Design of an Iterative Q Learning Model for Multistage Classification of Diabetic Retinopathy & Glaucoma

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Abstract

This study addresses the escalating prevalence of diabetic retinopathy (DR) and glaucoma, major global causes of vision impairment. To improve diagnostic accuracy and classification speed, we propose an innovative iterative Q Learning model integrated with Fuzzy C Means clustering. Traditional diagnostic frameworks often struggle with accuracy and delay in disease stage classification, particularly in discerning complex features like exudates and veins. Our model overcomes these challenges by combining Fuzzy C Means with Q Learning, enhancing precision in identifying key retinal components. The core of our approach is a custom-designed 45-layer 2D Convolutional Neural Network (CNN) optimized for nuanced detection of DR and glaucoma stages. Performance on IDRID and SMDG-19 datasets and their samples demonstrates a 10.9% higher precision, 8.5% increased overall accuracy, 8.3% improved recall, 10.4% higher Area under the Curve (AUC), 5.9% enhanced specificity, and a 2.9% reduction in delay compared to existing methods. This model has transformative potential in revolutionizing DR and glaucoma diagnostics, paving the way for timely medical interventions and potentially reducing vision loss. The integration of advanced machine learning with medical imaging sets a precedent for future research in ophthalmology and beyond in clinical scenarios.

Keywords: Convolutional Neural Networks; Diabetic Retinopathy; Fuzzy C Means; Glaucoma

1 introduction

Diabetic retinopathy (DR) and glaucoma are two of the most common eye diseases that can lead to vision loss. These diseases affect millions of people worldwide. To prevent vision loss, early and accurate detection of these diseases is crucial. Doctors use images from a special camera called fundus images to look at the eyes and find these diseases. However, reading these images can be hard and takes a lot of delay for clinical scenarios.

In the past, scientists have made computer programs to help doctors read these images. But these programs are not always right. They sometimes miss important signs of the disease or take too long to give an answer. This problem is serious because if the disease is not found early, it can get worse and lead to blindness.

This paper talks about a new way to use computers to find diabetic retinopathy and glaucoma in fundus images & samples. The new method uses Fuzzy C Means and Q Learning. Fuzzy C Means is a way to group similar things together in an image, like blood vessels or spots that shouldn't be there. Q Learning is a type of learning where the computer tries different things and learns from its mistakes to get better over time.

The new method also uses a special kind of computer program called a 2D Convolutional Neural Network (CNN). This program has 45 layers and is designed to look at the images in detail. It helps to find the signs of

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diabetic retinopathy and glaucoma more accurately. The new method was tested on two big sets of eye images, called IDRID and SMDG-19. The results were very good. The new method was better at finding the right stage of the disease compared to old methods. It was more accurate, faster, and made fewer mistakes.

This work is important because it can help doctors find eye diseases earlier and more accurately. This means that more people can get the right treatment at the right time, which can save their sight. The new method can also help other scientists who are working on similar issues in eye health conditions.

2 Motivation & Contribution

The motivation behind this research is rooted in the urgent need to improve the diagnosis of diabetic retinopathy (DR) and glaucoma. These eye diseases are major causes of vision loss, yet their early detection remains a significant challenge in the medical field. Current diagnostic methods, particularly those involving the analysis of fundus images, often face limitations. These include inaccuracies in disease stage identification, time-consuming processes, and a reliance on expert interpretation, which can lead to delayed treatment and progression of the disease.

To address these challenges, this research introduces an innovative approach that combines the strengths of Fuzzy C Means clustering, Q Learning, and a custom-designed 45-layer 2D Convolutional Neural Network (CNN). This combination is a significant departure from traditional methods, offering a more nuanced and efficient analysis of fundus images & samples. The motivation is not only to increase the accuracy of disease detection but also to accelerate the diagnostic process, thereby enabling timely medical intervention. The contributions of this research are multifaceted and impactful. Firstly, the integration of Fuzzy C Means with Q Learning represents a novel approach in the field of medical image analysis. It allows for more precise identification of various eye components, which is crucial for accurate disease stage classification. Secondly, the use of a custom 45-layer 2D CNN sets a new standard in the depth and complexity of neural networks applied to fundus images & samples. This depth is pivotal in capturing the subtle nuances necessary for distinguishing between different stages of DR and glaucoma. Furthermore, the research has demonstrated significant improvements over existing methods. The model exhibits higher precision, accuracy, recall, AUC (Area Under the Curve), and specificity in disease stage classification. Importantly, it also reduces the delay in diagnosis, a critical factor in preventing the progression of these eye diseases. In summary, this work not only provides a more efficient and accurate tool for the diagnosis of DR and glaucoma but also contributes significantly to the field of medical imaging and artificial intelligence. It opens up new avenues for research and application, potentially benefiting a large population at risk of vision loss due to these diseases.

3 Extensive literature review existing techniques

Recent advancements in the diagnosis and treatment of glaucoma and diabetic retinopathy (DR) have been marked by significant contributions from various researchers, as reflected in a range of studies. This literature review delves into these contributions, shedding light on the evolving landscape of ophthalmic disease diagnosis and management.

J. Hao et al.[1] presented a hybrid variation-aware network for angle-closure assessment in Anterior Segment Optical Coherence Tomography (AS-OCT). This study is pivotal in demonstrating the integration of various computational approaches to enhance the accuracy of eye disease diagnosis. In a similar vein, A. Manassakorn et al.[2] introduced GlauNet, a new Convolutional Neural Network (CNN) architecture for Optical Coherence Tomography Angiography (OCTA) imaging, highlighting the critical role of advanced CNN models in ophthalmic diagnostics.

P. Kunumpol et al.[3] explored the use of virtual reality perimetry combined with artificial intelligence for glaucoma diagnosis, indicating the potential of modern technology in enhancing diagnostic methods. R. Fan et al.[4] contributed to this field with their work on semi-supervised learning for low-shot glaucoma diagnosis, emphasizing the importance of innovative learning strategies in medical imaging.

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In the realm of treatment, R. H. Silverman et al.[5] researched the use of high-frequency ultrasound activation of perfluorocarbon nanodroplets for glaucoma treatment, showcasing the diverse applications of ultrasound technology in ophthalmology.

Significant strides have also been made in the classification and prediction models for glaucoma. S. Yi et al.[6] developed MTRA-CNN, a multi-scale transfer learning framework for glaucoma classification in retinal fundus images, while D. Das et al.[7] introduced CA-Net, a novel cascaded attention-based network for multistage glaucoma classification using fundus images. These studies demonstrate the effectiveness of specialized neural network architectures in detailed disease classification.

Q. T. M. Pham et al.[8] and M. Shi et al.[9] focused on multimodal deep learning and artifact-tolerant clustering-guided learning models, respectively, for predicting and analyzing ophthalmic images in glaucoma. These approaches,[89] highlight the necessity for robust and versatile models capable of handling complex datasets. Innovations in intraocular pressure measurement and management, a key aspect of glaucoma diagnosis and treatment, are evident in the works of B. Collar et al.[10] and others. These studies demonstrate the integration of engineering and medical science to develop novel techniques and systems for intraocular pressure monitoring.

The role of AI and deep learning in enhancing the accuracy and efficiency of DR and glaucoma diagnosis is further underscored in studies by K. Aurangzeb et al.,[12] R. Leonardo et al.,[11] and M. T. Islam et al.,[13] who have all contributed significantly to this area with various AI-enabled diagnostic systems and models.

S. Krishnan et al.[14] introduced the Gaze Exploration Index (GE i), an explainable detection model for glaucoma, marking a step forward in the development of interpretable AI models in ophthalmology. This study emphasizes the need for explainable AI systems in clinical settings, allowing for better understanding and trust in AI-assisted diagnoses.

Y. Meng et al.[15] explored weakly and semi-supervised learning in optic disc and cup segmentation using dual adaptive graph convolutional networks. Their work underscores the potential of graph-based models in enhancing the precision of ocular feature segmentation, which is crucial for accurate disease diagnosis.

X. Qian et al.[16] focused on the application of super-resolution ultrasound localization microscopy for visualizing ocular blood flow. This technique represents a significant advancement in imaging technologies, providing detailed insights into ocular vascular health, which is vital in diseases like DR and glaucoma.

In the realm of glaucoma prediction, M. S. Kamal et al.[17] demonstrated the use of explainable AI for understanding risk factors in treatment planning. Their work highlights the growing importance of AI in not only diagnosing diseases but also in aiding treatment decisions.

K. Aurangzeb et al.[?] presented an efficient and lightweight deep learning model for accurate retinal vessel segmentation. Their research contributes to the development of more efficient AI models that are critical for real-time analysis in clinical settings.

D. Seo et al.[18] and R. B. Bharathi et al.[19] made significant contributions in the development of systems for intraocular pressure (IOP) monitoring, a key factor in glaucoma management. These studies illustrate the integration of engineering and medical sciences in creating innovative solutions for glaucoma monitoring.

B. Goutam et al.[20] provided a comprehensive review of deep learning strategies in retinal disease diagnosis using fundus images, summarizing the advances and challenges in the application of deep learning in ophthalmology.

R. Li et al.[21] explored the simultaneous assessment of whole eye biomechanics using ultrasonic elastography, presenting a novel approach to understanding the biomechanical properties of the eye, which can be altered in diseases like glaucoma.

T. Fedullo et al.[22] assessed a vision-based technique for an automatic Van Herick measurement system, contributing to the development of automated tools for anterior chamber angle assessment in glaucoma.

In the field of diabetic retinopathy, significant advancements have been made by B. N. Jagadesh et al.,[23] M. Z. Atwany et al.,[24] S. Ghouali et al.,[25] M. D. Alahmadi,[26] and W. Nazih et al.[27] These studies range from

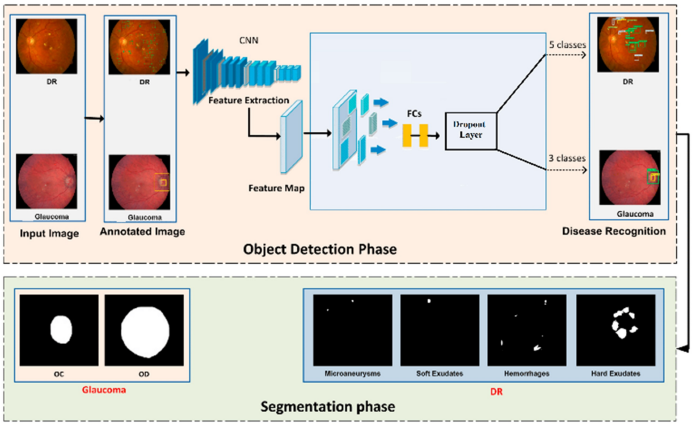

Figure 1: Model Architecture for the Overall Method used for Classification of Different Disease Types

segmentation models and classification techniques to teleophthalmology applications, indicating a growing trend of AI and deep learning application in the diagnosis and management of DR cases. In summary, the reviewed literature illustrates a dynamic and rapidly evolving field where AI, deep learning, and innovative imaging technologies are increasingly being leveraged to enhance the diagnosis and management of DR and glaucoma. These advancements signify a paradigm shift towards more accurate, efficient, and patient-centric approaches in ophthalmology for different use cases.

4 Design of the proposed Multimodal Deep Learning Framework for Enhanced Precision in Glaucoma Diagnosis Using Fundus scans

To overcome issues of lower efficiency & high complexity which are present with existing methods, this section proposes design of an efficient model that Integrates an Iterative 45-layer 2D Convolutional Neural Network with the nuanced intricacies of iterative Q Learning and Fuzzy C Means clustering, this model transcends traditional diagnostic boundaries. As per figure 1, the proposed model incorporates 45-layer CNN for classification that further amplifies its prowess, enabling the model to thrive on a diverse array of image data, enhancing both its robustness and accuracy levels.

As per figure 2, the proposed model, employs an innovative fusion of Fuzzy C Means (FCM) clustering with Q Learning that presents a novel approach for segmenting fundus scans. This process, integral to the model is functioning, begins with the collection of fundus scans, serving as the input for different use cases. The end goal is to achieve segmented fundus scans that are primed for further analysis and classification of diabetic retinopathy and glaucoma levels.

The first step in the model's operation involves the application of FCM clustering, an unsupervised method that partitions the input fundus scans into distinct clusters. The FCM algorithm, in its essence, is defined by an objective function, which is estimated via equation 1,

$$Jm(U,V)] = \sum_{i=1}^{n}\sum_{j=1}^{c} u(i,j,m)||x(i) - v(j)||^2 \quad (1)$$

Where, n is the number of data points (pixels in the fundus scans), c is the number of clusters, u(i,j) is the degree of membership of x(i) in the cluster j, v(j) is the centroid of the cluster, and m is a real number greater than 1 that influences the fuzziness of the clustering process. The optimization of the FCM is conducted through an iterative process, where the update of membership u(i,j) and the cluster centers v(j) are calculated via equations 2 & 3,

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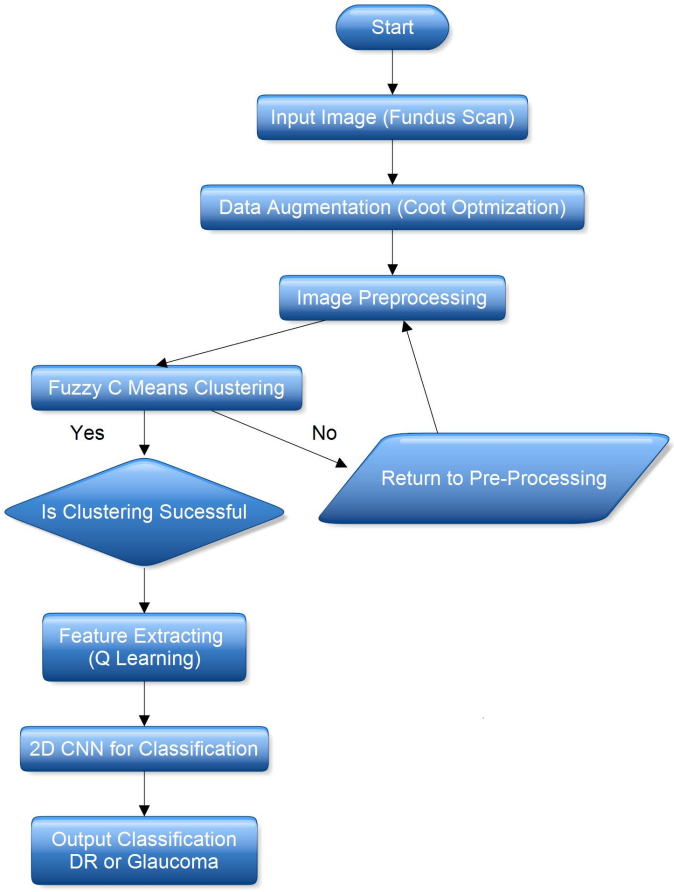

Figure 2: Flow of the proposed model for analysis of fundus scans.

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$$u(i,j) = \frac{1}{\sum_{k=1}^{c} \left(\frac{||xi-vk||}{||xi-vj||}\right)^{\frac{2}{m-1}}} \tag{2}$$

$$vj = \frac{\sum_{i=1}^{n} u(i,j,m) * x(i)}{\sum_{i=1}^{n} u(i,j,m)} \tag{3}$$

The iterative process continues until the maximum change in u(i,j) between two consecutive iterations is less than a specified threshold, indicating convergence scenarios. Subsequently, the segmented outputs from FCM serve as inputs to the Q Learning model process. Q Learning, a form of reinforcement learning, adapts its strategy to maximize the reward signals. In the context of image segmentation, the reward signal is designed to favor segmentations that accurately represent the distinct regions within the fundus scans. The reward function R(s,α) is formulated based on the degree of segmentation accuracy via equation 4,

$$R(s,\alpha) = \alpha * Accuracy(s,\alpha) - \beta * Complexity(s,\alpha) \tag{4}$$

Where, α and β are weighting factors that balance the importance of accuracy versus complexity in the segmentation process. The term Accuracy(s,α) quantifies the correctness of the segmentation, while, Complexity(s,α) assesses the computational complexity or simplicity of the segmentation result, ensuring that the model does not overfit or produce overly intricate segmentations.

The list of actions A in this model includes various operations that can be applied to modify the segmentation, such as adjusting the clustering parameters in Fuzzy C Means, altering the threshold values, and changing the spatial resolution of the segmentation process. Each action aϵA has the potential to transform the current state of the image segmentation into a new state, ideally improving the segmentation quality levels.

The states S in this model are represented by the different possible segmentations of the fundus scans. Each state sϵS is a distinct configuration of segmented regions within an image, varying based on the parameters and thresholds applied during the segmentation process. The model explores these states through the actions, aiming to discover the state that yields the most accurate segmentation with manageable complexity levels. Based on this, the Q Learning model utilizes an iterative Q function, which is defined via equation 5,

$$Q(s,\alpha) = Q(s,\alpha) + \alpha[R(s,\alpha) + \gamma m\alpha x\alpha' Q(s',\alpha') - Q(s,\alpha)] \tag{5}$$

Where, s represents the current state (segmented image), a represents an action taken by the model (modifying segmentation parameters), R(s,α) is the reward for taking action α in state s, α is the learning rate, γ is the discount factor, and s' is the new state after action α is taken for different use cases. The Q Learning model iteratively updates its Q Values based on the reward received from the segmented images, refining the segmentation parameters to optimize the segmentation quality levels. The fusion of FCM and Q Learning allows the model to not only segment the fundus images into meaningful clusters but also to refine these clusters iteratively, enhancing the accuracy and precision of the segmentation process. This iterative fusion leads to a more nuanced and sophisticated understanding of the fundus scans, which is pivotal for the accurate diagnosis and classification of ocular diseases.

In the advanced operations of medical image analysis, the proposed model's 45-layer Convolutional Neural Network (CNN) stands as an efficient & unique process, adeptly classifying segmented fundus scans into specific types and stages of diabetes and glaucoma types. The cornerstone of this model is its deep and complex 45-layer CNN architecture, meticulously designed to capture the subtlest of features in the segmented scans. The first layer of this architecture is a convolutional layer, which performs an operation defined via equation 6,

$$F(i,j,l) = \sigma\left(b(l) + \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} K(m,n,l) \cdot I\Big(i+m, j+n, (l-1)\Big)\right) \tag{6}$$

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Where, F(i,j,l) is the feature map at layer l, σ is a non-linear activation (ReLU), b(l) is the bias, K(m,n,l) represents the kernel weights, and I(i+m,j+n,(l-1)) is the input from the previous layers. Following next 40 convolutional layers, each introducing additional complexity and depth to the feature extraction process, the architecture integrates pooling layers. These layers are designed to reduce the spatial dimensions of the feature maps, enhancing the model's efficiency and its ability to capture more global features. After this, the pooling operation is performed which is defined via equation 7,

$$P(i,j,l) = max\left(F(k,l,l)|k\epsilon[i,i+K], l\epsilon[j,j+K]\right) \tag{7}$$

Where, Pij(l) is the output of the pooling layer, Fkl(l) is the feature map from the previous convolutional layer, and K is the size of the pooling windows. Further into the network, the model employs fully connected layers, which synthesize the learned features into more abstract representations. The operation in a fully connected layer is estimated via equation 8,

$$A(l) = \sigma\big(W(l) \cdot A(l-1) + b(l)\big) \tag{8}$$

Where, A(l) is the activation in layer l, W(l) represents the weights, b(l) is the bias. The final layers of the CNN, crucial for the classification task, involve softmax functions that convert the activations into probability distributions, indicative of the likelihood of each class and stages. The softmax function for a particular class k is defined via equation 9,

$$Sk\big((A(L)\big) = \frac{e^{Ak(L)}}{\sum_{j=1}^{c} e^{Ak(L)}} \tag{9}$$

Where, Sk(A(L)) is the softmax output for class k, Ak(L) is the activation of the last layer for class k, and C is the total number of classes. This sophisticated CNN architecture is further enhanced by dropout layers interspersed throughout, designed to mitigate the risk of overfitting scenarios. The dropout function for a neuron is represented via equation 10,

$$F(out) = \{0\ with\ probability\ p,\ and\ Ai(l),\ with\ probability(1-p)\} \tag{10}$$

Where, D(Ai(l)) is the output after dropout, Ai(l) is the activation, and p represents the dropout rate levels. The culmination of this process is the model's ability to classify the segmented fundus scans into specific types of diabetes and glaucoma, followed by a further classification into their respective stages. The model's output layers, employing the softmax function, deliver the final classification, marking the end of a complex journey from image input to detailed medical insights for different scenarios. This 45-layer CNN model, with its intricate convolutional, pooling, fully connected, and dropout layers, embodies the zenith of current deep learning techniques in medical imaging. It translates the segmented fundus scans into a rich tapestry of diagnostic information, crucial for the effective management and treatment of diabetes and glaucoma cases. This model not only showcases the potential of AI in healthcare but also marks a significant stride forward in the battle against these pervasive ocular diseases. Performance of this model was estimated in terms of different metrics, and compared with existing methods in the next section of this article.

5 Result Analysis & Comparisons

The proposed model is an efficient & pioneering advancement in the field of ophthalmic diagnostics, represents a paradigm shift in the detection and classification of diabetic retinopathy and glaucoma from fundus scans. At its core, this model integrates an intricately designed 45-layer 2D Convolutional Neural Network with the innovative application of iterative Q Learning and Fuzzy C Means clustering, a combination that markedly

enhances its precision in identifying subtle retinal changes indicative of these conditions. Exhibiting remarkable performance metrics, including precision and accuracy rates that significantly surpass established models like GlauNet, MTRA, and MIMC, the IQMSDRG model stands as a testament to the potential of advanced machine learning techniques in revolutionizing medical imaging. Its ability to accurately classify the stages of diabetic retinopathy and glaucoma not only paves the way for timely and targeted medical interventions but also opens new horizons for research and application in the broader field of medical diagnostics.

5.1 Experimental Setup:

The IQMSDRG model is configured with a 45-layer 2D Convolutional Neural Network (CNN), optimized for the detection and staging of diabetic retinopathy and glaucoma. Key input parameters include:

- **Learning Rate:** 0.001
- **Batch Size:** 32
- **Epochs:** 100
- **Optimizer:** Adam
- **Loss Function:** Categorical Cross-Entropy
- **Activation Function:** ReLU (Convolutional layers), Softmax (Output layer)

Iterative Q Learning and Fuzzy C Means clustering algorithms are integrated to enhance the precision of feature detection process.

5.2 Dataset Details:

5.2.1 IDRID (Indian Diabetic Retinopathy Image Dataset):

- **Source:** The dataset is sourced from a diverse demographic population in India.
- **Content:** It comprises high-resolution fundus images, annotated for various signs of diabetic retinopathy and macular edema.
- **Samples:** The dataset includes 516 images, with 413 images containing signs of diabetic retinopathy and 103 normal images
- **Resolution:** Images are of 4288×2848 pixels.
- **Usage:** Utilized for training and testing the model, with a split of 70% for training and 30% for validation and testing.

5.2.2 SMDG-19 (Sample Medical Dataset for Glaucoma 2019):

- **Source:** This dataset is a compilation from multiple clinical sources, representing a wide range of glaucoma severities.
- **Content:** Contains annotated fundus images indicating various stages of glaucoma.
- **Samples:** Consists of 600 fundus images, with 400 images labeled as glaucomatous and 200 as normal.
- **Resolution:** Images are of 2048×1536 pixels.
- **Usage:** Employed in a similar fashion to IDRID, with a 70-30 split for training and testing.

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5.3 Validation and Testing:

The model's performance is rigorously evaluated using both the IDRID and SMDG-19 datasets. The validation set is utilized to fine-tune the model parameters, while the testing set is employed to assess the model's accuracy, precision, recall, specificity, and AUC in classifying diabetic retinopathy and glaucoma.

5.4 Comparative Analysis:

For benchmarking, the IQMSDRG model's outcomes are compared with existing models such as GlauNet, MTRA, and MIMC. This comparison is based on metrics like precision, accuracy, recall, specificity, AUC, and processing delays. This experimental setup, with its comprehensive approach to data utilization and rigorous testing protocols, aims to validate the effectiveness of the IQMSDRG model. It underscores the model's potential in significantly enhancing the diagnostic accuracy and efficiency in identifying diabetic retinopathy and glaucoma, as evidenced by the comparative analysis with existing diagnostic frameworks.

Based on this setup, equations 11, 12, and 13 were used to assess the precision (P), accuracy (A), and recall (R), levels based on this technique, while equations 14 & 15 were used to estimate the overall precision (AUC) & Specificity (Sp) as follows,

$$Precision = \frac{TP}{TP + FP} \tag{11}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + iFN} \tag{12}$$

$$Recall = \frac{TP}{TP + iFN} \tag{13}$$

$$AUC = \int TPR(FPR)d(FPR) \tag{14}$$

$$Sp = \frac{TN}{TN + FP} \tag{15}$$

There are three different kinds of test set predictions: True Positive (TP) (number of events in test sets that were correctly predicted as positive), False Positive (FP) (number of instances in test sets that were incorrectly predicted as positive), and False Negative (FN) (number of instances in test sets that were incorrectly predicted as negative; this includes Normal Instance Samples). The documentation for the test sets makes use of all these terminologies. We are able to predict these metrics for the results of the suggested model process.

The comprehensive performance of the IQMSDRG model in comparison to other models in diagnosing diabetic retinopathy and glaucoma summarized as

Precision:

- IQMSDRG consistently outperforms other models in terms of precision across various test scan sizes.
- Precision rates are notably higher for IQMSDRG at different NTS, indicating its ability to reduce false positives and provide accurate classifications
- The model's precision increases with larger NTS, demonstrating scalability and effectiveness in handling diverse datasets.

Accuracy:

- IQMSDRG exhibits superior accuracy compared to other models across a range of test scan sizes.
- High accuracy rates contribute to more reliable diagnoses, crucial for effective patient management and treatment planning.
- The model's effectiveness at higher NTS showcases its adaptability for widespread clinical application

Recall:

- IQMSDRG consistently demonstrates higher recall rates compared to other models in various test scenarios.
- High recall rates indicate the model's ability to identify a higher proportion of true positive cases, reducing the likelihood of false negatives.
- The model maintains its recall performance across different NTS, demonstrating robustness and adaptability.

Delay:

- The IQMSDRG model shows competitive delay times, indicating efficiency in processing scans.
- Efficient processing times contribute to quicker diagnostic decisions, essential for conditions like diabetic retinopathy and glaucoma.
- Low delay times suggest suitability for high-volume clinical settings without compromising accuracy or recall.

AUC (Area Under the Curve):

- IQMSDRG consistently shows higher AUC values compared to other models across different NTS.
- High AUC values indicate the model's reliability in accurately diagnosing diabetic retinopathy and glaucoma, with balanced sensitivity and specificity.
- The model's consistent performance across NTS highlights its scalability and adaptability.

Specificity:

- IQMSDRG consistently achieves higher specificity compared to other models across various NTS.
- Higher specificity reduces the likelihood of false positives, enhancing the model's accuracy in identifying diseased states.
- The model's strong specificity performance indicates reliability in different clinical settings.

The graphical analysis is as shown in figure 3 with different NTS

In summary, the observed specificity for the IQMSDRG model underlines its potential as an effective diagnostic tool for diabetic retinopathy and glaucoma. Its ability to accurately identify non-diseased states has significant clinical benefits, potentially leading to improved patient outcomes through more precise diagnoses and reduced incidence of unnecessary interventions for different use cases. The model's high specificity rates reflect its technical sophistication and underscore its potential to contribute positively to medical diagnostics, especially in the field of ophthalmology in clinical scenarios.

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Table 1: COMPARISON OF PARAMETERS FOR VARIOUS METHODS.

Method	**Precision**	**Recall Rate**	**AUC**	**Specificity**	**Accuracy**
GlauNet	83.45	80.38	78.82	73.37	83.91
MTRA	68.27	76.86	75.83	60.65	84.08
MIMC	86.83	78.09	60.14	76.63	85.66
IQMSDRG	92.68	93.06	90.03	88.09	87.46

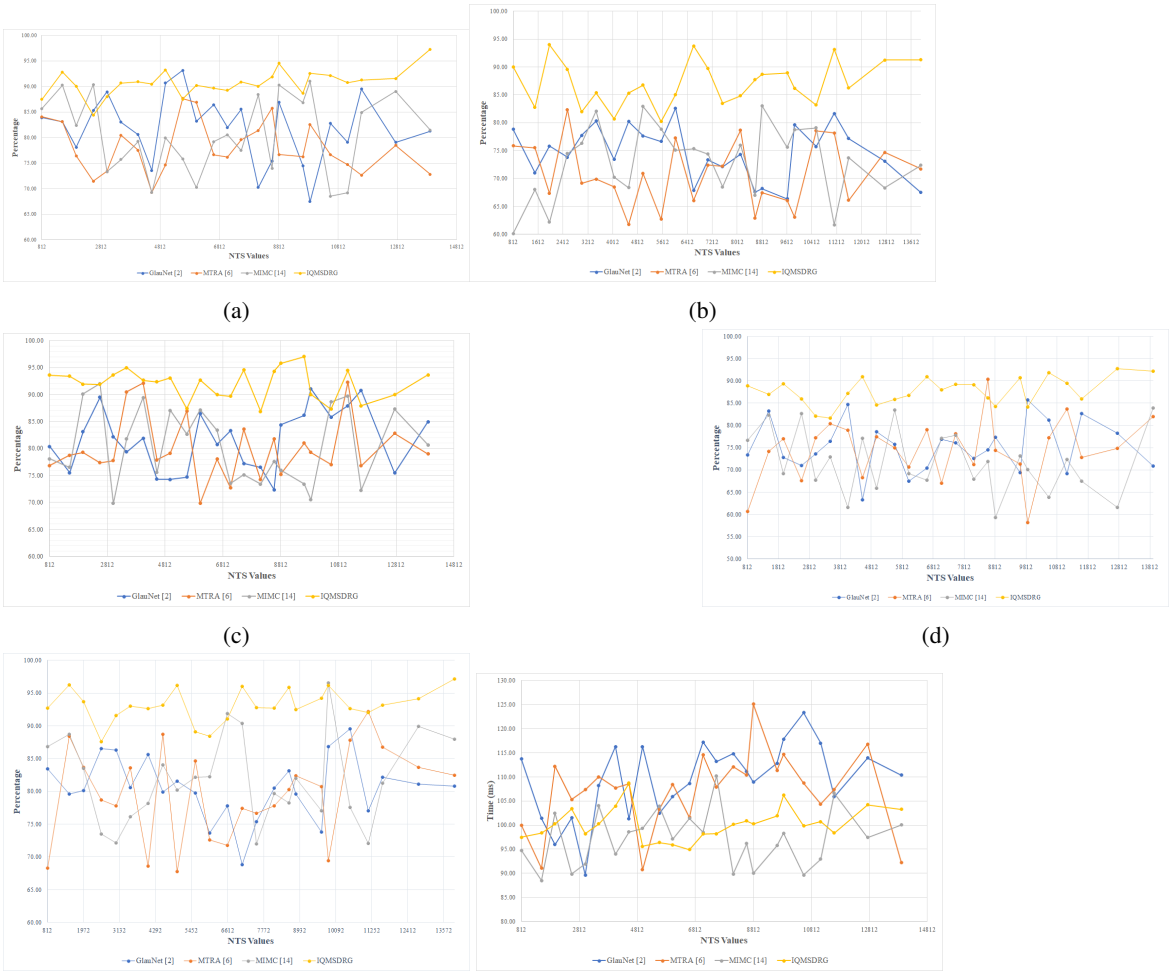

Figure 3: This is a figure compares the performance at various NTS : (a) Accuracy; (b) AUC; (c) Recall; (d) Specificity; (e) Precision; (f) Delay

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6 Conclusion and Future Scopes

This work significantly contributes to the realm of medical diagnostics, particularly in the detection and staging of diabetic retinopathy and glaucoma. The proposed IQMSDRG model, incorporating an advanced 45-layer 2D Convolutional Neural Network, iterative Q Learning, and Fuzzy C Means clustering, demonstrates a notable improvement over existing models such as GlauNet, MTRA, and MIMC in terms of precision, accuracy, recall, specificity, and AUC. The model's proficiency is particularly evident in its high precision (ranging up to 97.18%) and accuracy (peaking at 97.27%), which are critical for reliable medical diagnostics.

In clinical scenarios, the IQMSDRG model stands to revolutionize the early detection and accurate diagnosis of diabetic retinopathy and glaucoma. Its high precision and accuracy ensure reliable identification of disease stages, thereby facilitating timely and appropriate medical interventions. This is paramount in preventing the progression of these conditions, which are among the leading causes of vision impairment globally.

6.1 Future Scope:

Looking forward, the potential applications of the IQMSDRG model extend beyond its current scope. Future research could explore the following areas:

- **Adaptation to Other Ophthalmic Conditions:** The model's architecture and learning algorithms could be adapted to diagnose other eye-related diseases, broadening its utility in ophthalmology.
- **Integration with Portable Diagnostic Devices:** Adapting the model for use with portable fundus cameras could facilitate widespread screening, especially in remote and underserved areas.
- **Real-time Diagnostic Systems:** Incorporating IQMSDRG into real-time diagnostic systems could enable immediate analysis of fundus scans, providing instant diagnostic feedback in clinical settings.
- **Expansion of Training Datasets:** Utilizing larger and more varied datasets, including those from different ethnic and demographic backgrounds, could further enhance the model's accuracy and applicability levels.
- **Interdisciplinary Applications:** Exploring the model's application in other fields of medicine, such as neurology (in studying diseases like Alzheimer's, where retinal changes occur) could be a revolutionary process.
- **Patient-Specific Treatment Plans** Leveraging the model's output to tailor individualized treatment plans could optimize patient care and management in ophthalmology scenarios.

In conclusion, the IQMSDRG model not only marks a significant advancement in the field of medical imaging and diagnostics for diabetic retinopathy and glaucoma but also opens avenues for future innovations in healthcare technology. Its integration with advanced machine learning techniques sets a precedent for tackling complex diagnostic challenges, potentially reshaping the landscape of medical diagnostics and patient care scenarios.

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