Innovation and Integrative Research Center Journal
ISSN: 2584-1491 | www.iircj.org
Volume-2 | Issue-11 | November-2024 | Page 176-183

Deep Learning methods for diagnosing and categorizing Alzheimer's disease: A Review

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Abstract— **Alzheimer's disease is a progressive neurodegenerative disorder that primarily impacts memory and is most common among older adults, particularly those over the age of 65. It is a global health concern that requires early and accurate detection. However, manual diagnosis by healthcare professionals can be time-consuming and prone to errors due to the high volume of patients. While numerous techniques have been developed for diagnosing and classifying Alzheimer's, there remains a significant need for more precise solutions for early detection. This paper examines and compares various techniques for detecting Alzheimer's disease and proposes an improved model for detection, which will be implemented in our future research**

Keywords*— *Alzheimer's disease, Machine Learn==ing, Deep Learning, Magnetic Resonance Imaging (MRI).

I. Introduction

Alzheimer's disease (AD), commonly referred to as dementia, is a condition caused by the irreversible destruction of memory cells. This memory loss occurs due to the death of nerve cells and the deterioration of brain structures. It impairs the ability to carry out daily activities such as speaking, writing, and reading. In advanced stages, patients may experience severe complications, including heart failure and respiratory dysfunction, which can ultimately lead to death. The prescription of inappropriate medications often hinders the accurate and timely diagnosis of AD. Early diagnosis of Alzheimer's disease (AD) can significantly enhance a patient's quality of life through appropriate treatment. Although its symptoms progress gradually, the condition deteriorates over time as brain functions begin to fail. AD affects a large number of individuals annually, with projections indicating that one in 85 people will be living with the disease by 2050. It is recognized as the second most severe neurological disorder globally, with dementia symptoms developing in approximately 60%–80% of those diagnosed. To measure dementia severity, tools like the Global Deterioration Scale (GDS) and the Clinical Dementia Rating (CDR) scale are widely used, with the latter being particularly valued for its simplicity in facilitating collaboration between medical professionals and families. In individuals with AD, the brain undergoes structural changes, including enlarged ventricles and a reduction in the size of the cerebral cortex and hippocampus. Shrinkage of the hippocampus impairs episodic and spatial memory, while neuronal damage disrupts communication, affecting planning, judgment, and short-term memory. This neuronal degeneration leads to synaptic dysfunction, the breakdown of neuron connections, and further cell loss. Numerous studies have focused on classifying and detecting AD at different stages. The most common initial approach to diagnosing AD involves analyzing brain MRI scans. Medical professionals use these images to identify disease indicators such as tumors, brain matter changes, or degeneration. Given the severity of AD, extensive research is critical in this area. Deep learning and machine learning models have shown great promise in medical image analysis across various domains, including mammography, ultrasound, microscopy, and MRI. These models have demonstrated remarkable success in detecting and classifying diseases affecting the heart, lungs, brain, retina, breast, and bones. Despite their potential, however, relatively limited research has been conducted on applying these advanced techniques to the detection of Alzheimer's disease. This paper provides an overview of various techniques and models utilized for the accurate and efficient detection of Alzheimer's disease. It highlights the integration of multiple methods and models in expert systems and discusses the effectiveness of models proposed by different researchers.

II. Literaturer review

Several previous studies that have constructed in trails in Alzheimer's disease detection in the following:

Amar Shukla et al. examine different approaches for detecting Alzheimer's Disease (AD), noting the rising global prevalence of the condition. The paper explores the effectiveness of Automatic Pipeline Methods and Machine

ISSN: 2584-1491 | www.iircj.org
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Learning Techniques, which have achieved over 95% accuracy in single and binary classifications. However, challenges persist in multi-class classification, especially in differentiating between AD and Mild Cognitive Impairment (MCI). From the research, it can be seen that multi-modal techniques are vital for cross-checking AD detection for extra accuracy validation. The goals of improving diagnostic accuracy and more sophisticated methods for the detection of AD and its stages are the aspirations of the study [1].

As per Shahbaz and his colleagues, a study has been done for Alzheimer whose disease (AD) is a very common and well-known neurologic disorder that results in loss of memory and is irreversible and progressive. The corpus includes the application of six algorithms, such manners as k-nearest neighbors, generalized linear model, and others towards the ADNI dataset for the classification of the five stages of AD. This is based on how relevant it is in terms of hindering AD progression. The outcomes proved that the generalized linear model gave the best results with an accuracy level of 88.24% which shows that these techniques can be helpful in early diagnosis in healthcare [2].

A comparative study on machine learning techniques which determine and predict Alzheimer's disease was conducted by Morshedul Bari et al. Approximately 45 million humans suffer from the illness. It builds models such as support vector machines (SVM), logistic regression, decision trees and random forests using the 'Open Access Series of Imaging Studies(OASIS)' dataset. The study revealed that although all of the models achieved reasonable results, SVM had the best performance among the rest and does not seems to suffer from overfitting issues which are very common with other models. The study places emphasis on the significance of recognition at an earlier time and the use of machine learning algorithms that may help improve the accuracy of Alzheimer's diagnoses [3]. While speaking about the problems in identifying Alzheimer's disease, P. Kishore et al. have drawn attention to limitations in current methods that rely on behaviorial and social history reports. It is proposed that the machine learning methods should also be used along with AI to help improve the precision of diagnosis. The research utilizes a dataset which includes MRI scans along with other variables for the purpose of exploring relationships and improving classification accuracy. Since Alzheimer's disease has no known effective treatment at this time, it emphasizes the importance of diagnosis at an early stage for appropriate therapy. As per the findings, Support Vector Machine using the linear kernel model is more accurate than the other methods examined in the study [4]. Xiaomu Tang et al. apply machine learning techniques to MRI images to examine Alzheimer's disease (AD). The participants were placed into separate groups like cognitively normal (CN), early mild cognitive impairment (EMCI), late mild cognitive impairment (LMCI), and AD using the AD Neuroimaging Initiative (ADNI) database. SVM, decision trees (DT), and random forests (RF) were used to classify the data and also predict the disease status. Most of the accuracy was noted in CN versus AD discrimination, particularly with an area under the ROC curve AUC of 0.92 [5]. M. Rohini et al. applies machine learning approaches to classify cognitive impairment and Alzheimer's disease (AD) in the elderly. It differentiates AD from normal cognitive aging based on several indicators, including biomarkers, neuroimaging, and demographic information. The study begins with feature scaling and normalization before applying supervised learning techniques like SVM and multivariate linear regression. It can be shown in the study how the model demonstrates the ability to predict disease conversion based on 1000 baseline evaluations from the Alzheimer's Disease Neuroimaging Initiative (ADNI). In fact, these results point toward important benefits regarding differentiation between AD pathology and typical cognitive decline [6]. The increasing rate of dementia cases among the older generation has been addressed by C. Kavitha et al. by applying machine learning models for the early stage detection of Alzheimer's disease (AD). The research highlights the problems faced at the stage of diagnosis as well as the benefits associated with treatment at an early stage. Their research has implemented several machine learning techniques such as Decision Tree, Random Forest and Support Vector Machine to analyze the data especially from the Open Access Series of Imaging Studies (OASIS). The proposed method of classification is better than existing methods with an average validation accuracy of 83%. These findings are aimed at assisting physicians in diagnosing AD in order to provide early treatment and potentially reduce mortality rates [7]. A machine learning-based multimodal imaging computing framework focused on image analysis of Alzheimer's disease developed by Fatemah H. Alghamedy et al. is examined. It describes the way Alzheimer's disease functions which is to continuously dismantles the functional ability of the brain. It concentrates on the importance of isolating fragments of interest in MRI scans by employing the k-means clustering method after employing the CLAHE technique to improve the image's quality. A number of machine learning models for classification are applied after performing feature extraction based on Principal Component Analysis (PCA). The paper describes how critical it is to have an accurate diagnosis so as to be able to manage Alzheimer's disease effectively [8]. Deep learning technique for Alzheimer's disease (AD) is proposed by Hadeer A. Helaly et al. which incorporates convolutional neural networks (CNN) to augment deep learning approaches to aid in the recognition of early stage AD. It employs neuroimages consisting of 2D and 3D graded structural scans of the brain from the ADNI database to carry out medical image categorization of the various stages of AD. The system employs dual strategies like the transfer learning with architectural VGG19 model

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and some primary settings of CNN. The suggested web application for remote AD validation boosts the classification accuracy to 93.61% and 95.17% for 2D and 3D [9]. Gowhar Mohiud din dar et al. utilized a new framework to apply convolutional neural networks (CNN) on MRI image datasets for the purpose of categorizing different phases of Alzheimer's disease (AD). Considering the estimated increase of population suffering from dementia, along with its associated costs, it emphasizes the importance of early stages. Applying the pre-trained models like MobileNet and transfer learning, it classified the multi-class stage of the AD by reaching up to 96.6% accuracy. The proposed methodology focuses on the design of lightweight neural networks suitable for medical image processing and tends to outperform existing models [10]. Using MRI data, Swathi S. Kundaram et al. also explore a deep learning approach for the classification of Alzheimer's disease (AD). It introduces a deep convolutional neural network (DCNN) that classifies participants into three groups: normal control (NC), moderate cognitive impairment (MCI), and Alzheimer's disease (AD). The technology achieves a 98.57% accuracy rate on the ADNI dataset, surpassing conventional machine learning approaches requiring handcrafted features.
For proper patient care and possible future therapy, the authors of the article emphasize that an early diagnosis is important [11]. A. M. El. Assy et al. conducted research on a fresh convolutional neural network (CNN) design for Alzheimer's disease (AD) detection and classification using magnetic resonance imaging (MRI) data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. The designed model incorporates multiple CNNs with different filters for extensive detection which resulted in triple classification accuracy rates of 99.43% and 99.57% and 99.13%. Its design successfully interprets essential image features found in MRI studies to support accurate AD subtype identification and stage assignment necessary for developing personalized interventions [12]. In their research Noman Raza et al. tackles Alzheimer's disease (AD) which represents a degenerative neurological illness that affects brain function principally in patients over 60. The research employs transfer learning techniques to train a customized convolutional neural network (CNN) that processes gray matter (GM) images for MRI segmentation and classification. Multiple tests utilizing the proposed diagnostic model achieved 97.84% accuracy for determining early Alzheimer's disease indicators. The research invalidates pre-trained models [13] through demonstrations of innovative methods to enhance classification outcomes with lower training sample requirements. Y N Fu'adah et al. proposed a study focused on Alzheimer's disease that presents memory loss because brain neurons responsible for cognitive processes become damaged. Researchers developed a classified system to examine MRI datasets by employing Convolutional Neural Networks (CNN) based on AlexNet architecture. Using a total of 664 MRI scans, the study categorizes Alzheimer's into four stages: The stages in the analysis are non-demented, very mildly demented, mildly demented and moderately demented. The analysis method demonstrates a 95% accuracy rate making it a valuable diagnostic tool for Alzheimer's disease stages that provides healthcare providers with essential treatment information [14]. R.R. Janghel et al. developed a special deep convolutional neural network (CNN)-based system to detect early Alzheimer's disease through diagnosis processes. The novel preprocessing method for Alzheimer's picture datasets within this system leads to improved detection accuracy. Clinical evaluation enabled the team to achieve an impressive 99.95% diagnostic accuracy for Alzheimer's disease through fMRI scans thanks to data training from the Alzheimer's Disease Neuroimaging Initiative (ADNI). A research approach demonstrates how deep learning strengthens diagnosis procedures for Alzheimer's disease while implementing multiple classification methods [15]. Sunday Adeola Ajagbe et al. ,their research focuses on the early diagnosis of Alzheimer's disease using deep convolutional neural networks (DCNN) for image classification of magnetic The study by Sunday Adeola Ajagbe et al. uses deep convolutional neural networks (DCNN) to interpret magnetic resonance imaging (MRI) pictures and identify early Alzheimer's disease stages. This study integrates traditional diagnosis methods with DCNN demonstration of its superior feature extraction properties to examine digital diagnostic tools in healthcare. Thirty-two models face challenges due to limited real-world data and slow calculating speed during an analysis of their performance and accuracy insights using six evaluation measures that include accuracy and F1-score. Deep learning approaches applied in the results allow for faster and more precise identification of Alzheimer's disease [16]. In their article V. Sathiyamoorthi et al. introduce a diagnostic system that utilizes deep convolutional neural networks to evaluate MRI images for AD detection. The work demonstrates that proper image classification planning remains vital to differentiate healthy brain scans from scans showing brain damage. The research implements image processing methods including adaptive bilateral filtering and clustering which reduce image artifacts while enhancing diagnostic accuracy. The suggested methodology demonstrates its ability to early detection of AD and enhances diagnostic efficiency based on improved diagnostic performance measurements [17]. Manu Raju and associates suggested the study addresses the difficulties in detecting Alzheimer's disease because of comparable brain patterns by concentrating on the multilayer categorization of the condition using MRI images. It achieves 99% predicted accuracy by using deep learning techniques, particularly transfer learning with the VGG16 model. Correct staging of Alzheimer's disease between four phases including mild dementia to very mild dementia stands as a critical matter according to the research. The application of deep learning in medical

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ISSN: 2584-1491 | www.iircj.org
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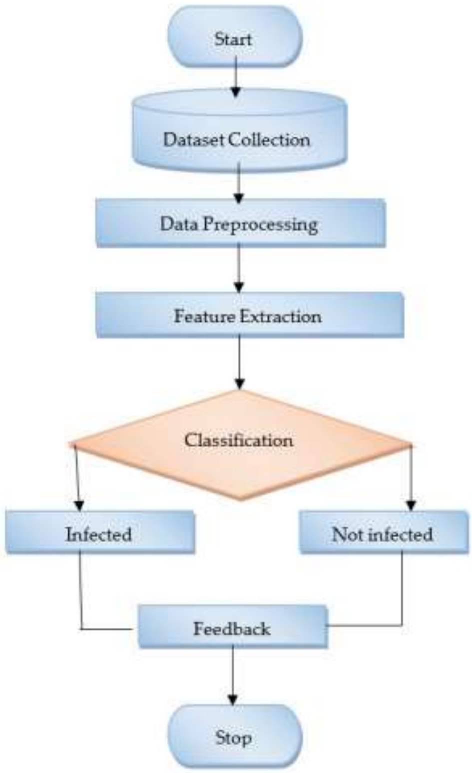
imaging is proven through the proposed approach which delivers superior outcomes compared to previous studies [18]. Bangyal Waqas Haider et al. Successful brain tissue damage prevention during AD treatment depends heavily on early detection according to the study because it explores the deep learning approach toward AD domain ontology construction. The study highlights the necessity of ontologies in biological research because we lack sufficient knowledge about Alzheimer's disease in the domain of knowledge. A Kenn-trained for AD detection analyzes data obtained from Kaggle using a convolution neural network together with multiple machine learning approaches. CNN achieves an accuracy of 94.61%. The results show deep learning provides a solution to improve ontology development which results in enhanced scalability with increased robustness [19]. The paper by Waleed Al Shehri et al. reviews AD detection strategies for this permanent neurological disorder which mainly impacts elderly patients. The article highlights the importance of early precise diagnosis through detailed discussion about labor-intensive manual processes that lead to repeated errors. The suggested method employs DenseNet-169 and ResNet-50 CNN architectures for deep learning techniques to classify AD stages between Non-Dementia and Very Mild Dementia and Mild Dementia and Moderate Dementia. The DenseNet-169 architecture achieved its training accuracy at 0.977 and its testing accuracy at 0.8382 according to the results presented in [20]. Suriya Murugan et al. performed research on DEMNET which represents a deep learning model built for early dementia and AD diagnosis through analysis of MRI pictures. The model achieves high performance levels on the Kaggle dataset by reaching 95.23% accuracy and 97% AUC which enables the system to address class imbalance problems. A Convolutional Neural Network architecture within the model allows both risk assessment of AD in individuals and the extraction of distinctive features. The model achieves accuracy of 84.83% during its robustness evaluation by validating performance using data from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database [21].

Author	Description	Methods	Performance Measure
Suriya Murugan et al.	The model was trained using a variety of datasets.	CNN	Accuracy-95.23%
Shagun Sharma et al.	The model incorporates activation function such as ReLu and SoftMax.	CNN VGG-16 (Feature Extractor)	Accuracy-90.4%
Waleed Al Shehri et al.	Model has ability to extract features from complex medical images.	CNN DenseNet-169 ResNet- 50	DenseNet-169 Accuracy-83.82% ResNet-50 Accuracy-81.92%
Waqas Haider Bangyal et al.	Multimodal feature extraction techniques, such as Random Forest, MLP, SVM, etc.	CNN	Accuracy-94.61%
Sunday Adeola Ajagbe et al.	Reduces computation time by removing redundancy from the dataset.	DCNN VGG-19 (Feature Extractor)	Accuracy-77.66%

III. PRAPOSED METHODOLOGY

The proposed framework comprises four pivotal steps: -



Data Collection:

Kaggle Dataset: This dataset consists of MRI images. The data has four classes of images both in training as well as a testing set:

Mild Demented, Moderate Demented, Non Demented, Very Mild Demented.

Data Preprocessing:

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1) Evaluation of Significance Graphs occurred as a step to determine which features produced the most significant impact on prediction accuracy. Each diagram shows the importance level of each feature in these visualization graphs. The evaluation method referred to as "feature significance" determines input characteristics value by their ability to predict target labels. The use of feature significance scores provides practical applications with better dependable and effective prediction models. Predictive modeling depends on these scores because they both supply relevant data insights about datasets and support model interpretation and help identify critical characteristics.

2) The Attribute Filtering Method functions as a technique which has successfully eliminated irrelevant and unneeded data from the dataset. The assessment technique uses data intrinsic qualities to evaluate features without depending on classification methods. The attribute filtering process incorporates different methods such as fuzzy logic together with distance measurements and correlation analysis with information gain and consistency evaluation and rough set theory. First, characteristics receive ratings before evaluation through univariate techniques which overlook contextual relationships or through multivariate approaches that efficiently handle redundant data collection. The final selection of features for future modeling work occurs during the last stage when choosing the most relevant characteristics from the ranking.

a. The methodology separates the dataset into training and testing divisions which dedicate 80% of data for training purposes and use 20% for testing purposes. The 8:2 data split establishes dependable model evaluations since it provides sufficient training data but also separates a specific portion for testing unseen samples.

b. The problem of diabetes prediction finds successful resolution through machine learning methodologies. The research determines if advanced machine learning systems should be utilized to generate predictive insights which detect diabetes within populations. Computer analysis benefits from this method because it uses 16 different features taken from the publicly available UCI Machine Learning Repository. A performance evaluation of Random Forest and K-Nearest Neighbors (KNN) together with AdaBoost and Bagging algorithms is done for prediction accuracy and stability. Various design analyses will be used to demonstrate the strengths and weaknesses of different strategies for accurate diabetes predictions in this research.

Random Forest Algorithm: The Random Forest algorithm, introduced by Bierman [18, 19], is a machine learning technique comprising multiple decision tree classifiers that operate independently. Each tree within the forest generates its own classification prediction, and the final output is determined by majority voting among the predictions. As the number of trees increases, the model's accuracy improves proportionally while simultaneously addressing overfitting issues [20]. This approach is particularly effective in achieving reliable results without requiring extensive hyperparameter tuning.

A large number of trees within Random Forest ensures its capability to resist overfitting which is its most notable advantage. Random Forest proves to be a dependable solution for multiple prediction jobs due to its reliability. Random Forest demonstrates superior performance in datasets containing categorical variables at the same time it excels in managing both missing data and missing values [21]. The preferred method for machine learning practitioners selects this model because of its high accuracy and easy implementation.

KNN operates by finding the K nearest data points when it needs to categorize a sample. The resulting points are called neighbors. A key concept behind KNN involves examining the classifications of nearest points to an isolated sample for determining its unknown category [22]. The classification method assumes that the unknown sample belongs to the category which dominates among the chosen K nearby examples.

The selection of K value is crucial because different K choices will create distinct classification results which influence the model accuracy. KNN requires users to locate the nearest K neighbors to the sample as its initial implementation step. A particular category emerges as the classification outcome after evaluating the categories belonging to these neighboring items [23].

KNN measures data point similarity through calculating distances with options including the Manhattan as well as Euclidean distance metric computations. Features from nearest proximity points guide KNN classification since it is an instance-based learning technique without predetermined statistical models. KNN implements efficient classification of new data by assigning points to the class that boasts the most similar measures through proximity computation [24].

AdaBoost: short for Adaptive Boosting, is a machine learning technique introduced by Yoav Freund and Robert Shapire in 1995. Its primary goal is to combine multiple weak classifiers to form a strong classifier. AdaBoost belongs to the broader family of boosting algorithms [25]. The core idea behind AdaBoost is to focus more on the misclassified samples during the training process, adjusting the sample distribution iteratively to improve classification accuracy. This iterative process continues until the weak classifiers have undergone a predefined amount of training, at which point the learning concludes [26].

The weight maintenance system of AdaBoost operates across the training data by adjusting its value during each weak learner iteration. The approach decreases the weights of correctly classified samples but increases weights of incorrectly classified samples by the current weak learner. The algorithm focuses its attention on difficult-to-classify cases during multiple training cycles because of this method which results in augmented performance. A classification model that delivers strong performance emerges from the combined weak learners developed by AdaBoost procedures [27].

A combination of weak learners becomes an improved and accurate model when you use "bootstrap aggregating" which implements "bagging" as an ensemble learning technique. Bootstrapping serves as the implementation method for bagging because it creates training subsets by randomly selecting data samples to replace individual basic classifiers. The research states that classifiers are trained on these subsets after which the combined output results from either voting procedures for classification or averaging processes for regression tasks [20].

This approach helps reduce variance and prevents overfitting, especially for high-variance models like decision trees. By using multiple diverse models, bagging increases the overall model's robustness and accuracy, making it a powerful tool in machine learning, particularly when combined with models prone to overfitting when used alone. Bagging can significantly improve the performance of weak learners by leveraging the wisdom of the crowd through ensemble techniques.

Conclusion

The approaches discussed have primarily been supported by traditional image processing or machine learning methods. Some studies have utilized deep learning-based transfer learning models, while others have employed CNN-based mechanisms. However, due to the hidden or complex architectures of these models, their actual performance remains unclear. Extracting valuable features that enable a system to identify Alzheimer's disease (AD) in MRI scans is crucial, but feature extraction has not been effectively emphasized in the mentioned works. Additionally, the design challenges of deep learning models, particularly in terms of their training and testing behavior, have not been thoroughly addressed. The future scope of this study involves developing a CNN-based model to classify brain MRI images into normal and Alzheimer's stages. This model aims to have a less complex design and be validated through qualitative and quantitative assessment metrics.

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