk. Guo *et al*. suggest that statistically significant text data and enhanced Deep Learning Algorithms (IDLA) could aid in the early diagnosis of Alzheimer's disease [8]. The recommended method effectively incorporates biassed neural network functionality to detect Alzheimer's disease. A network of specialized autoencoders is used in earlier diagnoses to distinguish between the progression of illness and normal aging. Using the ADNI Alzheimer's patient database, Janghel *et al*. presented a deep learning-based technique for Alzheimer's disease detection [9]. The dataset includes images from healthy individuals as well as fMRI and PET scans of Alzheimer's patients. Before using the VGG-16 structure of a convolution neural network for feature extraction, 3D to 2D image conversion and resizing are done. Finally, the decision tree classifiers, K mean clustering, SVM, and linear discriminate are used for classification. A method, that similarly integrates Hjorth parameters, has been proposed by Safi *et al*. to increase the accuracy of AD detection from EEG signals [10]. In addition, various signal decomposition methods are available, including Discrete Wavelet Transform (DWT), filtering into brain frequency bands, and Empirical Mode Decomposition (EMD). Various classification algorithms are also assessed, including K-nearest neighbors (KNN) [11], support vector machines (SVM), and regularized linear discriminant analysis (RLDA). Yang *et al*. have presented a Multi- source Ensemble Transfer Learning (METL) technique that guarantees source data transferability and good performance via ensemble learning by providing

 

our tri-transfer design and ensemble learning that leverages Tri-Training [12]. To help physicians accurately and promptly assess patients' stages of motor cognitive impairment (MCI) and implement preventative or delaying measures, an auxiliary delaying measure, diagnostic structure was proposed for the initial diagnosis of Alzheimer's disease according to METHL.

## ALZHEIMERS DISEASE STORY

The history of AD as it is described in this section is a compilation of details from the results of scholarly searches for AD publications. The selection process was limited to papers published between 2008 and 2019, and only the most recent publications were considered. The datasets used for exploring AD and mild cognitive impairment (MCI), the precursor of AD, were the focus of our study [13]. The methods and approaches employed by earlier researchers were examined. The term "Alzheimer's disease" was first utilized through Kraepelin in 1910, when the clinical definition of AD was still under consideration. Kraepelin discussed a distinctive group of cases with severe cell transformations that involve an excessive number of plaques, the death of approximately concurrent blasts of colorful neurofibrils to replace one-third of the cerebral cortex, and representing the most severe form of malnutrition [14]. It took more than a century for reliable descriptions of the clinical criteria for Alzheimer's disease (AD) to emerge, following the introduction of the first case by German psychiatrist Alois Alzheimer in 1906 [15]. Neurofibrillary sections and senile plaques were mentioned in the 1907 and 1909 descriptions of AD by Dr. Alois Alzheimer and Proskin, respectively. Nevertheless, no notable evidence of arteriosclerosis was discovered during a clinical examination of a patient's brain, even though this condition was thought to be included in the patient's diagnosis. Researchers from the Max Planck Institute of Neurobiology in Martinsried and the University of Munich, Germany, discovered in 1998 that plaques of amyloid and neurofibrillary cramps could influence specific brain regions [16]. This research is now recognized as the first documented case of Alzheimer’s disease (AD); more importantly, it aligns with the current definition of AD. Dr. Gerber and colleagues from the Max Planck Institute of Neurobiology's Psychiatric Department studied histological slices from F. Johan in 1997 [17]. Johan's brain tissues had been kept in good condition for over 90 years. The study was considered the second case of AD to be reported. Upon examination, multiple amyloid plaques were found in the cuts. Based on the aforementioned research, it appears feasible to perform a mutational analysis on pre-served brain tissue. The groundbreaking discovery made by Dr. Alzheimer was validated once more on the occasion of its centenary. A comparison of an AD-affected brain and a healthy brain is presented in Figure 1.

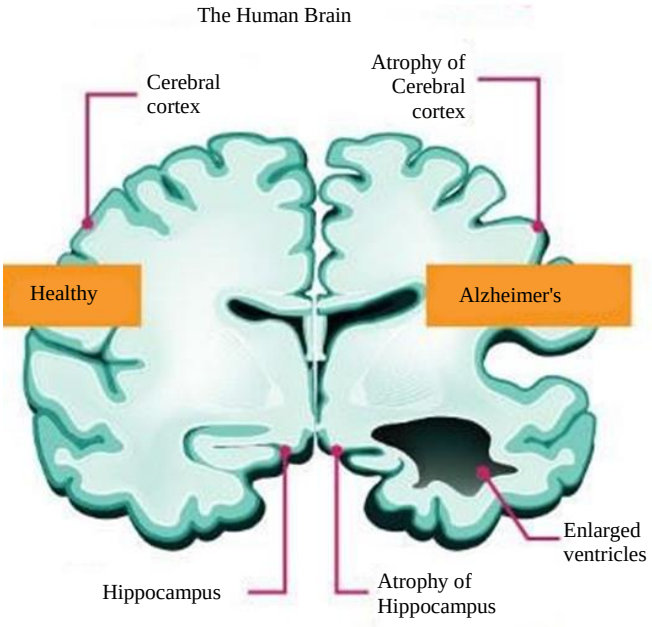


**Figure 1.** Progress of AD from MCI to severe AD.

 

At the moment, AD is the sixth most common cause of death in the United States. According to recent estimates, the disorder may even come in third place among the leading causes of death for elderly people, behind cancer and heart disease [18].

It is crucial to anticipate AD progression in its initial phases and to stop the disease from getting worse. Numerous medical tests and an enormous quantity of heterogeneous, multivariate data are needed to diagnose AD. However, because medical tests vary widely, manually comparing, visualizing, and analyzing data can be challenging and time-consuming [19]. Classifying MRI scans is an effective method for precisely predicting brain conditions, but it is a difficult task. However, new methods have been proposed to diagnose Alzheimer's disease (AD) in its early stages by effectively classifying brain magnetic resonance imaging (MRI) scans. These methods utilize Convolutional Neural Networks (CNNs) and label propagation techniques to enhance diagnostic accuracy and improve early detection [7].

**PROPOSED SYSTEM**

As the most prevalent type of dementia among Caucasians, Alzheimer's disease is the target of the suggested system. Alzheimer's disease is typified by diffuse brain atrophy, which can take several forms, including larger ventricles at hippocampal atrophy and other areas of the medial temporal lobes (MTL) and a reduced cerebral cortex. Anomalies in the GM and WM tissues have been found to have a substantial correlation with cognitive decline and have been connected to pathology in AD. To gain a comprehensive understanding of how AD develops, it is necessary to examine anatomical and neurological information collected from patients at different stages of the disease's transition. AD is a medical condition that has a high chance of developing in patients with mild brain injury. The findings indicate that there is a higher risk associated with converting from MCI to AD in healthy individuals. The majority of people are known to be affected by the amnesic variety of MCIs, or aMCIs. The idea that MCI is a representation of the preclinical stage of Alzheimer's disease is supported by the maximum yearly conversion rate from aMCI to AD. Previous research has shown that the entorhinal, para-hippocampal amygdala, and hippocampal cortices all atrophy as the disease advances. The use of hippocampus segmentation to determine brain size or shape has been extensively studied. Additionally, studies have demonstrated the significant predictive power of their GM tissue maps and cortical thickness in AD diagnosis.

Tensor-based morpheme tries, and voxel deformation was also examined (TBM) to reveal variations between groups. Since voxel-based morphometry (VBM) offers a voxel scale depiction of the regional grey and white matter (GM and WM) volume, it is an objective, spatially specific method of evaluating MRI data. This approach has a representation of the regional gray and white matter (GM and WM) volume. This approach, which has been used to treat both AD and MCI, predicts the likelihood that MCI will develop into AD by representing GM irregularity patterns that correspond to the disease's clinical stage. Due to the difficulty in identifying the presence and extent of WM atrophy, different MRI techniques are frequently used to evaluate the occurrence of microscopic tissue degradation in AD.

The use of CSF and structural imaging markers has been highlighted in the most recent set of diagnostic standards for AD and MCI. Between HC and MCI, the volumes of the lateral ventricles, the hippocampus region, and the CSF markers (Ab42, t-tau, and p-tau), can be used. Additionally, the combination can be used to diagnose Alzheimer's disease and moderate cognitive impairment in senior citizens. Recent developments in deep learning technologies have made it possible to learn the properties from the 3D patches that we took out and to accurately segment hippocampal data. We demonstrate the use of an MRI-based multi-tasking deep learning (MDL) approach for hippocampal segmentation and clinical score regression. Block diagram of the proposed model has been shown in Figure 2. Using PET imaging, researchers have demonstrated a strong correlation between biomarkers identified through deep CNNs and cognitive decline over time. A schematic representation of the typical steps involved in a conventional approach to diagnosing Alzheimer's disease is shown in Figure 1. The process begins with acquiring MRI slices, which serve as the foundation for further analysis.

 

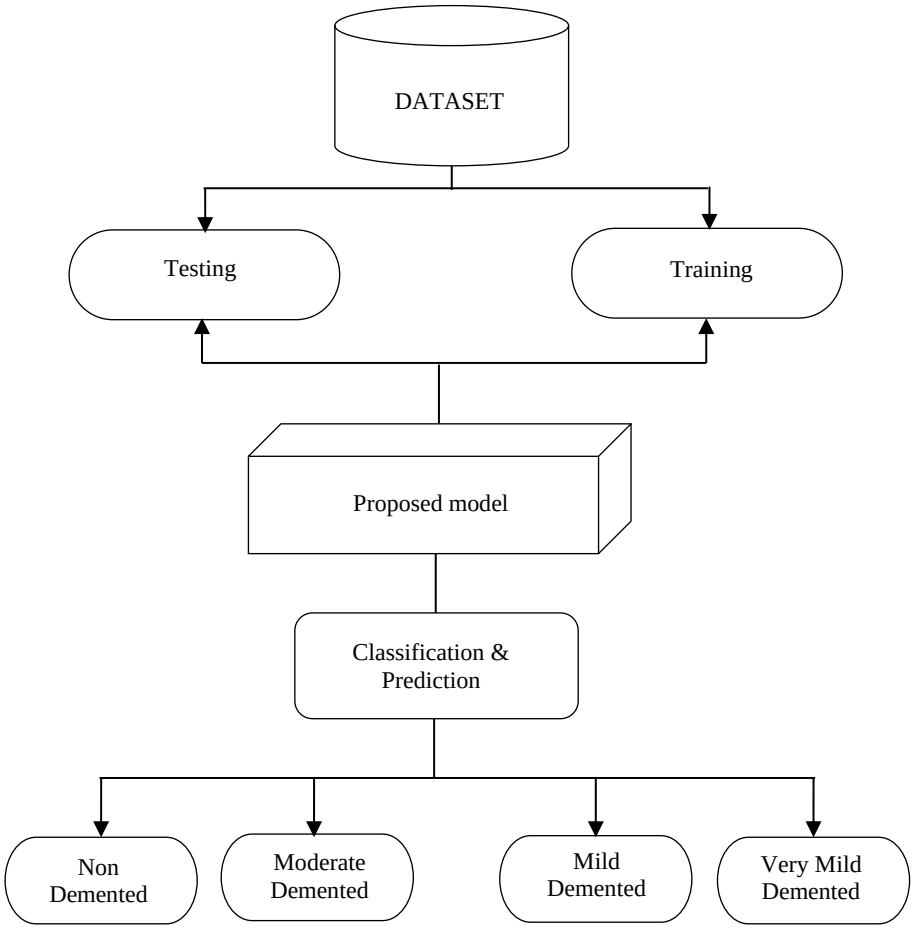


**Figure 2.** Block diagram of proposed model.

The following stage involves preprocessing the data to remove unnecessary information and reorganize it for easier reading. After preprocessing, the brain MRI scans data, and deep learning segmentation is used to extract the relevant features. For example, the patient's body size is an important consideration. Based on the input parameters, the classifier uses a deep learning architecture to predict the output.

## CONCLUSION

Based on a thorough review of the literature, we have determined that, overall, published papers in this field tend to concentrate on two primary research areas: biomarkers and neuroimaging, with an increasing amount of attention being paid to image analysis. While the work is considered comprehensive and well-done, it does not advance our understanding of AD's initial detection because most of the patients chosen already have the disease. This study examined some of the significant associated AD datasets, as well as diagnosis and detection. For preliminary neuroimaging studies, this method is workable.

## REFERENCES

1. Zhang F, Li Z, Zhang B, Du H, Wang B, Zhang X. Multimodal deep learning model for auxiliary diagnosis of Alzheimer disease. Neurocomputing. 2019; 361: 185–195.
2. Mehmood A, Maqsood M, Bashir M, Shuyan Y. A deep Siamese convolution neural network for multi class classification of Alzheimer disease. Brain Sci. 2020; 10(2): 84.
3. Hajamohideen F, Shaffi N, Mahmud M, Subramanian K, Al Sariri A, Vimbi V, Abdesselam A, Alzheimer's Disease Neuroimaging Initiative. Four-way classification of Alzheimer's disease using deep Siamese convolutional neural network with triplet-loss function. Brain Informatics. 2023 Dec;10(1):5.

 

4. Zhang Y, Dong Z, Phillips P, Wang S, Ji G, Yang J, Yuan TF. Detection of subjects and brain regions related to Alzheimer's disease using 3d MRI scans based on edge brain and machine learning. Front Comput Neurosci. 2015; 9: 66.
5. Abrol A, Bhattarai M, Fedorov A, Du Y, Plis S, Calhoun V, ADN Initiative, *et al*. Deep residual learning for neuroimaging: An application to predict progression to Alzheimer's disease. J Neurosci Methods. 2020; 339: 108701.
6. Ebrahimighahnavieh MA, Luo S, Chiong R. Deep learning to detect Alzheimer's disease from neuroimaging: A systematic literature review. Comput Methods Programs Biomed. 2020; 187: 105242.
7. Murugan S, Venkatesan C, Sumithra MG, Gao XZ, Elakkiya B, Akila M, Manoharan S. DEMNET: a deep learning model for early diagnosis of Alzheimer Diseases and Dementia from MR images. IEEE Access. 2021; 9: 90319–90329.
8. Guo H, Zhang Y. Resting state fMRI and improved deep learning algorithm for earlier detection of Alzheimer's Disease. IEEE Access. 2020; 8: 115383–115392.
9. Janghel RR, Rathore YK. Deep convolution neural network based system for early diagnosis of Alzheimer's Disease. IRBM. 2021; 42(4): 258–267.
10. Safi MS, Safi SMM. Early detection of Alzheimer's Disease from EEG signals using Hjorth parameters. Biomed Signal Process Control. 2021; 65: 102338.
11. Bhatkoti Pushkar. Early diagnosis of Alzheimer's disease: A multi-class deep learning framework with modified k-sparse autoencoder classification. Thesis. Australia: Charles Sturt University; 2019 Apr.
12. Yang Y, Li X, Wang P, Xia Y, Ye Q. Multi-source transfer learning via ensemble approach for initial diagnosis of Alzheimer's Disease. IEEE J Transl Eng Health Med. 2020; 8: 1–10.
13. Islam J, Zhang Y. Brain MRI analysis for Alzheimer's disease diagnosis using an ensemble system of deep convolutional neural networks. Brain Inform. 2018; 5(2): 1–14.
14. Liu M, Li F, Yan H, Wang K, Ma Y, Shen L, Xu M, ADN Initiative, *et al*. A multi-model deep convolutional neural network for automatic hippocampus segmentation and classification in Alzheimer's disease. NeuroImage. 2020; 208: 116459.
15. Neffati S, Ben Abdellafou K, Jaffel I, Taouali O, Bouzrara K. An improved machine learning technique based on downsized kpca for Alzheimer's disease classification. Int J Imaging Syst Technol. 2019; 29(2): 121–131.
16. Sarraf S, Tofighi G. Classification of Alzheimer's disease using fMRI data and deep learning convolutional neural networks. arXiv preprint arXiv:1603.08631. 2016.
17. Cui Z, Gao Z, Leng J, Zhang T, Quan P, Zhao W. Alzheimer's disease diagnosis using enhanced inception network based on brain magnetic resonance image. In 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM). 2019; 2324–2330.
18. Jabason E, Ahmad MO, Swamy M. Classification of Alzheimer's disease from MRI data using an ensemble of hybrid deep convolutional neural networks. 2019 IEEE 62nd International Midwest Symposium on Circuits and Systems (MWSCAS). 2019; 481–484.
19. Shahbaz M, Ali S, Guergachi A, Niazi A, Umer A. Classification of Alzheimer's disease using machine learning techniques. In Proceedings of the 8th International Conference on Data Science, Technology and Applications DATA. 2019; 1: 296–303.

 