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Breast Cancer Detection Using Features Fusion by Mammography and Ultrasound in GNNs

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Abstract

The breast cancer is one of the causes of cancer related death in all parts of the world and in this case, early and accurate cancer diagnosis is the key to enhancing patient survival and treatment results. Even though medical imaging techniques, e.g., mammography and ultrasound, are commonplace, the current computer-aided diagnostic strategies tend to be ineffective in terms of spatial interdependencies and complementary information among different imaging modalities. In order to overcome this drawback, this paper introduces a multi-modal breast cancer detection model, which aids in the representation of mammogram and ultrasound images as a graph, and uses the representational characteristics of Graph Neural Networks (GNNs) to learn complex spatial relationships among regions of interest. Two high-level architectures are explored, one is a Spatial-Temporal Graph Neural Network (ST-GNN) designed to learn the contextual appearance of the spatial dimension and the other is an LSTM-enhanced GNN (LSTM-GNN) designed to learn the temporal appearance of the temporal dimension. The experiment is carried out on a clinically validated dataset of 205 cases and 405 high-resolution mammogram and ultrasound images of participants gathered with the help of the standardized medical imaging device. Quantitative analysis proves that the ST-GNN is much better than the LSTM-GNN which has accuracy of 85, precision of 74, recall of 93, F1-score of 82 and AUC of 0.87 indicating the efficiency of spatial graph modeling in breast cancer detection. The findings validate the hypothesis that multi-modal fusion based on graphs will offer a strong and scalable solution to improve diagnostic accuracy, sensitivity, and clinical decision support in automated systems of breast cancer screening.

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1 Introduction

World Health Organization (WHO) declares that due to breast cancer nearly 10 million deaths have been recorded in 2020 [1]. Dead tissues in the breast cause these cancerous tumors. Breast cancer is mostly found in women but it cannot be gender specific anyone can develop it. Approximately 10 percent of women can experience breast cancer at any phase of their life. Breast cancer can develop in any region of the breast. Most breast cancers start in the lobules or the duct. However, detection at early stages can be lifesaving, motivating patients to get complete treatment, hence enhancing their survival chances and health conditions. Biomedical imaging techniques such as X-rays, mammography, magnetic resonance imaging (MRI), and ultrasounds are used to identify or detect cancerous cells in the breasts [2]. Mammograms and ultrasounds are used in this proposed study to train the system to locate the abnormal regions in the breasts. Breast cancer has two main types known as benign or malignant tumors. The benign tumor cells are restricted to the breast area and they can only grow within and they do not divide into other cells in the body. Whereas, a malignant tumor consists of cancerous cells that can grow abnormally. They can spread through the body infecting other tissues. Since cancer cells have different properties like shape, size, and location, detecting and locating the tumor tissues in the breast image is a critical process, and automation of this process is a challenge.

Machine learning techniques [3] have discovered a huge range of applications in various fields, including predictions, natural language processing, medical diagnosis, business intelligence, pattern recognition, etc. Its greatest potential was found in the medical diagnostic field [4]. A vast amount of data can be used to identify the abnormal specimen in the breast region that can help in diagnosing the cancer and further predictions can be made based on the results. The models can be trained using the patient's medical history, imaging data, and genetic data, which may lead to the prediction of such diseases and early detection can reduce the number of deaths.

Traditional statistical methods are not viable enough to provide pattern recognition information and it is also time-consuming based on the process involved in diagnosing the cancer. By using machine learning algorithms researchers can train models with better accuracy of breast cancer diagnosis, creating a better tool for doctors or radiologists for assistance. Furthermore, ML algorithms can be used to identify abnormal development of tissues in any part of the body, identify patients who are likely to develop breast cancer and provide a better picture of the disease.

This paper models the ultrasound and mammogram data into graphical structures to capture the complex relations and interdependencies in the data. It shows how breast cancer can be identified using two imaging techniques with the help of GNNs [5]. We have used two latest GNN models to classify the data based on its spatial and temporal properties. ST-GNN is used to capture the spatial region and LSTM-GNN shows the temporal outcomes of the data. An extensive literature review is presented in this paper for contextual purposes.

One of the main benefaction of this study is to combine two different modalities and show their synergy, which can enhance the potential results in the detection of breast cancer. Also it addresses the spatial context of the images to learn more about the informative features that can be missed during the evaluations. GNNs are used because they can capture all the necessary details related to the regions of interest and highlight the interdependencies of the fusion features

Cancer is a chronic disease caused by uncontrollable cell growth because cancer research is becoming more and more data-rich, it is a complicated phenomenon. Comprehending this information in a way that is comprehensible to both humans and computers can aid in the organization and evaluation of intricate cancer data [5]. Breast Cancer is a leading concern worldwide, millions of people are diagnosed with this disease each year. Looking at the deadly types of cancer, breast cancer has the highest survival rate with detection in stage I and II. Early cancer detection is a critical and stressful process and diagnosis accuracy can be challenging because the symptoms at these stages are difficult to localize.

Traditional approaches to breast cancer diagnosis are time-consuming and expensive, biopsy examination is a painful procedure and they may produce inconsistent results or be prone to human error. Artificial Intelligence can be used to overcome such problems with the potential to automate the processes leading to faster and more accurate diagnosis of the disease. Using ML and deep learning algorithms a vast amount of data from different techniques such as medical imaging techniques, genetic records, and clinical procedures can be analyzed in less duration of time and it can cut out a lot of manual work done by healthcare professionals at lower healthcare costs.

Breast cancer detection remains a critical healthcare challenge, necessitating innovative approaches to enhance accuracy and early diagnosis. In response, we propose a solution that harnesses the power of Graph Neural Networks (GNNs) to improve breast cancer detection using a unique dataset. This dataset, composed of 205 cases originating from the United States, presents cases warranting further investigation post-mammogram screenings. Each case is accompanied by 405 distinct images, capturing either the left or right side of the breast. These images, obtained through the iU22 x MATRIX medical imaging device, are available in both DICOM and JPG formats and possess dimensions of 2816 by 3584 pixels. Our proposed solution leverages GNNs to enhance breast cancer detection by effectively harnessing the spatial relationships within mammogram and ultrasound images. This approach not only demonstrates the potential of advanced machine learning techniques but also serves as a foundation for more accurate and early diagnoses in the realm of breast cancer.

1.1 Major Contribution

- Integration of Modalities: By combining mammogram and ultrasound images, the research showcases the synergy between these modalities. The integration of two distinct imaging techniques enhances the potential for accurate and comprehensive breast cancer detection.

- Graph-Based Representation: The research introduces a novel approach by representing breast images as graphs. This graph-based representation captures spatial relationships and enables the utilization of Graph Neural Networks (GNNs) for enhanced feature learning and classification.

- GNN Application: The utilization of Graph Neural Networks presents a significant contribution. GNNs are applied to the breast image graphs, exploiting their ability to model complex spatial relationships and learn informative features, particularly relevant to medical image analysis.

- Spatial Contextualization: The research emphasizes the importance of spatial context in breast cancer detection. By effectively capturing spatial relationships between different regions of interest, GNNs offer improved accuracy in identifying abnormalities.

- Multi-Modality Fusion: The research demonstrates the power of GNNs in seamlessly integrating information from mammogram and ultrasound images. This fusion of multiple modalities enhances the model's ability to make informed and accurate predictions.

This study is arranged into seven major sections. Section 1 has an background and introduction of the topic, section 2 has literature work, section 3 describes the data, section 4 explains the proposed methodology, then Chapter 5 describes the methodology. In section 6, we have discussed the results and finally, section 7 has the conclusion of the whole paper.

2 Related Word

Many researchers over the decades have studied deep learning, but major advancements in the medical field have been achieved recently. With these advancements, the area evolved as a top trend in the AI field. Robotics have already replaced doctors where precision is the top priority. Here we have listed the related work, which demonstrates the contributions and limitations of the previous research.

A multi-modal dynamics algorithm [6] highlights the significance of trustworthy multi-modal fusion in the context of integrating heterogeneous and high-dimensional data. The proposed Multi-modal Dynamics algorithm addresses the limitations of conventional approaches by dynamically evaluating the informativeness of features and modalities, ensuring reliable fusion. The empirical evaluations on multi-modal medical classification data sets provide compelling evidence of the algorithm's superiority, emphasizing its potential for advancing multi-modal classification in critical domains. Future research can further explore the applicability of Multi-modal Dynamics in other domains and extend its capabilities for handling additional challenges in multi-modal data integration.

Whereas, [7] emphasizes the importance of addressing the challenges associated with fully supervised mass detection through the utilization of weakly labeled data and self-training. The proposed framework showcases promising results by effectively refining the model using soft image-level labels and a sample selection strategy. However, existing methods cannot often reason across cross-view images guided by domain knowledge, which limits their performance.

The clinical significance of cross-view reasoning in mammogram mass detection, as the cross-views contain valuable complementary information for accurate diagnosis [8]. The introduction of the bipartite graph convolutions network provides a solution to incorporate the reasoning ability exhibited by radiologists. The experimental conclusions show the effectiveness of the presented algorithm, demonstrating its superiority over existing methods. The model's interpretability further contributes to its utility in clinical practice. Future research directions may involve the assessment of the proposed algorithm on diverse data sets and the exploration of additional strategies to enhance cross-view reasoning in mammogram mass detection.

The importance of explicitly modeling pairwise lesion correspondence in mammogram mass detection [9]. The proposed CL-Net framework offers a novel solution by combining the Lesion Linker and View Interactive Lesion Detector, providing end-to-end learning of lesion correspondence and detection. The performance on benchmark demonstrated state-of-the-art datasets and significant performance improvement over previous methods underscore the effectiveness and potential of CL-Net. Future research directions could explore the generalizability of CL-Net across diverse datasets and evaluate its performance in real-world clinical settings to validate its practical utility.

A novel is introduced that interprets the artificial intelligence (AI) model for automated detection along with the classification of heterogeneous calcification patterns distribution in mammograms [10]. The approach utilizes a unique graph convolution method to enhance interpretability. A graph-convolutions-network-based model was created to be evaluated based on classification performance metrics. The results demonstrate that the baseline models were outperformed by the presented model in terms of assessment metrics such as accuracy, F1 score, recall, precision, and area under multiple classes of receiver operating characteristic curves. The model gained high precision, sensitivity, specificity, F1 score, and accuracy. Moreover, it showed superior performance in classifying linear and diffuse patterns, as well as grouped and regional patterns compared to baseline models. The interpretability of the model is facilitated through visualization techniques, which focus on significant calcification nodes in the graphs.

The rapid research development in bio-technologies has led to important advancements in medical equipment, expanding the range of available imaging modalities. Optical Imaging, ultrasonic imaging, and Magnetic resonance imaging (MRI) have emerged as multi-modal systems with applications in the field of bio-medicine. Among these modalities [11], photo-acoustic imaging (PAI) has gained attention as a powerful tool that merges the principles of ultrasonic and optical systems. The SEODTL-BDC model [11] presents a novel approach to breast cancer detection and stratification, combining photo-acoustic imaging, deep transfer learning, and social engineering optimization. By utilizing bilateral filtering, lightweight segmentation models, feature extraction with ResNet-18, and stratification using models such as SEO-RNN, and SEODTL-BDC which achieved superior performance compared to existing methods. The results underscore the potential of this approach to improve the early detection of breast cancer and ultimately contribute to better patient outcomes.

To achieve the objective of enhanced BC classification, [12] implements a combined model, long short-term memory (LSTM), and convolutional neural network (CNN) using results from mammography and sonography. This hybrid deep learning approach grasps the strength of CNNs in image feature extraction whereas LSTMs in capturing time-dependent features to improve the accuracy of classification. A real-time dataset comprising 43 mammogram and ultrasound images gathered from 31 patients is utilized in this study. Each class consists of 25 benign and 18 malignant images. To augment the dataset and increase its size, various data augmentation techniques are employed, resulting in a total of 1032 images (516 for each modality). By combining mammogram and ultrasound images using a CNN-LSTM model, the algorithm achieves high classification accuracy and outperforms traditional uni-modal CAD systems. The results underscore the potential of this approach to improve early BC diagnosis, reduce unnecessary biopsies, and enhance clinical decision-making.

Table 1: Related Work in Breast Cancer Detection

Study (Citation)	Algorithm	Approach
Han (2022)	MMD	Trust Fusion
Liu 2020)	Bipartite GCN	Cross-View Reasoning
Zhao (2022)	CL-Net	Lesion Corr.
Yao (2022)	GNN	Calcif. Detect.
Althobaiti (2022)	SEODTL-BDC	PA Imaging
Atrey (2023)	CNN-LSTM	MM Classification
Xi (2022)	MCEM	Tumor Diagnosis
Zebari (2021)	HTMLF	Image Proc. and Fusion

The fusion of mammography and ultrasound images has shown potential in improving the accuracy of tumor classification in breast cancer diagnosis [13].

However, conventional fusion models often overlook the correlation between the two modalities, which occurs in finite performance refinement. To resolve this issue, a correlation embedding modality model has been presented for breast cancer diagnosis, which combines mammography and sonography. In combination with optimizing the correlation among mammography screenings and ultrasound screenings techniques and the classification loss in individual modalities, the model learns more than one mapping to project ultrasound and mammography from their original feature positions into a common label space.

An evaluation is conducted on a dataset comprising mammography and ultrasound images of 73 patients. The evaluation results on a dataset comprising ultrasound and mammography images showcase the effectiveness of the presented method [13] in accurately diagnosing breast tumors.

Using mammogram images breast cancer detection combines hybrid threshold, machine learning, and fusion techniques. The experimental evaluation [14] on multiple benchmark datasets showcases the effectiveness and superiority of the approach. By leveraging wavelet transform, an improved fractal dimension approach, and a genetic algorithm for feature reduction, the proposed method achieves accurate stratification of malignant and benign breast tumor. The fusion of results from multiple blocks enhances the final decision-making process. The study handsout to the field of breast cancer diagnostics and underscores the potential for improved early detection using advanced image processing and machine learning techniques.

A commentary [15] discusses the application of deep neural networks (DNN) in breast cancer diagnosis and imaging techniques within computational radiology. Recent studies focus on developing AI-driven tools to enhance digital mammogram interpretation. These AI-driven systems offer the potential for improved diagnostic accuracy and efficiency by learning intricate patterns in mammographic images. Integration of AI in radiology workflows aims to standardize processes, enhance patient care, and improve diagnostic accuracy by automating tasks like lesion detection and classification, ultimately benefiting patient care through accurate and timely diagnoses.

3 Dataset

The dataset was collected from King Abdulaziz University. It has 405 ultrasound and mammogram case data. Annotation of the dataset is done by three different radiologists [16].

These ultrasound (US) images were captured using the iU22 x MATRIX medical imaging device and are available in both DICOM and JPG formats. The dimensions of these images are 2816 by 3584 pixels.

The significance of ultrasound becomes evident following a mammogram, as mammography excels at identifying early-stage abnormalities, while ultrasound plays a crucial role in detecting more advanced stages. Notably, some of the ultrasound diagnoses align with mammogram findings, while most ultrasound-diagnosed images are categorized as BI-RADS 0 based on mammogram results.

It is important to note that the US images are provided in their raw form, lacking annotations. The data set covers cases that are benign, cancerous, and normal. It also includes information about the pathology and the histories of the patients. The age and prior screenings are included since they can be relevant to the researcher's research. Since BI-RADS categories are seen to be crucial pieces of knowledge for a digital mammography data set, they were also recorded. On the data set, the authors provide DICOM and JPG formats [16].

3.1 Mammogram and Ultrasound Images

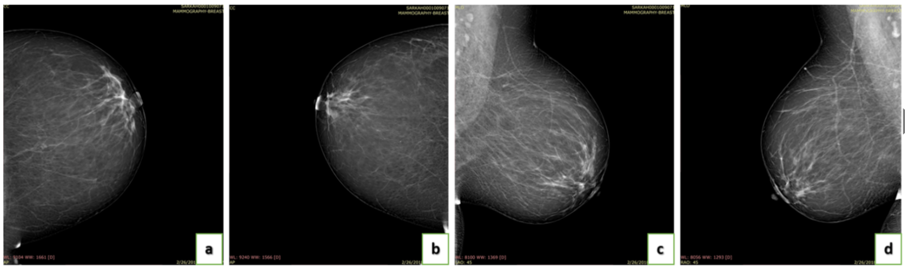

Figure 1: a) CC left breast b) CC right breast c) MLO right breast d) MLO left breast

Figure 2: a) BI-RADS 1 left breast b) BIRADS 3 c) BIRADS 4

The data acquired is unsupervised so, to add labels to the data we have used the K-Means clustering technique to classify the data. K-Means is a popular clustering algorithm used to group similar data points based on their features. In this case, we have a dataset with information about patients, including their ID and mammogram/ultrasound results. To apply K-Means to this dataset, first, we will remove the patient column as it is a unique identifier. Then BIRAD scores are encoded in numerical values. After the feature selection, we have chosen the number of clusters to be formed. The results will now get us the clusters formed for each record.

4 Proposed Methodology

Breast cancer poses a significant global health challenge, demanding precise detection and accurate diagnosis for improved outcomes and survival rates. Recent years have witnessed a pivotal role of technology in healthcare, with Data Sciences playing a crucial role in analyzing medical datasets. Emerging machine and deep learning (DL) methods, such as Graph Neural Networks (GNNs), became essential tools for healthcare workers, providing a better understanding of complex data structures.

Neural Networks (GNNs) are now providing a better understanding of complex data structures. Now, we can use GNNs to get a better understanding of breast cancer tumors, enhancing the analysis of different imaging techniques. By utilizing the architecture of GNNs in the analysis of medical datasets, healthcare professionals and researchers can gain deeper insights into the disease, predict abnormalities with higher precision, and ultimately provide better ways for efficient patient care.

GNNs use deep learning approaches to reach certain conclusions based on the structural information present in medical datasets, such as patient records, mammogram and ultrasound images, and diagnostic reports. Unlike traditional machine learning methods, GNNs are designed to model relationships and dependencies among data points explicitly. GNNs use graph datasets based on two main parts of the input graphs: their nodes and their edges for making decisions. In the context of breast cancer, these relationships can hold crucial clues about disease progression, risk factors, and diagnostic markers.

In this study, GNNs are used to find potential abnormalities in the breast cancer dataset. GNN architecture is used to work on a multimodal approach that is mammograms and ultrasound datasets. Graph structures are created to deduce conclusions based on the BIRAD scores of the patient's data. Through this research, we can aim to get an understanding of how GNNs can handle the complexity of data and revolutionaries inherent to breast cancer management, from detection to treatment. Finally improving the diagnostic approaches.

4.1 Graph Neural Networks (GNNs)

GNNs employ deep learning approaches to draw conclusions based on structural information within medical datasets, including patient records, mammogram and ultrasound images, and diagnostic reports. Unlike traditional machine learning methods, GNNs explicitly model relationships and dependencies among data points, using graph datasets with nodes and edges. In the context of breast cancer, these relationships offer crucial insights into disease progression, risk factors, and diagnostic markers. Graph Attention Networks (GAT), Graph Convolutional Networks (GCNs), GraphSAGE, and Graph Isomorphism Networks (GIN), Gated Graph Neural Networks (GGNNs) are a few examples of well-liked GNN architectures. The issue and dataset being handled often influence the choice of GNN architecture and hyperparameters. GNNS Architecture involves the following steps:

- **Graph Representation**:
  Nodes represent entities or data points in the graph. Edges represent connections or relationships between nodes. An adjacency matrix is a fundamental component of a GNN, encoding the graph's topology. It is a binary matrix indicating which nodes are connected through edges.
- **Node Features**:
  Each graph node typically has associated feature vectors. These features can be attributes or characteristics of the nodes (e.g., node labels, numerical values, embeddings).
- **Message Passing**:
  The core idea of GNNs is to perform message passing between neighboring nodes in the graph. Each node aggregates information from its adjacent nodes and updates its representation.
- **Layers and Stacking**:

GNNs consist of multiple layers, with each layer performing message passing and feature updates iteratively. Outcome of first layer becomes the value for the next layer. These layers can be stacked to increase the model's depth and capture more complex patterns in the graph.

- **Node Classification or Graph Tasks**:
  For different graph related tasks we use GNNs, such as node classification, graph classification,link prediction, and suggestion. In node classification, GNNs predict labels or properties for each graph node is based on the information gathered during message passing.
- **Aggregation Functions**:
  Different GNN architectures use various aggregation functions.Common aggregation methods include mean aggregation, sum aggregation, attention mechanisms, and more. The choice of aggregation function can impact the GNN's ability to capture different types of information from neighbors.

In this study, GNNs are utilized to identify potential abnormalities in a breast cancer dataset. The GNN architecture adopts a multimodal approach, incorporating mammograms and ultrasound datasets. Graph structures are created to deduce conclusions based on the BIRAD scores of the patient's data.

4.2 ST-GNN (Spatio-Temporal GNN)

The ST-GNN model extends the capabilities of GNNs by incorporating spatio-temporal aspects into breast cancer analysis. This model leverages the temporal dynamics of patient data to enhance predictions, offering a more comprehensive understanding of disease progression.

ST-GNN known as Spatio-Temporal Graph Neural Network, a kind of neural architecture built to handle data that has both spatial and temporal properties. It is particularly useful for modeling and analyzing data, where information varies not only across different locations but also over time. ST-GNNs are widely used in various applications, including the medical field, where they can be used to analyze and make predictions based on Spatiotemporal medical data. ST-GNNs are an extension of GNNs, which involves working with data that combines both spatial (location-based) and temporal (time-based) information, which is common in fields like transportation, environmental science, and healthcare.

Their contribution to the medical field involves predicting disease spread over time, monitoring patient's health vitals, drug interactions over time in the body, and many more cases like these. In our scenario, ST-GNNs are used to prepare the data for training a machine learning model to predict BIRAD scores for future patients based on their test results. The dataset contains information related to breast cancer screenings. Each patient has two main screening results i.e. mammograms and ultrasound. BIRAD system is used in this dataset to categorize the results, which will help in the assistance of medical decisions.

The data is preprocessed for the construction of graphs before applying the ST-GNN model. The data is cleaned and transformed into a numerical format to train the model on the categorical nature of data. Then a Spatio-temporal graph is created to represent a relationship between patients and their screenings. The nodes of the graph represent the patient data and the edges show the spatial relationship of the patient's medical results. In the final step, the ST-GNN model is applied to the data with convolutional layers for spatial processing and attention-based layers for temporal modeling.

After the application of the ST-GNN model, the data is trained and validated. Loss functions and evaluation metrics are applied to find the accuracy of the model. Once the model is trained, we can use it to predict BIRAD scores for future patients.

4.3 LSTM-GNN

The LSTM-GNN method aggregates the power of Long Short-Term Memory networks with GNNs to capture temporal dependencies in breast cancer data. This enables the model to make predictions based on the sequential nature of medical information.

LSTM-GNN, or Long Short-Term Memory Neural Graph Network, is a hybrid neural network architecture which joins the strong points of Long Short-Term Memory (LSTM) networks and Graph Neural Networks (GNNs) to process and model sequential data within a graph-based context. This architecture is often used for tasks where you have sequential data associated with nodes in a graph and we want to gather both the time based dependencies and the relational information between nodes in the graph.

Following are the main steps of LSTM-GNN Working

- **Graph Representation**: In LSTM-GNN, a graph is constructed where nodes represent entities (e.g., objects, users, patients), and edges represent relationships or interactions between these entities. This graph could be static or dynamic, depending on the nature of the problem.
- **Node Features**: Each node in the graph has associated features, which can include attributes of the entities or any relevant information.
- **Temporal Sequences**: In addition to the graph structure, we have sequential data associated with each node. This data evolves and represents the temporal aspect of the problem.
- **LSTM Component**: The LSTM part of the architecture is responsible for modeling the temporal dependencies within the sequential data for each node. It takes in the sequential data as input and uses its memory cells and gating mechanisms to capture patterns and dependencies over time. This helps in understanding how the features associated with each node change and evolve.
- **GNN Component**: The GNN part of the architecture is responsible for capturing relational information between nodes in the graph. It aggregates information from neighboring nodes and updates the features of each node based on the features of its neighbors. This step allows the model to consider the context and relationships between nodes.
- **Integration**: The LSTM and GNN components are typically integrated into different ways depending on the specific task. One common approach is to use the LSTM to process the sequential data and update the node features over time. Then, the GNN component uses these updated features to perform message passing and aggregation over the graph structure.
- **Task-Specific Output**: Finally, the integrated information is used for the task at hand, which could be node classification, link prediction, graph classification, or any other relevant task.

LSTM-GNN is powerful because it combines the ability of LSTMs to model temporal dependencies with the capacity of GNNs to capture relational information in graph-structured data. This makes it suitable for various applications where both the temporal evolution of data and the relationships between entities in a graph are difficult to manage and analyze.

Through this research, we aim to comprehend how GNNs, ST-GNN, and LSTM-GNN can handle the complexity of breast cancer data, revolutionizing the entire breast cancer management process, from detection to treatment, and ultimately improving diagnostic approaches.

4.4 Block Diagram

The model of the proposed solution shows the architectural view of this study. It includes all the necessary steps involved in the process.

1. Dataset

The initial step is to get the mammogram data. For this study KAS-BDMS dataset is used which is widely known for breast cancer research purposes.

2. Data Preprocessing

Data filtering and preprocessing is an important steps to eliminate the null values and transform categorical values into numerical values for application in models.

3. Graph Construction

Convert the images into graph structures. Each node could represent a region of interest, and edges represent spatial relationships between these regions.

4. Model Architecture and Training

Designing a suitable architecture for the implementation of graph structure including graph convolutional layers, pooling layers, and fully connected layers. After the model implementation, the data is trained.

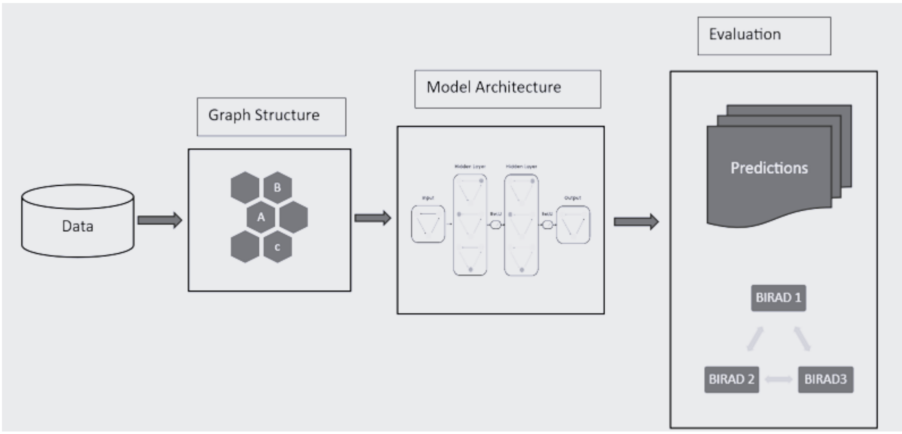

Figure 3: Block diagram to show the model's architecture

5 Methodology

In this study, mammograms and ultrasounds are analyzed to determine the spatial relationships and interactions within breast images. After the examination, the findings are categorized by the BIRAD system which uses a numerical scale and specific categories to describe breast imaging findings, with each category indicating a different level of suspicion for malignancy.

We have used two main GNN architectures to carry out the experimentation, ST-GNN and LSTM-GNN. ST-GNN stands for Spatio-Temporal Graph Neural Network, which is a neural network architecture designed to handle data that has both spatial and temporal properties. LSTM-GNN, or Long Short-Term Memory GNN, is a hybrid neural network that joins the strengths of LSTM networks and Graph Neural Networks (GNNs) to process and model sequential data within a graph-based context.

5.1 Clustering

The actual data was not labeled due to which we must perform clustering to categorize the patients based on their BIRAD evaluations. We will use these labels for testing and training the models, as it identifies the hidden patterns and structures within the data. In our case, clustering identifies the groups of patients with similar mammogram and ultrasound characteristics.

To find the most suitable clustering method for our data, we have compared the K-means and DB-SCAN clustering. K-means clustering helps in creating clusters based on the spherical properties of the data, as our data is based on spherical properties so the data is divided into two main classes according to the values. We can see that K-means separates the classes so, it has an advantage over the DS-SCAN method. The ST-GNN is divided into several layers for the best results, the first layer is graph convolution in which it updates the nodes' features based on the graph structures and weight matrix.

5.2 Graph Representation of Patient-Breast Screening Relationships

The concept of creating edges between patients and their corresponding breast cancer screening results is the main aspect of organizing and representing the data in a graph. The graph dataset will help us in handling complex relationships between entities, making them particularly well-suited for this data, where relationships between patients and their breast screening are highly interconnected. In a graph data model, data is represented as nodes (vertices) and edges (relationships) connecting these nodes. Here is a detailed explanation of how patient-breast screening results relationships work in this context:

Nodes:

- **Patients**: Each patient is represented as a node in the graph. This node contains patient-specific information, such as their name, unique identifier, date of birth, gender, contact details, and other relevant data.
- **Medical Reports**: Each medical report is also represented as a node in the graph. These nodes typically contain information related to the medical report itself, such as its name (e.g., "Right Mammogram," "Left Mammogram," "Right Ultrasound," "Left Ultrasound"), date of the report, the healthcare facility where it was generated, and possibly key medical findings or conclusions.

Edges

- **Patient-Breast Screening Relationship**: To represent the connection between a patient and their medical analysis, we created edges (relationships) between the patient node and each of their medical report nodes. These edges signify that a patient has multiple medical reports associated with them.
- **Directionality**: In this scenario, the edges are typically directed from the patient node to the screening nodes. This directionality indicates that the patient is associated with the medical reports but not vice versa. In other words, we can traverse from a patient to their medical reports to retrieve information about the reports.

Attributes

Each edge in a graph can also have attributes associated with it. In this context, the edge between a patient and a medical report may include information about the relationship itself, such as the date the report was generated, the physician who ordered it, or any other metadata relevant to the patient-report association.

Querying and Use Cases

With this graph structure, you can perform various queries and analyses that are essential in healthcare, such as:

- Quickly find all medical screenings associated with a specific patient by traversing the edges from the patient node.
- Identifying patterns or trends in a patient's medical history by analyzing their connected medical reports.
- Tracing the referral chain by identifying which physicians ordered specific medical reports for a patient.
- Supporting decision-making processes, such as treatment planning, by providing easy access to a patient's medical history.

In summary, by establishing edges between patients and their medical screenings for breast cancer in a graph database, we can create a flexible and efficient data model for representing healthcare data. This approach allows us to easily navigate complex relationships in the medical domain, making it valuable for healthcare professionals, researchers, and administrators who need to access and analyze patient data and medical reports effectively.

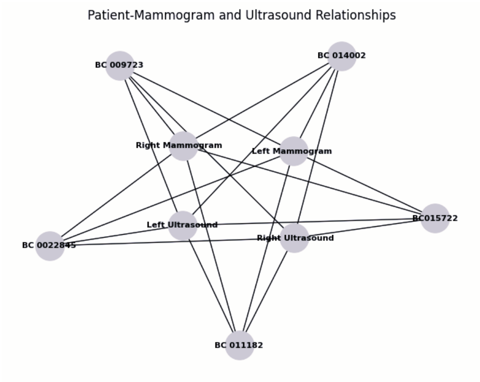

Figure 4: Patient Mammogram and Ultrasound Relationship

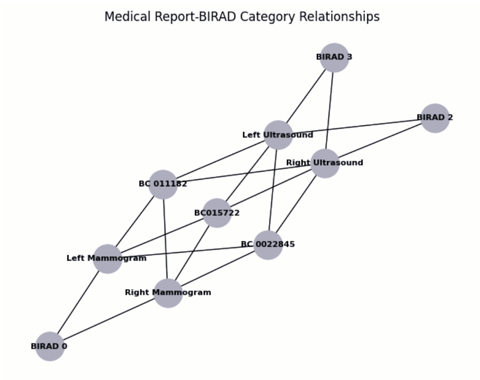

Figure 5: Medical Data and BIRAD Relationship

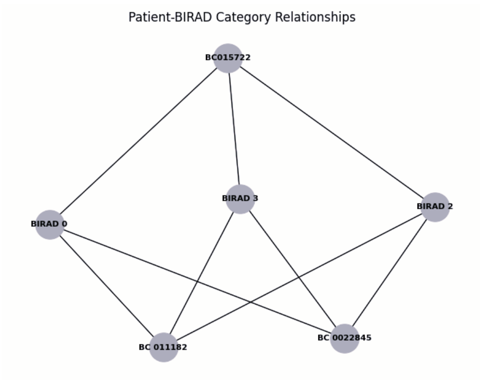

Figure 6: Patient and BIRAD Relationship

ST-GNNs are more suitable for both spatial and temporal relationships, in our data we can see that there is a lot of node feature dependency and if they are monitored for a period, they can provide evident results for future patients. Such links are patient IDs with their mammographs and ultrasound results, which are collected over time. ST-GNN can effectively capture how these results evolve. A complicated graph structure is formed with ST-GNN for this data. This shows the complexity of the dataset and its relationships. All the nodes are linked with patient ID and their respective medical data.

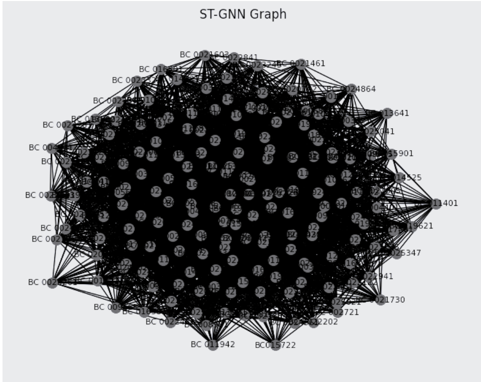

Figure 7: ST-GNN Graph

Working with these complex relationships between mammograms and ultrasound data, the analysis of breast cancer will become an easier and less time-consuming process. These graph structures will resolve the complexities of huge datasets and help us in predicting upcoming scenarios as well. The spatial properties of ST-GNN played a great role in handling the relationships between the mammograms and ultrasounds of the patient.

In summary, when we examine the performance of the model in detail, several comparative properties of performance can be seen. The ST-GNN model achieved a reasonably good performance, boasting an accuracy rate of 85 percent, indicating its ability to make correct predictions to a substantial degree. However, a closer examination of the confusion matrix reveals the presence of misclassifications, suggesting that it is not entirely error-free and occasionally errors in its predictions.

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5.3 Equation

$$z1 = \mathrm{ReLU}(W1 \cdot x + b1)$$

For linear transformations,

$$z2 = W2 \cdot z1 + b2 \tag{1}$$

Here softmax activation function is used,

$$y_{\mathrm{pred}} = \mathrm{softmax}(z2) \tag{2}$$

In this equation x is the input data, W1 is the weight and b1 is the bias of the first fully connected layer, whereas for the second fully connected layer W2 and b2 are the weights and biases. ReLU is defined as the rectified linear unit activation method applied element-wise. Softmax is the softmax function applied to obtain class probabilities.

Another method which is used in this study is LSTM. The LSTM-GNN model demonstrated an average level of performance, the confusion matrix indicated that the model performed well in correctly predicting the first class and it showed poor performance for the instances of the second and third class. It is a common issue in classification problems, and it might suggest that the model needs further tuning or that there is an imbalance in the dataset, with many more examples of the first class compared to the other classes.

In this study, the relationship between mammograms and ultrasound is converted into graph-like structures to dig out the data insights. The LSTM layer processes the input features using the following equations:

5.4 Equation

$$\text{LSTM Layer: } h_t^{(v)} = \text{LSTM}\left(\sum_{u \in N(v)} \text{GNN}(h_{t-1}^{(u)}, e_{(u,v)})\right) \tag{3}$$

In this equation $h_t^{(v)}$ denotes the hidden position of node v at t, and it is determined by applying the LSTM operation to the sum of GNN outputs for each neighboring node u in the set $N(v)$. The set $N(v)$ represents the neighboring nodes of v. The GNN operation is denoted as $\text{GNN}(h_{t-1}^{(u)}, e_{(u,v)})$ and involves the hidden position of node u at the $t - 1$ which is previous time and edge information between nodes u and v.

5.5 Equation

$$\text{LSTM Input: } h_t = \text{LSTM}(x_t, h_{t-1}) \tag{4}$$

$$\text{LSTM Output: } o_t = \text{LSTM}(x_t, h_{t-1}) \tag{5}$$

$$y = FC(o_{\text{last}}) \tag{6}$$

The first equation represents the input to the LSTM layer, where it is the input at time t, ht is the hidden position at time t, and h(t-1) is the hidden state of previous time $t - 1$. The second equation from the LSTM layer, with ot denoting the output at the time t. last is the last output of the LSTM sequence, and y is the output of the model.

The model uses Adam optimizer, which minimizes the loss:

5.6 Equation

$$W_{\text{new}} = W_{\text{old}} - \text{lr} \cdot \nabla L \tag{7}$$

The equation represents the update rule for the model weights, where Wnew is the new set of weights. W(old) is the previous set of weights or is the learning rate and L is the gradient of the loss considering the model parameters. After training, the model is tested on the test data set. Predicted labels are obtained and used for evaluation.

LSTM performed average on this dataset because, for the LSTM model, much more data is needed to train the model and improve the performance of the model. Due to the limitations of a public dataset of mammograms and ultrasounds, the model lacked the desired results. Class imbalance issues can also be a factor, affecting the performance of the model. Also, the random initializations of graph data can influence the results.

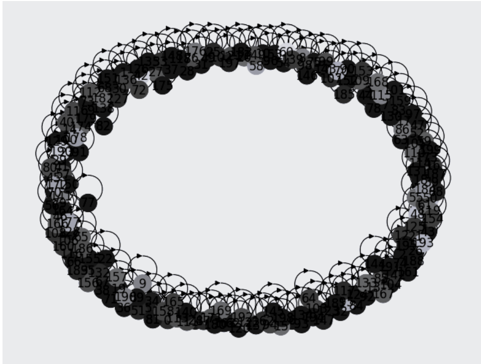

Figure 8: LSTM Graph

In summary, the LSTM-GNN substantially performs well while the ST-GNN performs well in this task, delivering notably accurate and precise predictions for BIRAD scores. However, further investigation and rigorous testing may be necessary to substantiate its robustness and reliability for potential clinical utilization.

6 Results

In this section, the results are shown after the evaluation of the proposed methods. The models were trained to predict the testing data with true labels: BIRAD categories and Patient ID. The model's performance is evaluated using evaluation metrics. In ST-GNN, we got better results as compared to LSTM-GNN.

6.1 Performance Evaluation

In this section performance evaluations are defined and used in this study,

6.1.1 Accuracy

Accuracy measures the truth of the model. It is the ratio of true instance predictions against the total instances.

The formula for calculating accuracy is given by:

$$Accuracy = \frac{TPositive + TNegative}{TPositive + TNegative + FPositive + FNegative}$$

6.1.2 Precision

Precision is used to measure the ratio of true predicted positives to total positive instances. It indicates the correctness of positive observations against all other positive outcomes.

The formula for calculating precision is given by:

$$Precision = \frac{TPositive}{TPositive + FPositive}$$

6.1.3 Recall

Recall is the true positive rate, which measures the true predicted positives to all actual positives.

The formula for calculating recall is given by:

$$Recall = \frac{TP}{TP + FN}$$

6.1.4 F1-Score

F1-Score joins precision and recall into a lone value, showing the balance between these two measures. It is used to highlight the imbalance between precision and recall.

The formula of F1-Score is:

$$F1 = \frac{2 \times Precision \times R}{Precision + R}$$

6.1.5 AUC

The area under the curve (AUC) is a graphical depiction of the arrangement of the correct positive rate and the incorrect positive rate. It refers to the AUC curve in the context of binary classification models.

6.2 Equation

The formula for AUC-ROC is given by:

$$AUC\text{-}ROC = \int_0^1 TPR(FPR^{-1}(t))\, dt$$

6.3 Performance Evaluation

As seen in the table, ST-GNN is seen to perform better with 0.87 AUC. Whereas, in LSTM-GNN the results were quite average.

Table 2: Performance Evaluation

Model	Accuracy	Precision	Recall	F1-Score	AUC
ST-GNN	85%	74%	93%	82%	0.87
LSTM-GNN	30%	31%	30%	28%	0.52

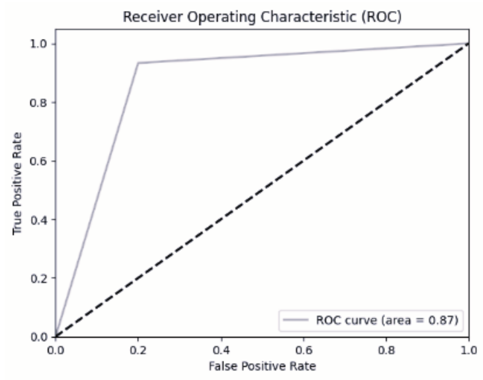

Figure 9: Area under curve ST-GNN

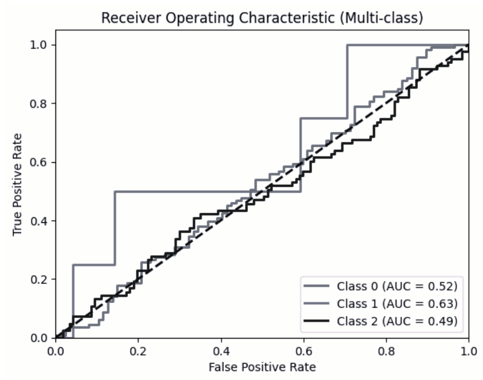

Figure 10: Area under curve LSTM-GNN

For some instances, the highest prediction probability is between the range 0.2 and 0.3 which means the model is quite confident in giving accurate predictions for instances in this range. The range of 0.7 to 0.9 also indicates the subset of data for which the model assigns high prediction probabilities. This shows that the model is working well for most of the data subsets.

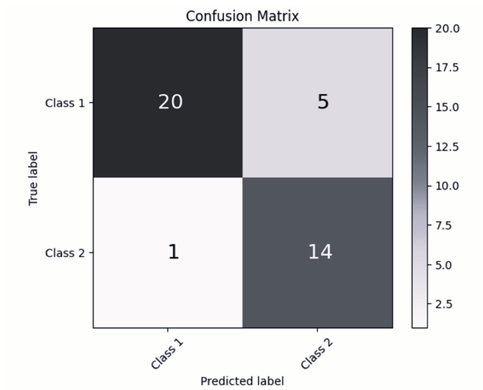

Figure 11: Confusion Metrix of ST-GNN

The confusion matrix of st-gun shows 14 correct positive predictions and 20 correct negative predictions by the model. However, it has also made 5 incorrect positive predictions and 1 incorrect negative prediction.

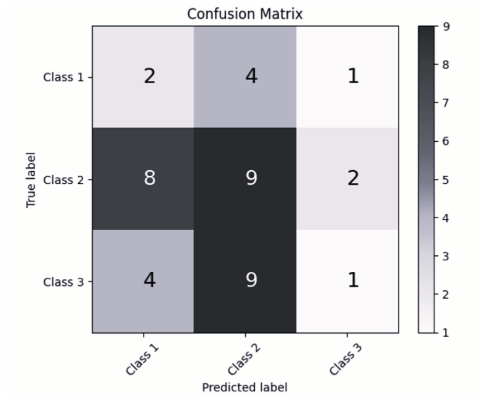

Figure 12: Confusion Metrix of LSTM-GNN

In the LSTM-GNN model, the predicted 2 instances for Class 1 were true positives. However, 4 instances were false positives. The model failed to identify 7 actual Class 1 instances, predicting them as false negatives. For Class 2, the model predicted 9 instances as true positives and also predicted 9 instances from other classes as Class 2 i.e., false positives. Overall, the model failed to identify 11 actual Class 2 instances. Finally, for Class 3, the model performed the worst, correctly predicting only 1 instance as true positive, incorrectly predicting 2 instances from other classes as Class 3. The model failed to identify 13 actual instances of the class, predicting false negatives. The model performed reasonably well for Class 2, the model had poor performance with Class 1 and Class 3.

The confusion matrix indicated that the model has a suboptimal, as evidenced by low precision and recall values for many classes. The performance is improved with more data as this is a relatively small dataset for conducting any conclusions of the model.

6.4 Summary

In summary, when we examine the performance of the models in detail, several comparative properties of performance can be seen. The ST-GNN model achieved a reasonably good performance, boasting an accuracy rate of 85 percent, indicating its ability to make correct predictions to a substantial degree. However, a closer examination of the confusion matrix reveals the presence of misclassifications, suggesting that it is not entirely error-free and occasionally has errors in its predictions.

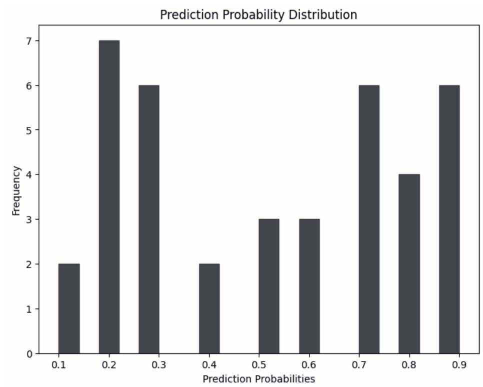

Figure 13: Prediction Probability ST-GNN

As we can see the model predicted Class 1 for sample 1 and Class 2 for sample 2 but other classes' prediction probabilities are quite high for the samples, this shows that the model performed averagely on the samples.

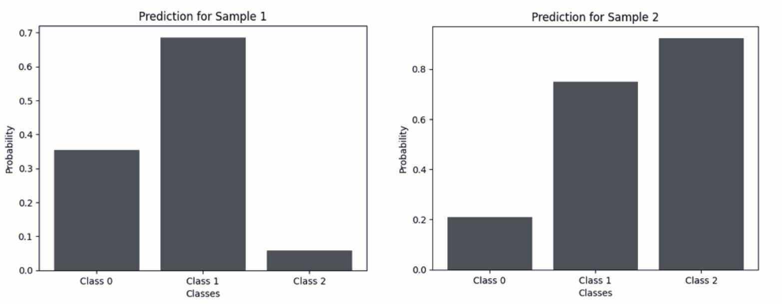

Figure 14: Predictions of LSTM-GNN

LSTM performed average on this dataset because, for the LSTM model, much more data is needed to train the model and refine the performance of the model. Due to the limitations of the public dataset of mammograms and ultrasounds, the model lacked the desired results. Class imbalance issues can also be a factor, affecting the performance of the model. Also, the random initializations of graph data can influence the results.

In summary, the LSTM-GNN substantially performs well while the ST-GNN performs well in this task, delivering notably accurate and precise predictions for BIRAD scores. However, further investigation and rigorous testing may be necessary to substantiate its robustness and reliability for potential clinical utilization.

7 Conclusion

In conclusion, the implementation of Graph Neural Networks (GNNs) models to the bio-medical dataset containing patient information and breast cancer diagnostic data, including mammograms and ultrasounds, represents a promising approach for improving breast cancer predictions and diagnosis. The dataset provided us with valuable patient-specific information, including BIRAD scores for both right and left mammograms and ultrasounds. ST-GNN and LSTM models have been utilized effectively in various fields, including medical applications on graph datasets. By modeling the relationships between patients and their diagnostic data as a graph, GNNs can capture complex patterns and dependencies in the data that may not be visible through conventional statistical or machine-learning approaches. However, it is important to note that the success of ST-GNNs and LSTM-GNN models in breast cancer prediction relies laboriously on the quantity and quality of the data used for validation and training. Additionally, rigorous evaluation and validation of the models on diverse datasets are essential to ensure their robustness and generalizability. In the future, the application of GNNs can be done in larger datasets to gain much more accuracy and precise predictions.

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