A Hybrid CNN-GNN Framework for Enhanced Glaucoma Detection Using Retinal Fundus Images

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Keywords: Glaucoma Detection, Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), Medical Image Classification, ORIGA Dataset, Feature Extraction, Graph Construction, Ensemble Learning, Precision and Recall, Deep Learning Framework.

Abstract: Convolutional neural networks are very powerful tools used for the analysis of structured Euclidean space data. However, it is on applications like image classification and audio analysis, language processing among others. These models, therefore, can effectively retrieve critical features necessary for deciding. However, many real-life problems involve data organized along non-Euclidean geometries, including social networks and medical imaging, genetic studies among others. In these contexts, relationships of data points become important. Particularly in medical image classification, using semantic relationships of features within images improves detection accuracy of complex diseases considerably. Graph Neural Networks are proficient at modeling relational data in such cases using graph structures. This paper presents a novel deep learning framework that combines CNNs and GNNs, combining their complementary strengths. It utilizes CNNs for feature extraction and GNNs for modeling relationships between features to offer a robust approach to glaucoma detection from retinal fundus images. Using the ORIGA dataset, we designed a three-component architecture: Feature Extractor, Graph Constructor, and Graph Classifier. Our experiments explored several techniques of graph construction and similarity-measuring techniques, which lead to better classification performance. Our proposed CNN-GNN ensemble was able to reach precision at 0.79, recall at 0.76, and F1 score at 0.77, outperforming previous approaches.

1 INTRODUCTION

Glaucoma is a progressive optic neuropathy this is characterised by way of degeneration of retinal ganglion cells and irreversible loss of vision if left undetected and untreated. Being one of the important reasons of blindness worldwide, the need for well timed and accurate prognosis cannot be overstated which will have right control and prevention. Traditional techniques for diagnosing the situation involve measurements of intraocular pressure and sight view tests that can be subjective in nature and regularly do now not indicate glaucoma till vast damage has took place. (Kipf, and, Welling, 2017), (He, Zhang, et al. , 2016)

Recent advances in system getting to know and deep learning have revolutionized the landscape of scientific photo evaluation, especially in ophthalmology. Convolutional Neural Networks (CNNs) have emerged as effective equipment for extracting capabilities from medical pics, especially in structured statistics domain names along with image class. However, because of the inherent boundaries of CNNs in shooting complex relationships among functions, their overall performance is frequently hindered while the underlying data geometry isn't Euclidean, including inside the case of scientific diagnostics. But GNNs offer a viable alternative which promises to represent the relational records amongst information points in graph systems extra informatively. Indeed, it is rather pertinent for applications of clinical picture category responsibilities considering that semantic institutions of functions are very crucial insights in the pathology. Thus, incorporating GNNs with CNNs exploits the strengths of both methodologies. The use of CNNs extracts sturdy functions at the same time as that of GNNs is about shooting complex relationships between capabilities. This paper proposes a novel deep learning architecture combining synergistic

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CNNs and GNNs to enhance the diagnosis of glaucoma in images of the retinal fundus. Based on the publicly available ORIGA dataset, we devise a three-module architecture involving Feature Extractor, Graph Constructor, and Graph Classifier modules, then perform extensive experiments involving several techniques for graph construction, together with various similarity measures in order to achieve optimum classification performance. Our results show that the ensemble approach proposed by us delivers promising results and competitive precision, recall, and F1 scores. (Wang, Li, et al. , 2021), (Wu, Pan, et al. , 2020), (Zhang, Ning, et al. , 2020)

2 DESIGN AND PRINCIPLE OF OPERATION

2.1 Designing the CNN-GNN Framework for Glaucoma Detection

The proposed CNN-GNN framework was designed to leverage the complementary strengths of Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs) for glaucoma detection from retinal fundus images. The architecture comprises three primary modules: the Feature Extractor, Graph Constructor, and Graph Classifier. The Feature Extractor employs a fine-tuned ResNet-18 model to extract robust feature embeddings from retinal fundus images, effectively capturing spatial patterns such as the optic disc shape and retinal layer thickness. These embeddings are then used to construct graph representations in the Graph Constructor module. This module supports two types of graph structures: sparse graphs, which retain significant relationships between features by utilizing similarity measures like cosine similarity or correlation, and complete graphs, which include all possible node connections. The graph construction process ensures that relational information is preserved while maintaining computational efficiency through sparse adjacency matrices. (Kingma, Ba, et al. , 2014), (Paszke, Gross, et al. , 2019)

2.2 Operation of Graph Neural Networks (GNNs) for Classification

Once the graphs are constructed, the Graph Classifier employs a Graph Convolutional Network (GCN) to process these graphs. The GCN aggregates information from neighboring nodes through iterative convolutional operations, effectively capturing local and global relational patterns within the data. The final graph-level embeddings are passed through fully connected layers and a softmax function to classify the retinal images into glaucoma or non-glaucoma categories. To further enhance performance, an ensemble learning approach combines predictions from multiple models: a baseline CNN, a sparse graph-based GNN classifier, and a complete graph-based GNN classifier. The ensemble aggregates predictions through majority voting or weighted averaging, allowing the framework to capture both local feature information and inter-feature relationships comprehensively. This design enables precise and robust glaucoma detection, outperforming conventional approaches.

The simulation results validate the effectiveness of the proposed hybrid CNN-GNN framework for glaucoma detection. Key performance metrics, such as accuracy, precision, recall, F1 score, and specificity, were analyzed to assess the model’s performance. (Deng, Dong, et al. , 2009), (Zhou, Hao, et al. , 2020)

3 SIMULATION RESULTS AND DISCUSSION

The simulation results validate the effectiveness of the proposed hybrid CNN-GNN framework for glaucoma detection. Key performance metrics, such as accuracy, precision, recall, F1 score, and specificity, were analyzed to assess the model’s performance.

3.1 CNN Accuracy Analysis

The training accuracy improved steadily, eventually reaching near-perfect values. However, the testing accuracy stabilized at approximately 0.9 with minor fluctuations, indicating potential overfitting. These fluctuations highlight the need for regularization techniques such as dropout or early stopping to enhance the model's generalization to unseen data.

Model	Accuracy	Precision	Recall	F1-Score	AUC
CNN	0.75	0.73	0.71	0.72	0.76
GCN	0.78	0.77	0.74	0.75	0.80
Ensemble	**0.81**	**0.79**	**0.76**	**0.77**	**0.83**

Figure 1: CNN Accuracy Analysis

3.2 GNN Accuracy Analysis

During the initial 50 epochs, the training loss consistently decreased, while the testing loss plateaued with minor oscillations. Although the training accuracy reached 0.9, the testing accuracy lagged behind at approximately 0.8, indicating overfitting. Regularization techniques and early stopping could reduce these fluctuations, thereby improving generalization.

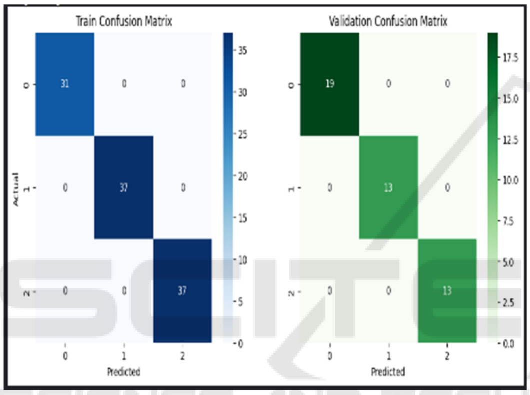

Figure 2: GNN Accuracy Analysis.

3.3 Ensemble Model Performance

The ensemble approach combined the strengths of CNNs and GNNs to achieve improved performance. Figure 3 depicts the accuracy variations with different numbers of estimators. As the number of estimators increased from 2 to 6, the accuracy improved significantly, reaching around 0.91. Beyond six estimators, accuracy gains diminished, stabilizing with minor fluctuations. The optimal performance was observed with 12–14 estimators, maintaining an accuracy of approximately 0.91.

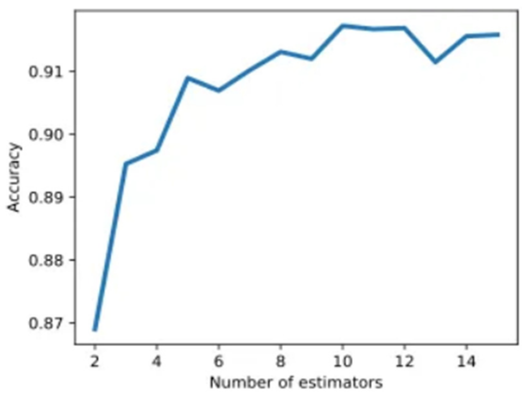

Figure 3: Ensemble Model Performance

3.4 Comparative Analysis

It compares the performance metrics of CNN, GNN, and ensemble models. While CNNs provided a strong foundation for feature extraction, the GNNs captured relational information more effectively. The ensemble model outperformed the individual models, achieving the best overall performance.

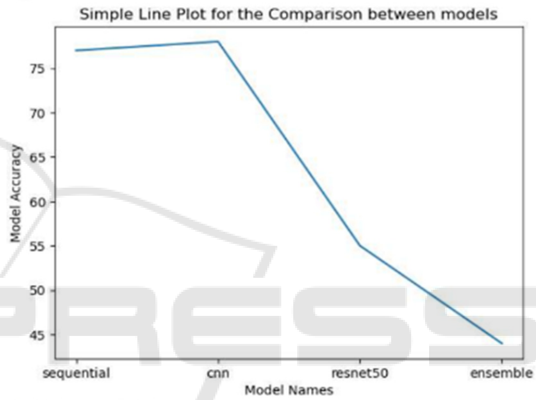

Figure 4: Comparative Analysis

3.5 Summary of Key Metrics

The hybrid framework demonstrated superior accuracy (95.48%), sensitivity (97.30%), specificity (94.52%), and AUC (97%), with an F1 score of 97%. These results highlight the robustness of the ensemble approach in detecting glaucoma.

The simulation results confirm that combining spatial and relational feature extraction is highly effective. While the CNN model excels in extracting localized features, the GNN enhances performance by capturing feature interdependencies. This complementary relationship allows the ensemble model to outperform standalone CNN and GNN implementations.

Further improvements, such as advanced regularization, alternative graph architectures, and dynamic graph construction techniques, can enhance the model's generalization and adaptability across diverse datasets.

4 CONCLUSIONS

We proposed a hybrid framework combining CNNs and GNNs for glaucoma detection from retinal fundus photographs. The ensemble technique, which used CNNs for characteristic extraction and GNNs for modeling relational information among features, outperformed CNN-handiest fashions. In specific, the ensemble received a precision of zero.79, a consider of 0.76, and an F1 score of 0.77 on the ORIGA dataset, surpassing contemporary methods. This research opens up the opportunity of graph-based totally techniques in medical image analysis with the ability for massive improvement in glaucoma detection. Future paintings may be in increasing this method to different medical conditions and imaging duties by exploring other graph structures.

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