



DCG-ANET: A DUAL-STREAM CAUSAL GRAPH ADVERSARIAL NETWORK FOR EARLY DETECTION OF ALZHEIMER'S DISEASE FROM MULTIMODAL BRAIN IMAGING

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ABSTRACT

Alzheimer disease (AD) is a rising health hazard that creates complicated mental loss and memory loss. Diagnosis within a reasonable time and at the right time is significant in retarding the occurrence or development of the disease and recovery of the patient. Although neuroimaging has increased our knowledge of changes in the brain as is witnessed in AD, the issue of accurate mapping of abnormal neural circuitry at both structural and functional levels is a complex one. To remedy this, a new Dual-Stream Causal Graph Adversarial Network (DCG-ANet) is proposed in this work, that takes advantage of the DTI data and rs-fMRI data to identify the strongest patterns relating to AD. Perceiving the architecture as a whole, parallel graph encoders with vision-transformer get to learn whole-brain representations, whereas the model embraces a temporal attention system that regulates changes in the functional connectivity as time progresses. Causal subgraph selection module identifies disease-relevant neural circuits and adversarial training improves the attention of the network to the discriminative features. Using the ADNI dataset, the proposed DCG-ANet achieved 94.3% accuracy, 90.6% F1-score, 91.2% recall, 89.9% precision, and 0.92 MCC, with stable training and validation loss convergence and superior ROC curve performance. The model performs exceptionally well in detecting early Alzheimer, and it is even better than the most sophisticated base techniques. It uses circuit level knowledge to provide an impressive performance. This implies that it has greater predictive power, strength and resilience to all the significant evaluation measures.



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I. INTRODUCTION

Among the conditions that are important indicators of Alzheimer disease (AD) are cognitive impairment, memory loss, altered behavior and personality, language impairment, visual-spatial awareness problems, apraxia, and executive problems. This is a progressive degenerative disorder of the brain that has a significant impact on social life and everyday life. Interestingly, mild cognitive impairment (MCI) can serve as a transition between normal aging and AD, but some of them may stay stable or even recover normal cognitive functioning. As the populations are ageing, and the life expectancy continues to rise, AD is becoming more and more common in the global arena, becoming a huge medical, social, and financial burden. It does not only affect the patients but also has a lot of effect on the families and caregivers, placing so much strain on the healthcare systems all over the world. This scenario highlights the urgency of early diagnosis, proper diagnosis and successful treatments [1]. The human brain is a complex system comprising of millions of interconnected neural networks which control sensory, motor and cognitive systems. The study of the mechanisms in which these neural connections change provides useful information about the mechanisms of disruption of normal brain networks and communication by AD. The research and medical practitioners can identify the pathological differences between AD patients and normal control (NC) individuals by exploring the structural and functional networks of the brain. In the last decade, unprecedented advancements in artificial intelligence (AI) and neuroimaging technologies have completely transformed the research on AD [2].

Emerging technologies of imaging including Diffusion Tensor Imaging (DTI), Functional Magnetic Resonance Imaging (fMRI), and Structural MRI (sMRI) have made possible mutual understanding of brain morphology, connectivity, and patterns of activity. DTI measures the white matter connectivity and microstructural integrity; sMRI measures the anatomical and volumetric changes, such as atrophy of hippocampal; and fMRI identifies the dynamic interactions in functional processes in the brain regions. The combination of such modalities gives the higher-quality temporal and spatial resolution, which makes it possible to understand the neural degeneration related to AD comprehensively. This has been further improved by AI-driven image analysis that provides automated, objective, and reproducible results that can be more sensitive and can be more diagnostic than results with traditional cognitive assessment methods [3]. To distinguish AD and NC or MCI, scientists started to pay attention to the unimodal neuroimaging techniques, the study of one imaging modality failure, sMRI, DTI, fMRI, in the context of a wider scope of AI-based diagnostic interventions. One of the first modalities that were used was structural MRI due to its capability to monitor the reduction of the grey matter and cortical thinning [4]. Although fMRI research showed impaired functionality connectivity in major neuronal networks like the default mode network (DMN), the DTI methods of research provided more insight into the breakdown of white matter tracks. Nevertheless, these unimodally-based methods had fundamental drawbacks. The limited computational ability and the simplicity of the algorithms that were in place meant that scientists were not able to effectively use the complementary information that was present in the modalities. As a result, such models have not been able to capture the comprehensive pathophysiological features of AD as they have not captured the intricate interrelationships between brain structure, function, and connectivity [5]. Unimodal means that the imaging is used alone, which is why multimodal neuroimaging fusion that combines the data of multiple imaging modalities to introduce a more holistic picture about the brain has gained popularity.

The combination of DTI, fMRI and sMRI provides a deeper insight into the progression of AD because it is able to simultaneously capture both anatomical and functional abnormalities [6]. Multimodal fusion allows to notice the slightest structural abnormalities with considerable functional consequences. As an example, the white matter degeneration seen in a DTI can lead to the decreased activity in certain regions of the cortices that can be seen in fMRI. The modern development of deep learning (DL) methods has made this integration much more useful and efficient. DNNs are automatic feature hierarchies on the multimodal data, which can be classified and interpreted more accurately. Such methods have demonstrated the possibility of early biomarkers of AD, enhancing the accuracy of predicting progression of MCI-to-AD and timely intervention measures [7]. The transformation of medical imaging has occurred due to the creation of generative models, particularly, GANs, which allow creating realistic synthetic data. In order to generate high-quality synthetic neuroimaging samples, GANs efficiently model complex data distributions through an adversarial game between a generator and discriminator. They relieve data scarcity and improve the generalization of diagnostic models in Alzheimer's research by enhancing low-resolution scans, addressing class imbalance, simulating missing modalities, and augmenting limited datasets [8]. Training instability, mode collapse, and hyperparameter sensitivity are some of the issues that arise when using GANs. Nevertheless, it has been shown that combining GANs with multimodal DL, GNNs, and attention-based mechanisms works well. While attention and Transformer architectures capture important inter-regional dependencies, GNNs model the brain as a graph of interconnected regions, offering interpretable insights into connectivity disruptions related to AD. Combined, they improve the accuracy and interpretability of the diagnosis, and thus, encourage their use in clinical practice [9].

Hybrid multimodal systems that combine GANs, GNNs, and Transformers have gained an increased role in the study of Alzheimer because they could handle missing or noisy modalities, learn local and global dependencies in brain imaging data, and learn robust and generalizable feature representations. Transformer-based feature extraction and GAN-based data augmentation result in these frameworks discovering latent features correlated with minute pathological alterations frequently undetected by conventional statistical models, and prove to be effective in classifying AD versus MCI and NC subjects. The combination of AI, deep learning, and multimodal neuroimaging has moved the concept of descriptive analysis to predictive modeling, in which the accuracy of diagnoses is increased, the ways in which illnesses develop are further understood, and personalized medicine that is unique to the particular neurobiological features of a particular patient can be developed. Since AD has remained a severe medical, social, and emotional burden, it is critical that more sophisticated forms of computational methods be employed to detect it at an early stage, diagnose and provide better treatment. The present work attempts to analyze the issue of what kind of description of atypical neural networks can allow to diagnose AD as early as possible on the basis of multimodal neuroimaging data. The solutions to enhance the diagnosis accuracy and interpretation with the assistance of the Alzheimer Disease Neuroimaging Initiative (ADNI) dataset [10] are suggested in this paper; these solutions are the proposed Dual-Stream Causal Graph Adversarial Network (DCG-ANet), which consists of the strong graph learning, time-series modeling, and adversarial learning modules. The prime contributions of this paper would be:

- A new DCG-ANet model is proposed, which integrated the dual-stream graph learning with causal subgraph search to detect AD in a precise and earlier way.
- The model uses Vision Transformer based encoder and can learn to capture structural and functional dynamics using DTI and Rs-fMRI data using a temporal attention mechanism.
- An adversarial training module is employed that aims to enhance robustness of the identified neural circuits with the purposes of identifying AD-related best features using a selection module of a causal subgraph.
- The efficacy of the model is demonstrated by extensive trials using the ADNI data (accuracy, F1-score, recall, precision, and training and validation losses are applied as assessment metrics).
- The suggested DCG-ANet performs better than current state-of-the-art procedures, especially at identifying early-onset AD and the provision of neural circuit interpretability.

The content of the remaining parts of the paper will be structured in the following manner: the second part will become a literature review of what has already been written by other authors on the subject. The section 3 offers the architecture and the methodology of the suggested DCG-ANet. The results of the experiment and comparison shall be presented in section 4. Finally, the research will be concluded stating the significant findings and avenues in the Section 5.

II. RELATED WORK

According to [11] proposed an innovative use of the online hand writing loop patterns to detect and classify the early stage of AD. The paper examines various types of data augmentation since there is insufficient data to be able to classify AD using behavioural data. In [12] suggested using a unique cross-modal transformer generative adversarial network (CT-GAN) to integrate structurally partitioned data, Diffusion Tensor Imaging (DTI), and resting-state functional magnetic resonance imaging (rs-fMRI). The most effective skills of retrieving complementary information in relation to rs-fMRI and DTI, as well as the dominance of efficacious functional information - the structural information mapping realized with the help of developed bi-partite approach. Time varying profiles of brain connections are challenging to the bi-attention mechanism in that it has no temporal modelling. According to [13] presented a recently created brain imaging-to-graph generation (BIGG) model that converts fMRI into employable connections for use in MCI studies. The proposed BIGG system avoids this by using diffusion denoising probabilistic models (DDPM), which gradually denoise the noise and conditional fMRI into effective connectivity using a GAN's denoising layer. The training process is time-intensive as well as two tuning is necessary, which is why the method is impractical in the real-world clinical setting, despite it being accurate. To describe anatomical-functional connections of the brain, [14] proposed a bidirectional graph generative adversarial network (BG-GAN). This dependence on graph structures that are handcrafted may cause suboptimal results when the method is applied to atypical subjects with non-standard patterns of connectivity. In order to solve problems in non-Euclidian domains, [15] suggests using graph neural networks (GNN). The multi-modal information is combined at the node connection and adjacency matrix levels, and each modality has its own branch of the multi-modal GNN structure. Finally, by carrying out late fusion, they joined together the first decisions obtained in every branch to produce a last prediction. The isolated treatment of procedural action of both modalities prior to merging them would be a source of losing shared cross-modal interactions at the early phase of learning. In [16] suggested a middle-fusion multimodal strategy for AD early detection. Here, the depth-specific separable convolution block with no activation function is utilised to recover data without loss.

The intricate modalities with one another are then made visible by combining middle fusion, mix skip connection, and weight sharing convolution blocks. The absence of attention mechanisms restricts the model to prioritise the salient areas or features to the Alzheimer progress. According to [17] provided a CNN model which was specifically developed with the help of recent methods to distinguish between the various forms of AD. This model can be employed as a diagnostic tool in order to prevent the development of the condition to the more advanced symptoms of dementia. The model is based mainly on the spatial characteristics and there is no incorporation of the structural-functional graph data, which decreases its interpretability at the neural circuits level. According to [18] proposed BrainDGT, a dynamic Graph Transformer model that enhances the diagnosis of brain diseases by adaptively recording and analysing brain activity related to modularity. BrainDGT evaluates the adjusting brain states and breaks the issue of permanent time duration. The model is based on two attentions: self-attention identifies significant temporal connections, and graph-attention identifies structural features of snapshots of the dynamic brain network. According to [19] suggested distribution-regularized adversarial graph auto-encoder (DAGAE) with a transformer to improve the accuracy of data-driven model to diagnose dementia and construct new artificial brain functional networks. One can retain the traditional topological properties completely as well as preserve the discriminative properties. By [20] introduced a novel multimodal, self-guided, and knowledge-infused GNN that incorporates domain information to generate models without the need to be provided by the user. They outline a specialised multimodal GNN that can be enabled by this uncurated knowledge to guide the learning process of the GNN to enhance the performance of the model and simplify the interpretation of predictions. Their methodology considers domain information as a natural language. According to [21] suggested an algorithm to automatically identify dementia which demonstrated the correlation between texts and images via a graph. First they transcribed the voices of the participants with help of an automatic speech recognition system.

A vision language model was then developed to form a bipartite graph that indicated the correspondence between the constituent parts of a given image and the descriptive terms that were associated with those parts. Lastly, they performed the classification of AD patients on a graph-level classification task using a graph convolutional network (GCN) on each subject as a graph. By [22] developed a multi-modal sparse interpretable GCN framework (SGCN) to identify the prodromal stage of AD referred to as moderate cognitive impairment (MCI). The clinical manifestation of AD and identified abnormalities were closely correlated. They were also capable of explaining the identified brain dysfunctions and the abnormalities in the sex-related connection at the level of large-scale neural networks in AD/MCI. In [23] provides a synthesis of recent research outcomes of the application of DL in multimodal neuroimaging in the diagnosis of AD. The part of the review procedure was the thorough search of the major databases, including PubMed, Embase, Google Scholar, and ClinicalTrials.gov among others. Subsequently, the relevant research was identified, and the results were analyzed. They gave priority to high-quality research and were applying a best-evidence technique to determine recurrent trends in literature. According to [24] described a DL architecture that using a cyclical round of diagnostic tests to diagnose the presence of AD, non-AD dementias (nADD), MCI, and NC individuals. They show a variety of models that could be used to accommodate various combinations of the clinical data that are regularly taken, such as the medical history, neuropsychological testing, neuroimaging, demographics, and functional assessments. They continue to demonstrate the extent to which these frameworks capture the accuracy of diagnosis of actual neurologists and neuroradiologists. In [25] suggested a framework by making use of GNNs, that works with graph-structured data. In their work, they use GNNs to analyse data on the AD Neuroimaging Initiative to binary and multi-class categorisation at the three phases of AD (CN, MCI, and AD). In [26] used DL models include EEGNet, Convolutional Neural Network-Long Short-Term Memory, Graph Convolutional Network (GCN), and multi-scale feature reconstruction GCN to derive differential entropy features in ERP data. They also employed a multilayer perceptron to derive features of TCM questionnaires. Following a feature fusion, ten-fold cross-subject binary (HC vs. MCI+AD; MCI vs. AD); ternary (HC, MCI, AD) classification tasks were conducted.

II.1 RESEARCH GAP:

There are still a lot of unresolved issues in the field of AI-based multimodal neuroimaging for AD identification. The majority of current approaches have limited capacity to capture comprehensive patterns of brain connections because they are unable to simultaneously represent the structural and functional relationships between DTI and rs-fMRI data. Existing transformer, GAN, and GNN-based models rely on manually specified graph topologies that limit subject-to-subject adaptability, fail to capture causal links between brain areas, or lack efficient temporal modelling of dynamic neural changes. Furthermore, its clinical usefulness is restricted by adversarial training instability and the poor interpretability of learnt features. In order to diagnose AD at an early stage with greater accuracy and explainability, a unified, causally interpretable, and temporally aware multimodal framework that can effectively integrate heterogeneous brain imaging data is urgently needed.

III. PROPOSED METHODOLOGY

III.1 DATASET

This study makes use of the publically accessible ADNI dataset [10], which includes multimodal brain images such as diffusion-tensor imaging (DTI) and resting-state functional magnetic resonance imaging (rs-fMRI). Four clinical stages—late mild cognitive impairment (LMCI), early moderate cognitive impairment (EMCI), Alzheimer's disease (AD), and normal control (NC)—are used to stratify the participants. The full dataset consists of 236 people, and a comprehensive demographic profile is given in Table 1. All image data were converted from DICOM to NIfTI format. The flow diagram for the suggested model is displayed in Figure 1.

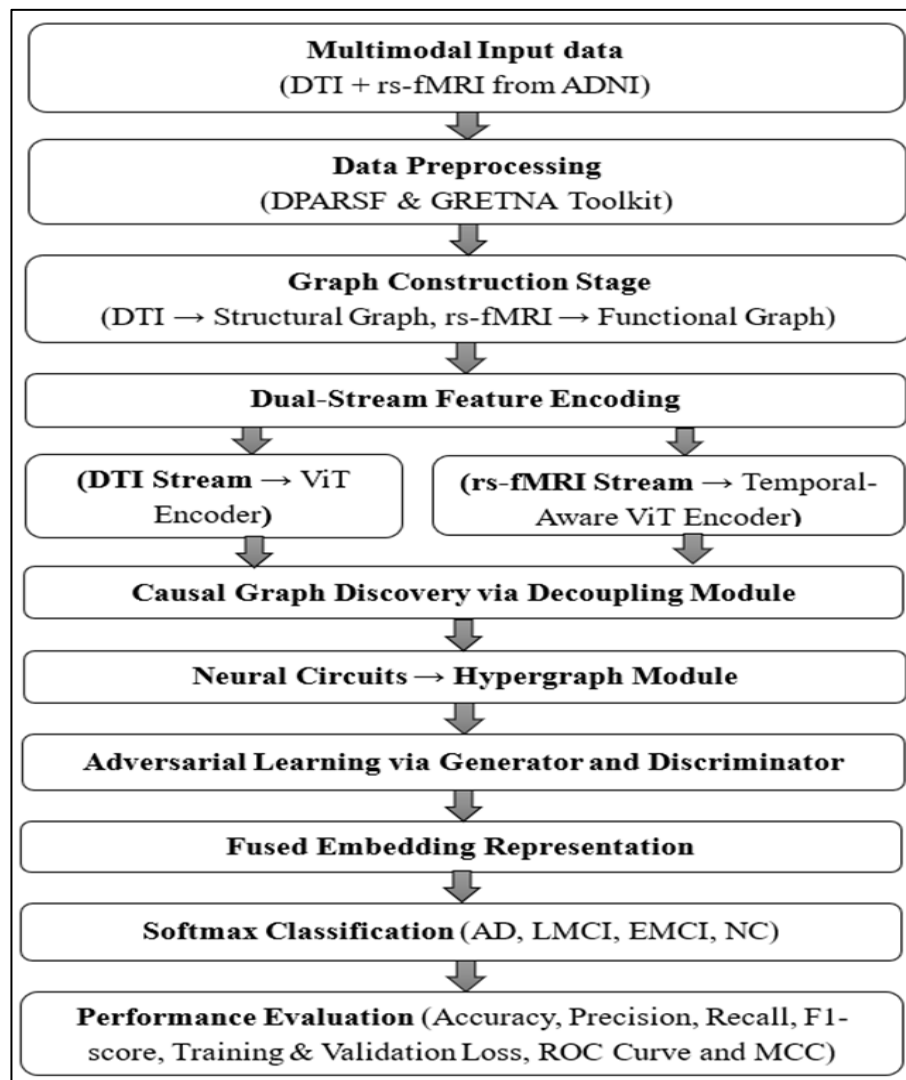


Figure 1: Flow diagram of proposed DCG-ANet model.

Source: Author, (2026).

Table 1: Dataset description.

Group	AD (62)	LMCI(42)	EMCI(55)	NC (74)
Male/Female	34M/28F	22M/20F	38M / 17F	33M / 41F
Age (mean $\pm$ SD)	76.3 $\pm$ 5.6	73.9 $\pm$ 6.1	74.9 $\pm$ 6.1	73.9 $\pm$ 6.1

Source: Author, (2026).

III.2 PREPROCESSING

In order to guarantee the quality, consistency, and comparability of the neuroimaging data for each participant, the data preparation stage is essential. The DPARSF (Data Processing Assistant for Resting-State fMRI) pipeline is used to preprocess the rs-fMRI data. Additionally, it involves a chronological series of steps, including slice timing correction, movement correction (realignment), spatial smoothing, temporal band-pass filtering to remove physiological noise (usually in the range of 0.01 to 0.08 Hz), and spatial normalisation to the standard brain atlas (e.g., MNI space). In order to create regional time-series data that serve as the foundation for building functional brain networks, the resultant clean, temporally limited BOLD signals are averaged in specific brain regions of interest (ROIs). Regarding the DTI data, the DTI raw diffusion images are processed with the use of the GREYNA (Graph Theoretical Network Analysis) toolkit. This comprises complete-brain tractography to approximate white matter fibre routes between ROIs, fit of tensors, brain removal, and correction of eddy circulation. The resulting structural connectivity matrix W^{DTI} is formed by counting the number of streamlines n_{ij} connecting each pair of ROIs i and j , and then normalizing through Equation (1):

$$W^{DTI}(i, j) = \frac{n_{ij}}{\max(n)} \quad (1)$$

This preprocessing ensures consistent spatial alignment and temporal normalization across subjects, enabling reliable graph construction and downstream feature learning.

III.3 GRAPH CONSTRUCTION STAGE

The preprocessed DTI and rs-fMRI neuroimaging data are subsequently converted to graph-structured forms after the preprocessing step, which are indispensable in exhibiting multifactor complex structural and functional brain connectivity patterns. Such transformation would allow the model to reason on brain regions as a set of nodes interconnected to each other, and allow graph-based learning at later stages.

DTI: A structural brain graph is generated in the case of DTI modality. The nodes used in this graph can be brain regions of interest (ROIs) that are predefined and often defined in a brain atlas e.g. AAL or Harvard-Oxford. Fiber tracking algorithms (e.g. deterministic and probabilistic tractography) are used to define the edges between nodes: they estimate the physical white matter connections among the various sections in the brain. The between-node edge weights are determined by the number or strength of the streamlines (fibers) connecting them, to make up the structural connectivity matrix. Mathematically the resulting graph is represented by as formulated in Equation (2):

$$G_s = (V, E_s) \quad (2)$$

Where, the set of structural edges and the set of ROIs (nodes) derived from DTI are denoted as E_s and V , respectively. Conversely, there is a series of functional brain graphs that are brought forth by the rs-fMRI modality. Again, the connections demonstrate how active diverse portions of the brain can be in relation to one another in a functional sense, i.e., the functional connectivity or the statistical relationship among the blood oxygen level-dependent (BOLD) time-series data of separate regions, with each node corresponding to a segment of the brain.

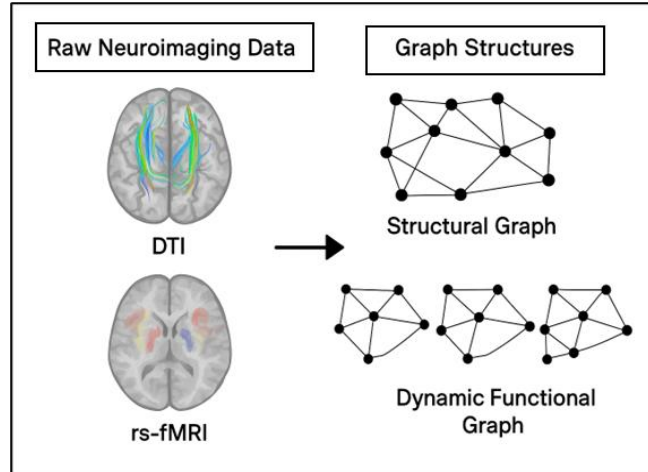


Figure 2: Graph construction from neuroimaging data.

Source: Author, (2026).

Based on the fact that rs-fMRI records dynamic brain activity within a period of time, the functional connectivity is not fixed. Rather, a dynamic graphical process is created developed by dividing the BOLD signal by time windows and calculating connectivity matrices by time slice. Each of the graphs in the sequence is labelled as in Equation (3):

$$G_t^f = (V, E_t^f), \quad t \in \{1, 2, \dots, T\} \quad (3)$$

Where G_t^f represents the functional connectivity graph at time window t , and E_t^f denotes the functional edges based on temporal correlations in that window.

This step guarantees well-endowed and complementary model representations: static but anatomically-informed structural graphs of DTI, and evolving functional graphs of rs-fMRI. In combination, these graphs form the basis of dual-stream feature encoding and causal analysis of the AD development in the further steps of the model. Figure 2 shows the process of graph construction from neuroimaging data: transforming DTI and rs-fMRI into structural and functional brain graphs.

III.4 DUAL – STREAM FEATURE ENCODING

To extract meaningful representations from both structural and functional graphs, the model employs two parallel Vision Transformer (ViT)-based graph encoders. In the DTI stream, the static structural graph G_s is processed through a transformer that treats the graph as an image-like structure, enabling global context capture via self-attention using Equation (4):

$$H_s = ViT_s(G_s) \quad (4)$$

In parallel, the rs-fMRI stream handles the dynamic sequence of functional graphs $\{G_1^f, G_2^f, \dots, G_T^f\}$ using a temporal-aware ViT, encoding each time step independently or via temporal attention using Equation (5):

$$H_t^f = ViT_f(G_t^f), \quad \forall t = 1, \dots, T \quad (5)$$

The latter are further employed in the temporal attention mechanism to ensure that changes in connectivity patterns, which matter to Alzheimer confirmation, are being recorded. The theoretical roots of this strategy are in the recent work of Dynamic Graph Transformer models of diagnosis of brain disorders that achieved better performance encoding temporal functional graphs with transformer architectures [18]. In sum, this two-stream and transformer-based encoding allows DCG ANet to learn both the static anatomical structure and dynamic functional connectivity, and forms a solid foundation to subsequent steps of causal subgraph discovery and multimodal fusion.

III.5 CAUSAL GRAPH DISCOVERY VIA DECOUPLING MODULE

Each encoded stream is passed through a Causal Subgraph Selector, which aims to isolate substructures most predictive of Alzheimer's progression. It does this by learning a binary attention mask $M \in \{0,1\}^{|E|}$ that identifies causal edges in the graph. The selected subgraph G_c retains only those edges marked as causal given by Equation (6):

$$G_c = (V, E_c), \text{ where } E_c \subseteq E, \text{ and } M_{ij} = 1 \text{ if edge } (i, j) \text{ is causal} \quad (6)$$

This selected process improves interpretability and computing efficiency by eliminating noise and unnecessary connections, preserving brain connection patterns that are significant to the condition. Furthermore, by concentrating on strong, disease-relevant connection traits rather than global correlations, our causal subgraph extraction lessens overfitting. Consequently, the model does not only enhance the precision of the diagnoses but also provides the insights that are neuroscientifically important as to the regions and pathways of the brain that are most likely to be associated with the evolution of the AD.

III.6 HYPERGRAPH MODULE

Causal subgraphs obtained from both the DTI and rs-fMRI streams are subsequently transformed into a hypergraph model. In contrast to regular graphs, hypergraphs, as defined by Equation (7), allow for the characterisation of intricate multi-region connections that are crucial in a neurodegenerative disease. The edges, or rather, hyperedges, may contain more than two nodes:

$$H = (V, E), \quad E = \{e_1, e_2, \dots, e_k\}, e_i \subseteq V \quad (7)$$

Neural circuits, which are groups of brain areas with co-dependent connectivity alterations in AD, are captured by this higher-order graph concept. Hypergraph structure is a more complex model of the neuronal communication networks that are affected by the AD as it models collective dependency among multiple brain regions at once, beyond the pair-wise interaction. The hyperedges may be functional communities or structural modules and this enables the discovery of high-order and subtle disruptions that otherwise may not have been detected with traditional graphs. The hypergraph formulation additionally enhances the generalisation of the model by averaging signals of many related nodes reducing the impact of inter-subject variability and local noise. Additionally, because shared hyperedges can show cross-modal correlations that reflect both structural integrity and functional synchronisation across the brain, this transformation enables the efficient merging of multimodal information from DTI and rs-fMRI streams. In this way, the hypergraph module serves as a link between modality-specific subgraphs and a single representation, allowing for more accurate characterisation of Alzheimer's development and deeper insights into disease-related network dynamics.

III.7 ADVERSARIAL LEARNING VIA GENERATOR AND DISCRIMINATOR

To ensure the learned causal representations are both robust and generalizable across different subjects and clinical conditions, this model employs a sophisticated adversarial learning framework. In this framework, two neural network components work in tandem [19]:

- The **Generator (G)** is designed to reconstruct or generate clean, noise-free causal graph embeddings from noisy or corrupted versions of these graphs. It attempts to learn meaningful and discriminative features by filtering out irrelevant or spurious information.
- The **Discriminator (D)** functions as a classifier that distinguishes between authentic, real causal graph embeddings and those generated by the Generator. Its role is to scrutinize the representations and provide feedback that guides the Generator to produce increasingly realistic embeddings.

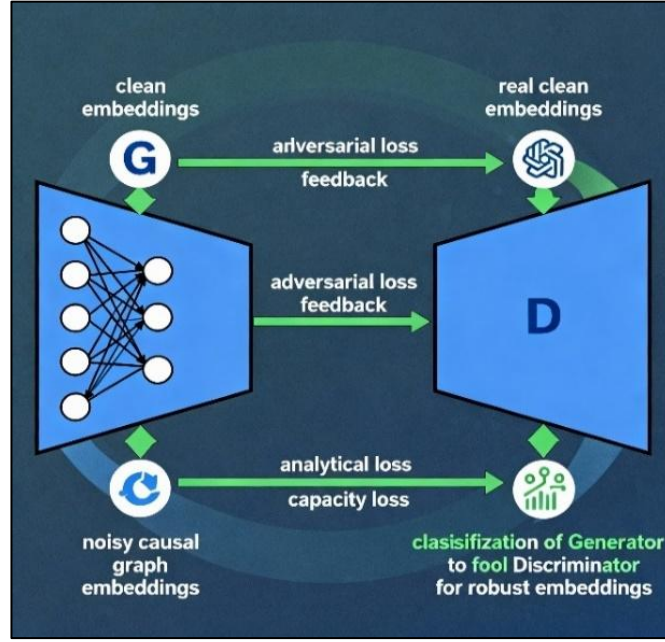


Figure 3: Schematic of the adversarial learning framework.
Source: Author, (2026).

These networks are trained as a min-max game in which the Generator aims to trick the Discriminator and the Discriminator aims to increase its differentiation accuracy. Because of this dynamic, the model is more likely to generate high-quality, noise-resistant embeddings that are helpful for tasks like illness categorisation. The adversarial learning framework's schematic is depicted in Figure 3, where Generator (G) reconstructs clean embeddings from noisy causal graph embeddings, Discriminator (D) distinguishes between generated and real embeddings, and feedback loops stand in for adversarial, analytical, and capacity losses. The training optimizes three losses stated in Equation (8), Equation (9) and Equation (10):

- **Adversarial loss:** This loss quantifies how well the Generator can deceive the Discriminator. Realism and representational accuracy are improved by minimising this loss, which forces the Generator to generate embeddings that are identical to real ones.

$$L_{adv} = E_{x \sim p_{data}}[\log D(x)] + E_{z \sim p_z}[\log(1 - D(G(z)))] \quad (8)$$

- **Analytical loss:** This element ensures that the reconstructed embeddings and the original clean embeddings are identical. By serving as a reconstruction constraint, it makes that the Generator stays close to the actual data distribution and preserves the significant semantic content required for efficient categorisation.

$$L_{anl} = \|\hat{Z} - Z\|_2^2 \quad (9)$$

- **Capacity loss:** This loss penalises subgraph size or complexity to keep the Generator from creating huge or complicated subgraphs that might overfit the data. It enhances the succinct, sparse, and broad-applicable acquisition of causal structures to the model.

$$L_{cap} = \lambda \cdot \|M\|_1 \quad (10)$$

Equation (11) gives the weighted sum of the whole loss:

$$L_{total} = L_{adv} + \alpha L_{anl} + \beta L_{cap} \quad (11)$$

By ensuring that these weights are adjusted accordingly, the model balances generating realistic embeddings and protection of important information as well as preventing a very complex model. This adversarial learning methodology makes the Alzheimer disease progression modelling more robust and promotes the creation of causal network features that are also generalised well to new data.

III.8 FUSED EMBEDDING REPRESENTATION

After adversarial learning, the results of the two streams, H_s (structural) and H_f (functional) are combined using a Cross-Attention technique. With the help of the module based on the use of the Equation (12), one can articulate the structural and functional properties in the model, indicating that there are areas where the two modalities demonstrate abnormalities:

$$Z^* = \text{CrossAttn}(H_s, H_f) \quad (12)$$

The combination of this produces one representation of the anatomical properties of the brain and the spatiotemporal dynamics.

In other words, the cross-attention module is trained to learn context-sensitive relations between structural embeddings based on DTI to query and functional embeddings based on rs-fMRI to key-value pairs. The resultant fused representation Z^* is better spaced by the fact that the model has the ability to detect subtle shifts in the patterns of brain connections associated with disease in the brain, thereby retaining the most discriminative information of both representations. The graphical representation of this fusion process is as a heatmap as shown in the accompanying image, where the structural embeddings are depicted on the y-axis and the functional embeddings are depicted on the x-axis. The intensity of each cell shows the amount of weight of interaction or attention between the two elements. Strong cross-modal correlation is indicated by brighter areas in the heatmap, which represent parts of the brain where both structural integrity and functional activity work together to produce diagnostic patterns.

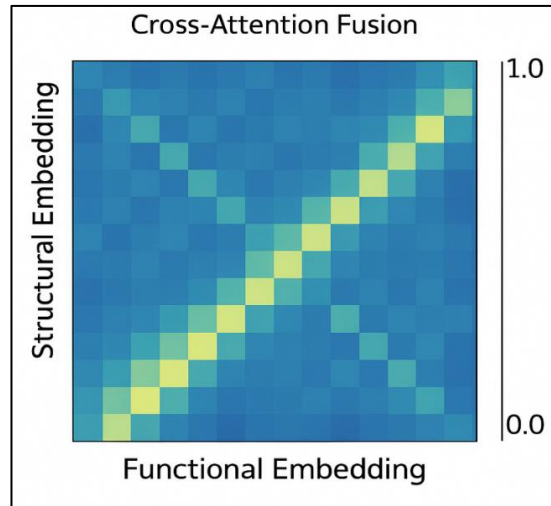


Figure 4: Fused embedding representation.
Source: Author, (2026).

Through this integrated fusion, the suggested model may benefit from both modalities in a synergistic way, increasing feature completeness, decreasing modality bias, and enabling more precise prediction of aberrant brain states or disease development. By merging complementary information from DTI and rs-fMRI, the model achieves a balanced and enriched multimodal representation, essential for robust clinical decision-making. Figure 4 shows this fused embedding representation.

III.9 SOFTMAX CLASSIFICATION

Finally, the fused embedding Z^* is fed into a fully connected classifier with a SoftMax layer, producing probabilities for four diagnostic classes using Equation (13):

$$\hat{y} = \text{Softmax}(W \cdot Z^* + b), \quad \hat{y} \in R^4 \quad (13)$$

The model will compute a probability distribution across:

- AD
- LMCI
- EMCI
- NC

Such an end-to-end framework allows structural and interpretable finding of early AD based on multimodal brain images.

IV. RESULT AND DISCUSSION

Using the ADNI dataset, the suggested DCG-ANet method gets compared with other cutting-edge methods for early AD identification, including Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Decision Tree (DT). Some of the parameters that will be applied to the assessment will be F1-score, training, validation loss, precision, recall, accuracy, Receiver Operating Characteristic Curve (ROC curve) and Matthew's Correlation Coefficient (MCC).

Performance Metrics:

- **Precision** – Measures the proportion of correctly predicted positives among all predicted positives using Equation (14):

$$Precision = \frac{TP}{TP+FP} \quad (14)$$

- **Recall (Sensitivity)** – Measures the proportion of correctly predicted positives among all actual positives using Equation (15):

$$Recall = \frac{TP}{TP+FN} \quad (15)$$

- **F1-Score** – Harmonic mean of precision and recall, balancing both metrics by Equation (16):

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (16)$$

- **Accuracy** – Fraction of correctly predicted samples among all samples through Eq. (17):

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (17)$$

Where:

TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

- **Training & Validation Loss** – Monitoring both training and validation loss aids in identifying overfitting or underfitting, while a smaller loss implies better model performance. It is a measure of how closely a model's predictions match the actual target values during training and assessment.
- **Receiver Operating Characteristic (ROC) Curve** – Plots True Positive Rate vs. False Positive Rate to evaluate classifier performance across thresholds using Equation (18):

$$TPR = \frac{TP}{TP+FN}, FPR = \frac{FP}{FP+TN} \quad (18)$$

- **Matthew's Correlation Coefficient (MCC)** – Measures overall classification quality, accounting for TP, TN, FP, FN using Equation (19):

$$MCC = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (19)$$

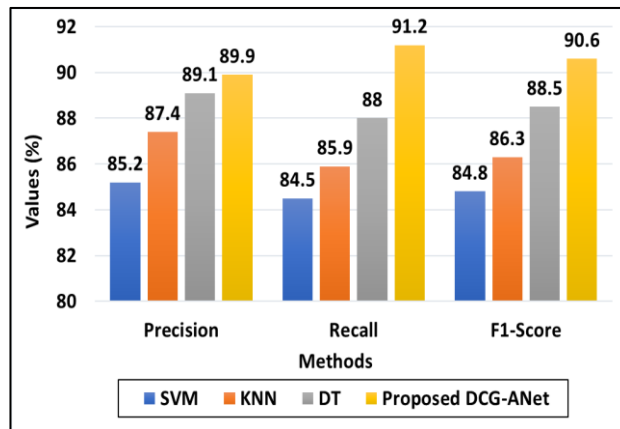


Figure 5: Precision, recall and F1-score comparison.
Source: Author, (2026).

Figure 5 draws parallels between the findings of four models which are: SVM, KNN, DT and the proposed DCG-ANet according to three evaluation measures: F1-Score, Precision, and Recall. The proposed DCG-ANet model achieves the best findings with 89.9%, 91.2% and 90.6% of accuracy, recall, and F1-score, respectively. DCG-ANet is 0.8% better in Precision, 3.2% better in Recall, and 2.1% better in F1-Score when compared to the second-best model (DT). This improvement has been attributed to the structure of the DCG-ANet that effectively integrates dual convolutional gating and attention mechanisms. This helps it identify complex spatial and temporal dependencies in rs-fMRI and DTI signals, and generalise and classify more accurately than standard ML models. According to Figure 6, the proposed models, DCG-ANet, KNN, DT, and SVM have the accuracy of 94.3%, 88.5%, 89.4%, and 86.7% respectively. The proposed DCG-ANet has a higher accuracy by 4.9%, 5.8% and 7.6% in comparison to the DT, KNN and SVM respectively. This excellent performance can be attributed to the special combination of dual-channel gated attention architecture in DCG-ANet that manages to capture the rich deep spatiotemporal regularities in complex neuroimaging signals (DTI and rs-fMRI). Due to the favorable distinction between features and the attenuated irrelevance of noise, DCG-ANet enhances classification accuracy and, therefore, makes it more reliable in early detection of AD

The suggested DCG-ANet model's training and validation loss curves across 50 epochs are displayed in Figure 7. A gradual decrease in both curves indicates good learning, and generalisation. The validation loss is also very close with minimal deviation during the training process whereas the training loss begins at around 0.03, and decays slowly to less than 0.003. According to the close proximity between training and validation loss, the model seems to be absent of overfitting and can continue to perform well on unseen data. By integrating dual-modality fusion and circuit-level attention, DCG-ANet mainly performs better due to feature representation and learning efficiency.

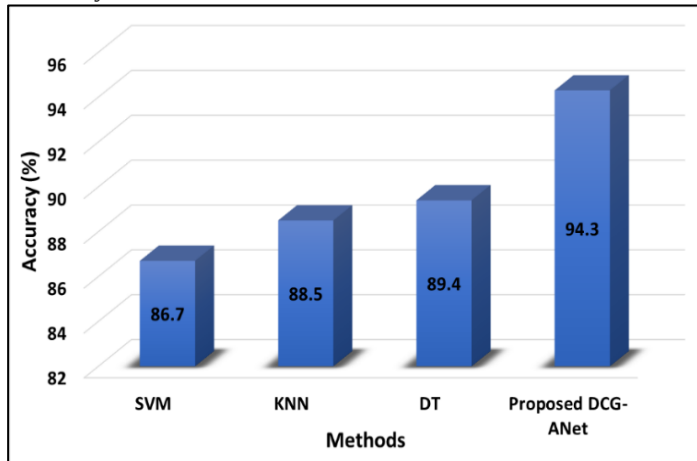


Figure 6: Accuracy comparison.
Source: Author, (2026).

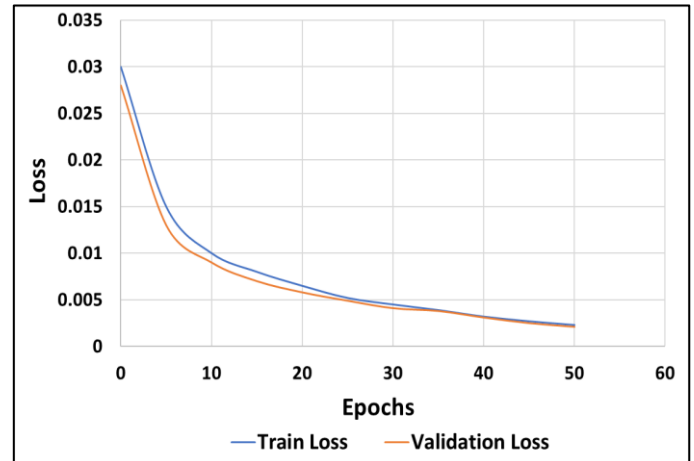


Figure 7: Validation and training losses of the DCG-ANet method.
Source: Author, (2026).

The ROC curves comparing the classification performance of SVM, KNN, DT, and the proposed DCG-ANet are shown in Figure 8. A greater True Positive Rate (TPR) at every threshold is indicated by the Proposed DCG-ANet (yellow curve), which continuously ranks higher than all other models across all FPR levels. For instance, DCG-ANet attains a TPR of 0.92 at FPR = 0.4, meaning it is around 24.3% better than SVM (0.74), 9.5% better than KNN (0.84), and 5.7% better than DT (0.87). Through improved feature representation and adept handling of subtle neuroimaging abnormalities, the Proposed DCG-ANet exhibits an average increase of around 10–15% over traditional classifiers across thresholds, indicating its greater capacity to identify Alzheimer's disease. The scores of SVM, KNN, DT, and Proposed DCG-ANet in the MCC are provided in the Figure 9. The Proposed DCG-ANet scores highest in MCC with the score of 0.92 compared to SVM (0.78), KNN (0.81) and DT (0.65). It is an increase of about 17.95%, 13.58% and 41.54% in comparison to SVM, KNN and DT respectively. The greater MCC value of the proposed DCG-ANet proves that it is able to find positive and negative cases better. The improvement is owed to the dynamic channel -graph attention mechanism within the model, which is able to capture the multimodal interdependencies resulting in more balanced and more accurate predictions even in difficult classification situations.

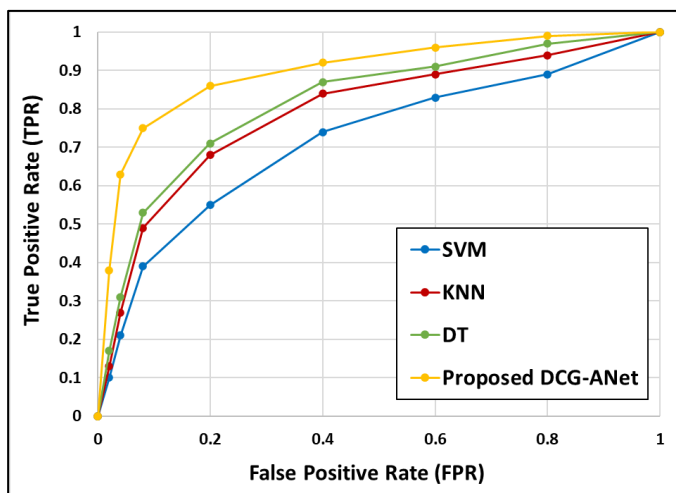


Figure 8: ROC curve comparison.
Source: Author, (2026).

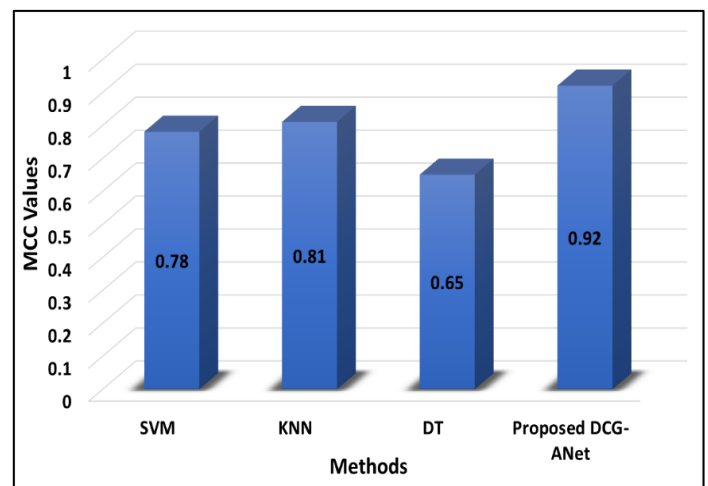


Figure 9: MCC comparison.
Source: Author, (2026).

V. CONCLUSION

This paper presents the development of DCG-ANet, which is a Dual-stream Causal Graph Adversarial Network, in detecting AD in its early stages based on multimodal neuroimaging data, i.e., rs-fMRI and DTI. DPARSF and GREYNA Preprocessing guarantee spatial and temporal consistency and make it possible to construct accurate structural and functional brain graphs. Two parallel ViT-based graph encoders depict the meaningful features, where the stable structure of white matter connectivity occurs in the structural stream, and the time-varying correlations in BOLD signals are in the functional stream. To fine-tune these embeddings, a causal subgraph disentangling mechanism as well as an analytical, adversarial and capacity loss functions is used with adversarial learning. The model is robust in identifying a subset of disease-relevant subgraphs, which would be particularly conducive to interpretation and diagnosis.

The model demonstrates strong performance, achieving 94.3% accuracy, 90.6% F1-score, 91.2% recall, 89.9% precision, and 0.92 MCC, with stable training and validation loss convergence and superior ROC curve performance, clearly surpassing several standard techniques. The non-invasive behavioural biomarkers that might with instrumental considerations be incorporated in the future are speech, facial expression and handwriting to enhance diagnosis accuracy and whereas intervention strategies can be applied in an earlier and comprehensive multi-modal manner.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Dinesh Kumar P.

Methodology: Dinesh Kumar P.

Investigation: Dinesh Kumar P.

Discussion of results: Dinesh Kumar P.

Writing – Original Draft: Dinesh Kumar P.

Writing – Review and Editing: Dinesh Kumar P.

Resources: Dinesh Kumar P.

Supervision: Dinesh Kumar P.

Approval of the final text: Dinesh Kumar P.

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Data Availability: The data used in this study are publicly available from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (<https://adni.loni.usc.edu/>) and can be accessed upon registration and approval

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