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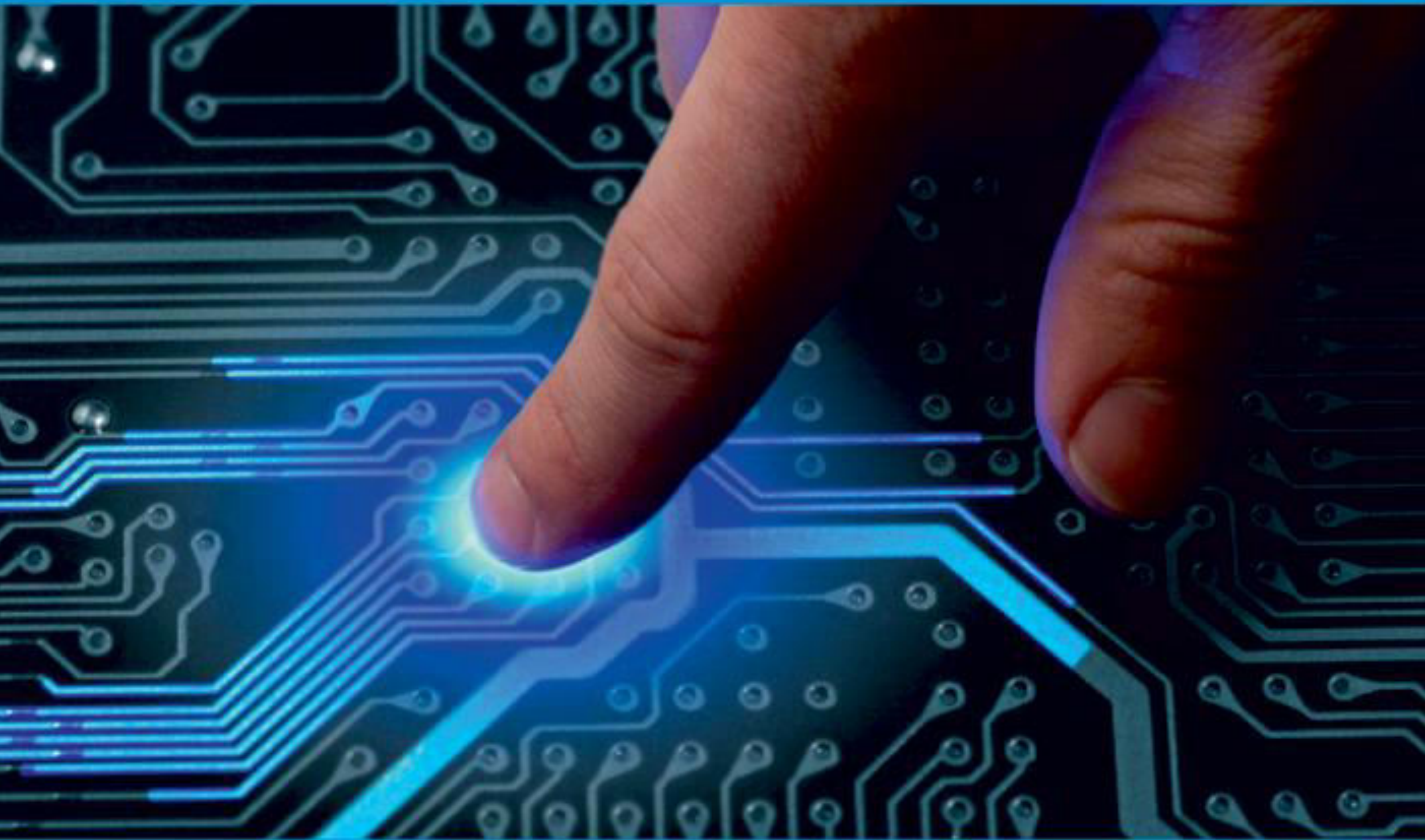

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Alzheimer Detection using Deep Learning

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ABSTRACT: Alzheimer's disease (AD) poses a significant challenge in healthcare due to its progressive and debilitating nature. Recent advancements in DL have shown promise in medical image analysis, particularly in enhancing the accuracy and efficiency of AD diagnosis. This study explores the usage of CNN in utilizing neuroimaging data for diagnosing Alzheimer's disease. Neuroimaging techniques such as PET scans and MRI offer valuable insights into the structural and functional changes associated with AD. DL models can detect intricate patterns indicative of AD pathology by analyzing huge information of neuroimaging scans. These models enable automatic classification of images into categories like Alzheimer's disease, MCI, and normal cognition. Integrating deep learning with neuroimaging data holds huge promise for enhancing the accuracy, speed, and scalability of AD diagnosis. Furthermore, it paves the way for developing state-of-the-art diagnostic tools and personalized treatment plans. This paper aims to provide insights into the possibility of DL in AD diagnosis and its execution for clinical practice and research by reviewing current methodologies and research findings.

KEYWORDS: Alzheimer Disease, deep learning, CNN, early detection and diagnosis.

I. INTRODUCTION

Alzheimer's disease involves the degeneration of brain cells, leading to the contraction of the hippocampus, reduction in cerebral cortex volume, and dilation of ventricles, ultimately leading to memory impairment. It affects patients social life. The Alzheimer's Association estimates nearly 6 million Americans suffer from the disease and it exists the 6th leading cause of death in the US. The estimated burden of Alzheimer's disease was $277 billion in the US in 2018. Primary identification of the Alzheimer disease will help in early treatment, which can stop the exaggeration of the symptoms. There exists no medication that stops or reverses the progression of AD. To effectively detect Alzheimer's disease, a comprehensive assessment involving various examinations like the mini-mental state examination, physical, and neurobiological exams, with a detailed patient history, is necessary. Manual diagnosis of Alzheimer's disease is time-consuming and susceptible to human error, making it logical to leverage the computational advantages of computers, such as speed and accuracy, for diagnosis.

The Convolution Layer processes the initial image using a type of convolutional filters to identify the characteristics present in different parts of the image. The Pooling Layer reduces the magnitude of the data being analyzed, thereby reducing the network's sensitivity to variations in the scene being analyzed. Common strategies employed in this layer include max pooling, which selects the maximum value in a given window, and averaging, which computes the average value within the window.This layer contributes to the final output, enabling various tasks to be performed. One distinctive feature of CNNs compared to traditional neural networks is their significantly greater number of layers. The depth of a neural network architecture refers to the length of the longest path between the intake and outturn neurons. While there is no precise threshold for determining when a network can be called "deep".

This layer contributes to the final output, enabling various tasks to be performed. One distinctive feature of CNNs compared to traditional neural networks is their significantly greater number of layers. CNNs are employed to reduce computation compared to regular neural networks. The convolution operation significantly streamlines computation while preserving the essential features of the data. They excel particularly in image classification tasks, as they can apply the same learned features across all positions within an image.

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Alzheimer's disease (AD) is a chronic condition characterized by brain atrophy and the degeneration of brain cells, leading to cognitive decline. It typically manifests in middle or old age and is marked by progressive deterioration of brain function. AD accounts for approximately 60–70% of dementia cases. Short-term memory loss is often one of the earliest and most prominent symptoms. As the disease advances, individuals may experience behavioral and language difficulties, confusion, mood swings, diminished motivation, and challenges in self-care. The decline in health can lead to emotional and psychological strain on both the individual and their caregivers. As the disease progresses, bodily functions deteriorate, ultimately leading to death. The average life expectancy post-diagnosis is typically less than nine years, although the rate of progression can vary among individuals..

In 2015, the global prevalence of Alzheimer's disease exceeded 29.5 million cases. Most cases typically begin in adults aged over 65, although around 4% to 5% experience early onset before reaching that age. Dementia, of which Alzheimer's disease is a significant contributor, accounted for approximately 1.9 million deaths in the same year. Alzheimer's disease is known to be one of the most costly diseases in developed nations. In India, over 4 million individuals are affected by dementia to varying degrees.

The projected rise in Alzheimer's disease cases is anticipated to quadruple by the year 2050. While there are medical interventions available to address the effects of the disease in its early stages, Alzheimer's disease itself progresses irreversibly. Hence, early detection of the illness is crucial not only from a clinical perspective but also socially and financially. The advancement of imaging and computational technologies has greatly aided medical science in the early diagnosis of diseases and the execution of corrective treatment measures. It is possible to identify the novel alterations brought about by AD by examining these changes both qualitatively and quantitatively and contrasting them with the typical functions and characteristics of the human brain. The Alzheimer's and normal control cases are categorized as AD (Alzheimer's disease), MCI (Mild Cognitive Impairment), and NC (Normal Control) individuals based on the morphological and anatomical changes. MCI is an intermediate stage between AD and Normal Controls. As a result, both quantitative and qualitative AD diagnosis is highly valuable in clinical settings as it can expedite treatment and enhance both the patient's and their caregivers' quality of life. Due to a number of technical and clinical problems, the present state-of- the-art diagnosis approaches have limited efficacy in clinical settings. Furthermore, there are very few techniques created expressly for the early diagnosis of AD. This work uses modern machine learning tools and methods, such as deep learning, to offer a state- of-the-art, simple, and early diagnosis scheme using Magnetic Resonance Images (MRI). This article suggests using a dataset of healthy control participants and ill subjects to develop an automated (machine learning) approach to predict AD. It divides the data into three categories: Alzheimer's disease, mild cognitive impairment (MCI), and normal. Compared to a traditional categorization prediction method, it facilitates radiologists and other healthcare practitioners in accurately predicting which category an MRI picture belongs to.

II. RELATED WORK

[1] S.Aruchamy, A.Haridasan, A. Verma, P. Bhattacharjee, S. N. Nandy, S.R.K.Vadali, "Alzheimer's Disease Identifying using ML Techniques in 3D MRI", 2020 International Conference.
The Author visualized 3D Structural MR-Images in 3 perpendicular planes namely Axial, Coronal, Sagittal planes. They have conducted feature extraction based on first order statistics for gray matter and white matter of all three orthogonal images. After that they calculated Co-relation matrix for feature reduction they used PCA (Principal Componet Analysis). Finally they did binary classification using SVM (Support VectorMachine), Naïve Bayes and logistic. Regression classifiers. They achieved accuracy of 99.9% on white matter using naïve bayes classifier.

[2] E. Yagis, L. Citi, S. Diciotti, C. Marzi , S. W. Atnafu, A.G.S.De Herrera"3D CNN for Detection of Alzheimer's Disease via structural MRI" 2020 . The Author have used 3D Structural MR-Images to get away from information loss which occur during 3D image slicing into 2D. For binary categorization of Alzheimer's and achieved accuracy of 73.4% ± 0.04(mean, standard deviation) and 69.9% ±0.06(mean, standard deviation) on ADNI and OASIS dataset respectively.

[3] Sarah Lee and David Clar, "Ensemble Methods for Alzheimer's Disease Detection in MRI Scans: A Comprehensive Survey", 2021 International Conference.
This survey paper focuses on ensemble methods For Alzheimer's disease detection, emphasizing howmerging several models can enhance classification performance and robustness. The paper primarily explores ensemble techniques, and it

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might not encompass individual deep learning architectures in detail. Additionally, it does not extensively discuss the computational complexity of ensemble methods. The authors review various ensemble techniques like bagging, boosting and stacking applied to AD detection. They also explore tactics for diversity among base learners and ensemble model selection Achieves competitive results and highlights the capability of transfer in medical image interpretation.

[4] Maria Garcia and Carlos Martinez, "Challenges and Future Directions in Alzheimer's Disease Detection from MRI Images: A Review", 2022 International Conference. This paper offers a summary of the present obstacles and forthcoming paths in Alzheimer's disease detection from MRI images, including issues related to dataset availability, interpretability, and model generalization.
While it highlights difficulties and forthcoming directions, this paper might not offer specific methodological details or result to the identified issues. The authors discuss challenges such as small and imbalanced datasets, model interpretability, and the need for explainable AI in AD detection.

[5] Robert White and Susan Taylor, "Multi-Modal DL for Alzheimer's Disease Diagnosis: A Survey",2020 International Conference. This survey paper centers on the integration of multiple modalities, including MRI images, PET scans, and genetic data, Leveraging DL technique for more accurate Alzheimer's disease diagnosis.
The paper primarily addresses multi-modal approaches and may not delve into the intricacies of single-modality analysis. Additionally, it does not extensively cover the computational challenges of handling diverse data types.
The authors review multi-modal data fusion techniques, including late fusion and early fusion, and discuss the capabilities of DL models to be applied to integrate data from various origins for AD diagnosis. They also emphasize the potential advantages of leveraging multi-modal data for improved accuracy.

[6] Emily Johnson and Michael Brown, "A Review of Transfer Learning methods for Alzheimer's Disease Detection in MRI Images"2019 International Conference. This survey paper focuses pertaining to transfer learning methodologies applied to Alzheimer's disease detection using MRI images. It discusses how pertained models and fine-tuning can be leveraged to improve model performance with limited labeled data. The paper primarily explores tl and may not cover the broader spectrum of deep learning methods. Additionally, it does not tackle the obstacles specific to multi-modal data integration. The authors review transfer learning paradigms such as feature extraction, fine-tuning, and domain accomodation for AD detection. They also discuss the choice of pretrained models and strategies for handling class imbalance. Shows improved performance compared to traditional methods, especially in early-stage detection.

III. METHODOLOGY

In the proposed methodology, the focus lies on extracting a multitude of shape and texture characteristics from the hippocampus region to facilitate the observation of Alzheimer's disease. This process involves leveraging CNN, an advanced deep learning technique, to derive characteristics from a training dataset. Through CNN, a training model is developed and fine-tuned, culminating in the formation of a validation model.

The training model is instrumental in learning intricate patterns and features present within MRI scans of individuals for Alzheimer's disease. Through iterative learning, it refines its understanding of these features, optimizing its capacity to discriminate between healthy and diseasedbrains. Subsequently, the validation model is derived from the training model, serving as a robust tool for assessing the validity and solidity of the learned features.

Upon completion of model training and validation, it is primed to analyze test data. MRI scans of individuals yet to be diagnosed are inputted into the validation model. Here, the model obtains relevant features from these images, focusing on the hippocampus region. These extracted features serve as crucial indicators for classifying the Alzheimer's category. By comparing the characteristics derived from test images against the learned patterns stored within the validation model, the system accurately discerns whether the individual is exhibiting signs of Alzheimer's disease.

1. This approach combines the power of DL with the intricacies of medical imaging to offer a robust and efficient method for Alzheimer's disease detection. By automating feature extraction and classification processes, it streamlines diagnostic procedures, potentially leading to earlier detection and intervention, thereby improving patient outcomes.

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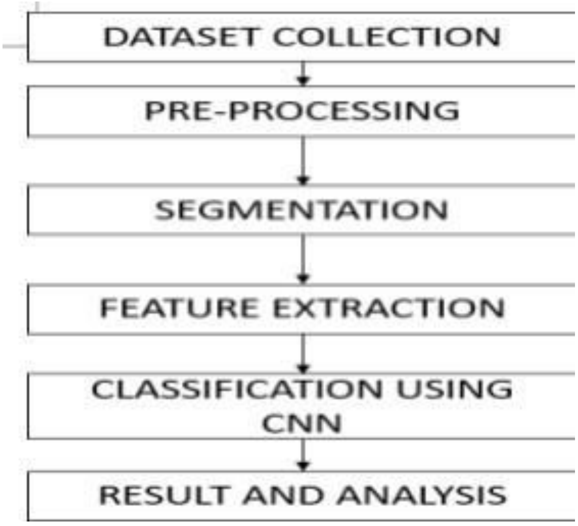
2. IMPLEMENTATION

Implementation is the way to improve the structure design by breaking down the system into modules and solving it as independent task. The total of modules for our system is six.



1. Data Collection and Preprocessing:

Gather ample dataset of medical figure, such as MRI scans or PET scans, from individuals for Alzheimer's disease.
Ensure the details is labeled and properly annotated to identify Alzheimer's disease cases.
Preprocess the snapshots by standardizing sizes, orientations, and pixel values to generate a consistent input for the DL model.

2. Data Splitting and Augmentation:

Divide the information into train, validity, and test sets.

The train set is utilized for model training, the validation dataset for hyperparameter optimization, and the evaluation dataset.
Utilize data augmentation methods, like rotation, mirroring, and resizing, to increase the variety of the train dataset and enhance model generalization.

3. Deep Learning Architecture Selection:

Choose a suitable deep learning structure for the task. CNN are utilized for image-based disease detection. Experiment with various pre-trained models (e.g., VGG, ResNet, or Inception) or design a tailored CNN structure that can efficiently abstract relevant features from medical images.

4. Model Training:

Train the DL model using the train data, using an appropriate loss function, optimizer (e.g., Adam or SGD), and batch size.
Implement early stopping and model checkpointing to avoid excessive fitting and save the good system based on validation performance.

5. Evaluation and Fine-Tuning:

Assessing the model's performance on both the validity set and the test set involves evaluating various metrics such as correctness, sensitivity, specificity, and the area under the receiver operating characteristic (ROC) curve (AUC).
Fine-tune the model by adjusting hyperparameters, adding regularization techniques (e.g., dropout or batch normalization), or exploring different architectures to improve performance.

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6. Interpretation and Clinical Integration:
Interpret the model's decisions by visualizing feature maps or using techniques like Grad-CAM to identify areas in the figure that contribute to the prediction.
Collaborate with healthcare professionals to evaluate the clinical relevance of the model's predictions and integrate incorporating the model within the diagnostic workflow, potentially building decision systems for Alzheimer's disease diagnosis.

METHODOLOGY

One kind of DNN is called a Deep-CNN, which is made up of several hidden layers, including convolutional, pooling, RELU, and fully connected normalized layers. CNN shares convolutional layer weights, which lowers the network's memory footprint and improves speed. The shared weights, local connectivity, and three-dimensional neuron volumes are the key components of CNN. The convolution layer uses a learnt kernel to convolution several sub-regions of the input picture to design a feature map. Next, when the error is low, a non-linear activation function is applied through the ReLu layer to increase the convergence properties. A portion of the picture or attribute map is selected for the pooling layer, and the representative pixel is the one with the high value among them or the average value.

System Architecture

As a result, the sample size is significantly decreased. Towards the output stage, convolutional layers and the conventional Fully-Connected (FC) layer are occasionally combined. Convolution and pool layers are typically employed in some combination in CNN architecture. Max pooling and means pooling are the two sorts of method by the pooling layer. The average neighborhood is computed inside the feature points in mean pooling, and within the maximum feature points in max pooling. The inaccuracy brought about by the neighborhood size restriction is decreased by mean pooling and keeps historical data. By deducting the mean deviation-induced parameterized error in the convolution layer, max pooling preserves more texture information.

ALGORITHM

Many domains, including speech recognition, pattern identification, and NLP, have effectively used CNN. Like an ANN, CNN is a feed-forward multilayer NN that processes input as it passes through the layers. There are numerous distinct layers that make up the In contrast to ANNs, each CNN neuron gets intake from a little area that is the same size as a convolutional kernel. It guarantees that the intake figure is transformed into potent features by the trained CNN, which can improve system performance. To elaborate further, these layers are:

1. Convolutional layer: The parameters of a CNN include a set of kernels that are initially randomly generated and then trained using the back-propagation algorithm. Each kernel, when applied to the input image, produces an activation map, with the number of activation maps determined by the number of kernels used in that layer. To introduce non-linearity into the network, the Rectified Linear Unit (ReLU) activation function is commonly employed.

2. Studies, such as one by Krizhevsky, have highlighted the importance of ReLU over other activation functions like sigmoid and tangent in CNNs. ReLU has been shown to facilitate learning more effectively. Moreover, compared to alternative activation functions, using ReLU can result in significantly faster training times while maintaining comparable accuracy levels,where x and y represent the activation map for the i-th input and j-th output, respectively. Convolution is defined by the symbol *, and b is the j-th output map's bias. The convolution kernel between the i-th and j-th intake and outturn maps is denoted by j. The network is made more non-linear by applying the ReLU activation function. **Max-pooling layer**: The pooling layer primarily serves to reduce the output size of convolutional layers in a convolutional neural network (CNN). This reduction in size helps manage computational complexity while retaining essential features necessary for recognition. Pooling achieves this by sampling the input data, typically through operations like max- pooling, where the maximum value within each pooling window is retained.

Although alternative pooling methods like average and min-pooling exist, max-pooling is the most commonly used. It has proven effective in preserving important features while downsampling the data, making it a popular choice in CNN

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architectures.

$$y_{j,k}^{i} = \underbrace{max}_{0 \le m,n < s} \left(x_{js+m,ks+n}^{i} \right)$$

Fully connected layers: The final layer of a CNN, which could be a convolutional or max-pooling layer, typically feeds into one or more fully connected layers resembling those found in ANN. In these fully connected layers, every neuron in a given layer is connected to every neuron in the subsequent layer through their outputs. This complete interconnection facilitates the extraction of complex features learned by the preceding layers, enabling the network to make high-level predictions or classifications.

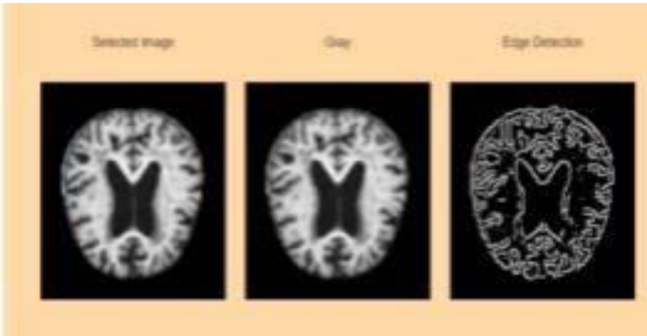
$$y^{(l)}(j) = \varphi^{(l)} \left(\sum_{i=1}^{N^{(l-1)}} y^{(l-1)}(i).w^{(l)}(i,j) + b^{(l)}(j) \right)$$

Softmax regression layer: In the fully connected portion of the neural network, the Softmax regression classifier is commonly employed for multi-class classification tasks. When dealing with a training sample with n labels and K classes, the Softmax classifier produces a K-dimensional vector for each test input. These vectors are probability distributions, with each component representing the approximate likelihood of the corresponding class label. Notably, the elements of the output vector sum up to 1, ensuring that the probabilities are normalized and reflect the relative likelihood of each class label given the input data .W=(w1,w2,...,wk) represents the set of parameters. The Softmax classifier's cost function is the cross entropy loss function, which may be computed as follows:

IV. RESULTS AND DISCUSSION

Deep learning methods for Alzheimer's disease detection have drawn a lot of interest since they may offer precise and effective diagnostic instruments. Early detection is essential for effective intervention and treatment planning of Alzheimer's disease, a neurodegenerative ailment marked by cognitive decline and memory loss. Using medical snapshots and other data sources, DL, a type of artificial intelligence, has demonstrated promise in automating the diagnosis process.

DL models can detect minute alterations linked to Alzheimer's disease by analyzing brain MRI data. CNNs, for instance, are able to identify patterns that point to structural problems or brain atrophy.



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V. CONCLUSION

Using DL methods for Alzheimer's Disease (AD) detection in MRI snapshots represents a significant breakthrough in medical imaging and neurology. This approach offers promising strides in accurately and early diagnosing AD, vital for prompt intervention and treatment.

Deep learning models analyze MRI images, identifying nuanced structural alterations in the brain linked with AD before clinical symptoms appear. This early detection enhances patient outcomes by enabling timely interventions and therapeutic strategies in the disease's early stages, potentially slowing its progression. By leveraging advanced algorithms, these models unveil intricate patterns within brain scans, aiding in the identification and classification of AD- related abnormalities with high precision.

This breakthrough carries vast potential in revolutionizing AD diagnosis and management, facilitating proactive healthcare practices and personalized treatment plans. Incorporating it into clinical practice could greatly enhance patient care, offering hope for improved standard of living for individuals affected by AD and their families.

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