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DIABETIC RETINOPATHY DIAGNOSIS USING NEURAL NETWORK ARBITRATION

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Abstract

In this research work, we have implemented an intelligent system for diagnosis of diabetic retinopathy. Diabetic retinopathy is a damage caused by diabetes to the retinal blood vessels. This causes the leak of blood and other fluid that resulted into swelling of retina tissue and cloudy vision. This can be classified into two; non-proliferative diabetic retinopathy and proliferative diabetic retinopathy. The dataset used for the implementation of this intelligent system is obtained from the freely available UCI machine learning repository. This system will aid physicians to accurately diagnose the disease. Such a system will make the diagnosis faster, accurate and easier as compared to manual diagnosis. Our novel system uses a feedforward neural network trained with backpropagation neural network. The results obtained in this work are compared with previously proposed systems using the same dataset. Experimental results indicate that our novel system outperforms the other systems in diagnosing diabetic retinopathy.

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Key words: diabetic retinopathy, neural network, diabetes, data mining, machine learning, pattern recognition.

1 Introduction

Diabetes Mellitus can be described as a chronic metabolic disease that occurs due to the failure of the pancreas to secrete enough insulin [1]. Diabetes is a

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chronic epidemic with nearly 350 million cases. The chronic hyperglycemia of diabetes is associated with long-term damage dysfunction and failure of different organs especially the eyes, kidneys, nerve, blood vessel and heart.

Diabetes mellitus can be placed into two etiopathogenetic categories. The first category is the type 1 diabetes. Type 1 diabetes mellitus occurs when the autoimmune system destroys the insulin that produces beta cell in the pancreas. Any patient suffering from type 1 diabetic can be identified by serological evidence of an autoimmune pathologic process that occurs in the pancreatic islets and by genetic markers. The second category of diabetes is called Type 2 diabetes. This is caused by the combination of the resistance to insulin action and insufficient compensatory insulin secretory response. Over 90% of the patient that contributed to the sharply rise in disease, incidence has type 2 diabetes and this is related to high consumption of calories dense food of low nutritional value, lack of exercise and increase the prevalence of obesity [2].

The global incidence of diabetes mellitus is set to rise from an estimated 382 million in 2013 to 592 million by 2030 [3]-[6]. World health organization (WHO) as estimated that 19% of the people living with diabetes in the world are from India and also by 2030, 80 million more people are expected to be living with diabetes mellitus in India.

The death rate caused by the complication of the diabetes mellitus has become a threat to already set up health care system in both the developed nation and the developing nations. Most of the morbidity is caused by the vascular complication of diabetes mellitus. Experience has shown that any patients with long-term type 1 or type 2 diabetes mellitus develops the macrovascular complication. This complication includes heart disease, peripheral artery disease and stroke. From statistics more than 70% of patient that developed such complications die eventually. Other micro-vascular complications that affect patient with long term diabetes are kidney (nephropathy), peripheral nerves (neuropathy), and eyes (retinopathy).

Diabetes Retinopathy is as well characterized as a chronic ocular disorder that developed in nearly all patients with long-term diabetic mellitus condition [7]. The most common microvascular diabetes complication may be referred to as diabetic retinopathy. Diabetes retinopathy has been found to be responsible for over 10,000 blindness cases yearly in United state of America [8]. After two decades of the disease, all patients living with type 1 diabetes suffer some degree of retinopathy as well as more than 80% insulin of insulin-treated type 2 diabetes and 50% of those not acquiring insulin [9],[10].

There are two factors that determined the risk of developing diabetic retinopathy. These are the duration and the severity of the hyperglycemia. From the population of people that lives with diabetes, the overall statistic of the prevalence diabetic retinopathy is one-third with the increased risk related to long-term disease duration, hypertension and high haemoglobin [11]. Current estimation of the population of people living with diabetic retinopathy shows that 127 million people were living with the disease in 2010 and there is an increase expectation of 191 million by 2030 [12]. Diabetic retinopathy is the leading cause of blindness in the united state of America. In India, the proportion of people living with diabetes that have diabetic retinopathy ranges between 18% - 26% of the diabetic patient population.

The symptoms of the diabetic retinopathy include blurred vision, sudden loss of vision in one of the eyes, seeing rings around light and dark spot or flashing light. There is a need to emphasise that not all diabetic retinopathy patients will experience severe vision loss which occurs only in advanced stages typified by diabetic macular oedema (DMO) and or proliferative diabetic retinopathy (PDR) [6[5]

Early diagnosis of diabetic retinopathy will help the physicians to treat the disease with modalities that have been proven to decrease the risk of severe vision loss by less than 90% [13].

Several approaches have been applied to design an intelligent or automatic system that can diagnose diabetic retinopathy with accuracy that is not enough for the application because of its significant in the medical field.

Wong et al., 2007 [14] used feedforward neural network as a classifier for four eye diseases. These diseases are normal retina, moderate non-proliferative diabetic retinopathy, severe non-proliferative diabetic retinopathy and proliferative diabetic retinopathy. The features that were fed into the neural network were extracted from raw images of retinopathy using image processing techniques. The authors obtained a sensitivity that is more than 90% and specificity of 100% from the classifier system. Priya and Aruna, 2013 [15] proposed an EYENET model for diagnosis of the retinopathy. This model was obtained by combining the modified probabilistic neural network (PNN) and a modified radial basis function neural network (RBFNN). The authors fed the features extracted from images of the diabetic retinopathy to the classifier for the classification. The accuracy of 96% is obtained from probabilistic neural network (PNN), 97.5% accuracy is obtained from modified probabilistic neural network (MPNN), the radial basis function neural network has an accuracy of 93.5%, the modified RBFNN has an accuracy of 95.5% and the proposed EYENET model has an accuracy of 98.5%. Akara et. al, 2009 [16] proposed an automatic system for detecting exudates from low contrast digital images of diabetic retinopathy patients with non-dilated pupils using Fuzzy C-means (FCM) clustering.

Besides, Ananthapadmanaban and Parthiban, 2014 [17] proposed diagnostic systems model on Nave Bayes and support vector machine to predict the early detection of eye diseases diabetic retinopathy. The authors discovered that the Nave Bayes method outperform the support vector machine with an accuracy of 83.37%. Chieng-Chien-Lung Chan et. al 2008 [18] proposed two data mining models which there performance were compared to determine the best performing model. C5.0 and neural network were the two proposed models by the authors. They obtained a performance of 58.62% sensitivity and 74.73% specificity from the C5.0 and also a sensitivity of 59.48% and 99.86% specificity from the neural

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network. Also, Mookiah et. al, 2013 [19] presented an automatic screening system for detecting the normal and diabetic retinopathy stages (NPDR and PDR).The features needed to train the classifier system were extracted from the fundus images. Thus, abnormal signs such as the area of hard exudates, the area of blood vessels, bifurcation points, texture and entropies were considered. The author fed thirteen statistical vital features extracted for the probabilistic neural network, Decision Tree and Support vector machine to compare in order to choose the best performing classifier. They obtained an average classification of 96.15%, sensitivity of 96.27% and specificity of 96.08% for = 0.0104 based on three-fold cross validation using probabilistic neural network classifier. Nayak et al., 2008 [20] proposed a computer-based approach for detection of diabetic retinopathy stages using fundus images. The authors employed image processing techniques, morphological approach, and texture analysis to extract the features in the fundus images. Such features include hard exudates, area of the blood vessels, and the contrast. These features are fed into the neural network for automatic classification. A recognition rate of 93%, the sensitivity of 90% and specificity of 100% were obtained from the automatic classifier system.

In this research work, we have proposed an intelligent system for early diagnosis of retinopathy diabetics. This system is model on artificial neural network to solve the problem of misdiagnosis of retinopathy diabetes by the physicians using manual approach. Also, time consumption in the diagnosis of the disease is also put under consideration. This system has been designed to diagnose diabetic retinopathy at a very fast rate with high accuracy.

The artificial neural network made up of a large amount of distributed neurons, which by adjusting the connection weight among neurons possesses the ability of learning from experience knowledge and this knowledge can be applied [21]. Artificial neural network is more appropriate for the diagnosis of the diabetic retinopathy because its employs mathematical weights for determining the probability of the input data belonging to a particular output. The artificial neural network has been successfully applied to several applications [22]- [29]. The artificial neural network comprises three layers which are input layer through which data is fed into the neural network. The hidden layer which is the processing unit of the neural network, it has the attributes of updating the weight in such a way that a better performance will be obtained in the network. The output layer is the third layer which gives out the result of the network.

The rest of the paper is organized as followed: section 2 is the material and method, section 3 is the design of the intelligent system, section 4 is the result evaluation and discussion and finally section 5 is the conclusion.

2 Method and material

The dataset used for this work is obtained from UCI machine learning repository. The dataset comprises features from the Messidor images that is set to predict whether an image comprises of the sign of the diabetic retinopathy or not

[30], [31]. The dataset is made up of 20 attributes with 1151 instant samples of the extracted features from the messidor images. The following are the attribute extracted from the messidor images [30]:

Attribute 1: The binary result of the quality assessment 0 = bas quality and 1= sufficient quality.

Attribute 2: The binary result of pre-screening where 1 means severe retina abnormality and 0 denotes its lack

Attribute 3-8: The results of MA detection. Each feature value denotes the number of MAs found at the confidence levels alpha = 0.5.1 respectively.

Attribute 9-16: Contain the same information as 3-8 for exudates. However, as exudates are represented bu a set of points rather than the number of pixels constructing the lesions, these features are normalized by dividing the number of lesions with the diameter of the ROI to compensate different image sizes.

Attribute 17: The Euclidean distance of the centre of the macula and the centre of the optic disc to provide important information regarding the patient health condition. This feature is also normalized with the diameter of the ROI.

Attribute 18: The diameter of the optic disc.

Attribute 19: The binary result of the AM/FM based classification.

Attribute 20: Class label 1 denotes that its contain signs of the diabetic retinopathy (Accumulative label for messidor classes 1, 2, and 3), 0 denotes no sign of diabetic retinopathy.

Designing an intelligent system for diagnosis of the diabetic retinopathy involve consideration of several techniques. These techniques range from data mining to the design of the intelligent classifier systems. These approaches are stated in stages as shown in Figure 1.

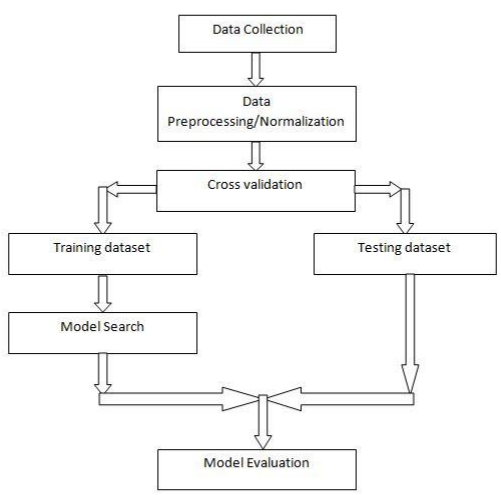

Fig1 Stages involves in designing the intelligent system

2.1 Data pre-processing

In these days, the real world databases are highly susceptible to noisy, missing and inconsistent data due to their typical huge size and their likely origin from multiple, heterogeneous sources. There are different techniques that can be applied to pre-process data in data mining. These includes: data cleaning where noise and correct inconsistencies are removed in the dataset, data integration merges data from multiple sources into a coherent data store. Also, data transformation such as normalization can be applied to improve the accuracy of the network. Therefore, for the network to have a better performance there is a need to transform the attributes values into homogenous and well-behaved values that yield numerical stability [32], [33]. This will increase the credibility of the ANN design.

Normalization is an approach commonly used for data pre-processing. The major reason for the normalization of the dataset is to scale value that will match the input neuron range. Therefore, since sigmoid function will be used as the activation function for the hidden neurons and output neuron. This has a value which range between 0 and 1. Then, the amplitude value of each vector will be found and use to divide the vector data to give a value range between 0 and 1. Table 1 shows the highest value of each attributes of the dataset for the first five attributes.

Attribute 1 (Attr. 1)	1
Attribute 2 (Attr. 2)	1
Attribute 3 (Attr. 3)	151
Attribute 4 (Attr. 4)	132
Attribute 5 (Attr. 5)	120

Table 1 The maximum value for first five attributes

After finding the maximum value of each attribute, each value will then be use to divide its corresponding vector to obtain a value ranging between 0 and 1 for each vector. Table 2 shows the first five unnormalized datasets and Equation 1 is a mathematical representation of the normalization approach.

Attribute	Samples				
Attr 1	1	1	1	1	1
Attr 2	1	1	1	1	1
Attr 3	22	24	62	55	44
Attr 4	22	24	60	53	44
Attr 5	22	22	59	53	44

Table 2 The unnormalized samples for Diabetic Retinopathy

$$\text{V.N} \quad = \quad \frac{\text{Value of each vector}}{\text{Corresponding maximum value}} \tag{1}$$

Table 3 shows the result obtained from normalizing the sample. The first five attributes with first five normalized sample is shown in Table 3.

Attribute	Samples				
Attr 1	1.000	1.000	1.000	0.000	1.000
Attr 2	0.000	1.000	1.000	0.000	0.000
Attr 3	0.317	0.311	0.218	0.198	0.059
Attr 4	0.348	0.333	0.250	0.227	0.068
Attr 5	0.375	0.3417	0.2417	0.2500	0.0750

Table 3 The normalized samples of Diabetic Retinopathy

3 Design of the proposed intelligent system

Being an intelligent system engineer, the main goal is to achieve a system that will outperform other previously designed systems. Besides, because of the significant of diabetic retinopathy in medical field, there is a need to design a system with high accuracy to avoid misdiagnosis by the physician diagnosing the disease manually. Such a system will also safe time consume in diagnosing a patient manually. Therefore, in this work this model is considered to ascertain the best outperform system needed for diagnosis of retinopathy diabetic. This system is feedforward neural network trained with backpropagation neural network.

In this proposed feedforward neural network for the diabetic retinopathy, there are three layers; the input layer, hidden layer and the output layer. The input layer is a non-processing layer. Its only represent inlet of the neural network. It is a layer where the dataset is being introduced into the neural network. The hidden layer is the processing layer of the neural network. It made up of activation function and has the ability of updating the weight. The third layer is the output layer. This is also a processing layer. It produces the result of the network. It should be noted that sigmoid activation function is used in this work as the activation function for the neurons at the hidden layer and output layer because of its soft switching ability and its simplicity in derivative. The dataset for the intelligent system (feedforward neural network trained with backpropagation algorithm) is divided into two; the training dataset and the testing dataset. The ratio 60: 40 is used to obtain the proportion for the training dataset and the testing dataset. This ratio is chosen because is the best proportion for determining training dataset and testing dataset in machine learning. This proportion helps the intelligent systems to overcome the problems that occur in machine learning such as overfitting and underfitting.

Therefore, out of 1151 dataset, 691 dataset is taken out as the training dataset while 460 dataset is obtained as the testing dataset. Also, an attribute present a neuron in the input layer of the system. Therefore, there are nineteen (19) neurons present at the input layer of the network with two neurons at the output layer of the network. These two neurons denotes whether a patient have diabetic retinopathy or not. The output neurons are coded diabetic retinopathy present (1 0) or no diabetic retinopathy (0 1). The number of neurons in the hidden layer is determined during the training of the intelligent system.

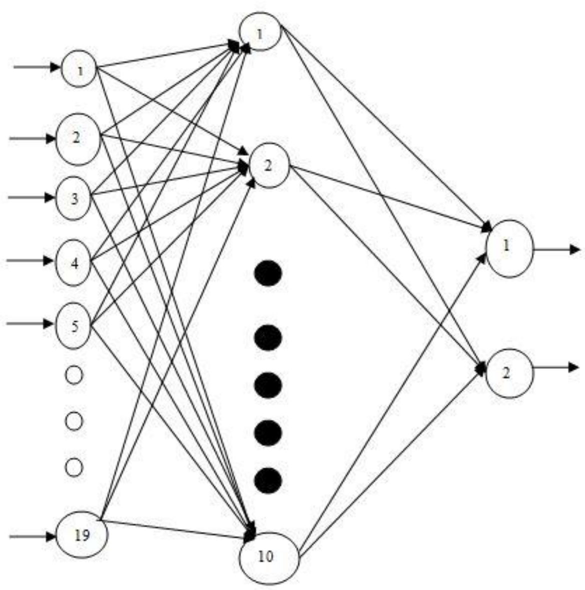

Fig2. The proposed intelligent system for diagnosis of diabetic retinopathy

For the training of the intelligent system, the batch algorithm is employed where the training dataset is fed into the neural network once with its corresponding target. Therefore, a matrix 19*691 sample is fed into the network with its corresponding target matrix 2*691. As we obtained a better performance from the training of the neural network system, the testing dataset (matrix 19*460) will then be introduced to the already trained system, at this time without its corresponding desired output. The result obtained from the system will be cross check with the desired output to obtain the performance of the system. Figure 2 shows the proposed intelligent system for diagnosis of diabetic retinopathy.

4 Result evaluation

To achieve a better performance for an intelligent system, several parameters have to be put under consideration. These include a learning rate, momentum rate and hidden neurons. The learning rate is the rate at which the network learns from the pattern introduced while the momentum rate determined the speed at which learning take place in the network. The hidden neuron is one of the main parameters that determine the performance of the network. Selection of the hidden neurons can be done considering three approaches [34]. These are (i) Fixed approach (ii) Constructive approach and (iii) Destructive approach. In fixed approach, certain hidden neuron will be selected and the network will be trained and tested on these selected hidden neurons. The network with the best performing hidden neuron out of these chosen neurons will be considered as the best network. In the case of the constructive approach, during the training of the network certain number of hidden neurons will be chosen then increasing the neurons until a better performance is obtained. Also, for the destructive approach, higher number of hidden neurons will be selected for training of the system then these neurons will be reduced until a better performance is obtained. In this work, constructive approach is applied for the selection of the hidden neuron. Two neurons are initially selected then increased until ten neurons are reached.

The ten (10) neurons produced the best performance of the system. Other parameters are also varied to enhance the network in reaching the best performance. Such parameters are learning rate and the momentum rate. The learning rate that produced the best performance of the system is 0.33 at the momentum rate of 0.77. Table 4 is the result evaluation table for the training and testing of the neural network.

No of Input neurons	19
No of hidden neurons	10
No of output neurons	2
No of training samples	691
No of testing samples	460
Training Time	0:44secs
Recognition rate	99%

Table 4 Result performance for the intelligent system

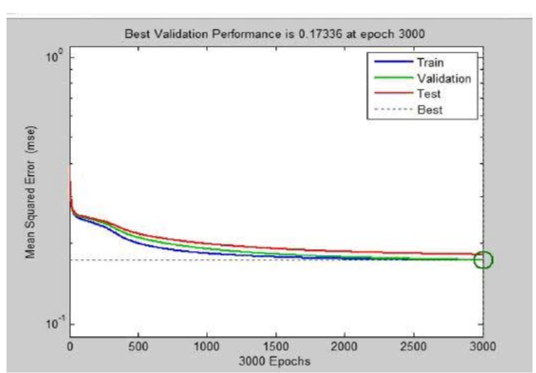

Fig 3: The minimum square error against epoch

To determine the best intelligent system that can be used to diagnose the diabetic retinopathy in any patients. There is a need to compare our proposed intelligent system with previously designed intelligent systems. This is done to ascertain the best intelligent system that will be more useful in diagnosis of the disease.

In Table 5, other previously designed models were compared with our new proposed model. It should be noted that our proposed model gave a recognition rate of 99% which outperformed the previously designed models. Although all other models also shown a better recognition rate but because of the significant of the disease in the medical field, the best recognition rate is required. Therefore, our model provides the best accuracy required or needed for diagnosis of diabetic retinopathy by the physicians.

Author(s) and Year(s)	Model(s)	Recognition Rate
Aruna et. al (2013)	PNN MPNN RBFN MRBFN EYENET	96% 97.5% 93.5% 95.5% 98.5%
Ananthapadmanaban and Parthiban (2014)	Naïve	83.37%
Our Proposed work (2016)	Neural Network	99%

Table 5 Performance comparison of our work with other previously designed systems.

5 Conclusion

Diabetes retinopathy has been discovered to be the cause of blindness all over the world. Also, misdiagnosis of the disease on the part of the physicians or patients not yielding to the prescriptions administered by the physicians in the early diagnosis of the patient for diabetes retinopathy.

Therefore, early accurate diagnosis of diabetic retinopathy is essential for medical practitioners. This will enhance the treatment of the disease before leading to complication by prescribing the accurate drugs and given medical advised to the patients.

In this work, an intelligent system for diagnosis of diabetic retinopathy has been developed. In proposing this model, we have taken into cognisance: the time required by this novel system for diagnosis of the disease, the effectiveness of the system of this system in terms of the best accuracy needed by the physician. Therefore, this novel model can diagnosis diabetic retinopathy in any patient at a very fast rate and obtained the best accurate result from the diagnosis.

It should also be noted that in order to ascertain the best intelligent system for diagnosis of diabetic retinopathy; several previously designed models were also considered. In spite of this, our intelligent proof to be the best among all these other models..

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