International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 06 June 2024
Page No: 1537- 1550
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0211

Certain Studies on Alzheimer's disease: A Comprehensive Review

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Abstract

The brain serves as the central control centre for our body, and as time progresses, an increasing number of new brain diseases are being identified. A brain disease is any medical problem or disorder that interferes with the brain's normal functioning. This review briefs about various types of deep learning models for neurological disorders, in addition to neurodegenerative conditions like Parkinson's and Alzheimer's. In addition to various dataset identifiers commonly used as the primary source of brain disease data in the reviewed studies, forty other methodologies are examined. AUC, sensitivity, specificity, accuracy, and other performance evaluation parameters have also been addressed and recorded. The key findings from the reviewed articles are briefly summarized, and several major issues regarding machine learning and deep learning-based diagnostic approaches for brain diseases are discussed.

Keywords: *Traumatic Brain Injury (TBI), Alzheimer's Disease (AD), Deep Learning, ConvNet.*

1. Introduction

A wide range of conditions that affect the brain's structure or function fall under the category of brain disorders. Congenital, acquired, degenerative, or traumatic factors can contribute to various brain disorders. Common examples encompass Alzheimer's disease, Parkinson's disease, epilepsy, and traumatic brain injury (TBI). The prevalence of Alzheimer's disease (AD) is estimated to be around 5% among individuals aged 65 and older, escalating to an astonishing 30% among those over 85 years old in developed nations. Projections suggest that by 2050, approximately 640 million people will receive a diagnosis of AD. The progression of Alzheimer's disease exhibits significant variability among individuals, with each person manifesting distinct symptoms at varying times. Distinguishing between different stages of the disease presents a challenge for researchers, primarily due to the limited variance between classes in various stages. Consequently, scientists have redirected their focus towards investigating the brain alterations linked with Alzheimer's disease to acquire a more profound comprehension of its diverse stages and the fundamental changes propelling its advancement. Early AD detection is imperative for formulating treatment approaches to decelerate its progression. Mild cognitive impairment (MCI) acts as the intermediary phase bridging normal cognitive function and dementia. Overall, the research scope in Alzheimer's disease is multidisciplinary and requires collaboration across various scientific fields, including neuroscience, genetics, biochemistry, neuroimaging, clinical psychology, geriatrics, and public health, to advance our understanding of the disease and develop effective strategies for prevention, diagnosis, and treatment.

2. A Detail Study on Alzheimer's disease Using Deep Learning Approaches

Deep Learning, a popular technique used to train the machine/ computer to learn from experience classify, and identify data and images similar to the human brain. The general process flow architecture of Alzheimer's detection and classification which is shown in Figure 1.

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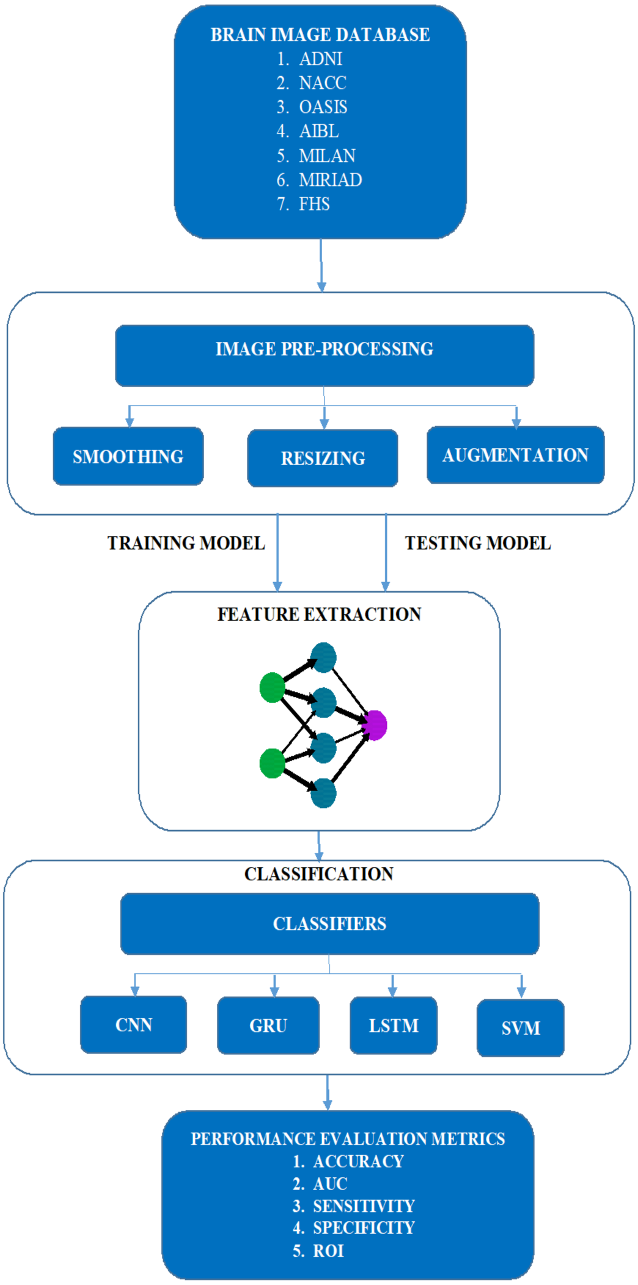

Figure 1 Process Flow Architecture of Alzheimer's Detection and Classification

3. Inception-v4 and ResNet

Inception-v4 and ResNet are well-known deep learning architectures used in computer vision tasks. The comparison suggests evaluating this model's [1] performance against these established architectures on the same OASIS dataset. This dataset is used to train and evaluate the models. The choice of dataset is crucial as it determines the generalization capability of the models to new, unseen data. Four measures are mentioned for assessing and contrasting the models: accuracy, recall, precision, and F1-score. Convolutional Neural Networks (ConvNets or CNNs) have remarkably succeeded in the image and video analysis tasks. When dealing with 3D data, such as medical imaging volumes (e.g., brain MRI scans), extending CNNs to three dimensions becomes essential. 3D ConvNets have displayed potential in medical imaging tasks, including the analysis of brain scans for Alzheimer's disease diagnosis and progression tracking. These models leverage the spatial information in three dimensions to capture intricate patterns indicative of pathological changes in the brain. It examines the effects of preprocessing techniques on the performance of this 3D ConvNet. Preprocessing steps may include normalization, augmentation, or other data transformations. The study [2] assesses how these steps impact the network's ability to extract relevant features and improve classification accuracy. The impact of data partitioning strategies is explored to understand how the choice of training, validation, and test sets influences the model's performance. Different partitioning methods, such as stratified sampling or k-fold cross-validation, are likely considered and evaluated to ensure robustness and generalizability. The research explores how the performance of the 3D ConvNet is affected by the size of the dataset. This analysis entails conducting experiments using different amounts of training data to evaluate the model's ability to generalize across datasets of various sizes and to identify any potential limitations or advantages linked to dataset size. Overall, the paper's contributions suggest advancements in the architectural design of 3D ConvNets for AD classification and a comprehensive understanding of factors affecting model performance. The developed approach, which utilized the random data partitioning method, achieved a faultless 100% for AD detection with a false alarm rate of 2.4% and an accuracy of 98.74% on the examination dataset. The study's empirical results also revealed that the selection of hyperparameters, preprocessing methods, subject-specific data partitioning, and dataset size influences the deep learning classifier's overall performance. A

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reliable classification technique that employs a Deep Neural Network and Random Forest feature selection. To improve the model's adaptability and efficacy, CNN is trained on a broad cohort that includes all four categories of the classification problem: HC, AD, MCI, and cMCI, and assessed [3] the resilience of this method, considering both precision and recall metrics. The study investigated the effectiveness of a novel strategy based on fuzzy logic and confirmed the reliability of the MMSE score in the classification of Alzheimer's disease. One often used cognitive screening tool is the Mini-Mental State Examination (MMSE) score. It assesses diverse cognitive functions, encompassing arithmetic, memory, and orientation. Widely employed in clinical contexts, the MMSE score provides a quick evaluation of an individual's cognitive status, aiding in detecting potential cognitive impairments or conditions like Alzheimer's. Higher scores on the MMSE, ranging from 0 to 30, signify more muscular cognitive function.

4. Recurrent Neural Network (RNN)

This one improves the existing predictive model, placing a particular emphasis on early diagnosis of AD. For the modelling of early detection of AD, the use of [4] Recurrent Neural Network (RNN) models is considered. This system offers 17 characteristics related to user demographics, medical history, and frequently asked questions, making it easy for users to self-diagnose. Timely and personalized medical guidance is available for individuals in the preclinical or early stages of probable Alzheimer's Disease through ADEDS. The LSTM RNN technique shows significant potential compared to models using neural networks, Bayesian networks, and tree-based algorithms. The testing accuracy peaks at around 86%, with an average testing accuracy hovering around 83.5%. Notably, the RNN AD-EDM outperforms other approaches by approximately 5%. In this study [5], utilized the convolutional neural network architecture known as AlexNet to classify different stages of Alzheimer's disease using fMRI datasets. The deep learning algorithm effectively categorized five distinct stages: standard healthy control (HC), significant memory concern (SMC), early mild cognitive impairment (EMCI), late cognitive mild impairment (LMCI), and AD. Leveraging GPU high-performance computing, our model showcased notable enhancements in classification accuracy. Following meticulous preprocessing of fMRI data, features were extracted and learned across multiple levels using the AlexNet model. The experimental outcomes revealed a notable average accuracy of 97.63%. Subsequently, the model underwent testing on independent datasets to assess class-specific accuracy, achieving 94.97% for AD, 95.64% for EMCI, 95.89% for LMCI, 98.34% for NC, and 94.55% for SMC. Furthermore, the AUC values for the ROC curves have been calculated as follows: 0.9334 for the SMC class, 0.9486 for the NC class, 0.9500 for the LMCI class, 0.9491 for the EMCI class, and 0.9422 for the AD class. In this study [6], initially the multiple deep 3D-CNNs have been constructed on various local image patches to condense each PET brain image into higher-level features. Subsequently, an upper high-level 2D-CNN, followed by a unique softmax layer to recognize the class, which integrates the high-level features extracted from multiple functions. This process generates latent multifunction correlation features for the corresponding image patches, facilitating classification. This method separately extracts comprehensive multi-level and multifunction features from various imaging functions, ensuring robustness against scale and rotation variations.

5. Methodology

The classification methodology [7] utilizes multiple cluster dense CNNs (DenseNets) to capture diverse local features from MR brain images, which are subsequently integrated for AD classification. The approach involves an initial step wherein the entire brain image is partitioned into distinct local regions, and several 3D patches are extracted from each region. In the subsequent stage, these patches are organized into clusters using the K-Means clustering method. Following this, a DenseNet is constructed to learn the distinctive patch features for each cluster, and the features learned from discriminative clusters within each region are combined for the classification task. Finally, the results from classification in different local areas are amalgamated to enhance the overall image classification. This method enables a gradual learning process, transitioning from MRI features at the local patch level to the global image level within the classification framework. Notably, preprocessing MRI images does not necessitate rigid registration or segmentation. Additionally, the technique's assessment entails the examination of T1-weighted MRIs obtained from a cohort of 831 participants, of which 199 were examined with AD, 403 with MCI, and 229 were NC patients, according to the ADNI database. The experimental results demonstrate the efficacy of this strategy with a remarkable AUC (Area Under the Curve) of 92.4% for AD vs. NC classification and a significant accuracy rate of 89.5%. Furthermore, the technique confirms its promising performance in classification tasks with an impressive accuracy of 73.8% and an AUC of 77.5% for MCI vs. NC classification. A CNN-based deep learning approach is developed in this work [8] to predict MCI-AD conversion using MRI data accurately. MRI scans are first prepared by processing them by applying age correction. Local patches are then taken from these photos and arranged into 2.5 dimensions. A CNN is trained with these patches from AD and NC to identify deep-learning characteristics unique to MCI patients. Next, FreeSurfer is used to mine structural brain image features to supplement CNN. Both feature sets are finally fed into an extreme learning machine classifier to anticipate AD conversion. This method is thoroughly verified with the help of standardized MRI datasets from the ADNI project. In leave-one-out cross-validations, it achieves an accuracy of 79.9% and an AUC of 86.1%. This strategy performs exceptionally well when compared directly to other state-of-the-art techniques, demonstrating better accuracy and AUC while preserving a favorable balance between sensitivity and specificity. These findings demonstrate the significant potential of the CNN-based method for utilizing only MRI data to forecast the transition from MI to AD. Notably, the total prediction performance is improved with the addition of age correction and supported structural brain image data. To develop and verify a deep learning model for predicting AD diagnoses individually and identifying MCI cases that can potentially become AD (c-MCI). This approach uses CNNs to evaluate 3D T1-weighted images taken from the ADNI dataset [9], especially for examining a single cross-sectional brain structural MRI scan. The CNN's ability to differentiate between AD, c-MCI, and s-MCI was evaluated, with the AD vs HC classification tests showing the highest accuracy, with 99% accuracy when using the ADNI dataset alone and 98% accuracy when combining the ADNI dataset with the non-ADNI dataset. Furthermore, CNNs consistently performed well on ADNI and non-ADNI pictures, differentiating between c-MCI and s-MCI patients with an accuracy of up to 75%. CNNs are a robust tool for automated diagnosis of Alzheimer's disease patients, allowing for easy use without specialized training. They can be applied to previously unexplored patient data and can potentially accelerate structural MRI adoption into everyday practice, facilitating patient assessment and management which is applicable to all stages of Alzheimer's disease. A novel attention-based 3D ResNet architecture is presented in this article [10] to diagnose AD and investigate putative molecular markers. There were 532 people in all, 227 of whom were AD patients and 305 of whom were NC. This method finds essential brain regions for AD categorization while improving classification performance by incorporating the attention mechanism. Additionally, the findings show that the attention-based network accurately detects important brain regions associated with AD, which correlates with notable alterations in grey matter. A system that uses deep neural networks and a wide range of medical data to diagnose AD in its early stages. This approach uses textual information about age, gender, and genetics and [11] fMRI images for training and data classification. Deep neural networks are trained using correlation coefficient data from resting-state functional MRI imaging details, the foundation upon which functional brain networks are built. This method shows a 20% improvement in classification accuracy over conventional approaches, indicating that combining deep learning with brain networks is a powerful tool for early diagnosis of neurological disease.

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6. Deep Learning Architecture

Methodology that demonstrates how well it works with a multitask learning strategy that makes use of hybrid feature maps and a discriminative convolutional high-order Boltzmann machine. The Contractive Slab and Spike Convolutional Deep Boltzmann Machine (CssCDBM) is a discriminative version of the original model [12] that directly categorizes EEG spectral pictures by integrating a label layer that demonstrates how CssCDBM may be extended to serve as a classification model instead of just a feature extractor. Next, the main novelty is to train CssCDBM in a multitask learning framework, which addresses tasks for both identification and verification using EEG spectral pictures to reduce overfitting. This method improves intra- and inter-subject variation, which is essential for the early detection of Alzheimer's disease. It performs better than several state-of-the-art methods in terms of high-level representation extraction. A novel deep learning architecture [13] that combines dual learning with a specially crafted layer for 3D separable convolutions is intended to detect MCI patients with an increased chance of developing AD in three years. Structural MRI, demographic data, neuropsychological data, and APoE4 genetic data are input features for this deep learning technique. In contrast to other models, our machine learning model has several unique features. First, the deep learning model multitasks by simultaneously predicting the conversion from MCI to AD and classifying AD against healthy controls. It was discovered that structural MRI scans, coupled with demographic, neuropsychological, and APoE4 data, were the most predictive combination of inputs. On the other hand, the predictive value was not significantly enhanced by the warp field metrics. With an AUC of 0.925 and a 10-fold cross-validated accuracy of 86%, the algorithm could distinguish between MCI patients who developed AD within three years and those with stable MCI. It also had a sensitivity of 87.5% and a specificity of 85%. This performance is the best obtained so far with comparable datasets. Additionally, the same network achieved 100% accuracy, sensitivity, and specificity and an AUC of 1 when categorizing patients with AD against healthy controls. With its potential to be applied to any 3D image dataset, the convolutional framework holds promise for developing computer-aided diagnosis systems that aim to anticipate various medical diseases and neuropsychiatric disorders through multimodal imaging and clinical data.

6.1. Work Proposes an Integrative Methodology

This work proposes an integrative methodology that comprises longitudinal cerebrospinal fluid (CSF) and cognitive performance biomarkers generated from the ADNI cohort in addition to [14] cross-sectional neuroimaging biomarkers at baseline. This approach combines data from multiple domains across time. It shows that when using individual data modalities separately, the prediction model for MCI conversion to AD attained an accuracy of up to 75% (with an AUC of 0.83). By adding longitudinal multi-domain data, this prediction model performed at its best, with 81% accuracy (with an AUC of 0.86).

6.2. Novel Deep Learning Method

A novel deep learning method utilizing this framework's Fully Stacked Bidirectional Long Short-Term Memory (FSBi-LSTM) and 3D-CNN is covered in [15]. The 3D-CNN architecture extracts deep feature representations from PET and MRI data. Then, FSBi-LSTM is used to retrieve buried spatial information from these deep feature maps to enhance overall performance further. This approach has been validated using the ADNI dataset. This method had an average accuracy of 94.82%, 86.36%, and 65.35% in distinguishing between AD and NC, pMCI and NC, and sMCI and NC, respectively. The paper presents a study on the use of Fludeoxyglucose F18 (FDG) in diagnosing and monitoring Alzheimer's disease (AD) using positron emission tomography (PET). It also presents operational deep-learning techniques and a set of CNN hyperparameters validated on a publicly accessible dataset for future model improvement, the work presents operational deep-learning techniques and a set of CNN hyperparameters that have been validated on a dataset that is accessible to the public. The method [16] shows potential for inclusion into clinical workflows; it has undergone rigorous model calibration and thorough external validation on large-scale, multi-institution data. With the help of 18F-FDG PET

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imaging investigations, radiologists and clinicians may be able to predict AD early on, thanks to this crucial decision support tool. A unique deep learning system for early AD prediction used fluorine 18 fluorodeoxyglucose PET brain imaging. The method achieved an 82% specificity and 100% sensitivity, with predictions made on average 75.8 months ahead of the definitive diagnosis.

6.3. Deep Learning Model

This work presents a deep learning model that mimics the diagnostic process usually used by doctors to assist in the [17] auxiliary diagnosis of AD. Clinicians frequently uses a range of neuroimaging findings and cognitive evaluations to diagnose AD. This method uses two independent CNNs to learn multimodal medical pictures. The consistency of these networks' outputs is then evaluated using correlation analysis. Lastly, clinical neuropsychological diagnostic and multimodal neuroimaging diagnosis findings are combined. This technique improves the accuracy of auxiliary diagnosis by simultaneously thoroughly examining the patient's pathology and psychology. In addition, the diagnostic procedure is simple to use and closely resembles a doctor's. To support end-to-end learning in a volumetric CNN model, four binary classification tasks are examined in this study: separating MRI-based AD from NC, pMCI from NC, (sMCI) from NC, and pMCI from sMCI. The study shows the decisions made by the model without the need for human input. The method [18] uses supervised transfer learning for the pMCI vs. sMCI classification job and convolutional autoencoder (CAE)--based unsupervised learning for the AD vs. NC classification challenge. A gradient-based visualization technique mimics the spatial influence of the CNN model's decisions to uncover important biomarkers linked to AD and pMCI. The outcomes show that this method outperforms existing network models in terms of accuracy, achieving 86.60% and 73.95% for the AD and pMCI classification tasks, respectively. This work uses deep CAE to perform an original exploratory analysis of AD. Combining imaging features derived from MRI data-driven decomposition with neuropsychological test results, diagnoses, and other clinical data seeks to identify relationships between cognitive symptoms and the underlying neurodegenerative process [19]. Regression and classification analyses are utilized to explore further and illustrate the distribution of these retrieved features in different combinations. Furthermore, the effects on the brain of each dimension of the autoencoder manifold are evaluated. The resulting imaging-based markers exhibit excellent predictive potential for clinical variables; for cognitive evaluation metrics, such as MMSE or ADAS11 scores, they show correlations greater than 0.6. Additionally, the accuracy of AD diagnosis is more than 80%.

6.4. Deep Learning Algorithm (IDLA)

The Improved Deep Learning Algorithm (IDLA) is being used to detect AD using text data, including age, sex, and genetic information. Resting-state functional MRI data is used to analyze brain connectivity and function. An autoencoder network distinguishes between disease progression and normal ageing. This method [20] reliably identifies AD by integrating biased neural network features. Compared to conventional classifiers using time series R-fMRI data, the algorithm shows significant improvements, with a standard deviation reduction of up to 45% under ideal conditions. The study used accelerometer data from 35 Alzheimer's disease (AD) patients at a daycare center to identify patterns corresponding to each disease stage. The data was [21] processed using a CNN model, which outperformed traditional feature-based classifiers with an F1-score of 0.897 and an accuracy of 90.91%, highlights the potential of mobility data as a valuable tool for studying disease progression and treating AD patients. The CNN-based approach significantly improved the accuracy of identifying AD phases compared to popular supervised learning models. This study focuses on a disease progression prediction framework that uses a 3D multi-information generative adversarial network (mi-GAN) to forecast an individual's brain's overall appearance over time. To ascertain the clinical stage of the estimated brain, a 3D DenseNet-based multi-class classification network optimized with focal loss is also utilized. The mi-GAN can produce high-quality individual 3D brain MRI pictures [22] using

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https://doi.org/10.47392/IRJAEH.2024.0211

multi-information from the baseline time-point and the subject's 3D brain structural MRI. The ADNI is used to conduct the experiments. The mi-GAN demonstrates state-of-the-art performance with a structural similarity index (SSIM) of 0.943 between generated and real MRI images from the fourth year. The accuracy of identifying pMCI from sMCI when mi-GAN and focal loss are combined is 6.04% better than when conditional GAN and cross-entropy loss are used.

7. Multiple Graph Gaussian Embedding Model (MG2G)

A new deep learning technique called the [23] Multiple Graph Gaussian Embedding Model (MG2G) converts high-dimensional resting-state brain networks into a lower-dimensional latent space, allowing it to acquire beneficial network properties. These latent distribution-based embeddings make it easier to quantitatively characterize the complex and varied patterns of brain connections across various brain areas. Moreover, they provide input for classical classifiers in various downstream graph analytic tasks, including statistically assessing significant differences between groups across different brain regions and early-stage AD prediction. The MG2G is used to identify brain regions with network changes linked to MCI, predict the transition of patients from MCI to AD, and determine the intrinsic latent dimensionality of magnetoencephalography brain networks.

7.1. Innovative 3D CNN Strategy for AD Diagnosis

An innovative strategy based on 3D CNN [24] enables the accurate use of structural MRIs to distinguish between mild AD dementia and MCI, as well as cognitively NC. Based on the sizes and thicknesses of previously discovered brain areas linked to the advancement of the disease, a reference model is built for comparison. An external independent cohort from the National Alzheimer's Coordinating Center (NACC) and an internal held-out cohort from the ADNI validate both models. The accuracy of the deep-learning model is demonstrated by its ability to identify between participants with moderate Alzheimer's dementia and those with motor cortex injury, with an AUC of 85.12. With the more complex challenge of MCI detection, it achieves an AUC of 62.45. Notably, it performs faster than the volume/thickness model, which necessitates the pre-extraction of volumes and thickness. The model also functions as a predictive tool: individuals with MCI who were mistakenly diagnosed with mild Alzheimer's disease dementia show a quicker rate of dementia progression over time.

7.2. Improved Utilization of ADNI Dataset with an 18-layer CNN

Based on neuroimaging data, DL approaches demonstrate the ability to effectively and precisely model the course of AD. The study examined many [25] biomarkers and datasets used in AD diagnosis. Important biomarkers for diagnosing AD include speech transcripts, genetic tests, MRI, fMRI, FDG-PET, amyloid-PET, Tau-PET, EEG, and MEG. The ADNI, OASIS, DementiaBank, HABS, and MCSA databases are notable datasets available for diagnosing AD. Even with the tremendous progress that DL has made in the area of AD diagnosis, some issues still need to be addressed. Overfitting, data quality, interpretability, transparency, and reproducibility are some of these problems. The research conducted in [26] significantly improves the use of the ADNI dataset by dividing training and testing samples to maximize accuracy using an 18-layer CNN. The study aims to use machine learning techniques to predict AD in advance. Consequently, the 18-layer CNN achieves a fantastic accuracy of 98%.

7.3. Memory Test for Detecting Cognitive Deficits

Demonstrated how well a memory test based on everyday activities can detect cognitive deficits [27]. Despite the small sample size, incorporating a group of healthy older persons has shown the task's ability to discriminate between individuals without cognitive deficits and those with them. Therefore, the study has the potential for identifying diseases at an early stage, identifying symptoms that are frequently missed, and enabling prompt intervention. This study aimed to evaluate how well a task based on everyday activities might identify cognitive impairment in AD patients. Twenty-four people participated in the survey: twelve older individuals (12 females, average

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https://doi.org/10.47392/IRJAEH.2024.0211

age: 81.75±7.8 years) diagnosed with AD and twelve older adults (5 males, average age: 77.7 ± 6.4 years) in the Healthy group. Everyday living-based intervention activities were administered to both groups at two distinct intervals, separated by three weeks. This methodology gains strength and reliability from the substantial degree of clinical importance, as demonstrated by the test-retest reliability results.

7.4. Unique MRI Formatting for Disease Stage Classification

A unique approach for classifying disease stages involves formatting MRI images to prevent data leakage. The dataset was then subjected to a rapid and straightforward registration-free preparation method. Several tests were carried out to evaluate the effectiveness of different 3D categorization designs. Finally, for the best-performing models, an ensemble learning strategy was used. An augmentation of the ADNI dataset was used to show how effective this process is. With AUC values of 91.28% and 88.42%, respectively, the ensemble technique [28] outperformed previous research in the literature regarding better identification between people with AD and MCI and between MCI and cognitive normal (CN). Additionally, the technique showed that it was possible to differentiate between the three stages of the illness. The study investigated the feasibility of creating a tool to differentiate between AD and HC persons utilizing information from the Timed Up and Go (TUG) test, a straightforward assessment of walking and balance [29]. When conducting the TUG test in front of a Kinect V.2 camera, joint position data from 47 HC and 38 AD individuals was gathered. After controlling for age and the Geriatric Depression Scale, 12 important features were obtained using statistical analysis and signal processing to distinguish AD from HC. Using a support vector machine classifier and these features, the model obtained an F-score of 97.67% and an average accuracy of 97.75% for five-fold cross-validation. The accuracy and F-score for leave-one-subject-out cross-validation were 98.68% and 98.67%, respectively. These results demonstrate the approach's potential as a novel quantitative supplementary tool for identifying AD in older persons. With the help of this ground-breaking research, AD patients can now be identified from HC thanks to the first-ever quantitative and thorough analysis of the TUG test using the Kinect V.2 camera and machine learning.

8. Automated MRI Classification for MCI, NC, and AD

This project aims to develop a deep learning algorithm to classify brain images into AD, MCI, and CN groups and extract useful AD biomarkers from [30] structural MRI. CNNs were used in this study on sMRI brain pictures taken from online databases containing ADNI datasets. This process included combining characteristics from several layers to convert magnetic resonance imaging images into higher-level features that were more succinct. This approach has fewer parameters, which lowers the computational complexity. With 97.00% accuracy for AD vs. CN, 96.29% for MCI vs. CN, and 88.00% for AD vs. MCI, the results show improved performance over some of the most widely used network models, including ResNet50 and VGG19.

An automated classification method that uses MRI scans to discriminate between MCI, NC, and AD. Utilizing a 3-D convolutional neural network [31], this technique ensures thorough image information extraction by accepting the complete 3-D MRI picture as input. Furthermore, a multichannel contrastive learning strategy mixes supervised classification loss with unsupervised contrastive loss by utilizing various data transformation techniques (such as introducing noise). The network's capacity for generalization and classification accuracy are both improved by this integration. Extensive experiments were performed on the ADNI dataset to validate the effectiveness of this approach. The multichannel contrastive learning technique enhances the network's overall generalization capacity and classification accuracy (AD versus NC: 4.19%; MCI versus NC: 4.57%).

8.1. Hybrid Model Integrating CT-MRI and EEG for AD Identification

Designed for the early identification of AD, the HEMRDTL model is a hybrid technique that integrates fused CT-MRI scans with electroencephalogram (EEG) data. This model [32]

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uses robust principal component analysis, deep VGG-19 approaches, and transfer learning. The process includes extracting features from fused CT-MRI and EEG signals and combining them with VGG-19 to classify the results. A pre-trained VGG-19 model first trained on the ImageNet dataset is adjusted to capture structural brain features in the context of fused CT-MRI. Concurrently, MRPCA—a robust dimensionality reduction method immune to noise and outliers—is tailored for feature extraction from EEG signals, reflecting the brain's functioning characteristics. Impressive metrics are achieved by the method: 98.1% recall, 99.1% accuracy, 99.3% precision, and an F1 score that is almost 99%.

8.2. Comprehensive Framework for AD Analysis using CNN

The implementation of four critical stages for AD analysis using a comprehensive framework based on CNN and deep learning methodologies: (I) preprocessing and data preparation, (II) data augmentation, (III) cross-validation, and (IV) classification and feature extraction using deep learning for medical image classification. Throughout these phases, two techniques are used. The first uses a simple CNN architecture, and the second uses the pre-trained VGG16 model, which was first trained on the ImageNet dataset and then modified via transfer learning and fine-tuning for use on other datasets. The effectiveness of both approaches is evaluated and contrasted using seven performance criteria. Unlike recent efforts, this approach analyzes AD effectively with a few labelled training samples and no prior domain knowledge. Interestingly, all diagnosis groups show a considerable improvement in performance according to the trial results. These approaches [33] address overfitting, memory consumption, and temporal regulation issues and are suitable for simple structures with low computing complexity. Additionally, they show promise in accuracy, with the tuned VGG16 model achieving 97.44% accuracy for AD stage classifications, compared to 99.95% and 99.99% for this CNN model in the same domain.

8.3. Preparation Techniques for Improved MRI Categorization

A novel feature selection technique called Neighbourhood Component Analysis and Correlation-based Filtration (NCA-F) was used [34] to pinpoint important cognitive traits in a given dataset. Afterwards, this NCA-F technique was used to train various machine learning classifiers, and the best classifiers were chosen for voting following their performance outcomes. An adaptive weight matrix is used in the voting process, where the weight is represented by multiplying a model's output label by the F1 score. Results show that adaptive voting achieves an accuracy of 93.92%, higher than the 90.53% accuracy of the traditional artificial neural network approach. This method significantly improves the detection accuracy of AD in its early stages. Furthermore, the accuracy has been enhanced by 12.12% compared to a recent study that used the same features. This work focuses on intelligent preparation techniques that substantially improve MRI image categorization performance. Additionally, it shortens the time needed for different learning algorithms to train. We converted a 4D dataset from the ADNI to a 2D format. Using preprocessing techniques such as histogram equalization, selective clipping, and grayscale image conversion improved the photos. Three learning algorithms—random forest, XGBoost, and CNN—were applied to classify AD after preprocessing. Computed results [35] on the dataset show better performance than previous research, with a sensitivity of 97.60% and an accuracy of 97.57%.

8.4. Graph Reasoning Module (GRM) for Enhanced AD Diagnosis

With the smooth integration of the Graph Reasoning Module (GRM) into CNN-based AD detection models [36], this innovation significantly improves the performance of AD diagnosis by simulating the complex interactions among various brain regions. The GRM is made up of three blocks: a Graph Convolutional Network (GCN) block for updating the graph representation, an Adaptive Graph Transformer (AGT) block for creating a graph representation based on the CNN-derived feature map, and a Feature Map Reconstruction (FMR) block for turning the learned graph representation back into a feature map. The experimental findings

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https://doi.org/10.47392/IRJAEH.2024.0211

demonstrate that adding GRM to the current AD classification model improves its balanced accuracy by over 4.3%. Surprisingly, with a balanced accuracy of 86.2%, the GRM-embedded model outperforms existing deep learning-based AD detection techniques, demonstrating state-of-the-art performance.

Table 1 State-of-the-Art Methods for AD Detection

S.NO.	CLASSIFIER	ACY	STVTY	SPCTY	AUC
1	CNN	-	71	-	92.9
2	3D CNN	92.8	93	92.9	92.5
3	RNN	92.4	92.6	92.5	95.2
4	AlexNet	95.1	95.3	95.2	-
5	Softmax and CNN	91.9	92.1	-	93.4
6	DenseNet and Softmax	93.3	93.5	93.4	90.3
7	Multi DenseNet and Softmax	90.2	-	90.3	-
8	ELM	96.2	96.4	96.3	94.9
9	CNN	94.8	95	94.9	84.6
10	Trained CNN	-	53.6	84.6	-
11	Autoencoder and softmax	98.2	95.4	98.3	78.2
12	Multiple learning	98.4	89.2	-	-
13	CNN	-	-	87	95.64
14	DBN and SVM	94.1	94.3	94.2	-
15	Multi RNN	92.1	92.3	-	-
16	LSTM	-	92.5	87.2	94.32
17	CNN	85.8	86	85.9	-
18	CNN	97.6	97.8	-	92.35
19	CNN	94.3	94.5	94.4	-
20	Autoencoder	92.4	92.6	92.5	93.44
21	CNN	90.91	-	-	-
22	3D DenseNet	60.4	-	-	-
23	MG2G	-	85.4	90.35	-
24	3D CNN	-	-	-	85.12
25	RNN	90.3	87.3	84.6	-
26	CNN	98	-	-	-
27	RNN	95	-	78.6	-
28	3D CNN	91.28	-	-	88.42
29	TUG TEST	97.75	98.68	-	-
30	CNN	97	96.29	-	84.5
31	3D CNN	95	-	78.6	93.44
32	VG19 NET	99.1	-	-	-
33	ImageNET	99.95	99.99	-	97.44
34	NCA-F	93.92	90.53	-	
35	CNN	97.57	-	-	-
36	GCN	86.2	-	-	-
37	CNN	85.4	-	-	78.6
38	CT	98.62	99.05	98.5	-
39	LSTM	98.6	96.7	95.1	74.5
40	SVM	98.2	95.4	98.3	78.2

9. DNA Methylation Database for AD Research

One crucial factor in the pathogenic processes of AD is DNA methylation. Several genes, regions, and CpG sites that are differently methylated in AD have been found recently, and these have [37] a great deal of clinical research promise. Unfortunately, there is currently no specific database to gather differential methylation data associated with AD in an organized manner. This database includes 16,709 differentially methylated items relevant to AD in diverse brain areas and blood cell types. The items include 209 genes, 2,229 regions, and 14,271 CpG sites. The DeepCurvMRI model aims to improve the precision of early-stage AD identification using MRI images by combining a CNN and the curvelet transform (CT). First, the MRI pictures were preprocessed using CT, and then the CNN model was trained using this new representation of the data. DeepCurvMRI [38] was trained on the Alzheimer's MRI images dataset that is accessible on the Kaggle platform for both binary and multi-class classification tasks. Using the leave-one-group-out (LOGO) cross-validation approach, DeepCurvMRI demonstrated impressive performance in multi-classification tasks, with accuracy of 98.62% ± 0.10%, sensitivity of 99.05% ± 0.10%, specificity of 98.50% ± 0.03%, and F1 score of 99.21 ± 0.08. The most outstanding accuracy in binary classification was 98.71% ± 0.05%.

9.1. EEG Integration with LSTM

In [39], a vast multichannel electroencephalogram (EEG) dataset is integrated with a Long Short-Term Memory (LSTM) network to create a computer-aided diagnostic (CAD) framework. Conventional approaches have ignored this critical interaction, even though both EEG rhythms and channels include critical biomarkers for AD diagnosis. In response, this work presents a novel framework designed to determine the ideal EEG rhythms and channels required for a successful diagnosis of AD. A real-time AD EEG dataset is used to evaluate the framework, and the results show that the most dependable biomarkers for AD identification are the gamma and beta rhythms seen in channels Cz, F4, P4, T6, and Pz combined. Here, the LSTM-based model used in the study performs better than the others. Table 1 is an extensive table that includes several performance measurements and the most recent techniques for diagnosing Alzheimer's disease.

9.2. Novel Parameters in Dynamic Functional Connectivity Analysis for MCI Detection

The viability of several novel parameters in dynamic functional connectivity (dFC) analysis aims to improve the accuracy of MCI (mild cognitive impairment) detection. Using a resting-state functional magnetic resonance imaging dataset of healthy controls (HC), early MCI (eMCI), and late MCI (lMCI) patients is part of the methodology. The pairwise Pearson's correlation of the dFC yields nine features in addition to RMS. These features include autocorrelation, spectral, amplitude, entropy features, and time reversibility. A Student's t-test and a Least Absolute Shrinkage and Selection Operator (LASSO) [40] regression are used to reduce the feature dimension. Afterwards, two classification tasks are performed using a Support Vector Machine (SVM): HC vs. lMCI and HC vs. eMCI. Computed performance metrics include the F1-score, area under the receiver operating characteristic curve, accuracy, sensitivity, and specificity. The findings show a significant difference between HC and lMCI in 6109 out of 66700 features and between HC and eMCI in 5905 features. Furthermore, these characteristics outperform several current approaches with exceptional classification scores for both challenges.

Conclusion

This survey provides critical new insights into the state-of-the-art deep learning and machine learning methods in brain disease research today. The most recent developments in machine learning have been disclosed; these include the kinds of data used and the effectiveness of machine learning methods in the early stages of Alzheimer's diagnosis. Improving the accuracy of classification is one of the most essential aspects. The need to increase the number of training data parameters increases with results accuracy. There is potential for better outcomes when hybrid algorithms are used and supervised and unsupervised, as well as machine learning and deep learning techniques are combined. The discourse on different types of brain disease data sources and feature extraction methods highlights the fluctuation inaccuracies based on the classifiers and feature extraction processes utilized in the systems. Additionally, the development of DL solutions is significantly impacted by concerns regarding the quality of training data and interoperability. This review is expected to provide valuable insights for researchers engaged in the broad fields of artificial intelligence and medical applications, mainly using machine learning and deep learning for Alzheimer's disease detection and early diagnosis.

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International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 06 June 2024
Page No: 1537- 1550
https://irjaeh.com
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