CLASSIFICATION OF DIABETIC RETINOPATHY DISEASE USING GNN

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***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) poses a significant global threat to vision and quality of life. Traditional diagnostic methods rely on manual examinations of fundus images, which are labor-intensive and subject to inaccuracies. Although Convolutional Neural Networks (CNNs) show potential for automating DR diagnosis, they struggle to retain essential information crucial for accurate detection. This challenge necessitates advanced diagnostic techniques.

The research addresses this need by integrating Graph Neural Networks (GNNs) to reimagine DR classification as a multi-label detection and classification task. The conventional manual examination process is time-consuming and prone to errors, adversely affecting patient outcomes. CNNs, while promising, face difficulties in preserving critical information for accurate DR diagnosis. Given the severity of DR & it's related issues requires urgent solutions. Current models fail to determine the specific grade of DR in fundus images, necessitating customized treatment plans.

This research aims to prevent blindness associated with DR and emphasizes the importance of early intervention [1]. The primary focus is on leveraging GNNs to develop an automated diagnostic system for assessing DR based on fundus images. Objectives include advancing lesion representation, achieving multi-lesion detection and classification, and ensuring robust performance across diverse datasets.

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 strategy has the potential to significantly enhance standards ophthalmic healthcare. Beyond reducing the risk of vision loss in diabetic individuals, it promises substantial contributions to the broader medical community's efforts to combat DR. Introducing GNNs [2]into DR diagnosis is expected to achieve unprecedented levels of accuracy, efficiency, and multi-lesion detection. The impact of this research extends beyond diabetic care, offering a model for automated medical diagnostics that can revolutionize the field.

The following sections include a review of previously used algorithms, the implementation of the GNN model, and a comparative analysis. Section II reviews and compares models, Section III defines evaluation metrics, Section IV details the GNN model implementation, and Section V presents results

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and model comparisons.

II. Related Work

Deep learning methods train models on labeled data to automatically segment regions of interest (ROI) by detecting lesions in fundus images [3]. While highly accurate and adaptable to various image types, these methods require large amounts of labeled data and have high computational needs. Convolutional neural networks (CNNs) and their variations, such as those trained on Kaggle EyePacs, IDRiD, and APTOS-2019, are the most used for DR classification.

A. Existing Models and variants for DR Detection

1) **Vanilla CNN** [4] [5] [6] - The Convolutional Neural Network (CNN) for diabetic retinopathy detection is specialized for retinal images, extracting features to identify indicators of the condition. Trained on diverse datasets, it exemplifies an effective approach to early diagnosis and treatment, with variations like multi-scale CNNs enhancing performance.
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, outperforming Inception V3 and VGGNet 19 for base 13. This approach effectively combines CNN transfer learning features with SVM for precise diabetic retinopathy classification.
4) **Transfer Learning** [7] - Transfer learning uses pre-trained networks like VGG16, ResNet50 V2, and EfficientNet B0, adapting them for diabetic retinopathy classification. This approach leverages pre-training knowledge to perform well even with limited labeled data.
5) **CNN Model on Tree structure** - The CNN, with advanced preprocessing & novel tree-based structures, successfully classifies DR 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 offers an innovative solution for diabetic retinopathy diagnosis, reducing the need for extensive expert annotations. By integrating auto-encoders and graph networks, it captures nuanced relationships in retinal images, enhancing diagnostic accuracy and adaptability across diverse datasets.

Each CNN iteration introduces features like attention mechanisms, dense connectivity, and residual connections to enhance image segmentation accuracy. These advanced models consistently outperform traditional CNNs, demonstrating superior performance and expanding image analysis capabilities across various domains

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. The datasets have been split in 70:30 for training and testing respectively for each dataset on which the model is run.

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 key metric in machine learning that measures the ratio of correctly predicted instances to the total instances in a dataset. It indicates how well a model correctly evaluates fundus images, providing an intuitive performance measure.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

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

2) **Cohen's Kappa Value (QWK)** – Cohen's Kappa, or the Kappa statistic, measures the agreement between predicted and true classifications, accounting for chance agreement & serves as a statistical measure to evaluate the concordance between two sets of categorical data. Ranging from -1 (complete disagreement) to 1 (perfect agreement), it provides a nuanced evaluation of model performance with categorical data.

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

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 DR diagnosis system uses a multi-stage approach to uncover correlations among symptoms. Data splitting and resizing is done as pre-processing of the images before representing the lesions as graph structures. Pre-processing steps involve removal of background & focusing

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 • Risk of overfitting • Limited task specificity due to learned features • 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 affects generalization. • Complexity due to auto-encoders and graph networks. • SAGN's complexity may limit explainability, complicating interpretation. • Effectiveness may vary with specificity of training domain.
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 can reduce interpretability and increase challenges. • Potential overfitting; ensuring generalizability to new data is crucial. • Effectiveness of preprocessing techniques like CLAHE depends on input image quality and characteristics.

on the fundus image, enhancing lesions and creating a lesion dependency matrix to learn correlations. It employs the Speeded-Up Robust Features (SURF) algorithm, known for its effectiveness in image processing, to detect and represent abnormalities in retinal images [19]. This enhances feature extraction by capturing distinctive keypoints and computing descriptors.

Extracted features are then clustered into K classes, with cluster centroids serving as node representations. A correlation graph is constructed from the co-occurrence of lesions and processed through a Graph Convolutional Network (GCN) to accurately identify and localize lesions such as microaneurysms and hemorrhages. The GCN uses advanced algorithms to improve lesion detection and classification.

The output from the GCN is integrated into a classification and severity grading module, which employs state-of-the-art machine learning algorithms to determine the precise DR stage. Cross validation is also enforced on the trained model after every epoch where it is evaluated against a validation set. This comprehensive approach combines robust image processing with advanced machine learning techniques, offering a detailed and effective method for DR diagnosis

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

A. Working of the model

Firstly, a graph structure represents correlations between DR symptoms, with lesions in retinal images as nodes. These correlations are processed through a Graph Convolutional Network (GCN), which updates node representations based on relationships between different lesion types, unlike traditional Convolutional Neural Networks (CNNs) that rely on spatial consistency. In the graph structure, each node represents a different lesion that is extracted and the edges represent the correlation of the lesions in terms of how one affects the other

Lesions are extracted using the Speeded-Up Robust Features (SURF) algorithm, which identifies abnormal regions regardless of size, shape, or color. SURF descriptors are clustered into K classes via K-means, with cluster centroids serving as node representations. Similarity between lesions is calculated using Euclidean distance in a 64-dimensional space, and co-occurrence of different lesion labels is assessed.

The model integrates features from both GCN and ResNet101, a deep CNN, through a multi-label approach. This fusion combines the label correlations learned by GCN with image features from ResNet101, producing final predictions based on the fused features. Cross-entropy loss is the used in the model as it perfectly harmonizes its use in both ResNet as well as GNN. The choice was made because of multi-class classification tasks like DR severity grading, where models often output probability distributions over the classes

In summary, the model performs a series of steps: representing lesions with a graph, extracting them using SURF, clustering descriptors, calculating similarity and co-occurrence, processing with a GCN, and fusing features with a multi-label model. This approach enables accurate DR diagnosis and staging from fundus images, enhancing 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

Computational requirements for training and deploying the GNN model compared to traditional CNNs do not necessarily come under the same umbrella however there are some factors that affect both. They are:

- GNNs and Graph Data: GNNs are designed to handle graph data, which can be more computationally intensive to process than the grid-like data structures typically used by CNNs for images.
- CNNs and Image Processing: CNNs have been heavily optimised for image processing, and there is mature hardware and software support for their efficient training and deployment.
- Model Size and Complexity: The computational requirements of both GNNs and CNNs are influenced by the size and complexity of the model architecture. Larger and more complex models generally require more resources. Same can be said for the Training data employed.

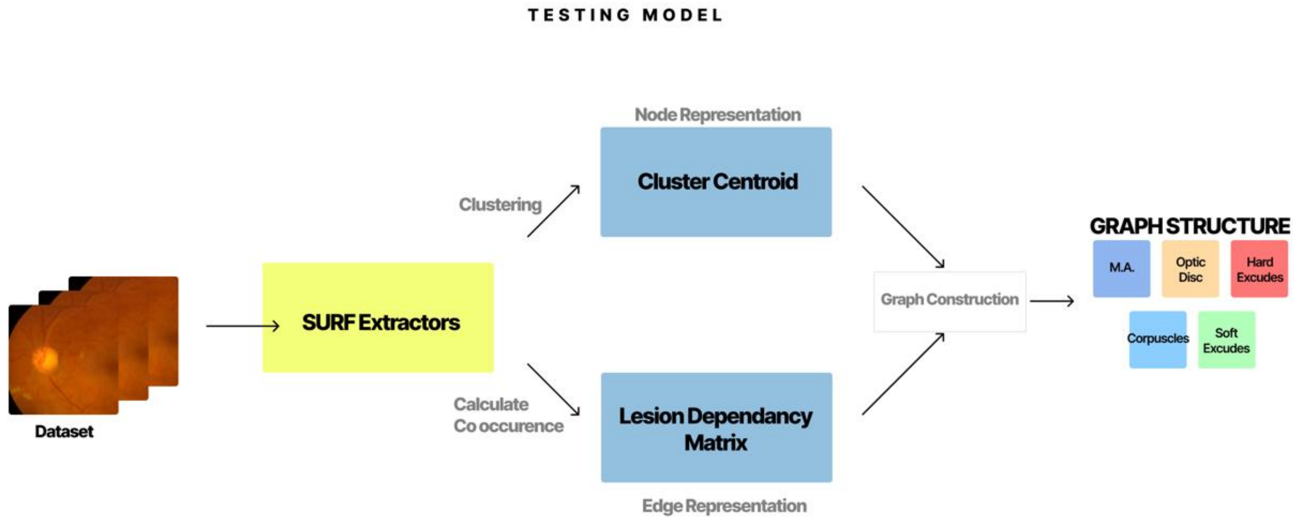


Fig. 1. Model Structure

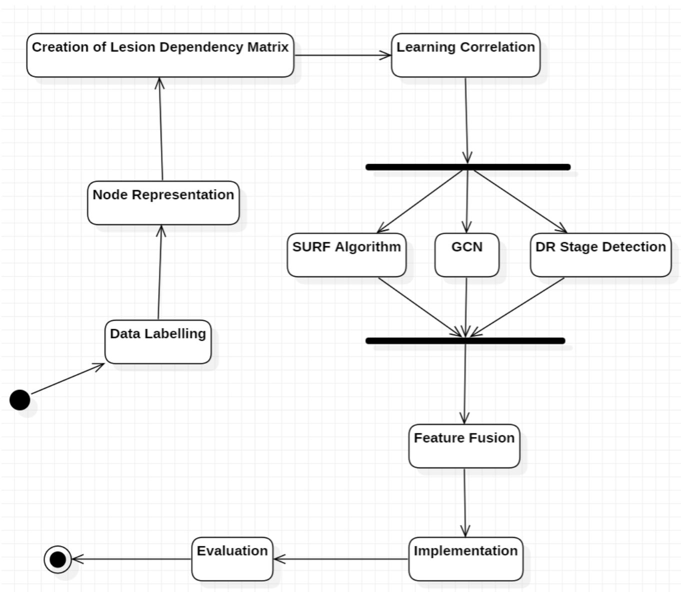


Fig. 2. Model Flowchart

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 III. The model generates a maximum accuracy of 87.8% for the IDRiD Dataset.

Doing a comparative analysis of all the models studied above, we can compare the methodologies by running the models on the same dataset. Table IV shows the comparison. Although some of the other models generate a higher accuracy, the GNN implementation provides other benefits such as multi-lesion detection, better correlation and detection of DR levels.

VI. Conclusion

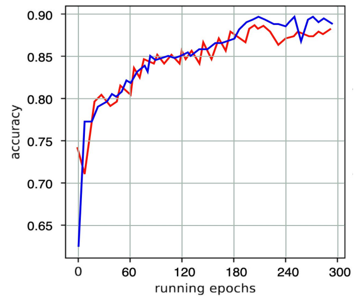
Segmentation of diabetic retinopathy (DR) lesions plays a crucial role in understanding an individual's health status and aiding in the diagnosis of various conditions, including diabetes and cardiovascular diseases. This study offers a comprehensive overview of the latest research endeavors in the field 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.

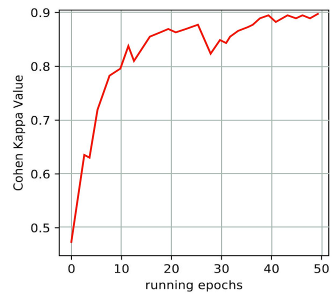
Both the SURF extraction method and GNN models have demonstrated significant advancements in segmentation accuracy compared to alternative approaches. Particularly, the Spatial Attention GNN is designed to handle noise and variations in input data, resulting in enhanced efficiency. Additionally, it automates 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. These enhancement aim at achieving refinement of the model that would include simplifying the approach to

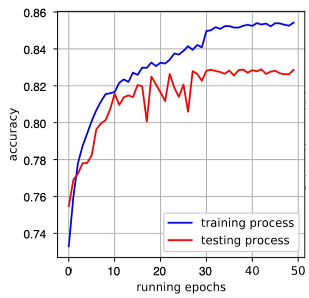
TABLE III
RESULTS GENERATED ON DIFFERENT DATASETS USING GNN.

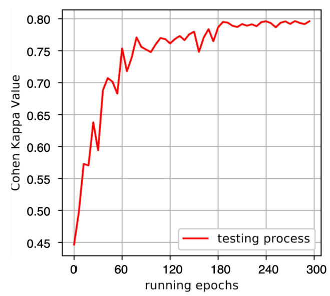
<table>
<tr><th>Dataset</th><th>Accuracy Curve</th><th>QWK Curve</th><th>Metrics</th></tr>
<tr><td>IDRiD</td><td>

IDRiD Accuracy</td><td>

QWK for IDRiD</td><td>

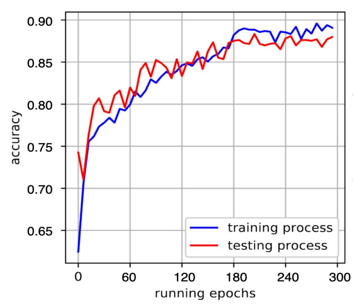
- Accuracy -87.8%
- QWK - 0.898
- Sensitivity - [0.989, 0.149, 0.694, 0.0, 0.0]
- Specificity- [0.77, 0.946, 0.794, 1.0, 0.979]

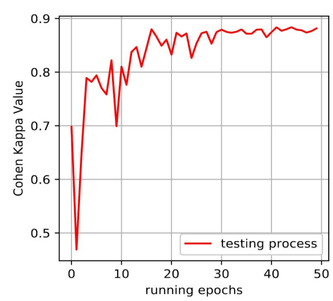
</td></tr>
<tr><td>EyePACS</td><td>

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>

create and process graph structures such as graph pruning, in turn focusing on increased accuracy. These enhancements would focus on Hyperparameter Tuning, investigating more sophisticated GNN architectures, such as Graph Attention Networks (GATs) or Graph Isomorphism Networks (GINs) & ensembling GNN with existing proven-good methods.

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 IV
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	APTOS	• Accuracy - 94.4% • Sensitivity - 84% • Specificity - 82.2%
CNN Based Detection using EfficientNet-B5	EfficientNet-B5 on Convolutional neural network (CNN)	APTOS	• Accuracy - 94% • QWK - 0.9402%
Classification using CNN and SVM	CNN, SVM, VGGNet, AlexNet & InceptionNet	APTOS	• Accuracy - 95.24% (For inception v3 and VGGNet)
Tree structure-based classification	CNN & Contrast Limited Adaptive Histogram Equalization (CLAHE)	APTOS	• Accuracy - 83.95%
Graph Neural Network	SURF Algorithm, Lesion Detection & GCN	APTOS	• Accuracy - 87.8% • QWK - 0.898

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