Artificial Intelligence based analysis of fundus images of retina to screen for diabetic retinopathy and cataract: A pilot study in North India

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Abstract- Introduction: Fundus examination is the first and foremost step in the diagnosis of vision conditions like diabetic retinopathy, cataract, corneal opacity and vitreous infection. But the fundus examination requires considerable experience and is subject to human errors. Artificial intelligence (AI) based analysis of fundus images of retina can be an answer to this problem. AI can be used even in the remotest areas where expert ophthalmologists are not available. Sevamob provides artificial intelligence enabled healthcare platform to organizations. It uses deep learning for image recognition, machine learning for triaging and computer vision for object counting. AI models of various medical conditions are first trained in the software from anonymized image data procured from various sources. To determine the accuracy of AI based point-of-care screening solution for fundus images of retina, an android smartphone / tablet with Sevamob app and a low end fundus camera were used. The system was operated by a nurse or a technician with minimal training

Methods: Fundus images of retina from clinically suspected diabetic retinopathy ,cataract, corneal opacity, vitreous infection and membrane hemorrhage were included in the study.

Results: Out of 151 fundus images, an expert ophthalmologist determined that 46 were negative, 53 were positive for diabetic retinopathy and 52 were positive for blur, which indicated the presence of one of more of the following conditions - cataract, corneal opacity, vitreous infection, membrane hemorrhage or obstruction in the eye. These fundus images were also analyzed by the AI system. The sensitivity and specificity of AI based system was 86.79% and 91.30% for diabetic retinopathy and 57.69% and 91.30% for blur.

Conclusion: This shows that Sevamob's AI based system can be very useful to screen for conditions like diabetic retinopathy, cataract, corneal opacity, vitreous infection and membrane hemorrhage and has the potential to replace an expert ophthalmologist in the future. Sensitivity and specificity also depend on the threshold used by our AI system.

Index Terms- Diabetic retinopathy, cataract, artificial intelligence, fundus images examination

To, The Editor Respected Sir,

I am submitting an original article manuscript titled "Artificial Intelligence based analysis of fundus images of retina to screen for diabetic retinopathy and cataract in North India: A pilot study to know the efficacy of the software" for your consideration.

Sevamob provides artificial intelligence enabled healthcare platform to organizations in India, southern Africa and the US. It uses deep learning for image recognition, machine learning for triaging and computer vision for object counting.

Diabetic retinopathy and cataract are common in these countries and due to lack of expert ophthalmologists, timely diagnosis is difficult. To overcome this issue, we have developed an artificial intelligence based system to screen for diabetic retinopathy, cataract, corneal opacity and vitreous infection in the fundus images of retina, simply with the help of technician or nurse.

We performed the above-mentioned study and came out with some interesting findings which we would like to publish in your esteemed journal. These findings could be applied by the clinicians right away and help screen for medical conditions in remote areas where ophthalmologists are not available.

Thanking you, Yours sincerely, Dr Ankit Agarwal Chief Medical Officer Sevamob ventures Limited, Lucknow, U.P, India

I. INTRODUCTION

Fundus examination is the first and foremost step in the diagnosis of diabetic retinopathy, cataract, corneal opacity and vitreous infection. But the fundus examination requires considerable experience and is subject to human errors. Also, in remote areas, due to lack of ophthalmologists, timely diagnosis is not possible. Artificial intelligence (AI) based analysis of fundus images of retina can be an answer to this problem. AI can be used even in the remotest areas where expert ophthalmologists are not available.

The use of artificial intelligence in medicine is currently of great interest.[1,2,3,4] The diagnostic and predictive analysis of medical photos, for instance, photographs of retina[6] and skin lesions, microscopic pathological images[8-10] and radiological images. are one of the clinical practice fields where artificial intelligence is expected to have a major influence.[5-13]. This potential usefulness is largely due to advances in deep learning with artificial deep neural networks (NN), which consist of a stack of multiple layers of artificial neuronal links that loosely simulates the brain's neuronal connections, and methods specialized for analysis of images, such as the convolution neural network, a particular form of deep neural network that conceptually mimics the visual pathway [11,14,15]. Adoption of artificial intelligence tools in clinical practice requires careful, meticulous confirmation of their clinical performance and utility before the adoption. The solution presented here empowers the ophthalmologists to gain an appreciation of and enable the assessment of the appropriateness of the AI system for diagnosis. We have also shown that current AI systems can aid in the timely diagnosis of medical conditions in resource constraint setting of developing countries like India. The use of artificial intelligence-based diagnosis and data regarding the same is scarce to our best knowledge.

Sevamob provides artificial intelligence enabled healthcare platform to organizations. It uses deep learning for image recognition, machine learning for triaging and computer vision for object counting. AI models of various medical conditions are first trained in the software from anonymized image data procured from various sources. The software can then be used to screen for these medical conditions in new samples. The system can work fully off line in last mile, low resource settings. We therefore planned this study with the aim to evaluate AI for identification of diabetic retinopathy, cataract, corneal opacity and vitreous infection.[21]

II. METHODS

This study is a retrospective observational study and this study was done at three Sevamob pop-up clinics at Lucknow, Jharkhand and Rajasthan, India. Fundus images of retina from 151 patients, who were suspected to have diabetic retinopathy, cataract, corneal opacity and vitreous infection, were taken to do this study. To determine the accuracy of AI based point-of-care screening solution for fundus images of retina, an Android smartphone/tablet with Sevamob app and a low end fundus camera were used. The system was operated by a nurse or a technician with minimal training. Nurse / technician takes fundus image from camera and the AI system uses deep learning to match patterns for

diabetic retinopathy or blur in the images. System also takes into account if patient is diabetic etc. Detection of diabetic retinopathy and blur was done onsite by Sevamob AI which worked fully offline on mobile and could be synced with the cloud once the network was available. A threshold of 70% was used to consider an image positive for a medical condition. An expert ophthalmologist determined if the images had diabetic retinopathy or blur. The evaluation of true positive, true negative, false positive and false negative was done based on the comparison between the expert's opinion and the AI result.

III. RESULTS

We analyzed 151 fundus images of retina for diabetic retinopathy, cataract, corneal opacity, and vitreous infection, as shown in table 1. Out of 151 fundus images, an ophthalmologist determined that 46 were negative, 53 were positive for diabetic retinopathy and 52 were positive for blur, which indicated one or more of the following conditions - cataract, corneal opacity, vitreous infection, membrane hemorrhage or obstruction in the eye. Based on these findings 'sensitivity, specificity, positive predictive value, negative predictive value, likelihood ratio of AI based system was calculated. These are depicted in table 1, 2 &3.

Analysis of Ophthalmologist					
Sample	Test	Positive	Negative		
	Diabetic Retinopathy	53	46		
Fundus images of retina	Blur (Cataract, Corneal opacity, Vitreous (infection, membrane, hemorrhage), Obstruction in the eye.)	52	46		

Table 1. Results of fundus examination by an ophthalmologist

Output of Vision Al					
	True positive	False negative	True negative	False positive	
Diabetic Retinopathy	46	7	42	4	
BLUR (Cataract, Corneal opacity, Vitreous, Obstruction in the eye.)	30	22	42	4	

Value	Value Blur
Diabetic Retinopathy	(Cataract, Corneal opacity, Vitreous or
	Obstruction in the eye.)
86.79%	57.69%
91.30%	91.30%
9.9	6.6
0.144	0.46
92%	88.23%
85.71%	65.62%
88.88%	73.46%
	Diabetic Retinopathy 86.79% 91.30% 9.9 0.144 92% 85.71%

Table 3. Diagnostic parameters for Vision AI

Image 1 and 2 show the probability of Diabetic retinopathy and Blur image in AI analysis

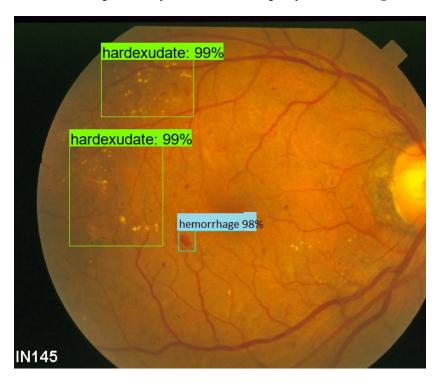


Image 1: Shows the marked area for diabetic retinopathy on the basis of 99% hard exudates and 98% hemorrhage in AI analysis

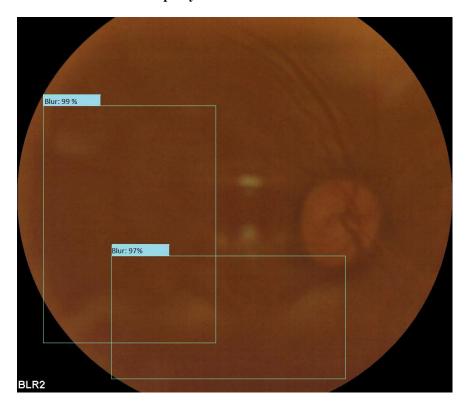


Image 2: Shows the marked area for Blur with 97% to 99 % probability in AI analysis

IV. DISCUSSION

In this pilot study, we have analyzed 151 fundus images of retina by AI system. The sensitivity and specificity were found to be good. This shows that this particular AI system may be very useful for analysis of fundus images of retina and can replace an ophthalmologist in the future. Sensitivity and specificity of AI also depend on the threshold set for the AI system used. In our study this threshold was set at 70% and this was decided after training and internal testing of samples at different thresholds of 5% intervals (50%-80%). We found optimal sensitivity and specificity at 70% threshold. It should be noted that this system is based on self-adjusting neural networks that adjust themselves to a boundary to which the input data and its outcome must convert. To our understanding the meaning of a self-learning classification system adjusts the "rules" to a given final outcome. At higher threshold, there were too many false negatives. At lower threshold, there were too many false positives. It finds appropriate that the implementation of an automated diagnosis or pre-screening system consists of several modules that should work independently from each other. To start with, the image should be of good quality. The system has used various enhancement techniques for the fundus images and a segmentation algorithm is developed to automate the process of detection of diabetic retinopathy and blur. Shape features extraction technique has been implemented to extract various shape features and finally for classification, the support vector machine was used as a pattern recognition tool to classify the objects in fundus images of retina. To the best of our knowledge such AI based pilot study for these set of medical conditions has never been done before in India or elsewhere in the world.

Gulshan et al. were the first to report the application of Deep learning for DR identification [23]. They used large fundus image data sets to train a convolutional neural networks (CNN) , Deep CNN in a supervised manner. They showed that the method based on DL techniques had very high sensitivity and specificity, and the AUC came up to 0.99 for detecting referable DR [24]. In the past two years, a number of DL models with impressive performance have been developed for the automated detection of DR [25-27]. Additionally, some studies applied DL to automatically stage DR through fundus images [26–29], making up the deficiency of Gulshan's study that they only detected referable DR but did not provide comparable data on sight-threatening DR or other DR stages.

ML algorithms such as RF and SVM have been applied to diagnose and grading cataract from fundus images, ultrasounds images, and visible wavelength eye images [30–32]. The risk prediction model for posterior capsule opacification after phacoemulsification has also been built [33].

The limitation of our study is the small sample size. A larger sample size study is further required to validate our system.

V. CONCLUSION

In this pilot study, automated AI based software for screening of various medical conditions has been tested. This AI based software method reduces screening time and human error. The system has an acceptable degree of accuracy, specificity and sensitivity.

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