Journal of Computational Intelligence in Bioinformatics
ISSN: 0973-385X Volume 4 Number 1 (2011) pp. 37–45

http://www.ripublication.com/jcib.htm

ANN Based Framework for Prediction and Treatment of Diabetic Retinopathy

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Abstract

Diabetes is fast becoming an epidemic in developed and developing nations alike. Diabetic Retinopathy (DR) is a common retinal complication associated with diabetes. Early detection of the disease via regular screening is particularly important to prevent vision loss. Screening such a vast number of patients involves lot of cost and money, besides DR doesn't progress at the same speed in all the patients. Various studies have shown that lots of physiological variables (age, gender, hypertension, obesity etc.) affect the course of the disease .The purpose of the present work is to differentiate the high risk patients from the low risk patients based on these physiological variables, so that the high risk ones can be screened and treated timely and the low risk ones can be referred for screenings at longer intervals. This can help save time and resources and help focus on those who need early intervention and treatment. Retrograde Data of around 100 patients with their physiological variables was recorded .All patients had Grade 1 DR. Their grading after 3 years was recorded presuming the physiological parameters stayed the same over the span of 3 years. DR grading was taken as per the Ophthalmologists assessment. Some patients had deteriorated to GRADE 3& 4 while others stayed at GRADE 1 or at the most moved to GRADE 2, implying that the interplay of the various physiological variables was affecting the course of Retinopathy. The dataset was divided into training and test set of 50 each. Artificial Neural Network was applied. Best prediction of around 90% was obtained. A Graphical User Interface was created where a file containing a patient's data of physiological variables can be uploaded and the probable grading of his DR after a span of 3 years can be predicted. Those at the risk of early deterioration (GRADE 3&4) can be referred for early intervention and treatment while once with lesser risk can be referred for screenings at longer

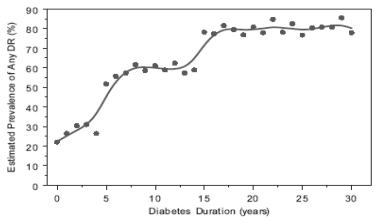
intervals. This will help in saving time and cost for both the patient and the specialists.

Index Terms*:* Diabetic Retinopathy (DR), Artificial Neural Network (ANN), Physiological parameters, Prediction, High risk.

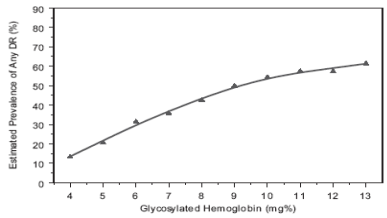
Introduction

Diabetes is fast becoming an epidemic in developed and developing nations alike. Its long-term complications, including retinopathy, nephropathy, neuropathy, and accelerated macro vascular disease cause major morbidity and mortality. Diabetic retinopathy (DR) is a common retinal complication associated with diabetes. Early detection of the disease via regular screening is particularly important to prevent vision loss.Course of Diabetic Retinopathy varies from patient to patient .The condition of Retinopathy doesn't deteriorate with the same speed in all the patients therefore there is a need to sort out and differentiate the high risk patients from the low risk so that they can be accordingly referred for the specialist's intervention. Classification of the severity of diabetic retinopathy and quantification of diabetic changes are vital for assessing the therapies. Below are the physiological factors which have been reported to affect the course of Diabetic Retinopathy (see Tabe1):-

Table 1: Showing relationship of DR with various physiological factors-disease duration, glycosylated hemoglobin and Systolic Blood Pressure.



1



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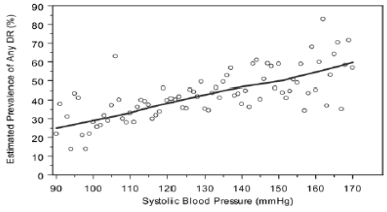

3

[1] Age
[2] Duration of disease [1]
[3] Hypertension [2]
[4] Antihypertensive drugs
[5] Smoking [3]
[6](Obesity)Body Mass Index [4]

[7] Blood sugar levels [5]
[8] Blood lipid levels
[9] Lipid lowering therapy
[10] Cardiovascular strokes history-y/n
[11] Chronic inflammation history-y/n
[12] Renal dysfunction-blood creatinine levels
[13] Blood urea levels
[14] Blood hemoglobin levels

Various studies have shown that modification of risk factors (e.g., increased physical activity, reduction in weight) or institution of treatment (e.g., diabetes and antihypertensive medications) may improve retinal vascular measures and might lower risks of diabetes, hypertension, and their complications [6]. Retinal image can indicate various diseases. Retinal arteriolar narrowing, for example, is associated with risk of diabetes and coronary artery disease, whereas retinal venular widening is associated with development and progression of diabetic retinopathy and risk of stroke [7]. Diabetic retinopathy is found in 60% of people; sight-threatening retinopathy is found in 2.0% of people who have had diabetes for >5 years and in 15.5% of people who have had diabetes for >15 years [8]. However, even in countries in which facilities for close monitoring of diabetes are available, there is no consensus on cost-effective, valid methods to screen and treat for diabetic retinopathy. Destruction of damaged retina by photocoagulation remains the primary treatment nearly 50 years after its introduction[9].It just helps to prevent further vision loss but unable to restore the damage already done to the retina Hence, there is a great deal of essentiality factor associated with development of an automated DR diagnostic system. Here we will be using Artificial Neural Network. Artificial Neural Network (ANN) has been used in a number of different ways in medicine and medically related fields. The principle advantages of artificial neural networks are that they are able to generalize, adapting to signal distortion and noise without loss of robustness. They are trained by example and do not require precise description of patterns to be classified or criteria for classification.

Material and Methods

The patient's data was acquired from a private eye hospital under the final subheadings-age, gender, duration of disease, history of hypertension, antihypertensive drugs, smoking, body mass index, blood sugar levels, blood lipid levels, lipid lowering therapy, Cardiovascular strokes , any H/O Chronic Inflammation, Blood creatinine, blood urea levels ,blood hemoglobin, and the grade of retinopathy. Grade of Retinopathy was recorded as per the clinicians' perception. It was a retrograde data recorded over a span of 3 years to observe the change in DR grading over the given period assuming that the given physiological parameters stay constant during this phase. Data for 100 patients was recorded. The idea is to be able to predict the course of DR over the span of 3 years given the values of the above physiological parameters. This is done to differentiate the high risk patients from the

low risk patients so that the high risk patients can be intervened early and can be called for frequent checkups and timely treatment while the low risk patients can be referred for less frequent, say annual checkups. This way treatment of the patients can be prioritized and the high risk patients can be screened and treated early to prevent any irreversible deterioration in their vision. The low risk patients can be spared from frequent checkups thus saving time and money.

Data Acquisition

Collection of medical data/history of patients(see Table 2) like - Age, Duration of disease, Hypertension, Antihypertensive drugs, Smoking, Obesity (BMI), Blood sugar levels, Blood lipid levels, Lipid lowering therapy, Cardiovascular strokes history-y/n, Chronic inflammation history-y/n, Renal dysfunction-Blood creatinine levels, Blood urea levels, Blood hemoglobin levels from an authentic medical institute(A private eye clinic in our case).Classification of the patients into four stages of disease(categories) – 1 for mild, 2 for moderate , 3 for severe, 4 for proliferative(Standard classification by the Ophthalmologists was followed) and training by the use of Artificial Neural Network.

Table 2: Values of various physiological parameters.

<table>
<tr><td>S.No</td><td>Physiological Parameters</td><td>Values</td></tr>
<tr><td>1</td><td>Obesity(Body Mass Index)</td><td><table>
<tr><td>Adults' BMI</td><td>Women</td><td>Men</td></tr>
<tr><td>underweight</td><td><19.1</td><td><20.7</td></tr>
<tr><td>In normal range</td><td>19.1-25.8</td><td>20.7-26.4</td></tr>
<tr><td>Marginally overweight</td><td>25.8-27.3</td><td>26.4-27.8</td></tr>
<tr><td>overweight</td><td>27.3-32.3</td><td>27.8-31.1</td></tr>
<tr><td>Very overweight or Obese</td><td>>32.3</td><td>>31.1</td></tr>
</table></td></tr>
<tr><td>2</td><td>Total Blood Cholesterol level</td><td><200 mg/dl normal blood cholesterol
200-239 mg/dl borderline-high
>240 mg/dl high cholesterol</td></tr>
<tr><td>3</td><td>Serum Creatinine</td><td><table>
<tr><td>Women</td><td>Men</td></tr>
<tr><td>0.5 to 1.0 mg/dL (about 45-90 µmol/L)</td><td>0.7 to 1.2 mg/dL (60-110 µmol/L)</td></tr>
<tr><td>1-1.2 mg/dl-</td><td>1.2-1.4 mg/dl-</td></tr>
</table></td></tr>
</table>

		mild	mildly raised	
		1-1.5 mg/dl- moderate	1.4-1.7 mg/dl- moderate	
		>1.5 mg/dl- severe	>1.7 mg/dl- severe	
4	Serum Urea	10-14 mg/dl-Normal 14-16 mg/dl- mild 16-18 mg/dl –moderate >18 mg/dl- severe		
5	Blood Sugar	80-120 mg/dL Hyperglycemia –Y/N		
6	Blood Pressure	Normal 120/80 mm of Hg Hypertension – Y/N		

Data Cleaning, Normalization, category Identification

- Data for around 100 patients were taken.
- All the patients were starting with Grade 1 DR
- Their physiological parameters were recorded.
- Their DR grading after 3 years were recorded.
- DR Gradings were followed as per the Specialists' evaluation

Prediction

Predictions of the stage of disease of the patient in the near future and hence take decisions regarding his further treatment.

Platform used :- Windows

Technology used :- MATLAB 2008b , C++

Results

Three Datasets are being used:-

1. Dataset1: It consists of the medical data of patient, each patient having 15 features.

2. Dataset2: Here, a 16^{th} feature is added which is:-

$p_{16} = \sum (p_i * wi)$ from i = 1 to 15

Where p_i = feature value of the i^{th} parameter

w_i = weightage of the i^{th} parameter.

3. Dataset3: Here, all 15 feature values are being changed by:-

$p_i = (p_i * w_i) / [\sum (p_i * w_i) \text{ from } i=1 \text{ to } 15] \text{ from } i=1 \text{ to } 15$

Some weightages were being given to all the parameters according to the fact that how these features are going to affect a patient. The weightages have been adjusted to give better results on training by ANN (see Table 3):-

Table 3: Weightages given to various physiological parameters.

S.No	Physiological Parameter	Weightages
1	AGE	0.3
2	DURATION OF DISEASE	0.6
3	HYPERTENSION	0.7
4	ANTIHYPERTENSIVE DRUGS	0.5
5	SMOKING	0.8
6	OBESITY(BMI)	0.4
7	BLOOD SUGAR LEVELS	0.6
8	BLOOD LIPID LEVELS	0.6
9	LIPID LOWERING THERAPY	0.3
10	CARDIOVASCULAR STROKE HISTORY Y/N	0.5
11	CHRONIC INFLAMMATION HISTORY Y/N	0.2
12	BLOOD CREATININE LEVELS	0.7
13	BLOOD UREA LEVELS	0.7
14	BLOOD HEMOGLOBIN LEVELS	0.2

1. Classification done By SVM_HMM-A hybrid approach of SVM_HMM was used and yielded the following result (see Table 4)

Table 4: Accuracy of the classification done by SVM_HMM.

Datasets	Accuracy of the classification
Dataset 1	88
Dataset 2	90
Dataset 3	75

2. Training and Classification done by Artificial Neural Network-The dataset was divided into 2 sets of 50 each-training and the test set and was trained using ANN(see Table 5)-
   a. By varying the no. of neurons
   b. By varying the training parameters
   c. By retraining if the results were not good.

Table 5: Classification by Artificial Neural Network.

Datasets	By nftool	By nntool
Dataset 1	74%	76%
Dataset 2	86%	90%
Dataset 3	84%	88%

3. Cross Validation of the dataset using ANN-The dataset was divided into 4 parts a, b, c, d each of 25 and cross validation was done (see Table 6).

Table 6: Cross Validation of the dataset using ANN.

Data	Train	Test	Accuracy
Data1	abc	d	92%
Data2	bcd	a	92%
Data3	abd	c	94%
Data4	acd	b	91%

4. Graphical User Interface was created where on uploading an unknown patients' file with the recorded physiological parameters, the expected stage of the patient' DR after 3 years can be predicted(see figures 1&2). The patients with the prediction of Grade 3 or Grade 4 DR can be labeled as 'high risk' and can be called for frequent screenings and an early an timely intervention while the ones with a prediction of Grade 1or Grade 2can be sent for less frequent six monthly or annual screenings.

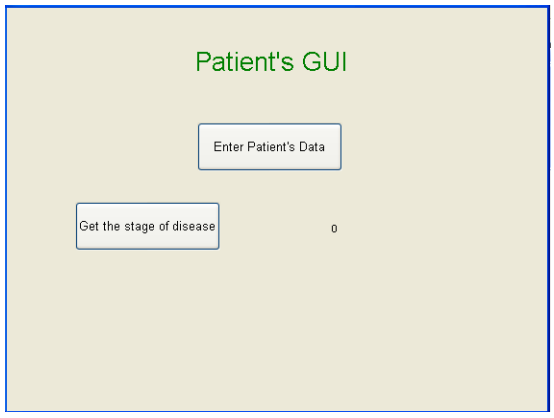

Figure 1: The Graphical User Interface for predicting the DR Grade of a patient.

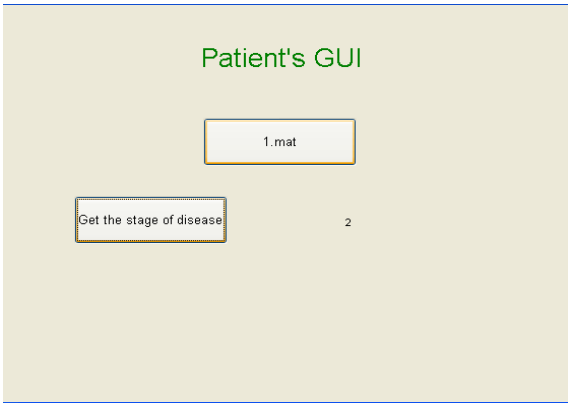

Figure 2: After loading the file of the patient given his physiological parameters.

Discussion

The Artificial neural network after training and classification is giving the prediction of 90%.The file of a new patient can be uploaded, using the Graphical user Interface and his DR grade after 3 years can be predicted. If the predicted grade is GRADE 3or GRADE 4, then such patients are identified as 'high risk' (the contributing physiological parameters might lead to early deterioration and vision loss) and referred to the Specialist for immediate management and regular short interval follow ups, while the ones who stay at GRADE 1&2 are the 'low risk' patients and can be referred for more prolonged annual or biannual checkups.

There is however scope to further improve the prediction:-

1. Results can be further improved by increasing the size of dataset.
2. Neural Network can be further improved.
3. Prediction can be done by taking into consideration many other features of the patient.
4. Time span of the data can be increased (>3 years) to observe a wider range of the course of the disease.

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