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Eye Diseases Classification Using Back Propagation Artificial Neural Network

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K E Y W O R D S

Back Propagation, Eye Diagnosis, Feature Extraction, Hue, Min, Max, Diff (HMMD) color space, Laws Feature.

A B S T R A C T

A human eye is a vital organ responsible for a person's vision. So, the early detection of eye diseases is essential. The objective of this paper deals with diagnosing of seven different external eye diseases that can be recognized by a human eye. These diseases cause problems either in eye pupil, in sclera of eye or in both or in eyelid. Color histogram and texture features extraction techniques with classification technique are used to achieve the goal of diagnosing external eye diseases. Hue Min Max Diff (HMMD) color space is used to extract color histogram and texture features which were fed to Back Propagation Artificial Neural Network (BPANN) for classification. The comparative study states that the features extracted from HMMD color space is better than other features like Histogram of Oriented Gradient (HOG) features and give the same accuracy as features extracted directly from medical expert recorded symptoms. The proposed method is applied on external eye diseases data set consisting of 416 images with an accuracy rate of 85.26315%, which is the major result that was achieved in this study.

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1. INTRODUCTION

The human eye is the most important organ among the five senses, so early detection of external eye diseases has become an important issue in medicine. Pattern recognition has a wide area of applications. One of these applications is in the medical field. Early detection of eye diseases prevents the diseases to become more complicated. It also reduces the burden in the

hospitals, as well as it enables people far away from hospitals to check the health of their eyes and take the necessary actions to prevent the worsening of eye disease conditions.

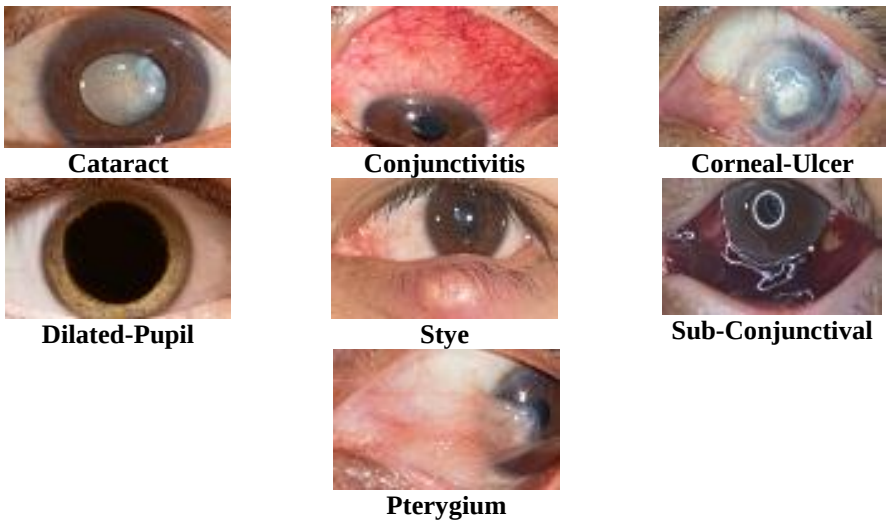

Figure 1: Seven External Eye Diseases.

Machine learning has proved that it has the ability to produce very good accuracy in diagnosing different medical conditions like chests X-ray, breast cancer, and many others. [1]

This paper classifies seven different external eye diseases (Cataract, Conjunctivis, Corneal-Ulcer, Dilated-Pupil, Stye, Sub-Conjunctival, and Pterygium) as seen in Figure 1. First, eye image is converted from (Red, Green, and Blue) RGB color space into HMMD color space. Second, non-linear quantization is applied on the resultant image. Third, histogram features besides texture features using Law features are extracted. Lastly, these features are fed into Back Propagation for classification purposes.

This paper is organized as follows: In section 2, related work is discussed. In section 3, two types of feature extraction methods are discussed, while Architecture of Back Propagation used in this paper explained in details in section 4. The methodology used in this paper explained in section 5. Results & discussions presented in section 6. Finally, conclusions are illustrated in section 7.

2. RELATED WORK

Many studies were completed for diagnosing eye diseases, different feature extraction techniques and classification algorithms were developed in these studies. Some of them are discussed in this section, such as Cost-Sensitive deep residual convolutional neural network classifier was used to diagnose ophthalmic diseases using retro-illumination images in [2]. Only two kinds of eye diseases (Cataract, Conjunctivitis) were recognized through HOG features which classified by using minimum distance classifier in [3]. In another article, five eye diseases were selected to be classified utilizing HOG features with Artificial Neural Network [4]. Whereas, in Ref [5] medical expert recorded symptoms directly in the form of standard taxonomies from which features were extracted and four different classification methods (Decision Tree, Naive Bayesian, Random Forest, and Neural Network) applied on these features to identify eye diseases. Instead, Hybrid approach was implemented in [6], known as Neural Networks Decision Trees, where symptoms and physical eye conditions learned with neural network to acquire rules were fed to Decision Tree in order to diagnosis the eye diseases. Finally, Gray Level Co-occurrence Matrix (GLCM) was used to extract features that fed to Bayesian Regularization Back-Propagation Neural Network (BRBPNN) classifier to identify Corneal Arcus in [7].

3. FEATURE EXTRACTION

Feature extraction is the process of reducing the dimensions of an image to describe the image according to the extracted features. Different features can be extracted from the same image according to different feature extraction methods [8].

I. HMMD Color Space

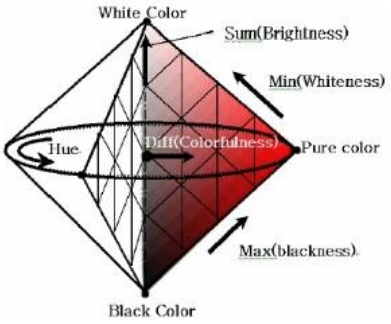

Figure 2: HMMD Color Space.[9]

HMMD is a more perceptual uniform color space. It stands for Hue (same as Hue in HSV (Hue Saturation Value) color space) Min, Max, Diff are the result of transform equations from RGB into HMMD color space.

$$Min = min(R, G, B) \quad (1)$$

$$Max = max(R, G, B) \quad (2)$$

$$Diff = Max - Min \quad (3)$$

In addition to these three equations, another component was defined is sum and its equation as follows:

$$sum = (Max + Min)/2 \quad (4)$$

HMMD color space has the shape of double cone as shown in Figure 2, and it can be defined from three of five components, either by Hue, Diff, and Sum (HDS) or by Hue, Max, and Min (HMM). As mentioned previously Hue is the same as in HSV color space, while Diff has the same property of Saturation in HSV color space, and Sum gives the brightness of the color [9].

1) HMMD Color Space Quantization

Four color space quantization points were defined on the HMMD color space: 256, 128, 64, and 32 bins. The quantization process as shown in Table I does as follows: HMMD color space is divided into five sub-spaces according to Diff component by the following intervals: [0, 6], [6, 20], [20, 60], [60,110], and [110, 255]. Then, each of these color sub-spaces are quantized uniformly depending on Hue and Sum components, where the quantization level of these component is determined[10].

TABLE I: HMMD Color Space Quantization.[10]

Component	Sub-Space	Number of Quantization Levels for Different Numbers of Histogram Bins			
		256	128	64	32
Hue	0	1	1	1	1
	1	4	4	4	4
	2	16	8		
	3	16	8	8	4
	4				

Sum	0	32	16	8	8
	1	8	4	4	4
	2	4			
	3	4	4	2	1
	4			1	

II.Laws Features

There are many approaches for extracting texture features. One of them is Law Mask texture features; it was created by Kenneth Ivan Laws in 1980. Laws features extracted by applying convolution operation between certain mask and the image to extract specific texture properties from the image. These masks obtained by combining one dimensional kernel .[11, 12] Laws combines five labeled vectors to form 2D kernel mask, each mask responsible of extracting certain property from the image when it convolved with that image.[13] The vectors are L5=[1 4 6 4 1] to enhance Intensity Level, E5=[-1 -2 0 2 1] to enhance Edges, S5=[-1 0 2 0 1] to enhance Spots, R5=[1 -4 6 -4 1].to enhance Ripples, and W5=[-1 2 0 -2 1] to enhance Waves.[14] The cross product of these five vectors in the horizontal and vertical directions to produce 25 2-D convolutional masks.[14]

4. BPANN

BPANN is one of Artificial Neural Network most popular methods used to optimize Feed Forward Neural Network training due to its flexibility, competence, and solve problems in many situations such as pattern recognition, function approximation, pattern matching, and associative memories,[15] since it is robust, fault-tolerance, and parallel solution. It is allow learning information collected from different sources or kinds.[16] BPANN is a supervised Learning Algorithm, in which the input is processed to map the desired output by reducing the error between the desired output and the calculated output driven from the inputs and the network learning.[17] with feed forward architectures, three different layers are constructed. Input layer, is a set of input neurons which accept input elements fully connected to the hidden neurons in the hidden layer. Hidden Layer, in turn, is fully connected to the output neurons in the output layer. The response of the neural network produced by the output layer is back propagated to the activation neurons in the hidden layer. In general, the information that feed to the neural network is propagated forward and backward layer by layer between input layer and output layer. [18] Weights are associated with each connection between input and hidden layers and between hidden and output layers. These weights determine the strength of the input vector. If the weight is positive, it excite the node output. If the weight is negative, it inhibit the node output.[18] The aim of the back propagation function is to reduce the error function in weight space by the gradient descent. This requires, at each step, the gradient of the error function must be computed in order to guarantee the continuity and differentiability of the error function. The structure of BPANN of two layers explained in Figure 3.

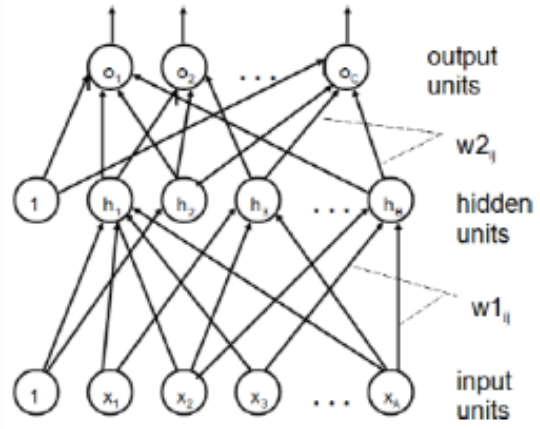

Figure 3: The Structure of 2-layer BPANN.[16]

Some of activation functions that provide the above conditions are sigmoid function, symmetrical sigmoid function, hyperbolic function, and others.[19] Symmetrical sigmoid function used in this paper is defined by the following equation:

$$y = \frac{1 - e^{-net}}{1 + e^{-net}} \quad (5)$$

And its shape is shown in the Figure 4 below.

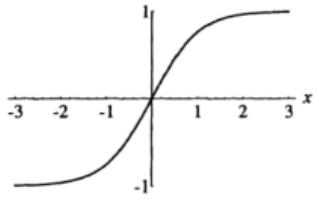

Figure 4: The Graph of the Symmetrical Sigmoid Function.[19]

$$net_j^h = \left(\sum_{i=1}^{A} W_{ij}^1 X_i\right) + b_j \quad (6)$$

where, $w_{ij}^1$is the weight of the connection between neuron i in the input layer and neuron j in the hidden layer. net_j^h is the result of activation function for the j^{th} hidden neuron. b_j is the bias for the j^{th} neuron.

$$net_j^o = \left(\sum_{i=1}^{B} W_{ij}^2 y_i\right) + b_j \quad (7)$$

where, w_{ij}^2 is the weight of the connection between neuron i in the hidden layer and neuron j in the output layer. net_j^o is the result of activation function for the j^{th} output neuron.

To assess the accuracy of the neural network, the mean square error quantifies the amount by which the estimated output differs from the desired output which, known as the error. Mean square error is widely used as a cost function in neural network due to its good performance in large datasets on real world problems.[20] The objective of back propagation is to minimize the neural network error described by the following equation.

$$E = \frac{1}{2}\sum_{i=1}^{n} (y_i - d_i)^2 \quad (8)$$

where, n is the number of network output. y_i is the i^{th} output of the network. d_i is the i^{th} desired output of the network.

The learning process of back propagation algorithm is an optimization problem that aims at finding the weight coefficients for a given training set. First of all, the weights are chosen randomly in range between (0, 1). Secondly, the training data are fed to the input neuron. Then, the output of the hidden layer and output layer are calculated according to the equations (6) and (7) respectively. The error between the network output and the desired output is calculated according to the equation (8), while the error for the output layer calculated according to the equation (9) [21].

$$\delta_i^O = y_i^O\left(y_i^O - d_i\right)\left(1 - y_i^O\right) \quad (9)$$

where, δ_i^O is the error of the i^{th} output neuron. y_i^O is the i^{th} output neuron, and the error for the hidden layer is calculated according to the equation (10).[21]

$$\delta_i^h = y_i^h(1 - y_i^h) \sum_{j=1}^{C} W_{ji}^2 \delta_j^O \quad (10).$$

where, δ_i^h is the error of the i^{th} hidden neuron. y_i^h is the output of the i^{th} hidden neuron. The weights modifications are calculated as follows:

$$\Delta w_{ij}(t) = \alpha \delta_i^l(t) y_j^{l-1} + \beta \Delta w_{ij}(t-1) \ (11).$$

where, Superscript l denotes the input layer while superscript $l-1$ denotes the hidden layer in case of the input-hidden weight. While superscript l denotes the hidden layer and superscript $l-1$ denotes the output layer in case of the hidden-output weight. α is the momentum term and β is the learning rate term. Lastly, t is the current iteration and $t-1$ is the previous iteration.
The Bias modification for each neuron in hidden and output layers calculated as:[21]

$$\Delta B_i(t) = \alpha \delta_i(t) + \beta \Delta B_i(t-1) \ (12).$$

The new weights and new bias for each neuron in hidden and output layers are calculated as:[21]

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t) \quad (13).$$

$$B_i(t+1) = B_i(t) + \Delta B_i(t) \quad (14).$$

where, $t+1$ is the next iteration.

5. THE PROPOSED METHOD

Seven external eye diseases (Cataract, Conjunctivis, Corneal-Ulcer, Dilated-Pupil, Stye, Sub- Conjunctival, and Pterygium) are classified in this paper. Figure 5 illustrates the block diagram of the proposed method. Data set of external eye diseases was taken from https://www.shutterstock.com/ , in which each image is converted from RGB color space to HDS color space, as shown in Figure 1. Each disease can be recognized by both its color and its texture. For color features, the converted images quantized into 32-bins as mentioned in section I, then, the color histogram was computed. For texture features, laws texture features were utilized. 25-Masks of Laws texture features are applied to Sum channel of HDS. As a result, the feature vector consists of 49 feature points that were obtained. Before feeding the feature vectors into back propagation neural network, the mean and standard deviation of all feature vectors were computed and each feature point subtracted from the computed mean and divided by computed standard deviation in order to standardize the feature points as a pre-processing step. The data set is partitioned into training set and test set according to the ratio (80:20) respectively. Finally, neural network built with single hidden layer in addition to input and output layers using OPENCV-MLP (Multi-Layer Perceptron) in JAVA Programming Language. In which, the input layer consists of neurons equal to the number of features in feature vector, the output layer consists of neurons equal to the number of eye external diseases, while the number of neurons in the hidden layer are computed according to the following equation (15):

$$no.of\ hidden\ neuron = \frac{(no.of\ input\ neuron + no.of\ hidden\ neuron)}{2} \quad (15)$$

The learning rate used is equal to (0.002), while the momentum term used is equal to (0.078). The error excepted is equal to (0.000001), and the number of iterations is equal to (1000).

6. RESULTS & DISCUSSIONS

The proposed method applies on seven external eye diseases that can be observed by a human eye only. These diseases cause problems either on eye pupil, sclera of eye, or both of them or on eye lid. Two types of features are used in this paper; color features and texture features. Table II shows HDS Color Histogram feature extraction is applied on a sample from

each disease. Table III shows Laws texture features extracted from a sample of each eye disease. Both of these features are normalized to have a unified scale (between 0 and 1) before feeding them to the network.

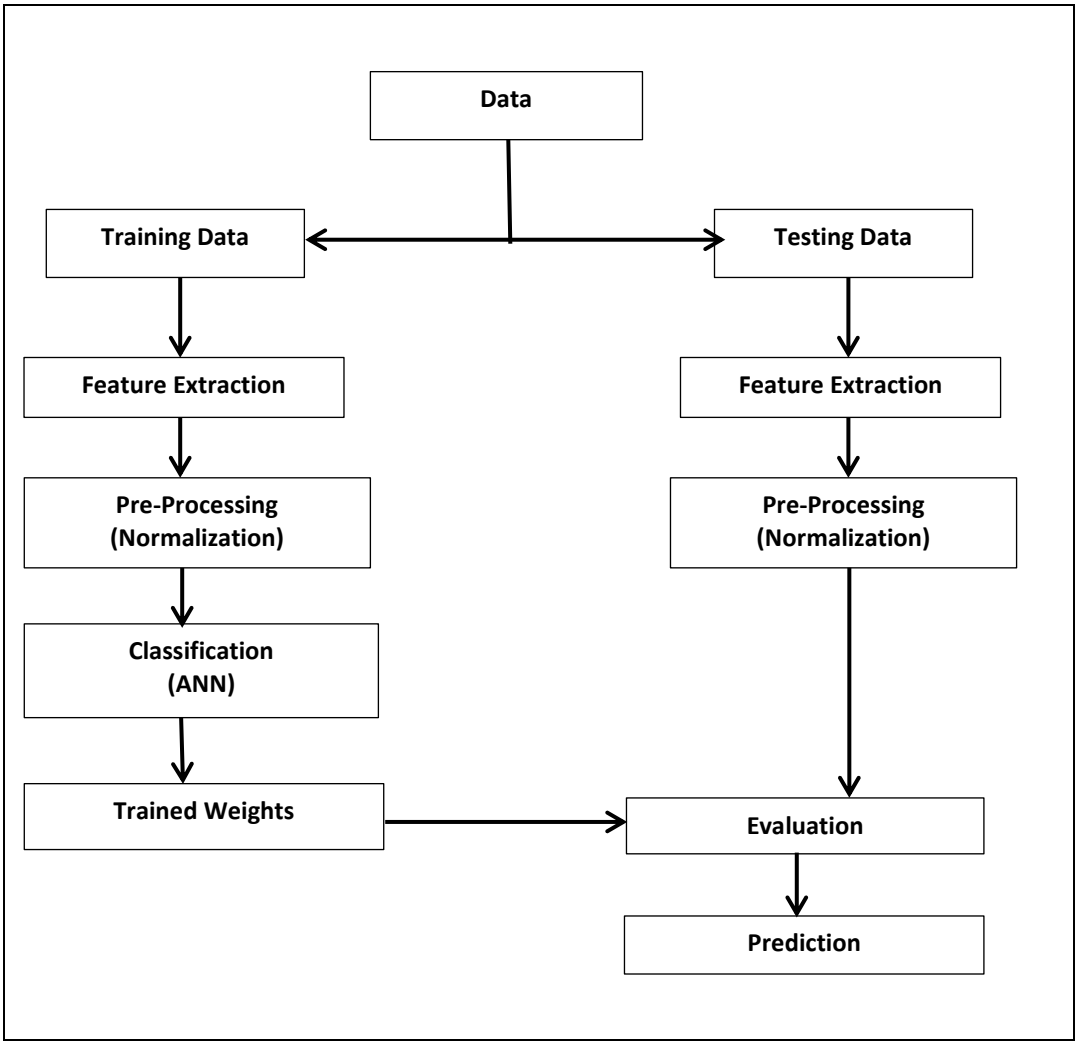

Figure 5: The Block Diagram of the Proposed Method.

The success of the neural network depends on making the predicted output the same as the desired output as much as possible using gradient descent. Experimental tuning the learning rate parameter did not lead to improvement in performance significantly. Precision of Stye and Dilated-Pupil diseases is 100%. Another two eye diseases (Corneal-Ulcer and Conjunctivis) have a precision greater than 90%, while the other three eye diseases have precision lower than 90%. Cataract precision is about 60%, while Pterygium precision is about 85%, and Sub-Conjunctival precision is about 75%. The last three eye diseases precisions affect the overall classification performance. Increasing the size of data set can lead to improving the classification performance. The accuracy achieved by the proposed method is equal to 85.26315%, and F1-Score measurement is also utilized and gives 85.95%, while sensitivity equal to 85.5%, and, specificity equal to 87.44%. Comparative study between the proposed method and related work is presented in Table IV.

7. CONCLUSION

The proposed method illustrates that the features extracted from HMMD color space are better features that give higher accuracy than HOG features in (1) in Table IV. Also, features extracted from HMMD color space gives approximately the same classification accuracy as compared to (5) in Table IV. In the future, additional external eye diseases like Cyst, Glaucoma, Keratitis, and Uveitis can be added to be classification.

TABLE II: Color Histogram Feature Extraction of Seven Eye Diseases.

Cataract	Conjunctivis	Corneal-Ulcer	Pterygium	Stye	Sub-Conjunctival	Dilated-pupil
62	0	0	60	82	0	125
29	0	15	25	4	25	24
14	0	1	11	0	31	14
58	1	0	3	0	3	9
36	0	0	3	0	0	6
15	2	0	0	0	0	34
39	0	0	1	0	0	1
396	0	1	930	169	1	765
158	276	63	250	322	86	95
206	48	46	75	264	129	0
202	4	0	4	32	0	0
0	0	0	44	5	3	512
9	0	0	2	0	90	230
193	0	0	3	0	16	100
4	0	0	2	0	0	14
76	0	93	216	8	57	226
390	34	874	25	6	627	48
858	13	5	5	0	70	150
96	9	0	7	2	14	114
80	0	56	208	5	80	67
283	544	376	28	1	112	3
119	468	98	56	1	195	1
25	131	1	0	1	1	0
0	21	335	687	2420	357	0
0	0	0	0	0	0	6
5	0	0	0	0	4	50
0	1753	1177	4	1	892	0
0	0	9	619	29	199	0
0	0	0	0	0	0	0
0	0	0	0	0	0	29
0	49	203	0	0	361	0
62	0	0	60	82	0	125

TABLE III: Laws Textures Feature Extraction of Seven Eye Diseases.

Cataract	Conjunctivis	Corneal-Ulcer	Pterygium	Stye	Sub-Conjunctival	Dilated-pupil
1752.791748	1565.850708	1100.722046	1452.144897	1495.967041	1546.809937	1070.377563
2.82E+08	3.34976224E8	1.19E+08	2.50E+08	3.32E+08	2.26E+08	1.31E+08
37.87215424	43.73278427	35.54897308	37.09519958	35.77283859	54.54650116	51.43429184
169136.5469	189746.0625	121805.9844	140036.75	162473.5156	295794.7188	359959.0313
50.95198822	49.91495132	33.85020447	42.42304611	47.81344223	47.82057571	37.27791595
220619.1875	249443.2188	94894.0625	183024.2813	249168.7813	184751.7031	169890.9063
66.80164337	121.5632401	101.6894379	71.74375916	138.3105621	117.659256	86.84279633

623046.1875	1718910.875	963024.75	584662.5625	1813844.625	1608470.25	1057172.875
356.6337585	316.7009583	238.7914886	291.4016418	298.3064575	339.276001	249.5064545
1.01E+07	9736398	4532998.5	8286297	9802411	8926314	6852615
233.862548828125	238.6282654	152.8076782	192.8765411	222.8677673	235.5508881	159.1893005
5160179	6595645	2033148	3893909.75	6426292	4630331	2839480.75
216.3278503	323.6425171	178.3393707	169.7722931	325.1549988	277.8200378	214.234024
5170109	1.11E+07	2682262.75	2455534	1.06E+07	6640234	7509961.5
36.35089111	59.61069871	46.43264771	38.13827133	55.77558136	59.61948013	53.03539276
133086.0625	397138.5625	191232.7344	142320.2031	270872.7813	363257.125	456602.0938
25.67764091	43.33607864	35.50068665	26.96323776	42.49135971	42.19835281	39.90260696
71035.92188	199673.3281	115586.7109	73586.28125	159945.8594	191009.7813	312909.6563

TABLE IV:Comparative Study.

Index	Author	Used Method	Obtained Accuracy
1.	[4]	Artificial Neural Network learned on HOG features	77%
2.	[5]	Decision Tree learned on patient symptoms	85.81%
3.	[5]	Naïve Bayes learned on patient symptoms	81.53%
4.	[5]	Random Forest learned on patient symptoms	86.63%
5.	[5]	Neural Network learned on patient symptoms	85.98%
6.	[6]	Neural Networks trained on (patient complain, symptoms and eye condition or cause) to extract rule for Decision Trees	92%
7.	[7]	BRBPNN applied on GLCM features	96%
8.	Our	BPANN learned on (HDS+Laws) features	85.26315%

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