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Automatic Classification Of Diabetic Retinopathy Levelsusing Convolution Neural network

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Abstract– Diabetic eye disease is a complexity that affects people having diabetes for a longer time. By affecting the blood vessels it can cause blurry vision or even blindness to the patients. Thus, detecting the eye disease at an early stage can help many of the diabetic patients to get the requiredtreatment and intern increases the survival rate. In the proposed system, the CNN algorithm of machine learning is used to detect the diabetic eye diseased by either using the thermal images. These images are pre-processed by converting them from RGB to GRAY based on which the required features are extracted. To detect the diabetic retinopathy, here the Convolution Neural Network is used to classify 5 stages of the diseased eye.

I. INTRODUCTION

Diabetic retinopathy is when damage occurs to the retina due to diabetes, which affects up to 80 percent of all patients who have had diabetes for 10 years or more. The expertise and equipment required are often lacking in areas where diabeticretinopathy detection is most needed. Mostof the work in the field of diabeticretinopathy has been based on disease detection or manual extraction of features, but this paper aims at automatic diagnosis of the disease into its different stages usingdeep learning. This paper presents the design and implementation of GPUaccelerated deep convolution neural networks to automatically diagnose and thereby classify high-resolution retinal. Images into 5 stages of the disease basedon severity. Diabetic retinopathy (DR), also known as diabetic eye disease, is when damage occurs to the retina due to diabetes. It can eventually lead to blindness. It is an ocular manifestation of diabetes. Despite these intimidating statistics, research indicates that at least 90% of these new cases could be reduced if there were proper and vigilant treatment and monitoring of theeyes. The longer a person has diabetes, the higher his or her chances of developing diabetic retinopathy. Diabetic retinopathy can be diagnosed into 5 stages: mild, moderate, severe, proliferative or no disease. The various signs and markers of diabetic retinopathy includemicro aneurysms, leaking blood vessels,retinal swellings, growth of abnormal new blood vessels and damaged nerve tissues [7]. DR detection is challenging because by the time human readers submit theirreviews, often a day or two later, the delayed results lead to lost follow up, miscommunication, and delayed treatment.Clinicians can identify DR by the presenceof lesions associated with the vascular abnormalities caused by the disease. Whilethis approach is effective, its resource demands are high. The expertise andequipment required are often lacking in areas where the rate of diabetes in local populations is high and DR detection ismost needed. The need for a comprehensive and automated method of DR screening has long been recognized, and previous efforts have made goodprogress using image classification, patternrecognition, and machine learning [7]. Thecurrent research in diagnosing diabetic retinopathy has been based on explicit extraction of features like micro aneurysmsand lesions through which the classification is performed. There has also been research in using machine learningtechniques to classify the image as normal or diseased [14, 15, 16]. This paper aims atproposing a diabetic retinopathy diagnosis model that automatically learns features which are pivotal in diagnosing the stageof the disease without explicit or manual feature extraction.

II. LITERATURE SURVEY

Diabetic retinopathy (DR) staging is important for the estimation of diabetes mellitus (DM) and the evaluation of associated retinopathy; it is also closelyrelated with proper management and prognosis of DR. In order to objectively and accurately determines the diabetic retinopathy stages, the goal of this paper is to introduce an image analysis-based approach to automatically differentiate the 5 stages of diabetic retinopathy based on fundoscopic images. Image analysis has been widely and successfully applied inbiomedical field, for example, to objectively differentiate embryonic:

a) Stage I: No diabetic retinopathy

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b) Stage II: Mild non-proliferative diabetic retinopathy
c) Stage III: Moderate non-proliferative diabetic retinopathy
d) Stage IV: Severe non-proliferativediabetic retinopathy
e) Stage V: Proliferative diabetic retinopathy Hard Exudates Micro- aneurysm or Haemorrhage Pre-retinal Hemorrhage Intra-Retinal Microvascular Abnormality (IRMA) Neovascularization Figure 1.

Fundoscopic images of different stages of diabetic retinopathy. (a) Stage I: No diabetic retinopathy; (b) Stage II: Mild non-proliferative diabetic retinopathy; (c) Stage III: Moderate non-proliferative diabetic retinopathy; (d) Stage IV: Severe non-proliferative diabetic retinopathy; (e) Stage V: Proliferative diabetic retinopathy.466 developmental stages [5] and classify severity of melanoma and nevi from skin lesions [6].

Deep Learning basedConvolution Neural Network (CNN) hasrecently been proven to be a promising approach for different medical image analysis [7]. Anthimopoulos deployed a deep convolutional neural network forlung pattern classification of interstitial lung diseases [8]. Esteva et al. in their

Stage	Dilated Ophthalmoscopy Observable Findings	Severity
I	No abnormalities	No DR
II	Micro-aneurysms only	Mild non-proliferative DR
III	Any of the following: - micro-aneurysms - retinal dot and blot haemorrhages - hard exudates or cotton wool spots No signs of severe non-proliferative diabetic retinopathy	Moderate non-proliferative DR
IV	Any of the following: - more than 20 intra-retinal hemorrhages in each of 4 quadrants - definite venous beading in 2 or more quadrants - prominent intra-retinal microvascular abnormality (IRMA) in 1 or more quadrants No signs of proliferative retinopathy	Severe non-proliferative DR
V	One or both of the following: - Neovascularization - Vitreous/pre-retinal hemorrhage	Proliferative DR

Table 1. INTERNATIONAL CLINICALDIABETIC RETINOPATHY & DIABETIC MACULAR EDEMA DISEASE SEVERITY SCALES

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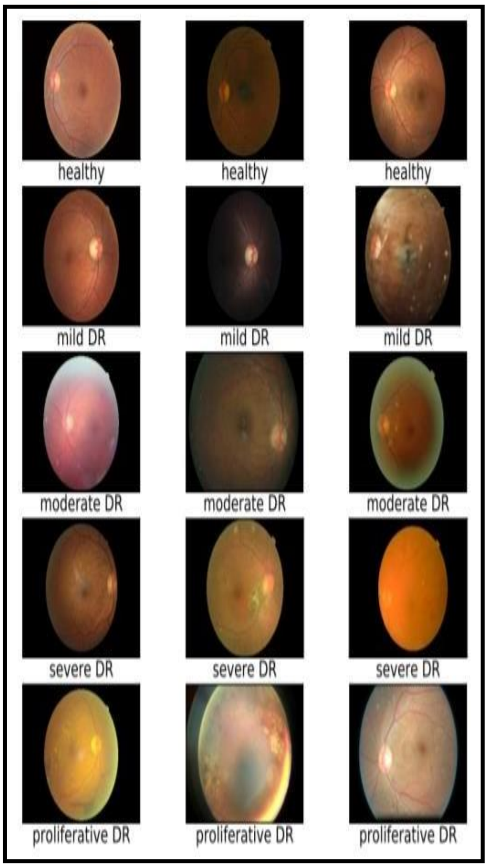

Figure 1 .image sample international clinical diabetic retinopathy & diabeticmacular edema disease severity scale images

III. METHODOLOGY

In order to achieve early diagnosis of diabetic retinopathy major effort will have to be invested into screening programs. Screening is important as up to one thirdof people with diabetes may haveprogressive DR changes without symptoms of reduced vision. In current screening programs only color fundusphotography is used, and the data are sent to a grading center for reading where expert human readers estimate the disease severity. The main disadvantage is the necessity for qualified experts to grade the images. This is impossible to achieve in countries with a shortage of qualified medical personnel.

The success of screening approach depends on accurate fundus image capture,and especially on accurate and robust image processing and analysis algorithms for detection of abnormalities

Following are some of the image processing algorithms for early detectiondiabetic retinopathy

1) Preprocessing
2) Localization and segmentation of theoptic disk
a) Characteristics of the optic disk
b) Optic disk localization
c) Optic disk segmentation
3) Segmentation of the retinal vasculature
a) Characteristics of the vasculature
b) Methods for segmentation of theretinal vasculature
4) Localization and segmentation ofretinopathy
a) Microaneurysms andhemorrhages

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b) soft and hard Exudates
c) Drusen
d) Revascularizations
e) Glaucoma
f) Diabetic Macular Edema

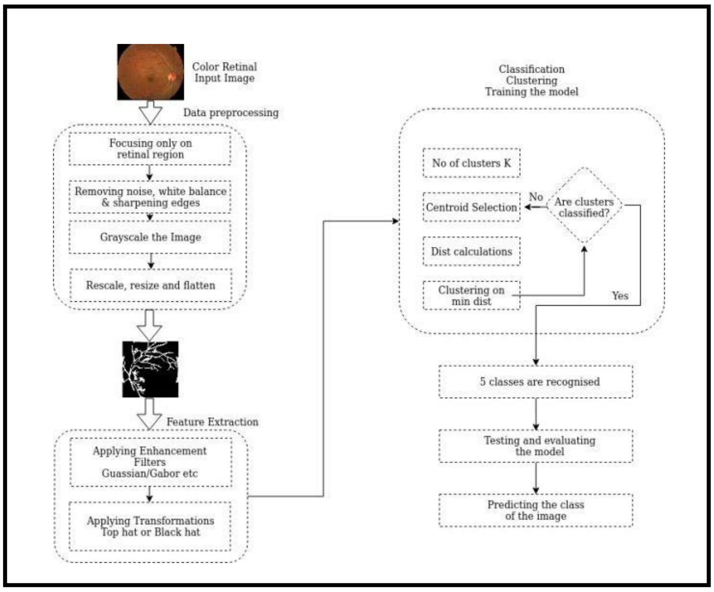

Fig. System Architecture

CNN RESULT

Epoch 1/50 3/3 [==============================] - 23s
8s/step - loss: 1.5589 - accuracy: 0.6000 - val_loss: 0.6127 - val_accuracy: 0.8000 Epoch 2/50 3/3
[==============================] - 18s
6s/step - loss: 0.5580 - accuracy: 0.8000 - val_loss: 0.5498 - val_accuracy: 0.8000 Epoch 3/50 3/3
[==============================] - 18s
6s/step - loss: 0.5376 - accuracy: 0.8000 - val_loss: 0.5270 - val_accuracy: 0.8000 Epoch 4/50 3/3
[==============================] - 18s
6s/step - loss: 0.5281 - accuracy: 0.8000 - val_loss: 0.5074 - val_accuracy: 0.8000 Epoch 5/50 3/3
[==============================] - 18s
6s/step - loss: 0.5015 - accuracy: 0.8000 - val_loss: 0.5035 - val_accuracy: 0.8000 Epoch 6/50 3/3
[==============================] - 18s
6s/step - loss: 0.5075 - accuracy: 0.8000 - val_loss: 0.5348 - val_accuracy: 0.8000 Epoch 7/50 3/3
[==============================] - 18s
6s/step - loss: 0.5318 - accuracy: 0.8000 - val_loss: 0.5070 - val_accuracy: 0.8000 Epoch
8/50 3/3 [==============================] - 17s
6s/step - loss: 0.5226 - accuracy: 0.8000 - val_loss: 0.5274 - val_accuracy: 0.8000 Epoch 9/50 3/3
[==============================] - 18s
6s/step - loss: 0.5212 - accuracy: 0.8000 - val_loss: 0.5064 - val_accuracy: 0.8000 Epoch 10/50 3/3
[==============================] - 16s
5s/step - loss: 0.5133 - accuracy: 0.8000 - val_loss: 0.5201 - val_accuracy: 0.8000 Epoch 11/50 3/3
[==============================] - 12s
4s/step - loss: 0.5196 - accuracy: 0.8000 - val_loss: 0.5067 - val_accuracy: 0.8000 Epoch 12/50 3/3
[==============================] - 13s
4s/step - loss: 0.5041 - accuracy: 0.8000 - val_loss: 0.5062 - val_accuracy: 0.8000 Epoch 13/50 3/3
[==============================] - 13s
4s/step - loss: 0.5043 - accuracy: 0.8000 - val_loss: 0.5169 - val_accuracy: 0.8000 Epoch 14/50 3/3

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[==============================] - 12s
4s/step - loss: 0.5254 - accuracy: 0.8000 - val_loss: 0.5111 - val_accuracy: 0.8000 Epoch 15/50 3/3
[==============================] - 13s
4s/step - loss: 0.5209 - accuracy: 0.8000 - val_loss: 0.5050 - val_accuracy: 0.8000 Epoch 16/50 3/3
[==============================] - 13s
4s/step - loss: 0.5105 - accuracy: 0.8000 - val_loss: 0.5269 - val_accuracy: 0.8000 Epoch 17/50 3/3
[==============================] - 12s
4s/step - loss: 0.5231 - accuracy: 0.8000 - val_loss: 0.5062 - val_accuracy: 0.8000 Epoch 18/50 3/3
[==============================] - 12s
4s/step - loss: 0.5027 - accuracy: 0.8000 - val_loss: 0.5033 - val_accuracy: 0.8000 Epoch19/50 3/3
4s/step - loss: 0.5008 - accuracy: 0.8000 - val_loss: 0.5047 - val_accuracy: 0.8000 Epoch 31/50 3/3
[==============================] - 13s
4s/step - loss: 0.5139 - accuracy: 0.8000 - val_loss: 0.5041 - val_accuracy: 0.8000 Epoch 32/50 3/3
[==============================] - 12s
4s/step - loss: 0.5103 - accuracy: 0.8000 - val_loss: 0.5308 - val_accuracy: 0.8000 Epoch 33/50 3/3
[==============================] - 12s
4s/step - loss: 0.5125 - accuracy: 0.8000 - val_loss: 0.5009 - val_accuracy: 0.8000 Epoch 34/50 3/3
[==============================] - 12s
4s/step - loss: 0.5021 - accuracy: 0.8000 - val_loss: 0.5072 - val_accuracy: 0.8000 Epoch 35/50 3/3
[==============================] - 12s
4s/step - loss: 0.5106 - accuracy: 0.8000 - val_loss: 0.5196 - val_accuracy: 0.8000 Epoch 36/50 3/3
[==============================] - 12s
4s/step - loss: 0.5088 - accuracy: 0.8000 - val_loss: 0.5063 - val_accuracy: 0.8000 Epoch 37/50 3/3
[==============================] - 12s
4s/step - loss: 0.5084 - accuracy: 0.8000 - val_loss: 0.5010 - val_accuracy: 0.8000 Epoch 38/50 3/3
[==============================] - 12s
4s/step - loss: 0.5008 - accuracy: 0.8000 - val_loss: 0.5014 - val_accuracy: 0.8000 Epoch 39/50 3/3
[==============================] - 12s
4s/step - loss: 0.5034 - accuracy: 0.8000 - val_loss: 0.5115 - val_accuracy: 0.8000 Epoch 40/50 3/3
[==============================] - 12s
4s/step - loss: 0.5131 - accuracy: 0.8000 - val_loss: 0.5018 - val_accuracy: 0.8000 Epoch 41/50 3/3
[==============================] - 12s
4s/step - loss: 0.5036 - accuracy: 0.8000 –
val_loss: 0.5078 - val_accuracy: 0.8000 Epoch42/50 3/3 [==============================] - 12s
4s/step - loss: 0.5097 - accuracy: 0.8000 - val_loss: 0.5020 - val_accuracy: 0.8000 Epoch 43/50 3/3
[==============================] - 12s
4s/step - loss: 0.5062 - accuracy: 0.8000 - val_loss: 0.5030 - val_accuracy: 0.8000 Epoch 44/50 3/3
[==============================] - 12s
4s/step - loss: 0.5059 - accuracy: 0.8000 - val_loss: 0.5157 - val_accuracy: 0.8000 Epoch 45/50 3/3
[==============================] - 12s
4s/step - loss: 0.5067 - accuracy: 0.8000 - val_loss: 0.5020 - val_accuracy: 0.8000 Epoch 46/50 3/3
[==============================] - 12s
4s/step - loss: 0.5030 - accuracy: 0.8000 - val_loss: 0.5053 - val_accuracy: 0.8000 Epoch 47/50 3/3
[==============================] - 12s
4s/step - loss: 0.5055 - accuracy: 0.8000 - val_loss: 0.5034 - val_accuracy: 0.8000 Epoch 48/50 3/3
[==============================] - 12s
4s/step - loss: 0.5047 - accuracy: 0.8000 - val_loss: 0.5066 - val_accuracy: 0.8000 Epoch 49/50 3/3
[==============================] - 12s
4s/step - loss: 0.5045 - accuracy: 0.8000 - val_loss: 0.5027 - val_accuracy: 0.8000 Epoch 50/50 3/3
[==============================] - 12s
4s/step - loss: 0.5033 - accuracy: 0.8000 -val_loss: 0.5057 - val_accuracy: 0.800

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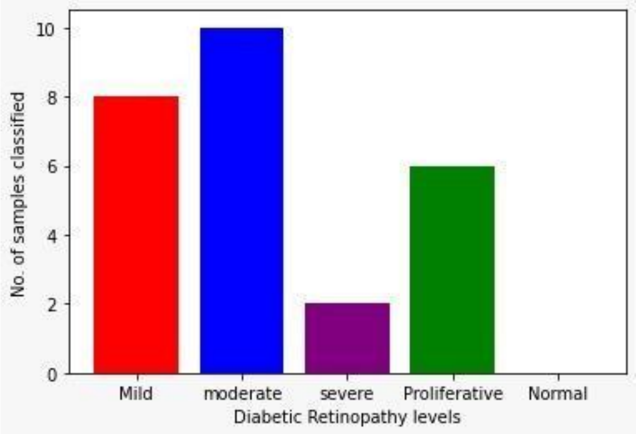

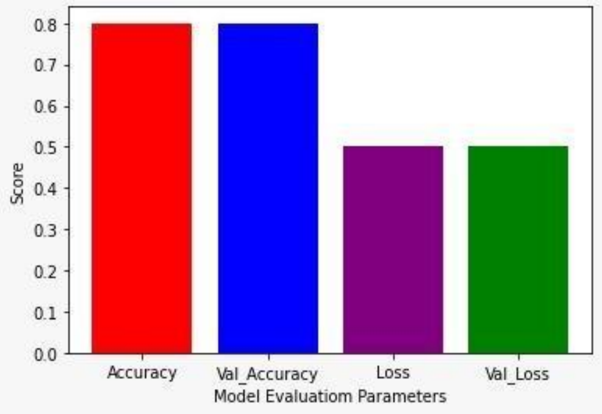

REFERENCES

[1] G. Danaei, M. M. Finucane, Y. Lu, G.M. Singh, M. J. Cowan, C. J. Paciorek, J.K. Lin, F. Farzadfar, Y.-H. Khang, G. A. Stevens, M. Rao, M. K. Ali, L. M. Riley,C. A. Robinson, and M. Ezzati, "National, regional, and global trends in fastingplasma glucose and diabetes prevalence since 1980: systematic analysis of health examination surveys and epidemiological studies with 370 country-years and 2·7 million participants," The Lancet, vol. 378,issue 9785, 2011, pp. 31- 40.

[2] L. Wu, P. Fernandez-Loaiza, J. Sauma,E. Hernandez-Bogantes, and M. Masis, “Classification of diabetic retinopathy and diabetic macular edema,” World Journal ofDiabetes, vol. 4, issue 6, Dec. 2013, pp. 290- 294.

[3] C. P. Wilkinson, F. L. Ferris, R. E. Klein, P. P. Lee, C. D. Agardh, M. Davis,D. Dills, A. Kampik, R. Pararajasegaram J. T. Verdaguer, and G. D. R. P. Group, “Proposed international clinical diabetic retinopathy and diabetic macular edema disease severity scales,” Ophthalmology,vol. 110, issue 9, Sep. 2003, pp. 1677-1682.

[4] T. Y. Wong, C. M. G. Cheung, M. Larsen, S. Sharma, and R. Simó, “Diabeticretinopathy,” Nature Reviews Disease Primers, vol. 2, Mar. 2016, pp. 1-16.

[5] H. Zhong, W.-B. Chen, and C. Zhang, “Classifying fruit fly early embryonicdevelopmental stage based on embryo in situ hybridization images,” in Proceedings of IEEE International Conference on Semantic Computing (ICSC 2009), IEEE, Sep. 2009, pp. 145-152.

[6] J. D. Osborne, S. Gao, W.-B. Chen, A. Andea, and C. Zhang, “Machine classification of melanoma and nevi from skin lesions,” in Proceedings of the 2011 ACM Symposium on Applied Computing (SAC 2011), ACM, Mar. 2011, pp. 100- 105.