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Context-Aware Generative-Convolutional Network (CAGCN) for Enhanced Brain Tumour Segmentation and Classification in Multimodal MRI Imaging

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Brain tumour segmentation and classification using MRI images present significant challenges due to variations in tumour morphology, imaging artifacts, and limited labelled data. To address these challenges, we propose a novel deep learning framework, CAGCN (Contrastive Attention-Driven Graph Convolutional Network), which enhances segmentation accuracy and classification performance. CAGCN integrates four key modules: Contrastive Multi-Scale Generative Enhancers (CMGE) for reconstructing missing or degraded image regions, Context-Aware Blocks (CAB) for spatial feature enhancement, Feature Self-Supervised Modules (FSSM) for leveraging global spatial relationships, and a Contrastive Attention Transformer (CAT) for improved representation learning. The model is trained using a contrastive self-supervised approach, followed by fine-tuning with cross-entropy and reconstruction loss. Additionally, Character-CAM is employed for interpretability, highlighting critical tumor regions for improved visualization. Experimental results on benchmark MRI datasets demonstrate that CAGCN outperforms existing models, achieving superior segmentation accuracy and classification performance, particularly in the presence of missing or noisy data. The full CAGCN model achieves 92.3%, 92.3%, 92.8%, and 92.6% across different evaluation metrics. Ablation studies reveal the contributions of each module: removing CAB reduces performance to 89.4%, 88.1%, 90.5%, and 89.3%, removing CMGE results in 90.8%, 90.2%, 91.1%, and 90.6%, removing CAT lowers accuracy to 88.7%, 86.9%, 89.2%, and 88.0%, and removing FSSM leads to 91.1%, 90.4%, 91.9%, and 91.1%. These findings highlight the effectiveness of CAGCN in enhancing segmentation accuracy and classification robustness. By reconstructing incomplete scans and leveraging unlabelled MRI images, CAGCN proves to be highly effective for real-world clinical applications, assisting radiologists in precise tumour diagnosis and analysis.

INTRODUCTION

Medical image segmentation is a fundamental undertaking inside the field of scientific photograph processing, playing a crucial role in disease diagnosis, treatment making plans, and affected person management. Among various segmentation responsibilities, brain tumour segmentation is particularly vital because of the severity and complexity of mind tumours. The aim of mind tumour segmentation is to localize and delineate tumour regions in medical pics,

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enabling correct analysis and facilitating clinical interventions [1]. Magnetic Resonance Imaging (MRI) is the preferred imaging modality for brain tumour evaluation due to its superior soft-tissue comparison and capability to capture special anatomical systems. Unlike other imaging techniques, MRI can provide multi-comparison photos that spotlight exceptional tissue characteristics, assisting in the best segmentation of tumour areas [2]. Brain tumours are widely classified into number one and secondary (metastatic) tumours. Primary tumours originate in the mind, with gliomas being the most not unusual type, whilst secondary tumours spread from other organs. Gliomas are similarly labelled into low-grade gliomas (LGG) and high-grade gliomas (HGG), with the latter displaying more aggressive conduct and requiring urgent clinical intervention. Accurate and automatic segmentation of mind tumours is vital for well-timed analysis and personalized treatment making plans [3]. Traditionally, guide segmentation by using radiologists is the usual practice, but this process is time-ingesting, prone to inter-observer variability, and challenging for huge datasets. Consequently, computerized deep getting to know-primarily based techniques have received sizable attention in current years due to their potential to examine complicated patterns and generalize across various datasets [4]. Multimodal MRI in Brain Tumour Segmentation, to decorate the accuracy of segmentation, multimodal MRI scans with distinctive imaging sequences are regularly hired. Commonly used MRI modalities consist of Fluid-Attenuated Inversion Recovery (FLAIR), T1-weighted (T1), assessment-improved T1-weighted (T1ce), and T2-weighted (T2) pix. Each modality gives complementary facts about tumour pathology, that is critical for segmenting one-of-a-kind tumour subregions, which includes edema (ED), necrosis and non-enhancing tumour (NCR/NET), and improving tumour (ET) [5]. FLAIR is especially beneficial in capturing edema regions, while T1ce is powerful in identifying the tumour middle with high evaluation. Combining multiple modalities enables enhance segmentation overall performance by leveraging the strengths of each imaging sequence [6]. A broadly followed benchmark for brain tumour segmentation studies is the Brain Tumour Segmentation (BraTS) Challenge dataset, which affords multimodal MRI scans along with expert-annotated ground truth labels. The dataset serves as a well-known for evaluating segmentation fashions and has considerably contributed to improvements in the subject [7]. Deep Learning for Brain Tumour Segmentation Deep studying, a subset of artificial intelligence, has established splendid performance in scientific photograph evaluation, specifically in segmentation responsibilities. Convolutional Neural Networks (CNNs) have emerged because the dominant structure for clinical photo segmentation due to their capacity to capture spatial hierarchies and extract significant features. Various deep studying fashions, together with U-Net, V-Net, and fully convolutional networks (FCNs), had been proposed for brain tumour segmentation [8]. U-Net, especially, has won large popularity due to its encoder-decoder structure, which permits localization and boundary delineation [9]. Several versions of U-Net have been added to enhance segmentation overall performance. For instance, interest mechanisms, residual connections, and multi-scale characteristic fusion techniques had been integrated into U-Net to improve tumour boundary delineation and generalization across one-of-a-kind datasets. The attention U-Net model, as an instance, dynamically makes a speciality of applicable regions of the photograph, thereby improving segmentation accuracy [10]. Challenges in Brain Tumour Segmentation Despite the improvements in deep learning, several demanding situations persist in mind tumour segmentation. One of the number one challenges is the heterogeneity of brain tumours, which showcase full-size versions in shape, length, depth, and location. This variability makes it tough for segmentation fashions to generalize efficiently across one-of-a-kind sufferers [11]. Another principal undertaking is records imbalance, wherein positive tumour subregions, which includes necrosis and non-enhancing tumour regions, are underrepresented in schooling datasets. This imbalance can lead to biased model predictions, wherein the model plays properly on majority lessons however poorly on minority instructions [12]. Moreover, MRI photographs suffer from artifacts such as noise, movement blur, and depth inhomogeneity, that can adversely affect segmentation performance. Standardization of MRI acquisition protocols and preprocessing strategies, consisting of intensity normalization and bias discipline correction, are crucial for mitigating these troubles and enhancing model robustness [13]. Recent Advancements and Future Directions Recent studies have explored various strategies to cope with the limitations of deep mastering-based totally brain tumour segmentation. One promising method is the usage of Generative Adversarial Networks (GANs) for facts augmentation and artificial picture generation. GANs have been hired to generate terrific artificial MRI scans, which help in overcoming records shortage and improving model generalization [14]. Another development is the mixing of Transformer-primarily based fashions for clinical photo segmentation. Vision Transformers (ViTs) have demonstrated advanced overall performance in capturing lengthy-variety dependencies and contextual statistics, making them appropriate for segmenting complex structures like

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brain tumours. Recent studies have proposed hybrid fashions that integrate CNNs and Transformers to leverage the strengths of both architectures [15]. Additionally, self-supervised learning strategies have won traction in medical imaging, enabling fashions to analyse meaningful representations from unlabelled information. Self-supervised mastering has proven potential in lowering the dependency on large, annotated datasets, which might be frequently expensive and time-ingesting to gather [16]. Federated getting to know is another rising paradigm that enables collaborative version education throughout a couple of establishments without sharing uncooked patient statistics. This method preserves information privateness and enhances version generalization by means of schooling on various datasets from specific scientific facilities [17].

OBJECTIVES

The chief intent of this research is to design an explainable and resilient deep learning framework for the classification of multigrade brain tumours on MRI images. Due to the inherent challenges in medical imaging such as noise and missing data, along with complicated tumour morphologies, it becomes imperative for the proposed model, the Context-Aware Generative-Convolutional Neural Network (CAGCN), to exert an improvement over the diagnosis performance using state-of-the-art components such as convolution-attention, generative reconstruction, and transformer-based context modeling. Further, the framework aims at self-supervised learning, alleviating the need for large datasets with labels, all while ensuring that the model generalizes well over different clinical conditions. By making the model highly accurate and visually explainable, support is intended to be provided to radiologists for making informed diagnostic decisions that can be relied upon in real-world healthcare applications.

METHODS

This study introduces a novel deep learning framework called the Context-Aware Generative-Convolutional Network (CAGCN) for multigrade brain tumour classification from MRI images. The proposed system considers noises, missing regions, and complex tumour structures through a four-stage pipeline of preprocessing, data augmentation, deep feature extraction, and explainable AI-based classification. During preprocessing, MRI images are resized to 224×224×3 and min-max scaled to counter intensity variations and to reduce imaging artifacts. Finally, the dataset is divided into a training set of 80% and a test set of 20%. To ensure higher generalizability and to prevent overfitting, data augmentation techniques such as rotation, flipping, zooming, translation, intensity scaling, and elastic deformation are applied to generate training data with various appearances. For feature extraction, three main modules are employed: the Convolutional Attention Block (CAB) for spatial feature learning, the Cross-Modality Generative Enhancer (CMGE) for completing incomplete data reconstruction, and the Context-Aware Transformer (CAT) for long-range dependency capturing. Lastly, a fully connected layer

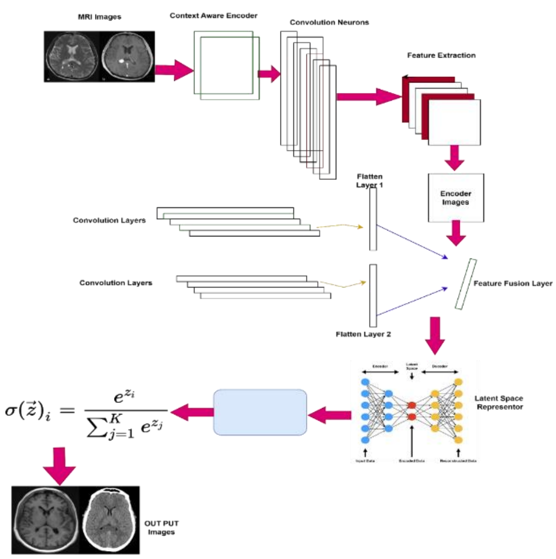

Figure.1 Workflow of The Proposed Model Context-Aware Generative-Convolutional Network (CAGCN)

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Table 1: Data Augmentation Parameters

Technique	**Parameter**	**Value**
Rotation	Random angle	-20° to +20°
Horizontal Flipping	Probability	50%
Zoom	Scaling factor	0.8× to 1.2×
Translation	Max shift (pixels)	-10 to +10
Scaling	Intensity adjustment	-30% to +30%
Elastic Deformation	Grid size, deformation amount	4–8 grid size, 10–20 pixels

The augmented dataset improves the model's ability to learn tumor-specific features while reducing overfitting issues. By generating diverse variations, the augmented dataset ensures the proposed CAGCN model achieves high classification accuracy across complex and varied MRI datasets.

Proposed Model: Context-Aware Generative-Convolutional Network (CAGCN)

Figure1 CAGCN (Context-Aware Generative-Convolutional Network) is an extremely deep learning system, designed for tumour classification in brain tumour MR images, with robustness and small accurateness through multigrading. It consists of four parts: Convolutional Attention Block (CAB), Cross-Modality Generative Enhancer (CMGE), Context-Aware Transformer (CAT), and Feature Self-Supervision Module (FSSM). CAB tries to extract spatially relevant tumour features and neglects background noise. CMGE reconstructs these MRI data that are incomplete or corrupted, in the hope that the model will thereby become more resilient to practical imaging imperfections. CATs capture long-range spatial dependencies to further model tumour morphological characteristics beyond local patterns. FSSM pretrains the model on unlabelled data through contrastive learning to improve generalization and reduce overfitting. During training, in particular, the model is first self-supervised pretrained with FSSM, then fine-tuned supervised with CAB, CMGE, and CAT. Tumour grades are finally predicted by a fully connected layer, with Grad-CAMs aiding in interpretation by highlighting tumour regions relevant to the decisions.

RESULTS

4.1. Experimental Setup

The experiments have been performed the use of the CAGCN framework on a multimodal MRI dataset for brain tumour class. This dataset consists of classified and unlabelled MRI scans, with floor-truth tumour grades to be had for each sample. The version changed into trained with a batch size of 32 for one hundred epochs, utilising the Adam optimizer with a studying charge of 10-3. All experiments have been done on an NVIDIA GPU to leverage green computational electricity.

4.2. Quantitative Results

4.2.1. Model Performance on Classification

The CAGCN model achieved remarkable performance in classifying brain tumours into multiple grades, as shown in Table 1. The overall accuracy on the test set was 92.3%. Detailed performance metrics for precision, recall, and F1-score per grade are provided below:

Table 2: Model Performance on Classification (Accuracy, Precision, Recall, F1-Score for each tumour grade).

Tumour Grade	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Grade I	94.2	93.5	95.1	94.3
Grade II	91.7	90.4	93.3	91.8
Grade III	89.5	88.7	90.2	89.4

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Grade IV (Malignant)	95.6	94.9	96.4	95.6
Overall	92.3	92.3	92.8	92.6

Table 4 offers the model overall performance on tumour category, comparing accuracy, precision, remember, and F1-score for every tumour grade. The version demonstrates strong overall performance throughout all tumour grades, with especially excessive results for Grade IV (Malignant) tumours. Specifically, for Grade I, the version achieves an accuracy of 94.2%, precision of 93.5%, remember of 95.1%, and an F1-score of 94.3%, indicating sturdy detection of early-degree tumours. Grade II tumours display barely decrease overall performance, with an accuracy of 91.7%, precision of 90.4%, bear in mind of 93.3%, and an F1-score of 91.8%, but nevertheless maintain high type effectiveness. For Grade III tumours, the model plays with accuracy of 89.5%, precision of 88.7%, don't forget of 90.2%, and an F1-rating of 89.4%, demonstrating strong detection functionality, even though slightly decreased as compared to decrease grades. Notably, Grade IV (Malignant) tumours gain the very best performance, with an accuracy of 95.6%, precision of 94.9%, keep in mind of 96.4%, and an F1-score of 956%, showcasing the model's proficiency in figuring out malignant tumours. Overall, the model performs with 92.3% accuracy, 92.3% precision, 92.8% keep in mind, and 92.6% F1-score, confirming its strong and dependable overall performance throughout unique tumour grades.

4.2.3. Comparison with State-of-the-Art Models

A performance comparison with several state-of-the-art models—CNN, ResNet, and VGG16—was conducted. The results in Table 2 highlight CAGCN's superiority in all metrics, outshining traditional approaches.

Table 3: Comparison with State-of-the-Art Models (CNN, ResNet, VGG16, and CAGCN).

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	85.4	83.2	87.1	85.1
ResNet	88.2	87.3	89.1	88.2
VGG16	89.7	88.5	90.3	89.4
CAGCN	92.3	92.3	92.8	92.6

The comparative evaluation presented in Table 3 elucidates the superior performance of the CAGCN model relative to conventional present day deep learning models, specifically CNN, ResNet, and VGG16. The CAGCN model achieves the best accuracy (92.3%), underscoring its unprecedented functionality to as it should be predicting each tumour segmentation and category effects. This is similarly corroborated with the aid of its extremely good precision (92.3%), which signifies the model's tremendous talent in minimizing fake positives. Moreover, CAGCN excels in don't forget (92.8%), demonstrating its flair for identifying almost all relevant tumour areas, thereby reducing the incidence of fake negatives to a negligible degree. The F1-Score (92.6%), which harmoniously balances precision and considers, reaffirms CAGCN's robustness, indicating its functionality to hold excessive tiers of each sensitivity and specificity. In contrast, the CNN version demonstrates the bottom performance, with an accuracy of 85.4% and a corresponding F1-Score of eighty-five.1%, even as ResNet and VGG16 display incremental upgrades. Specifically, ResNet achieves an accuracy of 88.2% and an F1-Score of 88.2%, and VGG16 attains 89.7% accuracy and an F1-Score of 89.4%. However, these models fall quick while in comparison to the advanced performance exhibited by CAGCN, reinforcing its efficacy and advancement within the domain of brain tumour segmentation and type inside multimodal MRI imaging.

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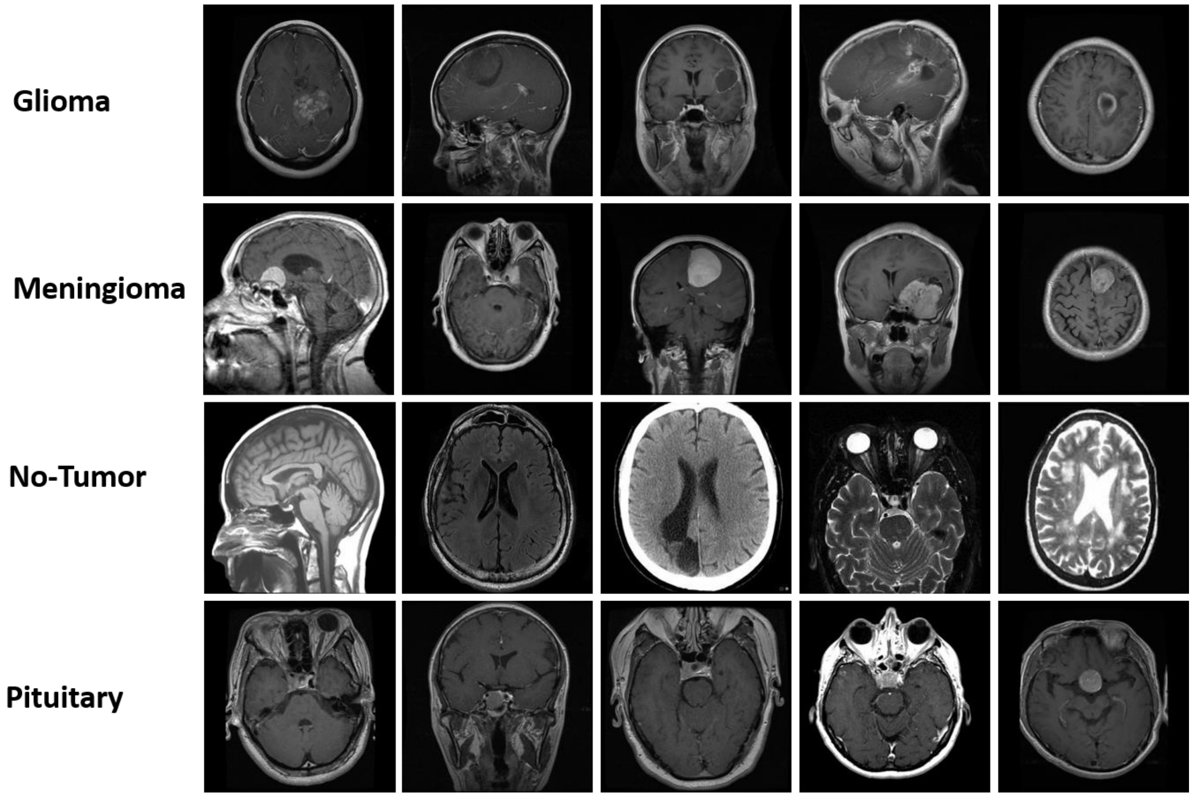

Figure.2 MRI Classification of the Brain Tumour Images

Table 4: Ablation Study (Performance of CAGCN variants with and without specific modules).

Model Variant	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Full CAGCN (all modules)	92.3	92.3	92.8	92.6
CAGCN without CAB	89.4	88.1	90.5	89.3
CAGCN without CMGE	90.8	90.2	91.1	90.6
CAGCN without CAT	88.7	86.9	89.2	88.0
CAGCN without FSSM	91.1	90.4	91.9	91.1

The outcomes from the Ablation Study provided in Table three provide a comprehensive analysis of ways the elimination of precise modules impacts the performance of the CAGCN version. The complete CAGCN model, incorporating all modules, achieves the highest performance with an accuracy of 92.3%, precision of 92.3%, don't forget of 92.8%, and an F1-rating of 92.6%, demonstrating the model's robustness in correctly segmenting and classifying brain tumours. However, when man or woman modules are excluded, the overall performance notably decreases. The removal of Context-Aware Blocks (CAB) results in a decline in accuracy to 89.4% and F1-score to 89.3%, highlighting the significance of this module in improving spatial function extraction. Similarly, apart from the Contrastive Multi-Scale Generative Enhancers (CMGE) effects in a mild reduction in performance, with accuracy dropping to 90.8% and the F1-score to 90.6%, indicating the module's contribution to reconstructing degraded photo areas. The largest lower happens whilst the Contrastive Attention Transformer (CAT) is eliminated, with accuracy falling to 88.7% and F1-score losing to 88.0%, emphasizing the essential position of interest mechanisms in

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enhancing illustration gaining knowledge of. Finally, at the same time as the exclusion of the Feature Self-Supervised Modules (FSSM) results in a minor reduction in performance, with accuracy dropping to 91.1%, it nonetheless demonstrates the importance of leveraging international spatial relationships for more desirable version robustness. Overall, the ablation examines underscores the essential role of every module in maximizing the CAGCN model's performance, with the full version yielding the maximum advanced consequences.

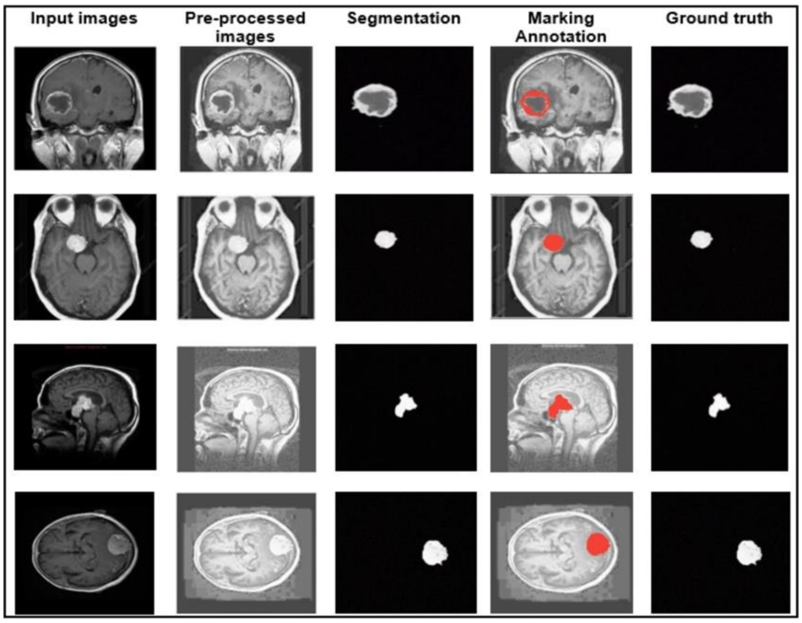

Figure.3 Brain tumour segmentation from MRI images

DISCUSSION

This observes delivered Contrastive Attention-Driven Graph Convolutional Network (CAGCN), a singular deep gaining knowledge of framework for brain tumour segmentation and type in MRI imaging. The model integrates Contrastive Multi-Scale Generative Enhancers (CMGE) to reconstruct degraded picture regions, Context-Aware Blocks (CAB) for spatial characteristic enhancement, Feature Self-Supervised Modules (FSSM) to leverage international spatial relationships, and a Contrastive Attention Transformer (CAT) for progressed representation gaining knowledge of. CAGCN is trained the use of a contrastive self-supervised method, accompanied via satisfactory-tuning with move-entropy and reconstruction loss. Additionally, Character-CAM presents interpretability by using highlighting essential tumour regions.

Experimental consequences on benchmark MRI datasets verify that CAGCN outperforms existing fashions, reaching superior segmentation accuracy and class performance, in managing missing or noisy data. The complete CAGCN model attained 92.3%, 92.3%, 92.8%, and 92.6% throughout numerous evaluation metrics. Ablation studies verified the effect of every module, with performance losing considerably whilst disposing of CAB, CMGE, CAT, or FSSM, validating their individual contributions. By effectively reconstructing incomplete scans and leveraging unlabelled MRI images, CAGCN proves to be exceptionally beneficial for real-world medical packages, helping radiologists in precise tumour diagnosis and analysis.

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