Diabetic Retinopathy Tracker System

Dafwen Toresa[1], Hazlyna Harun[2], Juhaida Abu bakar[3] and Nur Haslinda Abdul Hasan[2]
[1]*Faculty of Computer Science, Lancang Kuning University, Pekanbaru, Indonesia*
[2]*Data Science Research Lab. School of Computing, University Utara Malaysia, Malaysia*

Keywords: Early Detection, Diabetic Retinopathy, CNN, Automated Intelligence.

Abstract: The examination of retinal images is compulsory for ophthalmologists to spot features of eye diseases. Multiple studies and clinical trials have reported the benefit of early detection and timely treatment in reducing the risk of vision loss from Diabetic Retinopathy (DR) and decreasing the global burden of blindness. Active screening for DR is important because most patients who develop DR have no symptoms until the very late stages, and by then it is often too late for effective treatment. Multiple patient barriers to DR screening exist, including poor access to care rural healthy deprivation, lack of time, high out-of-pocket expenses, insufficient patient knowledge and awareness of DR, and lack of care coordination, especially among low-income populations, and ethnical minorities specifically in Malaysia. Hence, this project aims at developing an automated intelligence system based on fundus image captured by using a Convolutional Neural Network (CNN) trained by a Deep Learning (DL) algorithm. The system is named Diabetic Retinopathy Tracker system (DR Tracker) assists medical officers/technologists in rural areas in the screening process based on raw fundus images captured. In this project, 200 images were used for testing, while 2000 images were used for training. The results achieved optimum accuracy is 93.75%. This product innovation known as DR Tracker will contribute to an early screening process by improving the performance accuracy for the detection of DR based on the fundus image. By utilizing classification algorithms, such solutions have the potential to provide quick, accurate decision support at a low cost. It can benefit the patients in medically underserved areas that have limited numbers of ophthalmologists and rare medical resources.

1 INTRODUCTION

In 2020, the number of adults worldwide with Diabetic Retinopathy (DR), Vision-Threatening Diabetic Retinopathy (VTDR), and Clinically Significant Macular Edema (CSME) was estimated to be 103.12 million, 28.54 million, and 18.83 million, respectively; by 2045, the numbers are projected to increase to 160.50 million, 44.82 million, and 28.61 million, respectively (Sasongko, 2017). The World Health Organization (WHO) predicted that by 2030, Malaysia would have 2.48 million people suffering from diabetes (W.H.O., 2014). However, Datuk Seri Dr. Dzulkefly Ahmad, the previous Minister of Health, declared in 2019 that 3.6 million Malaysians have diabetes. This occurrence leads to Asia's highest and one of the world's highest rates. In Malaysia, diabetes has become a major concern. As a result, the Malaysian government is paying close attention to this problem and has devised a comprehensive plan and method to improve diabetes prevention, treatment, and control as a matter of urgency. The workload of repetitive tasks, on the other hand, is quite high.

Diabetic retinopathy (DR) is a serious eye disease associated with long-standing diabetes that results in progressive damage to the retina, eventually leading to blindness (Toresa et al., 2021). The disease does not show explicit symptoms until it reaches an advanced stage; however, if DR is detected early on, vision impairment can be prevented with use of laser treatments.

Regardless of the type of diabetes, all people diagnosed with it require yearly retinal screening in order to detect DR early and effectively treat it. Second, some of these patients are based in rural areas and could not visit an eye care provider. Thirdly, as such follow ups are required for years together, the attitude, and/or behavioral aspects negatively impact the patients practice despite knowledge of consequences. These issues can be solved with provision of an automated imaging system within easy reach of the patient (Avidor et al., 2020). Hence, there

Toresa, D., Harun, H., bakar, J. and Hasan, N.
Diabetic Retinopathy Tracker System.
DOI: 10.5220/0012446600003848

In *Proceedings of the 3rd International Conference on Advanced Information Scientific Development (ICAISD 2023)*, pages 187-191
ISBN: 978-989-758-678-1

has been an increasing interest in the development of automated analysis software using computer machine learning/artificial intelligence (AI) for analysis of retinal images in people with diabetes thus solving at least some part of the problem (Zhuang and Ettehadi, 2020). Second, some of these patients live in remote locations and are unable to see an eye doctor. Third, as a result, follow-up is essential.

For years, the attitude and/or behavioral traits have been a source of contention despite awareness, have a detrimental influence on the patients' practice of repercussions Provision can help to resolve these challenges (Sharif, 2020). The presence of an automated imaging device within easy reach of patients (Abed et al., 1999). As a result, there has been a surge of interest in the computer-assisted creation of automated analytical software. For the analysis of data, machine learning or artificial intelligence (AI) is used to retinal images in diabetics, therefore resolving at least a portion of the issue.

2 PREVIOUS WORK

Proposed classification of the grade of non-proliferative diabetic retinopathy at any retinal image. In order to extract features, used by a support vector machine, an initial image processing stage isolates micro aneurysms, blood vessels and hard exudates. To figure out the retinopathy grade of each retinal image used by a support vector machine. The evaluation was implemented in the software MatlabR. Getting better results from the support vector machine (SVM) than other machine learning algorithms (Carrera et al., 2017).

Proposed that the analysis which used the deep CNN method is extremely particular during an automated DR severity grading and also very useful during a large-scale database. Feature enhancing methods like matched filtering and region growing are combined with SVM and Neural networks and are utilized for various classification problems of DR severity. There has been growth of Graphics Processing Units (GPUs) because of the growth of a Deep CNN based feature extraction method. As a result, deep learning models for DR detection are popular among several researchers. Deep learning ensures high accuracy and performance and is a powerful tool for DR detection (Rajesh et al., 2022).

In their paper used a CNN method with a binary tree-based ensemble of classifiers to increase the performance. The model trained could provide usable point-of-care diagnostic services for DR. The model was so well equipped that it could even be used with other medical applications. The developed application could only diagnose images from a phone's gallery (Hagos et al., 9 01).

Another study, proposed a multi-categorical disease detector system by utilizing deep learning techniques. This study consisted of STARE (structured analysis of the retina) database and detected differentretina features like lesion, optic disk, and blood vessels. Thus, CNN was utilized for disease classification. The augmentation and normalization of images have been done to enhance the number of images to prevent the overfitting issue. The blood vessels were extracted using the morphological dilation, erosion, adaptive histogram equalization (AHE), and CLAHE. The optic disk removal was done with the aid of the Canny edge detector and thresholding of the images. The exudates appear due to leakage of blood vessels because of hypertension, diabetes, and vein obstruction. So, these yellowish exudates were mainly detected with Gaussian blurring and binary thresholding. The classification stage encompassed two main stages, training and testing stages. The training phase consisted of determining the representative classes and attributes from the training dataset. Further, the dataset was associated with the class to which it bears a resemblance; then the network determined the disease category of the conforming image (Rajan and Sreejith, 2018).

Proposed an automated system using a convolutional neural network (CNN) to detect diabetic retinopathy and its severity stage. The model was trained on approximately 88000 labeled retinal photographs, and a quadratic weighted-kappa metric was used to determine the classification efficiency. The proposed system acquired 82% accuracy in detecting the DR, 51% for assessing its current stage and a decent kappa value of 0.776. Results depicted that the effectiveness of the neural networkcan be used for a complex medical problem (Kwasigroch et al., 2018).

3 METHODOLOGY

The proposed method is developed and presented here. The flowchart of the processes is illustrated in figure 1. All the processes involved is explained in this section.

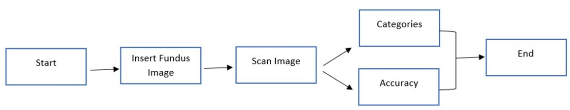

Figure 1: Methodology.

Process

1. *User Input Fundus Image*.
   A dataset of 2000 fundus images of type 2 diabetic patients were obtained from local hospital in Malaysia which is Hospital Universiti Sains Malaysia from Kerian and Kaggle website. The fundus images obtained have been categorized into Normal and Diabetic Retinopathy by optometrist. There are 850 normal retina images; and 1250 images of diabetic retinopathy that were used in this study. All the images had no link to the patients' identities.
2. *Preprocessing*.
   The collection included photos from patients of various ethnicities, ages, and illumination levels in fundus photography. This has an effect on the pixel intensity values in the photos, causing excessive variance unrelated to categorization levels. The photographs were likewise high resolution, requiring a large amount of RAM. The dataset was downsized to 512x512 pixels, which kept the detailed characteristics we were looking for but reduced the dataset to memory size.
3. *Training*.
   The CNN was initially pre-trained on 2000 images until it reached a significant level. This was needed to achieve a relatively quick classification result without wasting substantial training time. The network was trained using stochastic gradient descent with Nestrov momentum. A low learning rate of 0.0001 was used for 8 epochs to stabilize the weights.

Figure 2 shows the results of 2000 images validation accuracy which is 88.46% until reached final iteration.

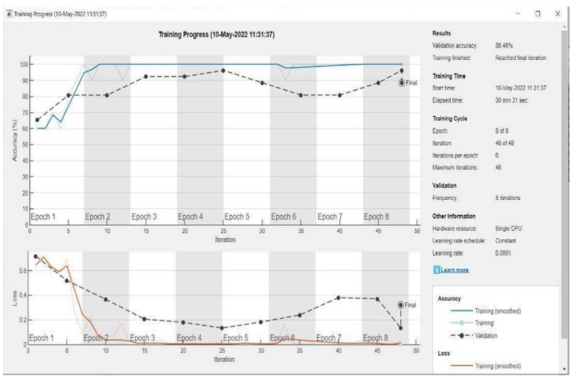

Figure 2: Training Progress.

4 RESULT AND DISCUSSION

In this project, there are 200 images that have been used for the testing phase. In this table, there are show us the image and the outcome the images which is accuracy. Based on this table, the result achieved optimum accuracy is 93.75%.

Table 1 displays the degree of accuracy of the test-phase photographs. The best accuracy for testing phase, which is 93.75%, was obtained using 200 images during testing and 2000 during training. All of the photographs used in this project's training and testing phases are raw images. In the testing step, we blend the images of normal and diabetic retinopathy to determine the accuracy. The outcome demonstrates AlexNet's convolutional neural network's good accuracy. The majority of the accuracy results for the test photos are 100%, and the lowest is 80.83%.

5 EVALUATION OF DR TRACKER SYSTEM

15 respondents were asked to engage in this survey in order to undertake the system evaluation. As a result, the developer has taken the initiative to request that educators (CNN-AI) from UNIMAP, UiTM, and Politeknik institutions examine the system. Respondents assessed the system's functionality and completed a questionnaire that was printed and made available before reviewing the system. The cornerstone for the system assessment was usability testing. Usability refers to how well something works, how well it completes its goal, and how happy the user is with it overall. The key aims of this testing are to determine whether or not the system's end-users can understand it, operate it effectively, and ensure that it has been well-developed. Following the recruitment of responders, each of them was evaluated using a 12 questions which were separated into three sections: Part A: Personal Details, Part B: System Efficiency, and Part C: Overall Evaluation.

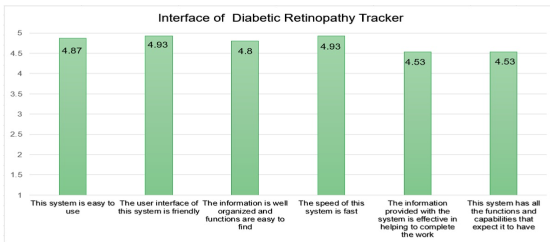

Figure 3: Interface of DR Tracker system.

Table 1: Accuracy of the test-phase photographs.

Image	Accuracy (%)
Image 1	100
Image 2	100
Image 3	95.45
Image 4	92.04
Image 5	100
Image 6	98.42
Image 7	82.31
Image 8	100
Image 9	99.00
Image 10	100
Image 11	96.98
Image 12	92.76
Image 13	100
Image 14	100
Image 15	80.83
Image 16	84.97
Image 17	81.99
Image 18	91.96
Image 19	100
Image 20	100
Image 21	100
Image 22	96.98
Image 23	90.95
Image 24	100
Image 25	93.53
Image 26	93.19
Image 27	94.79
Image 28	100
Image 29	100
Image 30	95.00
Image 31	100
Image 32	100
Image 33	88.01
Image 34	90.76
Image 35	97.17
Image 36	84.79
Image 37	84.09
Image 38	100
Image 39	99.97
Image 40	100
Image 41	94.79
Image 42	100
Image 43	100
Image 44	100
Image 45	86.97
Image 46	100
Image	Accuracy (%)
Image 47	95.97
Image 48	94.28

6 CONCLUSIONS

The AI DR tool can aid the doctor with fundus picture analysis, which helps to guide the next stages in the patient's therapy more swiftly. Furthermore, without mydriasis, clinicians may attend to more patients that require attention. Emerging healthcare technologies place a premium on decreasing visits to eye specialists, lowering total treatment costs, and increasing the number of patients seen by each practitioner. AI can assist health care professionals in reaching their objectives. Though technology can help in the health care industry, it should not be used to replace clinicians at this time. New advancements in the field of artificial intelligence are bringing new opportunities for running DR detection and grading systems.

Doctors will be able to detect the early stages of diabetic retinopathy by utilising the DR Tracker system. Experts in significant Artificial Intelligent and Convolutional Neural Network have reviewed this system. Based on this system review, the average score is around 4, indicating that the system was well created, even though certain features need to be added for future development.

When considering the future of Diabetic Retinopathy, we may conclude that a smart phone gadget attached to a retinal image capturing camera will be effective in diagnosing DR in any place. This can aid in overcoming the value and time constraints of traditional techniques. There are two general approaches to smartphone-based automated DR diagnosis. The first and most obvious option is a web-based diagnostic, while the second is a stand-alone independent smart phone software-based diagnosis. An independent smart phone application might allow patients in rural and distant places to readily request an automated diagnosis of DR. Another solution would be to employ a cloud-based diagnostic, which would allow users to constantly be up to current and have the most up-to-date information. Furthermore, the DR Tracker system may need to be enhanced by adding more features, such as a box to show where it identifies diabetic retinopathy in a retina image, the requirement to emphasise disease infection in the screening system, and a looking fine feedback to know whether the screening is in process.

ACKNOWLEDGEMENTS

I'd want to convey my heartfelt gratitude to everyone who made it possible for me to finish this report. I would like to express my heartfelt appreciation to Prof. Madya. Ts. Dr. Nor Hazlyna, Dr. Ts. Juhaida

Abubakar and Nur Haslinda Abdul Hasan. A special thanks to Miss Amiera Syazlin and Siti Naquiah for their assistance and support in completing the project.

REFERENCES

Abed, M., Muhammed, L., and Toman, S. (1999). Diabetic retinopathy diagnosis based on convolutional neural network. *J. Phys. Conf. Ser*, (1):1–8,.

Avidor, D., Loewenstein, A., Waisbourd, M., and Nutman, A. (2020). Cost-effectiveness of diabetic retinopathy screening programs using telemedicine: A systematic review. *Cost Eff. Resour. Alloc*, 18(1):1–9,.

Carrera, E., Gonzalez, A., and Carrera, R. (2017). Automated detection of diabetic retinopathy using svm. In *Proc. 2017 IEEE 24th Int. Congr. Electron. Electr. Eng. Comput. INTERCON 2017*, pages 6–9,.

Hagos, M., Kant, S., and Bala, S. (2019-01). Automated smartphone based system for diagnosis of diabetic retinopathy. *Proc. - 2019 Int. Conf. Comput. Commun. Intell. Syst. ICCCIS 2019*, (2005):256–261,.

Kwasigroch, A., Jarzembinski, B., and Grochowski, M. (2018). Deep cnn based decision support system for detection and assessing the stage of diabetic retinopathy. *Interdiscip. PhD Work. IIPhDW*, pages 111–116,.

Rajan, K. and Sreejith, C. (2018). In *Proceedings of the International Conference on Advances in Computational Mechanics 2017*. Springer International Publishing.

Rajesh, K., Santhanam, A., Sridhar, M., and Mohan, D. J. (2022). Diabetic retinopathy detection using convolutional neural network. *Int. J. Adv. Res. Sci. Commun. Technol*, pages 69–75,.

Sasongko, M. (2017). Prevalence of diabetic retinopathy and blindness in indonesian adults with type 2 diabetes. *Am. J. Ophthalmol*, 181:79–87,.

Sharif, N. M. (2020). Performance of image enhancement methods for diabetic retinopathy based on retinal fundus image. *ISCAIE*, pages 18–23,.

Toresa, D., Azrul, M., Shahril, E., Hazlyna, N., Abu, J., and Amnur, H. (2021). Automated detection and counting of hard exuyears for diabetic retinopathy by using watershed and double top-bottom hat filtering algorithm.

W.H.O. (2014). Global health estimates 2014 summary tables: deaths by cause, age and sex, by who region, 2000–2012. *World Heal. Organ*.

Zhuang, H. and Ettehadi, N. (2020). Classification of diabetic retinopathy via fundus photography: Utilization of deep learning approaches to speed up disease detection.