The Role of Machine Learning and Deep Learning in Early Alzheimer's Diagnosis: A Comprehensive Review

[1]K. Lakshmi Narayanan, [2]K.Karunya, [3]P. Kathambari, [4]M.Praba,
[1]Department of Computer Science and Engineering, Karpaga Vinayaga College of Engineering and Technology, Chengelpet, Tamilnadu, India
[2,3]Assistant Professor, Sathyabama institute of science and technology, Chennai, Tamilnadu, India
[4]Assistant Professor, , St.Joseph's Institute of Technology, OMR, Chennai, Tamilnadu, India
[1]narensid86@gmail.com, [2]karunsai.ifs@gmail.com, [3]sujeemithun@gmail.com,
[4]prabam@stjosephstechnology.ac.in

Abstract -- It is one of the most devastating neurological disorders that can affect people of advanced age, and Alzheimer's disease (AD) is one of such conditions. Memory loss is a prominent symptom that patients with Alzheimer's disease undergo. Those who suffer from Alzheimer's disease experience memory loss as a result of atrophy in the hippocampus, the amygdala, and other regions of the brain. Identifying and classifying Alzheimer's disease are regarded to be challenging research topics due to the enormous number of people who are affected by the disease and the absence of appropriate diagnostic methods. Reliable and efficient evaluation of early dementia has become an important area of research thanks to advancements in medical imaging technologies and computer-aided algorithms.

Because of the successes that deep learning has had in the field of picture classification, this trend has migrated to modern Artificial Intelligence (AI) technology. In order to evaluate dementia and diagnose the early stages of Alzheimer's disease, the purpose of this study is to present a survey and review of the most recent research that has been conducted utilizing deep learning algorithms. In this work, we address the initial phases of diagnosing Alzheimer's disease using an Internet of Things (IoT)-based deep learning model, as well as the problems and research topics that are currently being investigated. With the help of this research survey paper, we expect to have a better grasp of the study field and to have covered around fifty papers that have been published.

Keywords: Medical image, brain image analysis, Alzheimer's disease, disease diagnosis, machine learning, artificial intelligence and deep learning.

1. INTRODUCTION

The memory of a person with dementia, a neurological disorder, declines at an exponential rate. One form of dementia that disproportionately impacts the elderly is Alzheimer's disease (AD). The most prominent symptoms of Alzheimer's disease include a gradual deterioration in cognitive abilities and memory [1]. In Alzheimer's disease, the brain's overall gray matter diminishes. While the exact age at which Alzheimer's disease begins to manifest is unknown, the most of those who suffer from it are in their 60s and 70s. Researchers at the National Institute on Aging have shown that over 6 million Americans are living with Alzheimer's disease [2].

Over four million individuals in India are impacted by Alzheimer's disease, as reported by the Alzheimer's and Dementia Resources [3]. The global population of people living with Alzheimer's disease is increasing at a rate that is exponential. Because memory loss is common in both normal aging and AD, conventional measures like the memory test may miss the disease in some cases [4]. Traditional neurologic exams, including the memory test, may not necessarily reveal Alzheimer's disease, making neurologist diagnosis a challenging process. The complexity of brain tissue structures makes it difficult to visualize the alterations brought about by AD, which is a major obstacle to developing a brain image-based AD diagnostic method [5]. Figure 1 shows a comparison of normal brain scans with images impacted by Alzheimer's disease.

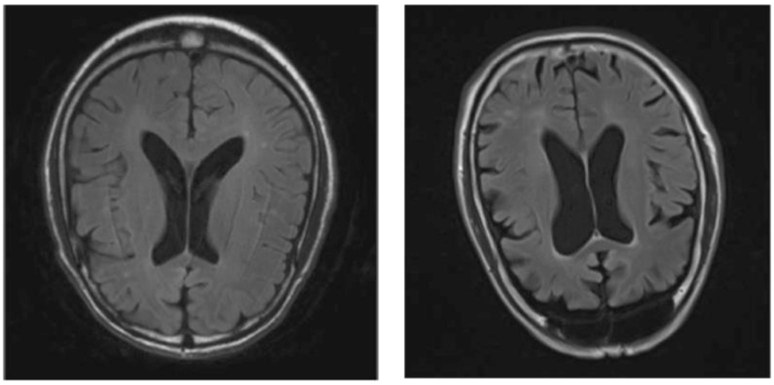

Fig. 1 Normal brain images vs. Alzheimer's disease images

After the initial discovery of Alzheimer's disease in 1906 by Dr. Alois Alzheimer [6], numerous international health organizations have put forward methods for diagnosing the condition. Since these procedures can be laborious and yield inaccurate results, researchers have been focusing on developing biomarkers that are based on changes in the human brain. Imaging methods for the brain can provide information about individual brain cells, which can be used to find important biomarkers. The manual neurologist's dementia diagnosis is laborious and inaccurate. While making a manual diagnosis, a number of factors come into play, including the patient's age, level of anxiety, and visual acuity. Scientists have been digging into the causes of the dramatic alterations in brain tissue that characterize both the onset and progression of Alzheimer's disease. Toxic changes in the brain may start long before an individual shows signs of Alzheimer's disease, suggesting that changes in brain tissues may start occurring much earlier in life [7]. Classification based on brain imaging is one of the effective methods for detecting Alzheimer's disease.

The first section serves as an introduction of Alzheimer’s disease, and the second discusses some recently published papers on Alzheimer's disease categorization using machine learning and deep learning approaches. Section 3 provides a comprehensive analysis and different techniques used for identifying the Alzheimer’s disease. Part 4 address the challenges in Alzheimer’s disease, need for the AD disease prediction and discuss the current study of AD disease. Finally, Part 5 included a concise review and outline of the paper's future objectives.

2. LITERATURE SURVEY

For Alzheimer disease detection, numerous researchers have created image processing techniques like machine learning and deep learning in recent decades. Kaur et al. studied Alzheimer's disease detection image enhancement methods [8]. Current Alzheimer disease detection approaches are tested using corrected red and green retinal pictures [9]. To find the best public healthcare Alzheimer's disease detection method, sensitivity and specificity are examined. The Li et al. technique segmented complicated images [10]. Background and target segmentation are used [11]. The retinal layer borders enable Alzheimer's and glaucoma diagnosis [12]. Using linear mixed modeling, Rao et al. simulated the impact of axial length, age, TSS, and ocular birefringence on Alzheimer disease diagnosis [13]. One image is randomly selected among 48 eye photographs to test the suggested approach.

For Alzheimer disease, peak signal-to-noise ratio (PSNR), photoreceptor layer status, and parallelism in OCT images, Uji et al. suggested interpolation and super-resolution (SR) [14]. Tests showed that interpolation and super-resolution (SR) algorithms can detect Alzheimer's illness. The Li et al. approach solves problematic image segmentation. Background-target segmentation is used in this method [15]. Alzheimer's illness has been identified using CNN's deep characteristics in recent years. Nonlinear appearance fluctuations do not affect deep characteristics. In response, various deep feature extraction-based solutions have been developed in the literature. A stacked deep polynomial network (S-DPN) developed by Zheng et al. [16] can improve characteristics representation from small samples, improving generalization. The next stage is to integrate multi-modality neuroimaging data and learn features using MM-S-DPN. Their categorization used SVM and embedded classifier.

They also used a CNN to include all multi-modality information from T1-MR and FDG-PET hippocampal images to diagnose AD [17]. A backpropagation algorithm trains the network, which has many convolutional layers (CL), pooling layers (PL), and fully connected layers (FCL) and is related with the output by the last layer. This paper used VGG's architecture to build its network. Using brain MRI, Cui et al. developed an augmented inception network to predict AD's early stage [18]. AD's sensitive brain areas are highlighted by histogram equalization and multi-threshold segmentation. One branch of two convolution layers (3x3 kernel) with sigmoid activation was added to the original inception model and multiplied with its output. Based on a single cross-sectional brain structural MRI scan, Basaia et al. developed a deep-learning model to predict AD and MCI [19]. This effort fixed overfitting using data augmentation techniques like picture rotation and translation and got a great result.

Liu et al. [20] claimed to predict clinical ratings using MRI data and CNN architecture. Data came from MRI landmark patches. As the clinical score was missing from the dataset, the suggested work used deep-learning techniques to guess it. Because the missing clinic score update used the complete clinical score, regression accuracy was reduced. Data training and validation are insufficient with machine learning and deep learning models. The manual neurologist's Alzheimer's diagnosis is slow and unreliable. Based on the above drawbacks, we examined and surveyed Alzheimer's disease's hurdles and combined them into one stage. IoT-based Alzheimer's disease classification must be developed further.

3. TOOLS AND TECHNIQUES

An accurate method for diagnosing Alzheimer's disease is currently being developed by researchers for the purpose of utilizing a number of different classification strategies. The following is a selection of research publications that are connected to the topic at hand and are based on some general classification methods. In the body of research that has been conducted, there are numerous approaches to categorizing and forecasting Alzheimer's disease. These approaches can be categorized into three distinct groups: statistical methods, segmentation methods, and deep learning methods.

3.1. Machine Learning Strategies of AD Disease

In the context of methodologies that are based on machine learning, there are a few procedures that need to be followed in order to provide an effective and efficient classification of Alzheimer's disease. Beginning with pre-processing, then moving on to feature extraction, and finally arriving at classification is the standard procedure. The process and workflow of machine learning based AD disease diagnosis is shown in Figure 3.

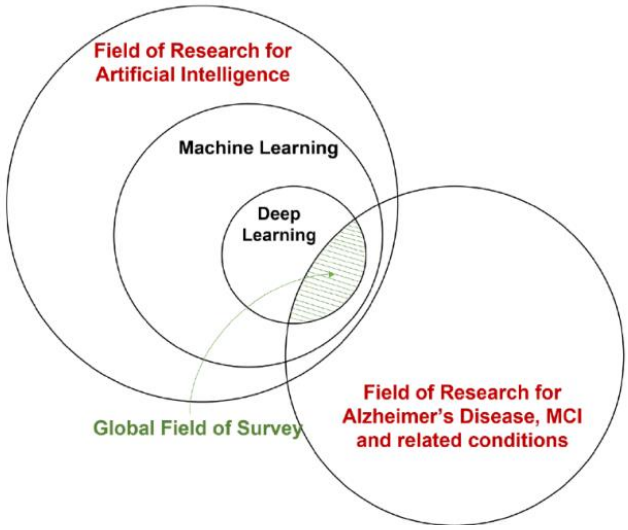

Fig. 2 Comprehensive Survey of the Field

- ❖ Dataset collection
- ❖ Pre-processing Phase
- ❖ Feature Extraction Phase
- ❖ Classification and Prediction

Dataset Collection: To begin the classification process, it is necessary to gather enough patient data and brain imaging to divide the population into distinct categories, such as Cognitive Normal and Alzheimer's disease. Most often used brain imaging techniques include structural magnetic resonance imaging (MRI), fluid-attenuated inversion recovery (FLAIR), magnetization prepared rapid acquisition gradient echo (MP-RAGE), T2-weighted functional magnetic resonance imaging (FMRI), positron emission tomography (PET), and others. In order to fully understand AD, it may be required to collect more pertinent data in addition to brain imaging. This could include the patient's medical history, MMSE score, genetic information, and more. Some of the most popular publically available online data sources for AD categorization include the Alzheimer's Disease Neuroimaging Initiative (ADNI) [21] and the Open Access Series of Imaging Studies (OASIS) [22].

Pre-processing Phase: In order to prepare images for further computations, a series of operations known as pre-processing is employed [23]. Among the many steps necessary to get an accurate classification result, pre-processing ranks high [24]. Prior to AD classification, images are often resized, noise isolating, skulls are removed, and morphological adjustments are made. Since brain imaging systems tend to gather a few extra pixels in the form of the skull, skull stripping is a crucial pre-processing step.

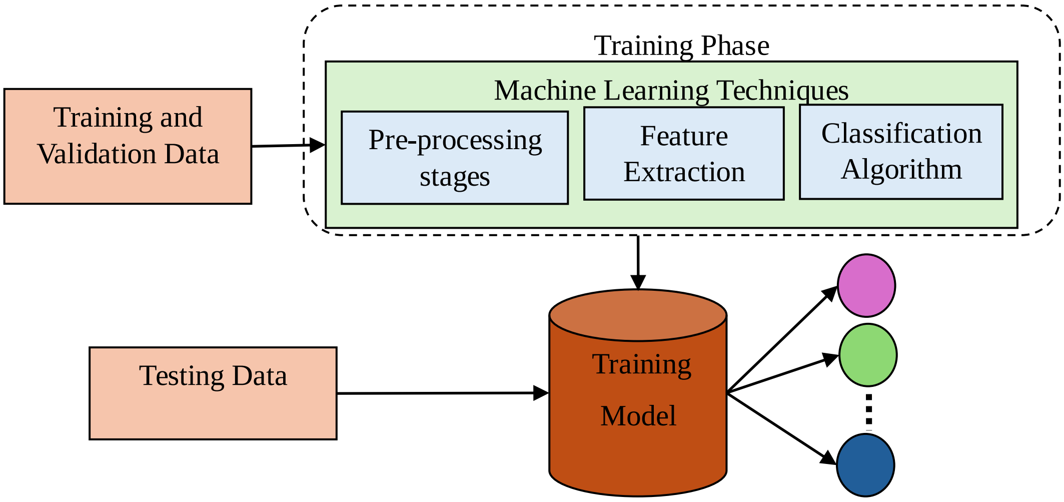

Fig. 3 Workflow of Machine Learning Techniques

Feature Extraction: Dimensionality reduction techniques like feature extraction (FE) identify important parts of input images as feature vectors [25]. FE creates new features from existing ones and extracts photo classification-relevant information. Compacted features can retain the original feature information [26]. Feature extraction enhances classification model training, speeds up processing, and boosts accuracy. Coloring, forms, textures, and other medical image analysis elements are best. Medical photos with unexplainable color use texture and shape-based feature extraction algorithms[27]. Machine learning approaches include PCA, ICA, LDA, LLE, and t-distributed Stochastic Neighbor Embedding for feature extraction.

Classification: Through the utilization of spectral or textural information, the process of image classification is carried out in order to categorize a collection of pixels according to certain characteristics. There are two different kinds of classification procedures, which are supervised and unsupervised classification methods or procedures [28]. Support Vector Machine (SVM), Nave Bayes, Stochastic Gradient Descent, K-Nearest Neighbours, Decision Tree, Random Forest, and Logistic Regression are some of the image classification methods that are widely utilized. Other methods include Logistic Regression and Decision Tree [29].

3.2. Deep Learning Strategies of AD Disease

Deep learning models include CNN, RNN, Auto Encoder, and Generative Adversarial Network (GAN). CNN and RNN models are used for image and text categorization extensively. CNNs are popular image segmenters and classifiers [30]. After performing well in the 2012 ImageNet Competition, CNNs gained notice despite their 1989 introduction. With more layers, neurons with millions of weights, and connections between neurons, CNN design is becoming more computationally complex [31]. As shown in Figure 4 CNN's fundamental block diagram, this includes following sequence of layers:

- Input Layer
- Convolution Layer
- Activation Function
- Pooling Layer
- Flatten Layer
- Fully Connected Layer
- Soft-max function.

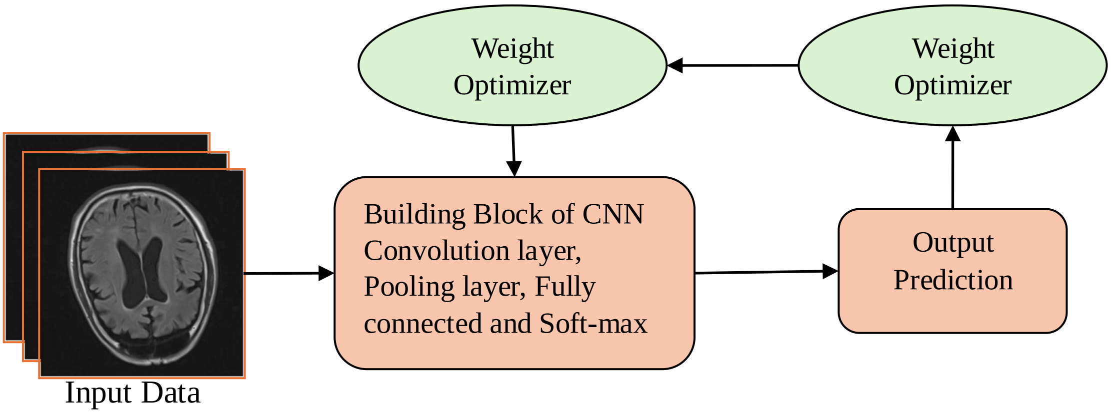

Fig. 4 General workflow of Convolutional Neural Network Model

Convolutional layers convolve input images across kernels to create feature maps. As values are transferred to the next layer, the pooling layer down-sample convolutional layer results using the maximum or average of the designated neighborhood. The loss function and CNN model output's last layers forecast input data. The loss function between prediction and ground truth labels is reduced while maintaining regularization requirements to generate network parameters. At each iteration until convergence, backpropagation adjusts network weights [32].

4. CHALLENGES IN ALZHEIMER'S DISEASE

In this sub section, we have address the challenges in Alzheimer's disease, need for the AD disease prediction and discuss the current study of AD disease.

4.1. Challenges in Alzheimer's disease

Though several studies of AD disease have been made in the past few decades, no algorithm has yet been developed to accurately diagnosis of AD disease using MRI images. The following are some of the challenges faced by the researchers during AD diseases.

- ❖ Human brain is a very complex non-linear structure.
- ❖ It requires correct and detail knowledge about the anatomy of brain to work on it.
- ❖ Variation in size and shape of brain.
- ❖ Intensity in homogeneity of MRI. It also requires basic knowledge on radiology to understand the MRI images
- ❖ We cannot have the normal and AD image for the same patient.
- ❖ The primary issue is lacking of real-time data for train the model or method.
- ❖ Alzheimer's disease is difficult to diagnose since it is hard to monitor and analyse a patient's pathology over the long term.

In addition to these, the quantity and quality of the images create a high computational cost which makes it difficult for near-real time applications.

4.2. Need for the Research

The paper needs to investigate to identify and classify regions of the brain that are particularly indicative of AD.

- ❖ The automatic AD classification is also very difficult, because of the low contrast of the anatomical structure in MRI.
- ❖ The research may helpful to doctors for the second opinion of Alzheimer’s disease diagnosis.

4.3. Current Research Area

Ambient Assisted Living (AAL) solutions could benefit from the Internet of Things (IoT) due to its widespread deployment and the predicted increase in the number of connected devices to over 20 billion by 2020. This has prompted researchers and businesses to explore potential applications in the medical profession. In order to keep track of patients' clinical status and prevent them from having to make repeated trips to the hospital, one country, the United Kingdom, has implemented a network of spatial sensors based on the Internet of Things. Our goal in doing this research was to examine how the Internet of Things (IoT) might be used to track the development of Alzheimer's disease.

Through AAL systems, the Internet of Things (IoT) enables the monitoring and control of diseases, and it also allows the health sector to respond to the varied requests of patients. The sensor's primary use case could be to aid patients and their loved ones with memory issues, face recognition, tracking a person's whereabouts, and the identification of symptoms and trends in behavior using the Internet of Things (IoT).

5. CONCLUSION

Alzheimer's is a very bad brain disease that affects a lot of people around the world. The number of people around the world who have Alzheimer's disease is rising quickly. The neurosurgeon's method of diagnosing AD by hand takes time and might not always give accurate results. Finding out if someone has Alzheimer's disease through brain scans has shown promise and takes less time. A lot of researchers have been trying to make a brain scan-based classification system that is easier to learn and takes less time. One of the most important steps in using brain scans to diagnose Alzheimer's is extracting features.

In this study, a lot of work has gone into coming up with different ways to find the different types of disease classification methods. Disease detection methods can be roughly put into two groups: those that use machine learning and those that use deep learning. In this study, the problems and open research topics of IoT-based machine learning and deep learning models are talked about. Our hope is that the survey paper, which looked at about 50 published papers, will help academics understand the idea of Alzheimer's disease a lot better.

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