

Develop a novel screening tool on mobile application to detect diabetic retinopathy or macular edema in primary health care.

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Abstract

Diabetic Macular Edema (DME) is a general vision, aggressive difficulty of diabetic retinopathy. DME can be evaluated by identifying exudates in all screening processes. In recent days recognizing diabetic retinopathy and diabetic macula edemas is most important to avoid complexity in terms of vision loss. Eye care industry concentrates on detecting and identifying deflection, infection and issues in retina. The main objective of this paper is to provide handheld devices based diabetic retinopathy diagnosis systems. In this paper a novel system is proposed and it uses a couple quantities of basic target variables to anticipate diabetic retinopathy and diabetic macula. The target variables are utilized to examine the testing and preparing information in a cross-sectional examination way. The recreation is completed in MATALB programming and the outcomes are contrasted and the current methodology.

Keywords: Diabetic retinopathy, Macular edema, Disease detection, Statistical models, Optical coherence tomography, Diagnostic tests, Diabetes mellitus.

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Introduction

The prior methodologies are focusing on researching diabetic retinal pictures utilizing different picture handling strategies. Those techniques were utilized to anticipate the sickness stages as typical, gentle, moderate and extreme. As indicated by the malady arranges, the patients are encouraged to take the treatment under various doses of the prescription. One of the prime propelling worries behind the advancement of the screening techniques for Diabetic Retinopathy (DR) is the productivity of laser photocoagulation treatment in counteracting visual misfortune. The whole medicinal industry construct applications basically engaged in light of recognizing and researching restorative pictures with a specific end goal to acquire the illness accessibility and seriousness of the stage. Different programmed analytic frameworks were created to identify retinal vein investigation and pathologies like Micro aneurysms, exudates and mellitus [1]. The rule result variable was the proximity of in any occasion treatable diabetic retinopathy (compelling, especially genuine or increasing [2] or Diabetic Macular Edema (DRDME). There are two unique systems utilized to distinguish and depict diabetic retinopathy, for example, non-mydrastic retinopathy and bio microscopy of the retina [2,3].

Overall industrial worlds the criticalities of diabetic retinopathy remain the major issue of preventable visual loss in persons of working age. One third portion of the blindness because of diabetes is reduced by adopting a strategy of

screening for diabetic retinopathy [4]. One of the articles [5] discussed about the rationale and supporting evidence for a screening programme for diabetic retinopathy. To reduce the blindness due to diabetic retinopathy is the main objective to go for screening programme. One of the national screening program is conducted in the UK has been estimated by using mathematical models based the natural history of the disease and prepared report yields a worldwide health gain [6,7]. These reports have the observational studies indicating the substantial reductions in the incidence of new blindness due to diabetic retinopathy after reduction of screening programs [8,9]. Only 80% of the sensitivity and specificity can be obtained by the direct ophthalmoscopy based screening [10-13].

One of the existing researches used a mathematical model to analyse the effectiveness of various screeners [14]. All the above authors address that most of the effective screening modality for diabetic retinopathy is retinal photography through dilated pupils. Diabetic retinopathy disease detection mostly obtained by screening on retinal images by applying various image processing procedures. The main motivation to develop a screening program for diabetic retinopathy is through the efficacy of laser photocoagulation treatment to avoid vision loss. The proliferative and non-proliferative conditions of the diabetic retinopathy diseases depend on the diabetic retinopathy and macular edema.

Information gathered in a general hospital is done with a specimen of diabetic patients checked by ophthalmologists. From the information the patients are isolated into two diverse

issues as had dementia, high near sightedness or another macular issue. The variables by and large considered are serious, exceptionally extreme or multiplying or diabetic macular edema. The finding of these two issues was made by clinical ophthalmological examination of the retina by roundabout ophthalmoscopy and bio-microscopy of the focal retina with a Topcon opening light, display SL-8Z utilizing a 78 dioptre lens and circuitous ophthalmoscopy with a 28 D lens by a specialist retinal ophthalmologist. Macular edema was characterized as the nearness of hard exudates or restricted retinal thickening inside a separation of 500 μm from the fovea.

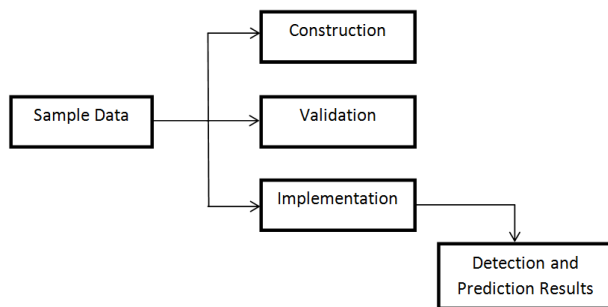


Figure 1. System model.

Construction

In order to evaluate the proposed system model (Figure 1) initially the novel frameworks do construction on the database. An inter cross verification based observation study is created by collecting 500 eyes-data from Indian diabetic patients suspected of having diabetic retinopathy and diabetic macular edema during the period from 2014 to 2015. The secondary variables used to determine the diabetic retinopathy and diabetic macular edemas are:

- Patient-ID
- Gender
- Age
- Glycated Haemoglobin (HbA1c)
- Foveal Thickness (FT)
- Visual Acuity (VA)

The obtained values from the screening and the ground truth values of the above variables are cross verified and the level of the DRDME is determined. From the collected dataset 80% of the data is used to construct the framework and 20% of the data is used to validate it. In this paper a multiclass support vector machine is used to predict the DRDME. A final score value is calculated from the classified data values. Finally Receiver Operating Characteristic curve (ROC) curve is drawn for the scored values and the risk values are established.

Validation

The objective variables are validated by calculating the area of ROC curve and compared with the ground truth (expected values) values from the observation. The tool was validated by

calculating the Area Under Curve (AUC) and comparing expected values from the observation.

Initially the Foveal Thickness (FT) is calculated from 200 to 400 μm where the respective points are 0 to 5. That is if the FT is <200 , then the point is 0, if it from 200 to 249 then the point is 1, if it is from 250 to 299 then the point is 2, if it is from 300 to 349 then the points is 3, if it is from 350 to 399 then the point is 4 and if the FT is greater than 400 then the point is assigned as 5.

Second the Glycated Haemoglobin (HbA1c) is calculated and the points are assigned. The HbA1c (%) is calculated from <8 to ≥ 8 where the respective points are 0 to 1. If HbA1c is <8 then the point is 0, if HbA1c is ≥ 8 then the point is 1.

Finally the Visual Acuity (VA) is calculated and points are assigned. The VA is calculated from 0 to 0.2 and the points are calculated from 0 to 3. If VA is from 0.9 to 1 then the point is 0, if VA is from 0.6 to 0.8 then the points is 1, if VA is 0.3 to 0.5 then the point is 2 and finally if the VA is from 0.0 to 0.2 then the points is 3.

From the above validation values the risk % is calculated to predict the DRDME. From the points, sum if the point is from 0 to 2, it is treated as low then the risk % is assigned from 1.45 to 15.35. If the point is 3, then it is treated as medium and the risk % is assigned from 39.15 to 39.20. If the point is 4, then it is treated as high and the risk % is assigned from 69.55 to 69.60. Finally if the point is ≥ 5 then it is treated as very high and the risk % is assigned as ≥ 89.05 .

Health Utility Model

In this paper the best utility model is characterized by wellbeing utility scores ascertained by demographic variables, medications, entanglements and comorbidities. The scope of the wellbeing score is from zero to one where zero speaks to death and one speaks to impeccable wellbeing. The movement of illness results in a reduction in the wellbeing utility scores. From the above discussion, it is clear and understood that the blindness can also be defined by visual acuity of the worst case scenario to be measured by 20/200 in terms of visual impairment.

On average health utility score for non-obese, diet-controlled without complications or comorbidities is 0.69. Foot ulcers, debilitating stroke, blindness, amputation, congestive heart failure and debilitating stroke result in substantial decrements in utility scores. For example, our proposed model suggests that the health utility score for a white woman with insulin treated type-2 diabetes treated high blood pressure and the end-stage retinal disease is 0.53 (0.689-0.038-0.034-0.011-0.078-0.53).

Implementation

The implementation is carried out in two different stages. One is image processing for detecting and identifying diabetic retinopathy in mobile device. The other one is data analysis on real time data collected from medical industries.

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In the first stage, the experiment is carried out using MATLAB software installed in Motorola smart phone with Android operating system and the results are obtained. If the feature values of the experimented input image is matched with the feature values of the normal ground truth image then displays the condition of the image is normal. Else the condition of the image is abnormal. The performance of the proposed approach is evaluated by experiment the proposed approach with numerous images. True positive rate, true negative rate, false positive rate, false negative rate are computed. The total number of input images experimented and number of images classified by the proposed approach is given in the below Table 1.

Table 1. Database image versus proposed approach classified image.

Images	No. of normal images	No. of abnormal images
Database	50	50
Proposed system	48	46

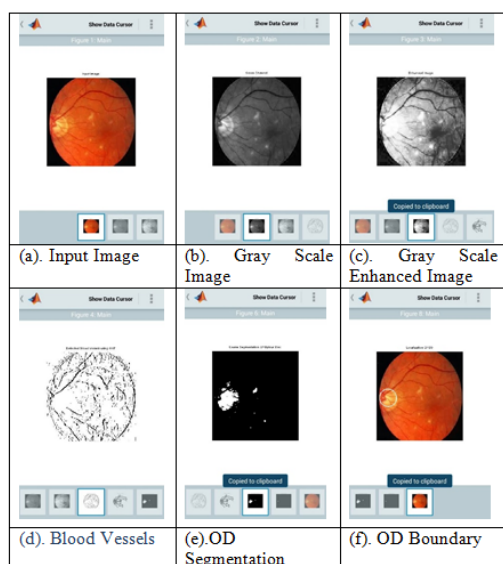


Figure 2. Various stages in diabetic retinopathy detection.

In the second stage of the implementation, the above construction based validation is implemented in MATLAB 2012 software and the performance is compared with the different kinds of datasets. The dataset is collected is involved diabetic retinopathy patients followed by the ophthalmological service of the Aravind Eye Hospital and College (Tamilnadu, India). All the patients are regular to the primary health (eye) check-up. From the entire data a portion of data is taken as trained data set, cross validated with the ground truth data values and the results are obtained. These obtained values are verified by one of the medical experts and saved as a trained set. This trained set further compared with the testing data set in order to predict the DRDME and its severity by the risk score. One of a patient is assumed as having diabetes if the

diagnosis had been made by a physician (ICD9-MC 250.X). The patients are excluded if they had dementia, high myopia, macular disorder, had laser treatment and surgery earlier, or taking any other anti-angiogenic drugs (Figure 2).

The diabetic retinopathy is investigated and classified as severe, very severe or proliferating or DRDME [15]. Detecting and classifying these two disorders is made by clinical ophthalmological investigation of the retina by indirect ophthalmoscopy and bio-microscopy of the central retina with a Topcon slit lamp, model SL-8Z using a 78 dioptre lens and indirect ophthalmoscopy with 28 D lens by an expert retinal ophthalmologist. It is well known that the macular edema is defined by the presence of hard exudates or by the retinal thickness within a distance of 500 μm from the fovea, and the degree of diabetic retinopathy was defined according to the study discussed [16]. The secondary variables are collected from the data collection of a hospital where the data concerning the types of diabetes, hypertension, dyslipidaemia, gender, smoking, age and HbA1c was the clinical history. The VA is obtained at the central area by dilating the pupil with a drop of tropicamide and measuring with spectral domain optical coherence tomography. The testing images are obtained from high quality scan device. The diameter is 6 mm centered on the fovea thereby using for study the central 1000 μm area (i.e. the central circle).

From the construction data there are 500 patient's data is taken as sample, where 200 had DRDME. In order to construct an area under ROC curve (AUC) different to 0.4, assuming a 96% of confidence level and expecting to find an AUC of 0.9, the contrast power was nearly 100%. A similar methodology has been used in other studies [16]. Using the same parameters in the validation sample (500 patients, 200 with DRDME); it is obtained a contrast power of 98.23%.

Discussion

The objective variables are taken in the form of mean, average and standard deviations whereas all the objective variables are as absolute and relative frequencies. The confidence level is taken as 5% in interval used for calculation. In this paper 80% of the data is used as testing data to predict the model and the remaining 20% of the data is used to validate the model to be constructed. Support Vector Machines (SVM) approach is used to predict DRDME clinically associated variables available in the data. Finally the number of matching score is obtained from the Support Vector Machines (SVM) as prediction result. From the score the probabilistic of the model is classified as:

- Low (<25%)
- Medium (25-50%)
- High (50-75%)
- Very High ($\geq 75\%$)

From the validation the area of ROC curve is calculated and the observed result is compared with the expected events model using X^2 test. The following table shows the number of trained, test, sensitivity, specificity of the entire data set taken for experiment. The following Table 2 shows the obtained

classified result by the existing binary logistic regression model [2].

Table 2. Result obtained by binary logistic regression model.

Objective variables	Construction (n=106)	Validation (n=36)	P-Value
DRDME	35	12	N/A
AbA1c (%)	7.7	7.9	0.113
Foveal Thickness (FT) (µm)	261.2	285.2	<0.001
Visual Acuity (VA)	0.7	0.7	<0.001

DRDME: Diabetic Macular Edema

Table 3. Result obtained by the SVM classifier.

Objective variables	Construction (n=300)	Validation (n=200)	P-value
DRDME	35	16	N/A
AbA1c (%)	7.7	8.7	0.113
Foveal Thickness (FT) (µm)	261.2	289.2	<0.001
Visual Acuity (VA)	0.7	0.9	<0.001

DRDME: Diabetic Macular Edema

Tables 2 and 3 shows the information about the construction sample has n=106 and n=300 cases of DRDME respectively. The validation sample is taken as n=36 and n=200 cases of DRDME for existing as well as proposed systems respectively. The number of disorders having macular edema obtained by the existing and proposed systems is given in Table 2 and in Table 3 respectively.

Table 4. Normal vs. abnormal classification.

Data	Available (numbers)	Manual classified (numbers)	Experimentally classified (numbers)
Normal	300	300	267
Abnormal (DRDME)	200	200	173

DRDME: Diabetic Macular Edema

From the entire data set there were 173 patients are classified as having DRDME out of 200. From the other secondary objective variables, it is obtained that majority of the DRDME is found in the age group of 70 to 85 yrs., and high HbA1c % is found in the age group of 60 to 70 yrs. From the score values the risk % is obtained from SVM the ROC curve is obtained and shown in Figure 3.

This paper is motivated to construct an innovative tool which can able to determine whether a diabetic patient has diabetic retinopathy or diabetic retinopathy macular edema, thereby the patients can be advised and taken to specialist in ophthalmology. This proposed prediction model is developed

in MATLAB and deployed in Android mobile for any non-experienced primary care physician can use for emergency situations.

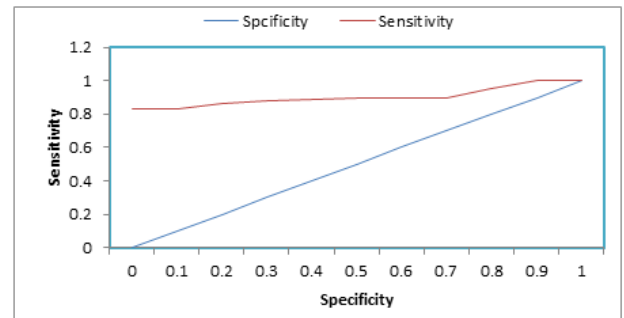


Figure 3. Area under the ROC curve of the scoring system.

The following figures show the stage wise results obtained in the experiment. The number of normal data versus abnormal data classification is done by SVM approach (Table 4). Figures 3 and 4 shows the number of data available in the data base and the number of abnormal data classified by the proposed framework. This framework is installed in the mobile device and verified the accuracy. The proposed framework has strength of its novelty where according to scoring system obtained from construction and validation on the data. It helps to any physician who can refer a diabetic patient to the ophthalmological specialist. All the parameters are obtained from the entire database and compare with the objective variables to interpret them in order to verify the abnormality.

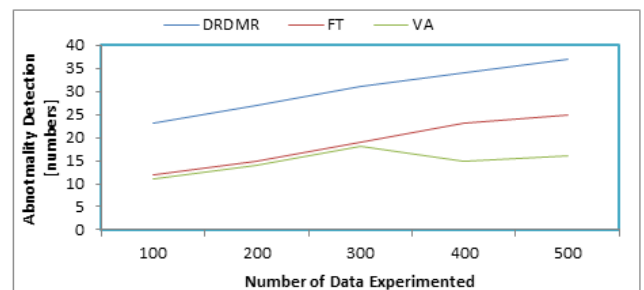


Figure 4. Performance evaluation.

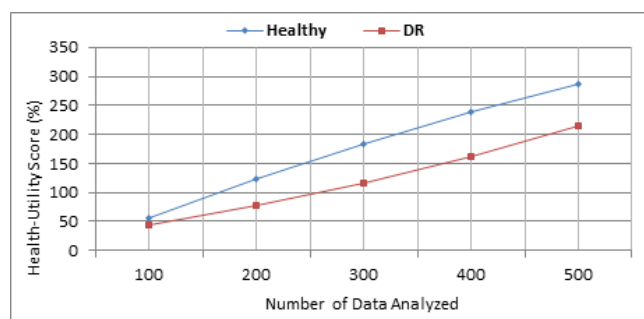


Figure 5. Health utility score evaluation.

Also the healthy and disease based results is obtained from the implementation and shown in the Figure 5. The health utility score is calculated by verifying various demographic variables. It is already discussed that the health score is from 0 to 1.

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According to the score the data is classified and it says that 45% of the data is affected by diabetic retinopathy and 55% of the data is not affected by diabetic retinopathy (i.e. Healthy). This is shown in Figure 5.

By changing the number of data taken for analysis the experiment is applied. According to the evaluation results approximately 45% of the data is classified as abnormal data (i.e. affected by diabetic retinopathy and 55% of the data is classified as healthy data. From the above results and discussion, using a hand held devices, analysing a patient data effectively is more helpful to a non-ophthalmologist in an emergency situation and it guide medical people to investigate any data at time from anywhere. Hence this approach is decided as a best suitable mobile application for analysing diabetic retinopathy in terms of images and data.

Conclusion

The main objective of this paper is to develop an automatic classification tool to predict the DRDME by construction and validation process on the given dataset. The proposed model constructed, validated and implemented a prediction tool for mobile devices based on a scoring system. This scoring system computes the risk (%) in terms of expected values on FT, VA and DRDME. This proposed approach behaves as an accurate decision tool in terms of prediction in diabetic patients' data. This is a suitable framework for any volume of data from anywhere in the world. In future enhancement, this tool can be used for image feature based prediction for DRDME.

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