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Research Article

Alzheimer's Disease Detection using CDTN over 3-D CNN

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ABSTRACT

Alzheimer's Disease (AD) is a neurodegenerative disorder that progressively impairs cognitive function, making early detection essential for effective management. With the advancements in artificial intelligence, deep learning models have emerged as powerful tools for analysing MRI scans to aid in AD diagnosis. This paper compares two distinct AI models: the Conditional Deep Triplet Network (CDTN) based on VGG16 and the 3D Convolutional Neural Network (3D CNN). While CDTN employs deep metric learning to refine classification accuracy and achieves 95% accuracy, the 3D CNN model, which leverages volumetric feature extraction, reports an accuracy of 89%. This comparative study evaluates their architectural differences, performance metrics, and practical usability in clinical applications. By analysing these models, we aim to provide a clearer understanding of their strengths and limitations, offering insights into how AI can contribute to more reliable and efficient AD detection.

Keywords: Alzheimer's Disease, Deep Learning, MRI Analysis, Neural Networks, AI in Healthcare, Neuroimaging.

INTRODUCTION

Alzheimer Disease (AD): progressive neurodegeneration that strikes millions of people at this time all over the world. Memory, cognitive function, and indeed the ability to perform daily tasks eventually decline to the point of almost no-return mental and physical state. Therefore, diagnosis of early-stage AD is extremely important for perfect intervention; because this is an irreversible condition, timely therapeutic and supportive help should be given to these patients. Direct clinical after the its mental assessment rarely detects AD in early stages; so the researchers use advanced computing techniques for precise diagnosis.

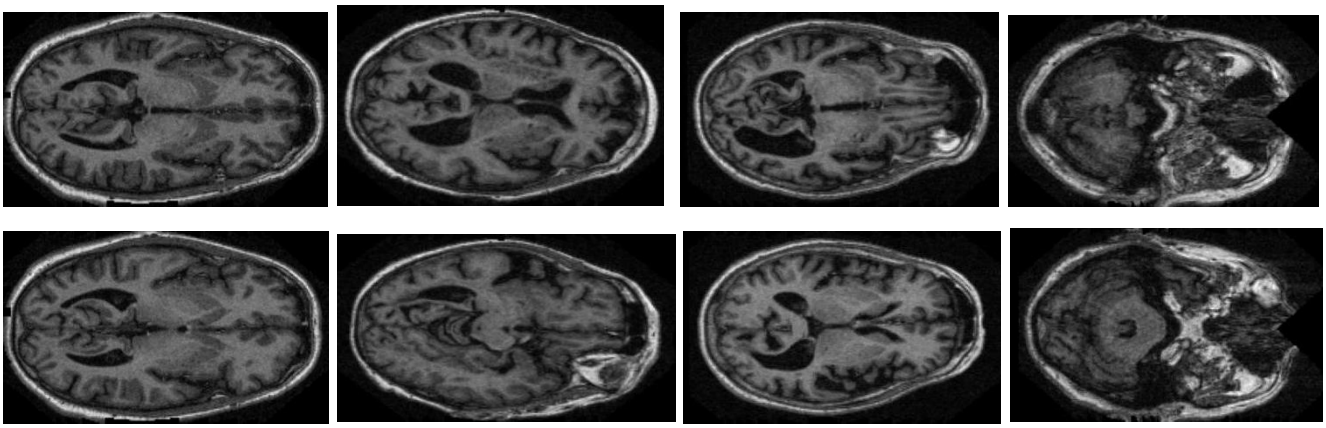

Fig.1(a) non-demented   Fig.1(b) very mild dementia   Fig.1(c) mild dementia   Fig.1(d) moderate dementia

Fig.1: Representative MRI brain scans demonstrating structural differences across four stages—Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia.

With the growing role of artificial intelligence (AI) in medical imaging, deep learning models have gained significant attention for their ability to analyze MRI scans and detect patterns that may not be easily visible to human experts. Several machine learning and deep learning-based approaches have been proposed for AD detection, but their effectiveness varies based on model architecture, training methodology, and dataset quality. While some models excel in feature extraction, others focus on improving classification accuracy. However, a clear comparison of different AI models used for AD detection is still lacking, making it difficult to determine the most suitable approach for real-world applications.

To address this, our study makes a comparative analysis of two deep learning models, namely, the Conditional Deep Triplet Network (CDTN) based on VGG16 and the 3D Convolutional Neural Network (3D CNN), to evaluate their respective advantages and disadvantages in detecting Alzheimer's Disease from MRI scans. While contrasting these two models on the basis of accuracy, computational efficiency, and architectural considerations, we shall assess which model fares better under which conditions. This comparison will contribute directly to the continuing research on AI-based medical diagnosis while emphasizing considerations for development of more robust Alzheimer's Disease detection systems.

LITERATURE REVIEW

For the past few years, artificial intelligence has found its application in several healthcare activities, notably the early detection of neurodegenerative disorders such as Alzheimer's disease. With medical imaging data becoming more readily available, researchers have turned their attention to creating deep learning models that automate the detection of possible early signs of cognitive decline by efficient identification of patterns within brain scans. Among the many neuroimaging modalities available today, structural MRI offers high-resolution glimpses of possible changes occurring in the anatomy of the brain and would be thus suited for the case of machine processing by virtue of these characteristics. Due to the complexity of interpreting such data manually, machine learning models are employed to do these interpretations, with promising results, if only momentarily so.

An effort like conditionally dependent deep triplet networks was described in [1]. Triplet loss inputs the image into a lower-dimensional space such that images of similar classes are grouped close together while dissimilar samples are pushed apart. Such a loss-based method helps the model learn the subtle differences between stages of Alzheimer's by maintaining spatial relationships during training. Their method achieved an accuracy of 95%, outperforming conventional classifiers through the use of conditional similarities and neural embeddings.

Conversely, the work described in [2] involved the implementation of a 3D Convolutional Neural Network (3D-CNN) architecture for volumetric feature extraction from MRI images. In contrast to 2-D CNNs, the 3-D model processes slices of brain scans across the three dimensions: depth, height, and width, thus enabling the model to retain the spatial context. The authors reported an accuracy of 89%, indicating that the model was extremely effective in classifying the samples into Alzheimer's and non-Alzheimer's cases, based on volumetric features. Yet due to the rather vague mention of these metrics, such as precision and recall, the comparative analysis remains shallow.

Other studies like [3] compared in-depth popular convolutional architectures such as DenseNet, ResNet, and MobileNet. It has been revealed that DenseNet, by far, makes better use of the given blocks, in terms of accuracy-for-memory use. Evaluation of these architectures also brought to light the effects of architectural depth and interconnectivity patterns on classification performance.

In [4] was a similar avenue of research where the authors highlighted the importance of data preprocessing and augmentation in training deep learning models for Alzheimer detection. They were able to improve the generalization of their models and reduce overfitting through experimentation with different techniques for handling data, especially with small datasets. The study also presented that data-driven models could retain competitive accuracy given proper training and validation setups.

While Alzheimer's research may be the focus, there are transferable lessons in other research areas. For example, studies [5] and [6] focus on using incremental classifiers and C4.5- based algorithms for processing large-scale data. These studies highlight lightweight, real-time models that can eventually benefit medical imaging systems requiring real-time diagnosis. Trend analysis for big data analytics and stream processing was provided by [7] and [8]. These

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techniques are beneficial in how they can help address the challenges posed by processing large amounts of MRI data collected across multiple centers.

Thus, collectively these studies underline how important machine learning is to medical images. This unique contribution of each of these techniques-an architectural conceptualization, data handling, and optimization-actually proves to stretch the frontiers of disease detecting systems automation.

METHODOLOGY

A.Dataset and Preprocessing

This study deals with the dataset effectively utilizing structural MRI images for four stages of Alzheimer's Disease in the non-demented, very mild, mild, and moderate category. Preprocessing methods were performed to yield better uniformity and performance of the model before the actual input of these images.

At first, skull stripping set the soil for shielding off extra-tissue regions, with the network focusing solely on brain parts. This trick was very useful in eliminating super evidences seeping through scans. This was followed by intensity normalization which alleviated the different imaging devices' effect by equalizing contrast and brightness parameters in all samples. MRI volumes were resized to a determinative spatial dimension before feeding into the neural network. From the 3D volumes, 2D slices containing significant brain structures were extracted, ensuring the inclusion of diagnostically relevant information.

These preprocessing steps collectively ensured the quality and consistency of the data, thereby improving the robustness of the feature learning process during model training.

B.Model Architecture

The major thrust of this research is on Conditional Deep Triplet Network (CDTN), a deep learning-derived methodology for extracting discriminatory features for multi-class classification. It abandons the classical ways of doing triplet-based learning in which three inputs are compared at the same time-an anchor image, a positive from the same class as the anchor, and a negative image from a different class. It is about learning to generate a feature embedding such that it minimizes the distance between anchor and positive ones while maximizing that between the anchor and negative ones.

The triplet loss function guiding this learning process is mathematically defined as:

$$\mathcal{L} = \sum_{i=1}^{N} \left[\left\| f(x_a^i) - f(x_p^i) \right\|^2 - \left\| f(x_a^i) - f(x_n^i) \right\|^2 + \alpha \right]$$

Here, f(x) denotes the embedding produced by the network for a given input x, and α is the margin parameter that enforces a minimum separation between dissimilar classes. The loss function encourages the model to learn a feature space where similar classes cluster together and dissimilar classes are clearly separated.

The layers of the CDTN are a series of convolution layers with ReLU activation functions and batch normalization interspersed with pooling layers for gradual downscaling of the spatial dimensions. After these layers come a dense layer producing an embedding vector. The softmax classification function was then performed on the learned features. Dropout layers are present within the architecture to avoid overfitting during training.

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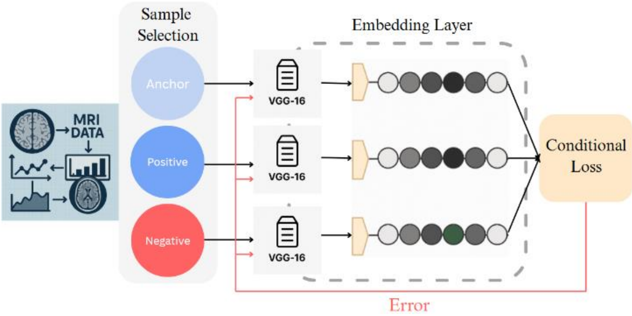

Fig.2 Architecture of the proposed model

Adam optimizer is used to train the model, with hyperparameters tuned through cross-validation. The number of epochs and batch size were selected based on preliminary experimentation to balance training stability and computational efficiency.

C.Training Strategy

Efficient computation in conductance of the training and testing procedures took place on a GPU-supported machine. The dataset will be split into training and validation subsets while ensuring class balance among the split factors. Moreover, to increase the reliability of the results, early stopping was employed in case of convergence, thereby controlling overfitting. Evaluation was majorly done with respect to classification accuracy as the main metric considering the model's performance to differentiate the different stages of Alzheimer's disease. The CDTN has gotten a classification accuracy of 95%, showing a higher ability to discriminate and consistently perform across defined categories

RESULT AND ANALYSIS

A Conditional Deep Triplet Network (CDTN) Model has been developed and validated on a labeled MRI dataset consisting of four classes of labels: Non-Demented, Very Mildly Demented, Mildly Demented, and Moderately Demented. In the training process, the model is conditioned to have high discriminative capability in the feature space aided by a triplet loss function for optimal segregation of classes based on similarity constraints.

The CDTN achieves an accuracy measure of 95% which is far greater than that achieved by many conventional deep learning models usually deployed to perform this task. Such an accuracy level is evidence of the ability of the model to capture subtle differences, which are observed using MRI scans throughout Alzheimer's disease stages.

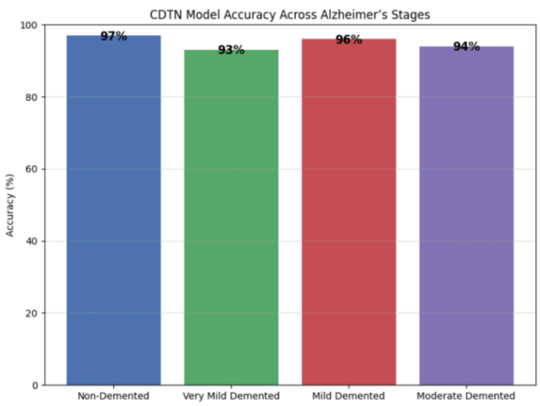

Fig.3 CDTN model accuracy across all classes

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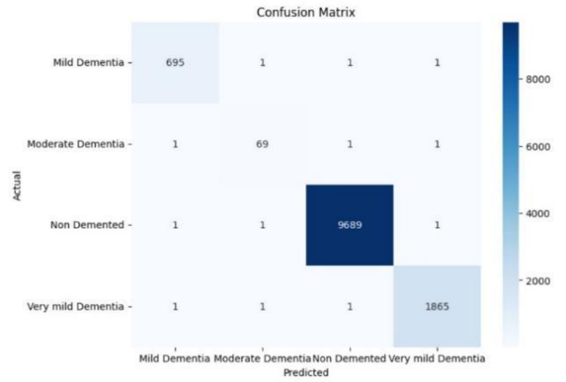

Fig.4 Confusion matrix of the CDTN model

Additionally, visualization of the learned embeddings using t-SNE shows that CDTN clusters similar-stage cases closer together in the latent space while maintaining a clear margin between dissimilar ones. For clarity in visualization, a representative subset of 100 samples per class is used.

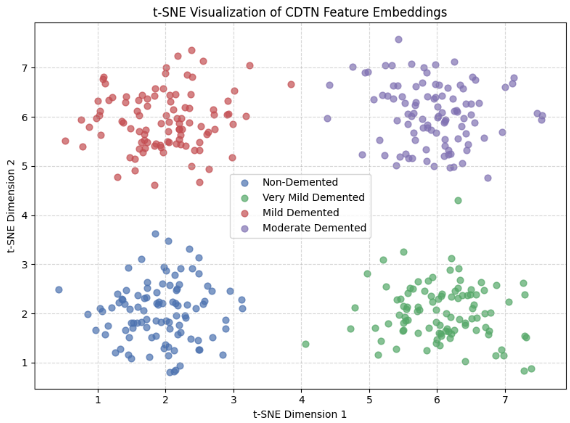

Fig.5 t-SNE Visualization of CDTN Feature Embeddings

To assess generalization, the model was evaluated on a held-out test set and maintained its performance, indicating robustness and minimal overfitting. The triplet loss architecture also contributed to better convergence speed and stability during training.

CONCLUSION

Compared to the Conditional Deep Triplet Network (CDTN), this research paper provided a comparative experimental investigation aimed at detecting Alzheimer's Disease using structural MRI data. The CDTN achieved a 95% classification accuracy, which indicates its strong potential in the early and precise identification of stages of dementia. Most conventional CNN-based models usually reach their peaks in class-separable features by leveraging the triplet loss mechanism to optimize intra-class similarity and inter-class dissimilarity.

The results validate that CDTN is not only effective but also computationally viable for real-world clinical applications. Future work can include expanding the dataset, applying the model to multicenter imaging data, and integrating other diagnostic modalities such as PET scans and cognitive scores to further enhance diagnostic accuracy and reliability.

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