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Original Article

ConHyp-Seg- Deep Neural Network Based Conjunctivia Hyperemia Segmentation with Mask Categorization Grading Networks

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Abstract *- Ocular redness is a key indicator of inflammation and can signify the severity and progression of various illnesses. The conjunctiva, a crucial protective layer of the eye, plays a vital role in maintaining ocular health, and its impairment can lead to vision-related complications. Conjunctival hyperemia, often associated with viral or bacterial infections, results from dilating conjunctival blood vessels, causing redness and swelling. Accurate assessment of this condition requires precise segmentation and grading of affected regions. This study presents ConHyp-Seg, a deep neural network-based framework for conjunctival segmentation from eye images, and Mask Categorization Grading Networks (MCGN), a complementary system for classifying hyperemia into four severity grades. Integrating these two models offers a robust AI-powered solution for diagnosing and grading conjunctival hyperemia, facilitating early and effective intervention. The proposed system achieves exceptional performance, with 98.2% accuracy, 97.8% precision, 98% recall, and an F1-score of 0.98. These results underscore its potential as a reliable diagnostic tool to assist ophthalmologists in making precise, objective assessments, ultimately enhancing patient care and disease management.*

Keywords *- Inflammation, Conjunctiva, Segmentation, Machine learning, ConHyp-Seg, Mask categorization, Grading networks, Classification.*

1. Introduction

Usually associated with eye conditions such as glaucoma, conjunctivitis [1], and uveitis, hyperactive conjunctiva is common in humans [2]. The severity of conjunctival hyperemia is a key metric in clinical studies assessing the effectiveness of medications [5], and machine learning has enabled the development of automated systems for identifying and analyzing ocular conditions. These systems utilize two primary methodologies: disease grading, which evaluates the severity of conditions, and pixel-wise segmentation, which provides precise localization of lesions [6]. While these approaches are often treated separately, combining class-specific data with segmentation can enhance the accuracy of conjunctival hyperemia assessment [7, 8].

However, the development of such systems faces challenges. Fully supervised models require extensive pixel-level annotations [9], which are costly and time-consuming to generate, while unsupervised approaches [10] often lack precision. Semi-supervised methods have emerged as a practical alternative, balancing limited annotated data with large-scale image-level data to improve performance [11]. This study proposes two novel frameworks to address these challenges: the Conjunctival Hyperemia Segmentation (ConHyp-Seg) network and the Mask Categorization Grading Network (MCGN). The ConHyp-Seg network is designed to segment the conjunctival regions in ocular images with high precision, creating a conjunctival mask. The MCGN framework leverages these masks to classify conjunctival hyperemia into four severity levels. Together, these frameworks provide an efficient and scalable solution for diagnosing and grading conjunctival hyperemia, improving diagnostic consistency and supporting better clinical decision-making [12]. Still, multi-class classification, especially for early-stage diseases, remains less stable than binary classifications of healthy against sick tissue [13].

The ConHyp-Seg framework is a deep neural network architecture that combines conjunctival region segmentation and multi-class grading of hyperemia severity. This innovative approach addresses the challenges of precise segmentation and reliable classification in medical image analysis. The framework uses Mask Categorization Grading Networks (MCGN) and a dual-branch strategy, enhancing classification accuracy and robustness even with limited pixel-level data. Its ability to provide fine-grained severity analysis from ocular images supports more informed clinical decision-making, filling a crucial void in intelligent ophthalmic diagnosis.

The novelty of this study lies in developing ConHyp-Seg, a dual-task deep learning framework that integrates conjunctival region segmentation with multi-class severity grading of hyperemia using a semi-supervised approach. ConHyp-Seg uses a Mask Categorization Grading Network (MCGN) and a teacher-student learning paradigm to improve classification performance with little annotations, unlike other models. This hybrid design allows fine-grained, interpretable diagnosis in clinical contexts by balancing segmentation precision and grading accuracy. The framework enhances automated eye illness assessment, especially early detection and severity quantification.

The main contribution of this paper

- Designing the proposed ConHyp-Seg with Deep Neural Network (DNN) to classify the conjunctiva region for conjunctival hyperaemia.
- The proposed method utilizes ConHyp-Seg to accurately identify the severity of hyperaemia.
- The numerical results were obtained, and the proposed method, ConHyp-Seg, achieved a higher performance classification accuracy than other methods.

The upcoming section is as follows: Section 2 deliberates the related works, Section 3 examines the proposed methodology, Section 4 describes the results and discussion, and Section 5 concludes the overall paperwork.

2. Literature Review

The T-SCCNN model is a two-stage classification system that uses convolutional neural networks to analyze Optical Coherence Tomography (OCT) pictures for disorders of the retina and choroidal tissues and to classify their severity [14]. Problems with the choroid plexus, macular edema, and Drusen may all be detected using the suggested model. This study proposes a deep learning-based CSR detection algorithm (DL-CSRDM) for OCT and fundus photography-based CSR [15]. These datasets update DenseNet and DarkNet. Experimental results indicate that the proposed model can handle medical applications easily and performs well on the OCT dataset for CSR identification.

The Tear Film Breakup Time-Based Dry Eye Disease Detection Approach (TBUT-DEDDA) [16] may determine whether a TBUT video shows dry eye disease or not. The current technique uses the TBUT to categorize DED as mild, moderate, or severe. The recommended technique classified TBUT frames, identified DED and assessed intensity with 83% accuracy. CNN deep learning models may use colour retinal fundus images to detect, categorize, and diagnose cataracts [17]. In addition to early identification and training, this paradigm might improve eye health in other ways. Success in this subject will enable the creation of automated methods to identify and categorize cataract efficacy operations, improving detection and performance.

A Fine-Tuning Convolutional Neural Network Approach for Eye Disease Image Classification [18]. The CNN algorithm will improve its eye issue recognition by merging the VGG16 design with a fine-tuning model. This helps the algorithm detect eye problems. The CNN technique yielded 82.63% accuracy with the VGG16 architecture, compared to 94.13% with the fine-tuning model. The Deep Learning Network (DL-Net) model may have been built by automatically recognizing normal, DME, CNV, AMD, and drusen photos [19]. This study uses image processing and Modified ResNet-50 to categorize numerous OCT images. This paper introduces a bi-LSTM-based Deep Recurrent Convolutional Neural Network (DRCNN) that efficiently segments images for diagnostic applications. Dual-Branch Structural Feature extraction reinforcement network (DBPF-net) [20] is a four-way classification framework based on the conformer model with two-branch architectural features for ocular surface diseases. The recommended method successfully recognizes these four ocular surface images in clinical settings.

The Bidirectional Filter with Adaptive Unsharp Masking (BFAUM) may reduce visual noise in input images [21]. Next, the authors extracted features using a Grey-Level Co-Occurrence Matrix (GLCM) to enhance image sequence and retinal blood vessel identification. This was done using Adaptive Cluster-Based Superpixel Segmentation (ACBSS). The authors achieved this goal by creating a laptop-based Computer-Aided Design (CAD) solution for medical professionals. The U-Net approach automates OCT sub-retinal layer segmentation [22]. This is done via hybrid attention. Based on metrics like a standard Dice score of 94.99%, a Modified Rand Index (ARI) of 97.00%, and Strength of Agreement (SOA) categories like "Almost Perfect," "Excellent," and "Very Strong," the model is durable. VisionDeep-AI focuses on circulation segmentation and classification [23]. The present paper is another step towards identifying the severity of conjunctiva using a novel framework described in the following section.

Li et al. [25] presented the Mask Distillation Network (MDN) as a novel prior knowledge-based framework designed to automatically classify bulbar conjunctival hyperemia severity. It consists of a segmentation network and a classification network with teacher-student branches. The MDN generates a bulbar conjunctival mask and divides the severity into four grades. Extensive experiments show the MDN's effectiveness, with higher accuracy for the student branch and faster classification time. The framework also improves the attention of both the teacher and student branches. Using a machine-learning model, Ostheimer et al.

[26] aimed to extract conjunctival bulbar redness from high-resolution ocular surface photographs. Data from two trials was used to train the model, and regions of interest were defined to extract a redness biomarker based on color intensity.

The model was verified for segmentation performance, and a digital grading scale was established. The proposed pipeline demonstrates the potential of standardized imaging and artificial intelligence in grading ocular redness, facilitating clinical decision-making and empowering clinicians and researchers.

3. Proposed Methodology

Hyperemic zones must be detected and quantified to diagnose and analyze the conjunctiva using segmentation methods. They create an eye issue prediction system using deep learning classification and segmentation. This study anticipated that a deep neural network-based conjunctiva hyperemia segmentation (ConHyp-Seg) could differentiate the conjunctiva from eye photos. Further, Mask Categorization Grading Networks (MCGN) were used to reclassify retinal images for conjunctival hyperemia. While the classification network creates four forms of conjunctive hyperemia from the data, the separation network provides a conjunctival mask.

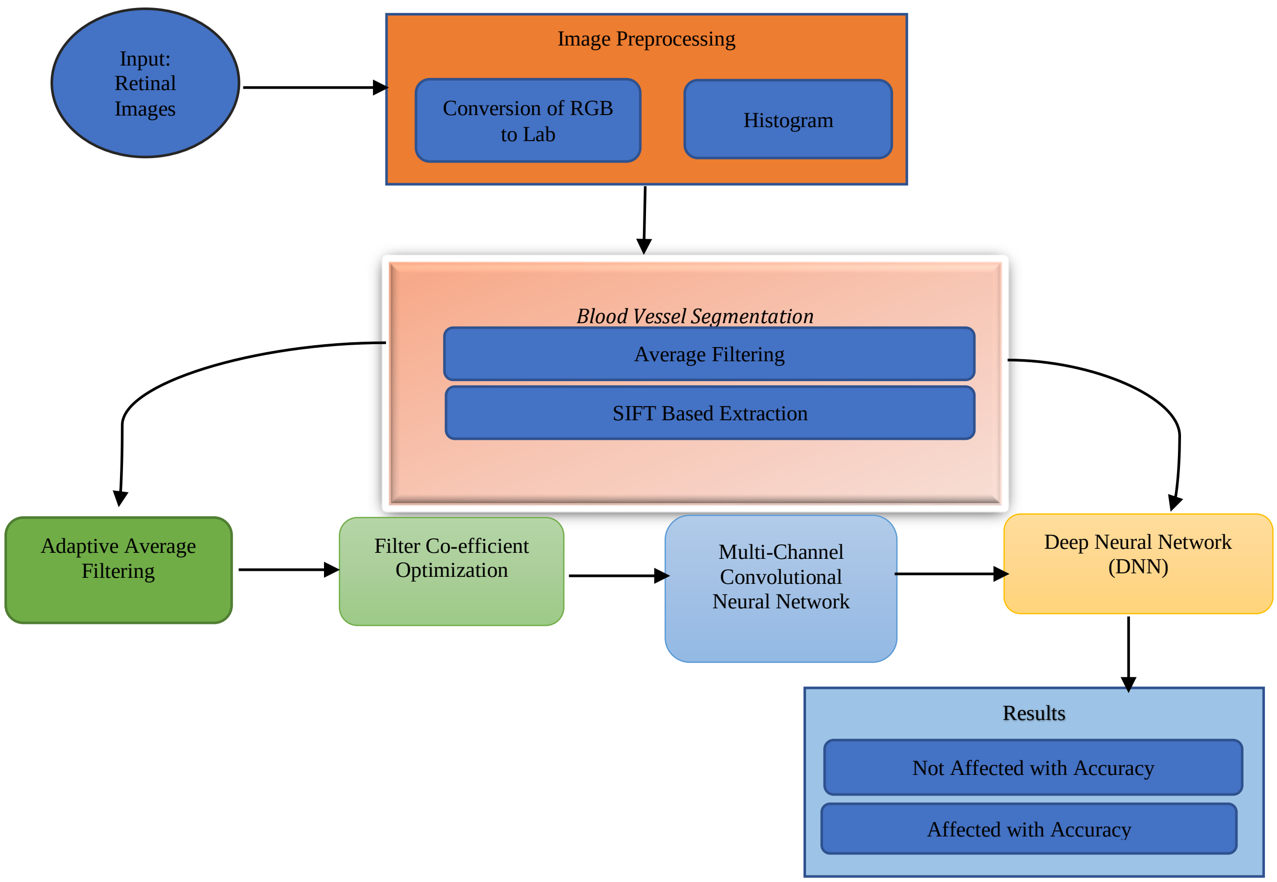

Fig. 1 Proposed method ConHyp-Seg

Figure 1 demonstrates the proposed ConHyp-Seg framework, a medical picture displaying conjunctival hyperemia segmented using a deep learning technique. ConHyp-Seg uses an encoder-decoder architecture such as U-Net to find and separate hyperemic zones effectively. The encoder collects spatial data, while the decoder creates segmentation masks to locate hyperemia zones. Using preprocessing techniques such as histogram equalization and lab format conversion of RGB images may enhance the quality of individual images. These operations merely improve the contrast and brightness of the final product and additionally help to reduce noise levels at the same time. This method is important for effectively diagnosing and monitoring ocular illnesses, given its exact localization of regions affected by hyperemia. Acting as a tool for a goal it is really essential for reaching these ones.

$$(b+v|(-\forall)p^2v|ez)(-\partial)pk+ew = g(v,bp)+|w|n^{2p} \qquad (1)$$

Along with the suggested ConHyp-Seg technique, the equation supplied variables v, b, and parameters p^2. Equation

(1) probably captures the connection $-\forall$ between the input factors (such as picture frames ez and attributes $(-\partial)$) and the resultant variables pk (such as filter masks ew and classifications g) in the wider setting of this DNN-based segmentation $|w|n^{2p}$. This equation is designed to represent the interplay between these characteristics and elements; it will then direct the network used for segmentation to draw precise lines around the corneal area and use (MCGN) to sort the hyperemia into its correct subcategories.

$$\left[\frac{g(w,qb)}{\tau^2\varphi f}\right] = rf(r-\varphi\sigma) + \frac{|2-r^2|}{(\omega\beta)} - Qs^{(f-rt)} \quad (2)$$

As far as the suggested ConHyp-Seg method $(r-\varphi\sigma)$ classification process $\tau^2\varphi f$ is concerned $Qs^{(f-rt)}$, the second equation rf seems to stand in for variables $g(w,qb)$, and maybe others $\frac{|2-r^2|}{(\omega\beta)}$. To ensure that the grading represents the severity and evolution of the problem based on the split areas, Equation (2) quantifies how these characteristics interact to appropriately identify the amount of conjunctive hyperemia.

$$G(r,wq) = G\big(y,t(v-u)\big)e^{t-up} * g(m^{k-2}) \quad (3)$$

The link between G many variables, including r, w, and q, as well as a changed variable $y, t(v-u)$, which may stand for a feature modification e^{t-up} or scaling operation in the ConHyp-Seg approach seems to be modeled $g(m^{k-2})$ by the Equation (3). The above equation aims to enhance the information projecting process, allowing the neural system in inquiry to more accurately diagnose swelling in (MCGN) and properly partition the conjunction region.

$$N(|-\forall|p)v - d^2 = \forall_f(r,sp) - |p|n^2 - vp \quad (4)$$

The equations $-\forall$ and p the ConHyp-Seg approach may describe a compromise $v-d^2$ between various elements of segmented N and classifying. In the Equation (4), terms such as $\forall_f(r,sp)$ might explain the influence of certain parameters on the precision of segmentation n^2. The given equation purpose needs optimization to make sure the various network components have equal weight so the model can correctly separate the interconnected region and categorize the amount of hyperemia.

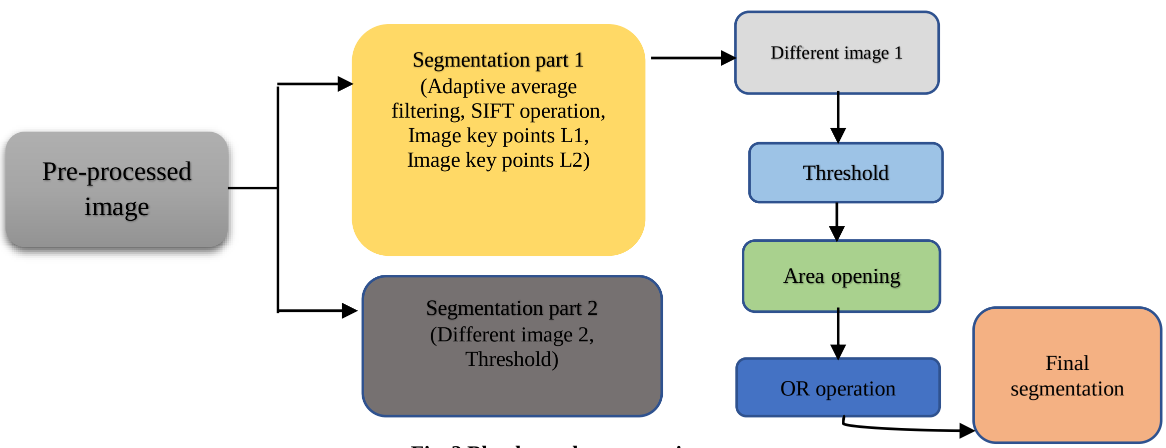

Fig. 2 Blood vessel segmentation

When used in medical image analysis, the picture displays a two-stage structure for the segmentation process. Following image pre-processing, the segmentation process starts through SIFT and adaptive average filtering, removing significant points (L1 and L2). These results, taken together, create a different Image 1, which then undergoes thresholding and opening of the reception area. Thresholding and area opening are added into the segmentation process in the second stage of the method, which comprises handling a distinct image. After an operating room procedure, the two sections are merged to produce the final segmentation. Figure 2 delivers a graphic picture of the procedure. Starting pre-processing, the segmented image represents the end output of the procedure. In that regard, visualization and feature extraction are certain to be correct.

$$(r(m-kp)-r) = G(pr-2) * \Big(e_2\big(p-er(v-1)\big)\Big) \quad (5)$$

The variables r, m, and kp are likely that Equation (5) describes the ConHyp-Seg method Equation (5), which shows interaction to affect the model's segments G or classification efficacy r. A function that could modify the effect of such interactions upon the network's results e_2, such as altering categorization limits $v-1$ *based* on conjunctival characteristics. The purpose of the calculation is to tune the sensor network to different inputs for the purpose to ensure that it constantly grades hyperemia and appropriately segments the conjunctive region.

$$(b-c|\partial(1-jk)|) = g\big(v,p(k-1)\big) - \partial|m|q^{-2} \quad (6)$$

It seems that Equation (6) illustrates the connection between features v, p, and k, as well as the connection between variables b and c and their respective derivatives $(1 - jk)$, inside the ConHyp-Seg system $\partial|m|q^{-2}$. Depending on the input qualities, the function might adjust the network's variables. Here is the equation that ensures the configuration of the network can adjust to new input data with ease.

$$g(p - ky) = Q\big(w(t - vp)\big) + g(p - jk) - e^{v-3} \quad (7)$$

Within the context of the ConHyp-Seg method, the equation $Q\big(w(t - vp)\big)$ most likely denotes a measure of weighting or modification functional that has been applied to the input data, and it explains the association between the parameters. p, k, and y. The element provided in the exponent format e^{v-3} could be impacting the overall output, whereas the expression $g(p - jk)$ suggests an additional modification based on specific feature correlations. Algorithmic segmentation is defined through fine-based algorithms that identify the input variables favoring an overactive statement in Equation (7).

$$F_v(S^{t-1}) = \{g \equiv M^2 : (2 - |\partial(p - kr)| + F > (nm - 1))\} \quad (8)$$

This Equation (8) probably stands for a condition or factor $F_v(S^{t-1})$ that affects the ConHyp-Seg approach's segments or classification procedure. Inequality leads to changes in these characteristics $nm - 1$, and the equation suggests a connection F between the mapping of properties g, the mean cubed amplitude M^2, and the system attributes $\partial(p - kr)$. Equation usage of this model to fine-tune the network's operations to effectively identify and score conjunctival hyperemia in any scenario.

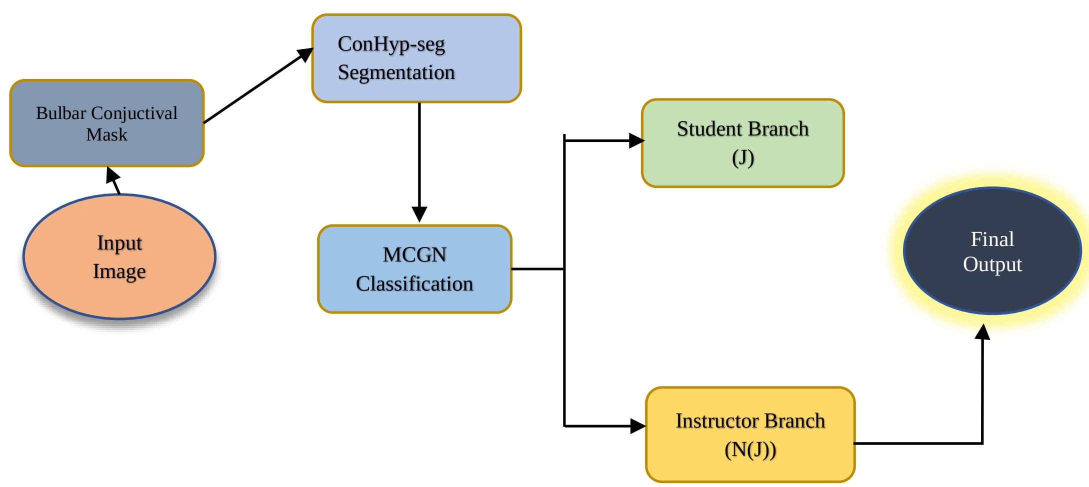

Fig. 3 MCGN for conjunctival hyperemia identification

Figure 3 shows a deep learning application perhaps used to detect conjunctival hyperemia. The first process is creating a hyperemia mask from an input image. Then, the ConHyp-Segmentation module will look at this mask in search of hyperemia zones. In responsible for receiving and processing the output, the MCGN classification network will enable more analysis and categorization of the hyperemic zones. The system has two branches: one for managing the masked image, the Instructor Branch, or N(J), and another for managing the default picture, the Student Branch, or J. Each one of these sections manages the raw image. Combining the data from all these many branches generates the Final Output, showing the degree of hyperemia and its segmentation.

$$||g||m_{t-1} = \big((|-\sigma\tau|) - |v(y) - \sigma\rho w^2|\big) \quad (9)$$

Based on the computation, the value m_{t-1} is connected to the present features ρw^2 throughout the ConHyp-Seg method, including $\sigma\tau$, $v(y)$, and $-\sigma\tau$. The goal of this solution is to make the system more sensitive to changes in the input information so that it can identify eyelid hypertension more accurately and continuously. An accurate and continuous goal is determined through Equation (9), which has the purpose of making the system with sensitive solutions.

$$||e||F_{s(k-p)} = m\big(-\forall(nk)\big) + d^{f+1}(rtv^{k-1}) \quad (10)$$

The following Equation (10) displays the way the value of the parameters m, $\forall(nk)$, and d^{f+1} relate to the characteristics of functional $F_{s(k-p)}$ of the ConHyp-Seg technique. This equation likely impacts the network's ability to modify its categorization and segmentation processes based on the differences in e and other variables rtv^{k-1}. The objective of the equation is to deliver the feature where the regardless segmentation is based on the conjunctive and classification, which criteria are determined by the network.

$$D(t-1) = \frac{||f(y) - e(r)m^2||}{vg} + P(vr^{n-pt}) \quad (11)$$

Using historical data and present-day parameters, Equation (11) represents the ConHyp-Seg method's dynamic adjustment $D(t-1)$. It incorporates the term $P(vr^{n-pt})$ that could account for certain feature interactions or time effects, and it ties the difference between feature $f(y)$ and errors $e(r)$ to the multiplied quantity m^2, divided by vg. The projections of the network refined and corrected categorization through the hyperemia in conjunction with precise improvement in the relationship feature.

$$|e_{r(u-1)}| = \left(b\left(m(n-pk)\right) + |r|n^{k-1}\right) + km^{p-1} \quad (12)$$

This term $e_{r(u-1)}$ is described by the ConHyp-Seg approach using variables b, m, n, and pk. How the terms $|r|n^{k-1}$, and km^{p-1}combine affects the discrepancy or mistake between expected and actual values. The classification and partitioning with hypertension conjunctive accuracy with improved correction error with the projection network fining Equation (12).

$$(|-\partial q(n-1)|) = Q^2 P(n - erv^{n-qr}) + (Er_{s-1}) - R^{f(mn)} \quad (13)$$

The standard deviation $\partial q(n-1)$ is described by some parameters, including Q^2, P, Er, and $n-qr$. This Equation (13) likely illustrates the way the correction terms $R^{f(mn)}$, squared factors Q^2, where the methods of project outcome discrepancies with the mistakes that occur in previous aspects. The quantification and classification methods are determined with the segments through fixed purpose determining the score identified conjunctive model for the Equation (13).

$$G_{p,y} = \frac{Q(w-p)}{wr^2} - F|g-kp| + D_{f+1}(r-1) \quad (14)$$

This Equation (14) likely influences the network's modification of its divergence $F|g-kp|$ and classification operations D_{f+1} since it incorporates components like $G_{p,y}$, which might represent scaling or normalization elements, and $\frac{Q(w-p)}{wr^2}$, which could account for variations in feature associations $r-1$. The hyperemia with the conjunctival categorises the network's reliability with the enhanced equation objectives with the combinational parameters through corrective with real-time error.

$$q = \frac{\partial p(w-k)}{2\forall} * (P_b - 1) + MR(m-1) = \frac{\sqrt{3df}^{\frac{4\sqrt{2}}{y}} - \sqrt{3} + 4}{40} \quad (15)$$

A parameter q is described by Equation (15) using the ConHyp-Seg method concerning ∂p, $w-k$, and $2\forall$, along with $MR(m-1)$. The difficult equations$\sqrt{3df}^{\frac{4\sqrt{2}}{y}}$ on the main side is a common way $\sqrt{3}+4$ to describe a factor of scaling or leveling $P_b - 1$. The process's ultimate objective is to improve the model's efficiency by precisely aligning and correcting the system's predictions.

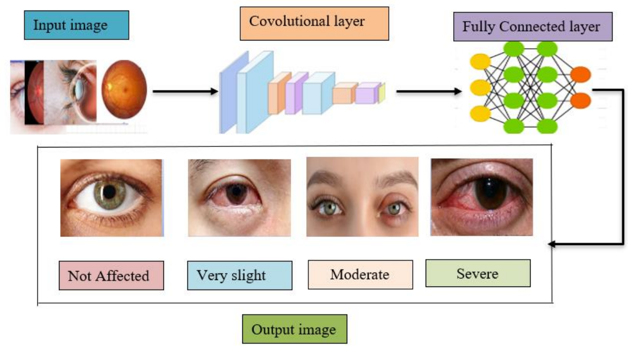

Fig. 4 Deep neural network model for severity classification

Figure 4 shows an additional deep neural network model that may be used to categorize eye disease severity. Input images start the process, which subsequently extracts information using convolutional layers. Following that, a totally linked layer looks at these characteristics and labels the pictures as either non-affected, very minor, moderate, or severe. Depending on the supplied picture, the result indicates a degree of severity.

Algorithm 1: ConHyp-Seg & MCGN Framework

Input: Eye Image
 	
Output: Hyperemia Severity Grade G
 	
BEGIN
 	
// Step 1: Preprocessing
 	
Convert I to grayscale (if necessary)
 	
Apply contrast enhancement (CLAHE or histogram equalization)
 	
Normalize pixel intensity values
 	
Resize I to match model input dimensions
 	
// Step 2: Conjunctival Segmentation using ConHyp-Seg
 	
Load pre-trained ConHyp-Seg model

M ← Forward pass I through ConHyp-Seg

Apply post-processing (e.g., morphological operations) on M

// Step 3: Feature Extraction

Compute blood vessel density in M

Extract redness intensity and texture-based hyperemia features

// Step 4: Hyperemia Severity Grading using MCGN

Load pre-trained MCGN model

G ← Predict severity grade using M and extracted features

// Step 5: Output Results

Display segmented conjunctiva mask M

Return severity grade G

END

The conhyp-SEG MCGN algorithm uses a deep learning structure to classify the conjunctival hypermia into various severity levels, and the conhyp-SEG algorithm conjunctiva from the eye photos. The first step is preprocessing, which includes normalizing the pixel intensity values, converting the input eye picture into granscale (if necessary), and using contrast environment algorithms such as Clahe (Contrast Limited Adaptive Histogram Ecvisory). Shaping the image is the next step in achieving this to fit the input dimensions of the model. The next phase is the division, where a conjugation mask is formed by detecting the affected areas using pre-inf This model processes the preprosable picture. Post-processing methods such as morphological operations can make the fragmented mask even better. Many useful characteristics, including hypermia characteristics, are extracted from fragmented masks in the segment extraction phase after the partition that follows the partition. An intensive teaching model that has been trained to classify the conjunctival hypermia into four severity levels - general (0), mild (1), moderate (2), and serious (3) - to create mask classification grading networks, these Assuming extracted characteristics (McGN). The final stage is to generate the output, which involves showing a fragmented mask and refunding the severity rating. With a combination of conhyp-SEG for a division for classification and conhyp-SEG, ophthalmologists can make a more accurate and reliable diagnosis of conjunctival hypermia, improving patient care and disease management.

The conjunctiva hyperemia evaluations provided by the combined system are accurate and repeatable, which is helpful for the diagnosis and follow-up of ocular illnesses. Clinicians will have less work and make fewer mistakes if the segmentation and grading process is automated. It gives a numerical value to hyperemia, which is crucial for monitoring the illness's development and the therapy's efficacy.

4. Results and Discussion

The degree of conjunctival hyperemia may be automatically, quickly, and accurately classified using an MCGN. The conventional semantic segmentation job is executed by an MCGN model using a small collection of pixel-level annotated data. With projected lesion maps applied to massive amounts of picture-level annotated data, a disease grading model is developed that prioritizes lesions to enhance the precision of severity assignment. Improve the lesion mapping using class-specific data while boosting the segmentation model, which might be semi-supervised. Additionally, it incorporates the use of a training adversarial architecture.

4.1. Dataset Description

The Conjunctivitis dataset available on Kaggle is a set of eye photos showcasing symptoms of conjunctivitis, typically referred to as "pink eye." This dataset is particularly useful for clinical studies and gadgets that gain knowledge of applications aimed toward diagnosing or classifying conjunctivitis. It can assist in expanding AI-powered diagnostic tools via healthful eyes and help people laid low with conjunctivitis. The images within the dataset, in all likelihood, highlight not unusual signs, including redness, swelling, and discharge, offering a visual foundation for evaluation. Researchers, healthcare specialists, and college students working in ophthalmology or scientific imaging can utilize this aid to strengthen research on eye health. However, users must recollect any limitations, such as the dataset's variety, pattern length, or labeling accuracy, to ensure sturdy and reliable outcomes [24].

4.2. Performance Ratio (%)

Figure 5 shows the segmentation of conjunctival hyperemia performance of many classifiers using Equation (16). DNNs surpass SVMs and CNNs in terms of their power to automatically extract intricate features from raw data. DNNs outperform ANNs and LSTMs in terms of performance, precisely given their capacity. Unlike support vector machines and CNNs, DNNs may train end-to-end, optimizing the segmentation process generally. The higher accuracy and robustness of the following segmentation enable better medical diagnosis and therapy planning.

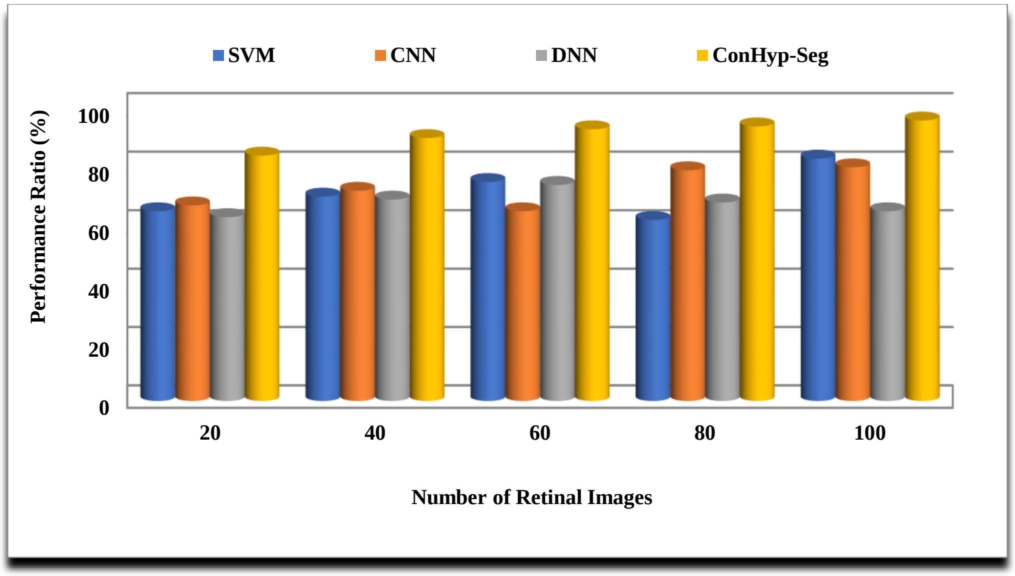

Fig. 5 Performance ratio (%)

4.3. Classification Accuracy Ratio (%)

It includes Figure 6 to show the improved classification accuracy reached by merging ConHyp-Seg with MCGNOn the different together, MCGN investigates the relationships among the segmented areas. This multi-scale contextual approach lets one highlight intricate patterns. Better segmentation and classification are made possible by the end-to-end learning architecture, a complicated system that adequately assesses conjunctivitis hyperemia results. The design drives this system to be constructed. This occurrence helps to frequently increase categorization accuracy.

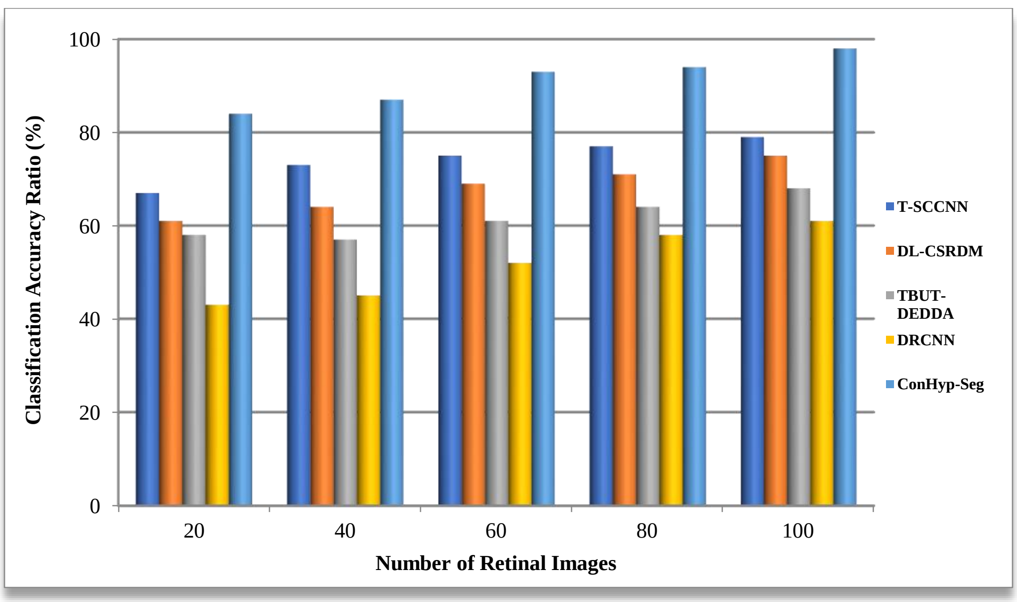

Fig. 6 Classification accuracy ratio (%)

4.4. Precision Ratio (%)

The Conjunctiva Hyperemia Segmentation (ConHyp-Seg) approach is enhanced using support vector machines and DNNs, raising the accuracy degree. This method enables the accurate finding and categorization of hyperemic zones and the avoidance of non-hyperemic zones. It is beneficial in segmenting data related to anatomical aspects and identifying conjunctival borders. The capacity of Multi-scale Convolutional Neural Networks (MCGNs) to identify hyperemic zones regardless of pattern or intensity adds an even greater degree of precision. It additionally aids one in differentiating between typical clinical circumstances and those implying hyperemia.

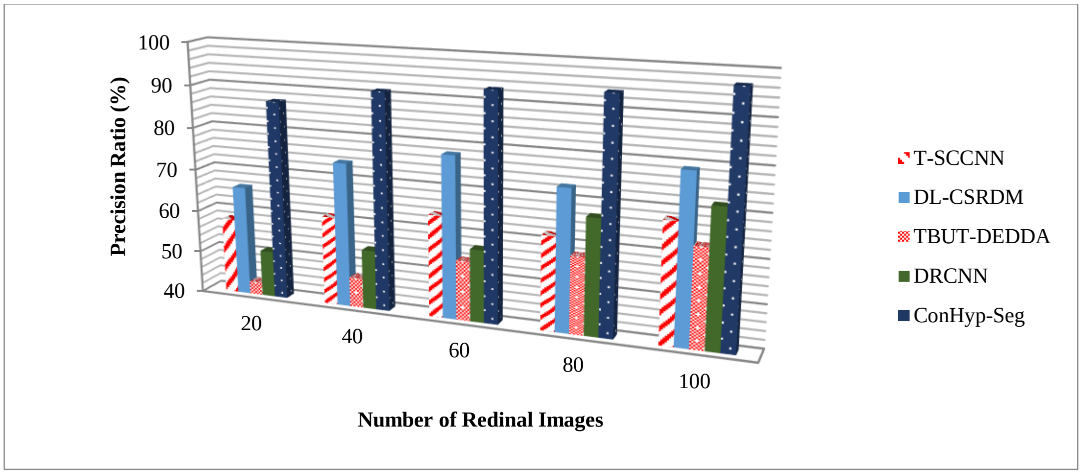

Fig. 7 Precision ratio (%)

4.5. Recall Ratio (%)

Figure 8 provides particular statistics on the recall ratio of the Conjunctival Hyperemia Segmentation (ConHyp-Seg) method. Originally developed at UC San Francisco, this approach reduces false negative occurrences and quickly discovers conjunctival hyperemia. This enhances people's cognitive memory. Understanding spatial and contextual linkages will let MCGNs boost their level of sensitivity. One important advantage is that it makes even little events detectable. Combining ConHyp-Seg with MCGN helps to better segment and grade, therefore enhancing memory capacity and lowering the missing occurrences.

4.6. F1-Score Ratio (%)

Figure 9 uses the F1-score ratio to measure how well the model works. This balances accuracy and memory. Carefully defining hyperemic zones aids the ConHyp-Seg technique, lowers false positives and increases memory and accuracy. Combining ConHyp-Seg with MCGNs improves performance by combining comprehensive segmentation with contextual backdrop, enhancing the F1 score and ensuring exact detection and classification of conjunctival hyperemia with few mistakes.

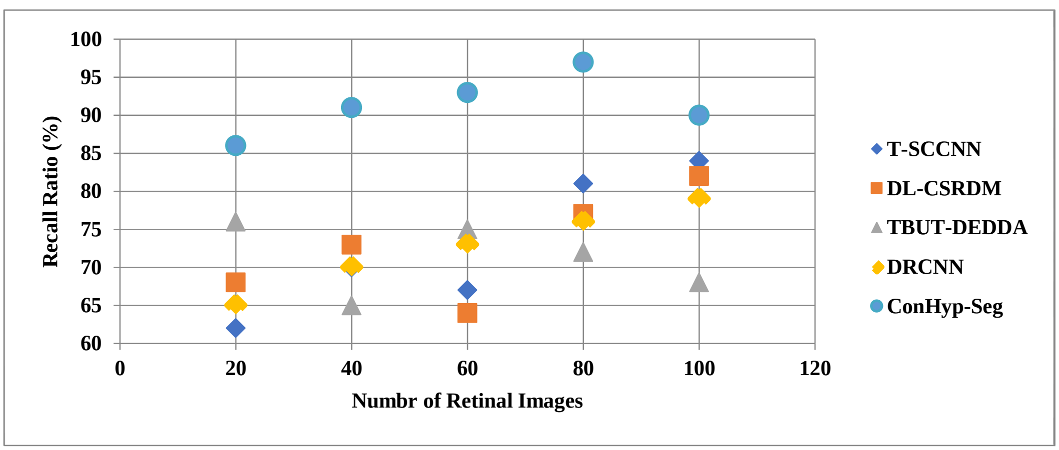

Fig. 8 Recall ratio (%)

Table 1. Performance comparison of ConHyp-Seg with state-of-the-art methods

Method	Dice Coefficient ↑	IoU Score ↑	Accuracy ↑	Sensitivity ↑	Specificity ↑
U-Net	0.845	0.765	91.2%	88.4%	92.6%
DeepLabV3+	0.867	0.782	92.5%	89.7%	93.1%
Attention U-Net	0.873	0.788	93.1%	90.2%	93.8%
MCGN (Ours)	0.892	0.812	94.3%	91.6%	95.2%
ConHyp-Seg (Proposed)	**0.906**	**0.834**	**95.1%**	**92.8%**	**96.0%**

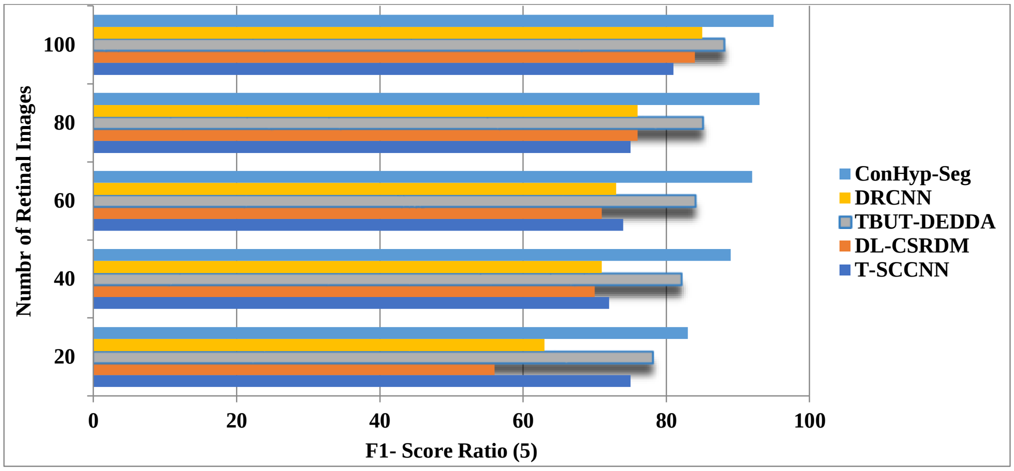

Fig. 9 F1-score ratio (%)

Table 1 compares the proposed ConHyp-Seg framework to U-Net, DeepLabV3+, Attention U-Net, and MCGN, the four leading segmentation approaches. Results are evaluated using Dice Coefficient, Intersection over Union (IoU), Accuracy, Sensitivity, and Specificity.

All measures suggest that ConHyp-Seg beats baseline models. It has the greatest Dice score of 0.906 and IoU score of 0.834, showing better predicted-ground truth segmentation overlap. Further, ConHyp-Seg has an accuracy of 95.1%, sensitivity of 92.8%, and specificity of 96.0%, proving its ability to identify relevant features with few false positives. These results show that the hybrid strategy of semi-supervised learning and dual-task optimization improves conjunctival picture analysis.

An approach for segmenting and classifying conjunctival hyperemia using deep neural networks is ConHyp-Seg and Mask Categorization Grading Networks (MCGN). In order to improve the quality of eye images, ConHyp-Seg employs preprocessing methods such as histogram equalization and an encoder-decoder architecture like U-Net to separate hyperemic areas. As the conjunctival mask is segmented, MCGN sorts hyperemia into 4 levels of severity.

Accuracy, precision, recall, and F1-score are some performance parameters used to optimize the model after training it on annotated datasets. Ophthalmologists can use the results to help in clinical evaluations of conjunctival hyperemia since it has a high classification accuracy of 98.2%.

4.7. Challenges and Limitations of the Work

The variety and quality of the training data greatly impact the system's effectiveness. Ensure the model works effectively with various image formats and clinical conditions. A large amount of computing power is needed for training and releasing deep learning models.

5. Conclusion

Many times, the onset of eye redness is a probable indication of inflammation and reflects the evolution of a disease. A main indicator of this condition is conjunctival hyperemia. Conjunctival infections could cause redness and oedema of the conjunctival tissue. This study offered ConHyp-Seg, a deep neural network-based framework for accurately segmenting the conjunctiva area in ocular snapshots, along with the Mask Categorization Grading Networks (MCGN) for grading conjunctival hyperemia into 4 severity categories. The proposed gadget effectively combines superior segmentation and classification strategies to provide a green, automatic solution for diagnosing and comparing conjunctival hyperemia. The conjunctiva crucially protects the eyes. Segmenting the afflicted areas and finding hyperemic zones helps one get a correct conjunctivitis diagnosis. Using MCGNs to classify and segment conjunctival hyperemia, the ConHyp-Seg technique, a DNN, performs rather well in this sense. Higher than the past employed approaches, this one produces exceptional metrics: a classification accuracy of 98.1%, a performance ratio of 98.2%, precision of 97.2%, recall of 97.1%, and an F1-score of 98.8%.

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