# Classification of Diabetic Retinopathy


Ayush Goel

Apoorv Gaurav Agarwal

*B.E. CSE*

*BIT Mesra, Jaipur Campus*



**Abstract- Diabetic Retinopathy (DR) is an eye disease that can affect people with diabetes. It is the most common cause of vision loss among people with diabetes and the leading cause of vision impairment and blindness among working-age adults. However, if it is treated properly during its initial stages, the chance of blindness is reduced thereby signifying the importance of its detection. Digital color fundus images are becoming increasingly important for the diagnosis of Diabetic Retinopathy and other methods that address this problem (But, they have some drawbacks like being accurate for small set of input data). This paper proposes the use of Artificial Neural Network, thereby classifying the diabetic retinopathy with the use of large input dataset (containing textual data regarding digital color fundus images).**



**Keywords: Diabetic Retinopathy, Artificial Neural Network, Classification, Backpropagation Algorithm**


## I.INTRODUCTION

Diabetic retinopathy is an ocular manifestation of diabetes which affects most of the patients who have had diabetes for more than 20 years or so. It is a serious sight threatening complication of diabetes that eventually leads to blindness (Fig 1). The excess sugar flowing in the blood vessels of a diabetic person causes damage throughout the body including the eyes. This excess sugar causes progressive degeneration of retinal capillaries over time resulting in hemorrhages and exudates. Diabetic retinopathy occurs when the degenerated retinal capillaries leaks blood and other fluids. This causes retinal tissue to swell, resulting in cloudy or blurred vision. In its initial stages, patients generally don't show any symptoms, however, in later stages, patients experience floaters, blurred vision, distortion, and progressive visual activity loss. These symptoms eventually leads to hemorrhage and blindness (in severe cases when the disease is left unchecked). The vision change during the stages of diabetic retinopathy is shown in fig 2.

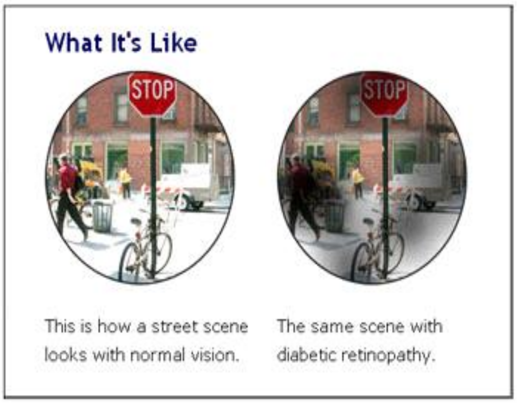


Fig 1: Effect of Diabetic Retinopathy on vision

Diabetic retinopathy can be identified by the presence of lesions associated with vascular abnormalities caused by the disease [1]. While this approach is effective, its resource demands are high. It is carried out by a trained clinician who examines and evaluates digital color fundus photographs of the retina (fig 3). Its diagnosis [2] includes Visual Activity Test through Pupil Dilation, Ophthalmoscopy, Optical Coherence Tomography, Sit lamp Bio Microscopy, Retinal Screening Programs,etc.


Fig 2: Effect on vision based on the stages

Various computational approach have also been suggested. Use of 'Moat Operator' [3] to automatically detect features of non-proliferative diabetic retinopathy, an artificial neural network using fuzzy C-means clustering [4], stereoscopic digital imaging via teleophthalmology[5],Cox regression Model[6]etc have been proposed for computational approaches.


Fig 3: Stages of Diabetic retinopathy

Artificial Neural Network have been used for the classification of diabetic retinopathy. The use of biological methods requires professional equipment and professionals who are expertise in the field, which cannot be made available to the various rural areas. The time taken for evaluation of an individual is quite high making the process slow. As stated earlier, it is possible to successfully reduce the chances of blindness if the treatment is carried under initial stages. Hence, it is important to verify the disease in an individual. The proposed approach makes the use of artificial neural network, which classifies and tells whether the individual is suffering from diabetic retinopathy or not. It is a simple approach which can be easily followed and quite accurate results can be obtained with some basic inputs.

## II. METHOD

Artificial Neural Networks (ANN) are important data mining tool used for classification. It is an attempt to build a machine that will mimic brain activities and be able to learn. An ANN usually learns by examples. If it is supplied with enough examples, it should be able to perform classification and even discover new trends or patterns in data. Basic ANN is composed of three layers, input, output and hidden layer. Each layer can have a number of nodes and nodes from input layer are connected to the nodes from hidden layer. Nodes from hidden layer are connected to the nodes from output layer. Those connections represent weights between nodes.

The idea behind Backpropagation (BP) algorithm is quite simple, the output of ANN is evaluated against desired output. If results are not satisfactory, connection (weights) between layers are modified and the process is repeated again and again until the error is small enough. Random weights are used between the connections of the nodes. Error at the output layer of the network is calculated by presenting a test cases. Weights are then updated between the layers propagating error backwards till input of the layer. This forms one iteration. At the end of iteration,test patterns are presented to the network and its prediction performance is evaluated.

The concept of Steepest-Descent method is used in BP algorithm to reach a global minimum.

## III. MATERIAL

The dataset contains features extracted from the Messidor image set to predict whether an image contains signs of diabetic retinopathy or not. All features represent either a detected lesion, a descriptive feature of an anatomical part or an image-level descriptor.

No. of Instances-1152

No. of Missing Value- N/A

Dataset Characteristics- Multivariate

No. of Attributes- 20 (including Target Values)

Attribute Characteristics- Integer, Real

### *A. Attribute Information*

A) The binary result of the quality assessment [0 = bad quality and 1 = sufficient quality].
B) The binary result of pre-screening, where 1 indicates severe retinal abnormality and 0 its lack.
C-H) The results ofMicroaneurysm (MA) Detection. Each feature value stands for the number of MAs found at the confidence levels alpha=0.5,....,1 respectively.
I-P) contain the same information as (C-H) for exudates. However, as exudates are represented by a set of points rather than the number of pixels constructing the lesions with the diameter of the region of interest to compensate different image sizes.
Q) The Euclidean distance of the center of the macula and the center of the optic disc to provide important information regarding the patient's condition. This feature is also normalized with the diameter of the region of interest.
R) The diameter of the optic disc.
S) The binary result of the amplitude-modulation/frequency-modulation based classification.
Z) Class label 1 = contains signs of DR, 0 = no signs of DR] (Target Values)

## IV. ARCHITECTURE of ANN

*A. Number of Layers:*

Every NN has three types of layers: *input*, *hidden*, and *output*. In proposed architecture of artificial neural network, we have following specifications:

- Has one Input Layer
- Like the Input layer, ANN has exactly one Output layer
- One Hidden layer (as it can approximate any function that contains a continuous mapping from one finite space to another[7].
- Input Layer -19(since 19 features)
- Hidden Layer - 14
- Output Layer - 1

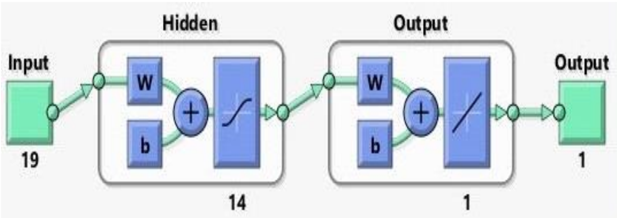


Fig 4: Network Size

*B. No. of Neurons*

Using too few neurons in the hidden layers will result in something called underfitting. Underfitting occurs when there are too few neurons in the hidden layers to adequately detect the signals in a complicated data set. Too many neurons in the hidden layers may result in overfitting. Overfitting occurs when the neural network has so much information processing capacity that the limited amount of information contained in the training set is not enough to train all of the neurons in the hidden layers [8].

Methods for determining the correct number of neurons to use in the hidden layers, such as:

- The number of hidden neurons should be between the size of the input layer and the size of the output layer.

- The number of hidden neurons should be 2/3 the size of the input layer, plus the size of the output layer.

- The number of hidden neurons should be less than twice the size of the input layer.

These three rules provide a starting point to consider [7]. Ultimately, architecture of neural network comes out to be 14 nodes in Hidden Layer and 1 node in Output layer. Input layer consists of 19 nodes due 19 features in Input dataset.

*C. Setting Weights:*

The way to control ANN is by setting and adjusting weights between nodes. Initial weights are usually set at some random numbers and then they are adjusted during ANN training. According to Fogel[9], the focus should not be at changing one weight at the time, changing all the weights should be attempted simultaneously. During the ANN training weights are updated after iterations. If results of ANN after weights updates are better than the previous set of weights, the new values of weights are kept and iteration goes on.

*D. Dividing of Data Sample:*

Dataset is divided mainly into three sets –

- Training Set- 75%
- Validation Set – 5%
- Testing Set- 20%

Since, Backpropagation Training Algorithm doesn't have attribute for tuning Validation of sample dataset, thus Validation set kept low to 5% of the total dataset available.

*E. Learning Rate and Momentum*

Setting right learning rate could be a difficult task, if learning rate is too small, the algorithm might take a long time to converge. On the other hand, choosing large learning rate could have opposite effect, the algorithm could diverge. Sometimes in NN every weight has its own learning rate. This paper uses Learning Rate of 0.46 along with Adaptive Learning Rate Algorithm which drastically reduced errors.Also, learning rate is decreased by a factor of 0.3.

Larose[10] claimed that momentum term represents inertia. Large values of momentum term will influence the adjustment in the current weight to move in the same direction as previous adjustment. Thus momentum is set to be 1.1.

*F. Epochs*

An epoch is a measure of the number of times all of the training vectors are used once to update the weights. For batch training all of the training samples pass through the learning algorithm simultaneously in one epoch before weights are updated.

By testing on different values of epochs we reached to an optimal value of epochs to be 10,000 that fits for our network.

*G. Activation Function*

The activation function used is Sigmoidal Function in hidden layer because it ranges between -1 to 1(to decrease range). Pure Linear function is used in Output Layer because it needs to classify between Yes and No.

## V. ANN TRAINING ALGORITHM (BACKPROPAGATION ALGORITHM)

Rojas [11] claimed that Backpropagation algorithm could be broken down into four main steps. After choosing the weights of the network randomly, the back propagation algorithm is used to compute the necessary corrections. The algorithm can be decomposed in the following four steps:

- Feed-forward computation
- Back propagation to the output layer
- Back propagation to the hidden layer
- Weight updates.

The algorithm is stopped when the value of the error function has become sufficiently small. This is very rough and the basic formula for BP algorithm. There is some variation proposed by other scientist but Rojas definition seems to be quite accurate and easy to follow. The last step, weight updates is happening throughout the algorithm.

Out of many available algorithms tested only two came out with high success rate i.e. Bayesian Regularization Backpropagation Theorem &Lavenberg Training Algorithm .Backpropagation Training Algorithm exists out of which Bayesian Regularization Backpropagation Theorem suited best to this ANN (it uses more memory than largely used Lavenberg Training Algorithm but gives better performance and it is well suited for datasets consisting of 2 classes, i.e. in this case– 0 and 1)[12]

## VI. RESULT

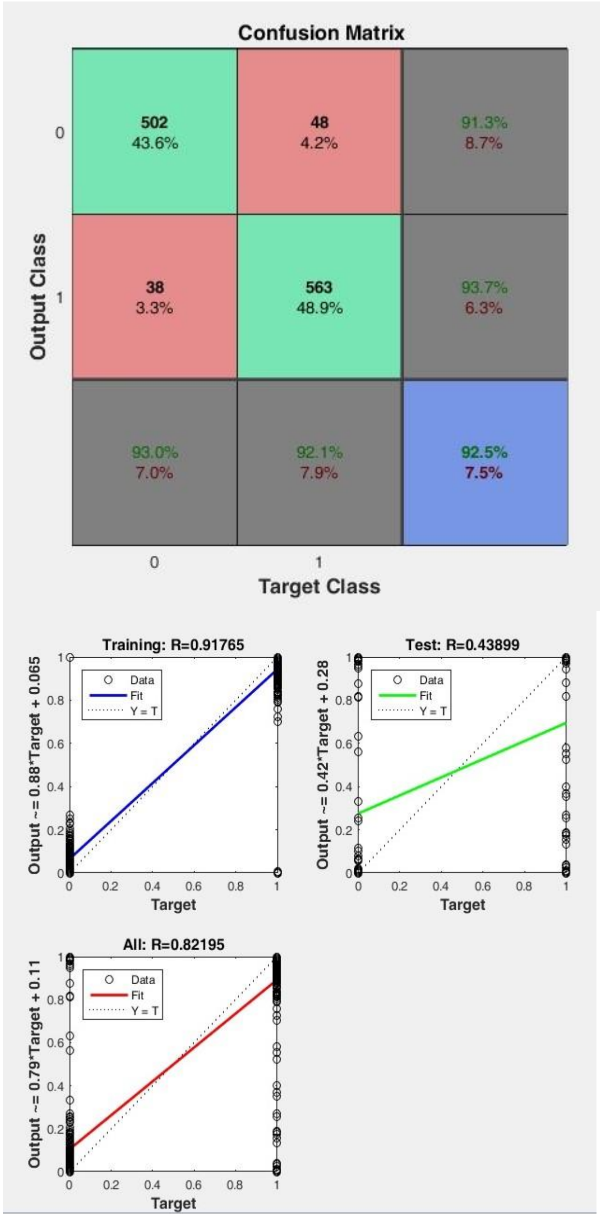


Fig 5: Result

The performance (mean square error) of the mentioned setup is 0.112 which varies within a 0.015 range. Since the dataset of Messidor images* used in this research has 1152 instances, the discovery of the disease is quite accurate.

## VII. CONCLUSION

Diabetic retinopathy is a concerning disease which must be treated in its initial stages for preventing the eye blindness. Neural Network is a popular optimization process which when implemented with Backpropagation theorem gives better results as compared to the traditional biological approaches. The proposed method makes the use of a simple artificial neural network circuit which can be implemented easily on a system even by a non-professional. The preciseness of the method can be improved, if further studies are done in this direction.

## VIII. REFERENCES


1. Source www.kaggle.com/c/diabetic-retinopathy-detection (as on 27/7/16)
2. C. Sinthanayothin et al. 2002, Automated detection of diabetic retinopathy on digital fundus images.
3. A Osareh et al. 2003, Automated identification of diabetic retinal exudates in digital color images.
4. Tennant MT et al. 2001, Identification of diabetic retinopathy by stereoscopic digital imaging via teleophthalmology: a comparison to slide film,
5. Ronald Klein et al. 1984, the Wisconsin Epidemiologic Study of Diabetic Retinopathy III. Prevalence and Risk of Diabetic Retinopathy When age at diagnosis is 30 or more years.
6. Balint Antal, Andras Hajdu, (April 2014), 20-27, An ensemble-based system for automatic screening of diabetic retinopathy, Knowledge-Based Systems
7. Introduction to neural networks with Java (2nd edition), Jeff Heaton
8. MirzaCilimkovic, Neural Networks and Back Propagation Algorithm
9. D.B. Fogel. Blondie24: playing at the edge of AI. The Morgan Kaufmann Series in Evolutionary Computation. Morgan Kaufmann Publishers , 2002.
10. D.T. Larose. Discovering knowledge in data: an introduction to data mining. Wiley - InterScience, 2005.
11. Raul Rojas. Neural Networks:A Systematic Introduction. Springer, 2005.
12. Matlab Help Document.

*Dataset

- Dr. Balint Antal, Department of Computer Graphics and Image Processing Faculty of Informatics, University of Debrecen, 4010, Debrecen, POB 12, Hungary
antal.balint '@' inf.unideb.hu
- Dr. Andras Hajdu, Department of Computer Graphics and Image Processing Faculty of Informatics, University of Debrecen, 4010, Debrecen, POB 12, Hungary
hajdu.andras '@' inf.unideb.hu

Image Sources (as on 27/7/16)

1. http://www.eyestudioinc.com/services/diabetic-retinopathy/
2. http://li129-107.members.linode.com/about-low-vision-blindness/vision-disorders/diabetic-retinopathy/diabetic-retinopathy-overview/
3. http://www.mahaveereyehospital.com/diabetic-retinopathy-treatment-and-surgery-in-pune/