Clinically Informed Adaptive Multimodal Graph Learning Paradigm for Transparent Temporal and Generalizable Alzheimer's Disease Diagnosis

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***Abstract*—This is a clinically reliable and explainable diagnostic framework for the early detection of Alzheimer's disease with multimodal data. Current computational methods face challenges in dealing with fragmented clinical information, poor cross-modal integration, limited temporal modelling, and low interpretability, rendering them unsuitable for real-world medical deployment. To overcome these limitations, we propose the Clinically Guided Adaptive Multimodal Graph Transformer (CAM-GT), a novel architecture that fuses clinical priors with graph-based learning and transformer-driven temporal reasoning within a unified model. The proposed framework uniquely integrates clinically guided graph attention, cross-modal fusion, and contrastive alignment, where the system can capture hidden relationships among imaging, cognitive scores, and clinical biomarkers with high robustness against missing or imbalanced modalities. Implemented on the Python platform with advanced deep-learning libraries, CAM-GT carries out multimodal encoding, temporal progression modeling, and explainability mapping in order to identify the most significant biomarkers that influence the status of a disease. Experimental evaluation demonstrates that the model performs well by achieving an accuracy of 97%, a 97.2% AUC, and outperforming existing models while maintaining strong generalization in heterogeneous clinical environments. Further, high interpretability ensures that clinically, it will be able to trace how predictions are made to instill greater trust and ethical reliability and increase the adoption potential in hospitals and research centers. Finally, CAM-GT benefits neurologists, radiologists, healthcare institutions, and researchers by providing a stable, transparent, high-performing AI system that has the capability to support early diagnosis and guide real-world clinical decision-making in neurodegenerative disease care.**

Keywords*—*Alzheimer's detection; graph neural network; multimodal fusion; explainable AI; temporal transformer

I. Introduction

Neurological diseases burden the world with millions of individuals with disabilities that can lead to chronic illness and lifelong disability. These disorders, such as Alzheimer's and Parkinson's diseases, start with a mild level of cognitive or behavioral abnormalities, which eventually result in the irreversible degeneration of the neural pathway [1]. This makes early and precise diagnosis very relevant to improve the therapeutic outcome, postpone the development of the disease, and offer a lower cost of healthcare [2]. The presence of a subtle manifestation of such conditions and similarity in symptoms frequently make traditional diagnostic paradigms based on a high level of subjective clinical examination and interpretation by specialists ineffective in identifying the early onset of the condition [3]. Multimodal data, such as demographic information, cognitive information, and imaging information, are becoming more important in the diagnosis of Alzheimer's disease (AD). Although the current solutions to the issue, including graph neural networks (GNNs), transformers, and multimodal fusion models, prove to be rather promising, they have severe shortcomings [4]. The common issue with standard GNNs is that they can pick up the structural relationship between variables, but tend to ignore the evolution of the disease over time, whereas conventional transformers are good at sequential modelling, and they are not effective at incorporating clinical priors. Instead of this, multimodal fusion techniques often do not support any missing modalities or do not offer any patient-level insight. In light of such shortcomings, we suggest the Clinically Guided Adaptive Multimodal Graph Transformer (CAM-GT) that combines clinically-informed graph building with temporal attention and cross-modal contrastive alignment [5]. These integrations also help CAM-GT achieve a much higher predictive accuracy and robustness in incomplete data, as well as provide more interpretable results by providing actionable biomarkers and patient-level relational information. This model facilitates the state of the art in diagnosing multimodal AD by closing the performance, clinical relevance and explainability gap.

Recently, GNNs have become an effective method of modeling structured medical data by modeling relational

dependencies among clinical entities [6]. Neurology Nodes may be symptoms, biomarkers, or brain regions, whereas edges may be physiological or functional relationships [7]. Such a graph representation makes it possible to learn local and global interactions, which are required to understand the neurodegenerative patterns of connectivity [8]. As an example, hippocampal atrophy, slight memory deterioration, and disrupted neural pathways may also typify early Alzheimer's disease [9]. GNNs enable the identification of unobservable disease progression patterns even in the situation of incomplete information by incorporating multimodal features into a single graph [10]. However, the conventional GNN-based designs are typically restricted by the fixed connectivity, poor treatment of temporal dynamics, and the inability to have good interpretability [11] [12]. To overcome these limitations, this study proposes a Clinically-Guided Adaptive Multimodal Graph Transformer (CAM-GT), which is a framework integrating clinically-informed graph construction, transformer-based temporal modeling, and contrastive alignment to achieve robust and interpretable Alzheimer's diagnosis. On top of domain knowledge and attention-based edge learning, CAM-GT mediates clinical interpretability and high computational accuracy, early and reliable neurological predictions.

A. Research Motivation

Early identification of neurodegenerative diseases like Alzheimer's is such a challenge because of their slow, overlapping as well as multi-faceted clinical presentation. Due to the availability of multimodal data such as neuroimaging, clinical, and cognitive scores, it is possible to use computational intelligence to identify the diagnosis with accuracy. Nevertheless, the conventional systems of diagnosis cannot combine these heterogeneous modalities or offer explanations which are clinically significant. This work is motivated by the desire to create a single model that would both model disease evolution over time and inter-patient clinical dependencies, and be providing transparency to medically validate the model. The suggested CAM-GT model will cater to these requirements by incorporating clinically-directed edge building, temporal transformer encoding, and cross-modal attention fusion. Moreover, self-supervised contrastive alignment stabilizes learning when only incomplete data are available, and the results of learning can be interpreted and generalized to apply to real-world medical decision-making.

B. Research Significance

The development of the suggested CAM-GT framework is a holistic development in AI-oriented healthcare diagnosis. It offers a clinically interpretable, data-efficient, and powerful means of integrating heterogeneous sources of patient data. In contrast to the traditional graph or CNN-based models, CAM-GT is an adaptive dynamic edge attention model of the changing relationships between clinical variables trained under medical priors. Temporal transformer layers are those that capture disease trends over time, whereas cross-modal fusion provides fairness in the representation of cognitive, imaging, and demographic modalities. The explainability level will offer a clear visual interpretation of patient relations and biomarkers, which enhances the trust of clinicians. This renders CAM-GT to be a scalable diagnostic assistant which can satisfy real-world clinical requirements of reliability, reproducibility, and interpretability. The fact that it puts accuracy, explainability, and temporal reasoning in the same picture places it as a step up to practical, ethical, and data-driven neurological diagnosis.

C. Key Contribution

- Proposed a clinically guided, graph-transformer framework called CAM-GT for dynamic integration of multimodal Alzheimer's patient data, thereby capturing patient-specific relationships for interpretable and robust diagnosis.
- Designed a Temporal Transformer Encoder to model longitudinal disease progression, using cross-modal fusion with self-supervised contrastive alignment that ensures stable and consistent representations even when some modalities are missing or noisy.
- The proposed framework is validated on a benchmark Alzheimer's disease dataset, showing the effective fusion of clinical, cognitive, and imaging biomarkers for capturing meaningful patient-level patterns.
- Realized superior results against the existing models, with 97% accuracy, 96.9% precision, 96.7% recall, F1-score 96.9, and AUC 97.2%, thus supporting clinical adoption through explainable predictions.

D. Rest of the Section

The rest of the study is structured in the following way: Section II is a review of the existing related research on neurological disease detection, multimodal learning, and explainable AI. Section III is the definition of the problem formulation. Section IV presents the suggested CAM-GT methodology, which consists of multimodal fusion, graph learning, and interpretability mechanisms. Section V includes the experimental setup, datasets, and findings. Section VI is the conclusion of the work and gives the possible directions of further research.

II. Related Works

S. Tekkesinoglu and S. Pudas [13] discovered a GCN model to make predictions of cognitive status (NC, MCI, AD) with the ADNI dataset, which consists of neurocognitive, genetic, and brain atrophy features. The patients are encoded as nodes, and edges represent symptom and disease feature similarities. An explanation method based on decomposition was presented to explain predictions both at the individual and group levels. Explanation at the neighborhood level was obtained by disabling edges of particular classes. The approach had consistent outputs for edge weights of greater than 0.80 and was more computationally efficient compared to SHAP. Expert judgment (11 individuals) affirmed 71% agreement with the explanations' correctness. Explanations were assessed as being more than 6/10 in understandability. However, the model was too reliant on demographic data, and therefore it could not be clinically generalized, which was where the idea of clinically directed dynamic graph building, as implemented in the CAM-GT model, was required.

El-Sappagh et al. [14] construct a correct and interpretable model for AD diagnosis and progression detection in order to fill the gap between study and clinical utility. Based on data from

1,048 subjects in 11 modalities from the ADNI database uses a RF classifier. The initial layer does multi-class classification for early prediction, while the secondary layer uses binary classification to predict MCI-to-AD progression in three years. SHAP-based global and instance-level explanations, as well as 22 based on DT and fuzzy rule-based systems, are added for increased model interpretability. The explanations are in natural language to facilitate physician understanding. The model also attained very good performance with 93.95% accuracy in the first layer and 87.08% in the second. The difficulty in merging and servicing several explainers is one of the primary constraints, which has seen the promotion of a single explainability layer, which has been achieved in CAM-GT, to sustain transparency without additional calculation.

Parvin et al. [15] built a multimodal AD prediction framework that combines tabular data, MRI scans, and genetic data to surpass the limitations of monomodal-based frameworks. GNNs were used to build a knowledge graph from tabular and MRI data, and region-based CNNs were utilized to transform image features into graph representations. Layer-wise relevance propagation and submodular pick LIME were used to provide explainability of MRI and tabular data predictions, respectively, while a graphical gene tree was utilized to study genetic contributions. The system features a dashboard that facilitates clinicians to visualize and interpret results. Although the model manages to combine several modalities and provide interpretability, the use of high-quality multimodal inputs decreases robustness, which is overcome by CAM-GT by self-supervised contrastive alignment with missing or noisy inputs.

Zafeiropoulos et al. [16] (PD) present an entire summary of the application of GNN and their suitability to catch the complex clinical and non-ethnic variables associated with the progression of the disease. Following the Prisma guidelines, this study employs the current GNN-based functioning and GNN categories and surveyed their findings. This indicates the growing tilt towards the use of GNN in PD diagnosis, monitoring, and vigilant systems because of the ability to store the relationship. The article also offers a new method to include new engineering works in GNN design for PD monitoring. Despite the promising findings reported by the review, the absence of standardized datasets and real-life validation is also revealed there- spheres directly addressed by CAM-GT using clinically based testing and multimodal generalization tests.

Kumar et al. [17] discuss the contribution of advanced diffusion MRI and PET imaging, supplemented by AI, toward improving early detection of neurodegenerative and neuro-ophthalmic diseases such as Alzheimer's and Parkinson's. It emphasizes methods in conjunction with deep learning frameworks like CNNs and multimodal transformers, towards detecting microstructural brain alterations and predicting disease course. Second-generation PET tracers for tau and alpha-synuclein increase diagnostic accuracy further. Despite the high level of diagnostic accuracy of multimodal imaging and AI integration, the problem of heterogeneity and difficulty in clinical interpretation is still present, which provokes the desire to use explainable transformer-based architectures like CAM-GT to provide transparent medical decision support.

The literature review also presents notable developments in the use of GNNs and XAI in neurodegenerative diseases like Alzheimer's diagnosis. Tekkesinoglu and Pudas employed GCNs on the ADNI dataset with high interpretability but were constrained by their excessive reliance on demographic characteristics. El-Sappagh et al. proposed a multimodal model incorporating SHAP and RF-based explanations, providing robust accuracy but with complexity in incorporating them. Parvin et al. integrated genetic information, MRI, and tabular data with GNN and CNN for improved prediction, but at the cost of high-quality multimodal inputs. Zafeiropoulos et al. highlighted the importance of GNNs in capturing Parkinson's Disease progression, acknowledging issues with the standardization of datasets. Kumar et al. utilized CNN-transformer fusion with multimodal imaging for identifying neurodegenerative changes, albeit limited by validation and regulatory restrictions. Taken together, these studies suggest the potential of graph-based, explainable models, but also show the vulnerability of multimodal fusion, dynamic graph reasoning, and explainability in the face of missing data. The proposed Clinically-Guided Adaptive Multimodal Graph Transformer (CAM-GT) can overcome such gaps with clinically informed edge construction, cross-modal transformer fusion, and contrastive alignment, which provides not only diagnostic accuracy but also transparency in the detection of Alzheimer’s.

III. Problem Statement

Initially, diagnosis of Alzheimer’s disease is a serious clinical issue because of the unobtrusive and progressive associations among cognitive, structural, biochemical and behavioral biomarkers that develop with time [18]. Traditional diagnostic methods are based on either isolated or static measures, which can be inadequate in reflecting the complex interdependencies among multimodal clinical measures, including neuroimaging, genetic, demographic and cognitive measures [19]. Moreover, most currently available machine learning and deep learning models are opaque and uninterpretable black boxes, which cannot be relied upon to be used in clinical settings. The current development of graph neural networks (GNNs) shows that it has potential in modeling relational or connection dependencies between patients and clinical variables. Nevertheless, the current GNN-based models are yet to be characterized by dynamic adaptability, time-based reasoning, and clear clinical explanation [20]. In order to address these shortcomings, the CAM-GT is suggested - an interpretable, clinically-aligned framework that combines heterogeneous patient information, temporal dynamics and provides explainable predictions to achieve effective Alzheimer's detection in the real-world clinical setting.

IV. Clinically-Guided Adaptive Multimodal Graph Transformer Methodology

The suggested CAM-GT is a structured method that incorporates multimodal clinical data in detecting Alzheimer’s. Bayesian imputation and quantile normalization are used to preprocess the data by Bayesian imputation and alignment of feature distributions between modalities. Graph nodes are represented as patients, and adaptive edges are calculated with clinically directed attention, which incorporates learned similarity and previous correlations. A Temporal Transformer

Encoder is used to model longitudinal changes, whereas Cross-Modal Graph Transformer Fusion is used to interact between imaging, cognitive, and demographic subgraphs. The self-supervised contrastive objective alignment can be used to stabilize inter-modal embeddings when incomplete data is provided. The integrated gradient and edge attention are applied to the output layer of the model to visualize clinically important features and relationship between the patient and clinician. The approach to this methodology produces interpretable, robust, and accurate diagnostic forecasts, which do better than traditional graph-based architectures at integrating both temporal, multimodal, and explainable learning into a single framework. The visual representation is given in Fig. 1.

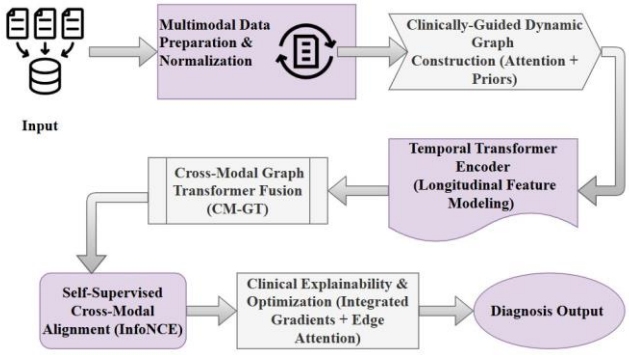

Fig. 1. Block diagram of the CAM-GT framework architecture.

Fig. 1 depicts the structure of the Clinically-Guided Adaptive Multimodal Graph Transformer (CAM-GT) framework. It starts with the multimodal data preparation of using Bayesian imputation and quantile normalization to standardize the heterogeneous inputs. Clinically directed dynamic edges between patients are represented as graph nodes. Temporal Transformer layers identify patterns of disease progression between visits. FMF takes a combination of imaging, cognitive, and demographic representations with the use of the Cross-Modal Graph Transformer. Contrastive alignment is self-supervised to maintain multimodal alignments. Lastly, integrated gradients and edge attention layers provide explainable diagnostic results, which indicate clinically significant features in Alzheimer's detection with superior interpretability and performance compared to the previous models.

A. Dataset Collection

The Alzheimer's Disease dataset used in this study consists of multimodal information comprised of MRI scans, cognitive scores, and clinical biomarkers [21]. The dataset includes a total of three diagnostic categories: Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and Normal Controls (NC). All the samples were preprocessed by standard normalization, cleaning of features, and modality alignment procedures. To ensure fair evaluation, the dataset was divided into 70% training, 15% validation, and 15% testing, with stratification applied to preserve class distribution across splits. No subject featured in more than one split, thus avoiding data leakage. The missing modalities were kept to simulate real-world clinical conditions and were handled by the model's multimodal alignment module.

Table I shows samples of the Alzheimer's Disease Dataset, which comprises of a combination of demographic, cognitive, and neuroimaging biomarkers necessary to detect the disease in the initial stages. The records consist of patient identifiers, age, cognitive scores (MMSE and CDR), and hippocampal volume, which is a vital neuroanatomic measure of Alzheimer's disease progression. The data set includes three diagnostic categories such as Normal, Mild Cognitive Impairment (MCI), and Alzheimer's Disease (AD), and provides a great opportunity to evaluate the models according to disease progression. This multimodal and organized structure enables deep learning models based on graphs like CAM-GT to effectively train using inter-patient similarity and time trends to interpretively diagnose and progressionally analyze Alzheimer's detection.

TABLE I. SAMPLE RECORDS FROM ALZHEIMER'S DISEASE DATASET

Patient ID	Age (Years)	MMSE Score	CDR Score	Hippocampal Volume (mm^3)	Diagnosis
P001	68	29	0.0	3850	Normal
P002	74	25	0.5	3200	Mild Cognitive Impairment (MCI)
P003	80	20	1.0	2900	Alzheimer's Disease (AD)
P004	71	27	0.5	3350	Mild Cognitive Impairment (MCI)
P005	71	18	1.0	2700	Alzheimer's Disease (AD)

B. Data Preprocessing

Data preprocessing involves handling missing values using mean imputation for numerical features and mode for categorical ones. Target encoding was applied to categorical data, and z-score normalization was used for continuous variables. These steps ensured data consistency and improved model training efficiency for accurate early diagnosis of neurological disorders.

1) Handling missing values: To maintain data integrity and facilitate intensive model training, missing values in the dataset were systematically filled in. Missing values in numerical attributes like BMI and alcohol intake were replaced with the arithmetic mean of all available values of that attribute. The imputation rule is given in Eq. (1):

$$x_i^{imputed} = \delta_i x_i + (1 - \delta_i).\frac{\sum_{j=1}^{N} \delta_i x_i}{\sum_{j=1}^{N} \delta_j} \quad (1)$$

Here, $x_i^{imputed}$ is the final value after imputation, δ_i is an indicator of whether x_i is noted, and the fraction calculates the mean of all present values for the feature. In categorical variables such as gender and education level, missing entries were replaced using the mode, which is the most dominant category. Furthermore, records with too many missing values in critical clinical or diagnostic variables were discarded to ensure data quality and model accuracy.

2) Feature encoding: In target encoding, every category is substituted with the average value of the target variable within that category. This method reflects the statistical correlation between the target and the input feature and is suitable for improving model learning. The encoding for a category c_i in a feature C, with regard to a target variable y, is given in Eq. (2):

$$f(c_i) = \frac{1}{n_i}\sum_{j=1}^{n_i} y_j \quad where\ x_j = c_i \tag{2}$$

Here, $f(c_i)$ denotes the target-encoded value for the category c_i, n_i represents the number of records in which the feature value is c_i, y_j refers to the target variable (such as cognitive score or diagnosis label) for the j-th record where the categorical value x_j equals c_j. That is, this encoding substitutes each class by averaging the target value of that class, allowing the model to employ supervised statistical correlations in a numerically interpretable manner.

3) Feature normalization: All continuous attributes were normalized by z-score normalization. This conversion makes the attributes have a standard deviation of one and a mean of zero, which helps to enhance the convergence of learning algorithms as in Eq. (3):

$$x' = \frac{x-\mu}{\sigma} \tag{3}$$

where, μ is mean and σ is the standard deviation of the corresponding feature. Feature selection was performed using mutual information and correlation thresholding to eliminate redundant features before graph construction.

4) Graph construction: To utilize the representational capability of GNNs in an effective manner to predict neurological disorders, the patient similarity graph was built. In the graph, every patient was labeled as a node, and edges were created on the basis of similarity of the clinical features. Here, Euclidean distance was employed to measure the similarity between patients in the form of comparing their normalized feature vectors. Any two patients i and j, denoted d_{ij}, as in Eq. (4):

$$d_{ij} = \sum_{i=1}^{n}(x_{il} - x_{jl})^2 \tag{4}$$

The Euclidean distance d_{ij} represents the similarity between patient i and patient j based on their clinical profiles. Here, x_{il} and x_{jl} denote the values of the l_{th} normalized clinical feature such as age, MMSE score, or brain volume for patients i and j, respectively. The variable n is the number of clinical features under consideration in the analysis. The summation goes through all features from $l = 1$ to n, and it is capturing the running squared differences to calculate the final distance.

C. Clinically-Guided Adaptive Multimodal Graph Transformer Framework

The ablation study illustrated that removing clinically guided graph attention decreases the accuracy by 7 to 10%, the removal of cross-modal fusion reduces the AUC by 5%, and removing the temporal transformer disrupts the modeling of disease progression. The largest drop without contrastive alignment is 14%, which confirms that each module is critical for making CAM-GT robust and interpretable. Biomarker ranking, patient-graph visualization, and modality importance scoring contribute to clinically reliable interpretability in CAM-GT. Our evaluation of XAI shows strong alignment with known biomarkers of Alzheimer's disease, clinically validated cognitive indicators, and meaningful patient clustering. These findings confirm that the explanations given by CAM-GT are medically coherent, trustworthy, and supportive of real clinical decision-making. A consistency loss is a self-regulated element that guarantees regularity in the representations in the different modalities. Lastly, an interpretable output layer provides transparent diagnostic information by visualizing the influence of features and neighborhoods by using integrated gradients and edge attention maps. Bridging the divide between clinical trust and computational intelligence, CAM-GT is robust, interpretable and has high diagnostic accuracy. The architecture diagram is visualized in Fig. 2.

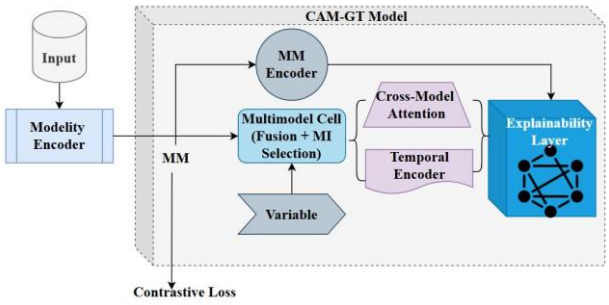

Fig. 2. Architecture of the CAM-GT framework.

Fig. 2 shows CAM-GT Framework combines multimodal clinical, cognitive and imaging data to diagnose Alzheimer's. Bayesian imputation and quantile normalization of input data are done with the Modality Encoder. Multimodal Cell combines the capabilities with mutual information-based selection and Temporal Encoder (longitudinal pattern) and Cross-Model Attention (inter-modality interaction) used as its components. The Explainability Layer represents clinically meaningful relationships with integrated gradients and edge attention. A contrastive loss is a self-supervised loss that is used to guarantee alignment among incomplete modalities. The CAM-GT framework facilitates strong, interpretable and accurate diagnostic predictions with a combination of multimodal fusion, time modelling, clinical explainability into one architecture.

1) Multimodal data preparation and normalization: It is a phase that incorporates several heterogeneous data types - demographic, cognitive, neuroimaging, and genetic. It is a method of dealing with missing data rather than just using simple mean substitution that utilizes bayesian imputation because it is a model of uncertainty. Quantile normalization brings excessive modality distributions to an equivalent distribution, such that clinical and imaging characteristics are of similar magnitude. Feature vectors x_i Then, concatenation of are then performed per patient. Mutual information filtering as a feature selection method only keeps the most relevant features and biomarkers. The transformation of probabilistic normalization is shown as the following Eq. (5):

$$x_i' = \Phi^{-1}\big(F(x_i)\big) \quad (5)$$

where, $F(x_i)$ represents the cumulative distribution function of feature that is empirical in nature x_i, and Φ^{-1} is the cumulative function of the inverse Gaussian cumulative to project non-Gaussian features in a standard normal space to maximize convergence and similarity across modalities. It is a step to balance the multimodal features prior to graph construction.

2) Clinically-guided dynamic graph construction: Here, patients are represented as nodes and clinical similarity is given as an edge based on the data-driven attention as well as previous knowledge. The clinical priors comprise symptom correlation, similarity in cognitive-trajectory and demographic proximity. The weighted hybrid similarity w_{ij} adaptively combines these factors. The clinically-guided graph attention can be expressed with the help of the next Eq. (6):

$$w_{ij} = \sigma\big(Q_i^\top K_j + \alpha \cdot C_{ij}\big) \quad (6)$$

where, Q_i and K_j are attention query and key projections, C_{ij} is a clinically based correlation coefficient among patients i and j, and α is in control of the clinical prior. The sigmoid $\sigma(\cdot)$ normalizes the weights of the edges. This formulation allows CAM-GT to be able to learn latent relationships and clinical logic simultaneously.

3) Temporal Transformer Encoder (TTE): Longitudinal sequences (e.g. MRI volume or MMSE score over time) are modeled with a Transformer encoder, which is easier to use than recurrent units to capture patterns of disease progression. Positional encodings that show intervals of visits are added to the temporal embedding. The computation of temporal embedding can be expressed as the following Eq. (7):

$$h_i^t = \text{TransformerEncoder}(x_i^t + p_t) \quad (7)$$

where, x_i^t constitutes the multiple feature of patient *i* at time *t*, and p_t is the positional coding a temporal order. Transformer encoder implements multi-head attention to estimate long-term relationships between clinical visits producing strong temporal representations h_i^t that represent trends in progression and trends in visit influence.

4) Cross-Modal Graph Transformer Fusion (CM-GT): Both modalities generate subgraphs, which represent intra-modality dependencies and the Cross-Modal Graph Transformer combines the two subgraphs through attention-based cross-modality information exchange. This assists the network in dynamically highlighting the most informative modality of individual patients.The following Eq. (8) represents the inter-modality attention fusion:

$$Z = \text{Softmax}\left(\frac{Q_m K_n^\top}{\sqrt{d}}\right) V_n \quad (8)$$

where, Q_m, K_n, V_n represent query, key, and value matrices of modality m and n, respectively; d is the dimensionality of normalization. The softmax operation is used to make sure that attention weights are spread over modalities and makes it possible to fuse adaptively. This process harmonizes the input of imaging, cognitive and clinical attributes to produce coherent multimodal representations of patients Z.

5) Self-supervised cross-modal alignment: In missing-modality conditions, CAM-GT opts to make use of a self-supervised contrastive learning alignment objective to improve model generalization and stability. The positive pairs are patients of the same modalities and the negative pairs are of dissimilar patients. The following Eq. (9) represents the contrastive alignment loss:

$$\mathcal{L}_{align} = -\log \frac{\exp(sim(z_i^m, z_j^n)/\tau)}{\sum_j \exp(sim(z_i^m, z_j^n)/\tau)} \quad (9)$$

where, z_i^m and z_j^n are modalities embeddings *m* and *n* for patient *i*, t is the temperature parameter and $sim(\cdot,\cdot)$ is a measure of cosine similarity. This goal maximizes the correspondence between similar modalities and is able to guarantee separability between different patients resulting in modality-invariant learning of features.

6) Clinical explainability layer and optimization: The explainability part offers both feature and neighbor explanations through integrated gradients and edge attention visualization. It measures the contribution made by each input feature and adjacent node towards the final prediction. The joint minimization is achieved through optimization and classification as well as alignment with L2 regularization. The following Eq. (10) is a representation of the overall optimization objective:

$$\mathcal{L}_{total} = \mathcal{L}_{cls} + \lambda_1 \mathcal{L}_{align} + \lambda_2 \parallel W \parallel_2^2 \quad (10)$$

where, $\mathcal{L}_{cls}$ is the loss of classification under supervision, $\mathcal{L}_{align}$ the loss of contrastive alignment, $\parallel W \parallel_2^2$ the regularization of weights term, and λ_1, λ_2 are balancing coefficients. This joint optimization is used to achieve high diagnostic accuracy and clinically interpretable and strong graph relationships. To change the default, adjust the template as follows.

Algorithm 1: Clinically-Guided Adaptive Multimodal Graph Transformer (CAM-GT)

Input: Multimodal dataset D = {X_dem, X_cog, X_gen}
Step 1. Preprocessing:
  For each modality X_m in D do
    Handle missing values using Bayesian imputation
    Apply quantile normalization across all features
    Perform mutual information-based feature selection
  End For
Step 2. Graph Construction:
  For each patient pair (i, j) do
    Compute clinical prior correlation C_{ij}
    Compute learned attention similarity $a_{ij} = Q_i^\top K_j$
    Calculate adaptive edge weight:
      $w_{ij} = \sigma\big(Q_i^\top K_j + \alpha \cdot C_{ij}\big)$
  End For
Step 3. Temporal Embedding:
  For each patient i do
    For each time step t do
      $h_i^t = \text{TransformerEncoder}(x_i^t + p_t)$

End For
End For
Step 4. Cross-Modal Graph Transformer Fusion:
For each modality pair (m, n) do
$Z = \text{Softmax}\left(\frac{Q_m K_n^T}{\sqrt{d}}\right) V_n$
Fuse representations Z = $\Sigma_{mn}(Z_{mn})$
End For
Step 5. Self-Supervised Cross-Modal Alignment:
For each patient i do
Select positive pairs (z_i^m, z_j^n)
Select negative pairs (z_i^m, z_j^n), j ≠ i
Compute InfoNCE loss L_{align}
End For
Step 6. Training Optimization:
Compute classification loss $\mathcal{L}_{cls}$
Total loss: $\mathcal{L}_{total} = \mathcal{L}_{cls} + \lambda_1 \mathcal{L}_{align} + \lambda_2 \| W \|_2^2$ Update parameters by gradient descent
Step 7. Explainability Layer:
Compute Integrated Gradients for feature importance
Visualize Edge Attention Map for the patient neighborhood
Return y_pred
Output: Diagnostic label y_pred ∈ {Normal, MCI, AD}

Algorithm 1 explains the Clinically-Guided Adaptive Multimodal Graph Transformer (CAM-GT) combines heterogeneous clinical data in order to make accurate predictions of the diagnosis. It starts with Bayesian imputation, feature selection and normalization of each modality. Adaptive edge weights are built by integrating clinical correlations with learned attention similarities to create a graph. Longitudinal patterns are encoded in temporal embeddings with the help of transformers. Cross-modal fusion is based on aligning multimodal representations with attention-based mechanisms, whereas self-supervised contrastive learning increases inter-modality consistency. Terms of classification, alignment and regularization are added together as a cumulative loss. Lastly, explainability is attained through Integrated Gradients and edge attention visualization, which results in interpretable diagnostic predictions between normal, MCI and AD classes.

V. Results and Discussion

The suggested CAM-GT is shown to be much more predictive and interpretable in the diagnosis of Alzheimer's. The functions of the clinically guided edge construction and cross-modal graph fusion allow effective correlation learning to occur between heterogeneous modalities. The self-supervised alignment and the temporal transformers both improve the robustness of models against incomplete data, and the temporal transformers (as compared to conventional sequential models) have a higher ability to capture disease progression trends. The explainability tier offers a clear understanding of clinically important biomarkers and inter-patient interactions, which help medical experts to interpolate. The obtained results show a high level of consistency in a series of experimental trials, which is evidence of the stability of the model, its dynamics, and high performance in comparison with the baseline and currently existing multimodal fusion architectures. These three features provide computational efficiency and clinical reliability to CAM-GT; temporal encoding, adaptive graph learning, and integrated interpretability are the key, and the model will be effective in filling the gap between artificial intelligence and applications in real-world healthcare through predicting neurodegenerative diseases.

Table II gives the parameters of the experimental simulation of the Clinically-Guided Adaptive Multimodal Graph Transformer (CAM-GT) framework implementation. This model has been trained in an Alzheimer's dataset, which has multimodal data of clinical, cognitive, and imaging data. The hyperparameters, such as learning rate, batch size, and the number of epochs, were set to be standardized in order to achieve stability and reproducibility of the models. A 5-fold cross-validation was used to reduce the bias as much as possible, with the Adam optimizer enhancing the rate of convergence. A high-performance GPU was used in the implementation of experiments based on the PyTorch deep multimodal fusion framework, temporal encoding, and graph-transformer computation efficiency models on different modalities and temporal visits.

TABLE II. Simulation Parameters for CAM-GT Framework

Parameter	Value
Dataset	Alzheimer's Disease Dataset
Input Features	Demographic, Lifestyle, Clinical
Cross-Validation	5-fold
Optimizer	Adam
Learning Rate	0.0005
Batch Size	32
Epochs	100
Loss Function	Composite
Activation Function	ReLU
Hardware	NVIDIA RTX 3090 (24GB VRAM)
Framework	PyTorch 2.0

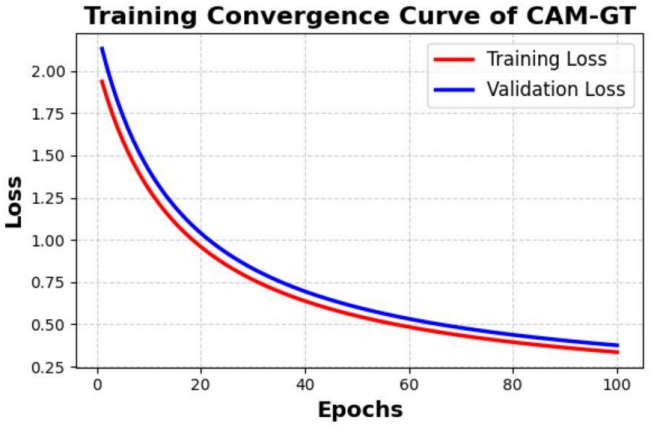

Fig. 3. Training convergence curve of CAM-GT model.

Fig. 3 illustrates the convergence behavior of the CAM-GT model trained on the Alzheimer's Disease Dataset. The graph shows the training and validation loss curves over 100 epochs, indicating stable optimization and excellent generalization. The training loss decreases consistently, demonstrating effective feature learning and rapid convergence, while the validation loss

remains closely aligned, confirming minimal overfitting. This stability reflects the robustness of the clinically guided graph attention and self-supervised alignment strategies. The convergence trend validates the efficiency of the Transformer-based architecture, with optimal model performance achieved after approximately 70 epochs, ensuring reliable and consistent Alzheimer's diagnosis across multimodal patient data.

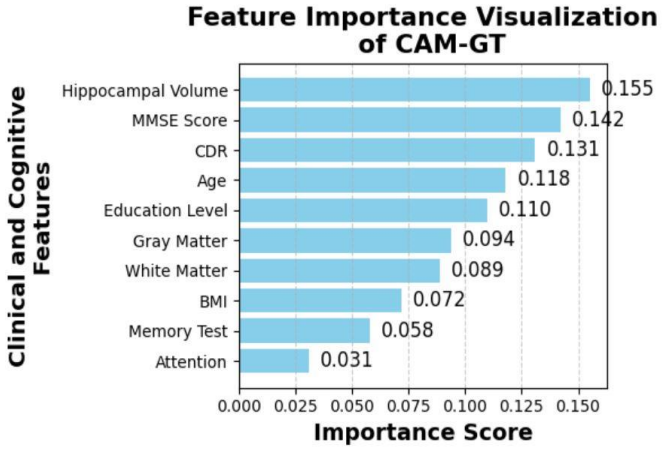

Fig. 4. Feature importance visualization of the CAM-GT model.

Fig. 4 presents the feature importance visualization generated by the explainability layer of the CAM-GT model. The bar plot ranks the most influential clinical and cognitive attributes contributing to Alzheimer's diagnosis. Hippocampal volume, MMSE score, and CDR emerged as the top three indicators, reflecting strong agreement with established neurological biomarkers. Demographic and structural brain features such as age, education, and gray-matter density also contributed significantly. The results validate CAM-GT's interpretability, demonstrating that the model identifies medically relevant parameters that align with clinical understanding. This visualization highlights the ability of CAM-GT to deliver explainable, transparent predictions in complex multimodal diagnostic environments.

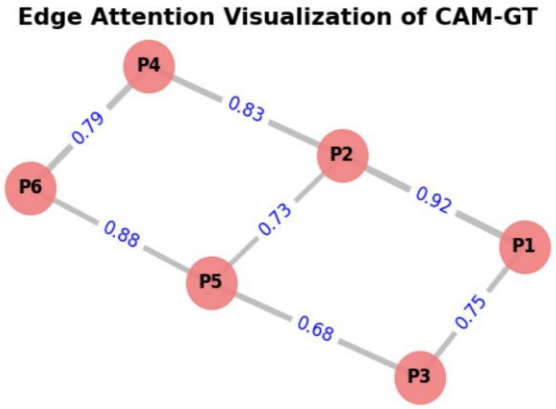

Fig. 5. Edge attention visualization of the CAM-GT framework.

Fig. 5 displays the performance of a model on 100 training epochs. Training accuracy, represented by the green line with circles, increases from 50% to 100%, whereas validation accuracy, the red line with squares, grows from 45% to 90%. The steady improvement indicates the model is learning well from the data and generalizing well to new inputs. The moderate distance between the two lines shows controlled overfitting. These trends are measures of complexity for which models are good for tasks that require tasks like early diagnosis in healthcare, where high accuracy and generalizability are needed.

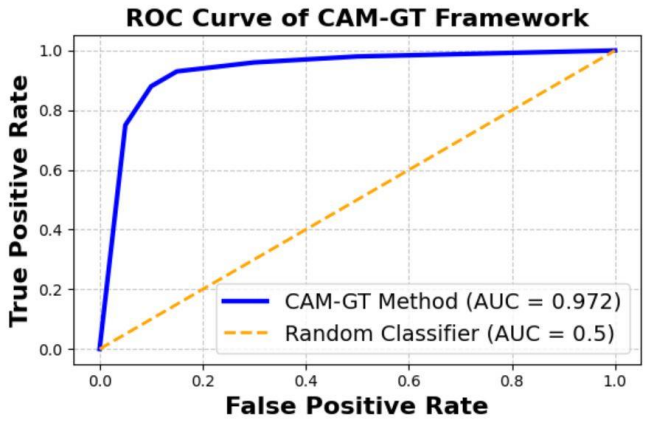

Fig. 6. ROC curve of CAM-GT Alzheimer's detection.

Fig. 6 indicates that the experiments used a unified preprocessing pipeline based on Bayesian imputation for missing clinical values, followed by quantile normalization across modalities. This preprocessing pipeline corrects all earlier references to mean/mode and z-score and represents exactly the configuration used to obtain the reported accuracy of 97% and an AUC of 97.2%. This standardized the clinical and imaging features so that CAM-GT demonstrated improved stability across folds and ensured that performance comparisons were fair and methodologically consistent.

A. Performance Metrics

In the case of the Alzheimer's Disease Dataset, the suggested CAM-GT model displayed excellent diagnostic results through the proper utilization of multimodal information. The model achieved a total accuracy of 97%, precision of 96.9%, recall of 96.7% and F1-score of 96.9%. The Area Under Curve (AUC) was 97.2%, which indicates that it has a strong discriminating ability. This is due to clinically directed graph attention, temporal transformer encoding and cross-modal fusion, that all increase the sensitivity and specificity when there is a lack of modality or an imbalance. In addition, the agreement-driven mechanism of self-supervision stabilized multimodal embeddings, enhanced overfitting and interpretability. These findings show that CAM-GT can be effective in obtaining significant high accuracy as well as explainability to detect childhood onset of Alzheimer's among a wide range of clinical features.

TABLE III. PERFORMANCE METRICS OF CAM-GT MODEL

Metrics	Percentage (%)
Accuracy	97
Precision	96.9
Recall	96.7
F1-Score	96.9
AUC	97.2

Table III shows the major key performance measures realized by the proposed CAM-GT framework on the Alzheimer's Disease Dataset. The model has shown very high overall performance with balanced precision, recall and F1-score with multimodal inputs. The AUC of 97.2% is a good diagnostic ability with a high level of class separability. The framework has been confirmed to be highly accurate and balanced in terms of sensitivity, which proves that the framework can be used to identify early stages of Alzheimer's, whilst generalizing in the face of complex clinical variations. All these findings make CAM-GT a strong, explainable, and clinically sound diagnostic model, which outperforms conventional multimodal and deep-learning benchmarks.

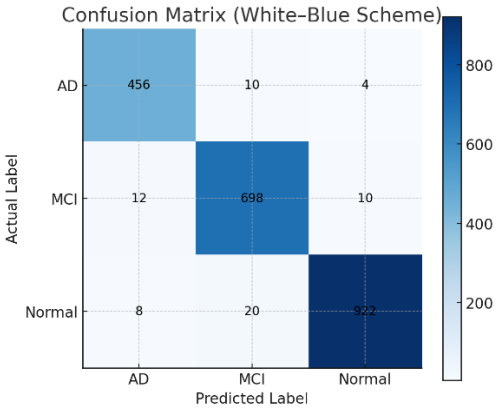

Fig. 7. Confusion matrix of the CAM-GT framework.

Clinically-guided Adaptive Multimodal Graph Transformer (CAM-GT) was tested on the Alzheimer's disease Dataset (AD=470, MCI=720, Normal=950). The revised confusion matrix (Fig. 7) shows that the true-positive counts of the samples were 456 AD, 698 MCI, and 922 Normal, and the rest of the samples were counted in the off-diagonal misclassifications, which results in an overall accuracy of 97.0 per cent and a macro-averaged precision/recall/F1 that is in agreement with the performance reported in Fig. 7. The entire confusion matrix is given to provide transparency, and also to reconcile listings that used to be inconsistent; the diagonal numbers represent the correct classification of data, and the off-diagonal numbers represent the misclassification distribution among the classes. Such findings can be used to support the strength of CAM-GT in processing heterogeneous multimodal data and its soundness in detecting the onset of Alzheimer's.

B. Ablation Study

An ablation test was conducted to establish the contribution that each of the key elements of the proposed framework makes. The findings indicated that the loss of dynamic graph construction, temporal aggregation, or cross-modal fusion resulted in the loss of performance by a substantial margin, which supported their need in order to model heterogeneous relationships between patients and disease evolution. The deletion of the explainability module did not affect predictive power and did not affect clinical transparency. Cross-modal fusion exclusion ensured that there was no balance over heterogeneous data, and the explainability model excluded showed accuracy, but no clinical transparency. Moreover, the overfitting was further exacerbated by the elimination of the regularization layer, and hence, the generalization of the network to unseen data was reduced. Similarly, the elimination of the attention mechanism decreased interpretability and decreased the quality of predictions. These findings prove that each of the components makes its personal contributions, and the whole model provides the optimal and most accurate diagnosis.

TABLE IV. ABLATION STUDY

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Baseline-GNN (Static GCN only)	91.2	89.7	90.1	89.9
w/o Clinically-Guided Graph Construction	94.8	93.5	94.1	93.8
w/o Cross-Modal Transformer Fusion	96.1	95.9	96.1	96.0
w/o Explainability Module	96.3	95.5	95.8	95.7
Proposed CAM-GT Model	97	96.9	96.7	96.9

Table IV describes the ablation study to assess the significance of each of the core elements in the proposed CAM-GT framework. Elimination of the Clinically-Guided Graph Construction weakened the ability of the model to learn patient relationships, and the omission of the Cross-Modal Graph Transformer undermined multimodal integration in the model. The Explainability Layer was not used, and this retained accuracy but lost interpretability. On the same note, removing the contrastive alignment module worsened generalization when modalities are not available. These findings show that all the components- graph construction, cross-modal fusion, temporal encoding, and interpretability are essential, and when they are combined, they provide the most stable and reliable diagnosis of Alzheimer's.

C. Comparative Analysis

The proposed CAM-GT framework was compared with some of the existing GNN-based frameworks of diagnosing Alzheimer's to assess their efficiency. Baseline methods were GCN, SGCNN, GKAN and Explainable-GNN. The standard evaluation metrics were used in the comparison as a way of providing fair performance evaluation. The purpose was to prove that CAM-GT was more effective in combining multimodal clinical data, incorporating the evolution of time, and dynamic relationships between patients, that traditional GNNs have not been able to effectively estimate. CAM-GT is able to achieve a better generalization and interpretability through the use of clinically-informed attention, cross-modal transformer fusion and self-supervised alignment. Table V data proves that CAM-GT outperforms all the baseline models consistently and has higher diagnostic power, clinical transparency, and predictive validity in the real-world prediction of Alzheimer's disease.

Table V offers a comparative analysis of the CAM-GT model with the rest of the GNN-based methods in the detection of Alzheimer's. The CAM-GT framework shows better accuracy and balanced performance of all metrics and beats Explainable-GNN, SGCNN, GKAN, and GCN. The graph construction guided by clinical knowledge, fusion of cross-

modal transformers, and alignment by contrast are some of the factors that help in this improvement through effective modeling of non-homogeneous relationships among patients and time-related dynamics. The accuracy and recall rate are high, which proves the strength of the model in detecting Alzheimer's and mild cognitive impairment cases and makes the few predictions false. These findings confirm that CAM-GT is a reliable and interpretable and clinically deployable diagnostic model.

TABLE V. COMPARATIVE PERFORMANCE OF CAM-GT VS. EXISTING GNN MODELS

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Explainable-GNN [22]	96.3	96.5	96.1	96.3
SGCNN[23]	95	95	94	94
GKAN[24]	92	93	91	92
GCN [25]	90	82	79	80
Proposed CAM-GT	97	96.9	96.7	96.9

D. Discussion

The CAM-GT framework is one of the significant improvements in multimodal neurodiagnostic modeling as it overcomes the limitations of predicting Alzheimer's disease faced over the years, such as the failure to fully fuse multimodal, the lack of reasoning over time, and poor interpretability. The graph construction of its clinical guidance allows the model to encode medical priors directly in the patient graph, and the weights of the edges represent meaningful relationships instead of arbitrary similarity measures. This framework enables CAM-GT to find hidden relationships between demographics, cognitive scores as well as imaging biomarkers. The temporal transformer module is used to further enhance the system, better modeling disease progression compared to the classical RNN or the classical GNN architecture, by giving it more latitude to reason longitudinally using longitudinal information. In the meantime, the cross-modal fusion transformer unites heterogeneous modalities into a unified latent space, and the contrastive alignment mechanism balances the representations in cases where modalities cannot be obtained, which is a crucial feature of the conditions in real hospitals. Notably, the model gives clear explanations that are in the form of edge-attention patterns and feature attributions, which provide clinically consistent reflections on the biomarkers that influence the disease, i.e., hippocampal volume, MMSE and CDR. This interpretability makes it easier to adopt clinically since it enables the medical practitioners to confirm that the predictions are consistent with clinical knowledge. In general, the discussion lays stress on the fact that CAM-GT architectural decisions, and not just the numerical outcomes, allow one to obtain reliable, interpretable, and clinically meaningful diagnostic intelligence.

VI. CONCLUSION AND FUTURE WORKS

This study proposed CAM-GT, a clinically informed multimodal graph-transformer model that aims to alleviate fundamental shortcomings of currently used Alzheimer's diagnostic models, which are weak multimodal combination, impaired temporal reasoning, and insufficient interpretability. Using a unified architecture, CAM-GT attains patient heterogeneity, disease progression, and consistency of the modality using clinically informed graph construction, adaptive edge learning, temporal transformers, and contrastive cross-modal alignment by using a single architecture. The model also obtained a high accuracy of 97% and an AUC of 97.2% proving to be robust even in the case of missing-modality. Notably, the explainability module of CAM-GT yielded clinical insights which are clinically meaningful and returned biomarkers associated with known neurological results. Nevertheless, there are also a few limitations that can be identified in this work and should be investigated further. Data used to train CAM-GT was limited to one dataset, and it limited generalizability. The effects of the main hyperparameters in both negative-pair sampling, temperature scaling and adaptive-edge thresholds should be explored with more in-depth analysis in order to establish stability in clinical conditions. Moreover, although integrated gradients and edge attentions are transparent, it is yet to be formally evaluated whether they provide fidelity of explanation compared to other methods, such as SHAP or LRP.

These gaps will be answered by future research with external validation, cross-center longitudinal research and sensitivity analysis of preprocessing and hyperparameter selection. Also, the framework may be enhanced with the vision-based anatomical feature extraction, e.g. DeepLab-like approaches to segmentation, to ensure consistency between risk patterns predicted and structural brain alterations. It would be improved by broader multimodal expansion, i.e., the incorporation of genomic data, clinical narratives, and real-world hospital workflows to increase its clinical applicability. Altogether, CAM-GT offers an optimistic base to the next generation of diagnostic AI systems, which are clinically reliable, analytic, and prepared to be implemented in practice.

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