Acta Scientific COMPUTER SCIENCES

Volume 5 Issue 6 June 2023

Literature Review

A Novel Method of Early Detection of Ad (Alzheimer's Disease)

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Received: April 03, 2023

Published: May 25, 2023

Abstract

Alzheimer's recognition and elimination is a challenging problem in the medical field. Before advanced imaging techniques like CT scans and MRI scans were available, invasive methods such as pneumo- encephalography and cerebral angiography were used. These methods have since been replaced by non-invasive imaging techniques, which provide improved visual information for surgeons. The three-step technique described for Alzheimer's disease identification main factor that influences, fragmentation, and morphology functionality of the images. Once the input picture has been grayscale for pre-processing, a high-pass filter is used to reduce noise and a median filter is applied to enhance image quality. Tumor characteristics are extracted using the wavelet transform, and the dimensionality of those features is reduced using PCA (principal component analysis). A kernel support vector machine is then used to assess the trimmed features (KSVM). K-fold cross-verification is utilized to further enhance the KSVM's effectiveness.

Keywords: Brain; Alzheimer; Disease; Thresholding; Morphological Operations; Kernel; PCA; SVM

Introduction

Devastating to both the sufferer and their loved ones AD is a progressive neurological ailment that affects a significant proportion of the world's older population. Memory loss, language difficulties, confusion, irritability, depression, a lack of drive, a failure to take care of oneself, and challenging behavior are all symptoms of AD. Individuals with advanced sickness often become socially isolated, lose the ability to care for themselves, and ultimately pass away. There are several genetic and environmental risk factors related to the development of AD, but the exact etiology is still unknown. Amyloid plaques, neurofibrillary tangles, and the disintegration of synapses in the brain are all symptoms of AD. There are currently no treatments for AD or its progression that are effective in clinical trials. Certain therapies may provide short-term relief of symptoms, and fitness regimens have been shown to improve long-term health and quality of life.

Diagnosing AD requires a thorough evaluation of the individual's health history, cognition assessment, tomography, and diagnostic tests to rule out other possibilities. The only way to get a proper diagnosis is to examine brain tissue, which is only possible after death. Clinical signs of AD are commonly misunderstood as signs of normal brain aging, leading to a delayed or incorrect diagnosis [1].

The burden of caring for individuals with AD can be significant, as they increasingly rely on others for assistance with daily tasks. Caregivers often experience social, psychological, physical, and financial difficulties [2]. Antipsychotics are sometimes prescribed to treat behavioral problems or psychosis due to dementia, but this carries a considerable risk of early death. While ongoing clinical trials explore the benefits of good nutrition, physical activity, and social engagement in dropping the menace of perceptive decline and AD, there is currently no definitive cure for this disease.

AD is a challenging diagnosis, as clinical evaluations can be misleading. Diagnosis typically depends on medical history, observations, and neurological and neuropsychological findings. Advanced imaging techniques and memory testing can aid in ruling out other conditions. DSM-5, NIA-AA and the International Working Group provide three different sets of diagnostic criteria. AD progresses from a preclinical stage to mild cognitive impairment and ultimately dementia. MCI is diagnosed based on cognitive impairment and the identification of biomarkers [3], while dementia is classified into probable and possible AD, based on steady cognitive decline and memory-related impairment. Definitive diagnosis can only be achieved through post-mortem evaluations.

Currently, there are no treatments that modify the course of Alzheimer's disease, so research has shifted toward prevention. However, there is no clear evidence supporting any specific measures to prevent AD, and studies have produced inconsistent results. Epidemiological studies have identified modifiable factors that may impact the likelihood of developing AD, but determining the effectiveness of interventions as primary or secondary prevention methods is difficult due to varying intervention durations, disease stages, and a lack of standardization in biomarker inclusion criteria. More research is required to identify effective preventative measures for Alzheimer's disease.

Literature Survey

AD is a serious neurological illness that affects thousands of people all over the globe. Attention to utilizing ML algorithms to identify and evaluate this illness at an earlier phase, when therapeutic options may be more successful, has increased in recent years. This article reviews many research efforts that have looked at applying ML methods to the problem of AD detection.

Using the Visual Geometry Group deep convolutional neural network, we may apply deep learning to identify minor cognitive impairment by segmenting brain tissue [4] in MRI scans. An amazing 98.73% accuracy was obtained using their approach. For feature extraction from neuroimaging data, a modified ResNet18 model [5] was presented, and it had a 99.09% accuracy rate in identifying AD's first stages.

Automatic encoders and a 3D convolutional neural network (CNN) for imaging data are used in a suggested approach for noise removal from MRI images [6], with 78% accuracy. The ADNI dataset and a variety of biomarkers were used in all of the investigations looking for signs of Alzheimer's disease in its earliest stages.

The phases of Alzheimer's disease may be identified with the use of a technique published in [7] that employs the VGG19 and DenseNet169 categorization frameworks. The Kaggle online data collection provided them with 6,000 tagged pictures to work with, and VGG19 achieved 94% accuracy with this dataset. Classification and identification of AD's early phases were accomplished using a voting classifier algorithm (with an accuracy of 84%) that relied on both hard and soft voting techniques [8].

MRI scans and ConvNets [9] were used to detect the early stages of dementia, achieving accuracy rates ranging from 88.37% to 97.65% for MCI AD.

Other studies utilized various techniques, such as deep learning algorithms for analyzing brain MRI images, EEG signals, and magnetoencephalography to detect AD. Support vector machines and other classification algorithms were also used for analyzing PET scan data [10]. Overall, the studies show promising results, highlighting the potential of ML in improving the diagnosis and treatment of AD.

The literature review discussed here offers a comprehensive understanding of various machine learning techniques utilized in detecting and diagnosing AD using diverse medical data types, including MRI, PET scans, EEG, and MEG. The studies demonstrate the potential of deep learning algorithms, such as CNNs and 3D-CNNs, for analyzing brain MRI images and detecting AD [11].

The analysis also emphasizes the use of a support vector machine (SVM) and other classification techniques for examining EEG and PET scan data. Results from this research highlight the need of developing and using effective feature extraction algorithms and visualization approaches to improve the precision with which AD is diagnosed. The research study also includes a comparison of deep learning methods for diagnosing neurological illnesses including Alzheimer's, Parkinson's, and schizophrenia [12]. In conclusion, the findings of this research are encouraging and provide strong evidence that machine learning may greatly enhance AD diagnosis and therapy.

Methodology

Thousands of people all over the globe are living with the effects of AD. While there is currently no treatment for the condition, early diagnosis is crucial for alleviating symptoms and enhancing patients' lifestyles. The current approach to diagnosing AD involves several traditional diagnostic methods, including medical history assessment, neurological and physical exams, cognitive and memory tests, and brain imaging scans such as MRI and PET. However, these methods may not always be accurate and may not detect the disease in its early stages.

To address this issue, researchers are exploring the potential of machine learning-based systems for detecting Alzheimer's disease. These systems use algorithms to analyze various types of medical data, including MRI and PET scans, EEG, and MEG, to detect changes in brain structure and function associated with AD. DL procedures such as CNNs and 3D-CNNs have shown promising outcomes in analyzing brain MRI images and detecting AD. Other classification algorithms such as SVM have been used to analyze EEG and PET scan data.

Efficient feature extraction methods and visualization techniques are crucial in improving the accuracy of AD diagnosis. The existence of AD may be detected through biomarker examinations including cerebrospinal fluid (CSF) testing, positron emission tomography (PET) scanning, and lab tests by evaluating proteins like tau and amyloid-beta, as well as alterations in the way the brain works and structures.

In addition, research has evaluated several deep-learning approaches for identifying neurological conditions including AD, Parkinson's, and Dementia. This research shows promise, indicating that machine learning may help with AD diagnosis and therapy. Further work in this area might improve diagnostics accuracy and reliability, which in turn could lead to faster identification and more positive therapeutic results for sufferers.

This study introduces a unique ML model for MRI-based diagnosis of Alzheimer's disease. There are a total of 664 MRI scans in the dataset, 200 of which are from mild AD, 64 from moderate AD, 200 from non-AD, and 200 from very mild AD. To enhance the local contrast in the pictures, CLAHE (Contrast Limited Adaptive Histogram Equalization) is used during pre-processing.

Objects are isolated from the background using Otsu's technique in the segmentation phase. Wavelet coefficients are extracted from four sub-bands (low-low, low-high, high-high, and high-low) using the DWT (Discrete Wavelet Transform) for feature extraction. After features have been extracted, they are typically reduced using PCA (principal component analysis). Common classification techniques include the SVM (Support Vector Machine) and the KNN (K-Nearest Neighbors method).

To partition an n-dimensional space into classes, SVM, a supervised learning method, seeks to find the optimal decision boundary (or hyperplane). Extreme points, also known as support vectors, are chosen by SVM and used to help form the hyperplane. K-Nearest Neighbors (KNN) is an alternative supervised learning method that uses the similarities between new and current examples to learn. It takes in all the information it can find and uses that information to determine how to file a new piece of information. Unlike parametric algorithms, KNN does not presuppose anything about the data and hence may be utilized for both regression and classification issues.

Nevertheless, the findings of applying the suggested approach to the categorization of MRI scans for AD are encouraging. Based on the results of the research, SVM seems to be superior to KNN for classification purposes. Accurate and trustworthy classification results may be attained by the article's emphasis on pre-processing, segmentation, feature extraction, and reduction. The proposed methodology (shown in Figure 1) may enhance Alzheimer's patient outcomes by facilitating earlier recognition and treatment.

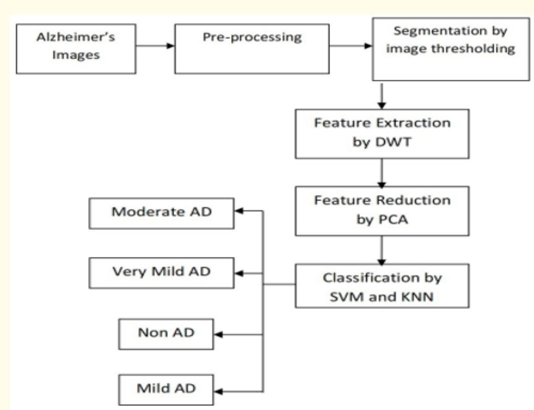

Figure 1: Framework of the proposed system.

There are several steps involved in developing an ML model for diagnosing AD, and all of them are essential to producing trustworthy findings.

To begin, an MRI dataset must be collected so that the ML model may be trained and evaluated. There are often mild, moderate, and extremely mild AD cases (shown in Figure 3, Figure 4,Figure 5, Figure 6 and Figure 7) as well as controls, in the dataset so that the model's accuracy may be evaluated over a wide range of conditions.

Implementation analysis

The data set is collected from the Kaggle data set which is publically available.

The images are then preprocessed to increase their quality for further examination. In order to better see the Region-of-Interest inside a picture, contrast enhancement methods like the CLAHE (Contrast Limited Adaptive Histogram Equalization) technique are performed (ROI).

Segmentation techniques are used to separate the object of interest from the background, with thresholding being a popular method. The Otsu method is commonly used to estimate the threshold value, which is then used to accurately separate the object from the background.

The feature extraction stage involves the application of the discrete wavelet transform (DWT) technique, which divides the image into four sub-bands based on the ROI. This results in representations of the horizontal and vertical directions of pixels at different wavelet levels, providing a comprehensive representation of the image.

PCA is used to narrow down the characteristics that are most important for classification from the large feature set acquired following feature extraction. This method reduces the complexity of the dataset by transforming correlated variables into uncorrelated ones.

SVM and K-NN are used by the ML model to categorize the MRI scans. K-NN finds the K closest data points to a new data point based on similarity, then assigns it to the category with the most comparable data points, whereas SVM generates an optimum decision boundary that may split n-dimensional space into distinct classes.

TPR (True positive rate), TNR (false negative rate), PPV (positive predictive value), F-score, accurateness, and AUC (area under the curve) are some of the performance measures used to assess a model's efficacy (shown in Figure 2). These metrics evaluate the model's capability of distinguishing between aberrant and normal AD pictures, as well as confirming the diagnosis of AD in brain MR scans.

Overall, the architecture for an ML model for AD diagnosis involves several crucial stages, each of which plays a crucial role in ensuring the model's accuracy and reliability.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{True Positive Rate (TPR)} = \frac{TP}{TP + FN}$$

$$\text{True Negative Rate (TNR)} = \frac{TN}{TN + FP}$$

$$\text{Positive Predictive Value (PPV)} = \frac{TP}{TP + FP}$$

$$\text{F-Score} = 2\left(\frac{PPV \times TPR}{PPV + TPR}\right)$$

$$\text{Area Under Curve (AUC)} = \int^{+\infty}\left(\frac{TPR(t) \times (1 - TNR(t))}{t}\right)dt$$

Where S represents the fragmented image, G represents the actual data, TP represents the true positive, FN represents the false negative, FP represents the false positive, and TN represents the true negative.

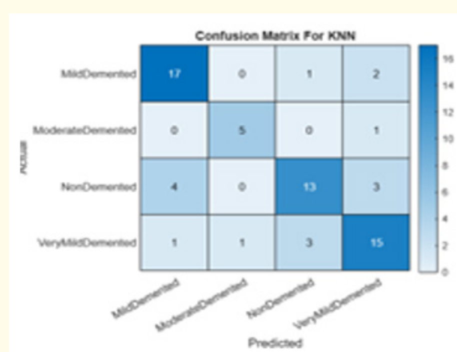

Figure 2: Confusion matrix of KNN.

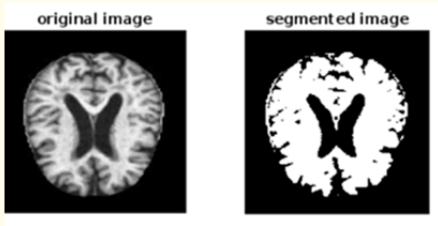

Figure 3: The predicted segmentation of Alzheimer's disease.

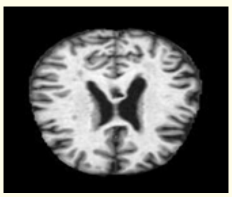

Figure 4: Very mild category AD.

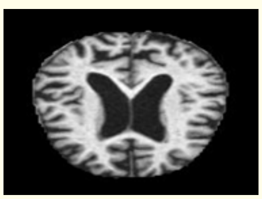

Figure 5: Moderate category AD.

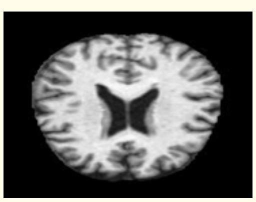

Figure 6: Nondemented.

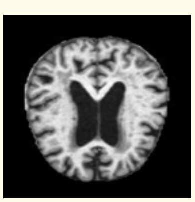

Figure 7: Mild category AD.

Conclusion and Future Enhancement

Alzheimer's is reclassified for performance capability, sensitivities, and early detection of individuals at elevated risk for AD since AD is now recognized as a global health problem. Clinical indicators, body fluids, and imaging examinations are only some of the criteria advocated for a more precise diagnosis of AD. Despite this, AD therapy is still symptomatic, and it has not been shown to improve prognosis. Changing one's diet and exercising more regularly is widely regarded as the first line of defense against Alzheimer's disease (AD) and has been demonstrated in several studies to enhance brain function and slow the progression of the disease without the use of medication.in this. In this work, the proposed method detects AD's different stages and their segmentation effectively.

Future Enhancement

As the results of our experiments show, the qualitative evaluation of brain pictures is important for finding and retrieving important information. Features of AD may be correlated with retrieved characteristics for further classification and analysis. Improve feature selection through in-depth analysis of optimal solutions by expanding the use of nature-inspired optimization. Intending to provide patients with more accurate predictions and recommendations, we plan to expand this study by enhancing learning algorithms and deep learning techniques for an optimal feature retrieval approach for effective classification tasks and by applying similarity measures to images of the brain.

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