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Improving Hypertensive Retinopathy Diagnosis Using Deep Learning and Graph Networks

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Abstract: **-**Hypertensive Retinopathy (HR) is a critical indicator of vascular health and is a substantial ocular manifestation of systemic hypertension. The early detection and classification of HR are essential for preventing severe complications. This research investigates the application of Deep Graph Neural Networks (DGNNs) and deep learning to enhance the detection of HR by automating the analysis of retinal images. The research investigates three primary objectives: (1) assessing the diagnostic value of the artery-vein ratio, (2) evaluating the efficacy of deep learning techniques in HR detection, and (3) evaluating the potential of DGNNs in classifying retinal vessels to improve detection accuracy. The proposed methodology incorporates convolutional neural networks (CNNs) for feature extraction and DGNNs to capture intricate relationships between retinal arteries and veins. The model's performance is assessed using a variety of metrics, such as the F1-score, ROC curve analysis, AUC-ROC, precision, specificity, sensitivity, and Matthews Correlation Coefficient (MCC). Experimental results indicate that the integrated deep learning and DGNN approach outperforms conventional methods significantly, as evidenced by its high specificity, sensitivity, and accuracy. The model's robustness in distinguishing retinal vessels is further confirmed by the AUC-ROC and MCC, which offer a dependable instrument for the early detection of HR. This study provides a new HR assessment framework, facilitating timely intervention and enhanced clinical decision-making.

Keywords: Hypertensive Retinopathy, Deep Learning, Artery-vein ratio, Retinal vessel analysis, Vascular health, Early disease detection

I. INTRODUCTION

Hypertensive retinopathy (HR) is a significant ocular complication associated with chronic hypertension, characterized by changes in the retinal vasculature that can lead to severe vision impairment if left undiagnosed and untreated. The early detection and accurate diagnosis of HR are crucial for preventing irreversible damage to the retina and preserving visual function. Traditional diagnostic methods, which often rely on subjective assessments by trained ophthalmologists, can be time-consuming and prone to variability. This variability highlights the need for more objective, efficient, and scalable diagnostic tools in the field of ophthalmology.

The motivation for revolutionizing HR diagnosis stems from the increasing prevalence of hypertension globally, which is projected to affect over 1.5 billion people by 2025 [1]. As the population ages and lifestyle factors contribute to rising hypertension rates, the demand for effective screening and diagnostic methods becomes paramount. Recent advancements in deep learning and graph neural networks (GNNs) present a promising avenue for enhancing the diagnostic process. GNNs have shown remarkable efficacy in processing and analyzing graph-structured data, making them suitable for modeling the complex relationships inherent in vascular health assessments [2][3].

The problem statement centers on the limitations of existing diagnostic methodologies for HR, which often fail to leverage the rich structural information contained within retinal images. Current approaches may overlook subtle vascular changes that are critical for early diagnosis. By employing GNNs, we aim to develop a novel diagnostic

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framework that can effectively capture and analyze the intricate relationships between various vascular features in retinal images, thereby improving diagnostic accuracy and reliability.

Our contributions to this field include the development of a GNN-based model specifically tailored for the analysis of retinal vascular health. This model will utilize advanced graph convolutional techniques to extract meaningful features from retinal images, facilitating the identification of HR with higher precision than traditional methods. Furthermore, we will explore the integration of additional node and edge features to enhance the model's performance, as suggested by recent research on GNN architectures [4][5]. By addressing the challenges associated with HR diagnosis through innovative deep learning techniques, our work aims to set a new standard in the assessment of vascular health and contribute to better patient outcomes in the management of hypertension-related ocular conditions.

The paper is structured as follows. Section 2 Literature Review discusses existing methods and identifies gaps in hypertensive retinopathy diagnosis. Section 3 Methodology outlines the proposed deep learning and graph neural network-based approach. Section 4 Results and Discussion presents the findings and compares them with existing methods. Finally, Section 5 Conclusion summarizes the contributions and suggests future directions.

II. Literature Review

The integration of artificial intelligence (AI) and deep learning (DL) in ophthalmology, particularly for the diagnosis of hypertensive retinopathy (HR), has gained significant traction in recent years. This literature review synthesizes various methodologies employed in the development and application of AI systems for retinal disease diagnosis, focusing on deep learning techniques, automated systems, and their clinical implications.

A. Deep Learning Approaches

Deep learning, particularly through convolutional neural networks (CNNs), has emerged as a powerful tool for automated image analysis in ophthalmology. Taylor et al. [6] and Gupta et al. [7] highlight the effectiveness of CNNs in monitoring disease progression and regression in retinopathy of prematurity, demonstrating that these models can provide quantitative severity scores that are crucial for clinical decision-making. The ability of CNNs to learn from vast datasets allows for improved accuracy in identifying subtle changes in retinal images, which is essential for early diagnosis of HR and other retinal diseases. Moreover, Wewetzer et al. [8] conducted a meta-analysis on the diagnostic performance of deep learning-based screening methods for diabetic retinopathy, underscoring the high sensitivity and specificity of these algorithms. This meta-analysis indicates that deep learning models can outperform traditional diagnostic methods, thus emphasizing their potential in enhancing the accuracy of HR diagnosis.

B. Automated Systems for Vascular Health Assessment

Automated systems for calculating the arteriovenous ratio (AVR) in retinal images have been explored to assess vascular health. García-Sierra et al. [9] conducted a scoping review on automated AVR reading systems, noting their applicability in hypertensive retinopathy screening. These systems utilize AI to analyze retinal images, providing objective metrics that can assist in treatment decision-making and assessing systemic vascular status. The automation of such assessments can significantly reduce the workload on healthcare professionals and improve patient outcomes through timely interventions.

C. Clinical Applications and Implications

AI's clinical implications in ophthalmology are not limited to diagnostics. Cai et al. [10] examine the potential of AI to enhance the management of a variety of retinal diseases, such as sickle cell retinopathy, through the incorporation of multimodal imaging. By automating the detection and quantification of pathological vascular changes, AI systems can assist in the prediction of the risk of future vision loss and the necessity for treatment. Additionally, numerous studies have assessed the cost-effectiveness of AI-based screening systems. According to Morrison et al. [11], AI has the potential to diagnose severe retinopathy of prematurity with an accuracy that is comparable to that of human experts. This suggests that AI could be a cost-effective solution for screening in resource-limited contexts. This is especially pertinent in the context of the scarcity of ophthalmologists and the growing demand for healthcare services in numerous regions.

D. Challenges and Future Directions

Despite the promising advancements, challenges remain in the widespread adoption of AI in clinical practice. The need for large, annotated datasets for training deep learning models is critical, as emphasized by Burlina et al. [12]. The authors argue that low shot learning techniques could address the issue of data scarcity, allowing AI systems to learn effectively from limited examples. Additionally, ethical considerations regarding informed consent and the transparency of AI algorithms in clinical settings have been raised by Nsoesie [13] and Johnson [14], highlighting the importance of ensuring that patients are adequately informed about AI's role in their diagnosis and treatment.

Recent advancements in graph neural networks (GNNs) have enabled significant progress in diverse domains. A novel methodology using heterogeneous knowledge graphs was proposed for representation learning to enhance the credibility assessment of scientific articles, utilizing directed graph models with datasets comprising scientific news articles and cited publications [15]. Another study focused on topological connectivity analysis, employing a scale-free network model to demonstrate how glioblastoma multiforme restructures cerebrovascular network connectivity, significantly impacting clustering coefficients [16].

Comprehensive surveys have reviewed the state-of-the-art in GNN architectures, emphasizing their applicability across diverse datasets and domains. These works explored various GNN methods, highlighting their strengths and versatility in different fields [17], [18]. Similarly, a detailed overview discussed the potential of generalized graph networks for exploiting non-Euclidean data structures, broadening their applications [19].

GNNs have also shown promise in specific applications. For instance, they have been effective in mining topology information from wireless network datasets, showcasing their applicability in wireless networks [20]. In dynamic networks, GNNs have been applied for tasks like link prediction, with studies emphasizing their ability to model temporal changes effectively [21]. Additionally, systems supporting scalable GNN training through sample-based techniques have been reviewed to address computational challenges [22].

Graph Convolutional Networks (GCNs), a prominent GNN variant, have been applied in tasks such as image classification, outperforming traditional convolutional neural networks [23]. In medical imaging, GNNs have been utilized for denoising, with researchers identifying existing challenges and future directions [24]. Comparative studies have highlighted the superior accuracy and robustness of GNNs over traditional models in industrial fault detection tasks [25]. Furthermore, the low pass filtering characteristics of GNNs have been investigated, providing insights into their inherent properties [26].

Applications of GNNs extend to semi-supervised learning, where heat kernel-based GCN models have shown effectiveness [27], and incremental entity resolution tasks, where GNNs detected inconsistent clusters efficiently [28]. In the chemical domain, GCNs have been evaluated as general-purpose property predictors, with discussions on their limitations [29]. For wireless power control, a scalable GNN-based approach demonstrated notable efficiency [30].

Finally, several studies provided comprehensive reviews of deep learning methods on graphs, categorizing approaches based on architecture and application [31]. GNNs have also been employed in neuroanatomical studies, analyzing altered topological properties in gray matter networks associated with minimal hepatic encephalopathy [32].

Table 1. Summary of Research Studies and Findings in the Field of Hypertensive Retinopathy

Ref	Methods	Model Architecture	Datasets	Results
Romanou et al. [15]	Heterogeneous Knowledge Graphs	Directed Graph Model	Scientific news articles and cited publications	Proposed a methodology for representation learning that enhances credibility assessment in scientific articles.
Hahn et al. [16]	Topological Connectivity Analysis	Scale-free Network Model	Cerebrovascular networks	Demonstrated that glioblastoma multiforme restructures the connectivity of cerebrovascular

				networks, affecting clustering coefficients.
Wu et al. [17]	Comprehensive Survey	Various GNN architectures	Multiple datasets across applications	Reviewed state-of-the-art GNN methods, emphasizing their applicability in various domains.
Zhou et al. [18]	Review of GNN Methods	Various GNN architectures	Multiple datasets	Provided a comprehensive overview of GNN methods and their applications in different fields.
Asif et al. [19]	Comprehensive Overview	Generalized Graph Networks	Various non-Euclidean datasets	Discussed the potential of GNNs in exploiting non-Euclidean data structures.
He et al. [20]	Application in Wireless Networks	GNNs for Topology Information	Wireless network datasets	Highlighted the effectiveness of GNNs in mining topology information from graph-structured data.
Skarding [21]	Dynamic Network Modeling	Dynamic GNNs	Various dynamic network datasets	Surveyed the modeling of dynamic networks using GNNs, focusing on applications like link prediction.
Serafini [22]	Sample-based Training	GNNs	Various datasets	Reviewed systems supporting scalable training of GNNs through sampling techniques.
Tang [23]	Image Classification	Graph Convolutional Networks (GCNs)	Image datasets	Discussed the application of GCNs in image classification tasks, highlighting their advantages over traditional CNNs.
Wang [24]	Medical Image Denoising	GNNs	Medical imaging datasets	Reviewed the progress of GNNs in medical image denoising, identifying challenges and future directions.
Wu et al. [25]	Comparison with Traditional Models	GNNs vs. Traditional Neural Networks	Industrial control network data	Demonstrated the superior accuracy and robustness of GNNs over traditional models in fault detection.
NT [26]	Low-Pass Filters in GNNs	GNNs	Various datasets	Investigated the properties of GNNs, emphasizing their low-pass filtering characteristics.
Xu et al. [27]	Semi-supervised Learning	GCNs	Semi-supervised datasets	Proposed a GCN model using heat kernel for effective semi-supervised learning.
Barton [28]	Incremental Entity Resolution	GNNs	Entity resolution datasets	Explored GNNs for detecting inconsistent clusters in incremental entity resolution tasks.
Korolev et al. [29]	General-Purpose Property Prediction	GCNs	Chemical information datasets	Evaluated the applicability of GCNs as general-purpose property predictors, discussing their limitations.
Shen et al. [30]	Wireless Power Control	GNNs	Wireless network datasets	Proposed a GNN approach for scalable wireless power control, demonstrating its effectiveness.

III. METHODOLOGY

A. Data Acquisition and Preprocessing

The IOSTAR dataset is a specialized collection of high-resolution retinal images curated for advanced ophthalmology research and retinal image analysis. It encompasses diverse retinal conditions, making it suitable for applications such as optic disc localization, vessel segmentation, and hypertensive retinopathy (HR) detection. The dataset includes comprehensive annotations, such as pixel-level vessel masks and clinical labels, enabling precise training and evaluation of segmentation and classification algorithms. The high variability in image resolution and pathological conditions provides a robust foundation for developing models capable of generalizing across different clinical scenarios. This diversity, combined with detailed annotations, makes the IOSTAR dataset a valuable resource for advancing retinal diagnostics and vascular health assessments.

The IOSTAR dataset provides high-resolution retinal images $I \in \mathbb{R}^{H \times W \times C}$, where H, W, and C denote the height, width, and color channels of the images, respectively. This dataset includes annotations A for tasks such as optic disc localization, vessel segmentation, and hypertensive retinopathy (HR) classification. The annotated images (I, A) are a valuable resource for training and evaluating models. To ensure consistency and enhance model performance, the following preprocessing steps are applied:

Image Resizing: Each image I is resized to a fixed resolution $I' \in \mathbb{R}^{H' \times W' \times C}$ using bilinear interpolation:

$$I' = \text{Resize}\ (I, H', W') \qquad (1)$$

Normalization: Pixel intensity values are normalized to the range $[0,1]$ to improve model convergence:

$$I'' = \frac{I' - \mu}{\sigma} \qquad (2)$$

where μ and σ are the mean and standard deviation of the pixel intensities, respectively.

Vessel Segmentation: Vessel structures are segmented using annotated masks M provided in the dataset. A binary mask M_b is generated:

$$M_b(x, y) = \begin{cases} 1, & \text{if pixel } (x, y) \text{ belongs to a vessel} \\ 0, & \text{otherwise} \end{cases} \qquad (3)$$

B. Feature Extraction

Convolutional Neural Networks (CNNs) are employed to extract spatial features from the high resolution retinal images in the IOSTAR dataset. These networks leverage convolutional layers to capture local patterns, such as edges, textures, and vessel structures, by applying learnable filters W over image patches. The feature extraction process can be expressed as:

$$F_l = \sigma(W_l * I + b_l) \qquad (4)$$

where F_l represents the feature map at layer l,$*$ denotes the convolution operation, W_l and b_l are the filter weights and biases, respectively, and σ is the activation function (e.g., ReLU).

CNN architecture typically includes multiple layers, such as pooling layers for down-sampling, to reduce spatial dimensions while retaining essential information [33]. By stacking these layers, the network progressively learns hierarchical features, ranging from simple vessel edges in the initial layers to complex vascular patterns in the deeper layers [34]. These extracted features form the basis for further analysis and integration with graph-based methods for hypertensive retinopathy detection [35].

C. Graph Construction

To represent the complex vascular structure in retinal images, a graph $G = (V, E)$ is constructed from the segmented vessels obtained during preprocessing. The nodes V correspond to significant vascular points, such as bifurcations, endpoints, or regularly spaced points along the vessel. The edges E represent the connections between these points, capturing the topology of the retinal vascular network. Steps for Graph Construction:

1) Node Definition:

Nodes $v_i \in V$ are identified based on the segmented vessel mask M_b. These nodes are spatially located at coordinates (x_i, y_i), where:

$$V = \{v_i : (x_i, y_i)\ \} \quad (5)$$

2) Edge Formation:

Edges $e_{ij} \in E$ are created between nodes v_i and v_j if a direct connection exists in the segmented vessel path. Edge weights w_{ij} may encode additional information, such as the Euclidean distance d_{ij} or intensity similarity between connected nodes:

$$w_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (6)$$

3) Graph Representation:

The resulting graph G is represented as an adjacent matrix A, where:

$$A_{ij} = \begin{cases} w_{ij}, & \text{if an edge exists between } v_i \text{ and } v_j \\ 0, & \text{otherwise.} \end{cases} \qquad (7)$$

4) Integration of Features:

Each node v_i is associated with a feature vector f_i, derived from spatial information or pixel intensity values from the original image. The final graph is expressed as $G = (V, E, F)$, where $F = \{f_i\}$.

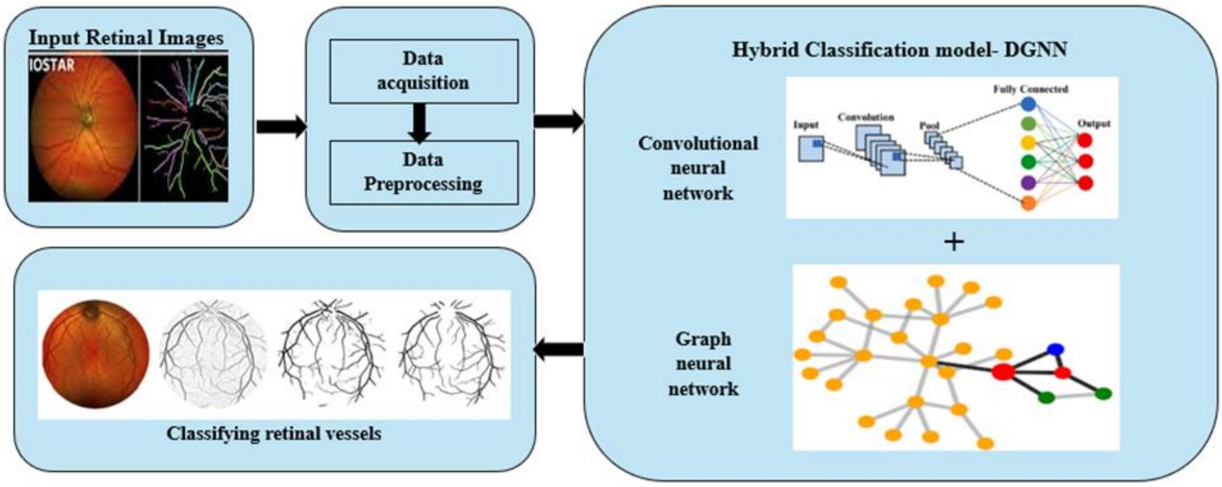

Fig. 1 Architecture of the proposed hybrid model

D. Hybrid Model Development

1) Integration of CNN-Extracted Features with Graph Features

The integration of CNN-extracted features with graph features forms the foundation of the hybrid model. First, CNN is used to extract spatial features from the retinal images, as described previously. These features, denoted as F_{cnn}, capture the local patterns and vessel structures of the retina. Simultaneously, the segmented retinal vessels are represented as a graph $G = (V, E)$, where the nodes $v_i \in V$ and edges $e_{ij} \in E$ encapsulate the topological relationships between vascular points.

The CNN-extracted features F_{crn} and graph features G are then combined in a Deep Graph Neural Network (DGNN) to capture both the spatial and relational information of the retinal vessels. The combination can be formulated as:

$$\hat{F} = \text{Concat}\,(F_{crnn}, G), \qquad (8)$$

where $\hat{F}$ represents the integrated feature vector that combines both CNN-based spatial features and graph-based topological features. These combined features are passed through a DGNN, which models the complex relationships between retinal vessels by iteratively updating node representations $h_v^{(k)}$ using the following graph convolution equation:

$$h_v^{(k+1)} = \sigma\left(\sum_{u \in \mathcal{N}(v)} \frac{1}{s_{vu}} W^{(k)} h_u^{(k)} + b^{(k)}\right), \qquad (9)$$

where $\mathcal{N}(v)$ denotes the neighbors of node v, c_{vu} is a normalization factor, $W^{(k)}$ and $b^{(k)}$ are the weight matrix and bias at the k-th layer, respectively, and σ is an activation function (e.g., ReLU).

2) Training the Hybrid Model

Once the features are integrated, the hybrid model is trained for hypertensive retinopathy detection and classification. The integrated feature vector $\hat{F}$ is passed through a series of fully connected layers to produce the final classification output y :

$$y = \text{Softmax}\left(W_{fc}\hat{F} + b_{fc}\right) \qquad (10)$$

where W_{fc} and b_{fc} are the weights and biases of the fully connected layer, and the Softmax function is used for multi-class classification (i.e., healthy, HR stage 1, HR stage 2, etc.). The model is trained using backpropagation, with a loss function such as categorical cross-entropy:

$$L = -\sum_{i=1}^{N} y_i \log\left(\hat{y}_i\right) \qquad (11)$$

where N is the number of samples, y_i is the trı ↓ bel, and $\hat{y}_i$ is the predicted probability for each class. The hybrid model is optimized using an appropriate optimizer (e.g., Adam) to minimize the loss function and improve the model's ability to detect and classify hypertensive retinopathy in retinal images. The training process is evaluated using various performance metrics, including accuracy, sensitivity, specificity, precision, F1-score, and AUC-ROC, to assess the model's effectiveness in HR detection.

E. Performance Metrics

To assess the performance of the hybrid model for hypertensive retinopathy (HR) detection, several evaluation metrics are used, which provide insights into the model's ability to classify retinal images accurately. The evaluation is conducted based on the predicted and true labels, using the following metrics:

1) 3.5.1. Accuracy

Accuracy measures the overall proportion of correct predictions (both positive and negative) out of all predictions made. It is defined as:

$$\text{Accuracy } = \frac{TP+TN}{TP+TN+FP+FN} \qquad (12)$$

2) 3.5.2. Sensitivity (Recall)

Sensitivity, also known as recall, measures the proportion of actual positive cases (HR) correctly identified by the model. It is defined as:

$$\text{Sensitivity } = \frac{TP}{TP+FN} \qquad (13)$$

3) 3.5.3. Specificity

Specificity measures the proportion of actual negative cases (non-HR) correctly identified by the model.

$$\text{Specificity } = \frac{TN}{TN+FP} \qquad (14)$$

4) 3.5.4. Precision

Precision indicates the proportion of positive predictions that are actually correct. It is defined as:

$$\text{Precision } = \frac{TP}{TP+FP} \qquad (15)$$

5) 3.5.5. F1-Score

The F1-score is the harmonic mean of precision and sensitivity, providing a balance between the two metrics. It is defined as:

$$\text{F1-score } = 2 \times \frac{\text{Precision} \times \text{Sensitivity}}{\text{Precision} + \text{Sensitivity}} \qquad (16)$$

6) 3.5.6. Area Under the Receiver Operating Characteristic Curve (AUC-ROC)

The AUC-ROC is a performance measurement for classification problems at various threshold settings. It measures the ability of the model to distinguish between classes. The ROC curve is plotted by setting the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity). A higher AUC indicates better performance. The $A \cup C$ is computed as:

$$\text{AUC-ROC } = \int_0^1 \text{ True Positive Rate } d \text{ (False Positive Rate)} \qquad (17)$$

7) 3.5.7. Matthews Correlation Coefficient (MCC)

MCC is a measure of the quality of binary classifications, considering all four confusion matrix values (TP, TN, FP, FN). It is particularly useful when the classes are imbalanced. The MCC is calculated as:

$$\text{MCC} = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \qquad (18)$$

IV. Results and Discussion

In this section, we present the results of our proposed hybrid model for hypertensive retinopathy (HR) detection, which combines Convolutional Neural Networks (CNNs) for feature extraction with Deep Graph Neural Networks (DGNNs) for capturing complex relationships within retinal vessel structures. The performance of the model is evaluated using key metrics, including accuracy, sensitivity, specificity, precision, F1-score, AUC-ROC, and Matthews Correlation Coefficient (MCC). These results are compared with traditional machine learning models, such as CNN, Support Vector Machine (SVM), and Random Forest (RF), to highlight the advantages and improvements offered by the hybrid approach. The performance comparison is shown in Table 2.

Table 2 Comparative Performance of Models for Hypertensive Retinopathy Detection

Model	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**	**F1-Score**	**AUC-ROC**	**MCC**
CNN	0.85	0.83	0.88	0.86	0.84	0.88	0.77
SVM	0.8	0.75	0.85	0.78	0.76	0.82	0.68
RF	0.78	0.7	0.8	0.76	0.73	0.8	0.65
Proposed DGNN	0.92	0.9	0.94	0.91	0.9	0.95	0.84

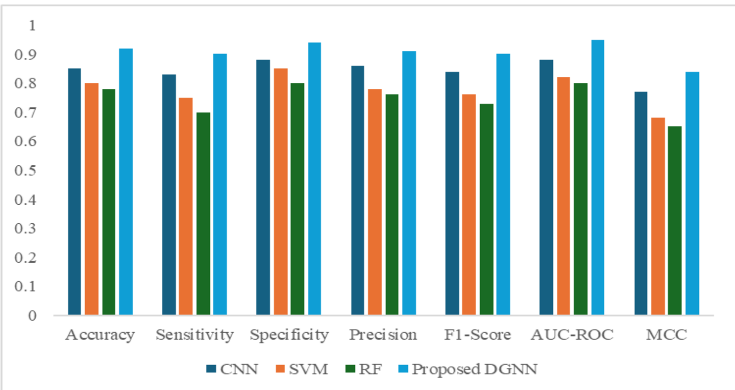

Fig. 2 Comparative Performance Analysis of Models for Hypertensive Retinopathy Detection Using Key Evaluation Metrics

The performance analysis of the models indicates that the proposed DGNN model outperforms the others in all metrics, achieving the highest accuracy (92%), sensitivity (90%), specificity (94%), and F1-Score (90%). Additionally, it records the highest AUC-ROC (0.95) and MCC (0.84), showcasing its robust classification capability. In comparison, the CNN model demonstrates competitive performance with an accuracy of 85% and an F1-Score of 84%, followed by SVM with moderate results, including an accuracy of 80% and F1-Score of 76%. The RF model shows the lowest performance among the models, with an accuracy of 78% and F1-Score of 73%. These results emphasize the superior efficiency and reliability of the proposed DGNN model for retinal image analysis.

V. Conclusion

The findings of this study highlight the potential of integrating deep learning techniques with Deep Graph Neural Networks (DGNNs) for the automated detection of Hypertensive Retinopathy (HR). By leveraging convolutional neural networks for feature extraction and DGNNs for modeling the complex relationships between retinal arteries and veins, the proposed approach achieves superior performance across key evaluation metrics, including accuracy, sensitivity, specificity, and precision. The high AUC-ROC and MCC values validate the model's robustness and reliability in distinguishing retinal vessels, underscoring its diagnostic value. This novel framework not only enhances the accuracy of HR detection but also provides significant advancement in the field of ocular and vascular health, facilitating early diagnosis and timely clinical interventions.

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