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Analyse and Detection of Diabetic Retinopathy using Image processing and Machine learning

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Abstract:

The point of the project was to develop an image processing algorithm that would allow us to proceeding fundus images of eyes to highlight the various symptoms of diabetic retinopathy. The project work with the development and implementation of algorithms to remove errors from the anatomical structure images (such as reflection), highlight hard exudates and blood vessel escalation Several new techniques including the usage of the Kirsch operator in detecting blood vessel proliferation were developed as part of the project. In addition, new algorithms were developed to remove reflections from initial fundus images which are an miserable result of using cheap and readily available fundus cameras. Thus, this project aims at developing highly robust algorithms which can detect diabetic retinopathy symptoms and highlight them in fundus images of very poor quality.

Thus, the extent of this study is to preprocess images to highlight diagnostic signs of the disease. These images can later be passed through machine learning code to identify the disease or they can even be checked by a physician who will thereby be more easily able to make an accurate diagnosis- thus down room for human error.

1 INTRODUCTION

Diabetic retinopathy is the leading cause of blindness among individuals between 25 and 74 years of age in the industrialized world. It affects three out of four diabetic patients after 15 years of disease time scale. Chronic hyperglycemia is the major factor leading to the increasing of diabetic retinopathy and other difficulty of the disease. The importance of long-term glycemic control has been conclusively established in the landmark clinical inquiry including the Diabetes Control and Complications Trial (DCCT), and the UK Prospective Diabetes Study (UKPDS).[2] However, the Process by which elevated blood sugar levels lead to the development of diabetic retinopathy and the anatomic changes visible histopathologically remain to be fully elucidated. pathways believed to be re-

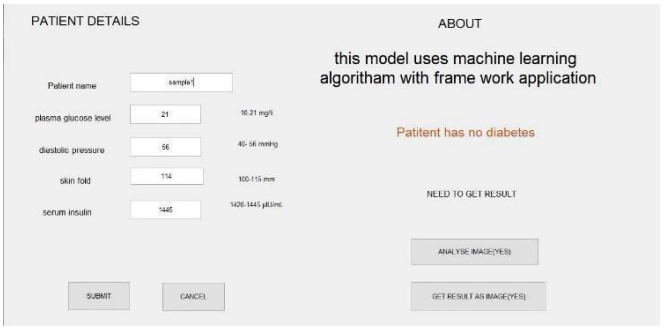
sponsible for the development of diabetic retinopathy and will highlight recent developments in genetics that provide intuition into the influential role of genetic susceptibility.

Diabetic retinopathy is common, treatable, and detectable using simple tools: consequently, it is the prototype of a disease that would benefit from organized screening.

TABLE 22.2. Recommended Ophthalmologic Examination Schedule for Patients With Diabetes Mellitus

Time of Onset of Diabetes	Recommended First Examination	Minimal Routine Follow-Up
Less than 30 years of age*	Within 5 years after diagnosis of diabetes	Yearly†
30 years of age or older*	At time of diagnosis of diabetes	Yearly†
Pregnancy in preexisting diabetes	Prior to conception and during first trimester	Physician discretion pending results of first trimester examination

Table reviews the screening schedule recommended by the Diabetes Association. Given the pile of missing serious retinopathy and the less-than-optimal performance of gen- eral clinicians using only directophthalmoscopy, only clini- cians with training and experience—in most cases op- tometrists and ophthalmologists—should screen patients. Any patient with macularedema, more than moderate non-proliferative retinopathy, or proliferative retinopathy



should be seen by eye care providers with experience in the management of diabetic retinopathy.

2 USER

MODULES

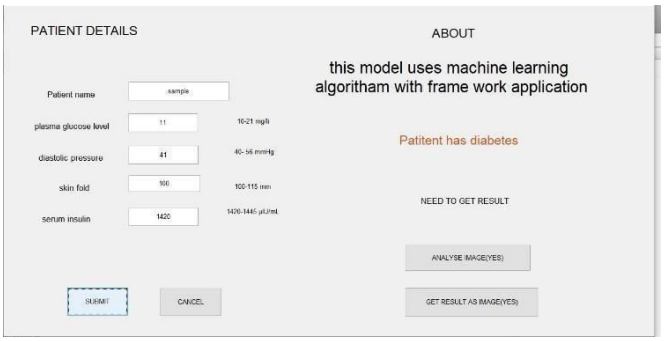
GENERAL

CHECK

Diabetes Mellitus is an increasingly widespread chronic disease characterized by the body's inability to metabolize glucose. The objective of this study was to build an effec- tive predictive model with high sensitivity and selectivity to better identify patients at risk of having Diabetes Melli- tus based on patient demographic data and the laboratory results during their visits to medical facilities by the given data Pima Indians Diabetes Database.

We first created a training dataset by randomly choosing 80% of all patients in the dataset and created a test dataset with the remaining 20% of patients. The training dataset has 10,647 patients and the test dataset has 2662 patients. We used the training dataset to train the model and used the test dataset to evaluate how well the model performs based on an unseen dataset. Using the training dataset and the 10-fold cross-validation method, we tuned the model hyperparameters to obtain the set of optimal hyperparameters that yields the highest area under the receiver operating characteristic curve (AROC).

The result from data set if has diabetes and shows a text label in static and changes when values altered



If the patitent has positive diabetes values shows a message prompt"PATITENT HAS DIABETES"

If the patitent has no negative result diabetes values shows a message prompt"PATITENT HAS NO DIABE- TES"

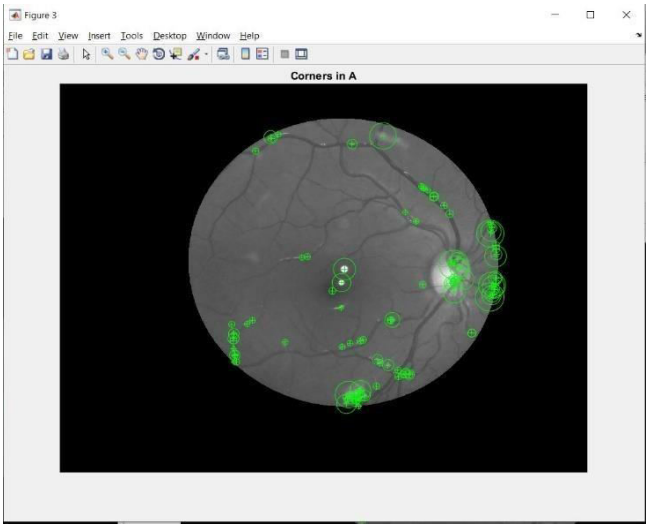
IMAGE CHECK

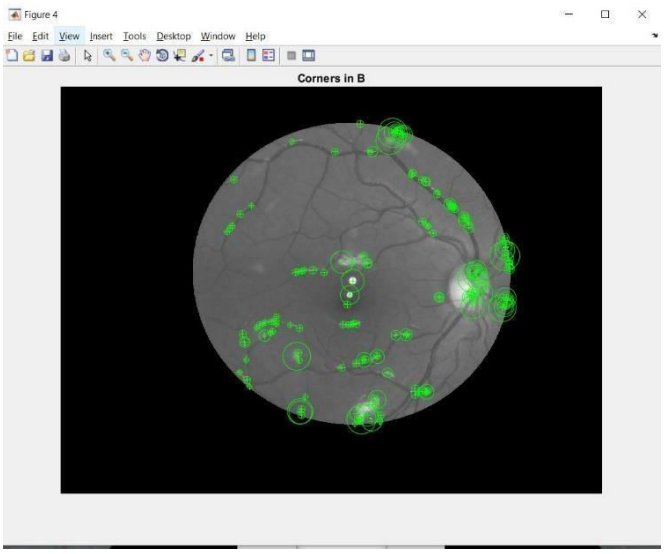
Potentially, algorithms performing automated analysis of retinal images may address the need for more affordable DRSP in certain settings. The Iowa Detection Program (IDP) was originally designed to meet the rising demand for DRSP . IDP evaluates digital retinal images in an auto- mated fashion for the presence of moderate or more severe DR as well as diabetic macular edema (DME) . The IDP has been validated in independent cohorts of people with DM, using internationally recognized DR grading standards and was reported to have diagnostic accuracy comparable to that of fellowship-trained

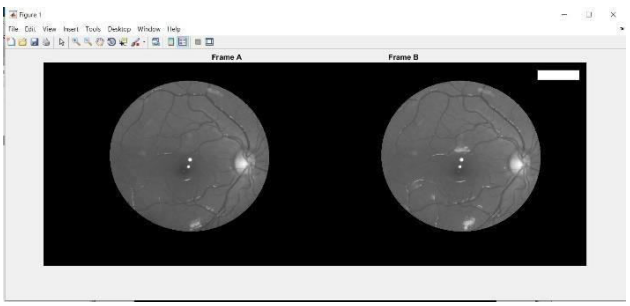
retinal specialists'.However, the performance of IDP is yet to be evaluated on popula- tions from Sub-Saharan Africa, especially in the context of a population-based study where majority of the subjects are without DM.

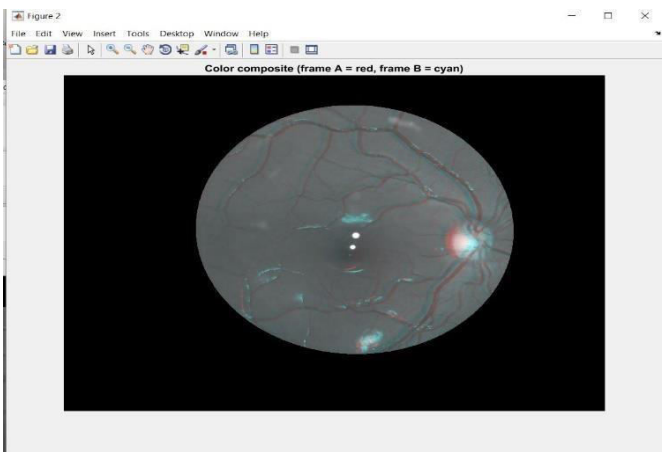
Images and clinical data of participants of the Nakuru Eye Study, were used for the automated image analysis via MATLAB software

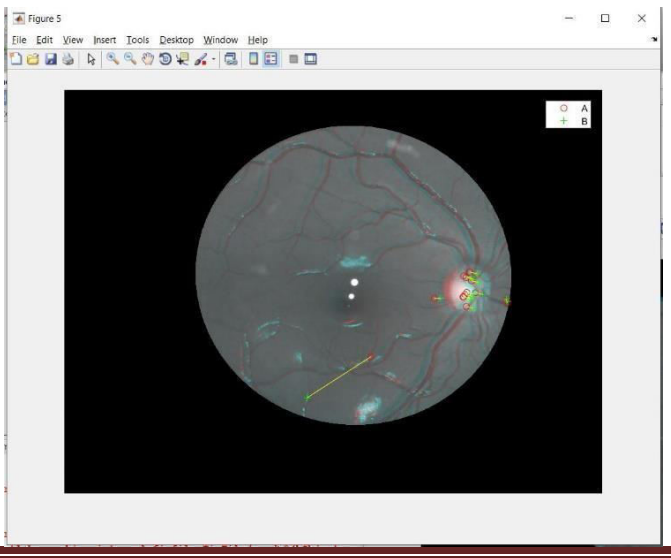
The primary cause of visual loss in people with diabetes is DME, which is more common in type 2 diabetes. The breakdown of the blood-retinal barrier causes leakage of dilated hyperpermeable capillaries and microaneurysms into intracellular and extracellular retinal tissue with subsequent fluid accumulation [9], [10]. Clinically signifi- cant macular edema (CSME) occurs if there is thickening of the retina involving the center of the retina (macula) or the area within 500 m of the center, if there are hard exu- dates at or within 500 m of the center with thickening of adjacent retina, or if there is a zone of retinal thickening one optic disc area or larger in size, any part of which is within one disc diameter of the center of the retina [9]. This definition of CSME generally refers to the threshold level at which laser photocoagulation treatment is considered. While visual loss occurs when macular edema involves the visual center, lesser degrees of DME may cause visual de- terioration.











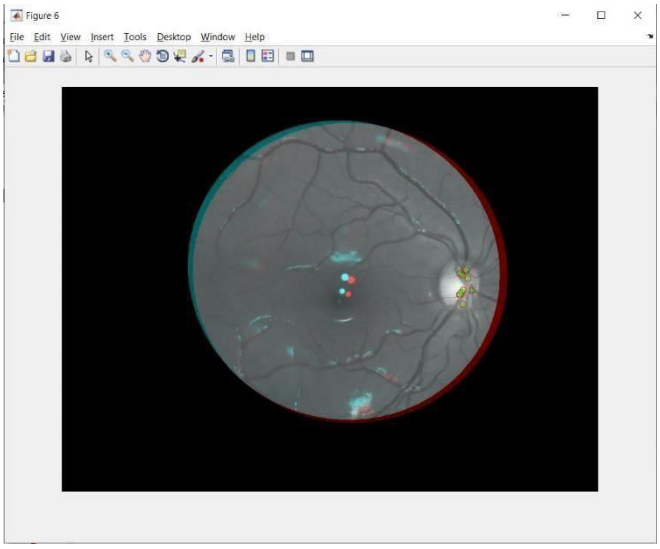


IMAGE ANALYSE

The ONH segmentation performance clearly indicated that pixel feature classification with biologically inspired fea- tures derived from color fundus images is a good starting point for the classification of the optic nerve head and likely also other 3-D structures of the retina. Importantly, it was shown that features benefiting from the understand- ing to the physiologic vision process outperform standard pixel features when segmenting the optic nerve head

5 EQUATIONS

.

thresholdValue =

122

No of objects:222
Area of exudates:3.326288e+04

allBlobECDs =

4.9601 3.6394

allBlobSolidities =

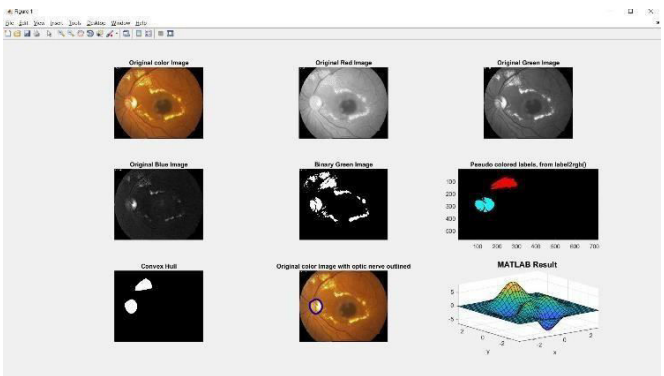
0.8348 0.8544

allBlobECDs =

1.0112 1.2337

roundestECDValue =

1.0112



roundestIndex = 1

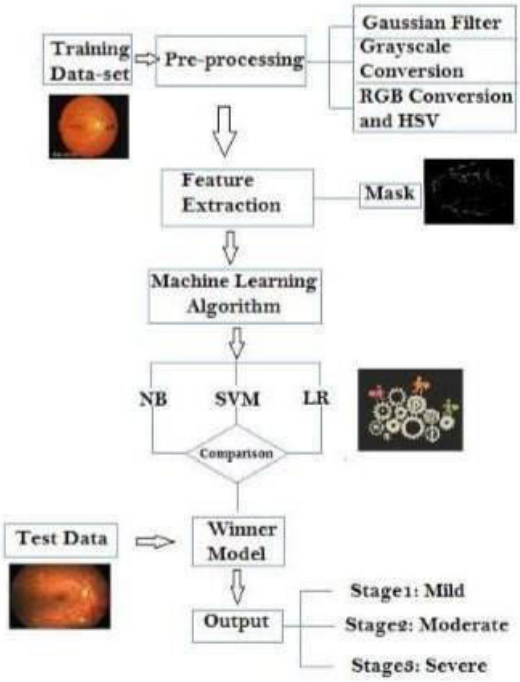
z = 3*(1-x).^2.*exp(-(x.^2) - (y+1).^2) ...
- 10*(x/5 - x.^3 - y.^5).*exp(-x.^2-y.^2) ...
- 1/3*exp(-(x+1).^2 - y.^2)

>> RESULT

3 PROPOSED METHOD

All of existing methods are good in some measures for detection and segmentation of exudates but still raise some problems with low intensity, low accuracy, less color contrast and sensitivity, nonuniform illumination images.Therefore, our proposed algorithm and tech- niques have ability to solve these problems by prepro- cessing techniques.All process is demonstrated in and step-wise details are explained below

Step 1: First of all, take a diabetic RGB human retinal image ◎
Step 2: Apply Gaussian Filter to remove noisefrom image. ◎
Step 3: Convert the RGB image into greyscale level◎
Step 4: Apply Machine Learning Algorithm to this image. ◎
Step 5: Compare the Resulted image with Test data. Step 6: Detect the stages. ◎
Step 7:Finally higher values of accuracy, sensitivity and lower value of error rate are obtained



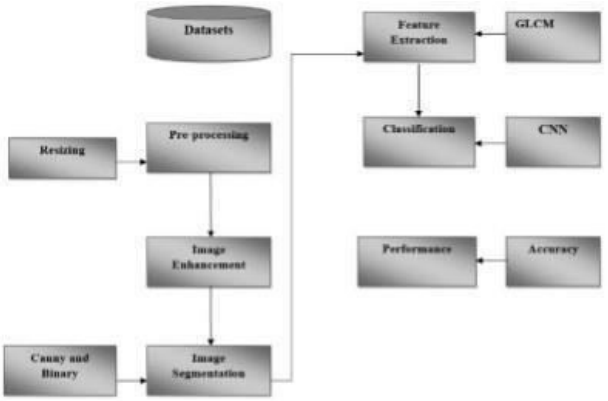
3 ARCHITECTURE DESIGN

Figures

4 CONCLUSION

The paper is about proposing an optimal model for Diabetic Retinopathy detection. Processing of Retinopathy images is very essential to get proper features. Statistical values can predict level of severity properly but in case of noisy images the chances of getting poor data will lead to lower accuracy. For getting better result selecting for proper features out of the image also important. Both CNN and DNN models are effective in term for image, be- cause of CPU training time of CNN getting affected in the study, in this case DNN outperforms CNN for training accuracy as well as validation accuracy. For future work model can train with GPU system, with more num- ber of processed data for getting higher accuracy result.

A standalone application will be good for identification of retinopathy images. Also, the proposed model can be integrated with existing NPDR screening algorithms in [40] for enhanced prioritization and resourcefulness of the present day eye-care delivery.



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