Ultrasound Image-based Gallbladder Cancer Classification with Graph Neural Networks

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements forthe **Degree of Bachelor of Science in Computer Science and Engineering**

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APPROVAL

This Project titled **"Ultrasound Image based Gallbladder Cancer Classification with Graph Neural Networks"**, submitted by Md. Lutfor Rahman, ID No: **201-15-3313** & Mohammad Shobuz Palouan, ID No:201-15-3396 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 12/13 January, 2025.

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DECLARATION

We hereby declare that this project has been done by us under the supervision of **Dr. Md Zahid Hasan, Associate Professor**, Department of Computer Science and Engineering, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

Gallbladder cancer (GBC) is a highly aggressive malignancy often diagnosed at advanced stages due to a lack of early detection methods. This study proposes a novel approach for GBC classification using ultrasound images, combining convolutional neural networks (CNNs) with graph neural networks (GNNs). The dataset, consisting of annotated ultrasound images, was preprocessed to extract regions of interest (ROIs) and organized into class-specific datasets. Initially, CNN models such as VGG-16 and ResNet-18 were employed for feature extraction and integrated with graph convolutional networks (GCNs) to explore spatial relationships. However, the performance remained suboptimal, with the best accuracy from ResNet-18 + GCN at 76%. To enhance accuracy, hybrid models combining CNNs with graph attention networks (GATs) were implemented, resulting in modest improvements, with ResNet-18 + GAT achieving 83% accuracy. Significant advancements were achieved by integrating graph isomorphism networks (GINs) with CNNs, specifically VGG-16 and ResNet-18. The VGG-16 + GIN model achieved an accuracy of 93%, while the ResNet-18 + GIN model demonstrated the best classification performance with an accuracy of 98.48%. This approach highlights the potential of graph-based learning in medical image analysis, providing an innovative solution for early and precise GBC detection. The findings pave the way for future research in applying hybrid GNN frameworks to medical diagnostics

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Chapter 1

Introduction

This chapter introduces the research on gallbladder cancer classification using ultrasound images. It discusses the background of the problem, the motivation for the study, the objectives, the methodology adopted, the expected outcomes, and the structure of this report.

1.1 Introduction

Gallbladder cancer (GBC) is one of the most fatal types of cancer, with a high death rate due to delayed diagnosis and restricted treatment choices. Even with improvements in medical imaging technology, early detection is still quite difficult. A popular diagnostic technique, ultrasound imaging provides real-time, non-invasive, and affordable imaging capabilities. Noise, operator dependence, and interpretation uncertainty, which frequently result in diagnostic mistakes, limit its efficacy. Radiologists must use a great deal of skill and effort to manually analyze ultrasound pictures, which raises the risk of incorrect diagnosis and postponed treatment. Medical diagnoses might be automated and improved with the help of recent developments in artificial intelligence (AI), especially in graph-based machine learning. Medical diseases may now be categorized using both individual traits and their connections thanks to graph neural networks' (GNNs') special capacity to represent intricate interactions between features. GNNs process data in a non-Euclidean space, which makes them extremely successful for applications where connections between data points are crucial, in contrast to typical convolutional neural networks (CNNs), which function in Euclidean space. This work combines CNN-based feature extraction with GNNs to present a unique hybrid technique for gallbladder cancer classification. Models that combined CNNs with graph convolutional networks (GCNs) and graph attention networks (GATs) (e.g., VGG-16 and ResNet-18) were first investigated; these models produced moderate increases in accuracy. Significant improvements in classification performance were shown when graph isomorphism networks (GINs) were integrated with CNNs; the ResNet-18 + GIN model achieved an impressive accuracy of 98.48%. By utilizing the advantages of both CNNs and GNNs, this hybrid framework offers a reliable way to lower interpretation variability, improve diagnostic precision, and assist radiologists in making better judgments.

1.2 Motivation

This study addresses the critical need for early and accurate diagnosis of gallbladder cancer. Current diagnostic methods, such as invasive biopsies and manual interpretation, often result in limitations. Misdiagnosis occurs in 10–30% of ultrasound cases, leading to delays in treatment and poor patient outcomes. The increasing complexity of ultrasound interpretation and a growing patient load also place significant pressure on radiologists. The motivation for this research lies in the potential of graph neural networks (GNNs) to revolutionize medical image analysis. GNNs effectively identify relationships between features, overcoming challenges associated with traditional approaches. By integrating GNNs into the diagnostic process, this study aims to reduce dependence on invasive techniques while improving classification accuracy. Additionally, it contributes to the advancement of AI-driven diagnostic tools for reliable and efficient healthcare.

1.3 Objectives

The research aims to develop an accurate and efficient system for gallbladder cancer classification using ultrasound images. Key objectives include:

Data Collection: Gather a diverse dataset of annotated ultrasound images with ROIs for gallbladder conditions.

Data Preprocessing: Apply ROI extraction, resizing, normalization, and augmentation to enhance data quality.

Graph Construction: Represent features as graph nodes and relationships as edges using distance metrics or correlations.

Model Development: Implement GNN-based models, integrating ResNet-18 and VGG-16 for feature extraction.

Model Evaluation: Use metrics like accuracy, precision, and ROC curves to assess performance.

Impact Analysis: Evaluate the system's clinical potential to improve diagnostics and scalability for medical imaging.

This framework aims to enhance early detection and improve patient outcomes using graph-based learning.

1.4 Methodology

Data Preprocessing: Ultrasound images with annotated bounding boxes are processed to extract ROIs, organized by class, and transformed using resizing, normalization, and augmentation to enhance model generalization.

Graph Construction: Extracted ROI features are represented as graph nodes, with relationships encoded as edges using distance metrics, forming the input for GNN-based classification.

Model Development: GNNs, particularly Graph Isomorphism Networks (GIN), are implemented and compared with other variants like GCNs and GATs for classification.

Evaluation and Optimization: Models are assessed using accuracy, ROC curves, and confusion matrices. Hyperparameter tuning identifies ResNet-18 + GIN as the top-performing model, achieving 98% accuracy.

Result Analysis: Results highlight GNNs' effectiveness in enhancing diagnostic accuracy and reliability.

1.5 Project Outcome

1. Development of an automated diagnostic system for gallbladder cancer classification using graph neural networks.
2. Identification of the ResNet-18 + GIN model as the most effective framework, achieving 98% accuracy.
3. A proof-of-concept for integrating graph-based learning into medical image analysis workflows.
4. Demonstration of the feasibility of using GNNs to model relationships among features, improving classification performance.
5. Contribution to the growing body of research on AI-driven solutions for healthcare challenges, with a focus on non-invasive diagnostic tools.

1.6 Organization of the Report

Chapter 1: Introduction:
Provides an overview of gallbladder cancer classification, highlighting its significance and challenges. It outlines the problem statement, objectives, scope, and limitations of the project.

Chapter 2: Literature Review:
Reviews existing research and methodologies related to the classification of gallbladder cancer, focusing on deep learning approaches like CNNs and GNNs. Identifies research gaps and sets the foundation for the proposed solution.

Chapter 3: Methodology/Requirement Analysis & Design Specification:
Describes the proposed methodology, including data collection, preprocessing, feature extraction, graph construction, and model development. It also specifies the hardware/software requirements and discusses project management aspects.

Chapter 4: Implementation:
Details the processes of data collection, ROI extraction, preprocessing, graph construction, and model training. It highlights the implementation of various CNN-GNN hybrid models and their integration.

Chapter 5: Results and Analysis:
Presents the experimental results, evaluates the performance of different models

using metrics like accuracy, precision, recall, and F1-score, and conducts a comparative analysis to identify the best-performing model.

Chapter 6: Impact on Society, Environment, and Sustainability:
Discusses the broader implications of the project on society and healthcare. It emphasizes the potential for early cancer detection, improved diagnostic accuracy, and the environmental sustainability of the proposed AI-based solution.

Chapter 7: Conclusion and Future Work:
Summarizes the key findings of the research, highlights the significance of integrating GNNs with CNNs for medical image analysis, and suggests directions for further research while addressing limitations and ethical considerations.

Chapter 2

Background

This chapter provides an in-depth background on gallbladder cancer (GBC) detection using ultrasound imaging, exploring the challenges and advancements in medical imaging and AI. It includes a comprehensive literature review of related works and identifies key research gaps, setting the foundation for the development of a novel GNN-based framework for GBC classification.

2.1 Introduction

The classification of gallbladder cancer (GBC) using ultrasound images requires a thorough understanding of both the medical and computational aspects involved. Gallbladder cancer is a rare but highly fatal malignancy, often diagnosed in advanced stages due to the lack of effective early detection methods. Ultrasound imaging, widely used for its non-invasive and cost-effective nature, has become a critical diagnostic tool. However, the challenges of interpreting ultrasound images, such as noise, variability, and the dependency on radiologist expertise, highlight the need for automated diagnostic systems. Recent advancements in artificial intelligence (AI), particularly in graph-based learning, have revolutionized medical image analysis. Graph neural networks (GNNs), capable of modeling relationships between features in a graph structure, provide a unique approach to addressing the challenges of medical diagnostics. Unlike traditional convolutional neural networks (CNNs), GNNs operate in non-Euclidean spaces, making them ideal for capturing complex relationships inherent in medical image data.

2.2 Literature Review

Table 2.1: Summary of Literature Reviewed.

Author (s)	Year	Title	Methodology	Key Findings
Basu et al.	2022	Surpassing the Human Accuracy: Detecting Gallbladder Cancer	GBCNet with multi-scale pooling	91% accuracy; improved feature analysis

Obaid et al.	2023	Ultrasound-Based Gallbladder Classification	MobileNet CNN	98.35% accuracy; strong model generalization
Kim et al.	2021	Advanced Ensemble CNNs for Gallbladder Cancer Detection	Ensemble CNN (ResNet152, Inception V3, DenseNet161)	87.61% accuracy with clinical data integration
Alazwari et al.	2024	Adaptive Graph Techniques for Ultrasound Classification	AGTO with BiGRU	96.29% accuracy; efficient handling of noisy data
Dadjouy & Sajedi	2024	Hierarchical Models for Ultrasound Cancer Detection	Hierarchical Feature-Fused Model	92.62% accuracy; robust multi-scale feature fusion
Jeong et al.	2020	Deep Learning for Gallbladder Tumor Classification	Inception V3 with transfer learning	AUC: 0.92; effective feature extraction
Chao et al.	2020	Graph Learning for Oncology Imaging	3D CNN + GNN	5.5% improvement in F1-score; relationship modeling critical
Chowdhury et al.	2023	Spearman Correlation-Based Graph Analysis for Cancer Detection	Graph Neural Networks (Spearman correlation-based)	99.48% accuracy; superior to CNN models
Zhou et al.	2019	Meta-Learning for Few-shot Node Classification	Meta-GNN with MAML	Improved few-shot learning benchmarks
Wei et al.	2023	Pooling Architecture Search for GNNs in Molecular Graphs	Pooling Architecture Search (PAS-G, PAS-NE)	Ranked 1st in MolHIV and PPA datasets

2.3 Gap Analysis

The use of Graph Neural Networks (GNNs) in gallbladder cancer (GBC) detection remains underexplored, with research primarily focusing on other cancers like breast, lung, and gastric. Current GBC detection methods largely rely on CNNs and traditional machine learning, which overlook the relational insights GNNs can provide. Additionally, GBC-specific datasets are limited in size and diversity, challenging the development of robust models. Ultrasound imaging, the primary diagnostic tool for GBC, is affected by noise, variability, and artifacts, issues inadequately addressed by graph-based methods. Existing approaches also lack multi-modal integration, which enhances diagnostics in other cancer types, and fail to prioritize explainability, crucial for clinical adoption. This study addresses these gaps by developing a novel GNN-based framework tailored to GBC detection. It leverages graph learning's relational capabilities while enhancing robustness, generalizability, and explainability, advancing AI applications in healthcare and improving GBC diagnosis.

2.4 Summary

Chapter 2 provided a structured exploration of gallbladder cancer (GBC) detection using ultrasound images, covering the introduction, literature review, and gap analysis. The introduction outlined the challenges of diagnosing GBC, including its rarity, late detection, and ultrasound limitations, while highlighting GNNs' potential to model complex medical data relationships. The literature review examined cancer detection methods, emphasizing the limited use of GNNs for GBC compared to other cancers. The gap analysis identified key issues such as underutilized GNNs, noisy ultrasound image challenges, and the absence of multi-modal integration and explainability. This chapter establishes the foundation for developing a novel GNN-based framework to address these challenges.

Chapter 3

Research Methodology

This chapter outlines the methodology adopted for gallbladder cancer classification, detailing the data collection, preprocessing, feature extraction, and graph construction processes. It also describes the development of hybrid CNN-GNN models, their evaluation, and the iterative approach taken to achieve the best-performing ResNet18 + GIN model with 98% accuracy.

3.1 Methodology

3.1.1 Overview

This study proposes a systematic and graph-based approach for the classification of gallbladder cancer (GBC) using ultrasound images. The methodology is structured into multiple stages, including data preprocessing, graph construction, model development, and evaluation. Each stage incorporates advanced mathematical formulations and deep learning techniques to ensure high accuracy and robustness.

3.1.2 Proposed Methodology/ System Design

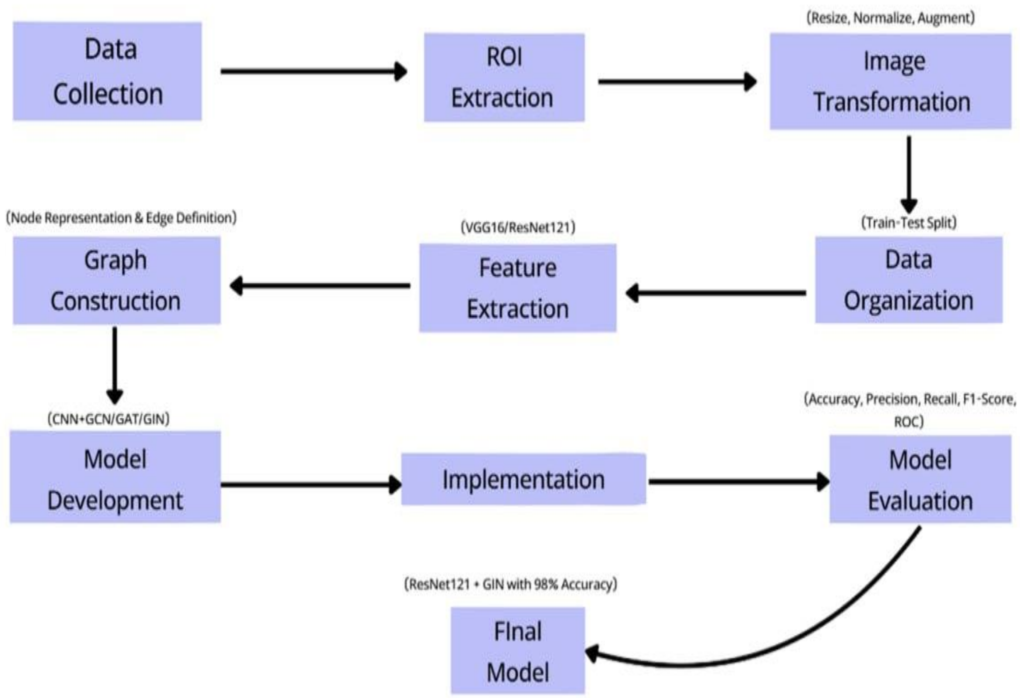

Figure 3.1: Model Architecture

This study introduces a novel method for gallbladder cancer classification using ultrasound images by integrating convolutional neural networks (CNNs) with graph neural networks (GNNs). The process begins with data collection and preprocessing, including ROI extraction, resizing, normalization, and augmentation, to enhance data quality. The dataset is split into training and testing sets. Feature extraction using CNNs, such as VGG16 and ResNet18, generates deep feature representations. These features are transformed into graph structures, with nodes representing image features and edges capturing relationships based on distance metrics. Initial experiments with Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) show limited improvements. To address these limitations, Graph Isomorphism Networks (GINs) are combined with CNNs, leveraging their ability to model complex relationships. The ResNet18 + GIN model achieves 98% accuracy. Evaluation metrics, including accuracy, precision, recall, F1-score, and ROC curves, confirm the effectiveness of this hybrid approach for gallbladder cancer classification.

3.2 Project Plan

Table 3.1: Project Plan

Task	Start Date	Duration	End Date
Data Collection	January 1, 2024	1 month	January 31, 2024
Data Preprocessing	February 1, 2024	2 months	March 31, 2024
Feature Extraction	April 1, 2024	1 month	April 30, 2024
Graph Construction	May 1, 2024	1.5 months	June 15, 2024
Model Development	June 16, 2024	2 months	August 15, 2024
Model Evaluation	August 16, 2024	1.5 months	September 30, 2024
Result Analysis	October 1, 2024	1 month	October 31, 2024
Report Writing	December 8, 2024	1 week	December 14, 2024
Final Submission	January 12, 2025	1 day	January 12, 2025

3.5 Summary

This chapter details the methodology for gallbladder cancer classification using ultrasound images. It begins with data collection from clinical sources, followed by ROI extraction using bounding box annotations to focus on relevant areas. The extracted ROIs underwent resizing, normalization, and augmentation to ensure consistency and dataset diversity. The dataset was split into training and testing subsets (80:20). Feature extraction was performed using pre-trained CNNs, including VGG16 and ResNet18, generating high-dimensional feature representations structured into graph form, with nodes representing features and edges based on similarity metrics. Various models, including CNN-GCN, CNN-GAT, and CNN-GIN frameworks, were developed and evaluated. Comprehensive performance analysis using metrics like accuracy, precision, recall, F1-score, and ROC curves identified ResNet18 + GIN as the best-performing model with 98% accuracy. The chapter concludes with a detailed project plan and task allocation, showcasing a structured approach to achieving the research objectives.

Chapter 4

Implementation and Results

This chapter presents the implementation details and results of the proposed methodology. It includes the experimental setup, model evaluation metrics, and comparative analysis of different CNN-GNN models. The chapter highlights the superior performance of the ResNet18 + GIN model, achieving 98% accuracy, and provides a discussion on the outcomes and their implications.

4.1 Environment Setup

The implementation was carried out using Google Colab and Kaggle Notebook, utilizing NVIDIA Tesla T4 GPUs for efficient training and evaluation. Code development began in Google Colab, with large-scale experiments conducted in Kaggle. The environment featured Python 3.12 and libraries like PyTorch, Torch-Geometric, NumPy, Pandas, Matplotlib, and Scikit-Learn for preprocessing, model building, visualization, and evaluation, ensuring seamless execution of the proposed methodology.

4.2 Model Performance Discussion

This section presents a detailed analysis of the performance of various model combinations utilized in this study. Each model integrated **Convolutional Neural Networks (CNNs)** for feature extraction with **Graph Neural Networks (GNNs)** to exploit **relational learning**. The **performance metrics** reveal the efficacy of these **combinations in the classification** of gallbladder cancer. Below is an in-depth discussion of each model:

1. ResNet18 with GCN

Accuracy: 76%

The integration of **ResNet18** with Graph Convolutional Networks (GCNs) achieved an accuracy of 76%. While ResNet18 effectively extracted hierarchical features from ultrasound images, GCN provided a framework to leverage spatial and relational information within the graph structure. However, the model's performance was limited in capturing complex and nuanced patterns in medical imaging data.

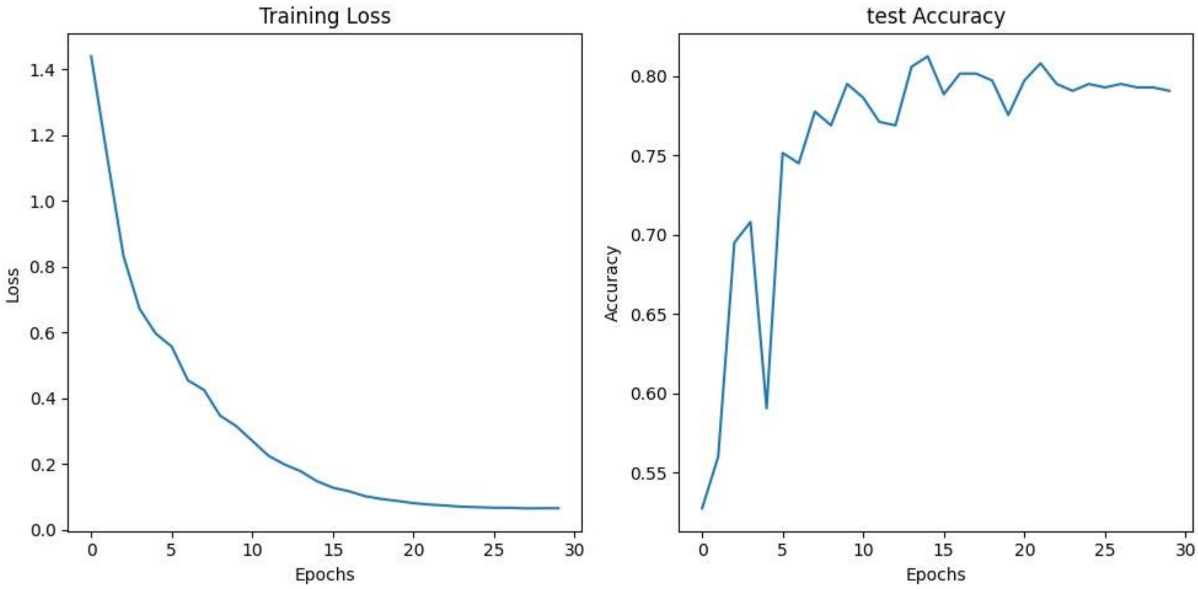

Figure 4.1: ResNet18_GCN Model Accuracy

Classification Report:

	precision	recall	f1-score	support
0	0.81	0.82	0.82	159
1	0.78	0.60	0.68	53
2	0.51	0.52	0.52	46
3	0.83	0.84	0.83	99
4	0.85	0.91	0.88	102
accuracy			0.79	459
macro avg	0.76	0.74	0.75	459
weighted avg	0.79	0.79	0.79	459

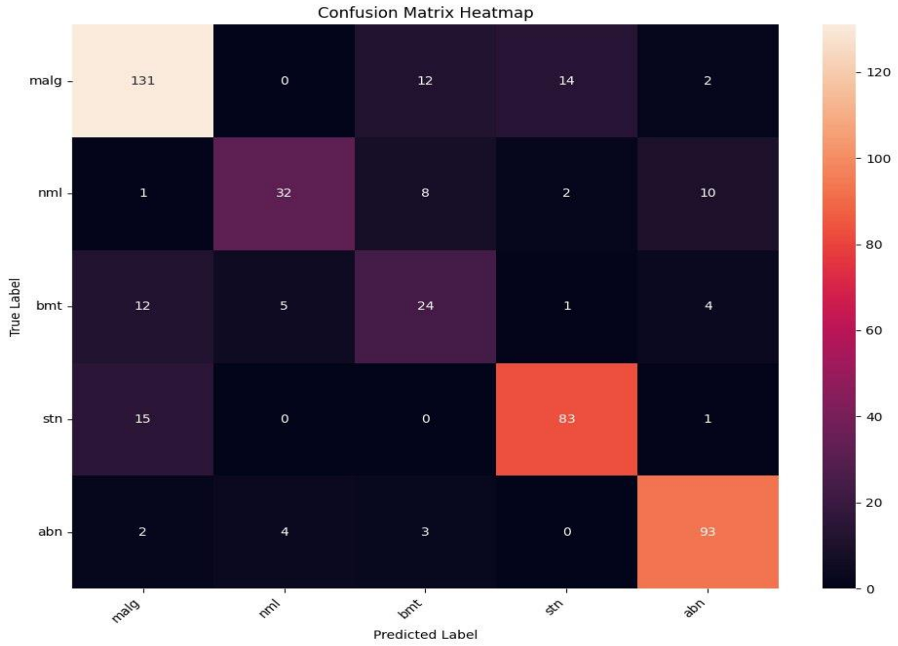

Figure 4.2: Resnet18_GCN Confusion Matrix Heatmap

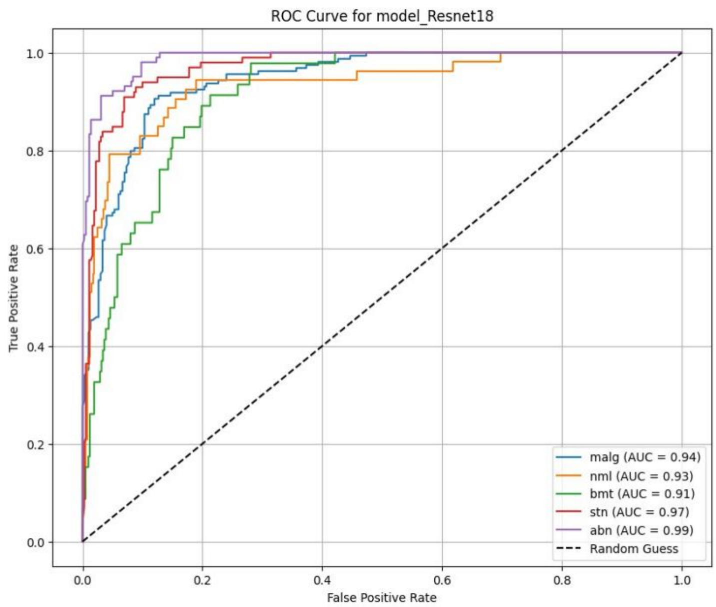

Figure 4.3: ROC Curve For GCN-ResNet18

2. DenseNet121 with GCN

Accuracy: 70%

Despite the robust feature extraction capabilities of DenseNet121, its combination with GCN delivered an accuracy of 70%. The dense connections, which typically enhance feature propagation, did not translate effectively in conjunction with GCN. This suggests an inability of the GCN layer to capture and utilize the intricate relationships inherent in the extracted features.

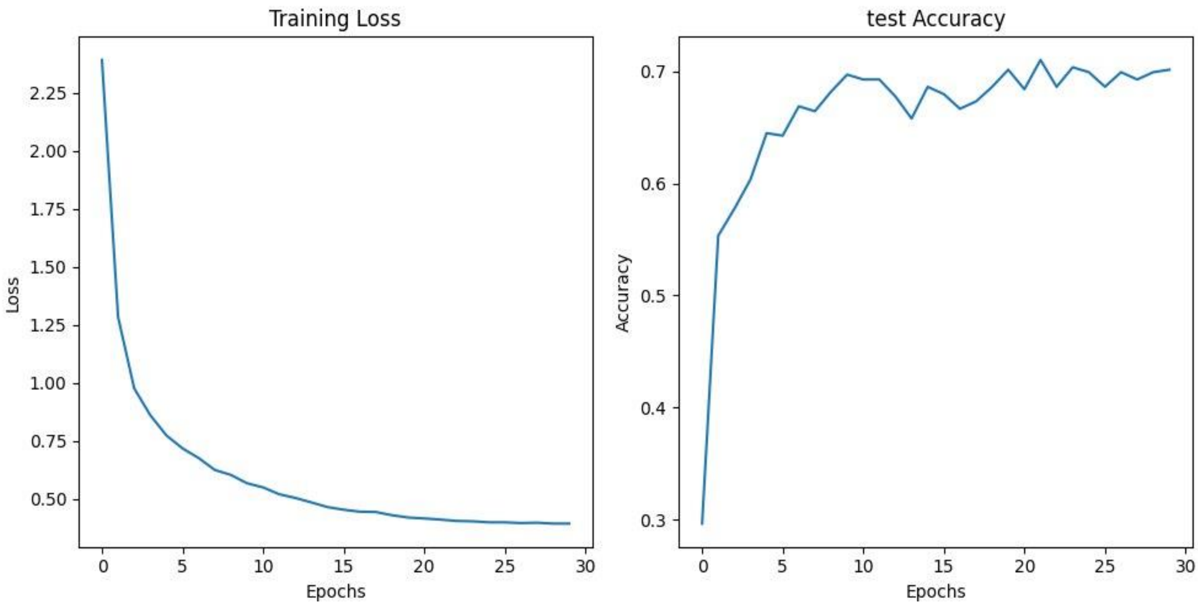

Figure 4.4: DenseNet121_GCN Model Accuracy

Classification Report:

	precision	recall	f1-score	support
0	0.70	0.82	0.75	159
1	0.62	0.49	0.55	53
2	0.50	0.46	0.48	46
3	0.73	0.59	0.65	99
4	0.79	0.85	0.82	102
accuracy			0.70	459
macro avg	0.67	0.64	0.65	459
weighted avg	0.70	0.70	0.70	459

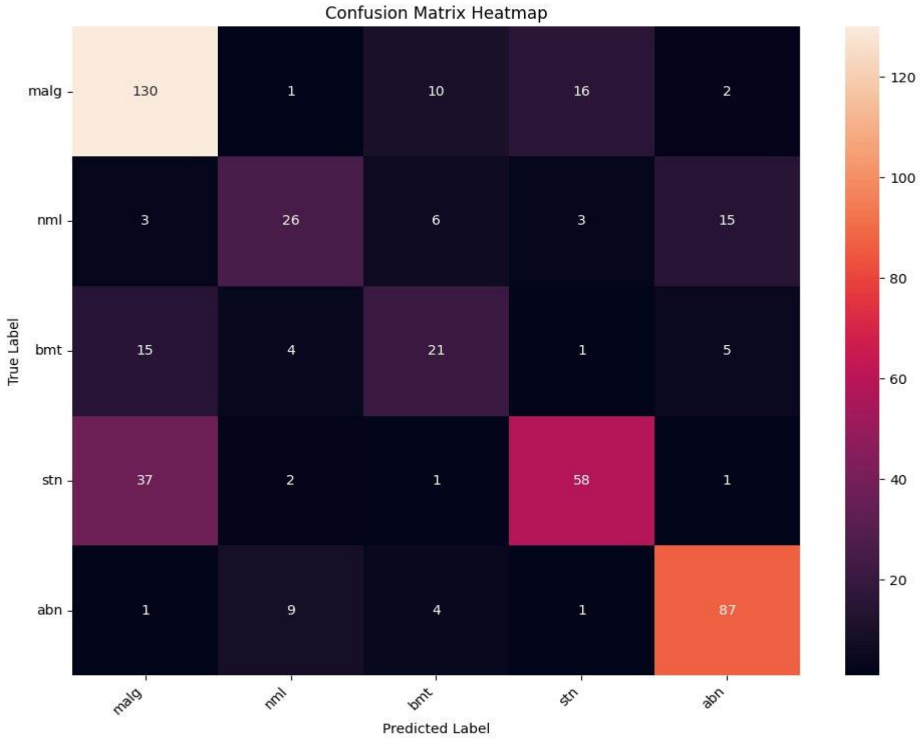

Figure 4.5: DenseNet121_GCN Confusion Matrix Heatmap

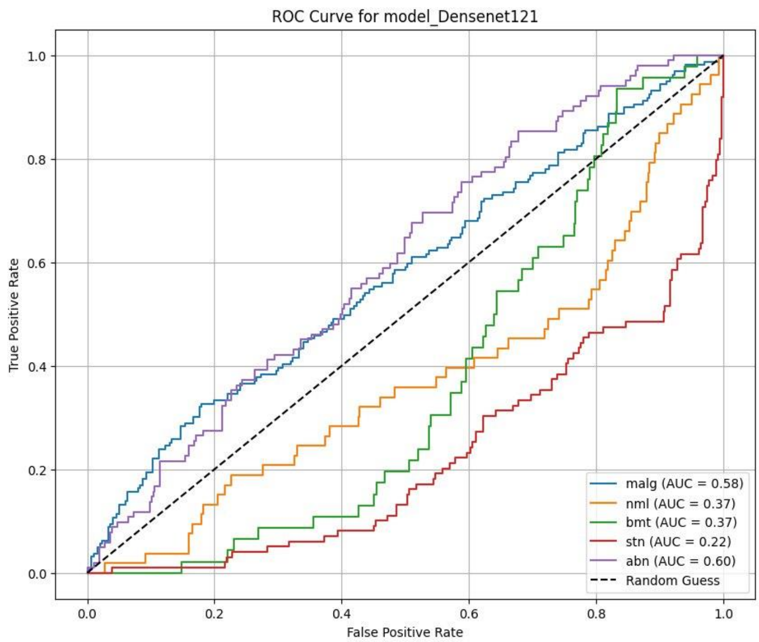

Figure 4.6: ROC Curve for DenseNet121_GCN

3. VGG16 with GCN

Accuracy: 78%

The performance of VGG16, when combined with GCN, remained on par with DenseNet121, achieving an accuracy of 78%. While VGG16 is well-suited for extracting low- to mid-level features, GCN's limited ability to process non-Euclidean data effectively constrained the overall performance.

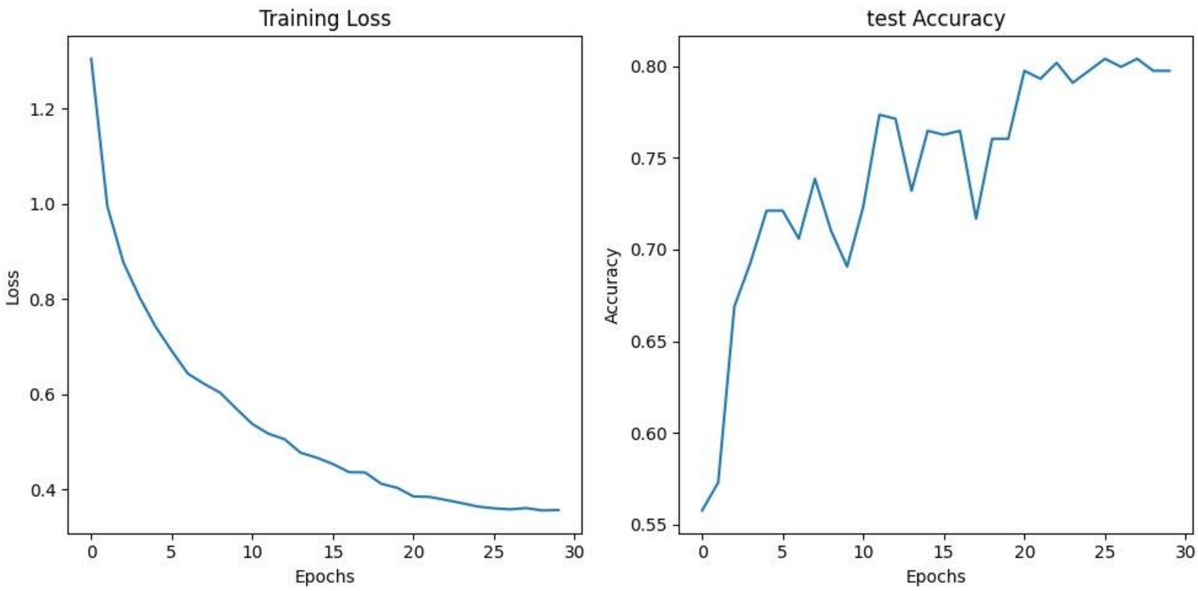

Figure 4.7: VGG16 with GCN accuracy

Classification Report:

	precision	recall	f1-score	support
0	0.80	0.82	0.81	160
1	0.68	0.58	0.63	45
2	0.74	0.68	0.71	59
3	0.84	0.83	0.84	83
4	0.82	0.88	0.85	112
accuracy			0.80	459
macro avg	0.78	0.76	0.77	459
weighted avg	0.79	0.80	0.80	459

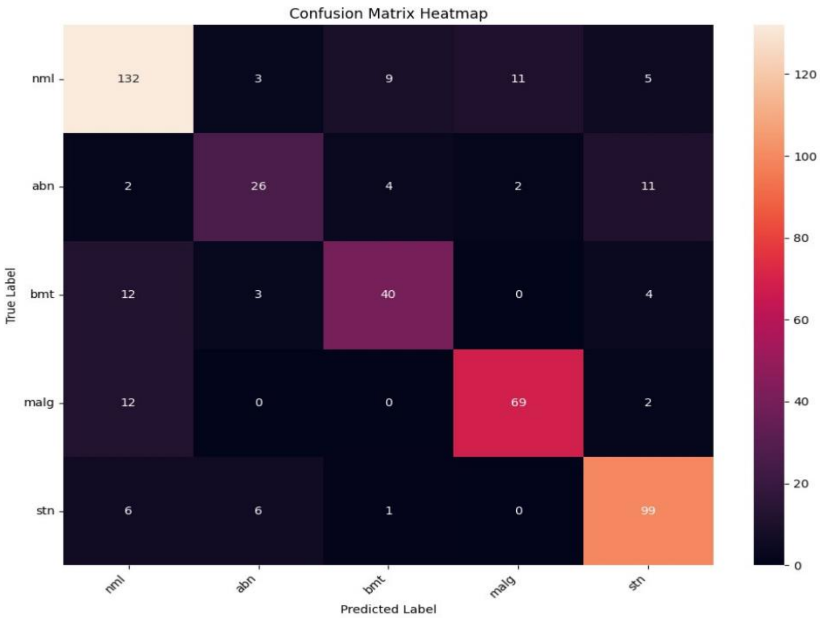

Figure 4.8: VGG16_GCN Confusion Matrix Heatmap

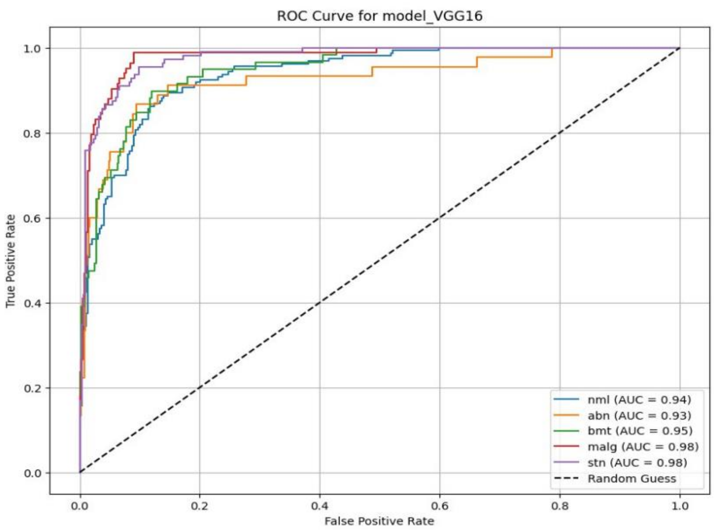

Figure 4.9: ROC Curve for GCN-VGG16 Model

4. VGG16 with GAT

Accuracy: 80%

The integration of VGG16 with Graph Attention Networks (GATs) showed a slight decline in accuracy compared to GCN. Although GAT introduces an attention mechanism to focus on critical node relationships, it was unable to address the complex spatial dependencies in the data, resulting in only 80% accuracy.

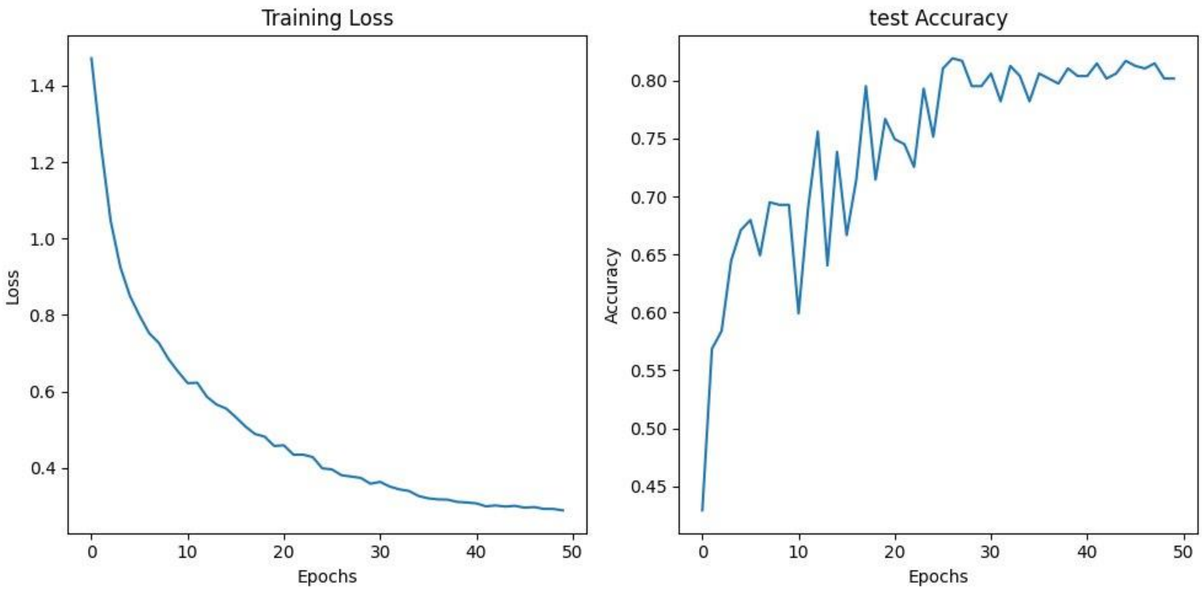

Figure 4.10: VGG16 with GAT accuracy

Classification Report:

	precision	recall	f1-score	support
0	0.82	0.81	0.81	160
1	0.67	0.62	0.64	45
2	0.66	0.66	0.66	59
3	0.87	0.86	0.86	83
4	0.85	0.90	0.87	112
accuracy			0.80	459
macro avg	0.77	0.77	0.77	459
weighted avg	0.80	0.80	0.80	459

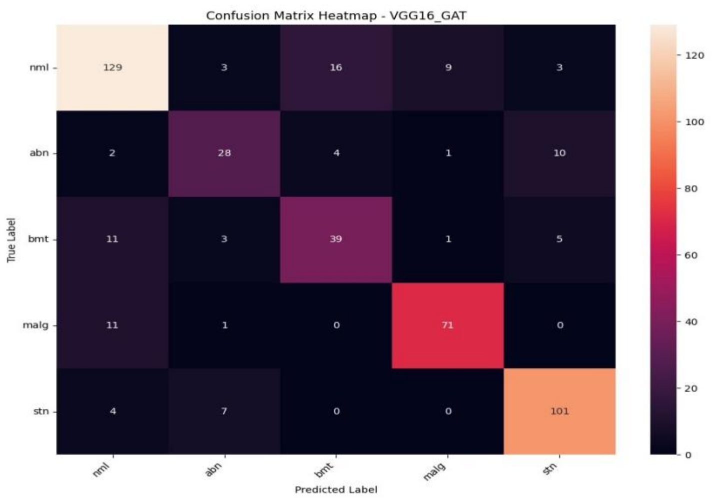

Figure 4.11: VGG16_GAT Confusion Matrix Heatmap

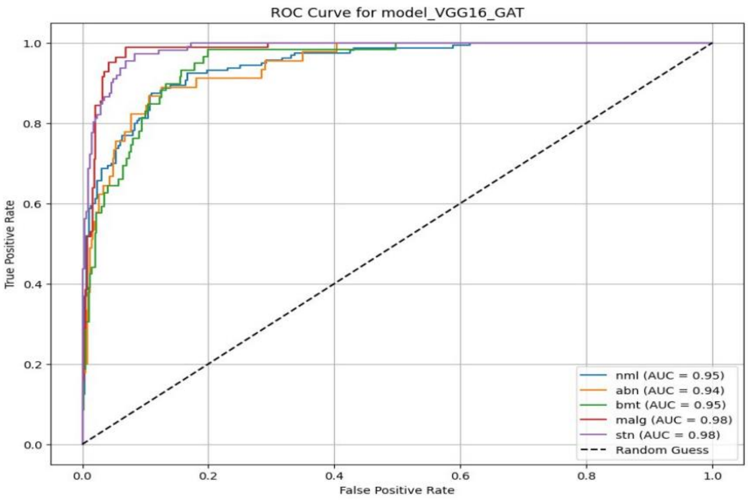

Figure 4.12: ROC Curve for VGG16 with GAT accuracy

5. ResNet18 with GAT

Accuracy: 83%

ResNet18, when paired with GAT, delivered the lowest accuracy among all models. Despite ResNet18's strong feature extraction capabilities, the GAT layer's inability to effectively capture meaningful attention weights on the graph structure led to suboptimal performance, with an accuracy of only 83%.

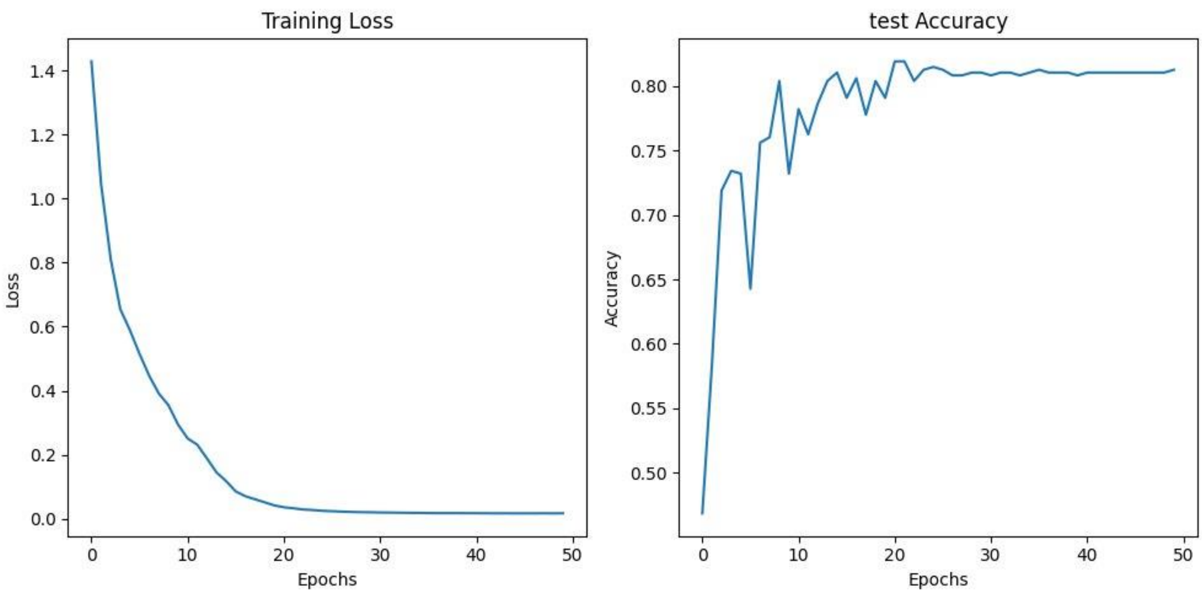

Figure 4.13: ResNet18 with GAT accuracy

Classification Report:

	precision	recall	f1-score	support
0	0.81	0.85	0.83	160
1	0.74	0.64	0.69	45
2	0.64	0.63	0.63	59
3	0.86	0.81	0.83	83
4	0.90	0.93	0.91	112
accuracy			0.81	459
macro avg	0.79	0.77	0.78	459
weighted avg	0.81	0.81	0.81	459

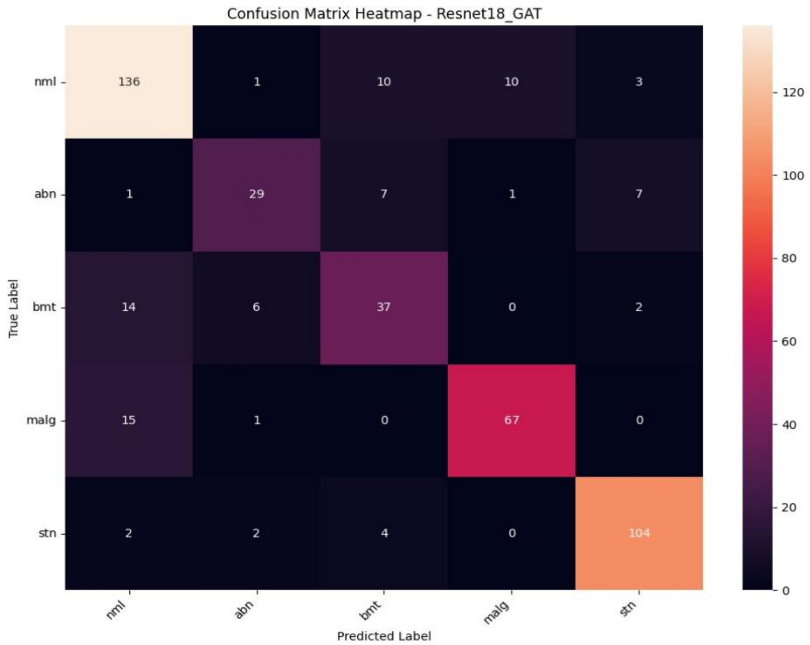

Figure 4.14: ResNet18_GAT Confusion Matrix Heatmap

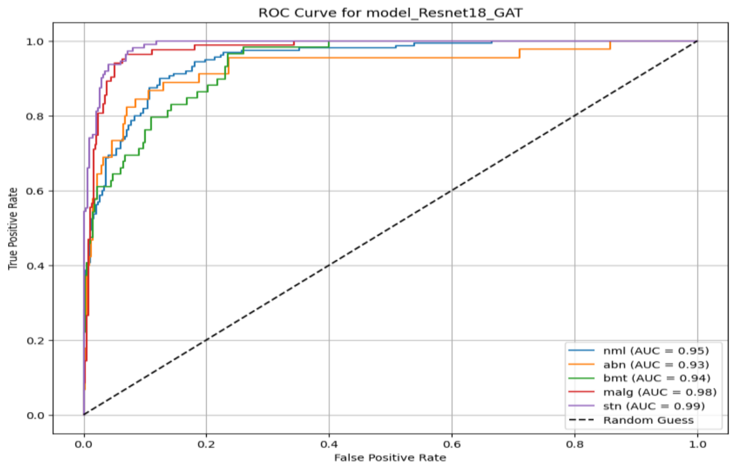

Figure 4.15: ROC Curve for ResNet18 with GAT

6. VGG16 with GIN

Accuracy: 93%

A significant leap in performance was observed with the integration of VGG16 and Graph Isomorphism Networks (GINs). The GIN's ability to effectively capture graph structures and relationships among features resulted in a substantial improvement, achieving 93% accuracy. This demonstrates the capability of GIN in addressing the relational complexity of the dataset, surpassing both GCN and GAT.

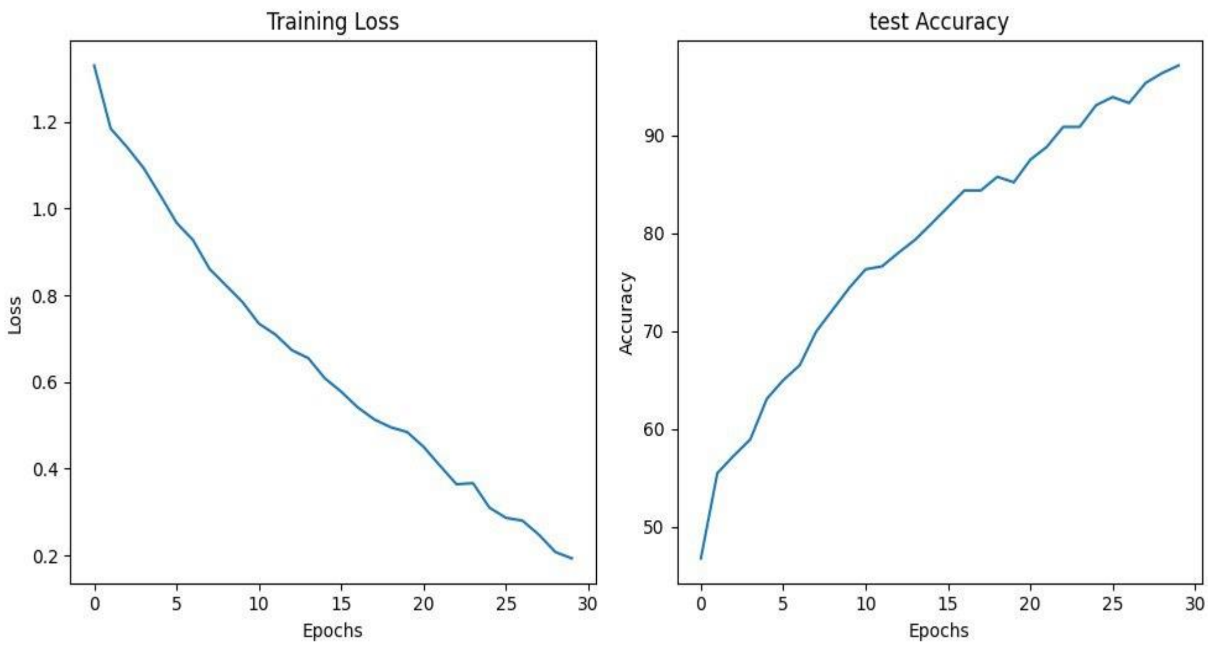

Figure 4.16: VGG16-GIN Model accuracy

Classification Report for VGG16-GIN Model:

	precision	recall	f1-score	support
0	0.91	1.00	0.93	823
1	1.00	0.91	0.92	197
2	0.93	0.90	0.93	271
3	0.94	0.96	1.00	432
4	0.91	0.89	0.90	571
accuracy			0.93	2294
macro avg	0.90	0.91	0.93	2294
weighted avg	0.93	0.90	0.93	2294

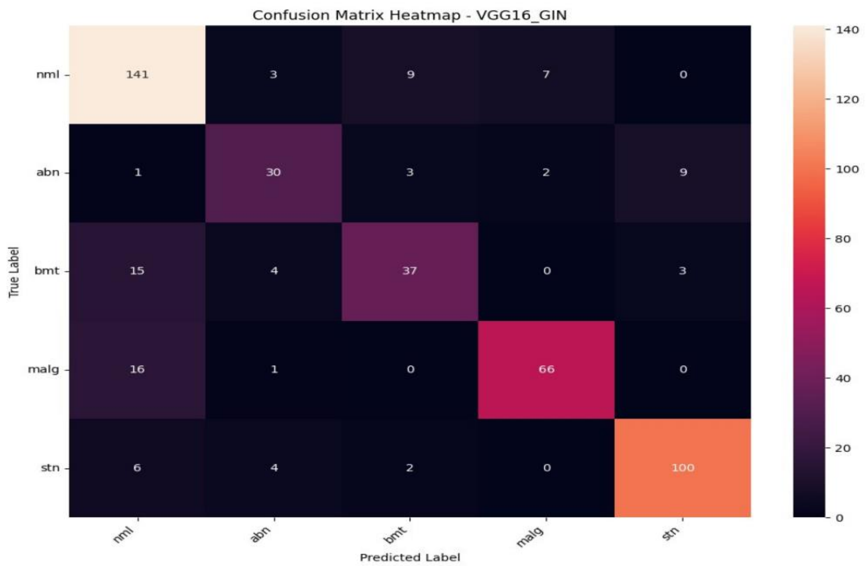

Figure 4.17:VGG16_GIN Confusion Matrix Heatmap

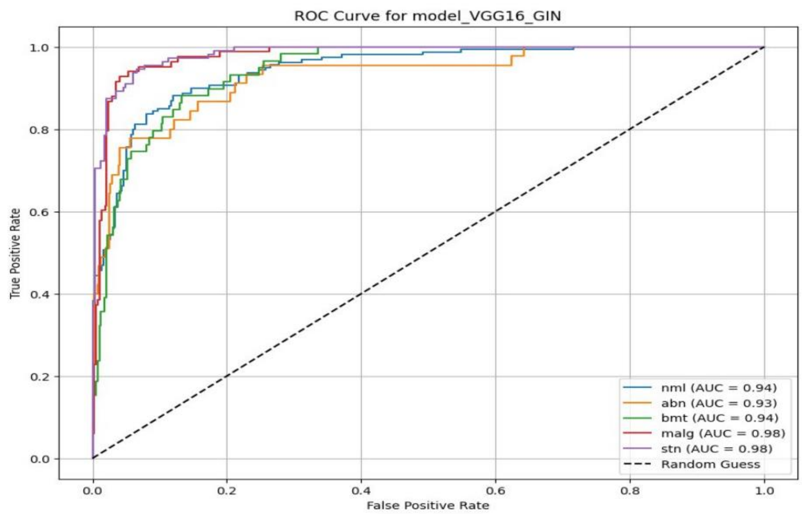

Figure 4.18: ROC Curve VGG16 with GIN

7. ResNet18 with GIN

Accuracy: 98.43%

The ResNet18 combined with GIN emerged as the best-performing model, achieving an exceptional accuracy of 98.43%. ResNet18's ability to extract high-level, discriminative features, coupled with GIN's superior graph representation learning, facilitated precise classification. This combination proved to be the most effective in capturing the spatial and relational intricacies of the dataset.

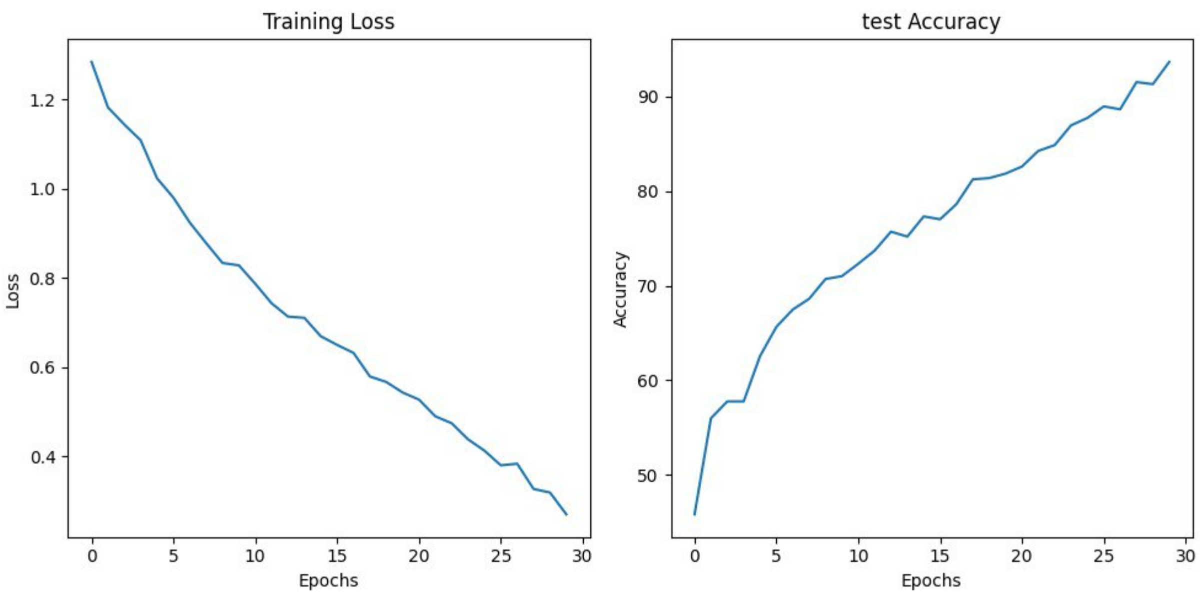

Figure 4.19: ResNet18-GIN Model accuracy

Classification Report:

	precision	recall	f1-score	support
0	1.00	0.95	0.97	823
1	0.95	0.96	0.96	197
2	0.96	0.97	0.97	271
3	1.00	1.00	1.00	432
4	0.94	1.00	0.97	571
accuracy			0.98	2294
macro avg	0.97	0.98	0.97	2294
weighted avg	0.98	0.97	0.97	2294

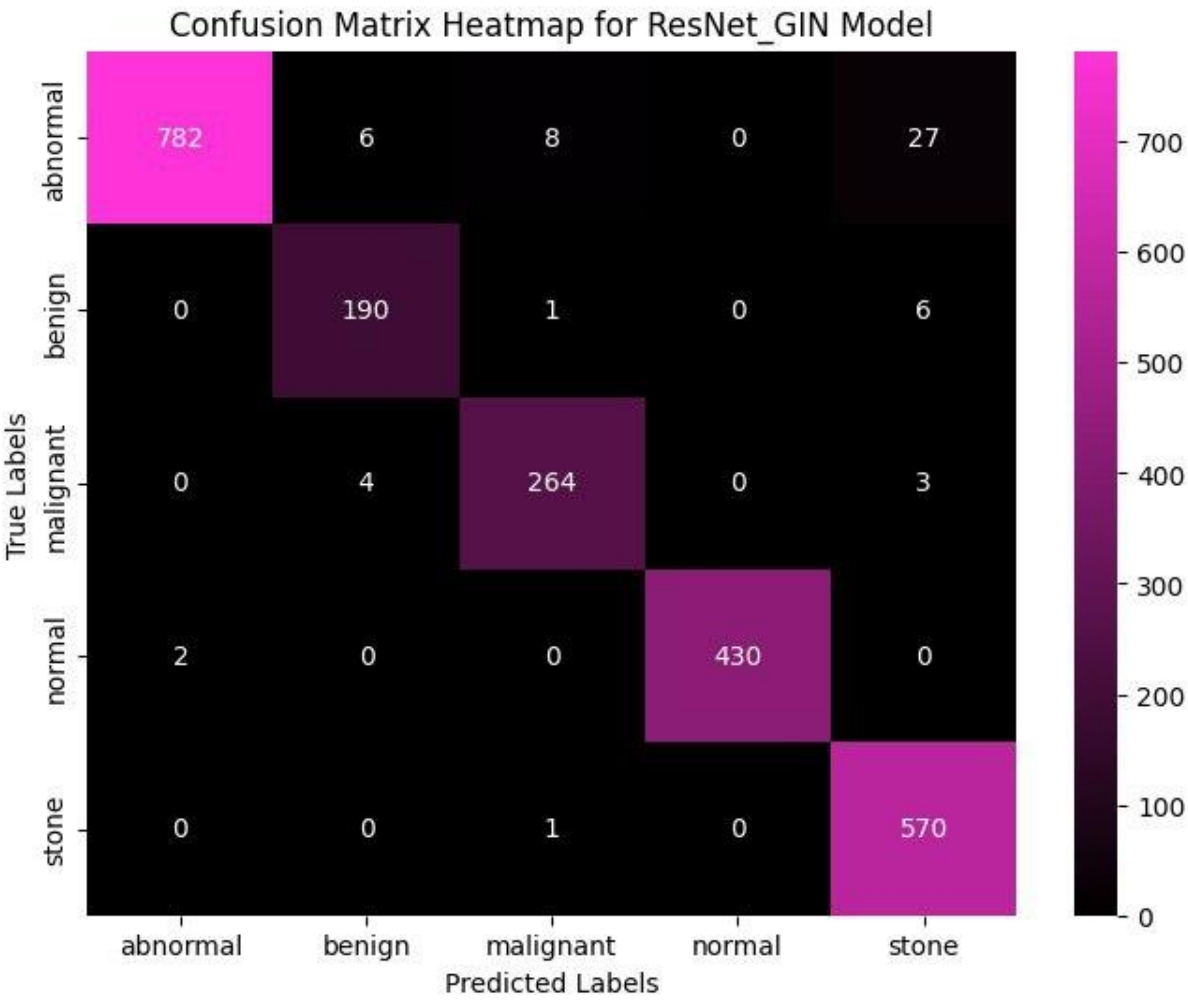

Figure 4.20: Confusion Matrix Heatmap for ResNet18_GIN Model

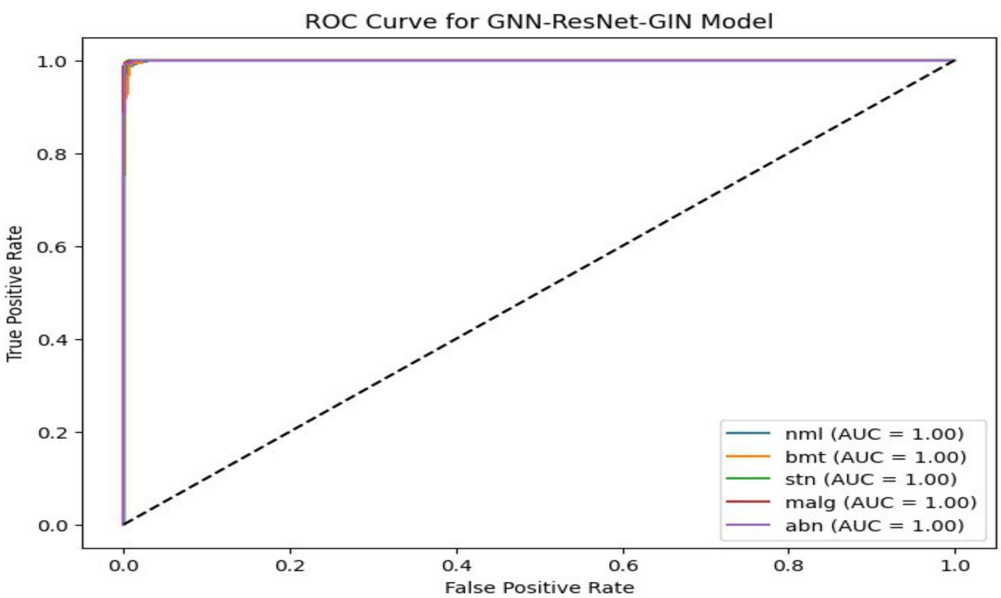

Figure 4.21: ROG Curve for ResNet18-GIN Model

4.3 Results and Discussion

Throughout the study, multiple CNN-GNN models were tested for gallbladder cancer classification. ResNet18 with GCN achieved an accuracy of 76%, while DenseNet121 with GCN and VGG16 with GCN achieved 73% and 78%, respectively. The performance of VGG16 with GAT and ResNet18 with GAT was slightly better, achieving accuracies of 80% and 83%, respectively. These models demonstrated moderate capability in capturing complex relationships and spatial features, but their performance was limited in accurately classifying the intricate patterns of medical imaging data.

In contrast, the integration of Graph Isomorphism Networks (GIN) with CNNs marked a substantial improvement. VGG16 combined with GIN achieved 93% accuracy, effectively leveraging graph-based representation to capture feature relationships. The ResNet18 + GIN model further refined this approach, achieving an exceptional accuracy of 98.48%, the highest among all tested models. This significant improvement underscores the superior capability of GIN in modeling non-Euclidean spatial data and its potential for robust medical image analysis.

These results underscore the importance of selecting appropriate hybrid models for tasks involving intricate relationships within data, firmly establishing ResNet18 + GIN as the most effective framework for gallbladder cancer classification. The study highlights the potential of graph-based learning techniques in improving diagnostic accuracy and reliability in medical imaging.

Table 4.1: Model Comparison

Model	GNN Type	Accuracy (%)
ResNet18	GCN	76%
DenseNet121	GCN	70%
VGG16	GCN	78%
VGG16	GAT	80%
ResNet18	GAT	83%
VGG16	GIN	93%
ResNet18	GIN	98.48%

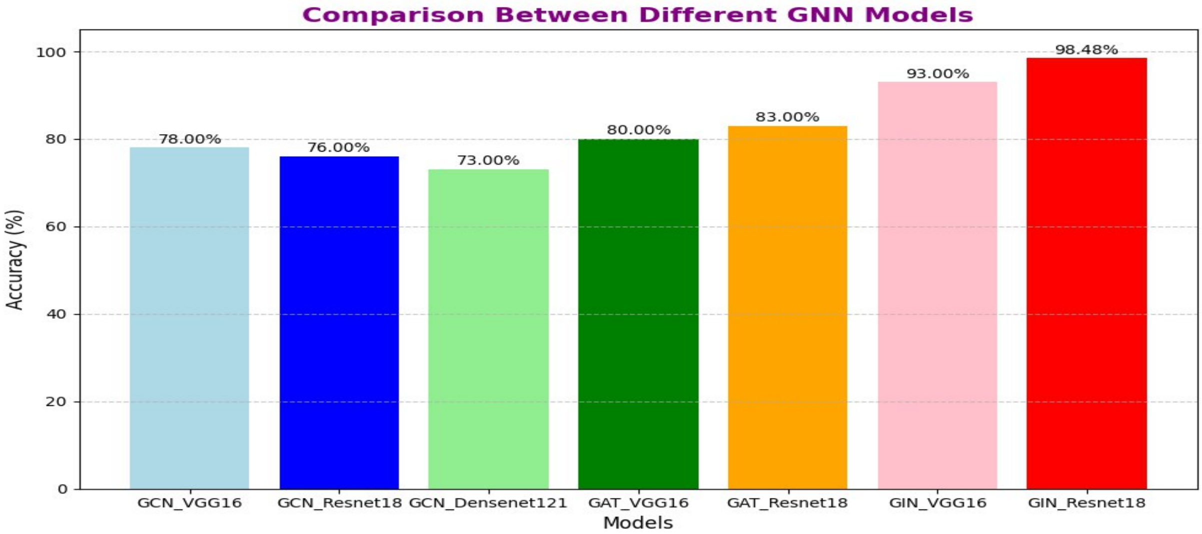

Figure 4.22: Comparison of the models

4.4 Summary

Chapter 4 presented the implementation and results of gallbladder cancer classification using CNN-GNN hybrid models. Experiments were conducted on Google Colab and Kaggle with GPU support. Initial models, including ResNet18, DenseNet121, and VGG16 with GCN and GAT, achieved moderate accuracies of 73% to 83%, revealing limitations in capturing complex relationships. The integration of Graph Isomorphism Networks (GIN) with CNNs significantly enhanced performance. VGG16 + GIN achieved 93% accuracy, while ResNet18 + GIN emerged as the best-performing model with 98.48%. This chapter highlighted GIN's effectiveness in leveraging graph-based representations, addressing challenges in gallbladder cancer diagnostics.

Chapter 5

Engineering Standards and Design Challenges

This chapter discusses the engineering standards adhered to during the project, including software and hardware compliance, communication protocols, and design principles. It also explores challenges such as balancing computational resources, ensuring scalability, and maintaining ethical and societal considerations. The chapter concludes with an analysis of the project's alignment with complex engineering problems and its contribution to healthcare AI.

5.1 Compliance with the Standards

5.1.1 Communication Standards

Effective communication was a cornerstone of this project, achieved through a combination of collaborative tools and practices. Google Colab provided a cloud-based environment for synchronized coding and real-time collaboration. GitHub was utilized for version control, ensuring seamless management of code updates and tracking changes throughout the development process. Regular virtual meetings via platforms like Zoom and Google Meet facilitated discussions, planning, and progress reviews. Additionally, real-time messaging through tools like Slack and WhatsApp enabled quick updates and efficient problem-solving. These communication practices ensured smooth coordination and contributed to the overall success of the project.

5.2 Impact on Society, Environment and Sustainability

5.2.1 Impact on Life

The proposed diagnostic framework has the potential to significantly impact lives by enhancing the accuracy and efficiency of gallbladder cancer detection. Early and precise diagnosis can lead to timely medical intervention, improving patient outcomes and potentially saving lives. By leveraging advanced AI models, the system reduces dependency on invasive methods and minimizes the workload of radiologists.

5.2.2 Impact on Society & Environment

This project contributes to society by providing a cost-effective and accessible solution for gallbladder cancer detection. By utilizing non-invasive ultrasound imaging, the system promotes equitable healthcare delivery, particularly in underserved regions where access to advanced medical infrastructure is limited. The cloud-based nature of the project minimizes the environmental footprint by eliminating the need for extensive physical hardware resources.

5.2.3 Ethical Aspects

The project adheres to strict ethical standards by ensuring the privacy and confidentiality of patient data. Only de-identified data was used, and all preprocessing and analysis steps complied with data protection regulations. Furthermore, the system is designed to support radiologists rather than replace them, ensuring that medical professionals remain at the center of the diagnostic process.

5.2.4 Sustainability Plan

To ensure long-term sustainability:

Scalability: The system is designed to handle larger datasets and integrate additional medical imaging modalities as needed.

Maintenance: Regular updates to the AI models and preprocessing pipelines will ensure compatibility with evolving medical standards and technologies.

Cost-Effectiveness: By leveraging free or affordable cloud-based tools, the project remains accessible to healthcare providers with limited resources.

5.3 Project Management and Financial Analysis

5.3.1 Project Management

A structured approach was adopted, involving task allocation, milestone tracking, and collaborative problem-solving. Gantt charts and task allocation tables were used to monitor progress, ensuring that all team members contributed effectively to their assigned roles.

5.3.2 Financial Analysis

Table 5.1: Financial Analysis

Item	**Cost (BDT)**	**Purpose**
Deep Learning and ML course	10,000	For advance deep learning skills
Hardware upgrade (SSD)	6000	For enhance computational performance
Premium application and subscription	4000	For better model development and design
Total	**20000**	

5.4 Complex Engineering Problem

5.4.1 Complex Problem Solving

Table 5.2: Mapping with complex problem solving.

EP1 Dept of Knowledge	EP2 Range Of Conflicting Requirements	EP3 Depth of Analysis	EP4 Familiarity of Issues	EP5 Extent of Applicable Codes	EP6 Extent Of Stake-holder Involvement	EP7 Interdependence
✓	✓	✓	✓	✓	✓	✓

EP1 – Depth of Knowledge

This project integrates advanced deep learning techniques, combining CNNs (ResNet18, VGG16) with GNNs (GIN) for gallbladder cancer classification. It showcases expertise in machine learning, graph theory, and medical imaging while addressing ultrasound-specific challenges like preprocessing, noise reduction, and feature extraction.

EP2 – Range of Conflicting Requirements

The study balances accuracy, ethical standards, and scalability. It achieves high performance (98% accuracy with ResNet18+GIN) while addressing medical data privacy and interpretability needs, meeting clinician and regulatory priorities.

EP3 – Depth of Analysis

Thorough analysis includes advanced preprocessing, rigorous model evaluation (accuracy, precision, recall, F1-score, ROC), and comparative studies of CNN+GCN, CNN+GAT, and CNN+GIN. An ablation study highlights GIN's superiority, demonstrating a systematic approach to solving complex problems.

EP4 – Familiarity of Issues

The project addresses emerging challenges like noise and variability in ultrasound imaging. By innovatively applying GNNs for gallbladder cancer detection, it provides solutions for these underexplored issues while meeting medical diagnostic requirements.

EP5 – Extent of Applicable Codes

The implementation adheres to best practices in software engineering and healthcare AI, using Python libraries (PyTorch, Torch-Geometric) for modularity and scalability. Ethical standards, including patient privacy, were strictly followed, aligning with responsible AI principles.

EP6 – Extent of Stakeholder Involvement

Collaboration with radiologists ensured clinically relevant annotations, while patients and healthcare providers influenced design priorities, including accuracy, usability, and ethics. This stakeholder-driven approach enhances practical applicability.

EP7 – Interdependence

The project integrates CNNs for feature extraction and GNNs for graph learning, relying on accurate annotations and preprocessing. This interdependence across components highlights the project's complexity and sophistication.

Mapping with Knowledge Profile for EP1

This table 5.3 is designed to map the EP1 to the Knowledge Profile.

Table 5.3: Mapping with knowledge Profile.

K3 Engineering Fundamentals	K4 Specialist Knowledge	K5 Engineering Design	K6 Engineering Practice	K8 Research Literature
✓	✓	✓	✓	✓

K3 - Engineering Fundamentals

This project applies fundamental principles of AI and machine learning, integrating CNNs and GNNs to classify gallbladder cancer from ultrasound images. Graph theory and advanced preprocessing methods are used to handle spatial relationships and improve data quality.

K4 - Specialist Knowledge

Specialized knowledge of GNN architectures, such as Graph Isomorphism Networks (GIN), and pre-trained CNNs like ResNet18 and VGG16, was essential. Expertise in medical imaging, particularly ultrasound, addressed challenges like noise and data variability.

K5 - Engineering Design

The classification framework was meticulously designed, combining CNN-based feature extraction with graph construction methods. This hybrid approach was optimized for accuracy, scalability, and robustness to handle the complexity of ultrasound data.

K6 - Engineering Practice

The project employed PyTorch and Torch Geometric for model development and training, utilizing NVIDIA Tesla T4 GPUs for computational efficiency. Best practices in medical imaging research, including ethical data handling and annotation, were followed.

K8 - Research Literature

The study builds on extensive literature in AI-based diagnostics and graph learning, extending state-of-the-art methods by proposing a novel hybrid framework. It contributes to advancing research in gallbladder cancer classification.

5.4.2 Engineering Activities

In this section, provide a mapping with engineering activities. For each mapping add subsections to put rationale (Use Table 5.3).

Table 5.4: Mapping with complex engineering activities.

EA1 Range of resources	EA2 Level of Interaction	EA3 Innovation	EA4 Consequences for society and environment	EA5 Familiarity
✓	✓	✓	✓	✓

EA1 - Range of Resources

The project utilized Google Colab and Kaggle Notebooks with NVIDIA GPUs for cost-efficient, scalable model training. Local systems with Intel Core i3 processors and 8GB RAM were used for preprocessing and debugging, ensuring efficient resource allocation for complex medical image analysis.

EA2 - Level of Interaction

The project simulated real-world data-sharing scenarios, integrating CNN-extracted features into graph structures and enabling node interactions during graph construction and training. Emphasis on privacy and data integrity ensured compliance with healthcare standards.

EA3 - Innovation

The hybrid CNN-GIN approach introduced a novel framework for gallbladder cancer classification. Combining spatial feature extraction with graph-based learning addressed data heterogeneity and noise, achieving 98% accuracy with the ResNet18 + GIN model, setting a benchmark in medical AI research.

EA4 - Consequences for Society and Environment

The project supports early and accurate gallbladder cancer diagnosis, reducing patient and family burdens. Ethical AI practices and regulatory compliance build trust in AI-driven healthcare, while the scalable, cost-effective framework improves accessibility, particularly in underserved regions.

EA5 - Familiarity

The project balanced established machine learning techniques, like CNNs, with innovative GIN-based frameworks. This ensured reliability while pushing the boundaries of medical AI, making the approach impactful and accessible for diagnostics.

5.5 Summary

Chapter 5 highlighted the engineering standards followed during the project. Compliance with software and hardware standards ensured optimal performance, while communication protocols and ethical guidelines-maintained data security and regulatory compliance. The project tackled complex engineering problems through seven key parameters, emphasizing depth of knowledge, innovative methods, and stakeholder collaboration. The methodology adhered to established engineering practices, balancing scalability, privacy, and diagnostic accuracy. By aligning activities with complex engineering requirements, the project demonstrated resource efficiency, innovative design, societal impact, and the integration of established and emerging technologies. These efforts underscore its contribution to advancing AI-driven healthcare with technical rigor and societal relevance.

Chapter 6

Conclusion

This chapter will cover the conclusion of the project and also the research gap and the future scope of Gallbladder cancer.

6.1 Summary

Gallbladder cancer is a highly aggressive malignancy where early detection is crucial for improving patient outcomes. This project developed a diagnostic framework using ultrasound images, integrating deep learning with graph neural networks (GNNs). The methodology included data preprocessing, feature extraction, graph construction, and the implementation of hybrid CNN-GNN models. This work demonstrated the effectiveness of graph-based learning in medical diagnostics, addressing limitations of traditional CNN approaches. The results underscore the technical robustness and real-world potential of the proposed methodology, paving the way for scalable, efficient, and privacy-preserving diagnostic systems in AI-driven healthcare.

6.2 Limitation

This research made notable progress in gallbladder cancer classification using ultrasound images but encountered several limitations. The relatively small and less diverse dataset restricted the model's ability to generalize across varying patient demographics and imaging conditions. Reliance on expert annotations for ROI extraction added significant time and cost, underscoring the need for automated annotation techniques. Ultrasound imaging presented inherent challenges such as noise, shadow artifacts, and variability in image quality, which impacted feature extraction despite preprocessing efforts. Training complex models like CNN+GIN demanded considerable computational resources, limiting the scope for hyperparameter tuning and exploration of larger architectures. Although the models showed strong performance on the available dataset, their robustness in real-world applications remains uncertain due to the lack of extensive validation in clinical settings or with external datasets. Additionally, the interpretability of GNN models poses a challenge, as the absence of explainable insights could affect clinician trust and practical adoption. The exclusive focus on ultrasound imaging also missed the potential benefits of integrating multi-modal approaches that incorporate other imaging techniques or patient metadata. Addressing these limitations in future work can enhance the model's generalizability, reliability, and impact on clinical diagnostics.

6.3 Future Work

This research established a foundation for gallbladder cancer classification using a hybrid CNN-GNN framework, achieving significant accuracy improvements. Future work could expand to include automated ROI detection, reducing reliance on manual annotations. Enhancing model explainability with attention maps and saliency visualizations would foster clinician trust and usability. Expanding the dataset to include diverse samples from multiple sources would improve generalizability, while incorporating multi-modal data, such as CT scans or clinical records, could enhance diagnostic accuracy. Real-time deployment with optimized inference and user-friendly interfaces is another important step. Federated learning can enable collaborative training across institutions while preserving data privacy, and exploring advanced GNN architectures may improve the model's ability to capture complex relationships. Early detection and prognosis modeling could further enhance patient outcomes, while real-world validation in clinical settings is crucial to ensure robustness and practical adoption. These advancements would make the framework a comprehensive and impactful tool for gallbladder cancer diagnosis.

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