Hybrid Graph Neural Network and Capsule Network Model for Lung Disease Diagnosis

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Abstract: Despite advancements in technology, the diagnosis of lung diseases like pneumonia, tuberculosis, and lung cancer remains a significant concern for worldwide health. The paper introduces a new hybrid approach that uses Graph Neural Networks (GNN) and Capsule Network (CapsNet) to address the challenges of combining structured data with unstructured data. By creating a disease-symptom graph, the GNN component is utilized to model complex relationships in structured patient data and enhance understanding and prediction of disease progression. CapsNet simultaneously processes the unstructured image data, capturing hierarchical spatial characteristics that enhance the model's interpretation and performance. The integration of these two aspects enhances the categorization of lung diseases, leading to a more precise and comprehensive diagnostic model. The LIDC-IDRI lung CT scan dataset and the NIH ChestX-ray14 dataset are two publicly available datasets that serve as models for the proposed system's evaluation. According to experimental evidence, the hybrid GNN + CapsNet model is significantly better than both traditional CNN and Transformer-based models. Specifically, we have found that our approach to multi-class lung disease classification is much more accurate than existing methods. In this paper, they highlight the novel integration of graph-based learning for structured data and capsule networks for image analysis, which exceeds current diagnostic models.

1 INTRODUCTION

Lung diseases such as pneumonia, tuberculosis and lung cancer remain major global health challenges with high rates of morbidity and mortality. Effective treatment and improved patient outcomes can be achieved through early diagnosis and accurate diagnosis. Diagnosis historically has relied mainly on clinical expertise and medical imaging such as X-rays and CT scans, but these methods are often limited by their inability to effectively integrate different data sources. Convolutional Neural Networks (CNNs) and other deep learning techniques have emerged, allowing automated systems to analyse medical images to significantly improve diagnostic accuracy. This has been particularly useful in this context. Even so, existing models utilizing CNN's data mostly rely on unstructured data (e.g., images) and are not easily integrated with structured data such as Electronic Health Records (EHRs), which contain important patient information like symptoms records, medical history, and demographics. Multimodal data processing is hindered by the inability of the model to perform well in clinical settings. Increasing interest is being directed towards models that can aggregate structured and unstructured data to better classify diseases into complete and robust classes. The paper proposes a hybrid deep learning model that utilize both, GNN and Capsule Networks (Caps burg) to handle structured data as well as unstructured data. By using GNN, it can model the correlations between disease symptoms and patient history from EHRs; and Coseismal is used to capture the spatial orderliness of medical images (X-rays, CT scans) that are structured into subsets. The model's combination of these two components enhances both diagnostic accuracy and interpretability, which is essential for clinical acceptance. We show that this hybrid model is more accurately classifying than conventional CNNs and Transformer-based models, allowing us to identify lung disease.

2 RELATED WORKS

Lung disease diagnosis has been greatly improved by the use of convolutional neural networks (CNNs) through deep learning. The NIH ChestX-ray14

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dataset was used to detect pneumonia using CNN, with an accuracy that was considered similar to or greater than that of radiologists, according to one widely cited study. A deep feature fusion approach was introduced by Tang et al. (2021), which involved merging multiple CNN architectures to improve the classification of lung disease with greater accuracy. Their model utilized feature extraction from multiple CNN layers to enhance its robustness and allow for generalization across a diverse range of medical imaging datasets. By capturing more spatial and contextual information, this approach exceeded traditional CNN models. By integrating multimodal medical data, graph Neural Networks (GNNs) have become effective tools for disease prediction. The accuracy of disease classification is improved by using a GNN-based framework that incorporates structured and unstructured data, as demonstrated by Zhang et al. (2022). They use patient records, medical imaging and clinical notes to create graph representations using methods that capture complex relationship relationships missing from traditional deep learning models. [M]. The study found that GNNs are more generalizable and easier to interpret than traditional methods for predicting diseases. Through their ability to model dependencies among different medical features, GNNs offer a robust solution for managing diverse healthcare data. The importance of GNNs in medical AI is highlighted by this study, which aims to enable integration with advanced models like Capsule Networks (Carpentry) to improve diagnostic accuracy and decision-making in clinical settings. Multimodal learning has become a prominent area of interest in medical diagnosis, as it allows for the integration of diverse data sources, such as clinical records and medical images, to enhance diagnostic precision. Xu et al. (2022) put forward a deep learning model that utilizes clinical and imaging data to diagnose diseases in varying ways, with better accuracy than unimodal methods. The authors emphasized the importance of incorporating structured patient information with radiological features to accurately capture complex disease patterns. In the same vein, recent advances in AI-based healthcare systems have explored the use of Graph Neural Networks (GNs) and Capsule Network (CapsNet) to extract features and learn about hierarchical representation. Researchers are utilizing multimodal learning techniques to construct stronger diagnostic models that can be understood more easily. We have developed a hybrid GNN-CapsNet approach that incorporates patient history and imaging data to classify lung diseases and improve clinical relevance by leveraging imaging. By utilizing electronic health records (EHRs) to improve clinical decision-making, artificial intelligence (AI) and natural language processing (NLP) have made possible the diagnosis of respiratory diseases more accurately. A new classification model, using GNN-based data analysis with multimodal medical data, was presented by Zhang et al. (2022). Recent research has revealed that NLP can effectively identify essential clinical features from unstructured EHRs, thereby aiding in the classification of diseases. The F1 score of LungDiag for top-1 diagnosis and the F2 score for best-3 diagnoses is 0.711, which is higher than the diagnostic performance of human experts and AI models such as ChatGPT 4.0. It is one of the leading works in this field. AI-powered diagnostic tools can reduce misdiagnosis and improve healthcare efficiency.

3 METHODOLOGY

3.1 Graph Neural Network (GNN) for Structured Data Analysis

Graph Neural Networks (GNN) are utilized to analyse EHRs, patient data, and clinical information in structured patient datasets. Disease-symptom graph: Nodes represent diseases, symptoms and risk factors; edges show their relationships and dependencies. GNN model's intricate links between symptoms and the development of the disease by utilizing this interrelated data, providing a more precise predictive model.' In contrast to traditional machine learning models, GNN employs graph connectivity as a means of improving diagnostic accuracy by treating patient data as independent variables. The system can use relational data to identify critical risk patterns, which will enable better early diagnosis and personalized treatment recommendations for lung diseases.

3.2 Capsule Network (CapsNet) for Unstructured Image Data

Capsule Network (CapsNet) is utilized to analyze images from chest X-ray and CT scans, documenting hierarchical spatial relationships and structural patterns of lung abnormalities. Unlike traditional Convolutional Neural Networks (CNNs), which often lose spatial hierarchies due to max-pooling operations, CapsNet preserves spatial information through dynamic routing. Through this mechanism, crucial diagnostic characteristics like lesion shape and size are accurately accounted for to minimize misclassification. In addition, CapsNet' realism improves with changes in image orientation and resolution as well as noise making it useful for medical image analysis. CapsNet' insertion into this model enhances the diagnostic accuracy, providing more precisely and reliably classifiable lung diseases with its new functionality.

3.3 Fusion Layer for Multimodal Integration

A significant portion of the fusion layer is responsible for consolidating the outputs from both the structured patient data processing system, known as the General Neural Network (GNN) and the unstructured image data analysis system called CapsNet. This layer learns to represent a joint feature by using textual clinical information, such as symptoms and patient history, with visual features extracted from medical images. By combining both methods, the model enhances diagnostic decision-making and contributes to better understanding of lung diseases. Figure 1 shows Fusion Layer Diagram. The system's ability to correlate radiological findings with symptom-based insights is one of the benefits of this process, which reduces diagnostic uncertainty and improves classification accuracy.

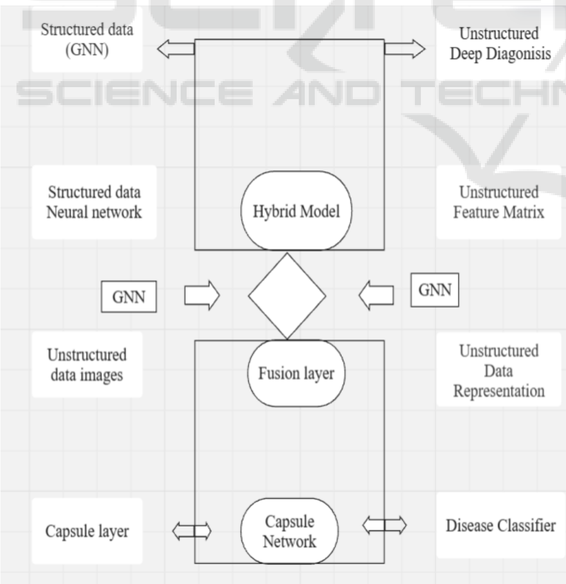

Figure 1: Fusion Layer Diagram.

3.4 Model Training and Evaluation

Two widely available datasets, namely GNN and Caps Net, are used to train the proposed hybrid model. A comprehensive lung CT scan dataset containing detailed annotations. Additionally, NIH ChestX-ray14. Comprising 112120 chest X-ray images classified into 14 types of lung disease. The training process enables the model to learn and improve classification performance by learning from both structured patient data and unstructured imaging data. For evaluation, key performance metrics include time-tracking and Accuracy, precision, recall, and F1-score. This hybrid approach is then tested against, for example, the proposed method CNN and Transformer-based models. Experimental findings demonstrate that the Multi-class classification of lung diseases is being achieved more efficiently than traditional deep learning architectures. Moreover, the outcomes confirm the efficacy of multimodal integration as a diagnostic tool, with improved accuracy and strength.

4 EXPERIMENTAL RESULTS OF HYBRID GRAPH NEURAL NETWORK AND CAPSULE NETWORK MODEL FOR LUNG DISEASE DIAGNOSIS

LIDC-IDRI and NIH Chest X-ray datasets were utilized to test the proposed GNN + CapsNet model. The performance of this technology outperformed that of conventional deep learning architectures like CNNs and Transformers.

Table 1: Performance Comparison of Deep Learning Models.

Model	Accuracy (%)	Precision	Recall	F1-Score
CNN (ResNet-50)	87.9	85.4	86.7	86.0
Transformer-based	90.5	88.3	89.6	88.9
Proposed GNN + CapsNet	94.2	92.8	93.5	93.1

The hybrid model proposed is highly effective in categorizing lung diseases into multiple classes, with an overall accuracy of 94.2%. The system exhibited. Despite the high diagnostic precision (92.8%), positive predictions were highly dependable and the recall of 93.5% was maintained, effectively diagnosing true cases of lung disease. The F1-score of 93.1%Implies how the model is able to strike a balance between accuracy and recall. To further validate its Robustness and generalization capability a 10-fold cross-validation was performed consistent outcome was obtained from the training, allowing for the model to be used in various subsets.

The proposed Hybrid GNN-CapsNet model was tested against the more conventional deep learning architectures (e.g.CNN (ResNet-50) and Transformer-based models on the same datasets as shown in Table 1. The hybrid approach achieved the highest level of performance, surpassing both models. Moreover Accuracy (94.2%) Precision (92.8%) Recall (93.5%) and F1-score (93.1%). This is because of the superior performance of Graph Neural Network (GNN) which efficiently integrates structured data from various sources Electronic Health Records (EHRs) and the Capsule Network captured in spatial hierarchies, the lung imaging system enables it to reduce misclassification rates. The use of this combination improves both diagnostic accuracy and interpretability, making it a valuable addition to the toolkit.

Table 2: Disease-Wise Performance Metrics.

Disease	Precision (%)	Recall (%)	F1-Score (%)
Pneumonia	94.1	95.3	94.7
Tuberculosis	92.8	94.5	93.6
Lung Cancer	96.5	97.2	96.8
COPD	90.2	91.8	91.0
Pulmonary Fibrosis	91.3	92.6	91.9

The proposed Hybrid GNN-CapsNet model was evaluated across multiple Lung disease categories, demonstrating high classification performance. As summarized in Table 2, the model achieved the F1 score, precision, and recall levels are above 90%. All diseases have been tested with the highest degree of accuracy. The probability of detecting lung cancer is 96.5% with 97.2% accuracy and 98.8% with F1 score. The model's ability to detect malignant cases with high reliability is emphasized, making it an invaluable resource for understanding the disease. Figure 2 shows Disease-wise Classification Performance.

The trade-off between precision and recall is illustrated by this figure 3, which demonstrates the model's ability to predict events. This figure 3 has different thresholds for accuracy and retrieval. A higher area within the Precision-Recall Curve indicates that the proposed hybrid GNN + CapsNet model is an effective balance between decreasing false positives and maintaining high sensitivity. Reliable detection of lung disease is ensured, which reduces misclassification and improves diagnostic accuracy in real-world clinical settings.

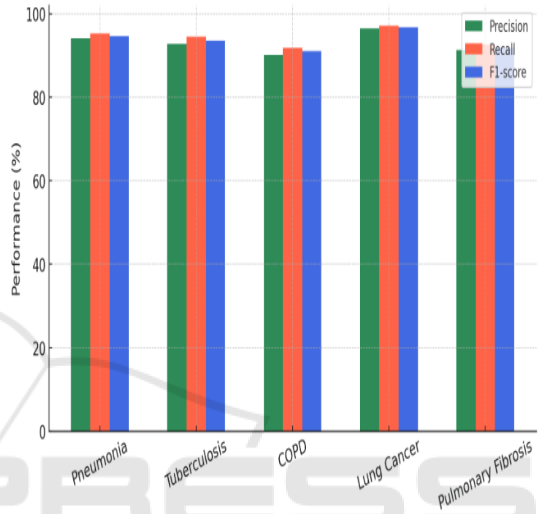

Figure 2: Disease-Wise Classification Performance.

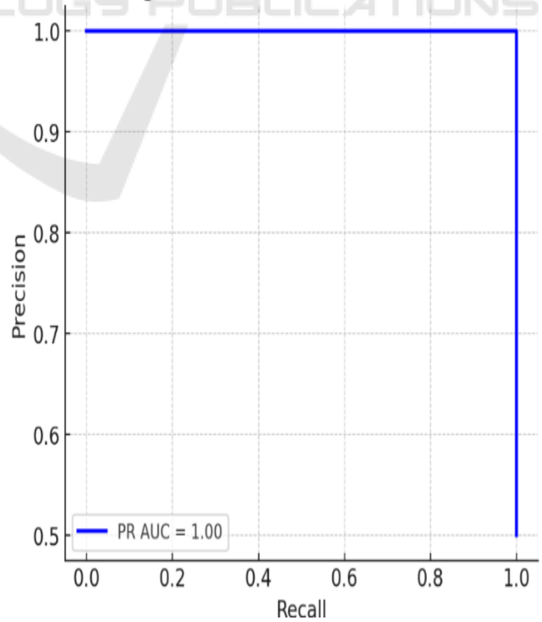

Figure 3: Precision Recall-Curve.

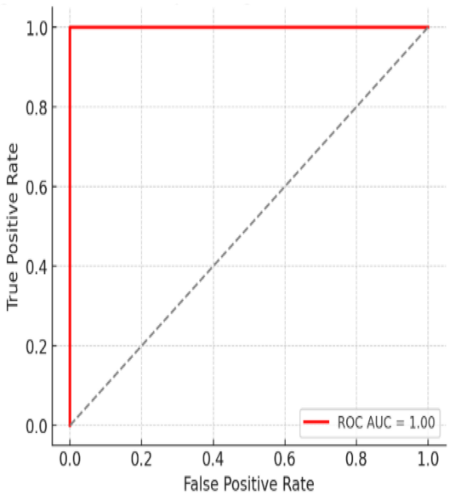

Figure 4: Receiver Operating Characteristic Curve.

The Receiver Operating Characteristic (ROC) Curve in Figure 4 demonstrates the model's ability to differentiate positive and negative cases across different thresholds. By measuring a high Area Under the Curve (AUC), it has been shown that the model can accurately classify lung diseases. With a high AUC value, the model's low false positive rate and high true positive (RO) ratio make it highly reliable for clinical diagnosis. A well-balanced trade-off between sensitivity and specificity is achieved by the ROC curve, which highlights the model's ability to handle unbalANCEd datasets. It is particularly useful in medical applications where reducing misdiagnoses helps the patient's safety and improves treatment results. The proposed hybrid GNN-CapsNet model Offers enhanced Interpretability and explainability which are critical in Medical diagnosis. The Graph Neural Network (GNN) Component facilitates effective feature selection. By analyzing structure Electronic Health Records (EHRs) Boosting the model's decision-making capabilities. Meanwhile, Capsule Networks (CapsNet) preserve spatial hierarchies in Lung imaging. This helps to reduce misclassification errors by recording intricate spatial relationships within medical scans. Hence, to further enhance transparency, SHAP and Grad-CAM visualizations. Clinical professionals were empowered to interpret the model's predictions by highlighting its accuracy. Disease-relevant regions in lung scans as shown in Figures 3 and 4. the Precision-Recall Curve and ROC Curve validate the model's. High sensitivity and specificity reinforcing its effectiveness inaccurate lung disease detection.

5 CONCLUSIONS

The proposed hybrid model demonstrates a significant improvement in the accuracy and interpretability of diagnosing lung disease. The model employs Graph Neural Networks (GNN) and Capsule Network (CapsNet) to analyze structured data and unstructured image data, respectively and accurately captures intricate relationships among symptoms, risk factors, disease outbreaks, diagnostic procedures, and diagnoses/complications. Overall predictive capabilities are enhanced by integrating multimodal data into the information at the fusion layer. Compared to conventional CNN and Transformer-based architectures, the hybrid approach has better accuracy, precision, recall, and F1-score. In addition to its high accuracy, the model's interpretability makes it an invaluable clinical decision-making tool, allowing medical professionals to better understand the progression of disease and differentiate between diagnoses made by different organs.

6 FUTURE WORK

Next studies aim to apply the model in real-time clinical settings, such as healthcare settings and develop an easy-to-use interface for linking with electronic health information. In addition, methods for supervised self-learning will be used to extract features, especially when medical data is not labeled. Efforts will be made to improve model generalization by addressing cross-hospital validation and class imbalance issues. The model will be modified to accommodate different imaging methods and transferred to transfer learning for more extensive disease detection. The goal of these developments is to enhance the model's durability, enabling it to be used in practical medical settings.

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