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ORIGINAL ARTICLE

Classification of diabetic retinopathy using ensemble convolutional neural network architectures

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ABSTRACT

BACKGROUND

Diabetic retinopathy (DR) constitutes a primary cause of blindness across all age groups. Ophthalmologists examine fundus images (FI) to detect and classify stages of DR. Development of deep learning can help clinicians to attain a larger volume in screening and diagnosing diabetic retinopathy, thereby decreasing the burden of visual impairment caused by DR. This study aimed to classify DR using ensemble convolutional neural networks (CNN) architectures.

METHODS

We used data from the Indian Diabetic Retinopathy Image Dataset which consist of typical diabetic retinopathy lesions at pixel level. The dataset contains typical diabetic retinopathy structures as well as normal retinal structures and is divided into three parts: segmentation, classification, and location. There are 516 original color fundus images in the classification used as training set (413 images) and testing set (103 images). We used ensemble CNN architectures to classify diabetic retinopathy as no DR, mild non-proliferative DR (NPDR), moderate NPDR, severe NPDR and proliferative DR (PDR) based on fundus image.

RESULTS

In this study we successfully created a model with ensemble CNNs to detect DR based on fundus images with area-under-the-curve, sensitivity, and specificity of 0.88, 0.89, and 0.90, respectively, which is on par with the most modern methods.

CONCLUSION

Based on the results, this model performs quite well in early detection of diabetic retinopathy and can be used to develop a more accurate model for detecting and classifying diabetic retinopathy. This model can also be used in assisting mass screening at lower cost without reducing diagnostic effectiveness.

Keywords: Diabetic retinopathy, deep learning, convolutional neural networks, early detection

INTRODUCTION

Diabetic retinopathy (DR) is developing into the main cause of global blindness. By 2045, the global DR prevalence is estimated to grow in number by 160.50 million.[1] In the early stages, DR patients usually do not have any symptoms indicative of visual disturbance. Hence some patients come to the ophthalmologist at a late stage of DR, making it difficult to prevent severe visual impairment or even blindness. Early diagnosis is one of the most important steps in providing prompt treatment for DR to avoid blindness.[1] In order to provide early diagnosis in DR, some countries have tried to develop programs for DR screening aiming at early and prompt diagnosis of DR. [2,3]

Diabetic retinopathy diagnosis is currently based on fundus visualization using direct or indirect funduscopy, slit lamp with condensing lens, fundus photography, or optical coherence tomography. Fundus photography is widely available but there is a need for trained physicians to interpret the photographs, on which to base the diagnosis of DR. These conditions call for more efficient approaches to escalate DR screening especially in areas with shortages of trained experts in DR diagnosis.[4,5]

Advances in artificial intelligence, especially deep learning, have grown extensively to assist medical care. The development of deep learning systems for DR diagnosis can help clinicians achieve larger volumes in screening and diagnostic approaches, and in providing earlier treatment to prevent blindness.[6,7] Previous studies have been conducted on developing deep learning models to detect DR, based on fundus images. One recent study that used the IDRiD dataset and ensemble convolutional neural networks (CNN) software, reached 71.84% accuracy. The results showed great promise and outperformed previous options in accurately diagnosing DR severity.[8] In another study, the researchers used LezioSeg, a multi-scale attention affine-based CNN for segmenting diabetic retinopathy lesions in images from the IDRiD dataset. The research achieved high accuracy rates for soft exudates, hard exudates, hemorrhages, and microaneurysms (area under the precision-recall curve (AUPR) of 81% for soft exudates, 86% score for hard exudates, 69% score for hemorrhages, and 40% score for microaneurysms). The study showed that their affine-based augmentation model produced results comparable to state-of-the-art methods. These studies suggest that ensemble CNNs and the IDRiD dataset were able to correctly detect and assess diabetic retinopathy. The results may vary depending on the CNN structure and architecture, training method, and dataset information. The issues discussed may cause some fluctuation or a lack of clear conclusions, even if the findings are generally reliable. Ensemble CNN architectures may affect multi-class and multi-label tasks, so that more research is needed.[9]

A previous study aimed to classify DR using the IDRiD dataset only used a single CNN architecture.[9] Our study aimed to use an ensemble CNN to achieve better performance of the deep learning model using the IDRiD dataset. This model can be used as diagnostic tool in assisting DR screening programs to establish an accurate early diagnosis. Therefore the aim of our study was to develop a computer-aided diagnostic tool for assisting DR screening programs with accurate early diagnosis.

METHODS

Image dataset

We used data from the Indian Diabetic Retinopathy Image Dataset or IDRiD dataset,[10] which consists of typical diabetic retinopathy lesions at the pixel level. IDRiD is a set of typical DR structures and normal retinal structures. This dataset was developed to facilitate the creation, validation, comparison, and further advancement of DR lesion detection algorithms utilized in clinical applications by the scientific community. The Indian Diabetic Retinopathy Image Dataset (IDRiD) is very important for many reasons, including: (i) much attention has been focused on how common diabetic retinopathy is in India. Diabetes retinopathy is a common reason why working adults around the world cannot see well. According to studies, a large number of persons in India who have diabetes are affected by diabetic retinopathy. As the number of persons with type 2 diabetes mellitus in India rises, so does the number of persons with diabetic retinopathy, which is now the main cause of vision loss; (ii) the IDRiD database is outstanding because it is an excellent representation of the Indian people, making it a truly unique resource; (iii) the collection has details on the hazards of such eye diseases as diabetic retinopathy and diabetic macular edema. It is helpful to find and fix these conditions early on with this information. This tool works really well to help build and test image analysis methods that are designed to find diabetic retinopathy in the

early stages; and (iv) the dataset project helps in important ways with research that aims to improve procedures to find, manage, diagnose, and treat eye disease. Using computer-aided detection tools, it enables persons to make tools that can help with screening large groups of persons for diabetes mellitus. On top of that, this technology helps clinicians use their time better. The Indian Diabetic Retinopathy Image Dataset can be used because it has special features that make it useful for Indians and other persons and because it can help to quickly find and treat diabetic retinopathy. Researchers and clinicians can both learn much from this resource. We used an ensemble CNN architecture to classify diabetic retinopathy based on fundus images. This study was conducted from January to February 2024.

Image classifiers

The IDRiD set is split into three parts: segmentation, classification, and location. There are 516 original color fundus images in the classification set. These are split into two processes: the first is to construct the training set (413 images) and the second is to construct the testing set (103 images). This dataset also includes information on DR severity and presence of diabetic macular edema for each image. The dataset has three main subtopics: lesion segmentation, disease severity grading, and retinal landmark localization and segmentation, which allow users to enable testing of the algorithms' generalizability. The pathologies and their distributions within the training and evaluation sets are shown in Table 2 and Figure 2.

The IDRiD dataset classifies DR into 5 classes, namely normal fundus, mild non-proliferative DR (NPDR), moderate NPDR, severe NPDR, and proliferative DR (PDR) based on the International Clinical Diabetic Retinopathy Scale. The fundus photographs were obtained by examining patients with a retinal fundus camera (model Kowa VX-10α) with a 50^0 field of view on a dilated pupil after instillation of one drop of 0.5% tropicamide. The DR grading was assessed by medical experts on the full set of 516 images in this dataset.[10]

Model metrics

Model performance was assessed using the area under the receiver operator characteristic curve (AUROC), which was calculated using the probability outputs for each class from the final layer of our neural networks. To assess the model's performance in disease screening, the AUROC score was calculated based on the prediction of healthy versus pathologic images. For assessment of disease classification performance, the AUROC was calculated based on the model prediction for each pathology class. The average AUROC for all classes was also calculated. Additionally, the sensitivity and specificity for disease screening and for each individual pathology was also measured.

The sensitivity was calculated based on the following equation

$$Sensitivity = \frac{TP}{TP + FP}$$

while the specificity was calculated with the following equation

$$Specificity = \frac{TN}{TN + FN}$$

In above equation, TP, FP, TN and FN stand for true positive, false positive, true negative, and false negative, respectively.

RESULTS

Study dataset

We used the IDRiD dataset comprising 516 original color fundus images that consist of 168 normal fundus, 25 mild NPDR, 168 moderate NPDR, 93 severe NPDR, and 62 PDR images.

Deep learning performances

Our developed algorithm achieved best performance using a fundus image size of 300 x 300 pixels. Our deep learning system shows a model to detect diabetic retinopathy with area-under-the-curve, sensitivity, and specificity of 0.88, 0.89 (65/73), and 0.90 (27/30), respectively (Table 1 and Figure 1).

Table 1. Validity of convolutional neural network to diagnose diabetic retinopathy

	Diabetic retinopathy (+)	Diabetic retinopathy (-)	Total
Convolutional neural network			
Positive	65	3	68
Negative	8	27	35
Total	73	30	103

Table 2. Diabetic retinopathy severity classification based on International Clinical Diabetic Retinopathy Scale[4]

DR Severity	Clinical Findings
No DR	No abnormalities
Mild NPDR	Micro-aneurysms only
Moderate NPDR	Any of the following: - Micro-aneurysms - Retinal dot and blot hemorrhages - Hard exudates or cotton wool spots No sign of severe NPDR
Severe NPDR	Any of the following: - More than 20 intra-retinal hemorrhages in each of 40 quadrants - Definite venous beading in 2 or more quadrants - Prominent intra-retinal microvascular abnormality (IRMA) in 1 or more quadrants No sign of PDR
PDR	One or both of the following: - Neovascularization - Vitreous/pre-retinal hemorrhage

Note: DR: diabetic retinopathy; NPDR: non-proliferative diabetic retinopathy; PDR: proliferative diabetic retinopathy

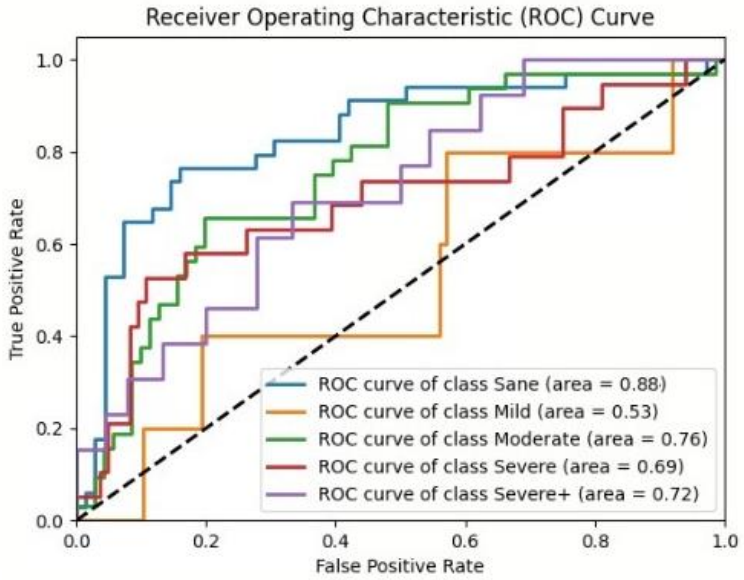

Figure 1. Area under the curve. Sane = no diabetic retinopathy ; Mild = mild non-proliferative diabetic retinopathy; Moderate = moderate non-proliferative diabetic retinopathy; Severe = moderate non-proliferative diabetic retinopathy ; Severe+ = proliferative diabetic retinopathy

DISCUSSION

Our model had 89.0% sensitivity and 90.0% specificity in diagnosing and classifying DR, thus being slightly higher in sensitivity compared to the study conducted by Raju et al.[19] and Lin et al.[20] which had sensitivities of 80.28% and 73.24%, respectively, in diagnosing DR. Both of the latter studies developed deep learning using CNN architecture to construct the algorithm. Raju et al.[19] used 35,000 fundus images and Lin et.al.[20] used 33,000 fundus images to produce the deep learning model, whereas our study used 516 fundus images. It may be an advantage of our study that our algorithm can detect more detailed fundus abnormalities with such a small number of photographs. We believe that further development of this model using more data can enhance the sensitivity and specificity of our model. The higher sensitivity is also a mark of the superiority of our model in terms of screening purposes.

Previous studies using the IDRiD dataset showed promising results for DR diagnosis. The study by Ali et.al.[9] has shown good results in identifying retinal pathology representing DR diagnosis such as microaneurysm, soft exudate, hard exudate, and hemorrhage. The limitation of the study of Ali et al. is that they did not classify

the severity of DR based on the fundus image, as was done in our study. Parsa et.al.[8] using ensemble CNNs and the IDRiD dataset achieved 71.84% accuracy, 88.76% specificity, and 86.02% AUC. Compared to their study, our CNNs performed better in all three parameters.

Computer vision-based applications are becoming more relevant in the biomedical imaging field. They offer the radiologist valuable decision support data that improves the diagnosis and assists medical personnel to be informed about the most efficient therapies for important medical diseases.[11-13] We used a convolutional neural networks (CNN) approach as the backbone. Convolutional neural networks act similarly to a human visual system by recognizing images and layering them before doing image processing and interpretation on the cerebral cortex.[14,15] We used a CNN architecture because this approach offers automatic local features extraction and application of multiple filters to extract different features from the images. As the layers of extraction deepen, more features are extracted for classification, thus enhancing the accuracy of the model. An ensemble of CNNs trained to reduce asymmetric loss outperformed individual models in detecting and classifying ocular diseases from retinal fundus pictures.[16-18]

The IDRiD dataset consists of fundus photography segmentation which makes it an excellent database to develop and test image analysis algorithms that can find DR at an early stage. Diabetic retinopathy is a devastating consequence of diabetes mellitus that can lead to irreversible vision loss. Automatic DR identification systems are crucial for early diagnosis of DR, which in turn speeds up the diagnostic process, saves money, and improves patient care by enabling earlier treatment.

Our study provided better performance compared to previous studies using the same IDRiD dataset. This improvement was achieved by using ensemble neural networks that provide more accurate performance compared to simple CNNs. These ensemble CNNs also allowed us to use a smaller dataset which provides comparable performances. The limitation of this study is that deep learning models developed based on single image recognition can incorrectly associate information with the disease. For example, the deep learning network can mistakenly learn to correlate the temporal location of the disc with diabetic macular edema (DME) after processing images from a subgroup of persons with a greater prevalence of DME and the optic disk being slightly temporal.[21] In terms of this situation, a segmentation of fundus photography identifying each pathology of DR classification from microaneurysms, venous beading, hemorrhages, and neovascularization, could help the network to do more advanced reading.

A deep learning model that can classify DR with a small dataset and offer dependable sensitivity and specificity has been demonstrated in this study. Therefore, our next steps will involve creating a deep learning model to recognize DR using images from an Indonesian fundus image dataset. We expect that this Indonesian population-based model will enable mass screening to improve DR diagnosis among the Indonesian population.

CONCLUSION

Based on the results, this model performs quite well in early detection of diabetic retinopathy, and can be used to develop more accurate models in detecting and classifying diabetic retinopathy. This model can also be used in assisting mass screening at lower cost without reducing diagnostic effectiveness. With the help of a deep learning model, clinicians can focus more on optimizing medical and surgical care for DR patients. Additionally, the referral of patients can be done earlier from areas without access to vitreoretinal specialists.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Author Contributions

HKA, HAT and AA contributed to study concept and design, and provision of study material. GAB contributed to data analysis. ET and HKA contributed to administrative support and data assembly. HKA, HAT, AA, ET and GAB contributed to manuscript writing and reviewing. All authors approved the final manuscript and will take public responsibility for the content of the manuscript submitted to Universa Medicina.

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Data Availability Statement

The dataset is available online as a public dataset.

Declaration of Use of AI in Scientific Writing

Nothing to declare

REFERENCES

1. Teo ZL, Tham YC, Yu M, et al. Global prevalence of diabetic retinopathy and projection of burden through 2045: systematic review and meta-analysis. Ophthalmology 2021;128:1580–91. doi: 10.1016/j.ophtha.2021.04.027.
2. He J, Cao T, Xu F, et al. Artificial intelligence-based screening for diabetic retinopathy at community hospital. Eye (Basingstoke) 2020;34:572–6. https://doi.org/10.1038/s41433-019-0562-4.
3. Bajwa A, Nosheen N, Talpur KI, Akram S. A prospective study on diabetic retinopathy detection based on modify convolutional neural network using fundus images at Sindh Institute of Ophthalmology & Visual Sciences. Diagnostics (Basel) 2023;13:393. doi: 10.3390/diagnostics13030393.
4. Vijayan M, Venkatakrishnan S. A regression-based approach to diabetic retinopathy diagnosis using Efficientnet. Diagnostics (Basel) 2023;13:774. doi: 10.3390/diagnostics13040774.
5. Ali G, Dastgir A, Iqbal MW, Anwar M, Faheem M. A hybrid convolutional neural network model for automatic diabetic retinopathy classification from fundus images. IEEE J Transl Eng Health Med 2023;11:341–50. doi: 10.1109/JTEHM.2023.3282104.
6. Arias-Serrano I, Velásquez-López PA, Avila-Briones LN, et al. Artificial intelligence based glaucoma and diabetic retinopathy detection using MATLAB - retrained AlexNet convolutional neural network. F1000Res 2023;12:14. doi: 10.3906/elk-2105-36.
7. Nagasawa T, Tabuchi H, Masumoto H, et al. Accuracy of diabetic retinopathy staging with a deep convolutional neural network using ultra-wide-field fundus ophthalmoscopy and optical coherence tomography angiography. J Ophthalmol 2021;2021. doi: 10.1155/2021/6651175.
8. Parsa S, Khatibi T. Grading the severity of diabetic retinopathy using an ensemble of self-supervised pre-trained convolutional neural networks: ESSP-CNNs. Multimed Tools Appl 2024;1:34. doi: 10.1007/s11042-024-18968-5.
9. Ali MYS, Jabreel M, Valls A, Baget M, Abdel-Nasser M. LezioSeg: multi-scale attention affine-based CNN for segmenting diabetic retinopathy lesions in images. Electronics (Switzerland) 2023;12:4940. https://doi.org/10.3390/electronics12244940.
10. Porwal P, Pachade S, Kamble R, et al. Indian diabetic retinopathy image dataset (IDRiD): a database for diabetic retinopathy screening research. Data 2018;3:25. https://doi.org/10.3390/data3030025.
11. Nadeem MW, Goh HG, Hussain M, Liew SY, Andonovic I, Khan MA. Deep learning for diabetic retinopathy analysis: a review, research challenges, and future directions. Sensors (Basel) 2022;22:6780. doi: 10.3390/s22186780.
12. Inamullah, Hassan S, Alrajeh NA, Mohammed EA, Khan S. Data diversity in convolutional neural network based ensemble model for diabetic retinopathy. Biomimetics (Basel) 2023;8:187. doi: 10.3390/biomimetics8020187.
13. Patil MS, Chickerur S, Kumar YVS, et al. Deep hyperparameter transfer learning for diabetic retinopathy classification. Turk J Electrical Eng Comput Sci 2021;29:2824–39. doi: 10.3906/elk-2105-36.
14. Abed MH, Muhammed LAN, Toman SH. Diabetic retinopathy diagnosis based on convolutional neural network. J Physics: Conference Series. IOP Publishing Ltd; 2021.
15. Kalpana Devi M, Mary Shanthi Rani M. Classification of diabetic retinopathy using ensemble of machine learning classifiers with IDRiD dataset. In: Suma V, Fernando X, Du KL, Wang H, editors. Evolutionary computing and mobile sustainable networks. Singapore: Springer Singapore;2022.pp.291–303. doi: 10.1088/1742-6596/1999/1/012117.
16. Pradhan A, Sarma B, Nath R, Das A, Chakraborty A. Diabetic retinopathy detection on retinal fundus images using convolutional neural network. In: Bhattacharjee A, Borgohain SK, Soni B, Verma G, Gao XZ. editors. Machine learning, image processing, network security and data sciences. MIND 2020. Communications in Computer and Information Science, vol 1240. Springer, Singapore. pp. 254–66. https://doi.org/10.1007/978-981-15-6315-7_21.
17. Indolia S, Goswami AK, Mishra SP, Asopa P. Conceptual understanding of convolutional neural network- a deep learning approach. In: Procedia Computer Science. Elsevier B.V.; 2018. pp. 679–88. https://doi.org/10.1016/j.procs.2018.05.069.
18. Taye MM. Theoretical understanding of convolutional neural network: concepts, architectures, applications, future directions. Computation 2023;11:52. https://doi.org/10.3390/computation11030052.
19. Raju M, Pagidimarri V, Barreto R, Kadam A, Kasivajjala V, Aswath A. Development of a deep

learning algorithm for automatic diagnosis of diabetic retinopathy. Stud Health Technol Inform 2017;245:559-63.
20. Lin GM, Chen MJ, Yeh CH, et al. Transforming retinal photographs to entropy images in deep learning to improve automated detection for diabetic retinopathy. J Ophthalmol 2018;2018:2159702. doi: 10.1155/2018/2159702.
21. Grewal PS, Oloumi F, Rubin U, Tennant MTS. Deep learning in ophthalmology: a review. Can J Ophthalmol 2018;53:309-13. doi: 10.1016/j.jcjo.2018.04.019.