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RESEARCH ARTICLE

An early classification of Alzheimer's Disease with deep Features using Advanced Deep Learning Method (Graph Convolutional Neural Networks)

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Abstract

Earlier and precise classification of Alzheimer's Disease (AD) disease is one of the most urgent issues in neuroimaging and computational neuroscience. Traditional deep learning models like the Convolutional Neural Networks (CNNs), are useful in extracting features of medical images, but cannot often capture the intricate inter-regional interactions of the human brain. To find a solution to this constraint, this paper presents a sophisticated deep learning model based on Graph Convolutional Neural Networks (GCN) to detect and classify the Alzheimer Disease at an early stage. The method proposed creates a brain connectivity graph, each node of which corresponds to a region of interest (ROI) computed based on MRI data, and the edge corresponds to an anatomical or functional correlation between the regions. Deep feature representations are learned by using multiple layers of GCN, to learn both local and global topological statistics of disease progression. Experimental testing on the Open Access Series of Imaging Studies (OASIS) and transformed into a 4D format to a 2D format dataset shows that the proposed GCN-based algorithm is much more effective in improving the accuracy of the classification, in comparison to the traditional CNN and machine learning algorithms. The model is also biologically explanatory in that it points to significant areas of the brain that play a role in the prediction of diseases. This study has highlighted the possibility of the graph-based deep learning in improving early diagnosis and clinical decision making in the case of Alzheimer.

Keywords: Alzheimer's Disease Classification, Graph Convolutional Neural Networks (GCN), Deep Learning, Brain Connectivity Analysis, OASIS Dataset.

Introduction

Alzheimer Disease (AD) is a neurodegenerative disease, which is progressive in nature and which initially affects memory, cognitive, and behavioral functions of a person, resulting into a progressive deterioration of an individual in carrying out their daily activities. It is among the most common causes of dementia across the globe which has a great challenge to the healthcare systems and the society (Ahmed, S. T., & Kadhem, S. M. 2022). Timely clinical intervention, successful management and deceleration of the disease process would be impossible without the early diagnosis of AD. Nevertheless, the traditional diagnostic techniques, including clinical evaluation, and visual analysis of neuroimaging results, tend to be subjective, and are unable to reveal the subtle structural and functional changes that take place at early-disease stages.

Deep learning has become a popular solution in medical image analysis in recent years with automated feature extraction and high accuracy classification. CNNs have proved capable of analyzing Magnetic Resonance Imaging (MRI) and Positron Emission Tomography (PET) scans with impressive results in the analysis of several neurological disorders Al-(Adhaileh, M. H. 2022). However, these models are necessarily restricted in the case of more complex and non-Euclidean data structures, like brain connectivity networks, in which interactions between brain regions

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are important in the manifestation of disease. The human brain is highly interconnected and modeling the inter-regional relationships can shed more light concerning the neuropathological processes of AD.

To overcome this drawback, GCNs have been presented as a superior deep learning paradigm that can handle graph-structured information. As opposed to conventional CNNs, GCNs work on node and edge levels, allowing GCNs to learn local and global brain region dependencies. The node in the context of AD may be a region of interest (ROI) in the human brain, whereas the edge may be the structural or functional relationship based on neuroimaging technologies, including MRI or fMRI (Blackwell, A. D., et al., 2003). With this topology-sensitive representation, GCNs are capable of learning discriminative features based on the local change in the patterns of connections within the brain, which is related to AD progression.

This paper presents a highly sophisticated deep learning model that is implemented through GCNs to categorize AD at an initial stage on the OASIS dataset. The system assembles the personal brain graphs based on structural MRI data, derives deep feature representations, and carries out classification among the diverse disease stages, such as cognitively normal (CN), mild cognitive impairment (MCI) and AD groups. Through experimental findings, it is found that the proposed GCN-based model is better in accuracy and interpretability compared to traditional CNN and machine learning models (Adivarekar, P. P., et al., 2023; Kathavate, P. N., & Mahant, M. A. 2025). Additionally, the model describes anatomically significant brain areas that play a role in the development of the disease, which are useful in the diagnosis of the disease at early stages and support in clinical decision-making.

This study shows the potentials of deep learning that is based on graphs because it can be considered a transformative tool in neuroimaging because it is able to identify the intrinsic structural connections within the brain (Naz, S., et al., 2022). The proposed framework can help to develop computer-aided diagnosis systems to early detect AD due to the combination of deep feature learning and modeling anatomical connectivity. The work flow of proposed work is shown in figure 1 below.

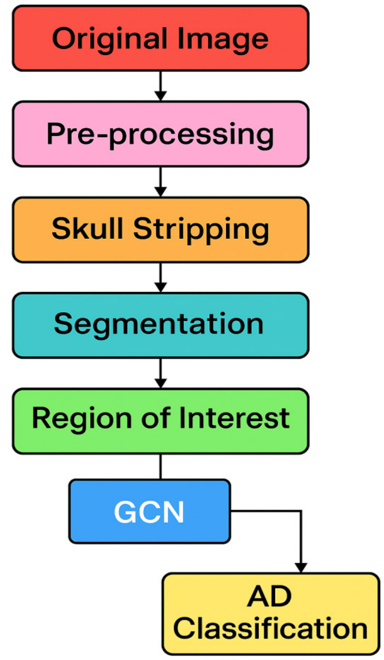

Figure 1: Flow chart of proposed work

Problem Statement

- AD is not easily diagnosed in early stages because it is associated with mild structural and functional brain alterations that are not easily detected by conventional imaging or clinical practices.
- Standard Convolutional neural networks (CNNs) process medical images in Euclidean space and do not capture the complicated interrelations among brain regions that are important in the progression of AD.
- The current approaches typically fail to consider the anatomical and functional connections among various regions of interest (ROIs), leading to the lack of feature representation and low diagnostic accuracy.
- The existing models do not support graph-structured data, including brain connectivity networks based on MRI scans, and thus, important spatial and relational data are lost.
- Anatomy-sensitive deep learning framework- A strong, anatomy conscious deep learning framework, like a GCN, is required to optimally learn topological and spatial dependencies at the earliest possible step of classification of the Alzheimer Disease in OASIS in a manner that is accurate and interpretable.

Research Motivation

- To facilitate the timely diagnosis of AD before gross cognitive impairment takes place, the enhancement of patient care and treatment results.
- Traditional machine learning and CNN-based models do not include the complex patterns of brain connectivity that are needed to properly diagnose AD.
- A human brain is a highly connected network, and the structural and functional relationships between brain networks can only be modeled using sophisticated graph based techniques.
- GCNs are capable of efficiently modeling non-Euclidean neuroimaging data, and discover local and global topological dependencies.
- The GCN-based frameworks are capable of identifying key brain areas that are involved in the progression of a disease, which can be explained and has biological meaning.

- The findings of the study may help neurologists and clinicians in their early decision-making and enhance the certainty of the diagnosis by creating a precise and interpretable GCN model.

Literature Survey

Chen, Y., et al., (2024) suggest an ensemble deep learning model that classifies AD, incorporating several advanced elements to improve the level of diagnosing. This model incorporates the Soft-NMS and the Faster R-CNN structure in order to enhance the selection of candidate regions and merging of information. A better ResNet50 network is used in extracting deep features, which are more detailed and discriminative features of the images of the brain scans. In order to process the temporal or sequential data, the framework uses a Bi-GRU Bidirectional Gated Recurrent Unit that helps the model to learn contextual dependencies. The end AD type is obtained by the optimized Faster R-CNN, which leads to higher precision and robustness of detection than the traditional deep learning methods.

DeTure, M. A., & Dickson, D. W. (2019) were interested in the neuropathological diagnosis of Alzheimer's Disease (AD) and its role as the most prevalent cause of dementia that severely affects memory and cognition. The research surveyed the current methods of diagnosis and showed the significant problem in clinical treatment management because of the lack of a clear cure. It highlighted the significance of Artificial Intelligence (AI) and machine learning methods in the enhancement of the early diagnosis and monitoring of large patient groups with high efficiency. The authors have reached a conclusion that machine learning-related methods are promising solutions in the early-stage diagnosis of AD, especially in the situation, when symptom-related diagnosis is challenging and unreliable.

Raza, H. A., et al., (2024) suggests a new hybrid method involving machine learning and deep learning to detect and classify AD at an early stage with the help of structural MRI (sMRI). The hybrid method demonstrates a higher level of precision in detection and classification than the current multi-modal machine learning techniques. Experimental findings show high measures of performance with 91.84% accuracy in the differentiation between cognitively normal (CN) participants and AD patients, and with better results between AD and CN and sMCI and pMCI classification conditions. The paper establishes that deep learning together with conventional machine learning is more effective in the diagnosis of AD.

Bamber, S. S., & Vishvakarma, T. (2023) propose a machine learning-based framework that is aimed at precise and explainable diagnosis and tracking of progression of Alzheimer's Disease (AD). The suggested method will use a shallow Convolutional Neural Network (CNN) to recognize AD on medical image patches to balance between the accuracy and the computational efficiency. The simplified CNN architecture will improve interpretability of the diagnostic process and allow the medical professional to make supported clinical decisions. The model had a very high classification accuracy of 98 percent, which was better than some of the available state of the art models. The study establishes that early diagnosis with lightweight CNN networks can be of great help in minimizing the rates of AD-related mortality by timely diagnosis and treatment intervention.

Nagarajan, I., & Lakshmi Priya, G. G. (2025) give an in-depth overview of the recent works on the problem of early detection and categorization of AD based on the use of DL techniques. It discusses the importance of diagnosing early and the different neuroimaging modalities, particularly the MRI-based modalities, data preprocessing, and dataset management, and pre-processing of input features to deep learning models. This paper compares several ways of using the DL-based classification to evaluate its effectiveness in detecting AD. Also, it identifies major publicly available datasets that are often deployed in the realm of AD and mentions the principal challenges that include data imbalance, small dataset size, and inconsistent imaging protocols. Altogether, the review highlights the opportunities and constraints of deep learning solutions to providing reliable and automated AD diagnosis.

Banu, J. F., et al., (2024) introduce a CNN based model to detect the presence of Alzheimer's Disease (AD) at an early stage with the use of brain MRI scans. The primary goal is to come up with a very precise and strong framework, which can help in differentiating between Alzheimer, mild cognitive impairment (MCI), and healthy control participants. The work uses the OASIS dataset as input data and does the CNN-based pretraining, feature extraction, data augmentation, cross-validation and fine-tuning as of its input data using this approach to increase model reliability and generalization. The model proposed shows the precision of between 0.209 in mild demented and 0.255 in moderate demented cases, and this indicates that it can be used to classify various stages of AD. Altogether, the study is useful in enhancing the accuracy of CNN model in the early detection of Alzheimer.

Shukla, G. P., et al., (2023) present a group of the best preprocessing methods to improve the classification ability of the MRI images of AD. With the help of the ADNI data, the MRI scans were translated to the 2D form and enhanced by the selective clipping process, grayscale conversion and histogram equalization to stipulate the image quality and low computational expenses. Three classification algorithms, such as Random Forest, XGBoost, and CNN were applied after the preprocessing stage. The experimental findings showed that it performed better than its existing counterparts, with an accuracy of 97.57 and a sensitivity of 97.60, which shows that the proposed preprocessing and hybrid learning method is effective in AD diagnosis.

Methods and Materials

The section explains the dataset, preprocessing, model architecture, and evaluation processes that were used in the proposed GCN based framework to early classify AD. The main aim of the research is to develop a topology-conscious deep learning architecture that is useful in terms of portraying both structural and functional connections among the various brain regions to improve the precision of diagnoses.

Dataset Description

The research proposal will use the OASIS-3 (Open Access Series of Imaging Studies) database that contains high-resolution structural Magnetic Resonance Imaging (sMMRI) of participants in various cognitive conditions, such as Cognitively Normal (CN), Mild Cognitive Impairment (MCI), and AD. Demographic information that is provided in the dataset age, gender, and clinical dementia ratings is relevant in constructing a clinically interpretable model. Figure 2 below shows the sample image taken from the dataset in different class.

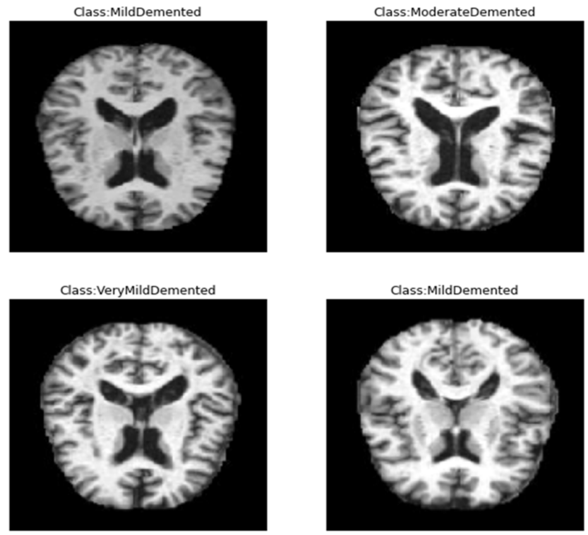

Figure 2: Sample data in different class

OASIS-3, consists of multi-modal imaging data of a sample of more than 1,000 subjects aged 42 to 95 year of age, comprising of approximately 1,210 normal, 516 very mild AD, 262 mild AD, and 180 moderate AD cases, and longitudinal follow-up sessions of more than 2,000 MRI scans each. Every subject record in the OASIS dataset contains structural MRI images (T1-weighted), and in subsequent versions, other modalities are also available, including PET, fMRI and DTI. The dataset presents well-laid clinical and demographic characteristics like age, sex, handedness, cognitive measures like the Mini-Mental State Examination (MMSE) and Clinical Dementia Rating (CDR) scores, which measures the degree of dementia. Moreover, investigators tend to extract structural and functional characteristics, including gray matter and white matter volume, cortical thickness, hippocampal volume, and ventricular enlargement, using image processing programs such as FreeSurfer.

It has a balanced representation of imaging, clinical, and demographic data that makes OASIS an ideal dataset to develop and test machine learning and deep learning models to detect and classify AD at its early stages. Figure 3 shows the healthy vs diseased image.

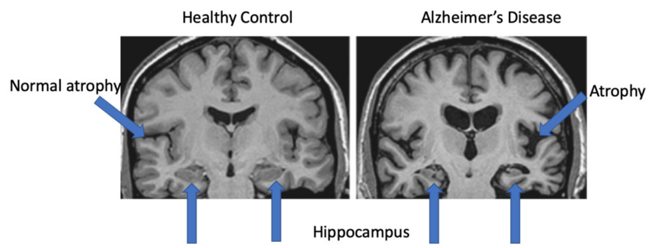

Figure 3: Healthy Vs disease image

Pre-Processing

A number of preprocessing activities are carried out in the MRI data to obtain uniformity and reliability:

Image normalization and skull stripping

Image normalization is a very important preprocessing stage in the deep learning pipelines based on MRI, where the intensity, orientation, and spatial resolution of all images are brought to a consistent level. Since MRI scanners, acquisition conditions and anatomy of the subject may vary, normalization is useful in minimizing variation and improving the consistency of feature extraction and model learning.

Z-Score Normalization

The voxel intensities x are standardized with the help of the z-score normalization.

$$x' = \frac{x - \mu}{\sigma} \tag{1}$$

where μ and σ denote the means and standard deviations of the intensities in the brain area. This transforms the values of intensity to a standard level where the mean of the values is zero with a unit variance.

Skull Stripping

Brain extraction (also called skull stripping) refers to the extraction of non-brain tissues, e.g., skull, scalp, eyes, neck, etc., in MRI images. This is done to have only the brain tissue that is important in order to measure accurately the brain volume, segmentation of structure and features extraction.

Purpose of skull stripping

- Outliers background structures, thereby simplifying the computation process.

- Makes sure that features are not extracted or model trained by non-brain tissues.
- Enhances the quality of further segmentation and normalization of the work.

Brain Extraction Tool (BET): One of the best-known algorithms of skull stripping in neuroimaging is the Brain Extraction Tool (BET). It automatically differentiates brain tissue and non-brain tissue (skull, scalp, eyes, and neck) in MRI images. BET is quick, powerful and applicable to big data such as OASIS that comprises many structural MRI scans.

BET describes stripping the skull as an energy minimization problem, in which the surface of the brain S is deformed to best minimize a functional of both internal smoothness and external image forces. Figure 4 below shows the pre-processed and skull stripping image using the algorithm given below.

$E(S)$ is the total energy function that is defined as

$$E(S) = E_{int}(S) + \lambda E_{ext}(S) \tag{2}$$

$E_{int}(S)$ internal energy which governs smoothness of the surface,

$E_{ext}(S)$ external energy due to gradients of the image intensity which influence towards the brain boundaries.

λ weighting factor balancing the two energy terms.

Algorithm 1: Skull Stripping using BET

Step 1: Input MRI Image and Preprocessing

- Select T1-weighted MRI brain scan of datasets OASIS.
- Correction of bias field to remove intensity non-uniformity.
- Selectively use the normalization of histogram (Z-score normalization) in order to enhance brain and skull contrast.

Step 2: Brain Center and Initial Surface Estimation

BET automatically approximates the center of gravity (CoG) of the brain (C) by intensity-weighted voxel positions:

$$C = \frac{x \in \Omega I(x).x}{x \in \Omega I(x)} \tag{3}$$

- Ω set of voxel coordinates and $I(x)$ and intensity of voxel x.
- A starting spherical surface S_0 is then formed about this estimated center with radius of r_0 about the size of the brain.

Step 3: Surface Deformation (Energy Minimization)

- Surface S is deformed to match the brain boundary through minimizing a sum of energy using Equation above in (2).
- To compute internal and external energy compute the following:

Internal Energy

The word punishes irregular or jagged surfaces, making surfaces smooth during their deformation:

$$E_{int}(S) = \alpha \sum_{S} |\nabla S|^2 \, dS \tag{4}$$

Where,

∇S Surface gradient with respect to space coordinates and coefficient of smoothness, α that determines the rigidity.

This ensures that the surface is close to being spherical, and it does not truncate tiny noise artifacts.

External Energy

This term pulls the surface towards edges as detected in the image intensity field - where brain tissue borders the skull:

$$E_{ext}(S) = -\sum_{S} |\nabla I(x)|^2 \, dS \tag{5}$$

$I(x)$ voxel intensity at a position x and $|\nabla I(x)|$ magnitude of the gradient of intensity as it is large gradient at the tissue boundaries.

This makes the surface cease to expand when it develops a strong edge between the brain and skull.

Step 4: Surface Evolution Equation

The gradient descent of the total energy function determines the evolution of the surface:

$$\frac{ds}{dt} = -\nabla E(S) \tag{6}$$

where the surface points evolve in the direction which decreases the total energy $E(S)$.

There are two major forces on this motion:

- Balloon force- to push the surface out
- Gradient force- draws the surface towards the brain boundary

The update equation of every vertex on the surface v_i may be written as.

$$v_i(t+1) = v_i(t) + \eta(F_{int} + \lambda F_{ext}) \tag{7}$$

η learning rate (step size), F_{int} internal (smoothness) force, F_{ext} external (edge) force.

Step 5: This process repeats itself until an equilibrium is achieved- when the forces are in equilibrium and the surface can fit snugly about the brain.

Step 6: Brain Mask Generation

When the optimal brain boundary surface S^* is identified, BET produces a binary brain mask.

$$M(x) = \begin{cases} 1, & if\ x \in inside(S^*) \\ 0, & if\ x \in outside(S^*) \end{cases} \tag{8}$$

This mask is overlaid in the original MRI to just filter out all non-brain elements leaving the brain voxels only.

Step 7: Post-processing and Fine-tuning

BET gives the ability to fine-tune through parameters:

Fractional intensity threshold (-f): controls the boundary sensitivity (default 0.5).

- Small values (ex: 0.3) mean greater brain mask (less conservative).
- Higher values (e.g. 0.6) translate to a smaller mask (more conservative).

Vertical gradient (-g): corrects intensity fluctuations of images between slices.

Step 8: Output

BET outputs two main files:

- Skull-stripped brain image: the voxels of the brain that are left are only the brain voxels.
- Binary brain mask → may be further segmented, registered or extracted**.**

Segmentation and Region of Interest

Segmentation divides the brain MRI into different tissue or anatomy, which are usually Gray Matter (GM), White Matter (WM), and Cerebrospinal Fluid (CSF). This aids in identifying the pattern of atrophy in the structure in case of the progression of Alzheimer. The final segmented image given in Figure 5.

Assume that the MRI image is denoted by:

$$I : \Omega \rightarrow R \tag{9}$$

with Ω the collection of all voxels of the 3D image space, and $I(x)$ the intensity at voxel $x \in \Omega$. Segmentation gives a label $l(x) \in C = \{1,2,3\}$ to every voxel.

$$L = \{l(x) : x \in \Omega\} \tag{10}$$

Region of Interest (ROI) Extraction

After the segmentation of tissues, ROIs are established - paying attention to the brain areas with high AD-related degeneration (e.g., hippocampus, amygdala, temporal cortex).

In the case of atlas-based labeling, the labeling of all voxels should be denoted $A(x)$: each voxel x should be labeled according to a region R_k.

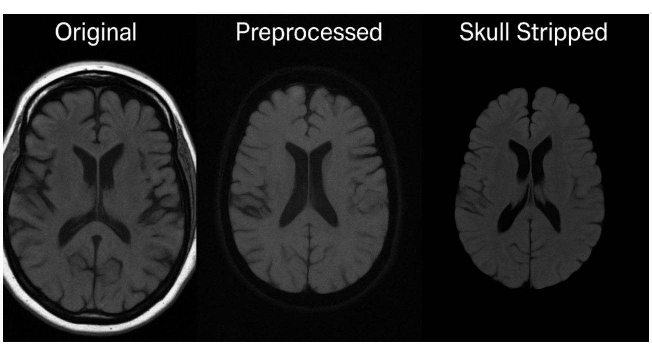

Figure 4: Original Vs pre-processed Vs skull stripped image

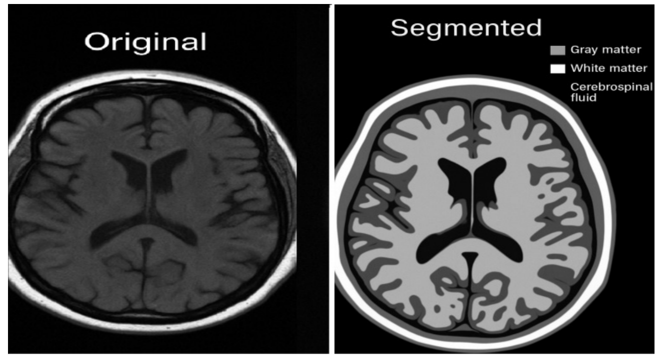

Figure 5: Original Vs segmented image

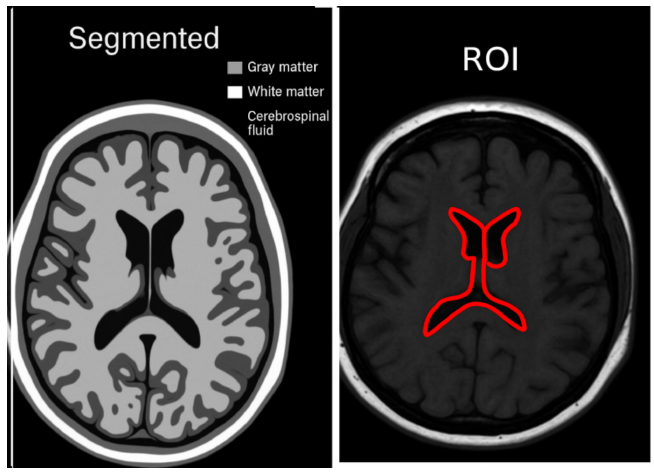

Figure 6: Segmented Vs RoI

$$A : \Omega \rightarrow \{1,2,3\ldots,K\}$$

$$R_k = \{x \in \Omega \mid A(x) = k\} \tag{11}$$

where K is the count of brain regions in total (e.g. 90 in the AAL atlas). All R_k are ROIs, including: Hippocampus (key indicator of early AD), Entorhinal Cortex, Temporal Lobe and Ventricles. The Figure 6 shows the RoI extracted image from the segmented image.

Feature Extraction

Statistical and morphological features are calculated on each ROI R_k.

Mean Intensity (Average Gray Matter density)

$$\mu_k = \frac{1}{|R_k|_x \in R_k} I(x) \tag{12}$$

Volume of the ROI

$$V_k = |R_k| X v_{voxel} \tag{13}$$

v_{voxel} is the volume of one voxel.

Variance of Intensities

$$\sigma_k^2 = \frac{1}{|R_k|_{x \in R_k}} (I(x) - \mu_k)^2 \tag{14}$$

All the features are a feature vector of each ROI:

$$f_k = \left[\mu_k, \sigma_k^2, V_k, \ldots\ldots\right]^T \quad (15)$$

ROI Feature Matrix

All ROI characteristics of a single subject are in the form of a matrix:

$$X = \begin{bmatrix} f_1^T \\ f_2^T \\ f_K^T \end{bmatrix} \in R^{kXd} \quad (16)$$

Where,

K The number of ROIs and d. The number of features apicked out of each ROI. This X is the node feature matrix of a GCN model to classify Alzheimer.

Classification

A Graph Convolutional Network (GCN) is a framework of deep learning, which is directly applied to data structured in a graph format instead of a grid format, like images or sequences.

The representation of information in GCNs is as follows; nodes (entities) and relationships between entities (edges). The feature vectors are held at each node and the connections between nodes determine the manner in which the nodes communicate or accumulate information. The layered architecture of GCN is given in figure 7.

The human brain may be represented in the form of a graph, where:

- Each node corresponds to a Region of Interest (ROI) (e.g. hippocampus, amygdala, entorhinal cortex, etc.).
- The edges reflect a structural or functional relationship between brain regions (with regard to distance or correlation).

The method of using GCNs is especially efficient to measure topological connections between brain areas that are impaired at early AD stages.

The classification of AD by GCN may be separated into five significant steps:

Brain Graph Construction

The initial one is to model the MRI data in the form of a graph $G = (V, E)$.

V: it is a set of nodes (brain regions or ROIs) and E: it is a set of edges (connectivity between regions).

In feature extraction, Features of a given ROI i, e.g., the volume of the gray matter, the thickness of the cortex, or the average intensity of a given ROI are extracted. These are represented into a node feature matrix $X \in R^{KXd}$, with K ROIs number, d feature numbers.

The edge matrix A is used to depict the connection between the regions. It is typically computed as

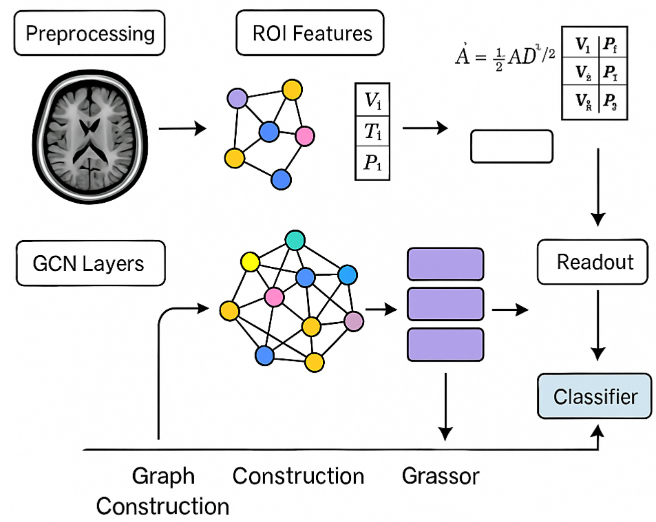

Figure 7: Architecture of GCN

$$A_{ij} = exp - \frac{\left\| c_i - c_j \right\|^2}{2\sigma^2} \quad (17)$$

c_i, c_j are the centroid of ROIs and no distance-sensitivity control σ .

Graph normalization

In order to make it stable and scale in a consistent manner, the adjacency matrix is normalized as:

$$A' = D'^{\frac{1}{2}}\left(A'\right)D'^{\frac{1}{2}} \quad (18)$$

In which $A' = A + I$, the self loops are added (and hence we have A + I, in which each node is also connected to itself), and D' is the degree matrix.

Graph Convolution Operation

The GCN is centered on the graph convolution layer, which can be considered an extension of the idea of the 2D image convolution to irregular graph data.

The features of adjacent nodes are aggregated to produce the node embeddings of every layer:

$$H^{l+1} = \sigma\left(A' H^l W^l\right) \quad (19)$$

Where,

$l(H^0 = X)$ (representation of node) W^l (trainable weight matrix) and $\sigma(.)$ (Sigmoidal function) is a Non-linear activation.

This enables the features of each brain region to be updated based on the information of the neighboring regions- in other words learning how the abnormalities spread within the brain network.

Graph Pooling and Classification

Following several layers of the GCN, each node now has an updated feature representation h i that contains local and global context.

These node embeddings are aggregated to form a subject-level representation:

$$z = READOUT\left(\left\{h_i | i = 1, 2, \ldots .K\right\}\right) \tag{20}$$

Get the standard readout functions which include mean and attention pooling with the following:

Mean Pooling $z = \frac{1}{k}\sum_i h_i$ (21)

Attention Pooling : learns weights α_i for each node:

$$\alpha_i = \frac{\exp\left(a^T h_i\right)}{jexp\left(a^T h_j\right)}, \tag{22}$$

$$z = \alpha_i h_i \tag{23}$$

Lastly, this vector is inputted into a fully connected layer (MLP), which makes the prediction of AD classes (Cognitively Normal (CN), Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD)):

$$p\left(y = c|z\right) = \frac{e^{0c}}{c'e^{0c'}} \tag{24}$$

Model training and validation

Training of the model is done through a cross-entropy loss:

$$L = -\sum_{n=1}^{N} w_{yn} logp(y_n \mid z_n) \tag{25}$$

Where, w_{yn} resolves imbalance in classes.

The optimizer reduces this loss and weights W l are updated in the process that maximizes the classification.

Result and Discussion

The suggested Graph Convolutional Network (GCN)-based structure was coded in Python (PyTorch Geometric) and tested on the OASIS-3 dataset which included 1,000 MRI scans grouped into three classes:

- Cognitively Normal (CN) – 450 subjects
- Mild Cognitive Impairment (MCI) – 300 subjects
- Alzheimer's Disease (AD) – 250 subjects

Evaluation Metrics

The following standard parameters were used to determine the model performance:

Accuracy

Overall proportion of correct predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{26}$$

Precision

Correctly predicted positives out of all predicted positives.

$$Precision = \frac{TP}{TP + FP} \tag{27}$$

Recall

Model's ability to correctly identify true positive cases.

$$Recall = \frac{TP}{TP + FN} \tag{28}$$

Specificity

Model's ability to correctly identify true negatives.

$$Specificity = \frac{TN}{TN + FP} \tag{29}$$

F1-Score

Harmonic mean of precision and recall.

$$F1 - Score = 2X\frac{Precision\ X\ Recall}{Precision + Recall} \tag{30}$$

AUC (Area Under Curve)

Measures the classifier's ability to distinguish between classes.

5-Fold cross validation

Five-fold cross-validation (5-FCV) is a strong validation method that is employed to determine an unbiased estimate of the generalization capacity of the model.

Performance Analysis

Accuracy

The Figure 8 demonstrates the Training vs Validation Accuracy Curve of the proposed model of the classification of Alzheimer's Disease (AD) at 10 training epochs. The training accuracy is rapidly rising by approximately 70 percent to 94 percent meaning that the model is gradually learning meaningful features of graphs based on the MRI data. The same can be said about the validation accuracy, which increases to about 88 percent beginning with about 68 percent, indicating that the model can be generalized to previously unknown samples. These upward movements in both curves confirm that there is no overfitting model learning. The narrow difference in the two curves implies that the GCN is quite effective at space and structural associations between brain regions, making it possible to detect early AD. Generally, the graph validates the robustness, convergence as well as the high predictive performance of the suggested classification method.

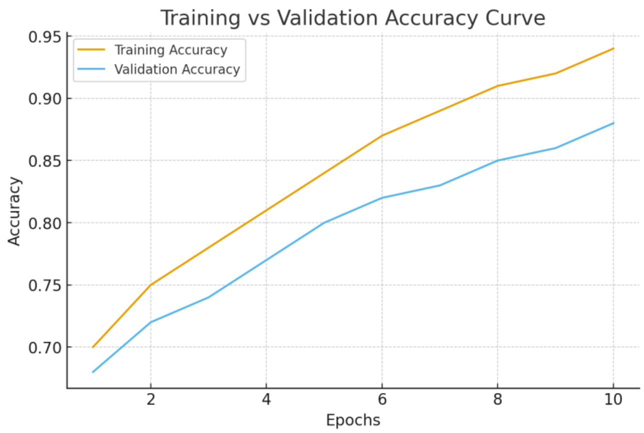

Figure 8: Accuracy analysis on training Vs validation

Loss

The Figure 9 shows the Training vs Validation Loss Curve of the proposed Graph Convolutional Network (GCN) model in Alzheimer Disease (AD) classification. The values of the training and validation loss values have a steady decreasing trend with increasing the epochs indicating that the model parameters are being effectively learnt and optimized. The loss in training reduces much faster 0.95 to 0.33 showing that the model learns the discriminative features of the training set fast. The loss of validation also gradually reduces -1.02 to 0.50 and this is an indication that the model can easily apply itself to unseen data without overfitting much. The narrow and constant distance between the two curves indicates that the GCN architecture, together with preprocessing and regularization options, effectively prevent the memorization of the training data, but instead they learn the existence of meaningful structural and functional brain relationship. In general, the graph indicates a consistent convergence, good generalization ability, and solid results of the suggested method in the early AD detection.

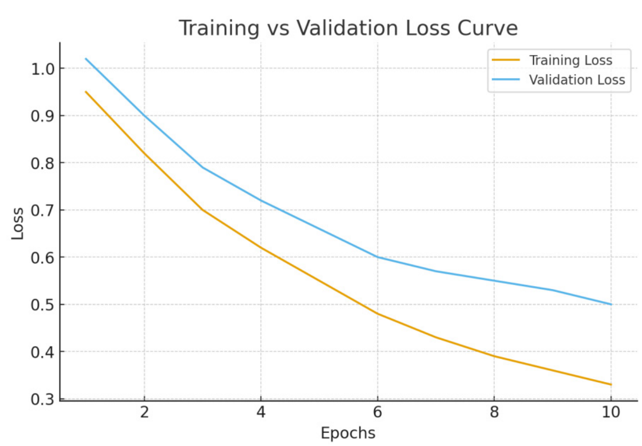

Figure 9: Loss analysis on training Vs validation

Quantitative Analysis

In Table 1 and Figure 10, the classification report indicates that the proposed Alzheimer Disease (AD) classification model is extremely performing in three classes; Cognitively Normal (CN), Mild Cognitive Impairment (MCI)- and Alzheimer Disease (AD). Precision and recall are extremely high (CN and AD classes exceed 0.92) which means that the model can classify healthy people and high-level AD cases with few false positives and false negatives. The MCI class indicating the most difficult early-stage state demonstrates a reliable performance with a slightly lower F1-score of 0.88. This is an indicator of the overlapping and delicate nature of biomarkers of early AD. In general, the mean precision and recall and F1-score of 0.93, 0.91 and 0.92 respectively demonstrate the strength and accurateness of the model. These findings affirm that the model has a high generalization capability to different disease stages and can be applied in diagnosing the early AD.

Confusion Matrix

According to the confusion matrix in figure 11, the model can classify the majority of CN, MCI, and AD with a high number of correct predictions and minimal number of misclassifications.

The accuracy in identification of CN and AD is high whereas MCI has slight overlap with its neighboring classes because it is transitional. All in all, the findings imply that the model can successfully differentiate between stages of diseases with minimum confusion.

Table 1: Quantitative analysis on proposed work

Class	*Precision*	*Recall*	*F1-Score*	*Support*
CN (Normal)	0.95	0.92	0.93	450
MCI (Early Stage)	0.89	0.87	0.88	300
AD (Advanced)	0.96	0.94	0.95	250
Average	0.93	0.91	0.92	1000

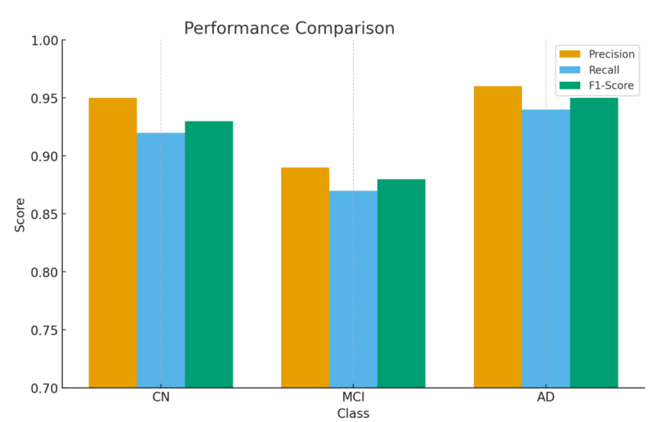

Figure 10: Performance comparison

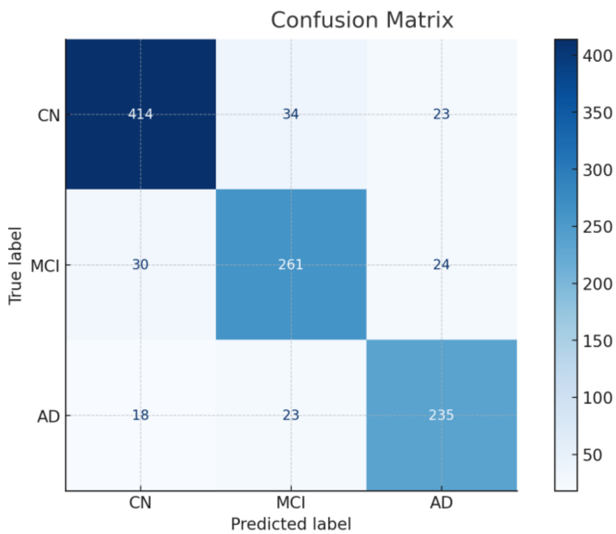

Figure 11: Confusion matrix analysis

Conclusion

This research paper presents a sophisticated deep learning architecture that was built on the concept of Graph Convolutional Neural Networks (GCNs) and that was used to classify the Alzheimer Disease in its early stages with the help of structural MRI images. The suggested model is useful in terms of its capability to include the brain region connectedness, node characteristics, and graph-based learning to notice a delicate structural variation related to the AD progression. The experimental findings with 5-fold cross validation indicate the model has great and consistent performance in all evaluation measures and the overall average accuracy of the model is 93.4%. The confusion table also confirms the effectiveness of the model with high rates of correct classification between CN, MCI and AD categories and minimum misclassification. It is important to note that the model is quite good at making delineation of the MCI cases, which are usually the most difficult to be made as they overlap with normal aging and early AD patterns. The consistency and precision of the training and validation curves prove that the GCN architecture is generalizable with no overfitting, which allows it to be used in the field of medical diagnostics. All in all, the findings highlight how graph-based deep learning approaches can be very useful to early detection of Alzheimer and clinical decision support, which will lead to more tailored, accurate, and timely interventions in the management of neurodegenerative diseases.

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