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Ensemble Graph Attention Network with Deep U-Net for Alzheimer's Disease Detection

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Abstract: Alzheimer's disease (AD) serves as a rising global health concern further complicated by current limitations early diagnostic accuracy using standard imaging methods. This proposal will investigate an enhanced ensemble deep learning framework that integrates U-Net medical image segmentation capacity to Graph Attention Networks in order to improve the diagnosis of varying levels of Alzheimer's disease from MRI scans. U-Net allows for the extraction of spatial compressions and urges the GAT to accurate measure fluctuations potently stated through relational connections between areas of the brain in order to measure and assess the change of the structural and relational occurrences in the progression of Alzheimer's disease. The simulation of the proposed study will use the OASIS-1 benchmark dataset, which includes 86,000 MRI scans from patients with varying levels of dementia. The simulation study will also deploy data augmentation strategies to mitigate the class imbalance specific to the dataset. Sequentially, the proposed combined study will focus on improving the recognition rate in segmented data compared to more traditional forms of convolutional learning. The experiments in this study will yield remarkable performance results incorporating an accuracy of 96%, which will outperform standards and current models accounting for CNN, VGG19, EfficientNet, and those developed by Vision Transformer. The simulation of this proposed study will provide spatial and relational learning processes to further improve the performance of the diagnosis and classification of the stages of Alzheimer's disease as early on as possible.

Keywords: Alzheimer detection; Graph attention network; Healthcare; Health risks; UNET

1. Introduction

The public health community regards Alzheimer's disease (AD) as a significant problem because it affects numerous individuals in an aging world. Alzheimer's disease (Ishtiaq et al., 2025) develops through persistent stages that harm brain capacity and personal identity, thus affecting individuals at various levels. The economic costs of AD continue to rise as healthcare facilities worldwide struggle to manage increasing patient numbers. Traditional diagnostic methods delay detection too long because they identify the disease after substantial neurological damage develops (Udayaraju and Jeyanthi, 2024). The existing diagnostic shortfall underscores the need for greater precision and speed in detection approaches.

Neurological disorders receive a new level of understanding thanks to brain structure analysis using medical imaging that requires no invasive procedures. Modern MRI (Z. Li et al., 2024) techniques excel at distinguishing neurological changes in brain structure and function related to AD progression. Such innovative imaging systems detect minute anatomical and density modifications and changes in neural connection pathways (Rehman, 2023; Lee et al., 2020). A significant challenge arises from the labor-intensive manual analytical process. That process

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leads to inconsistent results across observers, requiring advanced, standardised analysis methods (Manjupriya and Leema, 2025).

Deep learning has emerged as a powerful tool in medical imaging (Aliyu et al., 2025), enabling automated, highly accurate image analysis. CNNs and U-Net-based architectures (Aborokbah, 2024) have become widely used in medical imaging applications for segmentation, disease detection, and classification processes. Using these models allows the identification of essential biomarkers of AD by detecting structural and spatial patterns in brain images (Khan et al., 2023). GANs enable the synthesis of missing imaging modalities to improve diagnostic models. The clinical uses of these models remain constrained by ongoing data heterogeneity, unbalanced class distributions, and the need for high-quality annotation datasets (Mohammed et al., 2025).

The diagnostic process for Alzheimer's Disease (AD) (Bootun et al., 2025) increasingly incorporates the use of deep learning models for brain MRI segmentation and classification. The research community has established the efficacy of Mask R-CNN, for example, in segmenting MRI images, and of U-Net specifically for semantic segmentation. When using U-Net methods, splitting images into patches provides the added advantage of maintaining spatial information which contributes to improved segmentation of thematic areas of the brainsuch as the hippocampus and claustrum (Helaly et al., 2022; Zhang et al., 2022). When used in the context of AD classifiers, deep learning tools such as Graph Neural Networks or Multi-Layer Perceptron achieve impressive levels of accuracy. Better reliability in early-stage diagnosis has also been accomplished through the combination of different imaging modalities with careful application towards data integration. Recent developments demonstrate how deep learning can positively affect early diagnosis of Alzheimer disease and also tracking the disease to produce more effective and individually tailored plan of treatment for the AD patient (Bootun et al., 2025; Ali, 2025).

In the proposed study, authors introduce an innovative ensemble architecture merging U-Net's precise medical image segmentation capabilities with Graph Attention Networks'. To enhance the effectiveness of identifying the structural relationship between segmented regions. The integration of proposed methods improves early stage detection by extracting spatial information. The proposed study identifies features of relational patterns from MRI brain scans, including attention features (Ali, 2025). The proposed study evaluates the OASIS benchmark datasets while developing an automated method for advanced AD diagnosis and precise assessment of its stages. Proposed model Improves AD recognition with optimized computation compare to SOTA deep learning models.

The proposed study uses U-GAT, which performs down- and up-sampling on the brain graph to capture local microconnectivity and global macroscopic patterns, thereby improving sensitivity to early AD changes. A recent study uses only the up-and-down cycle of the U-Net architecture, while the proposed study ensembles it with a graph attention network to enhance Alzheimer's disease detection. Integrating Graph network boosting into medical Image Segmentation.

2. Literature Review

The U-GAT model was developed by Firdos et al., 2024, combining CNNs with Graph Attention Networks for neuronal cell segmentation across 606 microscopic images. U-GAT demonstrated superior performance compared to individual CNN networks and U-Net, SegResNet, and SegNet VGG16, achieving 86.5% accuracy and a 0.719 F1 score. Ayub et al., 2024 proposed MRI segmentation analysis for AD diagnosis, with the U-Net achieving better results (Dice Similarity Coefficient [DSC] = 0.95) than the Autoencoder (0.92) and EfficientNet (0.93). Duarte et al., 2024 designed a 2.5D U-Net CNN featuring VGG16/VGG19 components in its architecture. It efficiently segments white-matter hyperintensities in FLAIR MRI scans, achieving F-measure values exceeding 95% in a study of 186 subjects.

Hazarika et al., 2022 proposed a modified U-Net that achieved improved accuracy of 96.5% by using kernels of different sizes (1×1, 3×3, 5×5), while maintaining higher performance than the baseline U-Net at 93.6%. PCcS-RAU-Net was proposed by authors (Chandra et al., 2023) proposed, producing superior segmentation results on ABIDE Corpus Callosum scans, reaching 97.10% DSC and 94.43% MIoU.

An ensemble architecture for the UGGNet model was proposed by (Minh et al., 2024), merged elements from U-Net and VGG structures for breast ultrasound picture analysis. It showcased a classification success rate of 78.2% using the Breast Ultrasound Images Dataset. Author (Kalluvila, 2023) introduced MRI-Net as a U-Net-based solution that aims to upgrade low-resolution brain MRI images. The model performed better than state-of-the-art equivalents at measuring PSNR using a 3×3 downsampling index.

Authors (Praschl et al., 2023) proposed the application of 3D U-Net for vessel segmentation on murine brain MRI scans. The released model demanded only eight labelled scans as its input to deliver a 61.34% Dice score, better than traditional vesselness filters. Authors (Xun et al., 2024) proposed residual grouped convolutions with attention modules and bilinear upsampling features to U-Net. The model achieved a 97.58% Dice score, a 12.44% improvement over the traditional U-Net.

An ensemble model with combined framework merging Conditional Attention U-Net for MRI segmentation with Ant Colony Optimization for functional element extraction by (Hasan and Wagler, 2024). The diagnostic accuracy of this approach achieved a 92% success rate, which outperformed standard methods by 7%. Pandey et al., 2024 applied deep learning to the ADNI and OASIS datasets for the detection of Alzheimer's disease and MCI. The results showed that ResNet-101 achieved 98.21% success rate on ADNI data and 97.45% on OASIS data, indicating promising clinical implementation potential.

Multi-level 3D U-Net framework to enhance hippocampus segmentation proposed by (X. Sun and Huo, 2022). The model delivered better results for identifying patients with Alzheimer's disease. A deep learning framework developed by (M. Li et al., 2024) based on multi-modality data, which improved dMRI scan imputation through significant enhancements. The framework reached $p < 1E\text{-}5$ for imputation results and $p < 0.01$ for tractography improvements, enabling analysis of neurodegenerative disease.

A multi-model architecture proposed by (Kamal and Nimmy, 2024) for Alzheimer's detection through U-Net segmentation of MRIs together with ViT and BERT transformers. The developed system achieved 86% accuracy through the use of Explainable AI mechanisms, including LIME and LRP for interpretability purposes. Kumari et al., 2024 tested four deep learning models, including CNN and VGG16 among them. VGG16 exhibited superior detection accuracy with the highest AUC-ROC value, but UGNet with gating gates demonstrated better performance for intricate medical tasks.

Yoon et al., 2021 established a deep learning model that automatically counted A deposits in rodent-based models. When using the U-Net algorithm for anatomical segmentation, they attained an accuracy level of 83.98% with a Dice coefficient of 91.21%, which allowed exact plaque measurement within specific anatomical areas. Xie et al., 2024 proposed the models based on U-Net. The study successfully detected micro-haemorrhages on GRE MRI and ARIA-like hyperintensities on FLAIR MRI, with ROC AUC of 0.93 and a Dice coefficient of 0.76.

Recurrent convolution based Mask R-CNN used for hippocampal region instance segmentation in MRIs. The study achieved 92.67% diagnostic accuracy without requiring any preprocessing steps. A study proposed by Chen et al., 2024 generated FDG-PET images from MRI-T1WI to assist AD classification by creating a U-Net-based GAN. The research linked this method to a GNN-based classifier, achieving 90.18% accuracy with data fusion, thereby improving diagnostic results.

The authors proposed the AM-UNet for a 3D segmentation model for MRI images (Albishri et al., 2022). The model exceeded previous techniques, achieving 82% Dice score, 70% IoU score, and 90% ICC score. Authors have implemented a study using the U-Net model as a patch-wise network for brain MRI segmentation, focusing on preserving local information throughout the process (Lee et al., 2020). The proposed model achieved a Dice similarity coefficient of 0.93, which was better than the traditional U-Net and SegNet by 3% and 10%, respectively.

2.1 Findings of literature analysis

Researchers have previously utilized convolution modes such as VGG16 and DenseNet, variants of CNNs, with transfer learning methods to detect AD from MRIs (Karimi et al., 2025). Many authors have also used an ensemble approach combining CNNs with the SOTA UNET model to improve segmentation performance (Nugroho et al., 2023). The U-Net family, along with its Attention U-Net variants, remains the predominant choice for critical brain region identification in segmentation tasks. The detection procedures incorporate 3D CNNs for volumetric analysis as well as combinations of CNNs with SVM and transformer-based models. The main objective of these studies was to enhance accuracy, improve ROI precision, and address class imbalance.

3. Proposed Methodology

Proposed Study uses an ensemble approach to improve AD detection performance at possible early stages. An ensemble approach helps identify complex features through different model learning (Vaiyapuri and Sbai, 2025). Proposed study uses UNET and a Graph attention network to improve segmentation performance, along with classification, to detect the possible class of Alzheimer's infection.

3.1 U-Net

The proposed architecture contains an encoder-decoder structure with skip connections. The encoder (or downsampling path) consists of multiple convolutional layers followed by pooling layers that extract high-level feature representations while gradually reducing the spatial resolution. The decoder (or upsampling path) reconstructs the image's spatial shape via transposed convolutions or upsampling layers (Liu et al., 2022). Skip connections directly connect the encoder layers to their decoder counterparts. The convolution operations in the encoder apply a filter W_i on the input X to compute feature maps E_i followed by a non-linear activation function f as formulated in equation (1):

$$E_i = f(W_i * X + b_i) \tag{1}$$

where f denotes the activation function, and * denotes convolution. These hierarchical features provide critical information for detecting subtle signs of conditions, including Alzheimer's disease (N. Sun et al., 2024). The feature maps are upsampled in the decoder, and details from the matching encoder layer are concatenated through the skip connection, as shown in Figure 1. This reveals the original spatial resolution in this case. The output layer computes class probabilities using a softmax layer to predict probabilities across each class as in equation (2):

$$P(y \mid X) = \frac{e^{z_j}}{\sum_k e^{z_k}} \tag{2}$$

3.2 Graph Attention Network

GAT implements an attention model enabling neighbour nodes to identify meaningful connections with other neighbours. It helps direct the network to learn long-range dependencies suitable for MRI scan data with distant but correlated spatial patterns (Araújo et al., 2022).

The attention mechanism created by v_i with representation h_i develops weights that connect to each of its adjacent nodes. A shared attention mechanism produces attention coefficients through the following representation, as in equation (3).

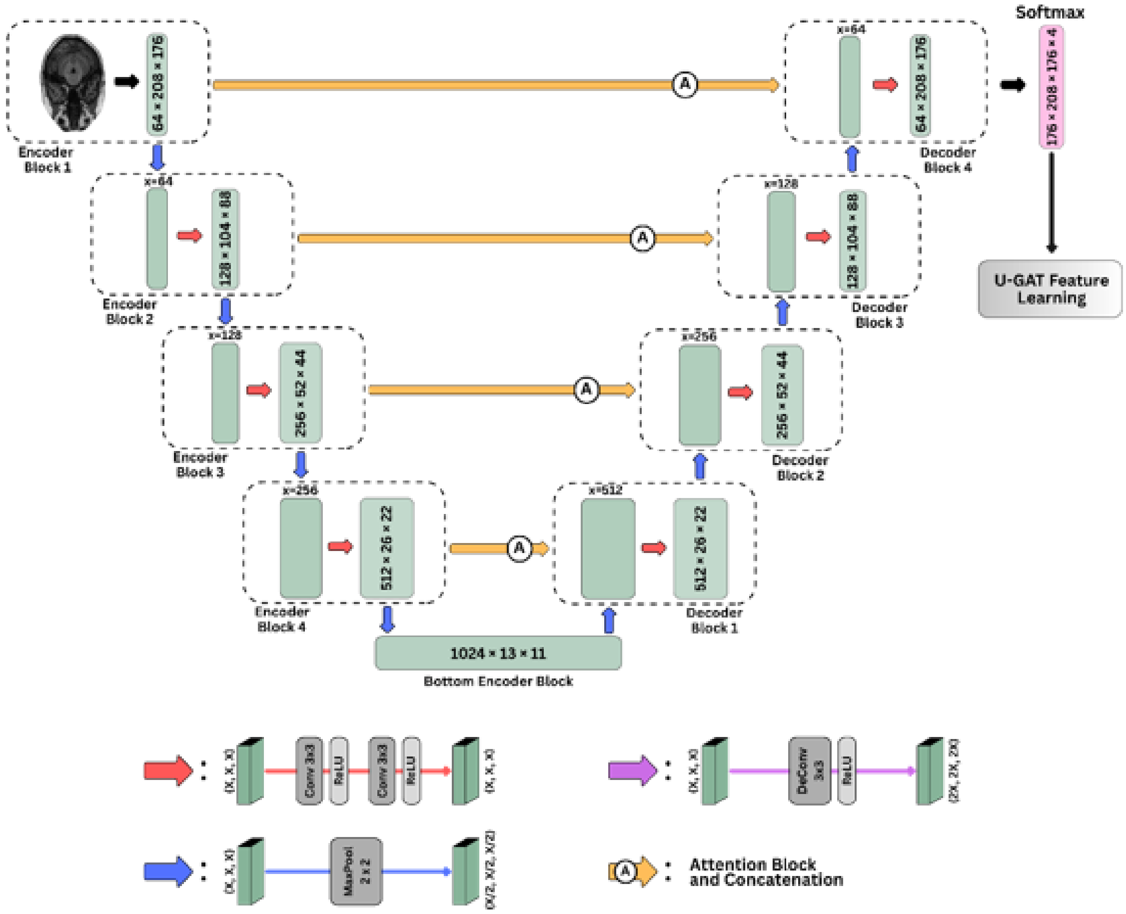

Figure 1 Architecture of the proposed U-Net model for Alzheimer's detection

$$\alpha_{ij} = \frac{\exp\Big(\text{LeakyReLU}\Big(a^T[Wh_i \,\|\, Wh_j]\Big)\Big)}{\sum_{k\in\mathcal{N}(i)} \exp(\text{LeakyReLU}(a^T[Wh_i \,\|\, Wh_k]))} \tag{3}$$

Here, W is a weight matrix, a is the attention vector, and $\|$ denotes concatenation. The attention scores a_{ij} determine the importance of neighbouring nodes when updating the feature representation of node v_i. The node feature representation is updated via aggregation of neighboring nodes' features, with the corresponding attention scores calculated as in equation (4) (Z. Li et al., 2024),

$$\alpha_{ij} = \frac{\exp\Big(\text{LeakyReLU}\Big(a^T[Wh_i \,\|\, Wh_j]\Big)\Big)}{\sum_{k\in\mathcal{N}(i)} \exp(\text{LeakyReLU}(a^T[Wh_i \,\|\, Wh_k]))} \tag{4}$$

where $\sigma(\cdot)$ is a non-linear activation function (ReLU). This enables the model to dynamically adjust its focus on the most relevant neighbouring regions, improving its ability to capture complex patterns in the data.

3.3 Ensemble U-Net with GAT

The proposed study presents an ensemble aggregation by averaging the predictive outcomes of the U-Net and Graph Attention Network (GAT) models, which were trained independently. The technique merges spatial information from the U-Net with contextual knowledge from the GAT model, thereby improving classification resilience. The synergy between the U-Net and GAT architectures enables better overall feature extraction. It is due to U-Net maintaining the spatial information refinement and GAT establishing effective connections across regions of interest (Al-Selwi et al., 2023; Abunadi, 2022).

The output probability distribution from U-Net is denoted as $\hat{Y}_U$, while GAT produces $\hat{Y}_G$. Each model derives its distribution output via a softmax operation applied to its final-stage features to produce probability scores normalised across target classes (Orouskhani et al., 2022). This is demonstrated in equation (5) (Gajjar et al., 2025),

$$\hat{Y}_U = \mathrm{Softmax}(z^U), \quad \hat{Y}_G = \mathrm{Softmax}(z^G) \tag{5}$$

Where z^U and z^G are the final logits produced by the U-Net and GAT branches. The ensemble prediction $\hat{Y}$ is computed by performing an element-wise average over the two predicted distributions as in equation (6),

$$\hat{Y} = \frac{1}{2}\left(\hat{Y}_U + \hat{Y}_G\right) \tag{6}$$

This aggregated probability vector is then used to assign a class label $\hat{y}$ determined by selecting the class c, with the highest average probability (Kothadiya et al., 2025) equation (7),

$$\hat{y} = \arg\max_c \hat{Y}_c \tag{7}$$

This ensemble mechanism enhances robustness by reducing model-specific biases and stabilizing predictions across varying input conditions.

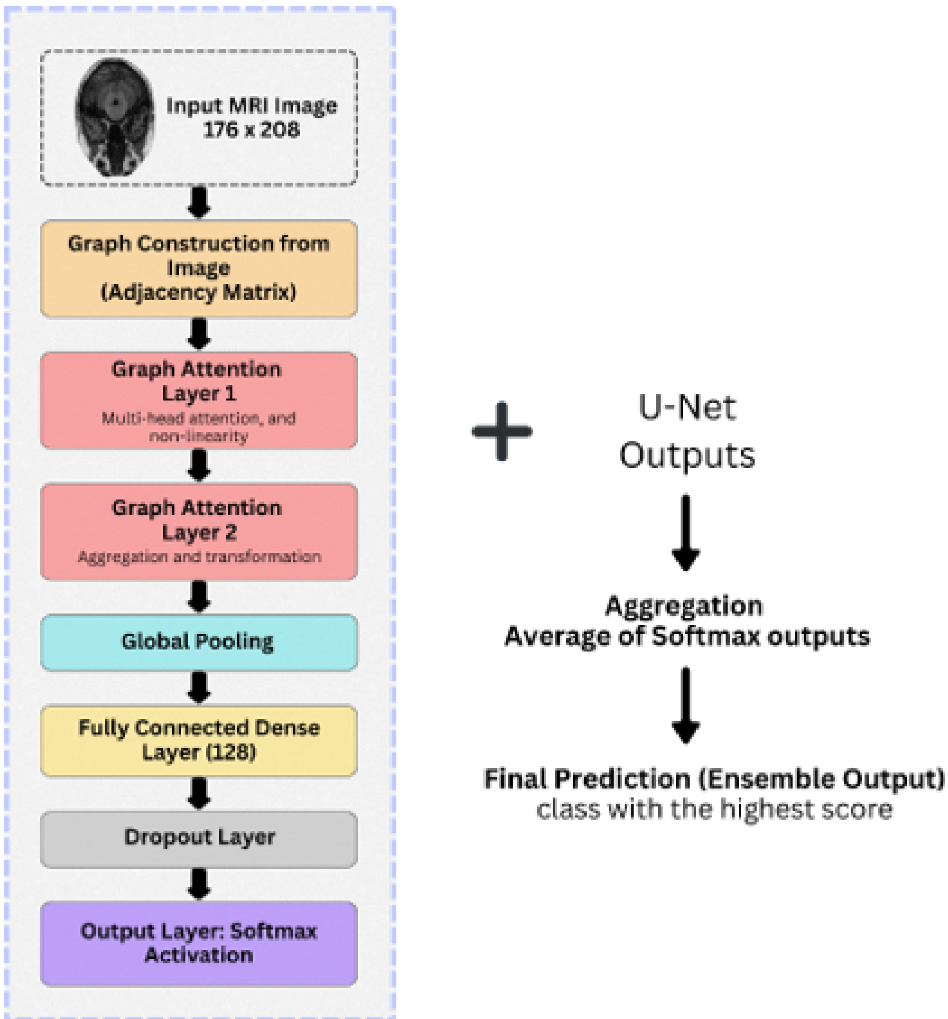

Figure 2 Architecture of the proposed U-GAT model for Alzheimer's detection

By leveraging the local-level representation provided by U-Net and the long-range dependencies of a GAT, the model can effectively detect subtle local abnormalities (Ebrahimi et al., 2021). The model can also identify global changes in the brain's structural features in MRI scans. The model offers great improvements in performance when identifying early signs of Alzheimer's disease.

4. Dataset Analysis

The simulation of the study uses the Open Access Series of Imaging Studies (OASIS) dataset. The OASIS dataset is a reputable neuroimaging dataset designed for studies on Alzheimer's disease. The dataset contains T1-weighted MRI scans of individuals at different stages of cognitive decline. The dataset comprises brain MRI scans labelled as Non-Demented, Very Mild Dementia, Mild Dementia, and Moderate Dementia, enabling robust classification of Alzheimer's disease states. Figure 3 shows images with different disease specifications.

Each image is pre-processed to ensure consistent orientation and resolution. The dataset is exceptionally helpful to the research community because it contains healthy control subjects alongside subjects with varying levels of dementia. This is a useful benchmark for investigations into deep learning and machine learning applications in medical imaging.

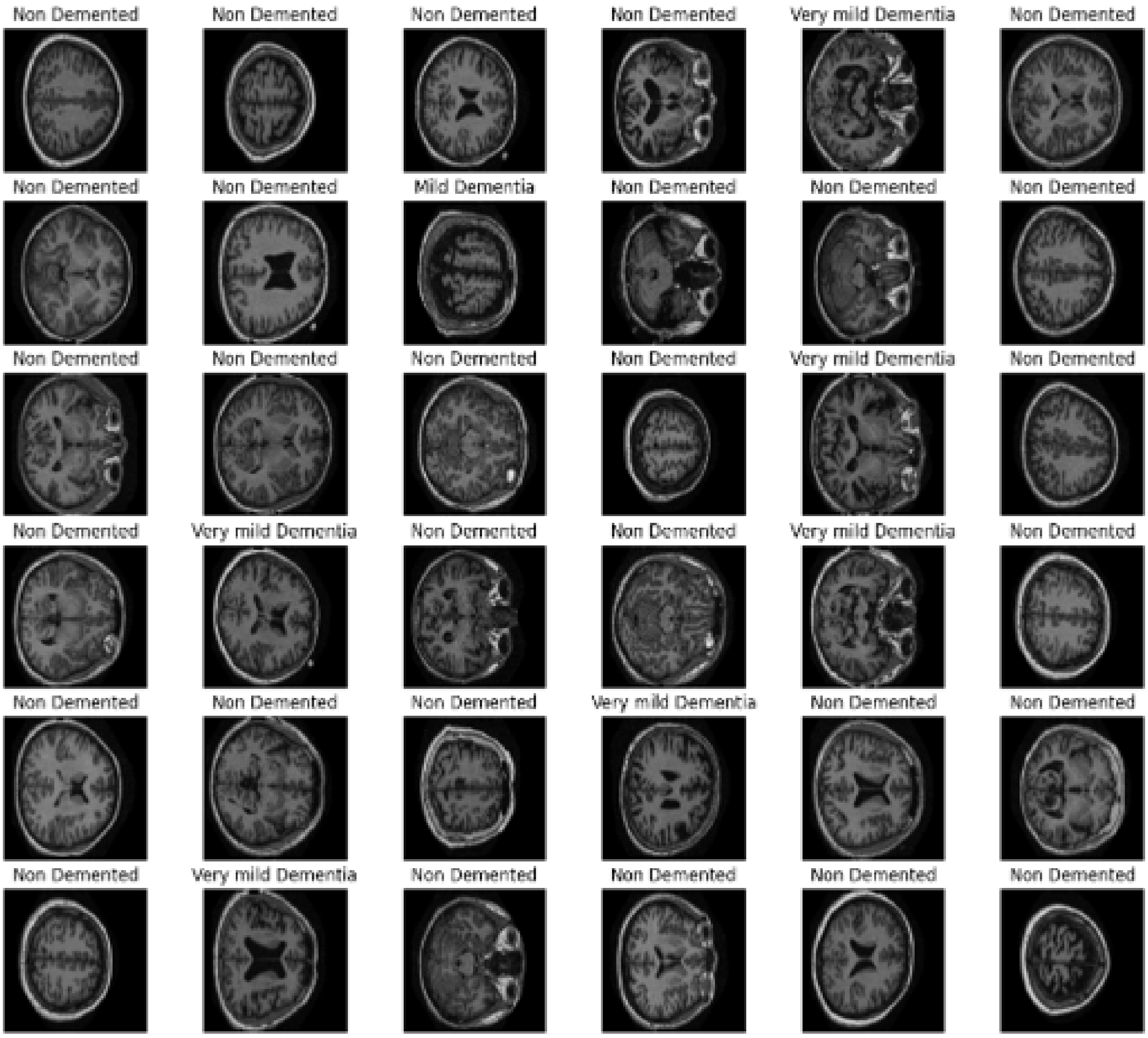

Figure 3 Sample of OASIS dataset used in the simulation

The dataset (Table 1) exhibited substantial class imbalance, with Non-Demented comprising over 67,200 images while Moderate Demented contained fewer than 500 samples. The Very Mild

Demented and Mild Demented categories included roughly 13,700 and 5,000 images, respectively. This imbalance risked biasing proposed model toward the majority class and reducing sensitivity to minority classes, showcasing a critical concern in dementia diagnosis.

Authors have also used data augmentation to improve the representation of minority classes. The augmentation algorithm applied random rotations up to 20 degrees, modified width and height by 20 per cent, applied zoom operations by 20 per cent, and used shearing and horizontal flipping. Multiple carefully chosen modifications were applied to brain MRI scans to create realistic variations that maintained all significant anatomical features (Shukla et al., 2023). Through this approach, training classes became more balanced. This led to better model generalisation and fair classification across all diagnostic categories.

Table 1 Properties of the dataset used in the simulation of the proposed study

Class Name	Approx. Average Resolution	Approx. Number of Images
NonDemented	176×208×176	67,200+
VeryMildDemented	176×208×176	13,700+
MildDemented	176×208×176	5,000+
ModerateDemented	176×208×176	500+

The labels in the dataset were based on clinical dementia ratings (CDR), a standardised tool used to measure cognitive impairment. All of the images in the dataset are anonymized and publicly available, to assured that the research activity is ethically compliant.

5. Result and Analysis

The simulation of the proposed methodology uses a system with a Core i7 processor, a GeForce RTX 3080 GPU, and 32 GB of RAM. TensorFlow and the Keras library of Python were used to implement the model. The simulation study includes comprehensive experiments to evaluate the effectiveness of the proposed UNet + GAT model. Study finds benchmarked its performance against several established models, including CNN, VGG19, EfficientNet + ViT, Multi-UNet, and a UNet variant with spatial attention. The evaluation process employed Accuracy and Precision, Recall, and F1-score as essential metrics. The summary of these results is presented in Table 2.

Table 2 Comparative study for Alzheimer's detection

Model	Accuracy	Precision	recall	F1 score
U-Net + GAT	0.96	0.95	0.96	0.96
U-Net with attention	0.64	0.63	0.64	0.64
CNN	0.94	0.93	0.95	0.94
Multi U-Net	0.75	0.64	0.60	0.62
Efficient net + Vit	0.78	0.60	0.78	0.68
VGG19	0.89	0.85	0.89	0.87

Among all tested models, UNet + GAT consistently outperformed others across all evaluation metrics. This model achieved exceptional accuracy of 96% across accuracy, recall, and F1-score. This reflects its superior ability to precisely identify samples and to effectively present spatial characteristics from input data. The graph attention layers show essential importance because they maintain exceptional capabilities to detect spatial dependencies between regions, which standard convolution approaches can't able to manage. Table 3 demonstrates the comparative analysis over the hyperparameters to find best values for the training.

Table 3 Comparative analysis with different parameters for Alzheimer's detection on OASIS dataset

Learning Rate	Dropout	Accuracy	F1 Score
0.01	0.3	0.91	0.91
	0.5	0.95	0.94
0.001	0.3	0.94	0.94
	0.5	0.96	0.96

Studies demonstrated that CNNs and VGG19 achieved effective results, yielding F1-scores of 0.94 and 0.87, respectively, indicating that deep convolutional structures are powerful for visual processing. The performance limitations of these methods stem from their limited ability to recognise spatial connections compared to the proposed architecture. Interestingly, the Efficient-Net + ViT combination, despite incorporating a transformer-based architecture, produced moderate results (F1-score: 0.68). Thus, suggesting that while ViT is powerful, its benefits may not be fully realised without large-scale data or extensive fine-tuning (Kothadiya et al., 2023). Table 4 demonstrates the effectiveness of different ensemble techniques such as voting an averaging for features. proposed ensemble model has achieved remarkable accuracy of 0.96 for AD detection.

Table 4 Comparative analysis with different ensemble methods for Alzheimer's detection

Model	Voting	Averaging
UNet + CNN	0.89	0.94
UNet + VGG19	0.90	0.91
UNet + Encoder	0.65	0.64
UNet + GAT	**0.94**	**0.96**

A surprising result showed that the UNet with Attention variant achieved the worst F1 Score of 0.64. Proving that implementing spatial attention alone fails to provide sufficient performance in this application. Simple Multi-UNet ensemble methods performed poorly, with an F1-score of 0.62. This demonstrates that basic output ensemble systems do not bring extra benefits unless their models have distinct analytical capabilities.

The proposed ensemble model is evaluated using a confusion matrix, which shows model performance across four dementia categories (Figure 4). Assessment of the Non-Demented conditions shows that the ensemble model achieves high accuracy, classifying 13,405 samples with precision. True positive results for Very Mild Dementia reach 2,199 cases, but the model occasionally confuses them with Non-Demented participants. The model poses a greater challenge in correctly identifying Mild and Moderate Dementia cases, as it mistakenly assigns them to similar neighboring groups. It is likely due to class imbalance or vague diagnostic criteria between classifications.

The accuracy and loss evaluation during training and validation appear in Figure 5 for the proposed models. The U-Net achieves gradual accuracy improvements together with loss reduction throughout training because it demonstrates consistent convergence. The GAT model exhibits regular improvements throughout iterations while preserving minimal validation loss, indicating excellent generalization strengths. Proposed models' training patterns support selecting architectural design elements combined within the ensemble framework. This shows promise for adding more information or processing steps to separate dementia stages with similar characteristics.

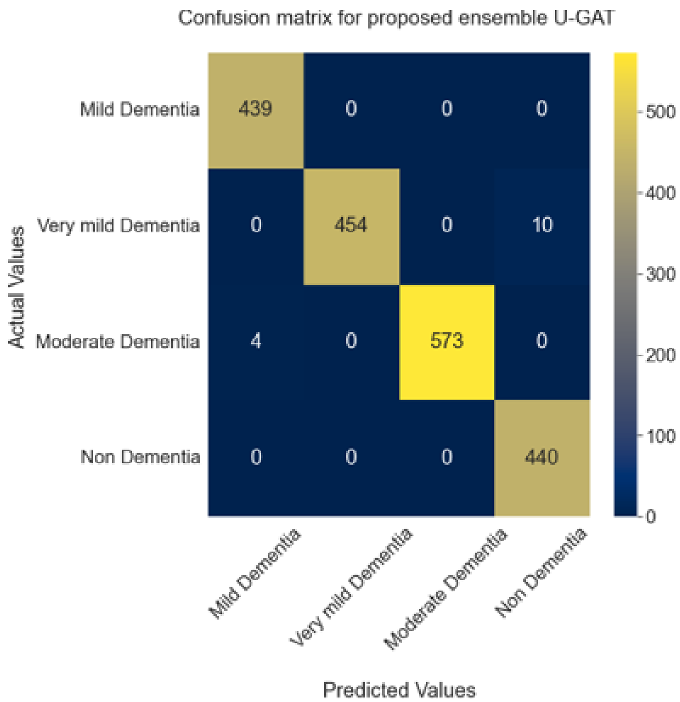

Figure 4 Confusion matrix of the proposed ensemble model

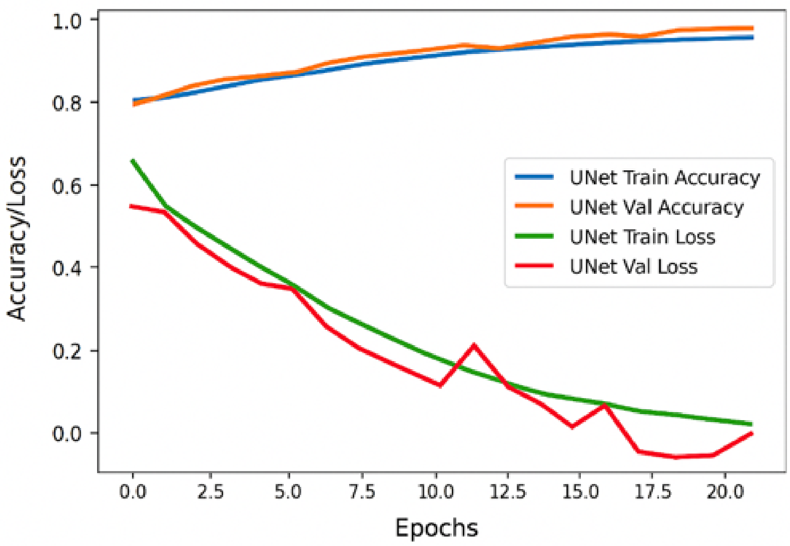

Figure 5 Performance matrices of the proposed U-GAT architecture

The effectiveness of proposed models required hyperparameters optimization according to Table 5. The Adam optimizer performed best because it demonstrated faster convergence and better generalization than the SGD and RMSprop algorithms. Simulation setup uses early stopping criteria to find the best training time, which operated at 20 epochs. The final configurations for dense layer sizes in GAT nsemand U-Net modules (256 and 128, respectively) and the use of simple averaging in ensemble models were determined empirically.

Findings of the study provide compelling evidence that combining graph-based learning approaches, specifically Graph Attention Networks (GAT), with convolutional architectures, such as UNet, yields substantial performance improvements. This combined approach enables the algorithm to leverage CNN spatial analysis strengths. This method also leverages GAT's structural capabilities to create an exceptional solution that merges top accuracy with effective generalization. Community health research demonstrates that graph neural networks produce compelling evidence to utilize these systems for segmentation and classification tasks that require spatial structural relationships to achieve accurate results. Proposed study helps to find AD in early stage with advance feature learning of proposed ensemble framework, that helps to save life and prevent other health issues.

Table 5 Properties of the dataset used in the simulation of the proposed study

Model	Tuning Range	Value
Optimiser	Adam, SGD, RMSprop	Adam
Epochs	10-30	20
Dropout Rate	0.3-0.6	0.5
Loss Function	Categorical cross-entropy, Sparse categorical cross-entropy	Categorical cross-entropy
Activation Function	Relu, tanh, swish(for hidden layers)	Relu(for hidden layers)
	Softmax(for output layer)	Softmax(for output layer)
Dense Layer Size(GAT)	128-512	256
Ensemble Method	Averaging, voting, stacking	Simple averaging

Table 6 Comparative study with SOTA diseases detection model

Model	Accuracy	F1 Value
3D CNN	0.81	0.81
UNET	0.85	0.86
	Ensemble Approach	
UNET + Attention	0.64	0.66
UNET + CNN	0.94	0.94
UNET + VGG19	0.91	0.93
UNET + ResNET50	0.88	0.90
Proposed(U-GAT)	0.96	0.96

Experimental study also expands the comparisons with SOTA segmentation model and ensemble approach for the segmentation. Table 6 demonstrates the comparative analysis with proposed ensemble approach. Feature averaging approach finds more appropriate compare to singular learning network 3D-CNN and UNET core model. Proposed study also compare with other ensemble approach to find effectiveness of proposed novel graph attention network.

6. Conclusions

Alzheimer is one of the deadliest disease of the globe. Identification of such diseases in the early stage may saves many lives. Many research and deep learning model has been introducing to detect the disease, still accurate and early detect with limited symptoms. Convolution and encoder based approaches were mostly used for segmentation to Identify Alzheimer disease. The proposed study uses ensemble deep learning approach to enhance Alzheimer disease detection. Simulation of study uses MRI scans as input source to detect the level of AD. simulation of proposed study finds 96% of accuracy on benchmark OASIS dataset. Authors have also analysis the effective ness of SOTA deep leaning models and possible combinations approaches of convolution studies. However, the graph based learning finds remarkable performance compare to other convolution based models. UNET performed well for the data segmentation approach, while proposed GAT with UNET finds comparative performance on unseen data compare to other combination with UNET model. Future research may explore integrating cognitive scores or PET scans to enrich prediction accuracy and clinical relevance.

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Author Contributions

Conceptualization: DK, DG, ARM, FS, TS ; methodology: DK, DG, TS; software: DK, DG; validation: AR, TS; writing—original draft preparation, AR, FS, TS; writing—review and editing: DK, DG, ARM, FS visualization: supervision: ARM, FS, TS; project administration: ARM, FS, TS; all authors had approved the final version.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

References

Abunadi, I. (2022). Deep and hybrid learning of mri diagnosis for early detection of the progression stages in alzheimer's disease. *Connection Science*, *34*(1), 2395–2430. https://doi.org/10.1080/09540091.2022.2123450

Albishri, A. A., Shah, S. H., Kang, S. S., & Lee, Y. (2022). Am-unet: Automated mini 3d end-to-end u-net based network for brain claustrum segmentation. *Multimedia Tools and Applications*, *81*(25), 36171–36194. https://doi.org/10.1007/s11042-021-11568-7

Ali, H. (2025). A meta-review of computational intelligence techniques for early autism disorder diagnosis. *International Journal of Theoretical and Applied Computational Intelligence*, *2025*, 1–21. https://doi.org/https://doi.org/10.65278/IJTACI.2025.1

Aliyu, B. S., Isuwa, J., Abdulrahim, A., Abdullsahi, M., & Hassan, I. H. (2025). Enhanced feature selection for imbalanced microarray cancer gene classification using chaotic salp swarm algorithm. *International Journal of Theoretical and Applied Computational Intelligence*, *2025*, 258–283. https://doi.org/https://doi.org/10.65278/IJTACI.2025.16

Al-Selwi, H. F., Aziz, A. A., Abas, F. B., Kayani, A., & Noor, N. M. (2023). Attention based spatial-temporal gcn with kalman filter for traffic flow prediction. *International Journal of Technology*, *14*(6), 1299. https://doi.org/10.14716/ijtech.v14i6.6646

Araújo, T., Teixeira, J. P., & Rodrigues, P. M. (2022). Smart-data-driven system for alzheimer disease detection through electroencephalographic signals. *Bioengineering*, *9*(4), 141. https://doi.org/10.3390/bioengineering9040141

Ayub, N., Shah, S. Z. A., & Assad, D. A. (2024). Leveraging deep learning for precise alzheimer's disease detection via mri image segmentation: A technical study [SSRN preprint]. https://doi.org/10.2139/ssrn.4974345

Bootun, D., Auzine, M. M., Ayesha, N., Idris, S., Saba, T., & Khan, M. H. M. (2025). Adamaex—alzheimer's disease classification via attention-enhanced autoencoders and xai. *Egyptian Informatics Journal*, *30*, 100688.

Chandra, A., Verma, S., Raghuvanshi, A. S., & Bodhey, N. K. (2023). Pccs-rau-net: Automated parcellated corpus callosum segmentation from brain mri images using modified residual attention u-net. *Biocybernetics and Biomedical Engineering*, *43*(2), 403–427. https://doi.org/10.1016/j.bbe.2023.02.003

Chen, K., Weng, Y., Hosseini, A. A., Dening, T., Zuo, G., & Zhang, Y. (2024). A comparative study of gnn and mlp based machine learning for the diagnosis of alzheimer's disease involving data synthesis. *Neural Networks*, *169*, 442–452. https://doi.org/10.1016/j.neunet.2023.10.040

Duarte, K. T. N., Sidhu, A. S., Barros, M. C., Gobbi, D. G., McCreary, C. R., Saad, F., Camicioli, R., Smith, E. E., Bento, M. P., & Frayne, R. (2024). Multi-stage semi-supervised learning enhances white matter hyperintensity segmentation. *Frontiers in Computational Neuroscience*, *18*, 1487877. https://doi.org/10.3389/fncom.2024.1487877

Ebrahimi, A., Luo, S., & Chiong, R. (2021). Deep sequence modelling for alzheimer's disease detection using mri. *Computers in Biology and Medicine*, *134*, 104537. https://doi.org/10.1016/j.compbiomed.2021.104537

Firdos, S. M., Mehack, Z., Muskan, S. A., BibiNadeefa, A., & Kamepalli, S. (2024). Enhancing alzheimer's disease prediction through deep learning models: A comparative study of googlenet, lenet, and unet. *Proceedings of the First International Conference on Innovations in Communications, Electrical and Computer Engineering*, 1–7. https://doi.org/10.1109/ICICEC62498.2024.10808306

Gajjar, D. B., Faldu, P., Kothadiya, D. R., Chaudhari, A. P., & Bhatt, N. M. (2025). Devitc: Deep-vision transformer to recognize originality of currency. *Computer*, *58*(5), 48–56. https://doi.org/10.1109/MC.2024.3514151

Hasan, M. E., & Wagler, A. (2024). A novel deep learning graph attention network for alzheimer's disease image segmentation. *Healthcare Analytics*, *5*, 100310. https://doi.org/10.1016/j.health.2024.100310

Hazarika, R. A., Maji, A. K., Syiem, R., Sur, S. N., & Kandar, D. (2022). Hippocampus segmentation using u-net convolutional network from brain magnetic resonance imaging. *Journal of Digital Imaging*, *35*(4), 893–909. https://doi.org/10.1007/s10278-022-00613-y

Helaly, H. A., Badawy, M., & Haikal, A. Y. (2022). Deep learning approach for early detection of alzheimer's disease. *Cognitive Computation*, *14*(5), 1711–1727. https://doi.org/10.1007/s12559-021-09946-2

Ishtiaq, U., Abdullah, E. R. M. F., Ishtiaque, Z., Nayer, F. K., Idris, S., & Rehman, A. (2025). Lung cancer classification via entropy-driven feature selection and deep learning architectures on multi-modal imaging data. *International Journal of Technology*.

Kalluvila, A. (2023). Super-resolution of brain mri via u-net architecture. *International Journal of Advanced Computer Science and Applications*, *14*(5).

Kamal, M. S., & Nimmy, S. F. (2024). Interpretable transformers for alzheimer disease diagnosis on multi-modal data. *Proceedings of the International Joint Conference on Neural Networks*, 1–8. https://doi.org/10.1109/IJCNN60899.2024.10651416

Karimi, M., Karimi, Z., Khosravi, M., Delaram, Z., Dehsheikhim, M. H., Najafabadi, S. A., & Tavakoli, N. (2025). Feature selection methods in big medical databases: A comprehensive survey. *International Journal of Theoretical and Applied Computational Intelligence*, *2025*, 181–209. https://doi.org/https://doi.org/10.65278/IJTACI.2025.21

Khan, A., Akbar, S., Alghanim, A., Hassan, S. A., & Ayesha, N. (2023). Automated hybrid model for detection and classification of brain tumor. *Proceedings of the Sixth International Conference of Women in Data Science at Prince Sultan University*, 79–84.

Kothadiya, D., Bhatt, C., Soni, D., Gadhe, K., Patel, S., Bruno, A., & Mazzeo, P. L. (2023). Enhancing fingerprint liveness detection accuracy using deep learning: A comprehensive study and novel approach. *Journal of Imaging*, *9*(8), 158. https://doi.org/10.3390/jimaging9080158

Kothadiya, D., Rehman, A., AlGhofaily, B., Bhatt, C., Ayesha, N., & Saba, T. (2025). Vgx: Vgg19-based gradient explainer interpretable architecture for brain tumor detection in microscopy magnetic resonance imaging. *Microscopy Research and Technique*, *88*(5), 1544–1554. https://doi.org/10.1002/jemt.24809

Kumari, R., Kohli, A., Sunil, A., Dadhich, A., Das, S., & Singh, R. K. (2024). Empirical evaluation of deep learning architectures in the early detection of alzheimer's disease through mri data analysis. *Proceedings of the International Conference on Intelligent Systems and New Applications*, 1. https://doi.org/10.58190/icisna.2024.85

Lee, B., Yamanakkanavar, N., & Choi, J. Y. (2020). Automatic segmentation of brain mri using a novel patch-wise u-net deep architecture. *PLOS ONE*, *15*(8), e0236493. https://doi.org/10.1371/journal.pone.0236493

Li, M., Magnusson, M., van Eimeren, T., & Ellingsen, L. M. (2024). Region-based u-net for accelerated training and enhanced precision in deep brain segmentation. *arXiv preprint*. https://doi.org/10.48550/ARXIV.2403.09414

Li, Z., Yao, T., Kanakaraj, P., Gao, C., Bao, S., Zuo, L., Kim, M. E., Newlin, N. R., Rudravaram, G., Khairi, N. M., Huo, Y., Schilling, K. G., Kukull, W. A., Toga, A. W., Archer, D. B., Hohman, T. J., & Landman, B. A. (2024). Multi-modality conditioned variational u-net for field-of-view extension in brain diffusion mri. *arXiv preprint*. https://doi.org/10.48550/ARXIV.2409.13846

Liu, S., Masurkar, A. V., Rusinek, H., Chen, J., Zhang, B., Zhu, W., Fernandez-Granda, C., & Razavian, N. (2022). Generalizable deep learning model for early alzheimer's disease detection from structural mris. *Scientific Reports*, *12*(1), 17106. https://doi.org/10.1038/s41598-022-20674-x

Manjupriya, R., & Leema, A. A. (2025). Efficient epileptic seizure detection with optimal channel selection and fixuppactbi-lstm deep learning model. *International Journal of Technology*, *16*(2), 706. https://doi.org/10.14716/ijtech.v16i2.7333

Minh, T. C., Quoc, N. K., Vinh, P. C., Phu, D. N., Chi, V. X., & Tan, H. M. (2024). Uggnet: Bridging u-net and vgg for advanced breast cancer diagnosis. *arXiv preprint*. https://doi.org/10.48550/ARXIV.2401.03173

Mohammed, H., Majeed, H., Al-mafrachi, B. A. R., Al-Khaffaf, M. S., & Saad, A. (2025). A novel deep learning approach for classification of abnormal teeth in panoramic x-rays. *International Journal of Theoretical & Applied Computational Intelligence*, 22–34.

Nugroho, H. A., Subiantoro, A., & Kusumoputro, B. (2023). Performance analysis of ensemble deep learning narx system for estimating the earthquake occurrences in the subduction zone of java island. *International Journal of Technology*, *14*(7), 1517. https://doi.org/10.14716/ijtech.v14i7.6702

Orouskhani, M., Zhu, C., Rostamian, S., ShomalZadeh, F., Shafiei, M., & Orouskhani, Y. (2022). Alzheimer's disease detection from structural mri using conditional deep triplet network. *Neuroscience Informatics*, *2*(4), 100066. https://doi.org/10.1016/j.neuri.2022.100066

Pandey, P. K., Pruthi, J., Alzahrani, S., Verma, A., & Zohra, B. (2024). Enhancing healthcare recommendation: Transfer learning in deep convolutional neural networks for alzheimer disease detection. *Frontiers in Medicine*, *11*, 1445325. https://doi.org/10.3389/fmed.2024.1445325

Praschl, C., Zopf, L. M., Kiemeyer, E., Langthallner, I., Ritzberger, D., Slowak, A., Weigl, M., Blueml, V., Nesic, N., Stojmenovic, M., Kniewallner, K. M., Aigner, L., Winkler, S., & Walter, A. (2023). U-net based vessel segmentation for murine brains with small micro-magnetic resonance imaging reference datasets. *PLOS ONE*, *18*(10), e0291946. https://doi.org/10.1371/journal.pone.0291946

Rehman, A. (2023). Brain stroke prediction through deep learning techniques with adasyn strategy. *Proceedings of the 16th International Conference on Developments in eSystems Engineering*, 679–684.

Shukla, A., Tiwari, R., & Tiwari, S. (2023). Review on alzheimer disease detection methods: Automatic pipelines and machine learning techniques. *Sci*, *5*(1), 13. https://doi.org/10.3390/sci5010013

Sun, N., Yuan, Y., Zhang, L., & Han, Z. (2024). Convolutional neural network image segmentation of alzheimer's disease based on multi-order 3d u-net. In A. Tallón-Ballesteros, E. Cortés-Ancos, & D. López-García (Eds.), *Frontiers in artificial intelligence and applications*. IOS Press.

Sun, X., & Huo, X. (2022). Word-level and pinyin-level based chinese short text classification. *IEEE Access*, *10*, 125552–125563.

Udayaraju, P., & Jeyanthi, P. (2024). Advances in alzheimer's detection: A multi-learning fusion approach using choroidal neovascularization analysis. *Proceedings of the International Conference on IoT Based Control Networks and Intelligent Systems*, 1497–1503. https://doi.org/10.1109/ICICNIS64247.2024.10823111

Vaiyapuri, T., & Sbai, Z. (2025). Bayesian optimized boosted ensemble models for hr analytics adopting green human resource management practices. *International Journal of Technology*, *16*(2), 561. https://doi.org/10.14716/ijtech.v16i2.7277

Xie, L., Yushkevich, P. A., Das, S. R., Wolk, D. A., & Gibson, E. (2024). Utilizing advanced artificial intelligence for automated detection and segmentation of amyloid-related imaging abnormality (aria). *Alzheimer's & Dementia*, *20*(S9), e093974.

Xun, S., Zhang, Y., Duan, S., Wang, M., Chen, J., Tong, T., Gao, Q., Lam, C., Hu, M., & Tan, T. (2024). Arga-unet: Advanced u-net segmentation model using residual grouped convolution and attention mechanism for brain tumor mri image segmentation. *Virtual Reality & Intelligent Hardware*, *6*(3), 203–216. https://doi.org/10.1016/j.vrih.2023.05.001

Yoon, H., Park, M., Yeom, S., Kirkcaldie, M. T. K., Summons, P., & Lee, S. H. (2021). Automatic detection of amyloid beta plaques in somatosensory cortex of an alzheimer's disease mouse using deep learning. *IEEE Access*, *9*, 161926–161936. https://doi.org/10.1109/ACCESS.2021.3132401

Zhang, Q., Yuan, Q., Lv, P., Zhang, M., & Lv, L. (2022). Research on medical text classification based on improved capsule network. *Electronics*, *11*(14), 2229. https://doi.org/10.3390/electronics11142229