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Research Article

State-of-the-Art AI Approaches for Alzheimer's Disease Detection from Brain MRI: A Systematic Literature Review

Bandaru A Chakravarthi [1], Dr. Gandla Shivakanth[2]

[1] *Research Scholar, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Hyderabad-500075, Telangana, India.*

E-mail: bandaru.chakry@gmail.com

[2]*Correponding Author, Associate Professor, Dept of CSE, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Hyderabad-500075, Telangana, India*

E-mail: shvkanth0@gmail.com

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ABSTRACT

The increasing occurrence of many non-transmittable diseases, such as adult-onset dementia disorders and neurodegenerative diseases, is correlated with the rapid aging of populations, particularly in the industrialized western world. A correct diagnosis made early on is essential to promote appropriate treatments, such as treatment and preventive measures. A method that is frequently used for the diagnosis of neurological illnesses is conventional magnetic resonance imaging, or MRI. There is mounting evidence that using artificial intelligence (AI) techniques in conjunction with magnetic resonance imaging (MRI) can significantly enhance the precision of dementia diagnosis across various subtypes. Numerous investigations have been carried out to look at aberrant brain structure conditions and to identify Alzheimer's and dementia disorders utilizing features taken from medical images. Based on these findings, it is critical to identify Alzheimer's and dementia patients at an early stage and to treat them with the right care. To make this diagnosis, high-quality magnetic resonance (MR) images are required. However, it also results in reduced spatial coverage and longer scanning and identification times, even if it produces high-quality images. In this setting, the discipline of biomedical image processing has experienced significant growth and has evolved into an interdisciplinary study area including numerous fields.

Among the most used types of data are images of the brain. In applications related to neurology, AI may help physicians make better decisions. For AI to be more effectively used in the brain, there are still important problems that need to be resolved. Building understandable AI algorithms and compiling extensive data are crucial to achieving this goal.

Keywords: Alzheimer's disease, Brain MRI, Medical Imaging, Systematic Literature Review (SLR)

1. INTRODUCTION

One common type of neurodegenerative condition that is irreversible and slowly ruins cognition in the mind is Alzheimer's disease. Intellectual and behavioral impairments are the result of degenerative changes in this condition that alter the forms and functioning of brain cells and structures [1]. This chronic condition progresses gradually at first and progressively worsens with time. Medication is expensive, and its true reasons are still unknown. Early diagnosis of Alzheimer's disease has become the focus of more and more academic research in recent years. By 2030, there will be 75 million more people experiencing dementia than there are currently anticipated to be (47.5 million). The number of dementia cases is expected to more than triple by 2050 [2]. The introduction of electronic neuroscience methods has led to an increasing acceptance of images from medical imaging management to diagnose brain diseases [3, 4].

The analysis of medical images can benefit from machine learning in drafting applications since it can identify important features that characterize the underlying patterns in data. Medical imaging has previously employed machine learning as a technique for pattern recognition. [5]. Analysis of medical pictures is currently making great strides thanks to deep learning. Medical image analysis tasks fall into several major categories, including segmentation, localization, detection, classification, and registration [6]. In order to extract the necessary tissue or region that is interesting from the collected pictures, classification is a crucial step. The U-net artificial intelligence model, which used convolutional networks for biomedical classification of images, was the most often used model [7].

1.1. Background: Alzheimer's disease (AD) is a progressive neurodegenerative illness that impairs memory and cognitive function in the elderly. It is difficult for a person with this disease to carry out daily chores. Unable to recall names of people and occasionally maps. Many research groups have been attempting to diagnose AD early using various machine-learning models over the past few years. There are several risk factors for AD, including age, heredity, education level, and concurrent medical conditions [8-9]. Alzheimer's disease cannot be cured or prevented with current medications. Reducing the risk of heart disease is the sole method to lessen the risk of Alzheimer's disease. People who have a high risk of heart disease also have a high risk of Alzheimer's disease, according to observations. Excess weight, high blood pressure, diabetes, and high cholesterol are major contributing factors. Since there is now no effective treatment for Alzheimer's disease, the only option is to keep the patient mentally stable and use medication to postpone the illness's symptoms. A doctor can better maintain their patient's mental health by predicting Alzheimer's disease early on, which also delays the disease's effects.

1.2. Motivation:

Human instinct and official measurements do not always agree in the current environment. Our unconventional and computationally costly new approaches, like AI, are what we need to use to overcome this challenge. Predictive and personalized medications are being provided by the growing application of machine learning techniques in illness imaging and prediction. This drift not only enhances patients' quality of life but also helps doctors make therapeutic decision choices and health economists during the analysis process. Examining medical records could cause radiologists to overlook other illness circumstances. Consequently, it only takes a few reasons into account and circumstances. Here, the objective is to pinpoint the knowledge gaps and possible advantages connected to Healthcare and AI frameworks derived information.

1.3. Objectives:

- Identifying the most effective AI algorithms and techniques for accurate diagnosis and early detection of Alzheimer's disease.
- Analyzing the performance of different AI approaches in terms of sensitivity, specificity, accuracy, and other relevant metrics.
- Investigating the role of brain MRI features and preprocessing techniques in improving AI-based detection of Alzheimer's disease.
- Discussing the potential applications, benefits, and limitations of AI-based detection of Alzheimer's disease in clinical practice and research.
- Identifying gaps and areas for future research in the development of AI-based detection methods for Alzheimer's disease.

1.4. Scope: The purpose of the current review is to present a thorough assessment and analysis of the most recent research on AD early detection and classification using cutting-edge AI methodology. Additionally, we offer a few preprocessing methods that help improve picture quality and maximize classification process efficiency. Additionally, it will highlight various difficulties encountered in related studies and how they overcame them. describing the steps involved in diagnosing Alzheimer's disease, from gathering information to classifying the disease

1.5. Structure of the Paper:

The paper's organization continues: Section 2 covers Methodology Section 3 Research Questions 4. AI Approaches for Alzheimer's Disease Detection. 5. Brain MRI Features and Preprocessing 6. Performance Evaluation. Section 7 Challenges and Barriers 8. Future Trends and Directions 9. concludes and plans future work.

2. METHODOLOGY-

2.1 Data Sources: This systematic literature review (SLR) precisely follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) criteria in order to methodically study the integration of AI Approaches for Alzheimer's Disease Detection. The objective is to guarantee a clear and well-organized evaluation procedure. The review, which was done using dependable sources like Google Scholar, IEEE Xplore, Scopus, and PubMed, covers all works published between 2018 and 2024. The abundance of AI Approaches for Alzheimer's Disease Detection Algorithms led to their selection. Furthermore, the abundance of information accessible allows for the analysis of related ideas and usage trends of the term comprehensibility.

2.2. Search Strategy: A complete set of papers was included following an extensive selection process that adhered to the PRISMA principles for systematic examinations. PRISMA principles were adhered to, and a systematic and exhaustive search technique was employed. Predefined search phrases, such as AI in Neuroimaging, Neuroimaging Biomarkers, Alzheimer’s disease detection, Computer Aided Diagnosis, MRI Based Diagnosis, Deep learning Alzheimer's MRI diagnosiswere checked, such as IEEE Xplore, PubMed, Google Scholar, and Scopus.

2.3 Selection Criteria: In the process of information research, AI Approaches for Alzheimer’s Disease Detection. It also assists with AI Approaches for Alzheimer’s Disease Detection from Brain MRI. The first source of articles used was Google Scholar, followed by IEEE Xplore, Scopus, PubMed, and thousand seven hundred from Google Scholar and six fifty from IEEE Xplore, Nine hundred from Scopus and sixty from PubMed. Following a comprehensive screening procedure that included identifying relevant papers and eliminating duplicates, one fifty articles were determined to be eligible for further assessment (Figure 1). The final selection of 60 papers adhered to PRISMA principles, ensuring a comprehensive and uniform examination based on preset selection criteria

2.4. Data Extraction: All works published between 2018 and 2024 are included in the review, which was conducted using credible sources such as Google Scholar, IEEE Xplore, Scopus, and PubMed. Their selection was prompted by the large number of AI Approaches for Alzheimer's Disease Detection. An initial search yielded three thousand three hundred and ten articles, which was then narrowed down to two thousand two hundred articles after removing one thousand two hundred duplicates. Further screening led to the exclusion of one thousand and ninety articles, and five hundred and fifty articles could not be retrieved. The remaining four hundred and seventy articles were considered for final evaluation, with two hundred and fifty articles excluded due to not matching the study's criteria and one hundred and fifty articles excluded due to lack of relevance to the study. Ultimately, fifty articles were selected for final assessment.

2.5. Synthesis Method: The choices about instruction are initiatives are made using Deep learning-based methods such Alzheimer's Disease Detection, Neuroimaging Biomarkers and machine learning. Deep learning Alzheimer's MRI diagnosis. Alzheimer’s disease detection AI.

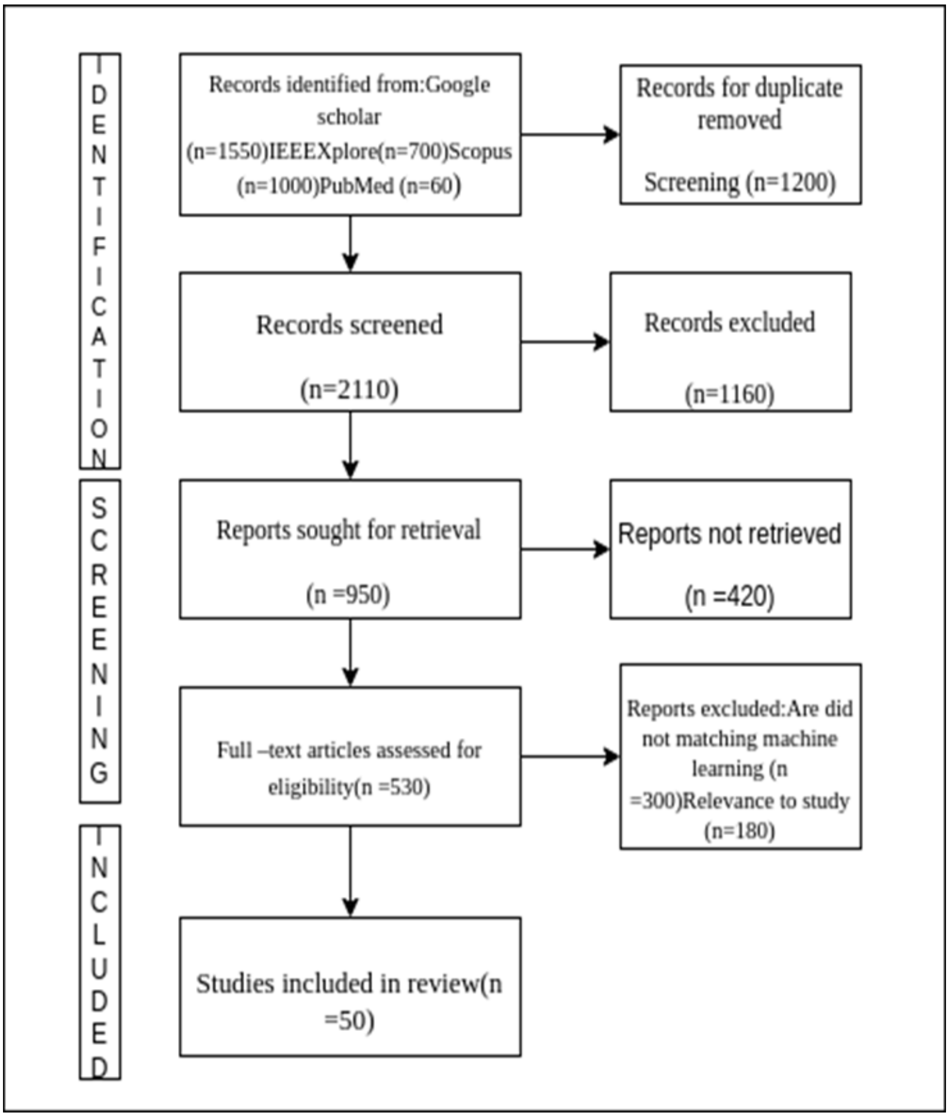

Figure 1. Prisma model

3. RESEARCH QUESTIONS

RQ1. What are the most effective AI algorithms and techniques for detecting Alzheimer's disease from brain MRI?

Convolutional Neural Networks (CNNs): These deep learning models are very good at classifying images, and they can even recognize patterns in brain MRI scans that are linked to Alzheimer's disease.

Recurrent Neural Networks (RNNs): RNNs can be used for time-series MRI data for early detection, while they are more frequently utilized for sequential data.

Automatic Image Segmentation: By segmenting brain structures, algorithms such as U-Net or Mask R-CNN help discover abnormalities unique to Alzheimer's disease.

Autoencoders: These are unsupervised neural networks that pick up effective input data representations. Variational autoencoders (VAEs) are a valuable tool for MRI image abnormality detection.

Graph Convolutional Networks (GCNs): GCNs recognize patterns associated with Alzheimer's disease by analyzing graph-structured data, such as brain connection networks obtained from MRI images.

Ensemble Learning: You can improve accuracy and resilience by combining several models (e.g., CNNs, RNNs, or decision trees).

RQ2. What brain MRI features and preprocessing techniques are most commonly used in AI-based detection of Alzheimer's disease?

MRI scans are frequently used to extract features, such as brain volume, hippocampus volume, and ventricular volume. These measurements offer details on the atrophy and tissue loss linked to Alzheimer's disease.
Texture Features: Variations in tissue texture and spatial patterns can be captured by texture analysis techniques like gray-level co-occurrence matrix (GLCM) features.
Histories of Intensity: The distribution of pixel intensities within different brain areas is described by histogram-based parameters such as mean intensity and standard deviation.
Shape Descriptors: Characteristics like surface area or cortical thickness that are linked to shape can provide useful information.
Methods of Preprocessing:
Skull Stripping: For MRI scans to concentrate on brain regions, the skull and non-brain tissues are removed.
Norming Intensity: Guaranteeing uniformity in intensity values among several scans.
Registering MRI scans spatially allows them to be compared to a shared anatomical area.

Noise reduction is the process of improving image quality by using filters or denoising algorithms.

Bias field correction: adjusting for differences in intensity brought on by artifacts in the scanner.

Resampling: Guaranteeing a constant voxel dimension for analysis that is consistent.

RQ3. How do AI-based detection methods compare to traditional methods for Alzheimer's disease diagnosis?

Artificial intelligence technology can be used to diagnose AD earlier and more accurately than traditional approaches. It can also expedite the diagnosis process and eliminate the laborious manual feature extraction that comes with traditional methods.

An irreversible neurological disease that is prevalent in the elderly is called Alzheimer's disease (AD). Artificial intelligence technology can be used to diagnose AD earlier and more accurately than traditional approaches. It can also expedite the diagnosis process by eliminating the need for laborious manual feature extraction. The uses of artificial intelligence algorithms, such as machine learning, convolutional neural networks, graph convolutional neural networks, cyclic neural networks, and other popular deep learning technologies, in AD diagnosis are reviewed in this research. We go over the benefits and drawbacks of each strategy before talking about its shortcomings and potential.

RQ4. What are the potential applications and benefits of AI-based detection of Alzheimer's disease in clinical practice?

Early Diagnosis and Prediction: Artificial intelligence algorithms are capable of examining large amounts of patient data, such as genetic data, imaging scans, and medical records, in order to find patterns and biomarkers that point to AD. In patients with mild cognitive impairment, this helps clinicians to anticipate the onset of dementia and make more educated diagnostic decisions.

Timely interventions and customized treatment options are made possible by early identification.

Enhanced Accuracy: AI models have the potential to outperform conventional techniques in AD detection thanks to their high accuracy.

The goal of explainable AI (XAI) strategies is to provide evidence for the reliability of these models' predictions so that medical professionals will find them more acceptable.

Customized Care: AI can assist in customizing care based on the unique characteristics of each patient, enhancing therapeutic approaches.

Personalized methods improve patient outcomes and cut down on pointless medical treatments.

4. AI APPROACHES FOR ALZHEIMER'S DISEASE DETECTION

4.1. Machine Learning (ML) approaches: It is important to have a better grasp of what machine learning actually is and what machine learning techniques are widely employed in AD prognosis before beginning the deep analysis of machine learning approaches [10-12]. Under the general heading of artificial intelligence, machine learning has several instruments to get statistically sound judgments based on prior knowledge. It draws on prior knowledge (training) to categorize fresh occurrences and forecast new trends. As powerful as machine learning in contrast to common statistical instruments. Within the device learning, a thorough comprehension of an issue, and is necessary to identify the algorithms' limits. comprehended thoroughly to produce beneficial effects. As a consequence, there is an excellent chance for achievement provided that experiments are carried out effectively, instruction is applied thoroughly and appropriately, and the outcomes are rigorously confirmed. Moreover, each method and technique used in machine learning is modified in some way. Some approaches, for example, are not relevant to other types of data because they are based on particular presumption or are intended for a specific type of data. For this reason, using many machine learning techniques on a given set of training data is essential [13].

There are three main categories of learning algorithms in machine learning: 1. Supervised instruction 2. Learning without supervision.3. Applied reinforcement. A training set of data is provided in supervised learning, and the computer is tasked with learning how to translate the input into the desired output. Using unlabeled and unclassified data, the unsupervised learning algorithms use self-learning. Interestingly, nearly all supervised learning techniques such as decision trees, artificial neural networks, genetic algorithms, and linear discriminant analysis are employed in the diagnosis and prognosis of AD.

Additional methods that are frequently employed include ensemble methods, AR mining, and SVM. In contrast to the previous methods, support vector machines, or SVMs, are a relatively newer technology and a well-known machine learning methodology today, however, they are seldom recognized in the field of AD prognosis. The other techniques, such as decision trees (DTs) and KNNs (K-Nearest Neighbors), are not frequently applied in AD forecasts. Nonetheless, a large number of excellent works were examined for this study [14-18]. But practically all of them lacked an authentic, validated dataset for AD, had neither internal nor external validation, used an excessive number of characteristics, leading to overtraining, and had no established benchmark against which to assess the outcomes.

Random Forest (RF), K-Nearest Neighbors (K-NN), Support Vector Machine (SVM), Logistic Regression Classification (LRC), and so forth are examples of common machine learning classifiers.

The recommended strategy for separating AD patients from healthy individuals uses an SVM classifier. The participants were split into two groups for the research, and the ROI brain region (amygdala, hippocampal, etc.) and brain material (white matter, gray matter, etc.) properties were extracted, accordingly. a brain region having the highest correlation with AD was identified by comparing the classification outcomes of the two experimental groups. An RF classifier-based strategy for classifying Alzheimer's disease was developed [19]. Cortical thickness, cortical surface area, cortical curvature, and hippocampus volume were among the features that were extracted. The proximity technique was used to weigh and fuse the output of each classifier to arrive at the final choice. Ultimately, the multiclassification model's recognition efficiency was a rate of. The K-NN classifier and the texture features of the hippocampal regions were used to examine the T1-weighted MRI images of AD patients. A classification accuracy was obtained with the GLCM technique.

Overall, there are clear limitations in machine learning research related to diagnosing Alzheimer's disease, despite some encouraging results. Voxel-based techniques are capable of obtaining all three-dimensional data from a single scan, but they are not tailored to particular anatomical features and treat all brain regions equally [20-21]. Voxel-based techniques also disregard local information since they handle each voxel separately, frequently with large computational loads and characteristic dimensions. The multifaceted slicing used in slice-based methods is instead of

the entire 3-D picture as input, which is capable of narrowing down and streamlining the network's many parameters [23]. But the slicing procedure necessitates some prior understanding, together with the selection of only one direction's worth of slices from the plane hence it is not possible to properly exploit the image's spatial data. Block-based techniques can make up for the loss of three-dimensional information in slice-based techniques, however, the majority of them employ integrated classifier techniques, meaning that feature extraction and classification inside each block happen independently of one another. Nevertheless, block-based methods struggle to effectively integrate the characteristics of each block due to the correlation between the tissue alterations in each brain. Roy-based techniques minimize the number of dimensions by extracting information from particular brain regions. However, an aberrant region might only make up a small portion of the ROI region that has been predetermined, and it might spread to other parts of the brain as well, losing identification data in the process. Furthermore, ROI-based approaches need specialists' prior knowledge to divide ROI. Using an integrated approach, all of the data located in the three-dimensional image is utilized to the fullest extent possible. Nonetheless, a significant quantity of redundant data exists for samples with modest lesions [24-26]. The global image-based approach also has a high computational cost and a high feature dimension, just like the block-based method.

4.2. Deep Learning (DL) approaches:

An array of algorithms called a neural network is utilized to identify patterns and information hidden in the MRI dataset. It functions similarly to how the human brain functions. The neurons in the neural network are called perceptrons, and they are arranged in layers. These mathematical functions, called perceptrons, categorize data from the MRI image collection in accordance with the specifications and unique design.

Typically, a neural network has two layers; however, this is insufficient for processing massive networks, like MRI pictures. Therefore, we extend the classical neural network with additional layers for deep learning [30-35]. Depending on the computer network, it might have anywhere from 10 to 100 layers. Every layer neuron saves some information, which it then transmits to the forward neurons. The concealed information in the MRI pictures is taken out when this data comes in from the network. The raw data is often collected by lower layer neurons.

A convolutional network extracts characteristics from the new matrix that is produced by multiplying two pictures that are represented in matrix form. A CNN carries out two tasks: feature extraction in the first instance and classification in the second. The capacity of CNN to learn and generalize the characteristics from big data collection is its main benefit.

The operational connectivity correlation matrices were initially generated from the brain functioning connectivity of rs MRI images. Each matrix was then coupled with the label, scanning device data, and the subject's gender to create the subject vector[23,34]. Next, the connection between vertices was determined to be the borders, and each subject vector was determined to be the vertex. Ultimately, node categorization allowed AD forecasting to be finished. Using the region of interest (ROI) as the vertex, computes the degree of data similarity inside the ROI region, graphs each MRI image, and ultimately achieves the goal of predicting AD by graph segmentation.

To create a prognostic framework that predicts the early stages between MCI and AD using longitudinal analysis, utilizing LSTM and a computerized device to produce image illustrations from MRIs [26]. They then combined this characteristic with manually created features like hippocampal volume estimation and demographics. Using LSTM autoencoders, produced MRI models of patient data and classified AD using a K-means clustering T-distributed Randomized proximity embedded technique (t-SNE).

4.3. AI approaches: The idea of artificial intelligence (AI) allows performance criteria to be optimized with the help of data or learning. In reality, learning occurs when the model parameter optimization is carried out using a training dataset or prior knowledge.
Forecasts can be evocative, used to glean knowledge from input data, forecasting, or both. Forecasting models are used to forecast the future. Two key objectives in machine learning are (1) processing large amounts of data and optimizing the model, and (2) validating the model and effectively expressing the solution. In certain cases, learning efficiency holds equal significance to classification accuracy. Furthermore, the system can learn and adjust to changes in various situations thanks to AI approaches.

A machine intelligence method that is gaining more attention across several academic domains is artificial neural networks (ANNs). It does, however, have the fewest operational applicability. For a variety of challenges, ANN can generate predictions with a high degree of accuracy. It was first created to mimic how the human brain works when

it comes to anticipating outcomes, spotting patterns, or picking up knowledge from past experiences. A computer program that uses machine learning and pattern recognition techniques to successfully create predictive models reflects this process [28]. Within an artificial neural network, the input data is obtained via input nodes, after which its values are increased by weight values preserved in the interconnections. Inserted in between the input and output layers, the hidden layer uses the output of the preceding layer as an input for the target prediction. Neural networks use an approach known as multilayer architecture. Furthermore, outcomes of the application of a function of transmission in the hidden layer are generated. Predictions like this one are sent to the output node.
A validated approach for MRI-based illness diagnosis was proposed. The initial phase was computing the two-level, two-dimensional DWT (2D DWT) of MRIs. The appropriate characteristics were extracted using PCA and LDA in the second stage. The final stage involved using the retrieved characteristics as input for each of the K-NN and SVM classifiers to identify normal MRIs and MRIs with various disorders [31, 40]. The success results collected indicate that the proposed strategy improves the recently disclosed techniques and yields high accuracy in classification rates while requiring fewer characteristics for the categorizing task.

5. BRAIN MRI FEATURES AND PREPROCESSING

5.1 **Feature extraction and selection:** Image feature extraction is the process of preparing the raw image data, removing superfluous elements' influence, and emphasizing the important information. Among the frequently employed techniques for feature extraction are: (1) Voxel-based Morphometry (VBM) [6]. (2) ROI techniques, or regions of interest (3) Approach approaches based on patches [7], (4) methods based on slices, and (5) ways based on global images. MRI image analysis frequently makes use of VBM techniques. The idea is to compare the variations in Voxel intensity in three-dimensional images, which should then represent the corresponding changes in the morphology of the brain tissue. Support Vector Machine (SVM) classifier and VBM extraction characteristics were integrated for the clinical diagnosis of AD [42]].

Research has revealed that in comparison to healthy individuals, patients with Alzheimer's disease exhibit some degree of atrophy in various brain areas (such as the amygdala, temporal lobe, hippocampal regions, etc.). The Roi-based approach improves the classification effect by removing the interference from unrelated brain areas by extracting the image features of targeted brain regions. developed a depth model for each of the 98 ROIs he identified using voxel preselection from MRI and PET data.

After that, every image underwent voxel-based MRI signal strength standardization. This means that each voxel's value was normalized by dividing the initial value by the image's original maximum value, producing a value between 0 and 1. Figure 2 summarizes the entire preparation pipeline.

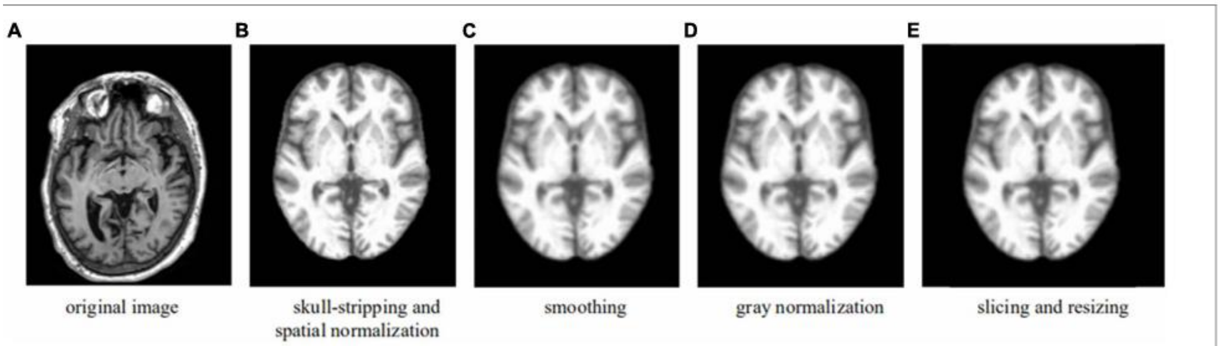

Figure 2. example pre-processing pipeline [16]

5.2 Image preprocessing and augmentation: There exist diverse techniques for pre-processing data that can be employed on clinical data sets related to Alzheimer's disease to enhance the precision and caliber of the analytical outcomes. Among the pre-processing techniques that the researchers employ most frequently are:

This is the procedure for bringing picture intensity values to a standard scale. This can be done to enhance the visual quality of the images utilizing methods including histogram equalization, contrast stretching, and normalization [35,36]. This entails expanding the dataset by including more permutations of the initial visuals, including altering the contrast or brightness or introducing noise.

5.3 **Brain region segmentation and analysis:** A precise forecast automated segmentation of brain components, including GM, WM, and CSF in MRI, is essential to large-scale intracranial volume research and quantitative analysis of the brain tissue. Pattern recognition and the Atlas-based technique are two conventional methods for segmenting brain tissues: Using an atlas and target images, atlas-based techniques compare intensity information. Owing to registration issues and a lack of consistent, dependable ground truth data, techniques like atlas-based and registration which are popular for human brain segmentation do not yield strong results for small, highly variable structures like the hippocampus [27,36]. The collection of local intensity features is used to categorize brain tissues in pattern recognition techniques. It has been suggested recently that atrophy of hippocampal AD[46,47].

As a result, hippocampal MRI segmentation may be useful in therapeutic settings. However, because of its tiny size, partial volume effects, anatomical variability, low contrast, low signal-to-noise ratio, fuzzy border, and close proximity to the Amygdaloid body, the hippocampus presents segmentation challenges in magnetic resonance imaging. Moreover, manual segmentation necessitates laborious expert analysis. According to a recent study, region growth, thresholding, and hippocampal segmentation using traditional techniques do not produce findings that are satisfactory.

6. PERFORMANCE EVALUATION

6.1. Security Metrics: A matrix of disorientation is used to assess the classification model's performance. An NxN matrix, where N is the number of classes in the dataset, is a confusion matrix. Since we are classifying binary data in our instance, N has a value of 2, meaning it can be either positive or negative. Using the confusion matrix, many model parameters, including accuracy, specificity, and sensitivity, may be computed:

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad 1$$

$$Precision = \frac{TP}{TP+FP} \quad 2$$

$$Recall = \frac{TP}{TP+FN} \quad 3$$

$$F1 - score = \frac{2.precision.recall}{Precision+recall} \quad 4$$

6.2. Comparative Analysis: The establishment of a framework to evaluate the progression of AD utilizing neuropsychological scores and MRI volumes is another important method for diagnosing and predicting the illness. utilizing the features selection approach in this framework. First, it shows how frequently researchers use deep learning and machine learning methods. Second, it displays the maximum accuracy that any particular algorithm has been able to accomplish. Deep learning techniques are widely used, which is explained by their remarkable accuracy especially when processing intricate three-dimensional data [49-50]. Many researchers choose to use deep learning models since they have proven to perform better in the field of Alzheimer's disease research. Deep learning approaches have been seen to use feature extraction and feature selection strategies to reduce diagnostic mistakes in the field of Alzheimer's diagnosis. In several research papers, machine learning approaches make use of deep learning. An analysis of studies in the field of medical image classification for Alzheimer's disease diagnosis shows that these methods face many challenges. The lack of intelligent feature selection strategies, especially for group intelligence methodologies, is one of the problems with present methodologies. To classify images, deep learning approaches have been used in most research projects; yet, a significant percentage of these techniques have been found to have high mistake rates. Table 1 comparisons table existing method.

Reference/Author	**Method**	**Performance**
AlSaeed, D., & Omar, S. F. (2022)	CNN	99%
Kamal, M., Pratap, A. R.(2022)	LS-SVM-RBF	58%
Ebrahimi, A., Luo, S.(2021)	TCN	91.56%
Feng, W., Halm-Lutterodt, N. V., (2020)	3D-CNN-SVM	93.71%
Pan, D., Zeng, A.,(2020)	CNN-EL	84%
Liu, M., Cheng,(2018)	CNNs	93.26%
Feng, C., Elazab, A.,2019	FSBi-LSTM	94.82%

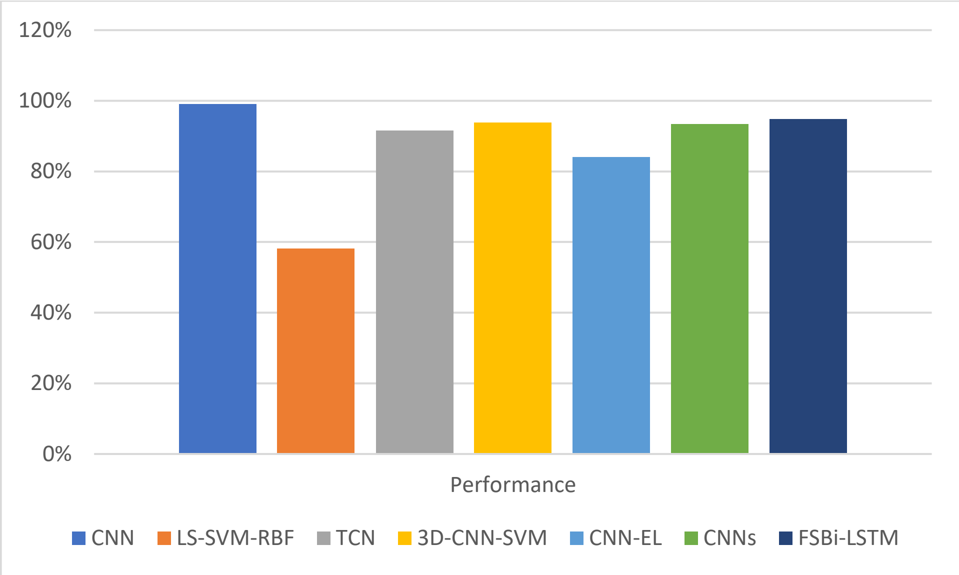

Figure 3. performance metrices

7. DISCUSSION AND CONCLUSION

7.1. Policy Implications for clinical practice and research: AI methods are becoming more and more useful for risk management, illness detection, and image-based diagnostics. They still need a few practical and technical solutions to reach their full potential. This chapter discusses the application of AI approaches to the review and presentation of several structural imaging modalities for the detection of AD and related conditions. Additionally, AI methods are being examined for AD detection, which causes serious health issues. Several experiments employing AI approaches were conducted with various image datasets [44,45]. When comparing AI algorithms, CNNs showed superior accuracy in contrast to the traditional machine learning approaches in AD detection Various AI methods for AD diagnosis are reviewed in conclusion. It's suggested that CNNs had the greatest success rate in identifying AD.

Though these models lack the capacity and generalizability associated with human learning, current AI algorithms are recognized with measurable consistencies in huge datasets and are frequently utilized across a breadth of different disciplines, including disease detection. Should artificial intelligence protocols enable computers to learn from fewer instances on their own, the results of the experiments may have far-reaching logical and cultural implications. Large models are capable of producing more complex results and flexible learning due to their larger memory and processing capability. It's getting more and more obvious that much more well-known figure assets won't be enough to generate computations appropriate for summarizing previous preparation sets and learning from a small number of prototypes. Shortly, mobility tests and intelligent surroundings may allow us to differentiate between dementia and normal aging.

7.2. Limitations: There are a few significant shortcomings in the current work that must be fixed. First, not all relevant papers were found by the database search, making it unable to find all eligible publications in its entirety. The search keywords listed in this work might not be enough to find all of the literature on AI and dementia together. We emphasized the identification of dementia illnesses with adult onset and the ML and DL algorithms linked to it. As a result, research on dementia in the working life was neglected. However, in this review, we only used three significant databases. This restricted the scope of related periodicals for investigating the area.

7.3. Conclusion: Alzheimer's disease is typified by neuronal loss and consequent brain abnormalities, which cause the affected person to behave and function differently. The process of brain resorption usually affects different parts of the brain and impairs cognitive function. As such, an approach that lessens the deficits brought on by brain atrophy and neuronal degradation is necessary for the treatment of Alzheimer's disease. The characteristic of this syndrome is a gradual deterioration in recent memory and information retrieval, which ultimately results in memory retrieval becoming impossible. This specific illness is more common in the elderly and is marked by difficulties identifying people, even those whom one is quite familiar with. The implementation of artificial intelligence approaches to feature selection from MRI images is examined in this work. The authors recommend that in order to enhance the performance and accuracy of diagnosis, future research efforts concentrate on feature selection and optimization techniques, such as whale improvement, gray wolf efficiency, and other modern optimization methods, and determine the most ideal features from MRI images.

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