Deep learning in developing clinical decision support systems using slit lamp biomicroscopy images : a review

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Abstract

Decision support is an indispensable component of contemporary healthcare delivery systems. In developing countries where the rural population often lacks access to sophisticated care facilities, high-end medical devices, highly experienced clinicians etc., automating clinical decision support can aid clinicians in early diagnosis of diseases and reduce the burden to some extent by reducing the manual routine tasks. Cataracts and corneal ulcers are worldwide causes of temporary or permanent blindness. As artificial intelligence (AI) becomes more pervasive in modern business and daily life, its applications in healthcare are expanding. In this study, the strengths and weaknesses of existing literature for early diagnosis of ocular diseases utilizing slit-lamp biomicroscopy images and AI technologies are evaluated. Following a comprehensive assessment of research publications, we found certain difficulties that must be addressed in order to improve the detection of eye illnesses.

Keywords: Deep Learning, Convolution Neural Network, Slit-lamp images

1 Introduction

Deep learning is the most promising and commonly used machine learning technology extensively used for illness identification. Deep learning technology has been used to evaluate medical images in a variety of areas in recent years. It has performed well in areas like registration and segmentation. Accordingly, the deep learning algorithm gets a lot of attention to solve various medical imaging problems. It is critical to present a high-quality assessment that evaluates trends and identifies future paths for deep learning applications in identifying corneal ulcers and cataracts using slit-lamp images. Corneal opacities affect around 4.2 million individuals worldwide, according to the World Health Organization's World Vision Report 1, released in October 2019.[1] Vision impairment is a significant financial burden worldwide. The annual global costs of uncorrected myopia and presbyopia, for example, have been estimated to reach US$ 244 billion and US$ 25.4 billion, respectively.[2]
A corneal ulcer is a defect in the epithelial layer of the cornea produced by bacteria, fungi, viruses, or acanthamoeba.[3] Mechanical stress or nutritional inadequacies can trigger it, and unchecked inflammation can lead to corneal necrosis. Some of the symptoms are progressive conjunctival redness, a foreign body sensation, discomfort, photophobia, and lacrimation. Slit-lamp inspection, fluorescein staining, and microbiological tests are used to make the diagnosis. The use of topical antimicrobials and, in some instances, dilating drops is necessary, and the patient should be sent to an ophthalmologist. In the United States alone, the yearly frequency of corneal ulcers is estimated to be between 30000 and 75000, and infectious keratitis accounts for around 12.2% of all corneal transplants done.[4, 5]
A cataract is a hazy, thick region in the eye's lens. Cataract occurs when proteins in the eye aggregate and lose their capacity to send clear pictures to the retina. The retina converts light that enters the eye through the lens into messages. The optic nerve transports the impulses to the brain. It progresses slowly and finally obstructs your eyesight.[6] Cataracts can arise in both eyes, however they do not usually form at the same time. Cataracts are fairly common among the elderly. According to the National Eye Institute, more than half of persons in the United States have cataracts or have had cataract surgery by 80.[7] Cataracts are currently detected by doctors using a slit lamp or a hand-held slit light under a slit lamp microscope to examine the state of the lens. Doctors draw results by comparing the participants' slit lamp pictures with regular gradations and crystal images. A comprehensive investigation is being conducted on early screening procedures for corneal ulcers and cataracts utilising slit-lamp images. To our knowledge, this is the first study to examine publically available datasets, preprocessing approaches, and quantitative scanning procedures for slit-lamp image-based diagnosis using standard performance criteria. Problems with the technique are also emphasised, as are suggested remedies defining future research subjects for slit-lamp image-based diagnostic equipment. This study discusses about corneal ulcers and cataracts. Then we get to the observation part, which is followed by the

discussion, limitations, and conclusion.

2 Corneal Ulcer

Table 1: Summarising the many DL methods used in the identification of corneal ulcers

DL systems	Task	Year	Testdata sets	Test images (n)	CNN	Evaluation Metrics
[8]	Binary classification	2021	SUSTech-SYSU dataset	712	VGG16 - Architecture excluded the top layer of the VGG16 base model and applied global average pooling to transfer the 4D tensor to a 2D tensor using a layer with 512 units	AUC(0.9798) ,Sensitivity(93.52%) ,Specificity(91.94%), Accuracy(92.73%) ,Positive predictive value(92.03%) , Negative predictive value(93.53%) ,Kappa(85.46%) ,Prevalence(49.65%)
[9]	Segmentation	2021	SUSTech-SYSU dataset	354 point flaky mixed and flaky corneal ulcer images	The core architecture is based on the widely known U-shape encoder-decoder structure, with the pretrained ResNet-34 acting as the encoder route to extract rich feature information from the input picture.	Dice(89.14%) ,Sensitivity(89.65%) ,Specificity(99.70%) , PCC(89.16%)

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DL systems	Task	Year	Testdata sets	Test images (n)	CNN	Evaluation Metrics
[10]	Segmentation	2022	SUSTech-SYSU dataset	712	semisupervised MsST-GAN based on cGAN architecture	MsST-GAN - Dice(89.90%),Sensitivity(91.03%) ,Jaccard Index(82.36%) ,PPMCC(89.89) ,Efficiency(0.0025) Semi-MsST-GAN-Dice(90.93%) ,Sensitivity(91.93%) ,Jaccard Index(83.79%) ,PPMCC(90.77%) ,Efficiency(0.0025)
[11]	Segmentation	2018	Zhongshan Ophthalmic Centre, Sun Yat-sen University	150	SLIC Superpixel Based Segmentation ,SVM Based Classification	PCC(92.08%) ,Accuracy(98.39%) ,Jaccard(87.05%)
[12]	Segmentation and Classification	2020	The Shanghai Eye, Ear, Nose, and Throat Hospital and the Affiliated Hospital of Guizhou Medical University	5,325 ocular surface images	Inception-v3 convolutional neural network architecture7 as the backbone of the proposed framework and the final classifcation layer of the Inception-v3 network was replaced with novel multi-task multi-label classifcation layers	AUC (0.930 for infectious keratitis), (0.934 for non-infectious keratitis)
[13]	Classification – Binary	2017	Private	48	Customised CNN	Dice(86%) ,Sensitivity(82%) ,Specificity(99%) ,PCC(99.3%)

Corneal Ulcer is a common cause of vision loss in the world's population. Infection is the most common cause of corneal ulcers. Dry eye, eye damage, inflammatory illnesses, using unsterilized contact lenses, and vitamin A deficiency are other reasons for corneal ulcers.[14] DL has revolutionized the diagnostic performance in identifying Corneal ulcers in recent years. Many organizations have demonstrated outstanding diagnostic performance using this method. On the SUSTech-SYSU dataset, paper [8] demonstrated that a DL system could reach an area under the receiver operating characteristic curve (AUC) of 0.9798 to identify Corneal Ulcer, with sensitivity and specificity of 93.52 percent and 91.94 percent, respectively. On the same data set, study [9] reported a sensitivity and specificity of 89.65% and 99.70%, respectively. Paper [10] recently published another DL system with excellent diagnostic performance. The DL system utilized was the semi supervised MsST-GAN, built using the SUSTech-SYSU dataset and based on the cGAN architecture. There were 712 photos in the test collection. The sensitivity was 91.93%. Study [13] used a customized CNN architecture and achieved sensitivity and specificity of approx 82% and 99%, respectively.

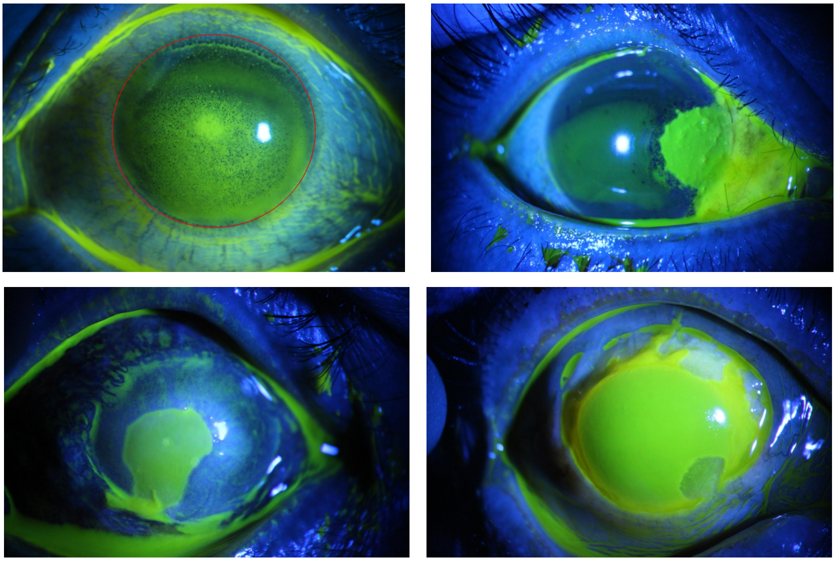

Fig. 1: Images from the SUSTech- SYSU dataset [15] affected by Corneal Ulcer.

3 Cataract

Table 2: Summarising the many DL methods used in the identification of corneal ulcers

DL systems	Task	Year	Testdata sets	Test images (n)	CNN	Evaluation Metrics
[16]	Detection and Grade prediction	2009	Singapore Retinal Image Archival and Analysis Network (SiRIAN) for Disease Prediction	5820	To identify anatomical structure in the lens image, a modified active shape model (ASM) is applied. To train a grading model for grade prediction, support vector machine (SVM) regression is used.	Success rate of feature extraction(95%), Mean error of automatic grading (0.36)
[17]	Detection and Classification (normal, mild, severe and unidentified)	2018	Dr.Sjamsu Clinic	NA	The grayscale method, median filter method and canny method is used to preprocess the slitlamp images. After that ,the hough circular method is used to automatically segment pupil from slit-lamp images. After the segmentation process,pixel scanning is used to extract mean intensity and uniformity from the pupil image. After the feature extraction process, classification is done by single perceptron based on the extracted feature.	Accuracy - 96.6%
[18]	Detection	2016	Images obtained from Cottage Hospital, Pandharpur and Lions eye Hospital, Miraj.	NA	NA	NA

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DL systems	Task	Year	Testdata sets	Test images (n)	CNN	Evaluation Metrics
[19]	Detection and Grading	2020	Marked Slit Lamp Picture Project (MSLPP) dataset created by He Eye Specialist Hospital (HESH)	16,103	YOLOv3 localises the nuclear area of the ocular lens. Following that, a deep learning network called ShuffleNet and a support vector machine (SVM) classifier were employed to classify cataract severity.	Accuracy(93.48%) ,Sensitivity(89.2%) ,Specificity(97.37%) ,Youden(0.846) ,F1(92.3%) ,Kappa(0.954)
[20]	Detection and Grading	2021	Private	1,335 slit-lamp photograph images and 637 retro-illumination images	Used custom CNN model which used 1)Region detection network for cropping 2)Data augmentation and transfer learning to improve perfomance 3)Generalized cross entropy to overcome bias 4)Class balanced to prevent loss skewed predictions	Accuracy(0·9992 and 0·9994 ,NO and NC) ,Sensitivity(98·82% and 98·51% ,NO and NC) ,Specificity(96·02% and 92·31% ,NO and NC)
[21]	Detection and Grading	2019	Private	157	Faster R-CNN, followed by a ResNet-101 based grading model	Mean Absolute Error(0.313), Accuracy(84.7%)
[22]	Detection and Grading	2015	ACHIKO-NC dataset	5378	Customized CNN (CRNN) followed by support vector regression (SVR) is used to detect and grade cataract.	Integral agreement ratio(70.7%) ,Decimal grading errors(88.4%) ,Integral grading errors(99.0%) ,Mean absolute error(0.304)

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DL systems	Task	Year	Testdata sets	Test images (n)	CNN	Evaluation Metrics
[23]	Detection , Classification and Grading	2017	Zhongshan Ophthalmic Center in Sun Yat-sen University	886	The lens borders and region of interest is automatically found in the pictures using two subsequent applications of Candy detection and the Hough transform, which are cropped, scaled to a fixed size, and utilised to build paediatric cataract datasets. These datasets are fed into the CNN inspired by Alex Network. The collected characteristics are integrated with vector machine (SVM) and softmax classifier.	(Classification-Mean Accuracy(97.07%) ,Sensitivty(97.28%) ,Specificity(96.83%)) (Three degree grading area-Mean Accuracy(89.02%) ,Sensitivity(86.63%) ,Specificity(90.75%)) (Density-Mean Accuracy(92.68%) ,Sensitivity(91.05%) ,Specificity(93.94%)) (Location-Mean Accuracy(89.28%) ,Sensitivity(82.70%) ,Specificity(93.08%))

Study [19] demonstrated that a ShuffleNet-based DL system could achieve an AUC of 0.9198 in Cataract detection, with sensitivity and specificity of 89.2% and 97.37%, respectively. Using slit-lamp photos, paper [20] demonstrated strong diagnostic (AUC of 0.9992, 0.9994; sensitivity of 98.82% ,98.51% and specificity of 96.02% ,92.31%) performance for nuclear opalescence (NO) and nuclear colour (NC).Using a modified CNN architecture (CRNN), paper [22] was able to obtain a mean absolute error of 0.304, 70.7% integral agreement ratio, 88.4% ratio of decimal grading errors, and 99% ratio of integral grading errors. Although tremendous progress has been made in this area, there are still certain limitations and need for development. To compensate for the specific variances in each individual's retina, the CNN training can be done more intensely. With minor tweaks, the systems may also be used to identify illnesses that have comparable effects to cataract. The devices' rapid and precise diagnosis can save ophthalmologists a lot of time in starting treatments and consequently saving the patient's vision. By training the systems with more diverse pictures and upgrading the architectural methods, the accuracy of the systems may be increased.

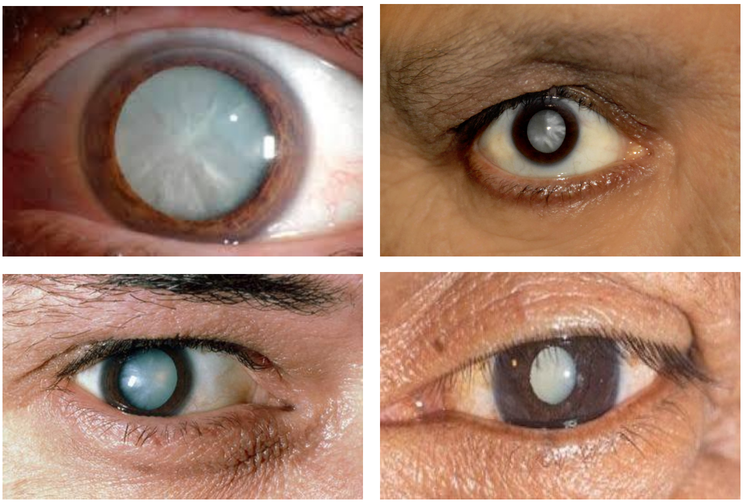

Fig. 2: Cataract-affected eye images.[24]

4 Key Observations

Image analysis techniques are aimed to use statistical neural network learning modules to evaluate essential elements of slit-lamp pictures, diagnose illnesses from images, and compare images with comparable properties. A computer-assisted automated early Corneal Ulcer screening approach may be a viable alternative to manual screening in rural and semi-urban areas where qualified professional ophthalmologists are few. Here are some of the significant findings from our survey.

CORNEAL ULCER

- Paper [8] had the highest sensitivity of 93.52 percent, while paper [13] had the lowest sensitivity of 82 percent. Study [8] utilised VGG-16 architecture, while study [13] used modified CNN. It demonstrates that the VGG-16 architecture produces the greatest results in terms of sensitivity.
- Paper [9] had the maximum specificity of 99.70%. The core architecture was built around the widely used encoder-decoder structure.
- Among the publications analysed, study [11] had the greatest Accuracy and Jaccard Index value of 98.39% and 87.05% respectively. SLIC Superpixel Based Segmentation and SVM Based Classification were employed.
- The research [10] employed semisupervised MsST-GAN based on cGAN architecture and had dice value of 90.93 percent and 89.90 percent for semi supervised and ablation supervised methods.

CATARACT

- We observed that the publication [16] had a feature extraction success rate of 95%, a mean error of 0.36 for automatic grading, and employed SVM regression.
- The study [21] had a mean absolute error of 0.313 employing faster R-CNN followed by a Resnet-101 based grading model while the paper [22] had a mean absolute error of 0.304 employing Customized CNN (CRNN) followed by support vector regression (SVR).
- The paper [20] graded slit-lamp cataract photos using nuclear colour (NC) and nuclear opalescence (NO) for more comprehensive research.
- The research [23] presented Accuracy, Sensitivity and Specificity for classification as well as Area grading, Density grading and location Grading.

5 Discussion and Limitations

DL has evolved into a viable method for interpreting ocular data from digital images, OCTs, and visual fields. It has been demonstrated to be a useful screening tool for common blinding illnesses such as AMD, DR, cataract and glaucoma.[25] Timely screening of these conditions will help decrease avoidable vision loss worldwide. The amount of input images needed to evaluate will reduce as DL methods develop, expanding access to underprivileged communities by minimizing medical work and shortages. While the potential of DL may appear to be limitless, there are also concerns. These concerns are justified, since inadequate DL training might have unanticipated and unfavourable repercussions.

- Interferences in slit-lamp pictures induced by sophisticated pathological characteristics of corneal ulcers, such as considerable variances in pathological forms between pointlike, point-flaky, and flaky corneal ulcers, blurring border, and noise. Correcting this will aid in increasing accuracy.
- The gathering of massive quantities of labelled pictures is one of the most difficult difficulties in creating viable deep learning algorithms, particularly those based on CNN models with deeper architectures. The key challenge is not the availability of large datasets, but rather the annotation of these pictures, which is costly and necessitates the services of experienced ophthalmologists. The solution is to create learning algorithms capable of developing a model from minimal data; this is an essential field of research both for DR diagnosis and medical picture analysis.
- Artificial intelligence and deep learning algorithms should be developed and tested in partnership with practising ophthalmologists.
- The papers ([8], [9], and [10]) evaluated their results using the SUSTech-SYSU dataset, which has a small sample size.
- Another constraint is the technology utilized for performance evaluation and training. Calculations were performed utilizing a hosted graphics processing unit, which may surpass the hardware capabilities of some healthcare PCs.
- A semi-automatic technique was utilized for corneal segmentation in the paper [11] . To identify the cornea, a fully automated technique is preferred.
- The approach described in the study [19], streamlines the difficult procedure of cataract screening and is widely utilized in Liaoning Province, China.
- Cataract Slit-Lamp Image Classification can be enhanced by integrating additional factors that influence cataract classification, however, it might result in intersecting features, forcing the addition of some more feature layers on the neural net perceptron.
- Cataract photographs from color images can be created employing complex image processing techniques. The appropriate distinction of veins and arteries might also be explored for pathology detection
- Future research can discover effective retinal analysis of various types of eye problems.

Despite its limitations, the survey results demonstrate that the work being done by various researchers and institutions on automatic identification of eye-related diseases is noteworthy and will hopefully be widely applied in eye-care centers and labs in the future.

6 Conclusion

The purpose of this survey is to first understand the context and relevance of cataract and corneal ulcer diagnosis. The automated screening of cataract and corneal ulcer can be advantageous in impoverished areas with limited health-care facilities, potentially saving millions of people's vision. The detection models utilised in the publications surveyed are robust and efficient, however they are not ideal; there is room for development that can enhance detection speed and accuracy. Deep Learning technology will become more linked into eye care as it improves, relieving doctors of tedious tasks. Ophthalmologists will be able to concentrate on patient interactions while improving medical and surgical treatment.

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