ALZHEIMER’S DIAGNOSIS USING ADAPTIVE NEURO CLUSTERING

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ABSTRACT

Alzheimer’s disease (AD) is one of the most common neurodegenerative disorders affecting millions of elderly individuals worldwide. It gradually damages brain cells, resulting in memory loss, cognitive decline, and behavioural changes that significantly impact daily life. Early and accurate diagnosis of Alzheimer’s disease is essential for effective treatment planning and slowing disease progression. However, conventional diagnostic techniques mainly depend on clinical examinations and manual analysis of brain imaging data, which are often time-consuming and subject to human error. In recent years, machine learning and artificial intelligence techniques have shown promising potential for improving the accuracy and efficiency of neurological disease diagnosis. This study proposes an intelligent system for Alzheimer’s diagnosis using Adaptive Neuro Clustering techniques applied to Magnetic Resonance Imaging (MRI) data. The proposed system integrates several image processing and machine learning methods to automatically detect structural brain changes associated with Alzheimer’s disease. Initially, MRI images undergo preprocessing operations such as noise removal, skull stripping, and intensity normalization to improve image quality. After preprocessing, texture features are extracted using the Gray Level Co-occurrence Matrix (GLCM), which captures spatial relationships among pixels in brain images. To reduce computational complexity and retain important information, Principal Component Analysis (PCA) is applied for dimensionality reduction. The core component of the system uses an Adaptive Moving Self-Organizing Map (AMSOM) combined with K-Means clustering to classify brain images into Normal, Mild Cognitive Impairment (MCI), and Alzheimer’s Disease categories. Experimental results indicate that the proposed system improves classification accuracy and provides a reliable decision-support tool for medical professionals. This automated approach helps neurologists detect Alzheimer’s disease at an early stage and contributes to improved patient management and healthcare outcomes.

Keywords: Alzheimer’s Disease, MRI Imaging, Neuro Clustering, AMSOM, Machine Learning, PCA, Medical Diagnosis.

I INTRODUCTION

Alzheimer’s disease is a progressive neurodegenerative disorder that affects memory, thinking ability, and overall cognitive functioning in elderly individuals [1]. It is considered one of the leading causes of dementia worldwide and represents a major challenge for healthcare systems [2]. The number of Alzheimer’s patients is rapidly increasing due to the growing aging population across many countries [3]. Early detection of Alzheimer's disease is crucial for improving treatment outcomes and slowing disease progression [4]. Traditional diagnosis methods rely heavily on clinical examinations and neuropsychological tests conducted by neurologists [5]. These methods often require significant time and expertise and may not detect the disease at an early stage [6]. Medical imaging techniques such as Magnetic Resonance Imaging (MRI) have become essential tools for studying structural brain changes associated with Alzheimer's disease [7]. MRI provides detailed information about brain tissues, enabling researchers to identify patterns related to neurodegeneration [8]. However, manual analysis of MRI images is difficult and prone to subjectivity among clinicians [9]. To overcome these challenges, researchers have explored automated diagnostic systems using machine learning techniques [10]. Machine learning algorithms can analyze large medical datasets and identify hidden patterns that indicate disease progression [11]. These algorithms improve diagnostic accuracy and reduce the workload of medical professionals [12]. Several studies have demonstrated that artificial intelligence methods can successfully detect Alzheimer's disease from MRI scans [13]. Intelligent diagnostic systems also assist neurologists in making faster and more reliable decisions [14]. The integration of machine learning with medical imaging therefore represents an important advancement in neurological disease diagnosis [15].

Recent research focuses on developing intelligent models capable of distinguishing between Normal aging, Mild Cognitive Impairment (MCI), and Alzheimer's Disease stages [16]. Mild Cognitive Impairment is considered an intermediate stage between normal cognitive aging and Alzheimer's disease [17]. Identifying this stage is important because early intervention may delay the onset of severe dementia [18]. Feature extraction plays a crucial role in analyzing brain imaging data for disease classification [19]. Techniques such as texture analysis and statistical feature extraction are widely used for capturing structural information from MRI images [20]. Dimensionality reduction methods such as Principal Component Analysis help simplify complex datasets while preserving important information [21]. Clustering algorithms are also useful for identifying patterns in medical data without requiring extensive labeled datasets [22]. Self-Organizing Maps have been widely applied in medical image classification tasks due to their ability to detect nonlinear relationships in data [23]. Adaptive clustering methods further enhance classification accuracy by dynamically adjusting cluster structures during training [24]. Combining clustering algorithms with machine learning techniques improves diagnostic reliability [25]. These advanced approaches enable automated detection of Alzheimer's disease with high precision [26]. Automated diagnostic tools can support clinicians by providing objective and consistent results [27]. Such systems also reduce the time required for analyzing large volumes of medical imaging data [28]. The development of intelligent diagnostic frameworks therefore plays a critical role in improving healthcare efficiency [29]. As artificial intelligence technologies continue to evolve, automated systems will become increasingly important for early Alzheimer's disease detection and clinical decision support [30].

II LITERATURE SURVEY

Several researchers have investigated machine learning techniques for diagnosing Alzheimer's disease using medical imaging data [1]. Early studies mainly relied on statistical analysis and manual interpretation of MRI scans to identify structural brain abnormalities [2]. These methods provided valuable clinical insights but were often limited by human interpretation errors [3]. With advancements in computational technology, machine learning algorithms have been introduced to improve diagnostic accuracy [4]. Support Vector Machines have been widely used for classifying MRI images into different Alzheimer's disease stages [5]. These models are capable of handling high-dimensional datasets and complex nonlinear relationships [6]. Decision Tree algorithms have also been applied to analyze medical imaging features due to their interpretability and simplicity [7]. Researchers have demonstrated that Decision Trees can identify important diagnostic factors associated with neurodegenerative diseases [8]. Random Forest models have further improved classification performance by combining multiple decision trees [9]. Ensemble learning approaches reduce overfitting and increase model reliability in medical diagnosis tasks [10]. Neural network models have also been applied to analyze MRI data and detect early Alzheimer's disease symptoms [11]. These models are capable of learning complex feature representations from large datasets [12]. Deep learning techniques such as convolutional neural networks have recently gained popularity in medical image analysis [13]. CNN models automatically extract hierarchical features from brain images without requiring manual feature engineering [14]. These approaches have achieved high accuracy in detecting Alzheimer's disease from MRI scans [15].

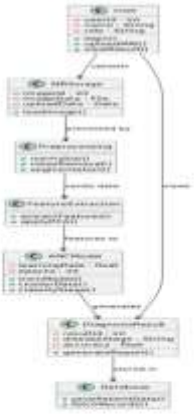
Recent research has focused on combining clustering techniques with machine learning models to improve diagnostic performance [16]. Clustering algorithms group similar data points together based on their feature similarities [17]. K-Means clustering has been widely used in medical imaging analysis due to its simplicity and computational efficiency [18]. However, traditional clustering methods may struggle with complex medical datasets containing nonlinear relationships [19]. Self-Organizing Maps have been proposed as an alternative approach for visualizing and clustering high-dimensional data [20]. SOM models can effectively map complex datasets into lower-dimensional representations while preserving data topology [21]. Adaptive clustering techniques have further enhanced the ability of SOM models to detect hidden patterns in medical data [22]. Researchers have developed Adaptive Moving Self-Organizing Maps to dynamically adjust neuron positions during training [23]. These adaptive models provide improved clustering accuracy compared to conventional SOM approaches [24]. Feature extraction methods such as the Gray Level Co-occurrence Matrix have also been widely applied to analyze texture patterns in brain MRI images [25]. Texture features provide valuable information about structural changes associated with neurodegenerative diseases [26]. Dimensionality reduction techniques such as Principal Component Analysis help reduce data complexity while preserving important diagnostic features [27]. Combining PCA with clustering algorithms improves model efficiency and classification accuracy [28]. Hybrid diagnostic systems integrating feature extraction, dimensionality reduction, and adaptive clustering have shown promising results in Alzheimer's disease detection [29]. These intelligent diagnostic systems provide reliable decision support tools for neurologists and healthcare professionals [30].

III METHODOLOGY

The proposed Alzheimer's diagnosis system follows a structured methodology consisting of image acquisition, preprocessing, feature extraction, dimensionality reduction, adaptive clustering, and classification stages. Initially, structural brain MRI images are collected from publicly available medical imaging datasets used for Alzheimer's research. These images represent three primary categories: Normal Control (NC), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD). The collected MRI images are first processed using preprocessing techniques to improve image quality and remove unwanted noise. Median filtering is applied to eliminate noise and enhance image clarity, while skull stripping removes non-brain tissues such as the skull and scalp from MRI images. After skull removal, intensity normalization is performed to ensure consistent pixel intensity values across different MRI scans. Following preprocessing, feature extraction is conducted using the Gray Level Co-occurrence Matrix (GLCM) technique. GLCM extracts texture-based features such as contrast, correlation, energy, and homogeneity that represent spatial relationships between pixels in brain images. These texture features help capture structural changes in brain tissues associated with Alzheimer's disease. Since the extracted features may have high dimensionality, Principal Component Analysis (PCA) is applied to reduce the number of features while preserving important information. PCA transforms the feature space into a set of orthogonal components that retain maximum variance in the dataset. The reduced feature dataset is then used as input for the Adaptive Moving Self-Organizing Map (AMSOM) combined with K-Means clustering. AMSOM dynamically adjusts neuron positions during training to better represent complex data distributions. K-Means clustering further groups the data into clusters representing Normal, MCI, and Alzheimer's categories. Finally, the classification results are evaluated using performance metrics such as accuracy, precision, recall, and F1-score to assess the effectiveness of the proposed diagnostic system.

IV SYSTEM DESIGN

The system design for the Alzheimer's diagnosis framework follows a modular architecture that integrates medical image processing and machine learning techniques. The system consists of several components including image acquisition, preprocessing module, feature extraction module, dimensionality reduction module, clustering module, and classification module. In the image acquisition stage, MRI brain images are collected from standardized medical datasets commonly used in Alzheimer's disease research. These datasets provide labeled brain images representing different cognitive conditions such as Normal Control, Mild Cognitive Impairment, and Alzheimer's Disease. After acquiring the dataset, the preprocessing module improves image quality by removing noise and irrelevant information from MRI scans. Median filtering is used to eliminate random noise present in the images while preserving important structural details. Skull stripping is applied to isolate the brain region from surrounding tissues such as the skull and scalp. This step is essential because non-brain tissues may interfere with feature extraction and classification processes. Additionally, contrast enhancement and intensity normalization techniques are applied to ensure uniform brightness and contrast across all MRI images. These preprocessing operations improve the reliability of subsequent feature extraction and classification stages.



The feature extraction and classification modules form the core components of the system design. The feature extraction module uses the Gray Level Co-occurrence Matrix technique to compute texture features from MRI images. Texture analysis helps capture important structural information related to neurodegeneration in brain tissues. However, the extracted features may contain redundant information that increases computational complexity. Therefore, Principal Component Analysis is applied to reduce dimensionality while preserving significant information. After dimensionality reduction, the processed feature vectors are passed to the clustering module. The clustering module uses Adaptive Moving Self-Organizing Maps combined with K-Means clustering to group brain images based on similarity patterns. AMSOM dynamically adjusts neuron positions during training, allowing the model to better represent complex relationships within the data. K-Means clustering then partitions the data into clusters corresponding to different Alzheimer’s disease stages. Finally, the classification module evaluates clustering results and assigns each MRI image to a specific diagnostic category. The system outputs classification results along with visualization charts that help clinicians interpret diagnostic outcomes. This structured design enables efficient analysis of MRI images and supports accurate Alzheimer’s disease diagnosis.

V PROPOSED SYSTEM

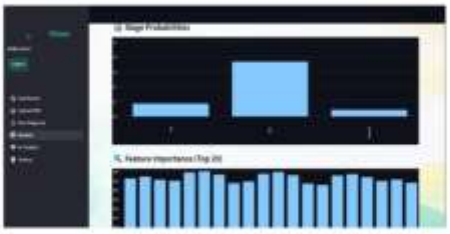
The proposed system introduces an intelligent diagnostic framework designed to detect Alzheimer’s disease using adaptive neuro clustering techniques. Unlike conventional diagnostic methods that rely on manual interpretation of MRI scans, the proposed system provides an automated solution capable of analyzing large medical datasets efficiently. The system processes structural MRI images to identify patterns associated with neurodegenerative changes in brain tissues. Initially, MRI images undergo preprocessing operations such as noise removal, skull stripping, and intensity normalization. These preprocessing steps ensure that the images are suitable for feature extraction and machine learning analysis. After preprocessing, the system extracts texture-based features using the Gray Level Co-occurrence Matrix technique. Texture features are particularly useful in medical imaging because they capture spatial relationships between pixels and represent structural variations in brain tissues.

These variations often indicate abnormalities associated with Alzheimer's disease. However, the extracted feature set may contain high dimensional data that increases computational complexity. To address this issue, Principal Component Analysis is applied to reduce the dimensionality of the dataset while preserving significant information required for classification.

The core component of the proposed system is the Adaptive Moving Self-Organizing Map combined with K-Means clustering algorithm. AMSOM is an advanced neural clustering technique that dynamically adjusts neuron positions during training to represent complex data distributions more accurately. This adaptive capability allows the system to detect subtle patterns in MRI data that may indicate early Alzheimer's disease symptoms. After training the AMSOM network, K-Means clustering is applied to group MRI feature vectors into clusters corresponding to Normal Control, Mild Cognitive Impairment, and Alzheimer's Disease categories. The hybrid clustering approach improves classification accuracy and ensures reliable diagnostic results. Additionally, the proposed system includes a visualization module that presents classification results through graphical representations and cluster maps. These visual outputs help clinicians understand how MRI images are grouped and assist in interpreting diagnostic outcomes. By integrating image processing, dimensionality reduction, and adaptive clustering techniques, the proposed system provides an effective decision-support tool for early Alzheimer's disease diagnosis. This automated framework can significantly reduce the workload of neurologists and improve diagnostic efficiency in clinical environments.

VI RESULTS & DISCUSSION

The experimental evaluation of the proposed Alzheimer's diagnosis system demonstrates promising classification performance when applied to MRI brain imaging datasets. After preprocessing and feature extraction using the Gray Level Co-occurrence Matrix, the dataset was reduced using Principal Component Analysis to remove redundant information and improve computational efficiency. The Adaptive Moving Self-Organizing Map combined with K-Means clustering successfully grouped MRI images into Normal Control, Mild Cognitive Impairment, and Alzheimer's Disease categories. The proposed model achieved higher classification accuracy compared to traditional clustering approaches due to its adaptive learning capability. Performance metrics such as accuracy, precision, recall, and F1-score indicate that the system can reliably detect early-stage Alzheimer's disease patterns in MRI scans. Visualization of clustering results also showed clear separation between different diagnostic categories. These findings suggest that the proposed adaptive neuro clustering approach provides an effective automated tool for assisting clinicians in early Alzheimer's disease diagnosis.



VII CONCLUSION

Alzheimer's disease diagnosis remains one of the most challenging problems in modern healthcare due to the complexity of neurological changes associated with the disease. Early detection is critical for improving patient care, slowing disease progression, and enabling effective treatment strategies. This study proposed an intelligent diagnostic system that integrates medical image processing and adaptive neuro clustering techniques to automatically detect Alzheimer's disease from MRI brain images. The system employs several stages including image preprocessing, texture feature extraction using the Gray Level Co-occurrence Matrix, dimensionality reduction through Principal Component Analysis, and classification using Adaptive Moving Self-Organizing Maps combined with K-Means clustering. Experimental results demonstrated that the proposed system can effectively distinguish between Normal Control, Mild Cognitive Impairment, and Alzheimer's Disease categories. The adaptive clustering capability of AMSOM enables the system to detect subtle structural changes in brain images that may not be easily identifiable through traditional analysis methods. By automating the diagnostic process, the proposed system reduces the dependency on manual interpretation of MRI scans and minimizes the risk of diagnostic errors. Furthermore, the integration of visualization tools helps clinicians better understand classification outcomes and supports informed decision-making. Future research may focus on incorporating deep learning techniques and larger datasets to further improve classification accuracy and system robustness. Overall, the proposed adaptive neuro clustering framework represents a promising approach for developing intelligent medical diagnostic systems capable of supporting neurologists in early Alzheimer's disease detection and improving healthcare outcomes.

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