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NEURAL NETWORKS FOR CLASSIFICATION OF EYE CONJUNCTIVITIS IN TELEHEALTH: A CONCEPTUAL ARCHITECTURE

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ABSTRACT

Telehealth systems have developed rapidly into more conventional ways that can provide medical assistance, especially for people in remote areas. Despite rapid technological and practical developments, there are still many knowledge gaps regarding the effective use of telemedicine. Annually, nearly 1-4% of the general population might experience conjunctivitis. This study is focused on an experimental design for the classification of degrees of severity in colour medical images in telemedicine, in particular red as one of the key symptoms in the diagnosis of various pathologies. The quality of digital images is a pivotal thing in terms of telemedicine for accurate diagnosis because degraded or distorted colours can lead to errors. This study focused on the use of digital images in teleconsultation, in particular images displaying conjunctivitis (red eyes) as a case study since this pathology integrates red in its diagnosis. The deep self-organising map is suggested to be applied to classify the different severities. Moreover, U-Net, a deep learning network, is proposed to employ the segmentation of eye images for better feature extraction. Although this approach is focused on the problem of red eye image classification, it can be extended in the future to also be applied to other pathologies.

KEYWORDS: ***Conjunctivitis, Deep Self-Organising Map, Neural Networks, Telehealth***

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1. INTRODUCTION

Conjunctivitis, commonly called pink eye, is a prevalent eye infection distinguished by inflammation, redness, and discharge. Conjunctivitis can be caused by different agents: viral (Muto, Imaizumi and Kamoi, 2023), bacterial (Bhat and Jhanji, 2021), or allergy (Tariq, 2024). Viral and bacterial agents are known to be highly contagious agents (A. Azari and Arabi, 2020). Therefore, it is important to diagnose them quickly to prevent the spread of disease in communal environments, especially in schools. Failure to recognise the severity level of conjunctivitis and not administering timely treatment may lead to vision impairments and corneal ulcers (Frost *et al.*, 2024). If conjunctivitis is to be diagnosed virtually, it is important to acquire distortion-free eye images. Variations in image colours may be due to multiple reasons, such as poor image quality, visual disturbances related to colour perception, interference due to lighting conditions, or reflection on the display or the viewing area.

In remote areas, people struggle to access health services quickly because of a range of challenges related to cost, time, communication, and transportation. In the recent past, telehealth systems have provided a considerable range of services for diseases like COVID-19. In 2019, a mere 1% of patients engaged with telehealth services (Hazratifard, Gebali and Mamun, 2022). However, with the COVID-19 outbreak, the rate of using telehealth has increased to more than 38% (Hazratifard, Gebali and Mamun, 2022). Telehealth involves using telecommunication technologies and Internet of Things (IoT) devices to provide healthcare services and information. Moreover, remote communities and stay-at-home patients can get quality medical services with the help of telehealth services. Furthermore, telemedicine technology is rapidly evolving and has improved its effectiveness and efficiency with the advancement of new technologies all over the world (Toritsemogba Tosanbami Omaghomi *et al.*, 2024).

In the telemedicine scenario, the specialist and the patient communicate remotely through computers. In addition to the history and data, doctors receive digital images that display different pathologies in the affected areas. Accurate colour distinction in digital images plays an important role in diagnosis. Physicians may perceive colours differently in these images for several reasons: visual disturbances related to colour perception, poor image quality or resolution, or interference due to lighting or reflection in the display or the viewing area.

This study aimed at the use of digital images in the "Store and Forward" (SAF) teleconsultation (Tensen et al., 2024). Two important critical challenges in SAF can influence the accuracy of the diagnosis when using digital images. First, image quality plays an important role in the diagnosis, which can reduce the transfer of health professionals. Second, differences in colour perception, which is an important natural cognitive process, could also affect diagnosis based on digital images. This study, which focused on the use of digital imaging and colour perception in telemedicine, is a multidisciplinary combination that integrated information systems, human factors, engineering, and health care.

There are existing systems and applications, such as EyeCareLive, ZEISS VISU360, Netra, and VSee which cater to remote diagnosis, monitoring, and treatment in the domain of ophthalmology. However, these platforms conduct remote eye exams mainly focusing on detecting vision impairments such as astigmatism and hyperopia. Also, in some of these applications, patients have to share previously taken images of their eyes for the diagnosis process.

Artificial Neural Networks (ANNs) reflect its generalisation and learning abilities through a mathematical emulation of human architecture. ANNs are used in many research domains due to their ability to model nonlinear systems. In the medical sector, ANNs are used for many tasks, such as image analysis, biochemical analysis, drug design, and diagnostic system development, among others (Shahid, Rappon and Berta, 2019).

This study reviews and proposes a methodology to classify severity levels of conjunctivitis unlike the mostly existing models focused on detecting the presence of conjunctivitis. Furthermore, it is proposed to use DSOM, a neural network architecture which introduces an unsupervised, self-organising structure that can map non-linear relationships between image data, making it uniquely suited for classifying eye disease levels.

The rest of the paper is organised as follows. Section 2 describes the use of neural networks for medical image analysis and the conjunctivitis classification-related work, while section 3 describes the proposed solution. The expected outcomes of the proposed architecture are discussed in Section 4, and the use of proposed techniques with justifications is conveyed under Section 5. The challenges and limitations of conjunctivitis classification in telehealth are critically revealed in Section 6. Section 7 expresses the conclusion regarding the whole study.

2. RELATED WORK

Use of neural networks in medical image analysis

In the telehealth sector, medical image classification plays a pivotal role. Among the different approaches used for this purpose, neural networks can be considered as a highly effective tool used for automated identification and diagnosis of various medical conditions. This section describes the application of neural networks in image classification.

In image classification problems, to achieve a good classification, it is important to extract the features correctly. Scale-invariant feature transform (SIFT) (Sundeep *et al.*, 2023) and intensity histograms (Jayachandran and Stalin David, 2018) are feature extraction techniques commonly used in medical imaging. Support Vector Machine (SVM) (Tchito Tchapga *et al.*, 2021), logistic regression (Awad, Hamad and Alzubaidi, 2023) and Naive Bayes (Al-Aidaroo, Bakar and Othman, 2012) are common classification algorithms used to train the extracted features. Apart from that CNNs can be used for complex image classifications. CNNs derive their name from the convolutional filters that have been used to compute image features (Fathi and Maleki Shoja, 2018). When comparing CNNs with SVM, a common classification algorithm, the main drawback observed in SVM is that developing them is quite slow and its performance is far from the practical standard (Shuqi Cui *et al.*, 2017).

In lung disease classification, accurately categorising images can be particularly challenging when there is high variability within the same class and when distinct classes share a high degree of visual similarity (Zak and Krzyżak, 2020). Therefore, when classifying medical images having texture-like features, it would be advantageous to go for a customised CNN framework as there are no high-level features to be learned by the network. This will also help to overcome over-fitting problems as there are a smaller number of parameters to be learned.

Most medical data contain missing values and noise. Therefore, finding a large medical image dataset without missing values is a challenging task (Kim, Kim and Yoon, 2019). With the help of the transfer learning technique, the data scarcity problem can be solved. The TL aims to train specific features of a new task by leveraging the knowledge learned from similar tasks. Figure 1 below illustrates the architecture of transfer learning.

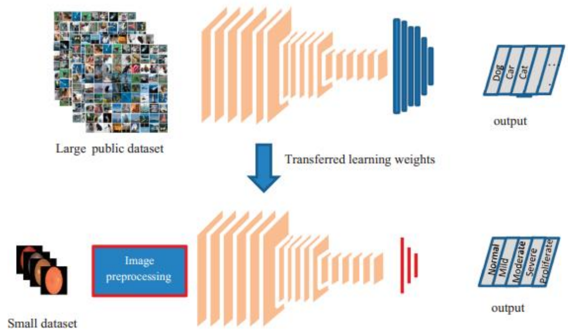

Figure 1: Transfer Learning architecture (A.M. Aslam Sujah, A. Fathima Sharfana, and Mohamed Sazni, 2022)

Table 1 below shows an overview of some model types that have been used as backbone models for TL.

Table 1: Overview of five backbone models

Model Type	Model	Released year	Parameters (all)	Dataset
Shallow and linear	LeNet5	1998	60,000	MINIST
	AlexNet	2012	62.3M	ImageNet
Deep	ResNet50	2015	25.6M	ImageNet

	InceptionV3	2016	27.2M	ImageNet
	DenseNet	2017	8.0M	ImageNet
	EfficientNet	2019	5.3M	ImageNet

According to the study by Sujah, Sharfana and Sazni (2022), the authors have created a transfer learning model to detect multiple ocular diseases in fundus images. Fundus images are the images of the back of the eye, which capture the appearance of the retina, optic nerve, and blood vessels. These images have been used to identify different fundus diseases such as diabetic retinopathy, glaucoma, cataracts, etc. In this study, the RestNet50 pre-trained model has been taken as the feature extractor since it outperformed the other CNN models such as EfficientNet-v3, Mobilet-v2, and Inception-v3. Not only single-label classification but also multi-label classification is also possible with the transfer learning technique.

Classifying severity levels of diabetic retinopathy is one of the biggest challenges faced by ophthalmologists. Enas Houby has created a model using transfer learning techniques to classify the stages (normal, mild, moderate, severe, proliferated_DR) of diabetic retinopathy (El Houby, 2021). In this study, VGG-16, a model trained using the ImageNet dataset has been used as the base model, and a dataset taken from Kaggle has been utilised to do the multi-class classification. Here, to overcome the class imbalance problem, data augmentation was performed by flipping and rotating the images by three angles.

In supervised deep learning, the accuracy of the image classification depends on the availability of annotated data. In the medical field, manual annotation is complex and requires a significant amount of time (Yadav and Jadhav, 2019). Therefore, large-scale annotated datasets are rarely to be found. Transfer learning techniques can be used to address the scarcity of annotated medical images. According to the study by Ahn et al. (2019), authors have proposed an architecture to learn features of unannotated medical images based on a model that is trained on an annotated dataset. Here, a convolutional auto-encoder (CAE), which can learn the global structures of images is placed atop pre-trained CNN to create a hierarchical unsupervised feature extractor. This architecture was tested using the medical Subfigure Classification dataset used in the ImageCLEF 2016 competition using GoogLeNet, ResNet, and ALexNet pre-trained models. The assembly of ResNet and GoogLeNet has achieved an accuracy of 87.87%.

Existing Conjunctivitis Detection Systems

“OphthaPredict” is a web-based application proposed by Jindal and his team to detect conjunctivitis in real time using EfficientNet deep learning architecture. Moreover, this is an application developed for the Indian healthcare sector focusing on helping Auxiliary Nurse Midwives (ANMs), Accredited Social Health Activist (ASHA) workers, and Primary Care Physicians (PCPs) in the diagnosis process. Three categories, including normal, viral, and bacterial, are identified with this developed model with an accuracy of 99% (Jindal, Handa and Goel, 2024).

The research titled "Severity Based Detection of Conjunctivitis and Drug Recommendation System Using CNN" employed multi-dimensional CNN architecture for the severity level classification. This research focuses mainly on viral conjunctivitis. Based on the infection severity level, the system recommends treatment options as well (Prakash *et al.*, 2023).

Sundararajan and D (2019) presented a deep learning-based system to detect conjunctivitis. Initially, eye images were pre-processed using median and wiener filters, where the median filter was used to remove salt and pepper noises and the wiener filter to remove blurred images. The authors of this study have employed a fuzzy technique for image segmentation. Moreover, data augmentation techniques have been used to solve the fitting problems that arise when training the deep learning model. The dataset has been trained three different times by changing the size of the training dataset and in the third step, a testing accuracy of 93% has been achieved.

For Adenoviral Conjunctivitis (Ad-Cs) detection, Günay, Göçeri, and Danışman (2015) have proposed a machine learning based system. The proposed system entails multiple steps for conjunctivitis diagnosis beginning with the region of infection segmentation.

Next, the intensity of redness in the eyes and the vascularisation have been measured. For sclera segmentation, they have employed the GrabCut segmentation algorithm (Lu *et al.*, 2017), and by thresholding, the noise in the segmented area has been removed. Furthermore, vascular extraction is done through Eigen decomposition of the Hessian matrix. Figure 3 shows the sclera segmentation process used in this proposed system. For this study, 18 healthy and 12 Ad-Cs eye images have been used for the training data set to extract features. Using Bayes and Random Tree algorithms they have achieved an accuracy of 96.7%. Moreover, the authors of this study have emphasised that Grabcut with Bezier-type curves would have given more accurate sclera segmentation.

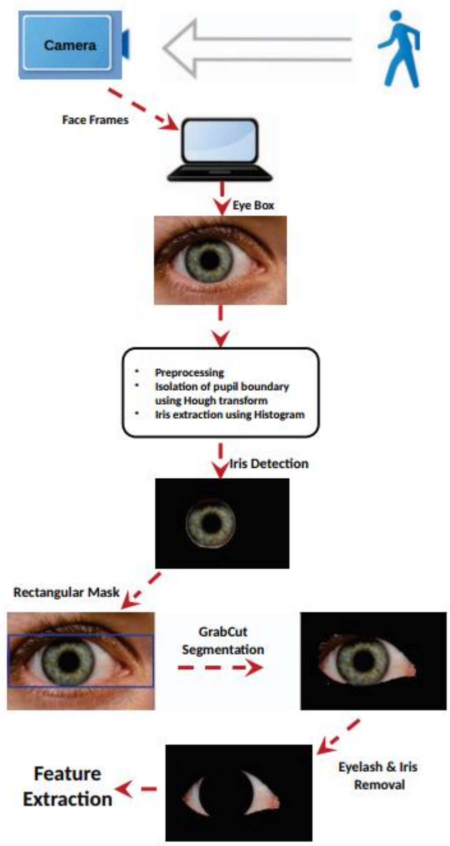

Figure 2: Sclera segmentation process (Tabuchi and Masumoto, 2020)

In the research by Tabuchi and Masumoto (2020), the authors proposed an artificial intelligence model to grade conjunctival hyperaemia severity levels as mild, moderate, and severe. The dataset used for this study consisted of 5008 slit lamp images taken at the Ophthalmology Department of Tsukazaki Hospital. Out of 5008 images, 872 images were taken for model validation and preliminary validation by graders. The Kappa coefficient was utilised to study the inter-rate agreement of the images. Based on the Japan Ocular Allergy Society's conjunctival hyperaemia severity grading system (JOAS grading), severity levels were identified by a JOAS specialist, and four (04) certified orthoptists and Kappa coefficients were calculated. Of the remaining 4008 images, 2707 images were selected as the final dataset. This dataset has been used to train six types of deep neural networks (DNNs), namely ResNet50, InceptionV3, Xception, Inception ResNet V2, VGG 19, and VGG 16. If half of the six DNN models gave the same grade as the experts, it was counted to be a correct answer. This study has shown a high correlation of 0.74 between the objective indicators and the AI grading results.

3. METHODOLOGY

The following experimental design is proposed for a precise classification of conjunctivitis into three severity levels: normal, mild, and severe.

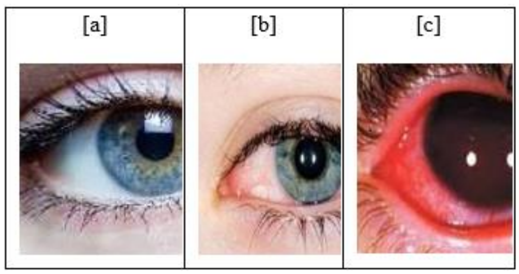

Figure 3: (a) Normal eye (b) Mild conjunctivitis infected eye (c) Severe conjunctivitis infected eye

Data Acquisition

Slit lamp images of both healthy and conjunctivitis-infected eyes need to be collected from a reliable source such as a medical institute or an eye clinic. It is preferred that all the images collected be taken from the same type of slit lamp.

Medical image collection needs to comply with ethical standards and patient privacy regulations. To ensure that, it would be required to obtain necessary medical clearances.

The complete process is illustrated in Figure 4 below.

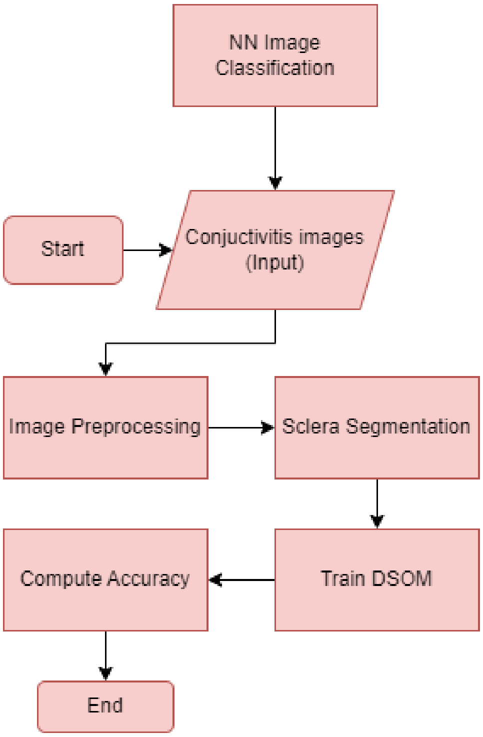

Figure 4: Image Classification Process Flow Chart

Image Preprocessing

In this phase, images will be subjected to preprocessing techniques for sharpening, smoothing, and reducing noise in the images. The collected slit lamp eye images will be sent through median and wiener filters to remove noise (Sundararajan and D., 2019). The median filter is a non-linear digital filtering technique used to remove noise while the wiener filter is a linear filtering technique used to restore the image degraded by noise.

Image Segmentation

For a better feature extraction, the sclera region of the eye covering the bulbar conjunctiva needs to be isolated. Lately, there is a higher inclination toward using deep learning techniques for the semantic segmentation of images. U-Net is one of the deep-learning networks that is designed for semantic image segmentation (Huang *et al.*, 2020). U-Net has an encoder-decoder architecture, where the encoder network is known to be the contraction path while the decoder network is called the expansion path. Here for sclera segmentation, ScleraSegNet, an attention-assisted U-Net model proposed by Wang et al. (2020) will be used.

To create a ScleraSegNet model, between the contract path and expansive path, a central bottleneck part will be introduced to enhance the separation of sclera and non-sclera pixels for learning more discriminative features. In the bottleneck part, four types of attention modules will be added. They are the spatial attention module (SAM), channel attention module (CAM), sequential channel attention and spatial attention module (CBAM), and parallel channel and spatial attention module (BAM).

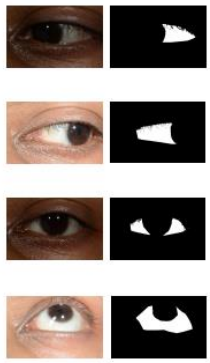

Figure 5: Sample MASD v1 eyes and corresponding segmented eyes (Wang *et al.*, 2020)

According to Wang et al. (2020), this ScleraSegNet model has achieved a precision value of 92.88% on the MASD v1 dataset. The provided Figure 5 below displays the results of sclera segmentation on sample images from the MASD v1 dataset using the ScleraSegNet model.

All the conjunctivitis-infected images will be subjected to sclera segmentation using the ScleraSegNet deep-learning model. Hyperparameters of the ScleraSegNet will be changed for better image segmentation.

Model Development

For model development, a Deep Self Organising Map (DSOM) will be employed. The Self Organising Map (SOM) uses a competitive learning technique that can detect features inherent to the problem (El Houby, 2021). In DSOM, there are mainly three layers, i.e. input, hidden, and output. The input layer is responsible for forwarding input images to the DSOM while the output layer is responsible for self-organisation. The hidden layer has two phases as SOM phase and the sampling phase.

Diagrams 6 and 7 below illustrate the two-layered DSOM architecture and the sampling layer creation in DSOM, respectively.

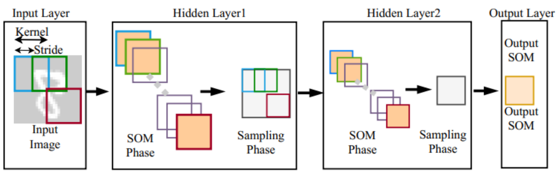

Figure 1: Two-layered DSOM architecture (Wickramasinghe, Amarasinghe and Manic, 2019)

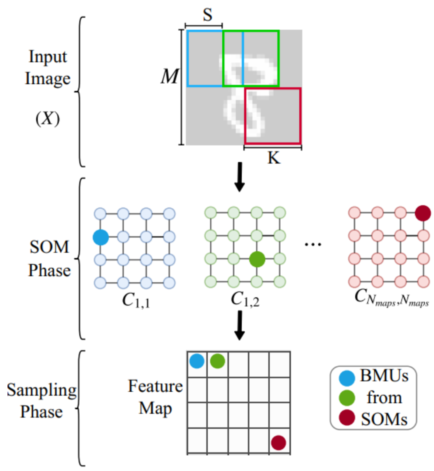

Figure 7: Sampling layer creation in DSOM (Wickramasinghe, Amarasinghe and Manic, 2019)

In the SOM phase, each image is segmented into small local regions called patches. These patches will be sent to its own SOM and for each SOM, the Best Matching Unit (BMU) will be found. As stated in equation (1) below, BMU or the winner neuron c will be calculated by reducing the Euclidean distance between the input image local region x(t) and the centres of all neurons in the SOM lattice (Aly and Almotairi, 2020).

$$c = \arg i \min\|(x(t) - mi(t)\|2 \qquad (1)$$

In the sampling phase for a particular hidden layer, all the BMUs of hidden SOM units will be combined expecting a 2D grid to be generated. The generated single 2D grid acts as the feature map to the next hidden layer. A classifier will be developed depending on the trained output layer SOM to label the input records (Wickramasinghe, Amarasinghe and Manic, 2019).

Model Evaluation

Evaluation of the developed model will be done by doing a domain expert evaluation. It is valuable to involve domain experts such as ophthalmologists, in this case, to evaluate the model's results. They can provide valuable feedback on the clinical relevance and accuracy of the classifications.

4. EXPECTED OUTCOMES

Following are the expected outcomes of the proposed application aiming to classify conjunctivitis in a telehealth setting.

- Real-time analysis: To make decisions based on the conjunctivitis condition of the patient, it is required to obtain real-time images of the infected eye(s) of the patient.
- Severity Classification: Based on the captured images and the symptoms told by the patients, the proposed system should be able to accurately classify the severity level as mild, moderate, or severe.
- Enhancing diagnostic accuracy: By utilising DSOMs, the system is expected to analyse the extracted sclera region of the real-time images in a manner that provides better severity classification. Integration with telehealth platforms: For virtual consultation, integrating the developed DSOM model for seamless classification.

5. DISCUSSION

In telehealth, the accuracy of diagnosis could be affected by different factors such as the level of knowledge, experience, brain memory weaknesses, and fatigue of doctors. Another factor that may affect the diagnosis is the lighting or reflections and the set-up of the distance between the eyes and the screen.

Neural Networks can provide a standardised objective tool to support the diagnosis process and minimise any human errors that may occur during the protocol. The human eye conditions could also affect the result in cases where the doctors themselves may have colour blindness or inconsistent colour vision and weaknesses, unknowingly. A biological imperfection in the human eye causes a problem with colour perception, and this could be overcome using Artificial Neural Networks (ANN).

Table 2 below compares the existing traditional machine learning systems with DSOM under different aspects.

Table 2: Comparison between Traditional ML systems and DSOM

Aspect	Traditional ML systems	DSOM
Feature Extraction	Requires manual feature engineering and relies on domain expertise.	Automates feature extraction from raw images, learning complex patterns.
Data Requirements	Needs a large, labelled dataset and may overfit if data is limited or unrepresentative.	More robust to limited labelled data and can leverage unsupervised learning for pre-training.
Complexity Handling	May struggle with complex images and variations in severity levels.	Effectively captures high-dimensional data and complex relationships.
Performance	Performance may plateau as complexity increases and is prone to biases from feature selection.	Typically achieves higher accuracy in classifying images of varying severity levels.

In this proposed methodology, DSOM is suggested compared to traditional machine learning (ML) systems for this problem due to its power to represent a high dimensional space into a space of lower dimension. The DSOM's powerful lattice neighbourhood structure could also be utilised for the visualisation of high-dimensional data, especially health condition images.

6. CHALLENGES AND LIMITATIONS

The work only aims at grouping the images into three groups (normal, mild, and severe). In the future, more groups could be defined, such as trace, mild, and very severe, to be more precise and detailed for diagnostic decision-making.

The representativeness and the diversity of data are important to build an effective SOM model. Ensuring a well-balanced dataset that covers all three severity levels of conjunctivitis is crucial. Biased training data may lead to inaccurate classifications. Moreover, selecting optimal parameters when training the SOM is a challenge.

In the telehealth sector, patient cooperation is important to make accurate diagnoses. Capturing the conjunctivitis-infected eye(s) of a patient can be challenging. This is mainly due to variations in focus and angles. This may affect the model's capability to make correct severity assessments.

7. CONCLUSION

The neural networks serve as a powerful tool for the support of telehealth consultation by image classification. Recently, emerging methods have been proposed by researchers to enhance the performance of the classifier by techniques such as data cleaning and transformation for better results. Despite their effectiveness and satisfactory results, neural networks still require a medical expert for monitoring and final decision after a critical evaluation of the Network's output.

This research proposes a neural network-based architecture for grouping images of patients showing conjunctivitis (pink eye) into three severity levels. Moreover, the utilisation of ScleraSegNet for accurate sclera segmentation and the implementation of unsupervised learning via deep self-organising maps will help for better classification.

Furthermore, the exploration of various neural network architectures for medical image classification and a comprehensive discussion on similar conjunctivitis classification techniques emphasise the importance of this field.

In conclusion, this study is crucial to acknowledge that the integration of neural networks into telehealth applications extends beyond conjunctivitis classification. The knowledge gained from this research can be used for further exploration into different ocular conditions and medical image analysis sectors.

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