Alzheimer's Disease+ feature extraction

Introduction

1. Alzheimer’s disease is the most common form of dementia and the fifth-leading cause of death among people over the age of 65. In addition, based on official records, cases of death from Alzheimer’s disease have increased significantly. Hence, early diagnosis of Alzheimer’s disease can increase patients’ survival rates. Machine learning methods on magnetic resonance imaging have been used in the diagnosis of Alzheimer’s disease to accelerate the diagnosis process and assist physicians. However, in conventional machine learning techniques, using handcrafted feature extraction methods on MRI images is complicated, requiring the involvement of an expert user. Therefore, implementing deep learning as an automatic feature extraction method could minimize the need for feature extraction and automate the process. In this study, we AlSaeed et al, (2022)

2. Alzheimer's disease (AD), a neurodegenerative disorder, is a form of dementia. Quick or early diagnosis of AD is essential, but most of the available studies have focused on clinical or survey-based data, leading to data inconsistency as many people feel hesitant or hide information due to disease and societal stigma. Nowadays, current computer-aided support and techniques are mainly based on feature extraction, but due to redundant or similarly extracted features, any specific model is not producing best performance. This paper Shankar et al, (2021)

3. Alzheimer’s disease (AD) is a neurodegenerative disease characterized by cognitive and behavioural impairment that significantly interferes with social and occupational functioning. Mild cognitive impairment (MCI) is a relatively broad clinical condition involving a slight memory deficit, which in many cases represents a transitional state between a cognitively normal (CN) condition and AD. Structural magnetic resonance (sMR) imaging has been widely used in studies related to AD because it provides images with excellent anatomical details and information about structural and contrast changes induced by the disease in the brain. Many published studies restrict their analysis to a few particular regions of the brain and search for structural changes caused by the disease. Recent studies start looking for new AD biomarkers using multiple brain regions and focusing on subtle texture changes in the image. Therefore, this study de Mendonça et al (2023)

4. Alzheimer's disease (AD) is a type of dementia that affects the elderly population. A machine learning (ML) system has been trained to recognize patterns to diagnose AD using an algorithm in an ML system. As a result, Taghavirashidizadeh et al, (2022)

5. Alzheimer's disease (AD) is one of the most serious neurological disorders for elderly people. AD affected patient experiences severe memory loss. One of the main reasons for memory loss in AD patients is atrophy in the hippocampus, amygdala, etc. Due to the enormous growth of AD patients and the paucity of proper diagnostic tools, detection and classification of AD are considered as a challenging research area. Before a Cognitively normal (CN) person develops symptoms of AD, he may pass through an intermediate stage, commonly known as Mild Cognitive Impairment (MCI). MCI is having two stages, namely StableMCI (SMCI) and Progressive MCI (PMCI). In SMCI, a patient remains stable, whereas, in the case of PMCI, a person gradually develops few symptoms of AD. Several research works are in progress on the detection and classification of AD based on changes in the brain. In this paper, we have Hazarika et al (2021)

6. The automatic diagnosis of Alzheimer's disease plays an important role in human health, especially in its early stage. Because it is a neurodegenerative condition, Alzheimer's disease seems to have a long incubation period. Therefore, it is essential to analyse Alzheimer's symptoms at different stages. In this paper, Amini, M. et al (2021)

7. Alzheimer's disease is basically a neurodegenerative disease that is impossible to fully be cured. It is one kind of dementia that occurs along with aging. It not only damages human memory but also affects behavior, movement, and responses to external stimulations. Moreover, AD breaks the connections of the neurons and spoils the brain cells. The worst sequel of AD is death. Though it cannot be properly cured, pre-detection can make an early treatment that might reduce the symptoms. AD can also be detected by analyzing brain images captured from several imaging techniques like Electroencephalogram, Magnetic Resonance Imaging, etc with the aid of machine learning algorithms. Machine learning algorithms are highly successful techniques in the case of processing and classifying the images to determine the stages of AD. In this paper, we Ali et al (2021)

8. Through the last three decades, functional magnetic resonance imaging (fMRI) has provided immense quantities of information about the dynamics of the brain, functional brain mapping, and resting-state brain networks. Despite providing such rich functional information, fMRI is still not a commonly used clinical technique due to inaccuracy involved in analysis of extremely noisy data. However, ongoing developments in deep learning techniques suggest potential improvements and better performance in many different domains. Our main Parmar et al (2020)

9. Morphological networks constructed with structural magnetic resonance imaging (sMRI) images have been widely investigated by exploring interregional alterations of different brain regions of interest (ROI) in the spatial domain for Alzheimer's disease (AD) classification. However, few attentions are attracted to construct a subband-based individual network with the sMRI image in the frequency domain. In order to verify the feasibility of constructing individual networks with subbands and extract features from the subband-based individual network for AD classification, in this study, we Feng et al (2021)

10. Alzheimer's disease (AD) is one of the diseases which brings great influences on the lives of the people. AD classification can serve as a supportive tool to help the doctor to analyze the brain images. One of the important steps in AD classification is feature extraction. Among the feature extraction techniques, Principal Component Analysis (PCA) is a widely used machine learning approach. Nevertheless, it is hard to decide the number of dimensions to be extracted after the transformation. The accuracy of the classification can be greatly affected by the number of dimensions to be chosen. Therefore, this paper has Yew, A. Y. L. et al (2021)

11. The aim of this work is to develop a Computer-Aided-Brain-Diagnosis (CABD) system that can determine if a brain scan shows signs of Alzheimer's disease. Acharya et al (2019)

12. Alzheimer's disease (AD) is a neurodegenerative disease that results in loss of cognitive ability of the patient. Computational intelligence, more specifically Deep Learning, has been a powerful method for AD diagnosis. In this work we

propose a model for AD diagnosis based on deep feature extraction for the classification using magnetic resonance imaging. This model Silva et al (2019)

13. Resting-state functional magnetic resonance imaging (rs-fMRI) has been used to construct functional connectivity (FC) in the brain for the diagnosis and analysis of brain disease. Current studies typically use the Pearson correlation coefficient to construct dynamic FC (dFC) networks, and then use this as a network metric to obtain the necessary features for brain disease diagnosis and analysis. This simple observational approach makes it difficult to extract potential high-level FC features from the representations, and also ignores the rich information on spatial and temporal variability in FC. In this paper, we Gao et al (2022)

14. Mild cognitive impairment (MCI) is the early stage of Alzheimer's disease (AD). In this paper, we Yue et al (2019)

15. Alzheimer’s disease is one of the famous causes of death among elderly. Diagnosis of this disease in the early stage is so difficult by conventional methods. Machine learning methods are one of the best choices for improving the accuracy and performance of diagnosis procedure. The heterogeneous dimensions and structure among the data of this disease have complicated the diagnosis process. Therefore, proper features are needed to solve this complexity. In this research, Hedayati et al (2021)

16. An algorithm is proposed for early detection of Alzheimer's disease and is focused on detecting the condition that would lead to Alzheimer's disease in future. Alzheimer's disease is a prevalent case now and it mostly affects the elderly people. The disease condition makes a person lose his memory and have trouble in doing his day-to-day activities, and progressively the condition leads to death. No treatment is available to completely cure the disease, but it would be beneficial if the disease is detected earlier as the necessary aid can be provided. The Mathew et al (2016)

17. Alzheimer’s disease (AD) is an acute brain disease that affects neural functions and destroys the memories and abilities of human beings. AD causes severe chronic, progressive, and irreversible cognitive declination and brain damage. It

is one of the most common forms of dementia that affects the elderly. Early identification of AD is critical for developing new treatment options. Artificial intelligence (AI) is an excellent tool for detecting AD since these methods are used in clinical settings as a computer-aided diagnosis (CAD) system and play an important role in detecting alterations in brain images for AD detection. This chapter Kapadnis et al (2023)

18. In this paper, we have combined experimental neurophysiologic recording and statistical analysis to investigate the nonlinear characteristic and the cognitive function of the brain. Spectrum and bispectrum analyses are Wang et al (2015)
19. Alzheimer's disease is a neurodegenerative disease in old age, early diagnosis will help to delay the progression of the disease. Presently, the features of brain functional diseases can be obtained with EEG analysis, but the relationship between characteristics of EEG and Alzheimer's disease has not been clearly clarified. In this work, Li et al (2021)

20. The encephalographic (EEG) signal is an electrical signal that measures the brain activity. Due to its noninvasive acquisition process, it is often used to investigate the presence of Alzheimer's disease (AD) or other common forms of neurodegerative disorders due to brain changes, that occur most frequently in older adults. Early detection of prodromal stages of AD, in which an individual has mild but measurable cognitive deficiencies with no significant effect on the functional activity of daily living, may help to reduce mortality and morbidity. This paper Biagetti et al (2021)

21. Positron Emission Tomography plays an important role as an Alzheimer's Disease (AD) early diagnosis tool, and also identifying Mild Cognitive Impairment (MCI) patients. The vast majority of 3D brain image-based computer aided diagnosis methods implemented so far relied simply on voxel intensity, as feature. In this article, Bicacro et al (2012)

22. This letter presents a novel computer-aided diagnosis (CAD) technique for the early diagnosis of Alzheimer's disease (AD) based on non-negative matrix factorization (NMF) analysis applied to single photon emission computed tomography (SPECT) images. A baseline normalized SPECT database containing normalized data for both AD patients and healthy reference patients is selected for this study. The SPECT database is analyzed by applying the Fisher

discriminant ratio (FDR) for feature selection and NMF for feature extraction of relevant components of each subject. The Padilla et al (2010)

23. Neuroimaging is an important research platform that can be very useful for eliciting new understanding on the complicated pathogenesis between genetics and disease phenotypes. Due to the extremely high dimensionality of image and genetic data, and considering the potential joint effect of genetic variants, multivariate techniques have been examined to detect Alzheimers disease (AD) related genetic variants expressed through single-nucleotide polymorphisms (SNPs). However, the image features used in support of those methods are not immediately related to the disease, and the detected genetic markers may not be related to AD. In this study, we Li et al (2017)

24. Speech and language based automatic dementia detection is of interest due to it being non-invasive, low-cost and potentially able to aid diagnosis accuracy. The collected data are mostly audio recordings of spoken language and these can be used directly for acoustic-based analysis. To extract linguistic-based information, an automatic speech recognition (ASR) system is used to generate transcriptions. However, the extraction of reliable acoustic features is difficult when the acoustic quality of the data is poor as is the case with DementiaBank, the largest opensource dataset for Alzheimer's Disease classification. In this paper, we Pan et al (2020)

25. Alzheimer's disease (AD) is the most common form of progressive and irreversible dementia, and accurate diagnosis of AD at its prodromal stage is clinically important. Currently, computer-aided diagnosis of AD and mild cognitive impairment (MCI) using 18F-fluorodeoxy-glucose positron emission tomography (18F-FDG PET) imaging is usually based on low-level imaging features or deep learning methods, which have difficulties in achieving sufficient classification accuracy or lack clinical significance. This research therefore aimed to implement a new feature extraction method known as radiomics, to improve the classification accuracy and discover high-order features that can reveal pathological information. In this study, Li et al (2019)

26. Alzheimer's disease (AD) is a prevalent neurodegenerative disorder that affects a substantial proportion of the population. The accurate and timely prediction of

AD carries considerable importance in enhancing the diagnostic process and improved treatment. This study Mohammad et al (2023)

27. Automatic computer-aided diagnosis (CAD) systems have been widely used in classification of patients who suffer from Alzheimer's disease (AD). This paper presents an automatic CAD system based on histogram feature extraction from single-subject gray matter similarity-matrix for classifying the AD patients from healthy controls (HC) using structural magnetic resonance imaging (MRI) data. The Beheshti et al (2017)

28. The Alzheimer's Disease (AD) has become a major threat of human health with its incidence rate ascending year by year. Early diagnosis of AD is very important for AD patients to keep life quality. The resting-state fMRI (rs-fMRI) which precisely reflects the brain changes on the resting state of individuals provides a quantitative approach, which has been introduced to distinguish AD patients from normal population. In this study, we Mao et al (2017)
29. Early diagnosis and therapeutic intervention for Alzheimer's disease (AD) is currently the only viable option for improving clinical outcomes. Combining structural magnetic resonance imaging (sMRI) and resting-state functional magnetic resonance imaging (rs-fMRI) to diagnose AD has yielded promising results. Most studies assume fixed time lags when constructing functional networks. Since the propagation delays between brain signals are constantly changing, these methods cannot reflect more detailed relationships between brain regions. In this work, we Hu et al (2022)
30. Alzheimer's Disease (AD) is a serious disease that destroys brain and is classified as the most widespread type of dementia. Manual evaluation of image scans relies on visual reading and semi-quantitative investigation of various human brain sections, leading to wrong diagnoses. Neuroimaging plays a significant part in AD detection, using image processing approaches that succeed the drawback of traditional diagnosis methods. Feature extraction is done through Wavelet Transform (WT). Feature selection is an important step in machine learning, where best features set from all possible features is determined. Mutual Information based feature selection (MI) and Correlation-based Feature Selection (CFS) captures the 'correlation' between random variables. Machine Learning techniques are broadly used in a classification problem, as it is simple, effective mechanisms and capability to train to contribute intelligence to the arrangement. Classifiers used in this Anitha et al (2021)

31. Alzheimer's disease is the most common form of age-related dementia. Early-stage diagnosis of Alzheimer is of major importance for the following reasons: Also, easily curable conditions like depression, poor nutrition and drug side effects may cause symptoms like early-stage Alzheimer. Moreover, recently some medications have been developed which successfully attenuate the symptoms and delay the progression of Alzheimer, but to be effective, they need to be applied as soon as possible. However, early-stage diagnosis of Alzheimer is very difficult since the symptoms are very mild and can easily be confounded with effects of normal aging. In this paper, we Plant et al (2011)

32. Alzheimer's Disease (AD) is long-term, progressive, degenerative cognitive illness and one of the causes of dementia. Dementia impairs an individual's ability to think, disrupting normal functioning. Conventional method of diagnosis is collecting symptoms from family members to analyse its impact and stage. MRIs are currently used worldwide for diagnosis and understanding how brain works. With recent advances in applying machine learning to medical images like MRI, it has become a key research discipline amongst experts and analysts. Existing methods of feature extraction from images include CNN, providing large number of feature sets that require great computation power and time to evaluate using traditional machine learning or deep learning algorithms. Consequently, we Bansal et al (2021)

Literature Review

1. AlSaeed et al, (2022) propose a pre-trained CNN deep learning model ResNet50 as an automatic feature extraction method for diagnosing Alzheimer's disease using MRI images. Then, the performance of a CNN with conventional Softmax, SVM, and RF evaluated using different metric measures such as accuracy. The result showed that our model outperformed other state-of-the-art models by achieving the higher accuracy, with an accuracy range of 85.7% to 99% for models with MRI ADNI dataset.

2. Shankar et al, (2021) proposes a novel mutual relationship–based feature selection model with high-altitude acute response like features for the brain-predefined feature areas using magnetic resonance imaging. The mutual relationship between features is used to avoid similar features or create discrimination between different features due to which accuracy gets affected.

In this work, four machine learning classifiers, namely decision tree, support vector machine (SVM), k-nearest neighbor, and Naive Bayes are used for developing predictive model and algorithms. To avoid overfitting in model selection, we have used a 10-fold cross-validation for model training and testing. We collected data set from Alzheimer's disease Neuroimaging Initiative repository. The performance of supervised classifiers was estimated with area under the receiver operating characteristic curve, accuracy, precision, recall, and F1 score assessment measures. The results indicate SVM to be the best performing classifier for prediction (SVM recording the highest average area under curve score of 0.936, accuracy of 94.1%, precision of 96.9%, recall of 96.6%, and F1-score of 96.8%) with 37 discriminant features.

3. de Mendonça et al (2023) proposes a new technique for MR image classification in AD diagnosis using graph kernels constructed from texture features extracted from sMR images. In our method, we first segment the MR brain images into multiple regions with the FreeSurfer. Then, we extract 22 texture features using three methods and define the graph-node attributes as the probability distributions of the extracted features. Next, for each texture feature, we build a graph and define its edge weights as the distances between pairs of node attributes using three distance metrics. After that, we use a threshold-based approach for graph edges removal and create the graph-kernels matrices. Finally, we perform image classification using Support Vector Machines (SVMs) with two graph-kernels. Results of our method have shown better performances for the CN×AD (AUC = 0.92) and CN×MCI (AUC = 0.81) classifications, and worse for the MCI×AD case (AUC = 0.78). This trend is consistent with other published results and makes sense if we consider the concept of Alzheimer's disease continuum from pathophysiological, biomarker and clinical perspectives. Besides allowing the use of different texture attributes for the diagnosis of Alzheimer's, our method uses the graph-kernel approach to represent texture features from different regions of the brain image, which considerably facilitates the image classification task via SVMs. Our results were promising when compared to the state-of-the-art in graph-based AD classification.

4. Taghavirashidizadeh et al, (2022) developing a feature extraction approach is critical for reducing calculation time. The input image in this article is a Two-Dimensional Discrete Wavelet (2D-DWT). The Time-Dependent Power Spectrum Descriptors (TD-PSD) model is used to represent the sub banded wavelet coefficients. The principal property vector is made up of the characteristics of the TD-PSD model. Based on classification algorithms, the collected

characteristics are applied independently to present AD classifications. The categorization is used to determine the kind of tumour. The TD-PSD method was used to extract wavelet sub bands features from three sets of test samples: moderate cognitive impairment (MCI), AD, and healthy controls (HC). The outcomes of three modes of classic classification methods, including KNN, SVM, Decision Tree, and LDA approaches, are documented, as well as the final feature employed in each. Finally, we show the CNN architecture for AD patient classification. Output assessment is used to show the results. Other techniques are outperformed by the given CNN and DT.

5. Hazarika et al (2021) analysed few existing state-of-art works for AD detection and classification, based on different feature extraction approaches. We have summarized the existing research articles with detailed observations. We have also compared the performance and research issues in each of the feature extraction mechanisms and observed that the AD classification using the wavelet transform-based feature extraction approaches might achieve convincing results.

6. Amini, M. et al (2021) the classification is done with several methods of machine learning consisting of -nearest neighbour (KNN), support vector machine (SVM), decision tree (DT), linear discrimination analysis (LDA), and random forest (RF). Moreover, novel convolutional neural network (CNN) architecture is presented to diagnose Alzheimer's severity. The relationship between Alzheimer's patients' functional magnetic resonance imaging (fMRI) images and their scores on the MMSE is investigated to achieve the aim. The feature extraction is performed based on the robust multitask feature learning algorithm. The severity is also calculated based on the Mini-Mental State Examination score, including low, mild, moderate, and severe categories. Results show that the accuracy of the KNN, SVM, DT, LDA, RF, and presented CNN method is 77.5%, 85.8%, 91.7%, 79.5%, 85.1%, and 96.7%, respectively. Moreover, for the presented CNN architecture, the sensitivity of low, mild, moderate, and severe status of Alzheimer patients is 98.1%, 95.2%,89.0%, and 87.5%, respectively. Based on the findings, the presented CNN architecture classifier outperforms other methods and can diagnose the severity and stages of Alzheimer's disease with maximum accuracy.

7. Ali et al (2021) propose an upgraded machine learning algorithm named Modified Random Forest (m-RF) to individualize between normal people and

people with the risk of having Alzheimer's disease. We have achieved an accuracy of 96.43% that is far better than other algorithms like Support Vector Machine, Adaptive Boosting, K-Nearest Neighbors, etc.

8. Parmar et al (2020) purpose is to utilize the potentials of deep learning techniques for fMRI data for clinical use. Approach: We present one such synergy of fMRI and deep learning, where we apply a simplified yet accurate method using a modified 3D convolutional neural networks (CNN) to resting-state fMRI data for feature extraction and classification of Alzheimer's disease (AD). The CNN is designed in such a way that it uses the fMRI data with much less preprocessing, preserving both spatial and temporal information. Results: Once trained, the network is successfully able to classify between fMRI data from healthy controls and AD subjects, including subjects in the mild cognitive impairment (MCI) stage. We have also extracted spatiotemporal features useful for classification. Conclusion: This CNN can detect and differentiate between the earlier and later stages of MCI and AD and hence, it may have potential clinical applications in both early detection and better diagnosis of Alzheimer's disease.

9. Feng et al (2021) propose a novel method to capture correlations of the abnormal energy distribution patterns related to AD by constructing nonsubsampled contourlet subband-based individual networks (NCSINs) in the frequency domain. Specifically, a 2-dimensional representation of the preprocessed sMRI image is firstly reshaped by downsampling and reconstruction steps. Then, the nonsubsampled contourlet transform is performed on the 2-dimensional representation to obtain directional subbands, and each directional subband at one scale is described by a column energy feature vector (CV) regarded as a node of the NCSIN. Subsequently, edge between any two nodes is weighted with connection strength (CS). Finally, the concatenation of node and edge features of the NCSINs at different scales is used as a network feature of the sMRI image for AD classification. Meanwhile, the support vector machine (SVM) classifier with a radial basis function (RBF) kernel is applied for categorizing 680 subjects from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database. Experimental results demonstrate that it is feasible to construct the subband-based individual network in the frequency domain and also show that our NCSIN method outperforms five other state-of-the-art approaches.

10. Yew, A. Y. L. et al (2021) developed a feature extraction method based on principal component and random subspace discriminant analysis (PCRSDA) to extract and select the features. The selection of the number of dimensions was determined by 10-fold cross validation where the features were selected randomly without replacement. The dataset in this paper was collected from Alzheimer's Disease Neuroimaging Initiative (ADNI) database across four time points. The classification results were 81%, 84%, 87% and 87% at time point of 24 months before stable diagnosis, 18 months before stable diagnosis, 12 months before stable diagnosis and at the stable diagnosis time point, respectively.

11. Acharya et al (2019) method utilizes Magnetic Resonance Imaging (MRI) for classification with several feature extraction techniques. MRI is a non-invasive procedure, widely adopted in hospitals to examine cognitive abnormalities. Images are acquired using the T2 imaging sequence. The paradigm consists of a series of quantitative techniques: filtering, feature extraction, Student's t-test based feature selection, and k-Nearest Neighbor (KNN) based classification. Additionally, a comparative analysis is done by implementing other feature extraction procedures that are described in the literature. Our findings suggest that the Shearlet Transform (ST) feature extraction technique offers improved results for Alzheimer's diagnosis as compared to alternative methods. The proposed CABD tool with the ST + KNN technique provided accuracy of 94.54%, precision of 88.33%, sensitivity of 96.30% and specificity of 93.64%. Furthermore, this tool also offered an accuracy, precision, sensitivity and specificity of 98.48%, 100%, 96.97% and 100%, respectively, with the benchmark MRI database.

12. Silva et al (2019) aims to classify AD vs. HC (Healthy Controls). The database used in this project is the Minimal Interval Resonance Imaging in Alzheimer's Disease (MIRIAD), for validation of the proposed method. We select thirty slices from the upper region of the brain, above the eyes, for the apprenticeship in this work. The Convolutional Neural Network (CNN) architecture is designed in three convolutional layers to extract the best features of the selected region. After that, we put the selected attributes in a vector for learning and detection of patterns by another technique of computational intelligence. Finally, the data are partitioned with the 10-folds cross-validation method and trained with the Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbor (K-NN) algorithms with different parameters for evaluation. The results of accuracy are 0.8832, 0.9607 and 0.8745, for the algorithms mentioned above, respectively.

According to a comparative analysis performed with other works of the literature, we can prove the efficiency and reliability of the model for the diagnosis of Alzheimer's disease.

13. Gao et al (2022) construct the Latent Space Representation Network (LSRNet) and use two stages to train the network. In the first stage, an autoencoder is used to extract potential high-level features and inner connections in the dFC representations. In the second stage, high-level features are extracted using two perspective feature parses. Long Short-Term Memory (LSTM) networks are used to extract spatial and temporal features from the local perspective. Convolutional neural networks extract global high-level features from the global perspective. Finally, the fusion of spatial and temporal features with global high-level features is used to diagnose brain disease. In this paper, the proposed method is applied to the ANDI rs-fMRI dataset, and the classification accuracy reaches 84.6% for NC/eMCI, 95.1% for NC/AD, 80.6% for eMCI/lMCI, 84.2% for lMCI/AD and 57.3% for NC/eMCI/lMCI/AD. The experimental results show that the method has a good classification performance and provides a new approach to the diagnosis of other brain diseases.

14. Yue et al (2019) propose a novel voxel-based hierarchical feature extraction (VHFE) method for the early AD diagnosis. First, we parcellate the whole brain into 90 regions of interests (ROIs) based on an automated anatomical labeling (AAL) template. To split the uninformative data, we select the informative voxels in each ROI with a baseline of their values and arrange them into a vector. Then, the first stage features are selected based on the correlation of the voxels between different groups. Next, the brain feature maps of each subject made up of the fetched voxels are fed into a convolutional neural network (CNN) to learn the deeply hidden features. Finally, to validate the effectiveness of the proposed method, we test it with the subset of the AD neuroimaging (ADNI) database. The testing results demonstrate that the proposed method is robust with a promising performance in comparison with the state-of-the-art methods.

15. Hedayati et al (2021) proposed method is introduced in two main steps. In the first step, ensemble of pre-trained auto encoder-based feature extraction modules are used to generate image feature from 3D input image and in the second step convolutional neural network is used to diagnosis Alzheimer’s disease. Three different classification cases, namely; Alzheimer’s Disease (AD) versus Normal Condition (NC), AD versus Mild Cognitive Impairment (MCI) and

MCI versus NC are studied. Obtained results show that accuracy rate for AD/NC, AD/MCI and MCI/NC are 95%, 90% and 92.5%, respectively. Also, for all cases sensitivity and specially sensitivity rates for proposed method confirm that it could be reliable for diagnosis AD in early stage and has less error to detect normal condition.

16. Mathew et al (2016) proposed algorithm uses Alzheimer's Disease (AD), Cognitively Normal (CN), Mild Cognitive Impairment non-convertible (MCInc) and Mild Cognitive Impairment convertible (MCIc) data from the ADNI (Alzheimer's Disease Neuroimaging Initiative) and it involves the process of pre-processing, feature extraction and classification. MCIc leads to Alzheimer's disease at a later stage. A combination of the Discrete Wavelet Transform (DWT) and the Principal Component Analysis (PCA) is used for the feature extraction and further subjected to classification using the Support Vector Machine (SVM). The multiple feature extractions with both the DWT and the PCA together give a better accuracy during classification compared to other algorithms.

17. Kapadnis et al (2023) discusses the recent methods and developments in medical image analysis and image processing for AD detection using AI. The primary objective of this chapter is the development of easy-to-implement methods that promote early AD detection based on deep feature extraction methods. We developed a deep feature extraction methodology with machine learning approaches to achieve a good performance in AD detection. Furthermore, some of the techniques that were used by previous researchers are reviewed. A discussion on the existing state-of-the-art methods, a review of emerging trends, and future research problems will round up the chapter.

18. Wang et al (2015) proposed to extract multiple effective features of electroencephalograph (EEG) signals from Alzheimer's disease (AD) patients and further applied to distinguish AD patients from the normal controls. Spectral analysis based on autoregressive Burg method is first used to quantify the power distribution of EEG series in the frequency domain. Compared to the control group, the relative power spectral density of AD group is significantly higher in the theta frequency band, while lower in the alpha frequency bands. In addition, median frequency of spectrum is decreased, and spectral entropy ratio of these two frequency bands undergoes drastic changes at the P3 electrode in the central-parietal brain region, implying that the electrophysiological behavior in AD brain is much slower and less irregular. In order to explore the nonlinear high

order information, bispectral analysis which measures the complexity of phase-coupling is further applied to P3 electrode in the whole frequency band. It is demonstrated that less bispectral peaks appear and the amplitudes of peaks fall, suggesting a decrease of non-Gaussianity and nonlinearity of EEG in ADs. Notably, the application of this method to five brain regions shows higher concentration of the weighted center of bispectrum and lower complexity reflecting phase-coupling by bispectral entropy. Based on spectrum and bispectrum analyses, six efficient features are extracted and then applied to discriminate AD from the normal in the five brain regions. The classification results indicate that all these features could differentiate AD patients from the normal controls with a maximum accuracy of 90.2%. Particularly, different brain regions are sensitive to different features. Moreover, the optimal combination of features obtained by discriminant analysis may improve the classification accuracy. These results demonstrate the great promise for scape EEG spectral and bispectral features as a potential effective method for detection of AD, which may facilitate our understanding of the pathological mechanism of the disease.

19. Li et al (2021) we hypothesize that there exist default brain variables (latent factors) across subjects in disease processes, decoding latent factor from brain activity contributes to the study of cognitive impairment. To that end, this work proposes to extract characteristics of Alzheimer's disease by combing latent factors of EEG with variational auto-encoder to realize disease identification. Primarily, power spectrum characteristics is investigated, and it is found that the dominant frequency of two groups is different. Further analysis reveals that latent factor distribution of Alzheimer's disease exists obvious differences with normal group in the theta frequency band. Moreover, the latent factors are projected onto the three-dimensional state space and the transient rotation of neural state is found, which shows the dynamic characteristics of latent factors. In addition, Takagi-Sugeno-Kang classifier is adopted, and multiple latent factors are fed into Takagi-Sugeno-Kang classifier for decoding. Compared with linear classifier, Takagi-Sugeno-Kang fuzzy classifier has better performance in classification of energy feature from sub-frequency bands of latent factors. The accuracy of identification could up to 98.10% when the combination of energy features of four frequency bands is used as model input. Collectively, this work provides a feasible tool for identification of neurological dysfunction from the view of latent factors, especially contributing to the diagnosis of Alzheimer's disease.

20. Biagetti et al (2021) proposes an investigation of the classification of AD from EEG signal using robust-principal component analysis (R-PCA) feature extraction algorithm. Four widely used machine learning algorithms such as k-nearest neighbor (kNN), decision tree (DT), support vector machine (SVM), and naive Bayes have been implemented and compared by using a custom dataset composed of 13 subjects healthy or affected by AD in order to asses their classification performance.

21. Bicacro et al (2012) we consider two alternative methods of feature extraction: 3D Haar-like features and histograms of gradient magnitude and orientation; their performance in the classification of AD vs. Cognitively Normal (CN), MCI vs. CN and AD vs. MCI patients is evaluated and compared to the one obtained when using voxel intensity only. Classification is accomplished through Support Vector Machines, after an automatic feature selection step. The features based on histograms of the gradient attained the best results in AD vs. CN discrimination, and 3D Haar-like features improved performance in all three classification tasks. These improvements encourage further investigation on these extraction strategies.

22. Padilla et al (2010) main goal of these preprocessing steps is to reduce the large dimensionality of the input data and to relieve the so called “curse of dimensionality” problem. The resulting NMF-transformed set of data, which contains a reduced number of features, is classified by means of a support vector machines based classification technique (SVM). The proposed NMF + SVM method yields up to 94% classification accuracy, with high sensitivity and specificity values (upper than 90%), becoming an accurate method for SPECT image classification. For the sake of completeness, comparison between another recently developed principal component analysis (PCA) plus SVM method and the proposed method is also provided, yielding results for the NMF + SVM approach that outperform the behavior of the reference PCA + SVM or conventional voxel-as-feature (VAF) plus SVM methods.

23. Li et al (2017) propose an ensemble model-based framework for firstly extracting 50 region-based image features whose values are predicted by base learners trained on raw neuroimaging morphological variables. This task is followed by performing sparse Partial Least Squares regression (sPLS) method on the extracted 50 AD related image features and pre-selected 1508 SNPs to detect the significant SNPs associated with the extracted image features. Instead of

modeling a direct link between genetic variants and disease label, we captured disease information indirectly.

24. Pan et al (2020) explore how to improve the robustness of the acoustic feature extraction by using time alignment information and confidence scores from the ASR system to identify audio segments of good quality. In addition, we design rhythm-inspired features and combine them with acoustic features. By classifying the combined features with a bidirectional-LSTM attention network, the F-measure improves from 62.15% to 70.75% when only the high-quality segments are used. Finally, we apply the same approach to our previously proposed hierarchical-based network using linguistic-based features and show improvement from 74.37% to 77.25%. By combining the acoustic and linguistic systems, a state-of-the-art 78.34% F-measure is achieved on the DementiaBank task.

25. Li et al (2019) 18F-FDG PET and clinical assessments were collected in a cohort of 422 individuals [including 130 with AD, 130 with MCI, and 162 healthy controls (HCs)] from the Alzheimer's Disease Neuroimaging Initiative (ADNI) and 44 individuals (including 22 with AD, and 22 HCs) from Huashan Hospital, Shanghai, China. First, we performed a group comparison using a two-sample Student's t test to determine the regions of interest (ROIs) based on 30 AD patients and 30 HCs from ADNI cohorts. Second, based on two time scans of 32 HCs from ADNI cohorts, we used Cronbach's alpha coefficient for radiomic feature stability analyses. Pearson's correlation coefficients were regarded as a feature selection criterion, to select effective features associated with the clinical cognitive scale [clinical dementia rating scale in its sum of boxes (CDRSB); Alzheimer's disease assessment scale (ADAS)] with 500-times cross-validation. Finally, a support vector machine (SVM) was used to test the ability of the radiomic features to classify HCs, MCI and AD patients.As a result, we identified brain regions which were mainly distributed in the temporal, occipital and frontal areas as ROIs. A total of 168 radiomic features of AD were stable (alpha > 0.8). The classification experiment led to maximal accuracies of 91.5%, 83.1% and 85.9% for classifying AD versus HC, MCI versus HCs and AD versus MCI .The research in this paper proved that the novel approach based on high-order radiomic features extracted from 18F-FDG PET brain images that can be used for AD and MCI computer-aided diagnosis.

26. Mohammad et al (2023) provides a thorough examination of AD prediction using the VGG19 deep learning model. The primary objective of this study is to investigate the effectiveness of feature fusion and optimization techniques in enhancing the accuracy of classification. The generation of a comprehensive feature map is achieved through the fusion of features that have been extracted from the fc7 and fc8 layers of VGG19. Several machine learning algorithms are employed to classify integrated features and recognize AD. The amalgamated feature map demonstrates a significant level of accuracy of 98% in the prognostication of AD, outperforming present cutting-edge methodologies. In this study, a methodology is utilized that makes use of the whale optimization algorithm (WoA), a metaheuristic approach to optimize features through feature selection. Feature optimization aims to eliminate redundant features and enhance the discriminatory power of the selected features. Following the optimization procedure, the F-KNN algorithm attained a precision level of 99%, surpassing the present state-of-the-art (SOTA) results reported in the current literature.

27. Beheshti et al (2017) proposed CAD system is composed of five stages. In the first stage, segmentation is employed to perform pre-processing on the MRI images, and segment into gray matter, white matter, and cerebrospinal fluid using the voxel-based morphometric toolbox procedure. In the second stage, gray matter MRI scans are used to construct similarity-matrices. In the third stage, a novel statistical feature-generation process is proposed, utilizing the histogram of the individual similarity-matrix to represent statistical patterns of the respective similarity-matrices of different size and order into fixed-size feature-vectors. In the fourth stage, we propose to combine MRI measures with a neuropsychological test, the Functional Assessment Questionnaire (FAQ), to improve the classification accuracy. Finally, the classification is performed using a support vector machine and evaluated with the 10-fold cross-validation strategy. We evaluated the proposed method on 99 AD and 102 HC subjects from the J-ADNI. The proposed CAD system yields an 84.07% classification accuracy using MRI measures and 97.01% for combining MRI measures with FAQ scores, respectively. The experimental results indicate that the performance of the proposed system is competitive with respect to state-of-the-art techniques reported in the literature.

28. Mao et al (2017) proposed a method to find the most distinctive features identifying AD patients from rs-fMRI images. The ALFF and ReHo parameters based on pre-processed rs-fMRI data were extracted, and some key parameters

of the brain functional network based on graph theory were calculated. Then we tested the recognition performance of different classifiers, and the best classification algorithm, that is, Support Vector Machine (SVM) with linear-kernel are selected. Finally through a recursive feature selection procedure, we got the most distinctive feature set. Additionally, this study also implies that there may be several changes in some particular ROIs of the brain during the AD development.

29. Hu et al (2022) use a deep learning-based Granger causality estimator for brain connectivity construction. It exploits the strength of long short-term memory in ever-changing time series processing. This research involves data analysis from sMRI and rs-fMRI. We use sMRI to analyze the cerebral cortex properties and use rs-fMRI to analyze the graph metrics of functional networks. We extract a small subset of optimal features from both types of data. A support vector machine (SVM) is trained and tested to classify AD (n = 27) from healthy controls (n = 20) using rs-fMRI and sMRI features. Using a subset of optimal features in SVM, we achieve a classification accuracy of 87.23% for sMRI, 78.72% for rs-fMRI, and 91.49% for combined sMRI with rs-fMRI. The results show the potential to identify AD from healthy controls by integrating rs-fMRI and sMRI. The integration of sMRI and rs-fMRI modalities can provide supplemental information to improve the diagnosis of AD relative to either the sMRI or fMRI modalities alone.

30. Anitha et al (2021) proposed work are Artificial Neural Network (ANN), Random Forest, Convolutional Neural Network (CNN), and Wavelet-based CNN. The superior ability of ANN is high-speed processing achieved through extensive parallel implementation, and this has emphasized necessity of research in this field. CNN has encouraged tackling this issue. This work proves that wavelet-based CNN performs better with a classification accuracy of 91.87%, the sensitivity of 0.94 for normal brain and 0.88 for AD affected brain, the positive predictive value of 0.91 for normal brain and 0.92 for AD affected brain, and F measure of 0.92 for normal brain and 0.90 for AD affected brain on ADNI MRI dataset of the human brain in detecting AD.

31. Plant et al (2011) introduce a bootstrapping-based feature extraction technique to identify early-stage Alzheimer's disease from resting-state functional resonance images. Our experiments demonstrate that subjects with early-stage Alzheimer's disease can be distinguished with an accuracy of 79% from age-

matched healthy subjects using a support vector machine on the extracted features.

32. Bansal et al (2021) propose an Optimised Crow Search Algorithm (OCSA) for early detection of AD based on raw MRI image features, yielding a highly representative dense embedding. The mapping learned between this embedding and image labels resulted in diagnosing 98.62% accuracy.

References

1. AlSaeed, D., & Omar, S. F. (2022). Brain MRI analysis for Alzheimer's disease diagnosis using CNN-based feature extraction and machine learning. Sensors, 22(8), 2911.

2. Shankar, V. G., Sisodia, D. S., & Chandrakar, P. (2022). A novel discriminant feature selection–based mutual information extraction from MR brain images for Alzheimer's stages detection and prediction. International Journal of Imaging Systems and Technology, 32(4), 1172-1191.

3. de Mendonça, L. J. C., Ferrari, R. J., & Alzheimer's Disease Neuroimaging Initiative. (2023). Alzheimer's disease classification based on graph kernel SVMs constructed with 3D texture features extracted from MR images. Expert Systems with Applications, 211, 118633.

4. Taghavirashidizadeh, A., Sharifi, F., Vahabi, S. A., Hejazi, A., SaghabTorbati, M., & Mohammed, A. S. (2022). WTD-PSD: presentation of novel feature extraction method based on discrete wavelet transformation and time-dependent power spectrum descriptors for diagnosis of alzheimer's disease. Computational Intelligence and Neuroscience, 2022.

5. Hazarika, R. A., Maji, A. K., Sur, S. N., Paul, B. S., & Kandar, D. (2021). A survey on classification algorithms of brain images in Alzheimer's disease based on feature extraction techniques. IEEE Access, 9, 58503-58536.

6. Amini, M., Pedram, M., Moradi, A., & Ouchani, M. (2021). Diagnosis of Alzheimer's disease severity with fMRI images using robust multitask feature extraction method and convolutional neural network (CNN). Computational and Mathematical Methods in Medicine, 2021, 1-15.

7. Ali, M. S., Islam, M. K., Haque, J., Das, A. A., Duranta, D. S., & Islam, M. A. (2021, April). Alzheimer's disease detection using m-random forest algorithm with optimum features extraction. In 2021 1st International Conference on Artificial Intelligence and Data Analytics (CAIDA) (pp. 1-6). IEEE.

8. Parmar, H., Nutter, B., Long, R., Antani, S., & Mitra, S. (2020). Spatiotemporal feature extraction and classification of Alzheimer's disease using deep learning 3D-CNN for fMRI data. Journal of Medical Imaging, 7(5), 056001-056001.

9. Feng, J., Zhang, S. W., Chen, L., Xia, J., & Alzheimer's Disease Neuroimaging Initiative. (2021). Alzheimer's disease classification using features extracted from nonsubsampled contourlet subband-based individual networks. Neurocomputing, 421, 260-272.

10. Yew, A. Y. L., & Rahim, M. S. M. (2021). Feature extraction of Alzheimer's disease classification based on principal component and random subspace discriminant analysis. J. Theor. Appl. Inf. Technol, 99, 61.

11. Acharya, U. R., Fernandes, S. L., WeiKoh, J. E., Ciaccio, E. J., Fabell, M. K. M., Tanik, U. J., ... & Yeong, C. H. (2019). Automated detection of Alzheimer's disease using brain MRI images–a study with various feature extraction techniques. Journal of Medical Systems, 43, 1-14.

12. Silva, I. R., Silva, G. S., de Souza, R. G., dos Santos, W. P., & Fagundes, R. A. D. A. (2019, July). Model based on deep feature extraction for diagnosis of Alzheimer's

disease. In 2019 international joint conference on neural networks (IJCNN) (pp. 1-7). IEEE.

13. Gao, L., Hu, Z., Li, R., Lu, X., Li, Z., Zhang, X., & Xu, S. (2022). Multi-perspective feature extraction and fusion based on deep latent space for diagnosis of Alzheimer's diseases. Brain Sciences, 12(10), 1348.

14. Yue, L., Gong, X., Li, J., Ji, H., Li, M., & Nandi, A. K. (2019). Hierarchical feature extraction for early Alzheimer's disease diagnosis. IEEE Access, 7, 93752-93760.

15. Hedayati, R., Khedmati, M., & Taghipour-Gorjikolaie, M. (2021). Deep feature extraction method based on ensemble of convolutional auto encoders: Application to Alzheimer's disease diagnosis. Biomedical Signal Processing and Control, 66, 102397.

16. Mathew, J., Mekkayil, L., Ramasangu, H., Karthikeyan, B. R., & Manjunath, A. G. (2016, December). Robust algorithm for early detection of Alzheimer's disease using multiple feature extractions. In 2016 IEEE Annual India Conference (INDICON) (pp. 1-6). IEEE.

17. Kapadnis, M. N., Bhattacharyya, A., & Subasi, A. (2023). Artificial intelligence-based Alzheimer's disease detection using deep feature extraction. In Applications of artificial intelligence in medical imaging (pp. 333-355). Academic Press.,

18. Wang, R., Wang, J., Li, S., Yu, H., Deng, B., & Wei, X. (2015). Multiple feature extraction and classification of electroencephalograph signal for Alzheimers' with spectrum and bispectrum. Chaos: An Interdisciplinary Journal of Nonlinear Science, 25(1).

19. Li, K., Wang, J., Li, S., Yu, H., Zhu, L., Liu, J., & Wu, L. (2021). Feature extraction and identification of Alzheimer's disease based on latent factor of multi-channel EEG. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 29, 1557-1567.

20. Biagetti, G., Crippa, P., Falaschetti, L., Luzzi, S., & Turchetti, C. (2021). Classification of Alzheimer's disease from EEG signal using robust-PCA feature extraction. Procedia Computer Science, 192, 3114-3122.

21. Bicacro, E., Silveira, M., & Marques, J. S. (2012, September). Alternative feature extraction methods in 3D brain image-based diagnosis of Alzheimer's disease. In 2012 19th IEEE international conference on image processing (pp. 1237-1240). IEEE.

22. Padilla, P., Górriz, J. M., Ramírez, J., Lang, E. W., Chaves, R., Segovia, F., ... & Álvarez, I. (2010). Analysis of SPECT brain images for the diagnosis of Alzheimer's disease based on NMF for feature extraction. Neuroscience letters, 479(3), 192-196.

23. Li, C., Fang, C., Adjouadi, M., Cabrerizo, M., Barreto, A., Andrian, J., ... & Loewenstein, D. (2017, October). A Neuroimaging Feature Extraction Model for Imaging Genetics with Application to Alzheimer's Disease. In 2017 IEEE 17th International Conference on Bioinformatics and Bioengineering (BIBE) (pp. 15-20). IEEE.,

24. Pan, Y., Mirheidari, B., Reuber, M., Venneri, A., Blackburn, D., & Christensen, H. (2020, October). Improving detection of Alzheimer's Disease using automatic speech recognition to identify high-quality segments for more robust feature extraction. In Proceedings of Interspeech 2020 (pp. 4961-4965). International Speech Communication Association (ISCA).

25. Li, Y., Jiang, J., Lu, J., Jiang, J., Zhang, H., & Zuo, C. (2019). Radiomics: a novel feature extraction method for brain neuron degeneration disease using 18F-FDG PET imaging and its implementation for Alzheimer's disease and mild cognitive impairment. Therapeutic advances in neurological disorders, 12, 1756286419838682.

26. Mohammad, F., & Al Ahmadi, S. (2023). Alzheimer's Disease Prediction Using Deep Feature Extraction and Optimization. Mathematics, 11(17), 3712.

27. Beheshti, I., Maikusa, N., Matsuda, H., Demirel, H., & Anbarjafari, G. (2017). Histogram-based feature extraction from individual gray matter similarity-matrix for Alzheimer's disease classification. Journal of Alzheimer's disease, 55(4), 1571-1582.

28. Mao, S., Zhang, C., Gao, N., Wang, Y., Yang, Y., Guo, X., & Ma, T. (2017, July). A study of feature extraction for Alzheimer's disease based on resting-state fMRI. In 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC) (pp. 517-520). IEEE.

29. Hu, Y., Wen, C., Cao, G., Wang, J., & Feng, Y. (2022). Brain network connectivity feature extraction using deep learning for Alzheimer's disease classification. Neuroscience Letters, 782, 136673.

30. Anitha, M., Karpagam, V., & Selvy, P. T. (2021). Diagnostic framework for automatic classification and visualization of alzheimer's disease with feature extraction using wavelet transform. NeuroQuantology, 19(7), 84.

31. Plant, C., Sorg, C., Riedl, V., & Wohlschläger, A. (2011, August). Homogeneity-based feature extraction for classification of early-stage alzheimer's disease from functional magnetic resonance images. In Proceedings of the 2011 workshop on Data mining for medicine and healthcare (pp. 33-41).

32. Bansal, S., Rustagi, A., & Kumar, A. (2021). Alzheimer's disease diagnosis based on feature extraction using optimised crow search algorithm and deep learning. International Journal of Computer Applications in Technology, 65(4), 325-333.,