Genetic Algorithms Based Approach for Dental Caries Detection using Back Propagation Neural Network

Paras Tripathi, C.Malathy, M.Prabhakaran

Abstract**: *The detection of dental caries from radiograph is a very challenging task for Dentists, often early forming caries are overlooked or misclassified. The goal is to assist dentists to detect these caries in early stages so that the severity of the decay caused by delayed treatment can be avoided. To solve this problem a system is proposed which is capable of recognizing dental caries from bitewing radiography. The dental caries radiograph has a certain number of grey level pixels which are a differentiating factor from normal teeth. Therefore, the system utilizes Local Binary Pattern (LBP) to extract second order statistical texture features. These extracted features would be utilized by a backpropagation neural network to characterize the severity of caries. The Hybrid approach will help further to optimize the hyperparameter problem in the neural network and increase accuracy in prediction.***

Index Terms: Local Binary Pattern, Backpropagation, Neural Networks, Genetic algorithm.

I. INTRODUCTION

Dental caries (tooth decay) are the 2nd most widespread disease in the world. It affects above 80% of children and a vast majority of adults in urban countries. Tooth decay affects more than one-fourth of U.S. children ages 2 to 5, half of those ages 12 to 15, and more than 90 percent of U.S. adults over age 40 [1]. The process of clinically inspecting affected teeth rely on visual cues which are difficult to detect from the naked eye. These hidden caries remain undetected and grow with time. Automated methods can help locate these newly forming caries in tricky areas like between the teeth. Therefore an accurate, automatic and fast method to detect dental caries is of great significance. A Machine learning based approach can be effective in identifying these caries in early stages compared to the visual diagnostic procedure which is slow and difficult.

For preprocessing of bitewing radiographs the image is first binarized and then masked with the original image to get the Region Of Importance. Then Local Binary Pattern is used to extract the histogram feature from the masked radiograph. The speed and accuracy are the prime factors for dental caries detection The automatic detection involves Local binary patterns for feature extraction and ANNs used as a classifier tool. The program was tested on radiographs with caries and without caries and the proposed framework could detect and classify the teeth radiographs with 95% precision. Concluding the aim of this work is: 1) identifying dental caries from radiographs 2)based on the feature extracted through the local binary pattern and 3)classified by ANNs into categories of caries and no caries.

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II. RELATED WORKS

Tooth Decay is the second most common disease worldwide, therefore, we require a method that could detect them in early stages and a lot of work has been done in this field and therefore a detailed survey performed in this field is presented in this section. In [2] the authors have proposed an approach to segment region from the background by applying the combination of region growing and edge detection which eliminates false boundaries and provide better segmentation. The segmentation by K-Means clustering is demonstrated in [3] where authors have proposed to form two clusters and analyze these clusters for the plaque. The authors in [4] perform automatic segmentation in carries the apply binarization and remove false boundaries which leads to darker spots which demonstrate the presence of caries in the teeth. The authors in [5] utilized boundary extraction and contour extraction and applied GLCM to details about the tooth.

III. PROPOSED WORK

3.1. Caries classification using and genetic algorithm bases BPNN Classifier

The primary goal of the proposed work is to train the BPNN for the classification problem. Getting the best accuracy and significant low error is a formidable task. Therefore selecting a learning rate is an important step for better results from the neural network. The paper presents a hybrid approach which optimizes the learning rate for the BPNN and hence avoids the potential problems of local minima and minimizes the mean square error for optimal results. The complete process is explained in Fig 1.

Dataset The dental X-ray images are acquired from the med lab archives of 800 images in the total dataset

3.2. Segmentation

The segmentation process strives to extract the most suitable region of interest to generate quality features for the images acquired from

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dental radiographs. The technique eliminates the unnecessary background by first binarizing the image and then using it as a mask for the original image. This reduces the background noise and provides a well-defined region of interest for feature extraction.

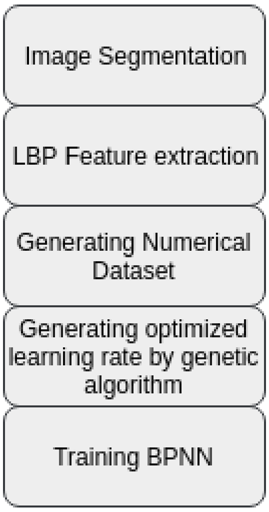

Fig. 1.The workflow for the classification

Fig. 2.The Masked Image with removed background

3.3. Feature extraction using Local Binary Patterns

The Local Binary Pattern(LBP) utilizes 2 properties of the textural feature in an image they are grayscale contrast and local spatial patterns. The LBP divides the image into grids of 3X3 adjacent pixels and modified to a certain radius length. If the adjacent pixel is brighter it is assigned 1 and 0 if its darker.performing the following iteration over complete image provides us with a value for each neighborhood which forms the LBP Histogram[6].

The LBP operator is applied to labeled image fl(x,y).

The I{A} is 1 if A is true and 0 if I{A} is false.

The varying size histograms are needed to be compared and hence normalization is required to compare differently sized histograms.

$$N_i = \frac{H_i}{\sum_{j=0}^{n-1} H_j}. \qquad (2)$$

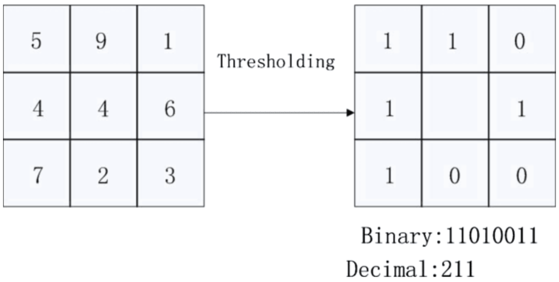

Fig. 3.Calculation of Histogram values from neighborhood pixels

3.4. Genetic Algorithm

The genetic algorithm is used in the BPNN to solve optimization problems that are based on natural selection in this case selection of the optimal learning rate from an initial population, It is based on the principle of biological evolution. The genetic algorithm produces a population till certain iterations of individual solutions. At each step, the genetic algorithm selects the individual which produces the least error from BPNN then uses it as a parent to produce subsequent children list of solutions. After certain generations, an optimal solution is generated.

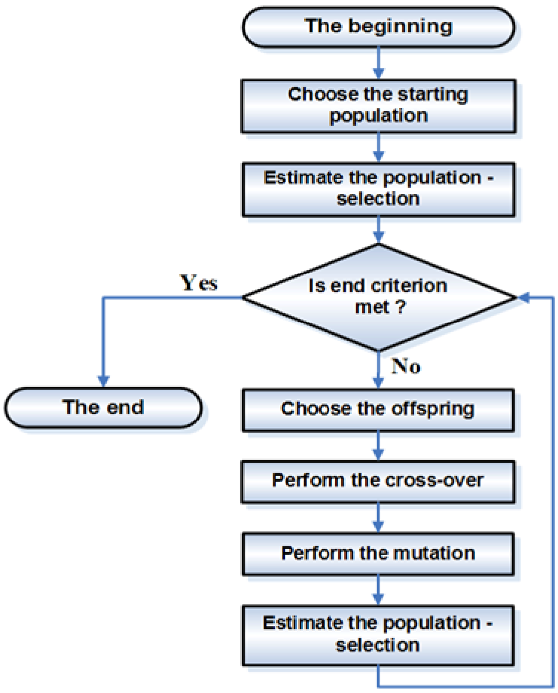

Fig. 4. Algorithm for Genetic Algorithm

3.5. Back-Propagation Neural Network

Artificial neural networks are a set of weights that are updated to an optimal value based on the mean square errors by comparing the input given to the network and output produced by it. The network used in this paper consists of an input layer, 1 hidden layer, and an output layer. The flowchart Fig. 5.shows how the genetic algorithm is embedded in the neural network and hence optimize the learning rate with each iteration. The BPNN architecture shows how the radiograph image is converted to its respective numerical features which are analyzed by The

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artificial neural network.

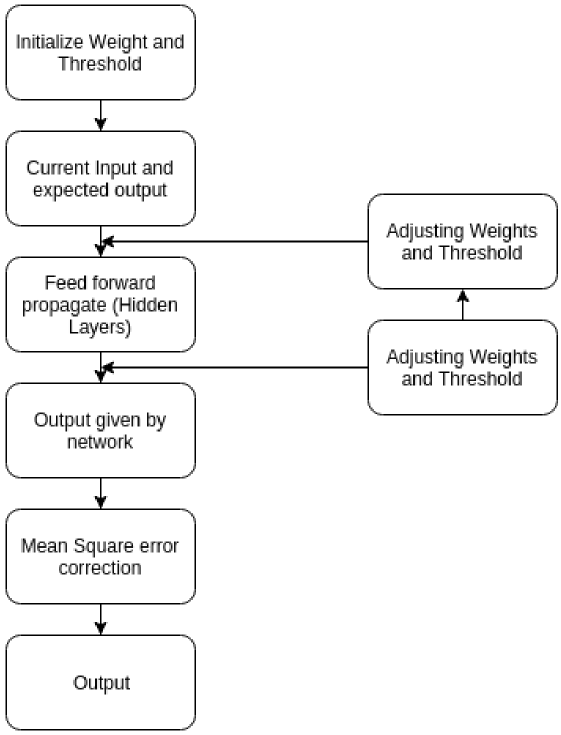

Fig. 5.Algorithm for Backpropagation Neural Network

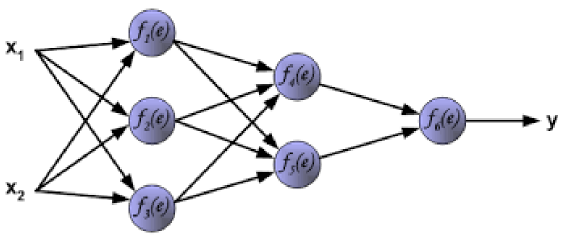

Fig. 6. Neural Network Architecture with Input, Hidden and Output Layers

IV. EXPERIMENT RESULTS AND ANALYSIS

Hyperparameters play a very important role in the generation of accurate results. Therefore a hybrid approach is utilized to get the optimum learning rate. The initial population of learning rate is taken into consideration for 10 generations and the process is repeatedly applied to get the best learning rate in each iteration. The mutation is performed with respect to the fittest element of the previous population by taking an average with it to find the search space effectively is shown in Table 1.

Table 1.Selection of best candidate in each iteration

Generation	Population	Mean Square Error
1	0.1	0.008998
	0.01	0.017194
	0.001	0.095921
	0.0001	0.195735
3	0.1	0.005772
	0.0775	0.006146
	0.087635	0.006194
	0.087512	0.006198
5	0.1	0.005782
	0.094375	0.005854
	0.093812	0.005854
	0.093756	0.005862
7	0.1	0.005776
	0.098593	0.005774
	0.098453	0.005758
	0.096878	0.005795
10	0.098646	0.005777
	0.098470	0.005771
	0.098453	0.005758
	0.098541	0.005791

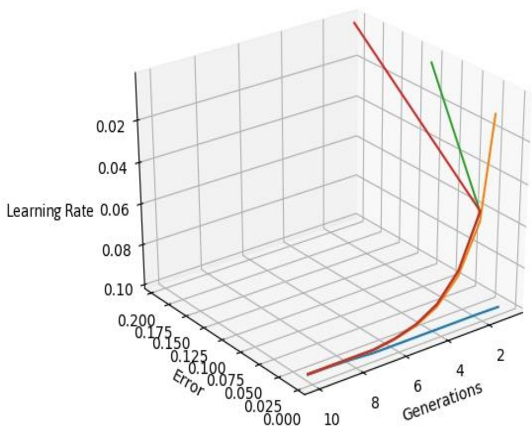

Fig. 7.The convergence of learning rates to an optimal value in 10 generations with minimized error

Once the optimal learning rate is generated by the genetic algorithm we utilize it for evaluating the accuracy of the BPNN.

The error of a back-propagating neural network should be reduced after every epoch which is demonstrated in Table 2:

Table 2. Reduction of error with each epoch

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Epoch	Mean Square Error
0	0.279273803084985
10000	0.007298751966825
20000	0.003278845346419
30000	0.002405979660704
40000	0.001975932173152

The decrease of error after subsequent iterations demonstrate that the machine is learning after each iteration and demonstrates and presents a hyperbolic learning curve in Fig. 8.

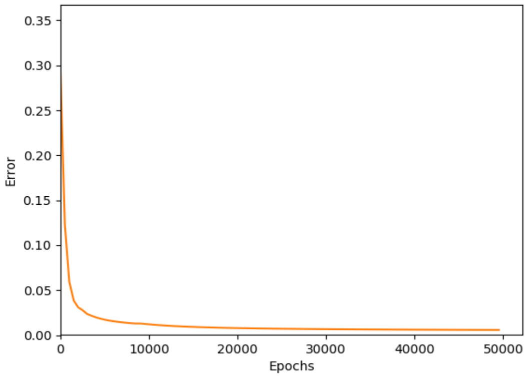

Fig. 8. Reduction of error with respect to each epoch

V. Conclusion and Future Work

This section demonstrated how a BPNN can be used along with the genetic algorithm to classify tooth with caries and without caries. The proposed hybrid approach enabled BPNN classifier produces training and testing accuracy of 95.42% with the reduced MSE of 0.0019 The future work is to perform a unified feature extraction method that can detect diseases with similar characteristics as of dental caries.

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