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Research paper

Artificial Intelligence Based on Modelling for Prediction of Alzheimer's Disease for Optimal Solution

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Abstract

Alzheimer's disease (AD) is an incurable neurodegenerative disorder that causes progressive brain deterioration. Beginning with mild symptoms, the disease gradually worsens over time, leading to brain tissue damage and eventual death, particularly affecting memory function. This paper introduces a multimodal approach in medical image processing, using machine learning for the classification and detection of AD. The procedure begins with image acquisition, where MRI images may suffer from noise and contrast issues. To address this, a Contrast Limited Adaptive Histogram Equalization algorithm is employed for pre-processing, enhancing image quality. For image segmentation, the k-means algorithm is used, leading to the identification of regions of interest. Feature extraction is accomplished through the Principal Component Analysis (PCA) algorithm. Finally, machine learning methods are used for the classification of processed images. The Support Vector Machine (SVM) with Radial Basis Function (RBF) classifier demonstrates the highest accuracy for diagnosing AD, followed by Artificial Neural Networks (ANN) and Iterative Dichotomiser 3 (ID3). The ANN algorithm exhibits higher sensitivity and F-score compared to other classifiers.

Keywords: *Alzheimer's disease, Image Processing, Classification, SVM, RBF*

1. Introduction

Information takes precedence in decision-making, overshadowing other accessible data. The significance of image processing has witnessed a remarkable surge over the past few decades, finding applications across diverse subfields. The addition of various imaging methods has been a catalyst for the expansive growth of image processing as a discipline. Digital image processing has branched into numerous emerging subfields of research, notably medical image processing, a subset of radiology. In this domain, data gleaned from medical imaging undergoes analysis to determine whether a disease is present or not. Diseases often manifest within the human body, with conditions such as brain tumors, Alzheimer's disease, cardiovascular disease, lung cancer, as well as breast cancer being prominent examples. Medical image processing plays a pivotal role in facilitating the easy testing and treatment of these ailments (1).

Multimodal computing proves to be particularly effective in the detection of Alzheimer's disease (AD). Its efficiency extends to various medical applications, encompassing the detection of lung cancer, breast cancer, as well as the classification and detection of medical images. The primary focus of current research is AD, a type of brain disorder that represents one of the most challenging neurodegenerative conditions in modern medicine (2).

Various medical imaging techniques, such as X-ray tomography (X-ray), computed tomography (CT), positron emission tomography (PET), ultrasound, as well as magnetic resonance imaging (MRI) (3), are commonly used for medical diagnosis. The choice of imaging technique depends on the specific circumstances of the patient and the organ system being examined. In cases of bone problems, it is standard practice to employ X-rays to capture images of the affected area in the patient's body. The ongoing research is centered on diagnosing AD, and magnetic resonance image processing is employed for this purpose due to its superior soft tissue contrast and non-invasive nature.

The pharmaceutical sector's healthcare system effectively caters to the medical requirements of nearly every person in the country. The majority of health conditions stem from dysfunctions within body organs and tissues. Image processing involves creating visual representations of the body interior through various imaging technologies to identify and address issues. Computer software is commonly employed for this purpose, making the subfield of medical image processing increasingly sophisticated and automated (5).

MRI, the non-invasive medical imaging method, generates images of internal organs and human tissues using high magnetic fields as well as radio waves. A proton MRI scanner uses a robust magnetic field to align the protons in the body's hydrogen atoms. Subsequently, radio waves are employed to spin these protons. Once the radio waves cease, the protons realign themselves, generating new radio waves independently. The equipment detects and captures these radio waves, producing detailed images of internal structures. MRI, commonly referred to as magnetic resonance imaging, is the preferred method when high-resolution images are essential, particularly in diagnosing brain abnormalities. This approach allows for imaging without exposing the individual to high-energy radiation, making it safer than many alternative imaging modalities.

By changing the order in which radio waves are obtained, different types of images can be generated. The repetition time (TR) represents the duration between variations in radio wave patterns applied to the same section. Tissues can be distinguished based on their relaxation times, with T1 and T2 referring to longitudinal and transverse relaxation times, respectively. The time constant T1 dictates how quickly stimulated protons return to their equilibrium state, while T2 is crucial for computing the rate at which protons go out of phase or towards equilibrium. Images are categorized by sequences, such as T1-weighted as well as T2-weighted MRI, with cerebrospinal fluid (CSF) used to differentiate them. In T1-weighted imaging, CSF appears black, while T2-weighted images show it as bright (6).

Alzheimer's disease (AD) was first identified by Dr. Alois Alzheimer in 1906, marking the beginning of our understanding of this devastating neurodegenerative condition. Annually, more than two million people worldwide receive a diagnosis of AD, making it one of the most prevalent forms of dementia. This progressive disease leads to the deterioration of the brain over time, starting with mild symptoms that gradually worsen as the condition advances. AD results in damage to and the death of brain cells, with memory being particularly vulnerable to these pathological changes.

Memory loss is the initial and most recognizable sign of AD. However, as the disease progresses and more brain cells are destroyed, additional signs and symptoms emerge, including significant behavioral changes, severe communication problems, and difficulties recalling places, people, or recent incidents. The progression of AD follows a predictable pattern, typically beginning in the hippocampus and entorhinal cortex before spreading to other brain regions. Individuals with advanced AD may reach a point where they are unable to perform daily activities independently, relying entirely on others for their well-being and survival (7).

While memory loss can result from normal aging-related brain changes, the memory impairment in AD is far more severe and progressive. To prevent the disease from worsening, early diagnosis is crucial for patient management and family planning. Although there is presently no known cure for AD, early identification may be able to halt or slow disease progression through various therapeutic interventions and lifestyle modifications. The primary pathological characteristic of AD is the degeneration of brain tissues and nerve cells, accompanied by the formation of amyloid plaques and neurofibrillary tangles (8).

The human brain, a vital and intricate component of the nervous system, consists of three main parts: cerebrum, brainstem, and cerebellum. The cerebrum, situated at the front of the skull, is the largest and most complex component of the nervous system, responsible for various mental functions including cognition, emotion, and voluntary motor control. The cerebrum is divided into two hemispheres, left and right, with the cerebral cortex (grey matter) forming the topmost layer and controlling this area. The cortex, composed of multiple layers, contains millions of nerve cells that process and integrate information from various sources.

"White matter," consisting of long nerve fibers connecting different brain regions, facilitates communication between distant areas of the brain. An early indication of AD is a decrease in grey matter in the cerebral cortex, which can be detected through advanced neuroimaging techniques. Inside the brain, subcortical structures like the hippocampus and basal ganglia play crucial roles in memory formation and motor control, respectively. The cerebrum is further divided into four lobes: frontal, temporal, occipital, and parietal, each responsible for specific cognitive and sensory functions (9).

In AD progression, the temporal lobe is frequently affected first, particularly the hippocampus and surrounding structures involved in memory formation. As illness advances, other brain regions also start to deteriorate in a predictable pattern, spreading from medial temporal structures to association cortices and eventually to primary sensory and motor areas. This degeneration contributes to the overall decline in brain volume associated with AD, which can be quantified using volumetric MRI analysis.

The cerebellum, situated just below the cerebrum, plays a vital role in both movement coordination and balance maintenance. It is responsible for ensuring smooth and precise motor functions, motor learning, and cognitive processing. Additionally, the cerebellum contributes to various autonomic processes, such as digestion, respiration, heart rate regulation, and temperature control, working in concert with the brainstem to maintain homeostasis (10).

The MRI method is particularly useful for providing dynamic diagnostic evaluation of brain volume and structure changes over time. To achieve correct diagnoses, the ability to recognize rapid changes in the brain through dynamic analysis is essential for monitoring disease progression. MRI, frequently referred to as magnetic resonance imaging, is a commonly used technique for accurate diagnosis of AD, especially in its early phases when structural changes may be subtle but detectable.

Reports produced by MRI conducted on individuals with AD often reveal modifications in the hippocampus along with the entorhinal cortex, which are among the first structures affected by the disease process. These changes include volume loss, shape alterations, and signal intensity changes that can be quantified using sophisticated image analysis techniques. Given the potential for errors and inaccuracies associated with human involvement in the diagnostic process, there is a growing need for more effective alternatives, such as automated systems that can provide objective and reproducible measurements.

The integration of MRI features and machine learning algorithms allows for the automatic diagnosis of AD, improving efficiency as well as minimizing potential human-related errors. These automated systems can detect subtle patterns in brain images that may be difficult for human observers to identify consistently. Machine learning approaches can analyze multiple features simultaneously and identify complex relationships between different imaging biomarkers that may not be apparent through traditional visual inspection.

Advanced image processing techniques enable the extraction of quantitative measurements from MRI scans, including volume measurements, cortical thickness analysis, and texture analysis. These measurements can serve as objective biomarkers for disease progression and treatment response monitoring. The development of standardized protocols and quality control measures ensures that these automated systems can be reliably implemented across different clinical settings and imaging platforms.

The literature review section provides an overview of contemporary methods for detecting AD using various computational approaches. The methodology section outlines a machine learning-based multimodal computerized approach for medical imaging, specifically designed for the classification and identification of AD. The process involves acquiring images, particularly MRI images that may initially exhibit noise and contrast issues that need to be addressed through sophisticated preprocessing techniques.

To address imaging artifacts and enhance image quality, the Contrast Limited Adaptive Histogram Equalization algorithm is used for image preprocessing, enhancing overall image quality, and improving the visibility of subtle anatomical structures. The subsequent step involves image segmentation using the k-means clustering technique, resulting in the segmentation of images and the detection of regions of interest that are relevant for AD diagnosis.

Following segmentation, the Principal Component Analysis (PCA) algorithm is employed to obtain relevant features from images, reducing dimensionality while preserving the most important information for classification. The final phase entails classification using various machine learning algorithms, each with different strengths and characteristics that make them suitable for different aspects of the diagnostic process (11).

Medical image processing encompasses several key stages: image preprocessing, segmentation, feature extraction, and classification. Each stage plays a crucial role in the overall diagnostic pipeline, and the quality of each step directly impacts the final diagnostic accuracy. Preprocessing, also referred to as image enhancement, constitutes the initial phase in the medical image processing workflow and is essential for ensuring optimal image quality for subsequent analysis steps.

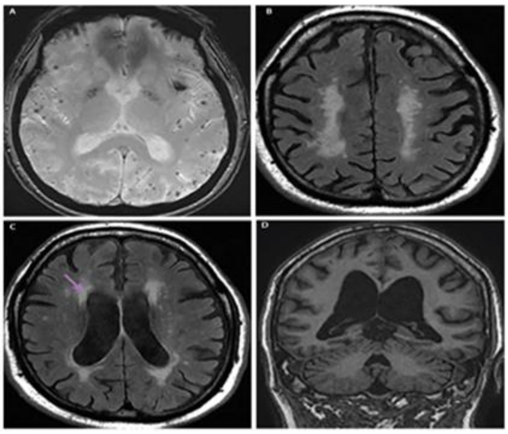

Fig. 1: Different MRI Images of Alzheimer's disease

2. Related Work

Priyanka and Balwinder (12) proposed using the Median Filter method to eliminate noise from medical images. In this approach, a sliding window calculates the median intensity of pixels to determine the resulting pixel intensity. The median filter effectively preserves image edges while minimizing random noise, with each pixel value set to the median of nearby pixel values.

Yousuf et al. (13) explored sequence statistics filters, developing an efficient solution for reducing noise in medical images. Their work demonstrated the use of median and mean filters to obtain noise-free pixel values, proving effective in mitigating noise and reducing visual artifacts, including Rician noise.

Jaya et al. (14) introduced the weighted median filter concept, beneficial for denoising by reducing high-frequency components and eliminating salt and pepper noise. This filtering method maintains edge integrity without distortion by analyzing background and foreground pixel mean values along with contrast.

Khajehnejad et al. (17) extracted relevant features related to AD from MRI volumes and Grey Matter segmentation using voxel morphometric analysis. They used PCA for dimensionality reduction and proposed a mixed manifold learning environment for feature vector analysis in a subspace.

Querbes et al. (18) developed a rapid, accurate, and fully automated assessment of cortical thickness. Their research indicated that cortical atrophy, measured by cortical thickness, may be associated with histopathologically validated abnormalities and disease progression.

Cuingnet et al. (19) demonstrated that cortical thickness testing yields less operator-dependent results compared to hippocampal volume measurements, which are heavily influenced by the administrator.

Liu and Shen (23) used a substantially Bayesian Kernelization technique, proving successful in differentiating between AD and non-converter MCI, though its accuracy in distinguishing between MCI-converter and non-converter was lower.

Luo et al. (25) introduced a deep learning approach based on three-dimensional brain MRI for automatic AD identification. Their system used a Convolutional Neural Network (CNN) for AD diagnosis, considering the 3D brain structure for accurate diagnosis. The CNN comprised three successive processing layer sets, two fully connected layers, and a classification layer.

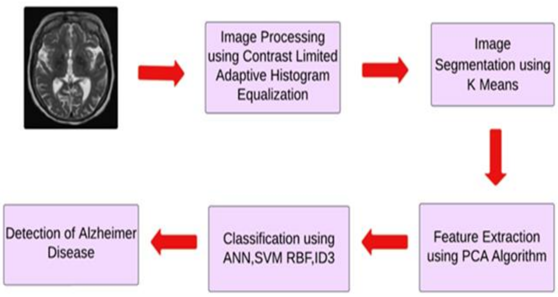

Fig. 2: Workflow overview for detection of Alzheimer disease

3. Methodology

The following section presents a multimodal computing approach for medical imaging that is based on machine learning, specifically for the classification and identification of disease. The process begins with acquiring images, particularly MRI images, which may suffer from noise and contrast issues. To enhance image quality, a Contrast Limited Adaptive Histogram Equalization algorithm is employed for pre-processing. Subsequently, image segmentation is performed utilising the k-means technique, leading to image segmentation and the identification of the region. Useful features are then extracted utilising the Principal Component Analysis (PCA) algorithm. Finally, ML techniques are applied for the classification of images. The overall process is depicted in a block diagram, as shown in Figure 2. This comprehensive approach aims to leverage machine learning techniques to enhance the accuracy and effectiveness of Alzheimer's disease classification and detection in medical imaging.

For accurate image recognition, the procedure of background extraction of the background must adapt to the unique characteristics of the specific image being utilized. In the context of Contrast Limited Adaptive Histogram Equalization, the histogram is constructed for the pixels only of to immediately surrounding it. Contrast Limited Adaptive Histogram Equalization imposes a "clip level" on the local histogram's height, hence restricting the highest contrast enhancement factor and managing the degree of contrast modification. The final image has significantly less noise because of this restriction.

Contrast Limited Adaptive Histogram Equalization is particularly effective in enhancing the appearance of mammography in minute areas, due to the white backdrop it produces, which increases the visibility of lesions to the naked eye. While this method facilitates differentiation between noise as well as signal, the images may still exhibit a certain level of coarseness (26). Despite this, the Contrast Limited Adaptive Histogram Equalization algorithm is considered superior to other methods in improving the visibility of small features in mammography.

In the area of medical image processing, segmentation is an essential approach that attempts to distinguish the unhealthy regions of an image from the healthy ones. This objective is achieved by dividing an image into distinct parts based on the similarity of those segments, making use of texture and intensity in the image. The segmented area of interest can then be utilized to extract essential information rapidly for disease diagnosis.

In medical image segmentation, the k-means clustering technique is commonly employed. During this process, the image is divided into several non-overlapping groups or clusters. Each cluster has a distinct collection of reference points that are assigned to every pixel. The k-means clustering method uses the given k reference points to split the data into k distinct groups (27). This segmentation approach proves effective in isolating regions of interest and facilitating the extraction of relevant information for medical diagnoses.

The method used for feature extraction is PCA (28). PCA is a method used for reducing linear dimensions, which proves beneficial in data analysis and compression (29). PCA is used to identify orthogonal linear combinations of the original data set attributes. This method allows for the combination of features that may not be directly connected. By capturing the most significant variations in the data, PCA helps simplify and represent the information in a more concise form.

By using each feature vector as input, a binary classifier, also known by its acronym, SVM, predicts the class of each vector. This technique establishes two groups, typically labeled as normal along abnormal, and creates a large space or margin between them. The SVM classifier tends to produce excellent results, particularly when combined with the right kernel (30). SVM works well with the Radial Basis Function (RBF) kernel, and the equation for the hyperplane of the linear SVM is as follows:

$$vv.ii + cc = 00 \quad (1)$$

Where, c-real number, i-feature vector and v-normal vector to the hyper-plane.

The classification procedure for medical disease detection often involves the use of artificial neural networks, commonly referred to as ANN. The functioning of an ANN is comparable to the way the human brain works. By examining a collection of previously labeled images, an ANN learns the essential information required to accurately classify an image into a specific category.

The basic building blocks of an artificial neural network (ANN), known as artificial neurons, are made to behave similarly to the real neurons in the human brain. In an ANN, neurons are joined to one another along the periphery of their structures. Neurons and edges can be given weights, and these weights can be changed as the learning process progresses. Most ANNs consist of three layers: the input layer, the hidden layer, and the final output layer. The total number of hidden layers can change, with the possibility of having one or multiple hidden layers or none. Adjustments to the weights within hidden layers are made until the desired outcome is obtained (31).

J. Ross Quinlan is credited with developing the ID-3 approach, also known as Iterative Optimizer-three. This was the first approach to utilize a dynamic decision tree as the basis for the approach. The main metrics used by the ID-3 approach are entropy and a measure of information gain. The iterative process begins with a node and gives each functional attribute an entropy value

In the concepts of entropy and information gain, attributes that produce datasets with the smallest possible error rates are referred to as "split attributes" in the strictest sense. Since target classes cannot be definitively categorised, the algorithm has to run through each step for every single data subset. A branch's terminal nodes are the nonterminal nodes that make up that branch's terminal node. Although they do exist, the split attribute is used to identify whether nodes inside a tree structure are non-terminal (32). The basis of decision tree-based algorithms for classification tasks is the ID-3 technique.

4. Results and Discussion

This experiment utilizes data gathered from Kaggle, which consists of 657 various samples. ML strategies, including ANN, SVM, RBF, and ID3, are employed for classifying the images. Every kind of Alzheimer including moderate disease, Huntington's disease, and normal MRI scans, is collectively referred to as Alzheimer's. A selection of a hundred images per category was made at random from a pool of six hundred images. This dataset and the chosen machine learning techniques aim to contribute to the classification and analysis of disease in medical imaging.

In this work, five parameters, accuracy, specificity, precision, sensitivity, along F-Score are used to compare the performance of various algorithms. These parameters serve as key metrics to evaluate and assess the effectiveness of the machine learning strategies used in the classification and analysis of medical imaging data, particularly in the context of disease.

The SVM, RBF classifier has the best accuracy of all available options for diagnosing Alzheimer's disease, as shown in Figures 03–07. Random ID3 and Artificial Neural Network come in second and third, respectively. in terms of accuracy, sensitivity, specificity, as well as F Score. The ANN technique exhibits significantly higher sensitivity and F-score compared to other classifiers. In terms of specificity, SVM, RBF is superior to other classifiers. These findings highlight the comparative performance of different classifiers in diagnosing disease by the given metrics

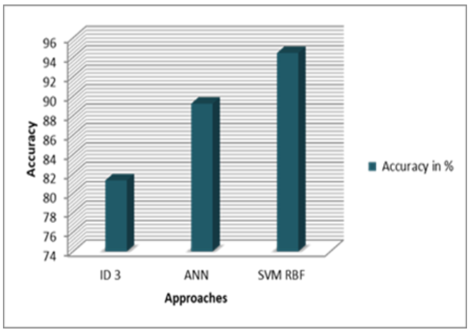

Fig. 3: Comparison graph of Accuracy

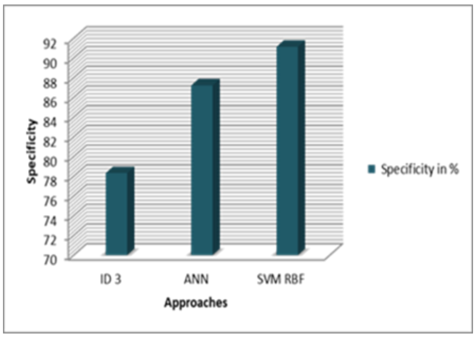

Fig. 4: Comparison graph of Specificity

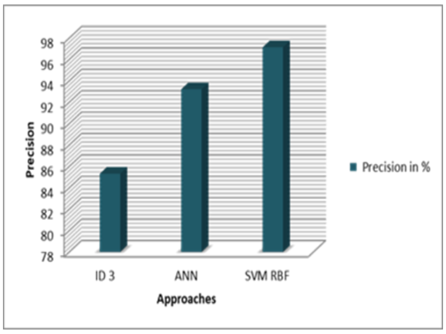

Fig. 5: Comparison graph of Precision

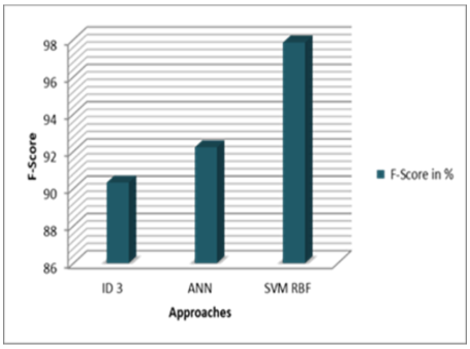

Fig. 6: Comparison graph of F-Score

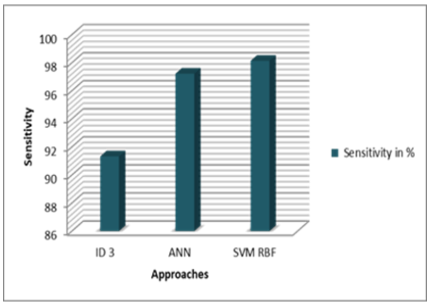

Fig. 7: Comparison graph of Sensitivity

5. Conclusion

The progressive loss of brain function over time, which is known as Alzheimer's disease (AD), initially presents as a mild condition that gradually intensifies. This neurodegenerative disease causes harm to brain cells, especially in people where it affects memory. This disease is primarily diagnosed by memory loss, and more symptoms appear as the disease increases. Slowly disappearing brain cells are the condition. Image processing in the medical field refers to the process of using different imaging technologies to create visual representations of the body's internal functions to diagnose and treat diseases. The present research offers a multimodal computing method for diagnostic imaging that is ML-based, aiming to classify and identify disease. The procedure first involves the acquisition of images, applying the context of Contrast Limited Adaptive Histogram Equalization algorithm as a pre-processor to MRI imaging issues related to noise and contrast, resulting in improved overall quality of the image. The k-means approach is employed to isolate and segment images, detecting areas of interest. Using the PCA approach, relevant features are extracted. In the last stage, images are classified using an ML technique. The SVM, RBF classifier demonstrates the highest accuracy for diagnosing disease, with the ANN and Random ID3 the ANN algorithms exhibiting higher sensitivity and F Score compared to other classifiers.

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Conflicts of Interest

None

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