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Development of Computer-aided Conjunctival Hyperemia Screening System based on Eye Image using Machine Learning Algorithms

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Abstract:Conjunctival Hyperemia is an eye disease, which in critical stage may leadto vision loss. The damage due to Hyperemia can be avoided, if detected and treated during early stages. There istremendousscope to develop automated Hyperemia diagnosis tool based on image dataset as training data to machine learning algorithms. In this proposed work, an attempt is made to develop such a system where feature vector is created using DCT and DWT. This dataset is used for training supervised learning algorithms namely like SVM, random forest and neural network. The work shows promising results with average 80% accuracy.

Keywords: Hyperemia,Conjunctival Hyperemia,SVM,Random Forest, Neural Network

1.Introduction

Human eye is one the most complex sensory organs. To maintain the continue vision capability, it is utmost important to keep it safe from various eye diseases, which may lead to loss of vision. Therefore,it is utmost to early detection and monitoring of eye disease, which may helpto control further disease progression and avoid any unintended results.

Figure 1: Conjunctival Hyperemia Disease (Sclera)

Conjunctival Hyperemiais caused by multiple factors. Conjunctival Hyperemia is generally caused by chronic or acute circumstances.The initial phase of the disease manifests asthe redness, burning or tearing in sclera section. The risk associated with this disease depends on the density and area covered by the red lesions (Figure 1). The common reasons include eye infection,allergy, irritation, smoke, pollutants, block tear vessels etc. At the initial stage, human eye cannot observe the preliminary micron level red lesions in the eye.Henceforth, ophthalmologist advicesfrequently eye checkupto detect any such eye disease at an initial phase and followappropriate diagnostic procedure to protect the vision ability.

The rest of sections of paper are organized as follows -Section2depicted the basic workflow for conjunctival hyperemia detection system. In section 3, various studies tomeasure conjunctival hyperemia are briefly described.In section4, methodology for feature extraction using DCT and DWT, isdescribed. In section5, three classifiers namely Support vector machine, Random Forest and Neural Network are described. The results are discussed in detail, in section 6. Final section includes the conclusion and future scope of work.

2.Image Analysis for Conjunctival Hyperemia Detection

As per the WHO report[1], there is severe shortage of eye specialists, especiallyin developing couturiers. Henceforth, ophthalmologists are facing challenges to do manual eye screening of billions of people. These issuesmotived the present research which aims to develop computer aided automated Conjunctival Hyperemia screener for detection and monitoring purposes. This will be achieved by designingimage analyzerusing supervised machine learning algorithms, which may provide thedesired support to eye-care professionals. The block diagram of the proposedworkflowis shown in the Figure 2. As shown in the figure, features will be extracted from pre-processed eye image which will be used for training classification models. These trained models will then be used for predictive analysis.

Eye Image

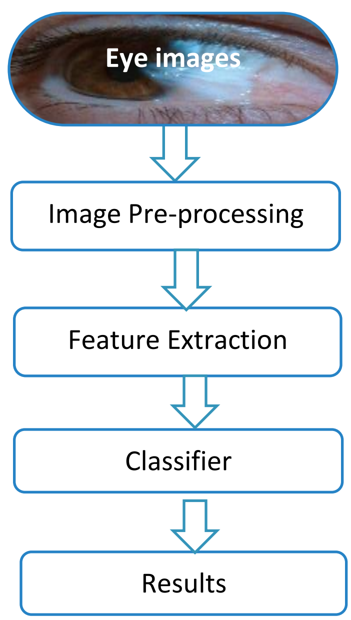

Figure 2: Basic Workflow

3. State of the Arts

The development of computer aided diagnosis is an evolvingresearch area, even though to get highly efficient and robust classifier tool require more model developments before use in clinical practices. The main challenges associate with medical image screener requires multiple testing before allow for medical practices. In this section a review of literature of is providedwhere the development of Hyperemia eye redness detection system is discussed briefly.

During the early developments, JorgenVillumsen *et al.*[2] proposed clinical tool to measure redness of eye.Itused image enhancement and other basic image analysis measurementapproaches to detect bulbar redness. Image enhancement technique proposed by them included two methods namely image smoothening and edge enhancement. The edge lines of vessels helped to grade redness from minor to moderate degree of redness and showed a correlation coefficient of 0.6. This advanced image analysis method gave better estimate of level of redness. The limitation of this methodis that it does not suit for analysis of images with low sharpness.Another study by Guillon and Saha [3]in 1996 developed a clinical tool to measure redness and to monitor diurnal variations in anterior segment of eye by analyzing and digitization of video recording of bulbar redness images. In this study, it was investigated that after comparing the objective method with subjective scaling between soft contact lens wearer and non-contact lens wearer, redness was maximum in soft contact lens wearers. This image analysis-based technique was suitable but it was still restricted to contact lens wearer and it was subject dependent.Cohen *et al*[4]proposed toreduce the dependence of the subjective operators, but it entailshigh cost in real time implementation. In the later year, the same research group proposedanother Conjunctival Hyperemia measurements toolusingmultivariate regression technique [21].

Fieguth *et al*[5] presented bulbar redness estimator which reliably predicts median clinical grades,howeverit shows linearity issue with higher grades.Wolfson *et al*[6]proposed redness screener using color extraction, thresholding and edge detection on individual image plane, but the linearity with higher grades scaling issue is still there.Sorbara *et al*[7]has added significant contribution in developing detection tool for the progressive development of bulbar redness, which provides more variability in gradingusing multi-subjective methods. On the other hand,Peterson *et al*[8]established objective grading method for the clinical ocular surface assessment based on regression analysis techniques. This method showsgood resultdespite variability in detecting ocular surface changes.

Brea *et al*proposed[9]a good frame selection approach for the grading of bulbar hyperemia using radial basis function network (RBF), though RBF network variability depends on feature to feature. In arecent development Sanchez *et al*[10], proposedartificial neural network-based measurement of hyperemia level of bulbar conjunctiva using transforming extracted features to different grading scales (Efron, CCLRU). In the subsequent year, Barreira *et al*[11]has showed that the machine learning techniques can be used to classify the extracted features.Here the features were computed from a video frame of the eye in different grading scale.Adnan *et al*[12] reported image segmentation-based approach for OCULUS Keratograph 5M redness measurement,though segmentation results varied on other subjects' images having different inputs parameters, like, noise, poor contrast, color intensity and the limited spatial resolution.

In latest development, multiple approaches were proposed by researcherson the development of classifier for diagnosis of redness. In one such study, Ellaria Macchi *et al*[13] proposed algorithm based on weighted Kappa statistics. Similarly, Huntjens *et al*[14] developed Advanced grading ophthalmic system (AOS) for conjunctival hyperemiaand Verma *et al*[15]proposed a method based on convolutional neural network (CNN).

Even though, the ongoing research has contributed to the development of Conjunctival Hyperemia measurementssystem, howeverhighly robust andsubject independent system require more attention. The present study aims to fulfill this gap partially by extracting different types of features and training supervised learning algorithms which can differentiate between normal eye and eye with conjunctivitis.

In the next section, the methodology adopted for present study is explained.

4. Methodology Used

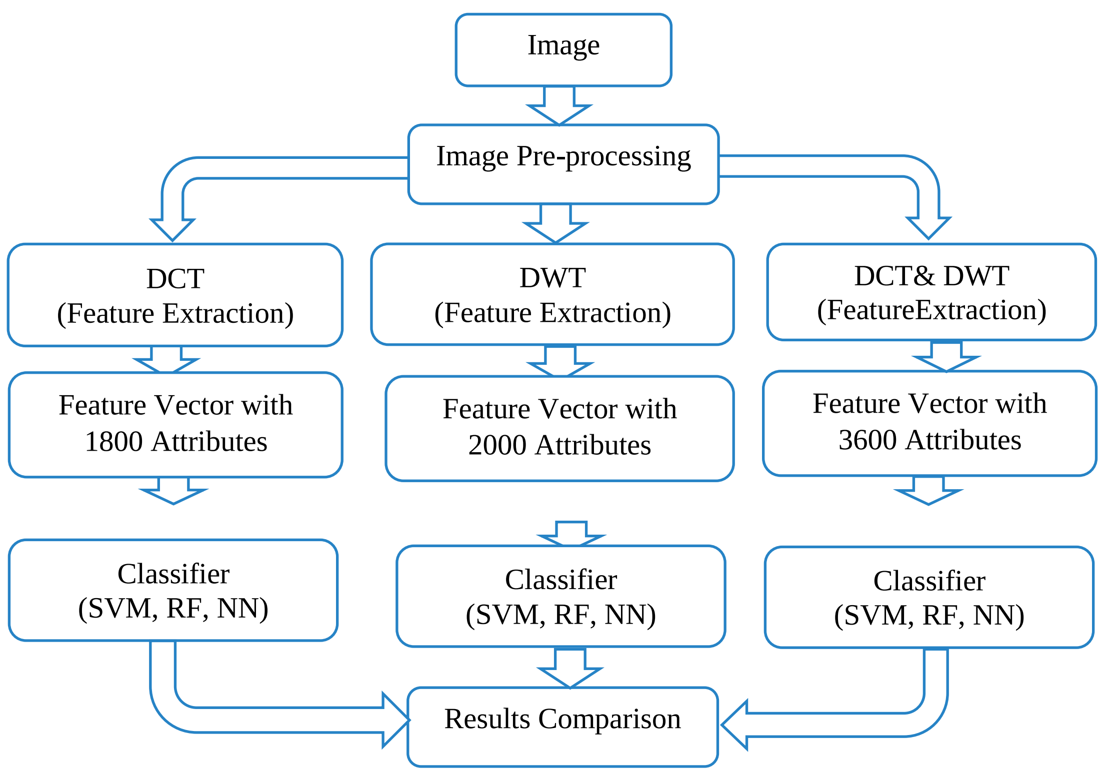

Figure 3: Methodology Followed

4.1. Image Pre-processing-During the first stage, the images are pre-processed before extracting the features. In the preprocessing part, spatial filtering is applied to remove the local variation, after which histogram equalization was done to further improve the contrast of images. The detailedmethodology is shown in the Figure 3.

4.2. Feature Extraction using Transformation methods-Forfeature extraction of grayscale images, transformation-based approacheswere applied, like Discrete Cosine Transform (DCT) and Discrete wavelet transform (DWT). Further, various feature subsets were constructed by combining these features. In the sections that follow, details of features are provided.

4.2.1. Discreate Cosine Transformation- The discrete cosine transform (DCT) represents an image as a combination of sinusoids withdifferent magnitudes and frequencies. In DCT transformed image, the important features of the image confines in few DCT coefficients. Each block in the DCT transformed image is known as basis function, where horizontal frequency increases from left to right, other hand vertical frequencies increase from top to bottom, as shown in the Figure 4. The first black block represents the DC coefficients of the image.The 2-D DCT transformation represents the visually significant information attributes of image with DCT cosine coefficients. The 2D DCT transformation equation of N by M image is defined in the equation 1, where f(i,j) represents the spatial domain and F(u,v) indicate the transformed domain image[16].

$$F(u,v) = \sqrt{\frac{2}{N}}.\sqrt{\frac{2}{M}}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1} f(i,j).\cos\left[\frac{\pi.u}{2.N}(2i +\right.$$

1.cosπ.v2.M2j+1).f(i,j)(1)

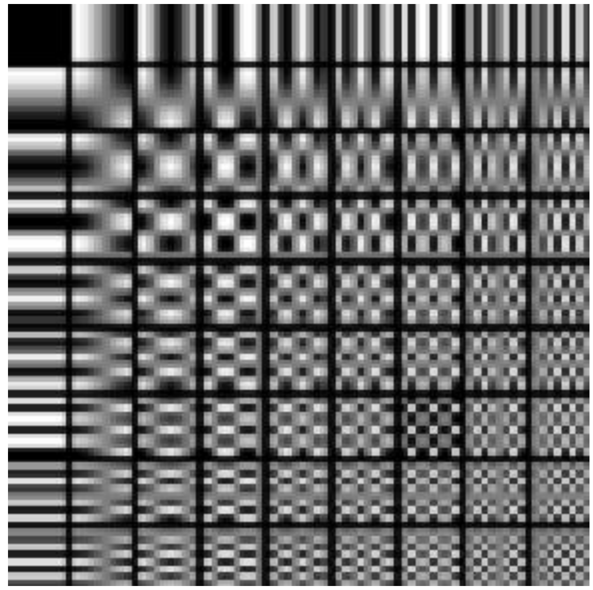

Figure 4: DCT Transform Basis Function (Source: semanticscholar.org)

After applying equation (1), the DCT transformation of grayimageswas computed as shown in Figure 5, respective DCT transformation is given in Figure6.

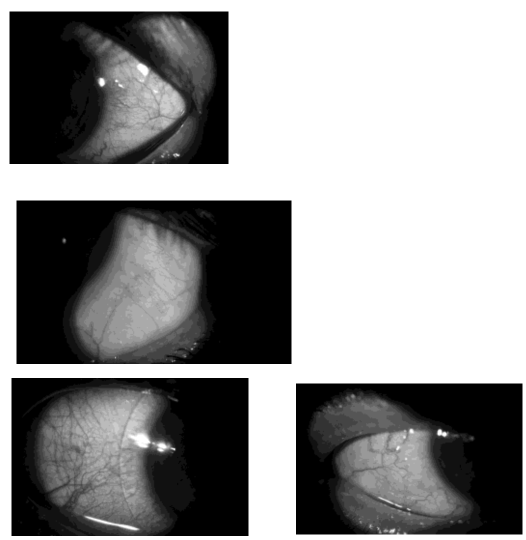

Figure5: Gray images

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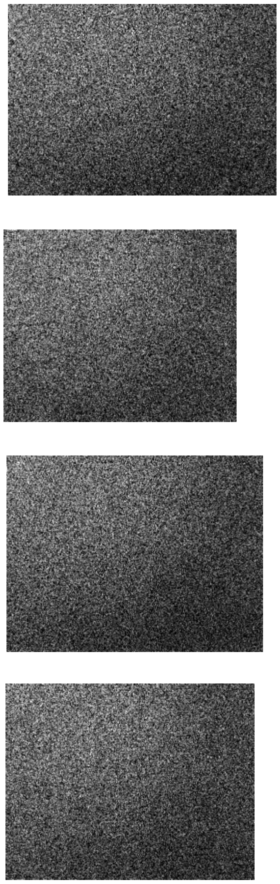

Figure 6:DCT transformation-based images

4.2.2.Discreate wavelet Transform-DWT represents signal or data in the form of specific wavelets, DWT decompose the signal in mutually orthogonal wavelets. The decision of wavelets based on scaling function which is define in (equation2) [22], the main condition is wavelets are orthogonal in all orientation.

$$\phi(x) = \sum_{-\infty}^{\infty} a\phi(Sx - i)(2)$$

Here S is the scaling function, more the scaling function must satisfy the following relation (equation 3)[22] to follow the orthogonality in translation operation

$$\int_{-\infty}^{\infty} \phi(x)\phi(x + xo)dx = \delta(o, xo)(3)$$

In discrete wavelet transform (DWT), signal decomposes with multiple wavelets. In first level of 2D image decomposition, four different quadrants of the image areused, each image quadrantis applied by LL, HL, LH and HH filters. Here L and H represent Low pass and High pass filtering respectively. After each step of filteringfollowed by 2:1 subsampling inx-y directions. DWT mainly computes coefficients of approximation (CA), Horizontal (CH), Vertical (CV) and detailed diagonal (CD) respectively[17]. DWT implementation on input images is shown in Figure 7.

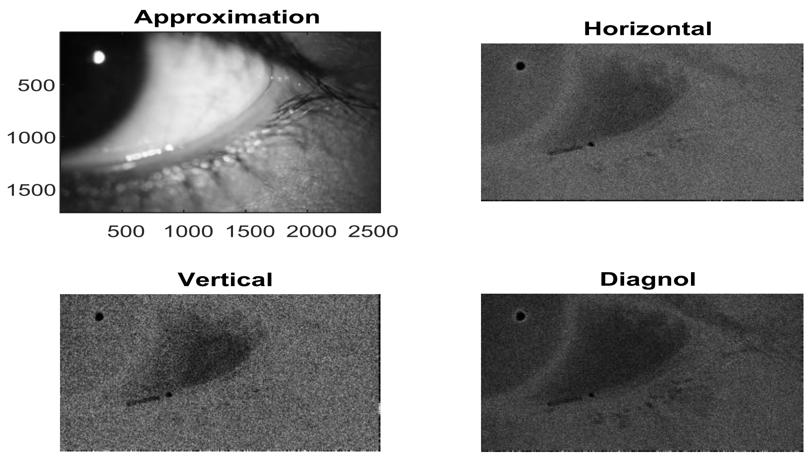

Figure7: DWT of gray image

4.2.3. Combined feature-set for training classification models –Further the two types of features were combined to construct training dataset. As discussed earlier, first few co-efficient captures most of the image information, the main feature set was constructed considering different number of DCT and DWT features. The optimal number of features to be used were then identified by analyzing the accuracy of classification models trained using these feature sets. In next section, classification methods used in present study are explained.

5. Classification

Classification is a task of assigning given set of data into different categories. Labeled data can be categories using classification algorithms. These predictive model-based algorithms provide mapping functions from input factor to discreate output factor. The fundamental objective is to distinguish which class/classification the unlabeled datapoint will fall into. In present study, the input features of15 eye-images are extracted. The description of the dataset isprovided in Table1.

Once the features are extracted from the images, different classifiersare employed to train and test the proposed model namely Support Vector Machine (SVM)[18], Random Forest (RF)and Neural Network (NN)[19].In the following sections details of these classifiers are provided.

5.1Support Vector Machine (SVM)-SVM is a powerful supervised linear model used for object classification and regression. Based on the position of hyperplane and support vectors, SVM categories image objects in multiple classes[18]. SVM tries to create a decision boundary or hyper plane in such a way that the separation between the two classes is as maximum as possible.SVM have many advantages like there is no need of feature selection and it performs well on high dimensional data to avoid from curse of dimensionality problem. SVM is trained with dataset to perform classification. The linear SVM is defined by Equation 4.

$$F(v) = W^T X + b \qquad (4)$$

where Xis vector containing data point from sample set, W weight vector and b represents bias coefficient, which separate positive instancesfrom negative instances based on Equation 5 conditional statements.

$$Y_i=\begin{cases} +1 \text{ if } f(Xi) > 0 \\ -1 \ otherwise \end{cases} \quad (5)$$

5.2. Random Forest-Random forest is popularly usedapproach to design decision tree classifiers, each tree generate a random vector based on independent set of values.All randomly generate tree vectors maintain the same probability distribution.In the proposed study model used 100 number of treesand maximal depth is 10. Moreover, gain ratio as split criteria. The classifier model is based on ensemble learning[19].

5.3. Neural Network-Neural network is popularly used architecture to implementmachine learning algorithms. In neural network, numbers of neural layers are cascaded to train the net as per required output [19]. The input feature matrix is applied at the input layer and based on learned weight factors, the decision node takes the result. In this proposed neural net classifier, model tested with 100 epochs with learning rate 0.01 to attain the reported result.

The results are discussed in the next section.

Performance Measures-
Performance of classifier is based on input samples that are correctly or incorrectly predicted by the classification model. In individual classification steps performance metrics are measured, namely accuracy, precision and recall [20].
Accuracy- It is simply a ratio of correctly predicted instances to totalnumber of instances. It is shown by an equation6[20]

$$Accuracy = \frac{\text{Correctly predicted instances}}{Total\ number\ of\ input\ instances} \quad (6)$$

Precision-It measures the fraction of correct positive instances to the number of positive instancespredicted by the classifier. It is given in equation 7.

$$Precision = \frac{\text{Correct positive instances}}{total\ number\ of\ positive\ predicted} \quad (7)$$

Recall- It measures the fraction of positive instances correctly predicted by classifier. It is shown in equation 8.

$$Recall = \frac{\text{Correctly predictive positive insta}}{\text{True positive instances}} \quad (8)$$

6. Test Images and Result

The locally acquired image databaseis used to train and test the classifier;databaseimages are acquired using slit lamp method.A total of 15images were there whichcomprised of7 diseased and 8normal images, some of the images are shown in the Figure 8.

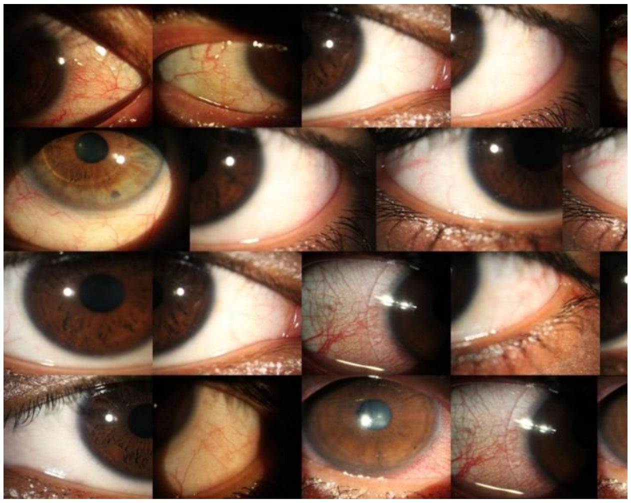

Figure 8: Eye Images

Table 1: Classification Results Accuracy

Techniques	Number of features	Accuracy		
		SVM	Random Forest	Neural Network
DCT	500	40	55	60
	1000	70	60	75
	1200	70	70	65
	1500	70	50	65
	1800	100	85	100
	2200	100	85	100
	2500	100	85	90
DWT	500	45	75	55
	800	45	65	40
	1000	45	70	55
	1500	85	70	85
	1800	80	70	80
	2000	90	70	80
	2500	90	70	70
DCT-DWT	1000	55	50	65
	2800	65	65	80
	3300	95	85	80
	3600	95	85	85
	3800	90	95	95

Once the feature vector is extracted using DCT and DWT, the model is tested through iterative process in multiple stepswhere feature size was incrementally increased. The proposed model is tested with 7 diseased images and 8 healthy images. The feature extraction step is implemented using MATLAB-19a and classification technique is simulated using Rapid-Miner studio (ver9.6). The detailed comparison results of all three feature extraction techniques are shown in Table 1, and results are also shown in bar plots (Figure 6,7 and 8).

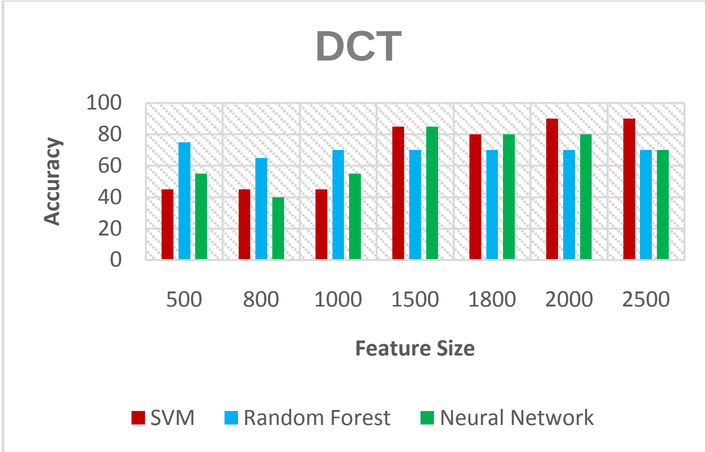

Figure 9: Results using DCT Technique

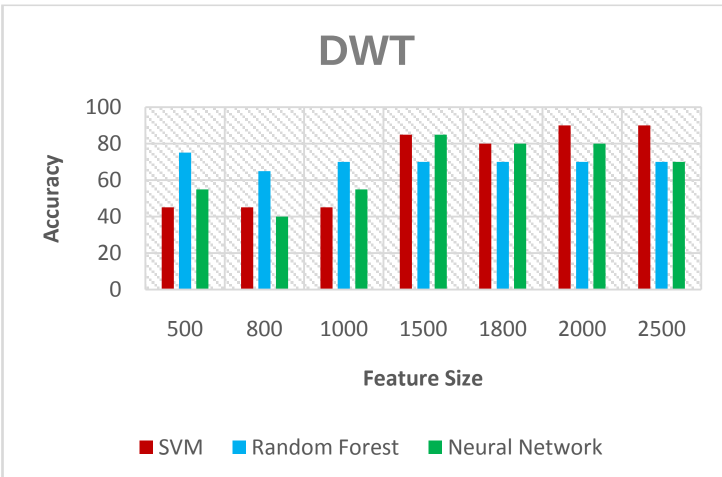

Figure 10: Results using DWT Technique

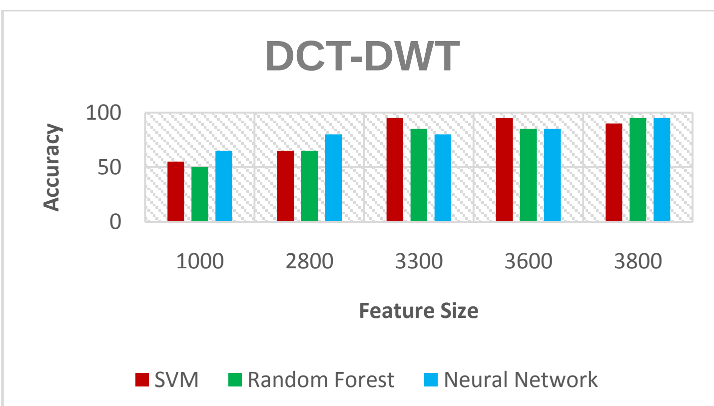

Figure 11: Results using DCT-DWT Technique

The proposed method explained in methodology section used Dct, Dwt and combined approach (DCT-DWT). We achieved best accuracy of 95% with combined approach DCT followed by DWT. It is evident that for present feature set, SVM is giving best accuracy (95%) with3600features.After these 3600 features,the result is degrading.Although the anticipated approach attained relatively satisfactory results as compared with predecessor methods mentioned in state of arts (Section 3),but there seems over fitting issue due to a smaller number of test images.

7.Conclusion

The impairment of Conjunctival Hyperemia can be avoided with the help of early detection and followingappropriate diagnosis. After observing the research gap, there isgreat scope for the development of automated computer aided Conjunctival Hyperemia screening system. In this proposed work, three approaches are employed for the red lesions detection, DCT, DWT and DCT-DWT for feature extraction and support vector machine, random forest, neural network for classification respectively. The proposed approach shows promising results as compare with other predecessor work with accuracy 95%, recall 100%, precision 87.50% for red lesions and 100% precision for white sclera regions. The locally created image database with slit lamp method is used to test the model.

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