CLASSIFICATION OF DIABETIC RETINOPATHY DISEASE USING GNN

Bhaumik Maan, Dr. Ashwini T. Sapkal, Vaishali Ingale, Abhinab Pratap Singh Chauhan, Piyush Yadav, and Rahul Lamba

***Abstract*— Diabetic retinopathy (DR) is a prominent global cause of blindness, requiring labor-intensive manual examinations of fundus images for diagnosis. While convolutional neural networks (CNNs) have shown promise in automating DR diagnosis, they often struggle to retain essential information. This study is driven by the urgent need to prevent DR-related blindness and the importance of early intervention in halting disease progression. Additionally, the aim to mitigate visual impairments and complications associated with DR. To accomplish these objectives, the aim is developing an automated diagnostic system that utilizes Graph Neural Networks (GNNs) to accurately detect and grade DR based on fundus images. The goals include advancing lesion representation, achieving multi-lesion detection and classification, and ensuring robust performance across diverse datasets. By pioneering the use of GNNs in this context, the system promises to revolutionize early DR detection and management by redefining DR classification as a multi-label detection and classification task, ultimately enhancing diagnostic precision. The model generates an accuracy of 87.8% along with lesions being represented in a correlation dependency matrix. This project represents a significant step in the field of DR diagnosis and severity grading, with the potential to significantly improve patient outcomes, reduce the risk of vision loss in diabetic individuals, and contribute to the broader medical community's efforts to combat DR and elevate patient care.**

***Index Terms*— Diabetic Retinopathy, Graph Neural Network, Image classification, Lesion Detection, SURF Algorithm.**

I. INTRODUCTION

DIabetic Retinopathy (DR) represents a significant worldwide threat to vision and overall quality of life. The conventional diagnostic process heavily depends on manual examinations of fundus images, a labor-intensive method fraught with subjectivity and accuracy limitations. While Convolutional Neural Networks (CNNs) show promise in automating DR diagnosis, their challenge in retaining essential information has propelled our research initiative. Addressing the imperative for precise and efficient diagnostic techniques, our project pioneers the integration of Graph Neural Networks (GNNs) to reimagine DR classification as a multi-label detection and classification task.

Manual examination procedures for diagnosing Diabetic Retinopathy (DR) are both time-consuming and prone to errors, adversely affecting patient outcomes. Although Convolutional Neural Networks (CNNs) exhibit promise in automating the diagnostic process, they encounter challenges in preserving essential information critical for accurate DR diagnosis. The urgency to prevent DR-related blindness and manage associated complications highlights the need for an advanced diagnostic system capable of discerning different levels of retinopathy-related damage. Current models lack the ability to determine the specific level or grade of DR in fundus images, necessitating tailored intermediate levels of treatment.

The research is propelled by the critical need to prevent blindness associated with Diabetic Retinopathy (DR) and underscore the importance of early intervention [1]. The primary focus revolves around leveraging Graph Neural Networks for the development of an automated diagnostic system for assessing DR based on fundus images. The project's objectives include advancing lesion representation, accomplishing multi-lesion detection and classification, and ensuring the robust performance of the system across diverse datasets. By directing our efforts towards these objectives, our aim is to lead a paradigm shift in the diagnosis and severity grading of DR.

The proposed approach entails the development of a robust Diabetic Retinopathy Grading system, employing state-of-the-art Graph Neural Network (GNN) architectures. Through the integration of advanced lesion representation techniques, the ultimate goal is to overcome the limitations inherent in existing diagnostic methods. The innovation lies in redefining Diabetic Retinopathy (DR) classification as a multi-label detection and classification task, enhancing early detection and management by categorizing severity levels of DR detected in fundus images.

This cutting-edge approach has the potential to significantly improve patient outcomes and raise the standards of ophthalmic healthcare. Beyond merely reducing the risk of vision loss in diabetic individuals, it promises substantial contributions to the broader medical community's efforts to

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combat DR. The introduction of GNNs [2] into the realm of DR diagnosis is anticipated to yield unprecedented levels of accuracy, efficiency, and multi-lesion detection. The transformative impact of this research extends beyond diabetic care, offering a model for automated medical diagnostics that can revolutionize the field.

Following sections contain a review of the previously used algorithms, implementation of the GNN model and a comparative analysis. Section II contains a thorough review and comparison between the models along with their advantages and disadvantages in the broader persective of DR detection. Section III defines the evaluation metrics used for model comparison. Section IV contains the implementation of the GNN model highlighting how the model actually works and allows in depth detection. Finally, Section V contains the results and discusses the models used determining the best one.

II. Related Work

Deep learning-based methods involve training model using a labelled training data to automatically segment regions of interest (ROI) by detecting lesions present in fundus images and labelling them [3]. These methods can be highly accurate and adaptable to different image types but it may need labelled data in large amount for training and validation and may have higher computational requirements. Convolutional neural networks and its variations are the most used methods available for classification of DR presenting high accuracy. It can show promising results even on the dataset of sample size. Models can be trained on publicly available datasets. Most popular datasets are Kaggle EyePacs, IDRiD and APTOS-2019.

A. Existing Models and variants for DR Detection

1) **Vanilla CNN** [4] [5] [6] - The fundamental Convolutional Neural Network (CNN) implemented for diabetic retinopathy detection represents a specialized architecture tailored for the analysis of retinal images. Trained on a diverse dataset, the network independently extracts hierarchical features, streamlining the identification of diabetic retinopathy indicators. Its practical application exemplifies a straightforward yet highly effective approach to automated detection, unlocking potential advancements in the early diagnosis and treatment of this condition with severe implications for vision. Many variations within a CNN model exists such as inclusion of multi-scale CNN or deep learning.
2) **EfficientNet-B5** - The detection model relies on EfficientNet-B5, a pre-trained deep neural network, achieving a remarkable accuracy in early Diabetic Retinopathy (DR) detection. EfficientNet-B5's architecture excels at extracting features efficiently, crucial for precision.
3) **CNN & SVM** - Implementing ResNet50 transfer learning with SVM yielded the highest accuracy for base 12, showcasing superior performance. Inception V3 and VGGNet type 19 demonstrated comparable results for base 13. The integration of CNN transfer learning features with SVM proved effective in the nuanced task of diabetic retinopathy classification. This model intricately leverages the strengths of both transfer learning and support vector machines, offering a sophisticated approach to achieve optimal diagnostic accuracy.
4) **Transfer Learning** [7] - Transfer learning involves the utilization of pre-trained neural networks such as VGG16, ResNet50 V2, and EfficientNet B0, adapting them specifically for diabetic retinopathy classification. This approach harnesses the knowledge acquired during the pre-training phase to excel in tasks characterized by a scarcity of labeled data.
5) **CNN Model on Tree structure** - The CNN, with advanced preprocessing and novel tree-based structures, successfully classifies Diabetic Retinopathy stages with high accuracy. Although having high accuracy, the model requires refinement and comparisons with traditional methods for enhanced medical image classification.
6) **Semi-Supervised Auto-Encoder Graph Network** [8]- SAGN presents an innovative solution for diabetic retinopathy diagnosis, alleviating the need for extensive expert annotations. Its adaptability to diverse datasets enhances accessibility, while its intricate architecture, integrating auto-encoders and graph networks, captures nuanced relationships within retinal images, elevating diagnostic accuracy

Each iteration of the CNN model and its counterparts brings distinctive enhancements, incorporating features like attention mechanisms, dense connectivity, residual connections, spatial attention, lesion dependencies, or evolutionary optimization. These modifications aim to elevate accuracy and effectiveness in image segmentation tasks. Successfully deployed across diverse domains, these models consistently outperform the conventional CNN architecture, showcasing superior performance and expanding the capabilities of image analysis and segmentation.

B. Comparative Analysis of Models

Table I shows a comparative analysis of the different methods used above with their respective advantages and disadvantages.

C. Datasets Used

Various datasets are available online which are employed when working with diabetic retinopathy. Each of the dataset contains fundus images categorized on the basis of the level of DR present in the eye. These categories are -

1) Class 0 for non-DR,
2) Class 1 for mild DR,
3) Class 2 for moderate DR,
4) Class 3 for severe DR, and
5) Class 4 for proliferative DR.

Table II shows the description of each of the dataset used.

TABLE I

DIFFERENT METHODOLOGIES EXERCISED IN DR DETECTION WITH THEIR ADVANTAGES AND DISADVANTAGES.

Method	Models Used	Advantages	Disadvantages
Predictive Analysis with Transfer Learning [9] [10]	• Transfer Learning • VGG16 • ResNet50	• Allows feature reuse • Improved generalization • Knowledge transfer & Reduced training time • Domain adaptation by using a trained model in different but similar domain	• Domain mismatch may occur in some cases • Limited task specificity due to learned features • Risk of overfitting • Loss of task-specific information • High computational resources for fine tuning large pre-trained model
Semi-Supervised Auto-Encoder Graph Network [11]	• Auto-Encoder Feature Learning [12] • B. Neighbor Correlation Mining • Graph Representation Module	• SAGN reduces the dependency on expert annotations • Enhanced accessibility by adapting to diverse datasets • SAGN can capture intricate relationships within retinal images, leading to enhanced accuracy	• Dependency on Initial Annotations, impacting its generalization to diverse cases • Model Complexity because of integration of auto-encoders and graph networks • Inherent complexity of SAGN might limit its explainability, making it challenging to interpret the decision-making process • SAGN's effectiveness may be influenced by the specificity of the domain it was trained on
CNN Based Detection using EfficientNet-B5 [13]	• EfficientNet-B5 on Convolutional Neural Network	• Pre-trained deep neural network, contributes to achieving a high accuracy • EfficientNet-B5's architecture allows for efficient feature extraction, enabling the model to discern intricate patterns	• Domain Specificity, model is influenced by the specific domain it was trained on • Data Dependence, Biases or limitations in the dataset may affect the model's performance
Classification using CNN and SVM [14]	• Convolutional Neural Network (CNN) • Support Vector Machine (SVM) • VGGNet • AlexNet • InceptionNet	• Versatility with Multiple Models, achieved by exploring multiple CNN architectures, including ResNet50, Inception V3, and VGGNet • Transfer-ability across bases with similar level of high accuracy	• The risk of overfitting exists, especially when dealing with relatively small datasets • Enforcing transfer learning may be influenced by the specificity of the domain it was trained on
Tree structure-based classification [15]	• Convolutional Neural Network (CNN) • Contrast Limited Adaptive Histogram Equalization (CLAHE)	• The utilization of CLAHE as a preprocessing technique enhances the quality. • Potential for Comparative Analysis, providing insights into the advancements achieved through the tree structure-based classification	• Complexity of Tree Structures, potentially making the model less interpretable and increasing the challenges • Potential Overfitting, model must ensure generalizability to new data is crucial to avoid performance issues • Effectiveness of preprocessing techniques like CLAHE and subsequent classification may be contingent on the quality and characteristics of the input images

III. EVALUATION METRICS

There are several metrics that can be used to evaluate the performance of a model. The two to be used are:

1) **Accuracy** – "Accuracy" is a common evaluation metric used in machine learning to measure how well a model can correctly predict the target variable. Specifically, it is the measure of ratio of correctly predicted instances to the total number of instances in the dataset. Accuracy

TABLE II
DESCRIPTION OF DATASETS USED.

Dataset	Sample Size	Description	Resolution	Format	Number of Images
IDRiD [16]	516	The IDRiD (Indian Diabetic Retinopathy Image Dataset) contains typical lesions associated with diabetic retinopathy and normal retinal structures, meticulously annotated at a pixel level. Each image (516 in total) in the dataset comes with comprehensive information regarding the severity of diabetic retinopathy and diabetic macular-edema, making it highly suitable for developing and evaluating image analysis algorithms specifically designed for the early detection of diabetic retinopathy.	4288x2848 pixels	JPG	• Class 0 - 168 • Class 1 - 25 • Class 2 - 168 • Class 3 - 93 • Class 4 - 63
APTOS 2019 [17]	3662	The APTOS 2019 Blindness Detection Database is comprised of 3662 retinal images taken under diverse lighting conditions. Collected from the Aravind Eye Hospital in India, the fundus images in this dataset are classified into five categories representing distinct severity levels of Diabetic Retinopathy (DR). This categorization makes the dataset well-suited for training models to recognize and understand multi-label lesions present in fundus images.	224x224 pixels	JPG	• Class 0 - 1805 • Class 1 - 370 • Class 2 - 999 • Class 3 - 193 • Class 4 - 295
Kaggle EyePACS [18]	35,126	The Kaggle EyePACS dataset is a collection of retinal images gathered for the purpose of diabetic retinopathy screening. This dataset encompasses a diverse range of retinal conditions and comes with annotations indicating the presence and severity of diabetic retinopathy. Its primary aim is to support the development and assessment of machine learning algorithms geared towards the automated detection and grading of diabetic retinopathy.	300*400 pixels to 6000*5000 pixels	JPEG	• Class 0 - 9143 • Class 1 - 5039 • Class 2 - 8302 • Class 3 - 6545 • Class 4 - 6097

test how many fundus images network correctly evaluate, which is intuitive for most tasks

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where, TP (True Positive), FP (False Positive), FN (False Negative), TN (True Negative).

2) **Cohen's Kappa Value (QWK)** – Cohen's Kappa, known as the Kappa statistic, serves as a statistical measure to evaluate the concordance between two sets of categorical data. When assessing a model, Cohen's Kappa is utilized to measure the agreement between the model's predicted classifications and the true classifications, considering the potential occurrence of agreement by chance. This metric provides a nuanced evaluation, accounting for chance agreement, and is particularly valuable in assessing the performance of models dealing with categorical outcomes. QWK values range from -1

(complete disagreement) to 1 (perfect agreement).

$$QWK = 1 - \frac{\sum_i^C \sum_j^C w_{i,j} O_{i,j}}{\sum_i^C \sum_j^C w_{i,j} E_{i,j}} \quad (2)$$

Where C is the number of classes, w is the weight matrix, O is the observed matrix and E is the expected matrix. $w_{i,j}$ is the weight penalization for the element i, j.

IV. Implementation

The proposed system architecture for diabetic retinopathy (DR) diagnosis adopts a multi-stage approach, aiming to elucidate the correlation among symptoms. To achieve this, we utilize the Speeded-Up Robust Features (SURF) algorithm, renowned for its robustness in image processing. SURF efficiently detects and represents abnormal regions in retinal images, thereby facilitating accurate DR diagnosis [19]. By capturing distinctive keypoints and computing descriptors, SURF enhances feature extraction and analysis, contributing significantly to the identification of diabetic retinopathy indicators.

Following feature extraction, the extracted features are clustered into K classes, with cluster centroids serving as node representations. Leveraging the co-occurrence information of lesions, a correlation graph is constructed and subsequently processed through a graph convolutional network (GCN). Lesion detection involves identifying and localizing abnormalities such as micro-aneurysms and hemorrhages within retinal images. This process entails the utilization of advanced algorithms, including Graph Neural Networks and pixel-level probability maps, to precisely identify and classify lesions associated with diabetic retinopathy. Through learning the relationships between the K different lesions, the GCN contributes to more accurate DR diagnosis.

The output from the GCN is seamlessly integrated into a classification and severity grading module. This module harnesses state-of-the-art machine learning algorithms to determine the precise DR stage for each patient, offering invaluable insights for medical professionals. By combining robust image processing techniques with advanced machine learning algorithms, our proposed system architecture presents a comprehensive and effective approach to diabetic retinopathy diagnosis and severity grading, ultimately enhancing patient care and treatment outcomes.

A. Working of the model

Firstly, a graph structure is utilized to depict correlations between symptoms associated with DR. Lesions within retinal images are represented as nodes in this graph, and their correlation information is passed through a graph convolutional network (GCN). Unlike traditional Convolutional Neural Networks (CNNs), GCN updates node representations without spatial consistency, enabling it to learn relationships between different lesion types.

To extract lesions from fundus images, the Speeded Up Robust Features (SURF) algorithm is employed. Due to the diverse nature of lesions in terms of size, shape, and color, SURF effectively identifies abnormal regions within the images. These lesions are characterized as irregular regions without precise locations or appearances.

Next, SURF descriptors extracted from the lesions are clustered into K classes using the K-means algorithm. The resulting cluster centroids serve as node representations for the lesions. Similarity between lesions is calculated using Euclidean distance in a 64-dimensional space, while co-occurrence of different lesion labels is also determined.

The model further incorporates a multi-label model to fuse features from both GCN and ResNet101, a deep convolutional neural network. This fusion enables the model to leverage both label correlations learned by GCN and image-wise features learned by ResNet101. The concatenated features are then linearly transformed to produce the final output, which consists of predictions based on probabilities obtained from the fused features.

In summary, the model operates through a series of steps including graph-based representation of lesions, lesion extraction using SURF algorithm, clustering of lesion descriptors, calculation of lesion similarity and co-occurrence, graph convolutional network processing, feature fusion with a multi-label model, and prediction based on the fused features. This comprehensive approach enables accurate and efficient diagnosis of diabetic retinopathy, ultimately determining the stage of DR present in the fundus image resulting in better recognition and treatment.

To implement our model. we used a High Performance Computer with our model running 300 epochs the following system configurations:

- CPU : Intel(R) Xeon(R) Silver 4216
- RAM: 47.1 GB
- GPU: Nvidia Quadro RTX 6000

Table III shows how the lesion extraction looks like after SURF Algorithm works upon the fundus images. The different lesions present in the fundus images are:

- Microaneurysms - Microaneurysms are tiny outpouchings or bulges in the walls of retinal capillaries. They are often the earliest clinically visible sign of the disease.
- Haemorrhage - Haemorrhage in the retina refers to the leakage of blood from damaged blood vessels within the retinal layers.
- Hard Exudates - Hard exudates are yellowish or white lipid deposits that accumulate in the retina, typically located in the outer layers of the retina. They are composed of lipids and proteins and are often associated with conditions such as diabetic macular edema.
- Soft Exudates - Soft exudates, also known as cotton-wool spots or retinal nerve fiber layer infarcts, are white or grayish lesions seen on the surface of the retina. They result from focal ischemia and infarction of retinal nerve fibers due to microvascular occlusion or damage.
- Optical Disc - The optic disc, also referred to as the optic nerve head, is the anatomical structure where the optic nerve exits the eye and enters the brain. It is located on the nasal side of the retina and appears as a pale circular area with a central depression known as the optic cup

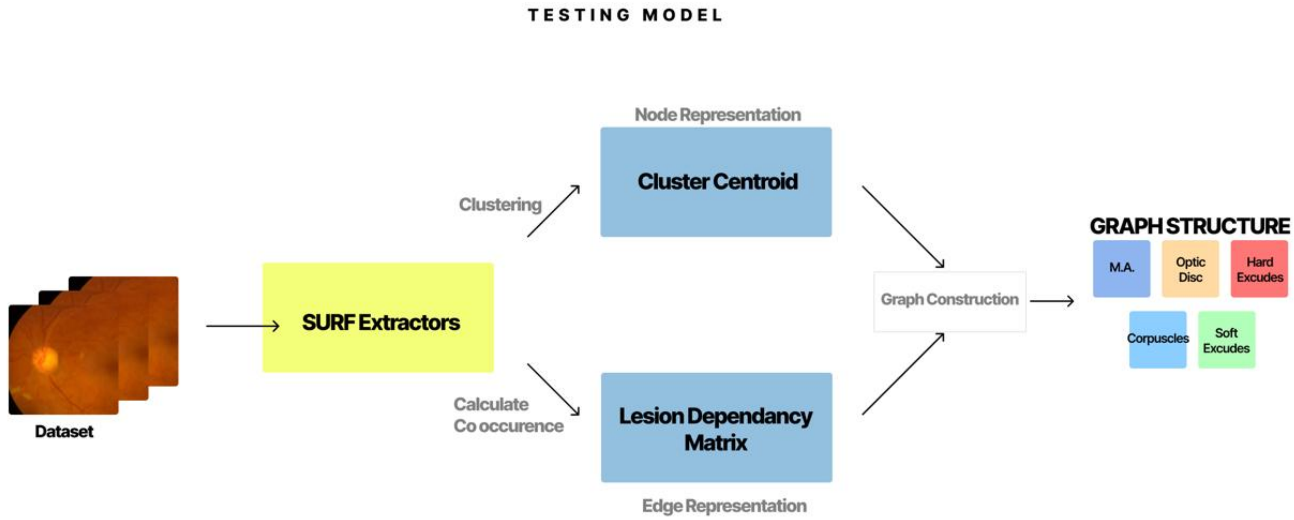

Fig. 1. Model Structure

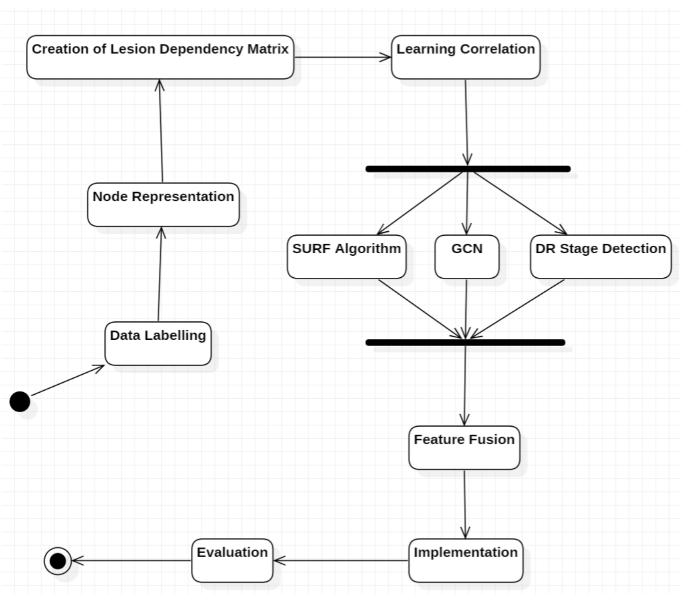

Fig. 2. Model Flowchart

V. Results and Discussion

Implementing the GNN model on three different datasets generates the following results. Evaluating the model on these datasets using our evaluation metrics shows a comparison on training and testing of the model in Table IV.

Doing a comparative analysis of all the models studied above, we can compare the methodologies by running the models on the same dataset. Table V shows the comparison.

VI. Conclusion

Segmentation of diabetic retinopathy (DR) lesions plays a crucial role in understanding an individual's health status and aiding in the diagnosis of various conditions, including diabetes and cardiovascular diseases. This study offers a comprehensive overview of the latest research endeavors in the field of image segmentation for diabetic retinopathy lesions. Among the emerging techniques, Graph Convolutional Network (GNN) models have shown promise as effective tools for retinal image segmentation tasks.

Both the SURF extraction method and GNN models have demonstrated significant advancements in segmentation accuracy compared to alternative approaches. Particularly, the Spatial Attention GNN is designed to handle noise and variations in input data, resulting in enhanced efficiency. Additionally, it automates hyperparameter optimization and exhibits faster convergence during training. However, each model has its own limitations, with the complexity of GNN posing challenges in interpretation and having limited control over specific architectural choices.

Despite these challenges, GNN models offer a promising avenue for improving diabetic retinopathy lesion segmentation, achieving an accuracy of 87.8%. While this may not be as high as some other models, leveraging a graph structure enables the model to establish dependencies among lesions present in the fundus image, thereby enhancing correlation detection. Continued research and optimization endeavors hold the potential to further refine segmentation accuracy and efficiency. Ultimately, the ongoing development of GNN models has the capacity to significantly enhance the accuracy of diabetic retinopathy lesion segmentation, leading to improved recognition and management of various cardiovascular and retinal conditions.

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TABLE III
LESION DETECTION USING SURF ALGORITHM

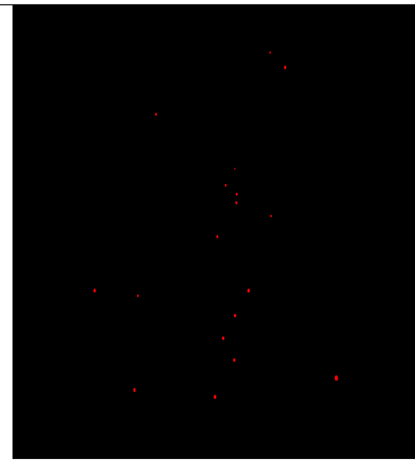
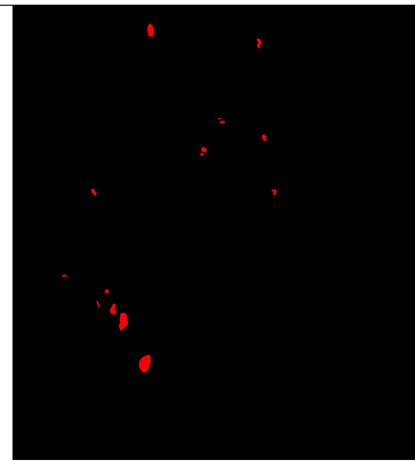
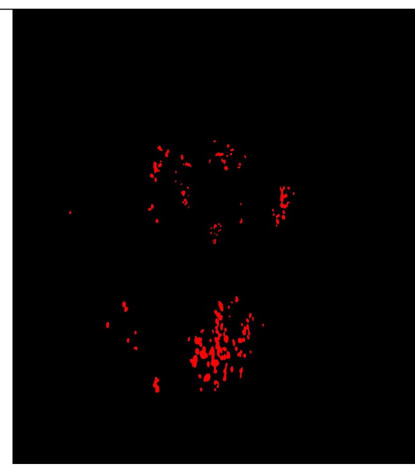
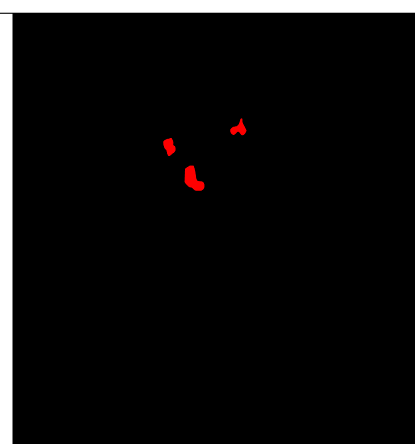
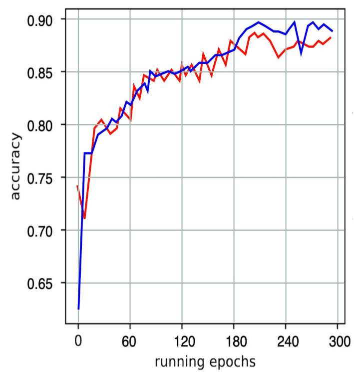
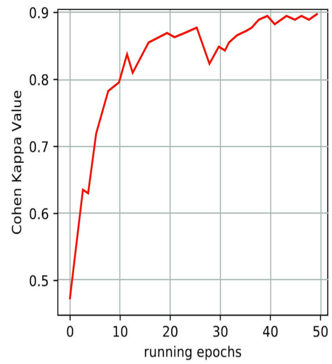
Lesion Name	Fundus Image	Lesion Extraction
Micro-Aneurysms		
Haemorrhages		
Hard Exudates		
		

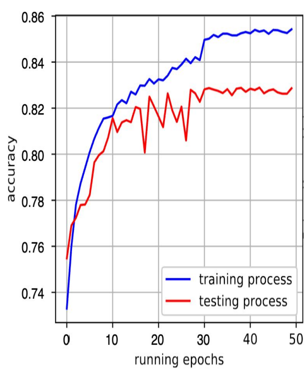
TABLE IV
RESULTS GENERATED ON DIFFERENT DATASETS USING GNN.

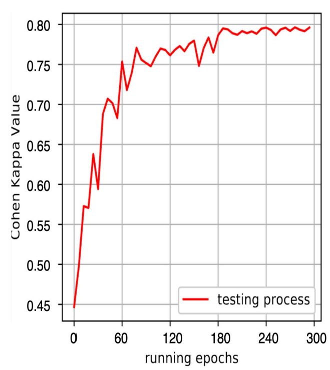
<table>
<tr><th>Dataset</th><th>Accuracy Curve</th><th>QWK Curve</th><th>Metrics</th></tr>
<tr><td>IDRiD</td><td>


IDRiD Accuracy</td><td>


QWK for IDRiD</td><td>

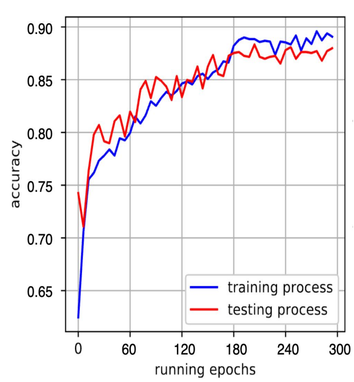
- Accuracy -87.8%
- QWK - 0.898
- Sensitivity - [0.989, 0.149, 0.694, 0.0, 0.0]
- Specificity- [0.77, 0.946, 0.794, 1.0, 0.979]

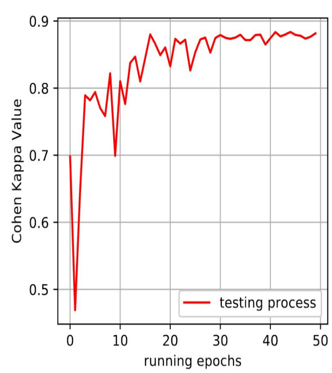
</td></tr>
<tr><td>EyePACS</td><td>


EyePACS Accuracy</td><td>


QWK for EyePACS</td><td>

- Accuracy - 82.7%
- QWK - 0.788
- Sensitivity - [0.954, 0.262, 0.819, 0.0, 0.0]
- Specificity- [0.679, 0.911, 0.721, 1.0, 0.934]

</td></tr>
<tr><td>APTOS-2019</td><td>


APTOS Accuracy</td><td>


QWK for APTOS</td><td>

- Accuracy - 87.12%
- QWK - 0.87
- Sensitivity - [0.988, 0.219, 0.721, 0.0, 0.0]
- Specificity- [0.630, 0.973, 0.788, 1.0, 0.997]

</td></tr>
</table>

TABLE V
DIFFERENT METHODOLOGIES EXERCISED IN DR DETECTION WITH THEIR METRICS.

Method	**Models Used**	**Dataset**	**Metrics**
Predictive Analysis with Transfer Learning [20]	• Transfer Learning • VGG16 • ResNet50	APTOS	• Accuracy - 80%
Semi-Supervised Auto-Encoder Graph Network	• Auto-Encoder Feature Learning • B. Neighbor Correlation Mining • Graph Representation Module	APTOS	• Accuracy - 94.4% • Sensitivity - 84% • Specificity - 82.2%
CNN Based Detection using EfficientNet-B5	• EfficientNet-B5 on Convolutional Neural Network	APTOS	• Accuracy - 94% • QWK - 0.9402%
Classification using CNN and SVM	• Convolutional Neural Network (CNN) • Support Vector Machine (SVM) • VGGNet • AlexNet • InceptionNet	APTOS	• Accuracy - 95.24% (For inception v3 and VGGNet)
Tree structure-based classification	• Convolutional Neural Network (CNN) • Contrast Limited Adaptive Histogram Equalization (CLAHE)	APTOS	• Accuracy - 83.95%
Graph Neural Network	• SURF Algorithm • Lesion Detection • Graph Convolutional Network	APTOS	• Accuracy - 87.8% • QWK - 0.898