Performance Analysis of Learning Algorithms for Automated Detection of Glaucoma

Anupama B C[1], Sheela N Rao[2]

[1]Research Student, Department of Electronics & Instrumentation, JSS S&TU, Mysuru 570006, India
[2]Assistant Professor, Department of Electronics & Instrumentation, JSS S&TU, Mysuru 570006, India

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Abstract - *Human Eye is one of the major sensory organs in the body. Eye can be affected by different types of diseases like Glaucoma, Diabetic Retinopathy, age related macular etc. Glaucoma is an eye disease which steals vision slowly starting from peripheral vision and progresses toward the central vision at a later stage. This disease damages the optic nerve and leads to irreversible vision loss. Fundus photography has been found to be a very useful modality for the detection of eye related abnormalities. Various types of feature extraction from fundus images, that can be used for the detection of Glaucoma has been suggested by different authors. The main objective of this work is to extract different types of features from fundus images in order to come out with best suitable set of features that can help in automated detection of Glaucoma and evaluate it using learning algorithm. Different combinations of these features have been given to Support Vector Machine (SVM) and KNN to classify the images as normal and glaucomatous. A tenfold cross validation is performed using the extracted features and a comparative study has been carried out in terms of Accuracy, Sensitivity, Specificity, Positive Predictive Value (PPV) and Negative Predictive Value (NPV) Performance evaluation has been done with and without applying feature reduction techniques. Best accuracy of 97.5% has been achieved when Wavelet features are used.*

***Key Words*: Glaucoma, Fundus image, Information gain, SVM, KNN**

1. INTRODUCTION

Glaucoma is one of the common causes of blindness with about 79 million in the world likely to be afflicted by the year 2020 [1]. The progressive degeneration of optic nerve fiber is one of the way of characterizing glaucoma. This causes structural changes of the optic nerve head (optic disk) and fiber layer, and leads to failure of the visual field. The early detection of glaucoma and ensuring essential treatment can prevent permanent vision loss [2]. The pressure of the non-glaucomatous should be 21 mm of Hg, if it increases the optic nerve will be damaged causing permanent vision loss [3].

There are two main types of Glaucoma (i) Primary Open Angle Glaucoma (POAG) and (ii) Angle Closure Glaucoma (ACG). POAG is the most common form of Glaucoma accounting for at least 90%of all Glaucoma cases [7].

The Intra-Ocular Pressure (IOP), which maintains a permanent shape of the human eye and protects it from deformation, rises because the correct amount of fluid cannot drain out of the eye. With POAG, the entrances to the drainage canals work properly but a clogging problem occurs inside the drainage canals [8]. This type of Glaucoma develops slowly and sometimes without noticeable sight loss for many years. It can be treated with medications if diagnosed at the earlier stage. ACG happens when the drainage canals get blocked. The iris is not as wide and open a sin the normal case. The outer edge of the iris bunches up over the drainage canals, when the pupil enlarges too much or too quickly. Treatment of this type of Glaucoma usually involves surgery to remove a small portion of the outer edge of the iris

Colour fundus imaging (CFI) is preferred modality for large-scale retinal disease screening that can be used for glaucoma assessment. The non-invasive technique is used to acquire fundus images [4].

Due to high cost, technique of detecting glaucoma from 3-D images are not available at primary care centres and therefore solution built around these imaging equipment is not appropriate for a large-scale screening program [5] [6].

Fundoscopy enables ophthalmologists to examine the optic disc. Optic disc appears as a yellowish circular body, centred with optic cup which is slightly brighter area than optic disc. Circular rim area between optic cup and optic disc is called neuroretinal rim (NRR). Ratio of Cup area to disc area called Cup to Disc Ratio (CDR) is one of the noticeable structural change that occurs if glaucoma progress. CDR value ≤0.5 indicates normal eye [9].

Cup size increases in glaucomatous eyes, resulting in increase of CDR and decrease in NRR. Thus, CDR and NRR are two key structural changes to detect glaucoma using Fundoscopy. In glaucoma image, due to increase in the size of cup brighter region in the optic disc increases thus increasing the overall image entropy, mean, variance and colour spatial and textural information. Thus along with CDR and NRR, image intensity and textural information can also be used to detect glaucoma [10].

NRR thickness based on Inferior, Superior, Nasal and Temporal (ISNT) rule is also being used as a reference for glaucoma detection. Inferior region is the bottom region of NRR, Superior is the top region of NRR, Nasal and Temporal are the right and left regions of NRR in case of right eye, in case of left eye nasal and temporal are the left and right regions respectively. ISNT rule states that in a normal eye thickness of NRR is such that inferior region > superior region > nasal region > temporal region [11].

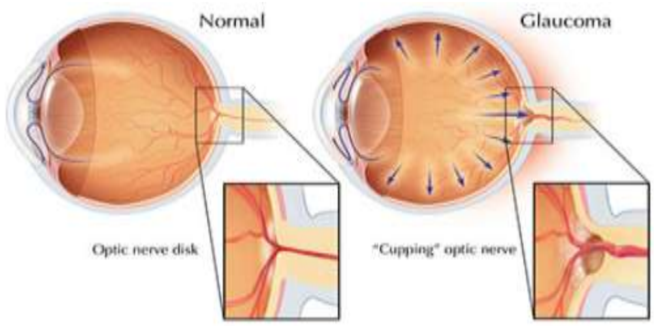


Fig - 1: Fundus image of Normal and Glaucoma Eye

The main objective of this work is to extract features from fundus images that can help in automated detection of Glaucoma and evaluate the performance of learning algorithms that is best suitable for the classification of Glaucomatous image.

2. METHODOLOGY

The methodology that will be used in this work is shown in the block diagram

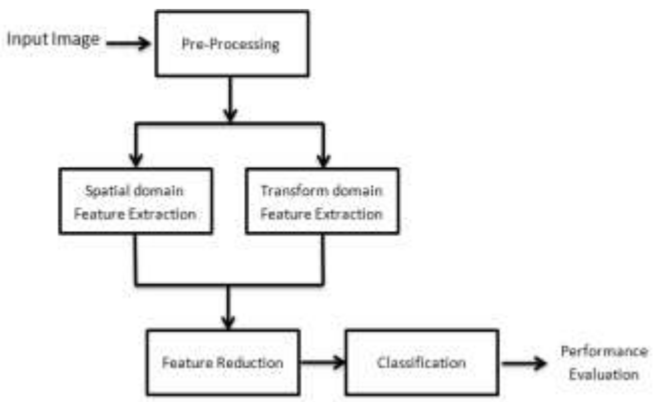


Fig - 2: General Block Diagram of Proposed System

1. Image Database

Fundus images are used in this work and the images required for this work has been collected from Shushrutha Eye Hospital, Mysuru. The Fundus dataset used consists of 60 images among which 30 images are normal and 30 images are Glaucomatous in nature.

2. Preprocessing

The aim of pre-processing is to improve the image data by suppressing undesired distortions or enhancing image quality to help for further processing and analysis task.

Green channel extraction

Fundus image are RGB images consisting of RED, GREEN and BLUE component images. Green component images have best contrast. Therefore green component images is extracted and used for further processing. Images should have good contrast before the features are extracted. Contrast of the green component images are further enhanced by applying Contrast Limited Adaptive Histogram Equalization (CLAHE).

Feature extraction

Feature extraction is the process of extracting certain characteristic attributes and generating a set of meaningful descriptors from an image. It is used to find a feature set of tissue that can accurately distinguish normal and abnormal images. Various feature extraction methods has been proposed using which lot of features from medical images can be obtained. However, it is difficult to select significant features from the extracted features.

Progression of glaucoma leads to an increase in size of optic cup resulting in an increase in the bright intensity pixels of the image. This increase in intensity of image can be observed in intensity and texture related features extracted from image. Texture features can also be used to classify an image as glaucoma or healthy and can be used in computer aided glaucoma systems to discriminate between glaucoma and non-glaucoma [10].

Spatial Domain Textural Feature

Texture is defined as specific spatial arrangement of intensities in an image. Texture features are subdivided into statistical texture features and structural texture features. In statistical texture features, pixel value's spatial distribution is computed by calculating local features in the image. Statistical features can be first order, second order or many orders depending upon the number of pixels involved in feature extraction and computation [10].

Gray Level Co-occurrence Matrix

Gray-level co-occurrence matrix is one of the most known texture analysis methods that estimates image properties related to second-order statistics by considering the spatial relationship between two neighboring pixels, where the first pixel is the reference pixel and the second pixel is the neighbor pixel. We have extracted 14 features form GLCM [10].

Gray Level Difference Matrix

GLDM calculates the Gray level Difference Method Probability Density Functions for the image. 12 features are extracted from GLDM.

Local Binary Pattern
Local binary patterns (LBP) is a type of visual descriptor used for classification in computer vision. It has since been found to be a powerful feature for texture classification. LBP is the particular case of the Texture Spectrum model proposed in 1990. LBP was first described in 1994.It has since been found to be a powerful feature for texture classification. We have extracted 59 features from LBP.

Histogram of Oriented Gradient (HOG)
The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. The technique counts occurrences of gradient orientation in localized portions of an image. This method is similar to that of edge orientation histograms, scale-invariant feature transform descriptors, and shape contexts, but differs in that it is computed on a dense grid of uniformly spaced cells and uses overlapping local contrast normalization for improved accuracy [12]. We have extracted 81 features from HOG.

Transform Domain Features
Discrete Wavelet Transform

A discrete wavelet transform (DWT) is any wavelet transform for which the wavelets are discretely sampled. We can represent a discrete function f(n) as a weighted summation of wavelets φ(n), plus a coarse approximation Ø(n)

$$f(n) = \frac{1}{\sqrt{M}} \sum_k W_\emptyset(j_0.k)\emptyset_{j_0.k}(n) + \frac{1}{\sqrt{M}} \sum_{j=j_0}^{\infty} \sum_k W_\varphi(j.k)\varphi_{j.k}(n) \quad (1)$$

Where j0 is an arbitrary starting scale, n = 0, 1, 2….M

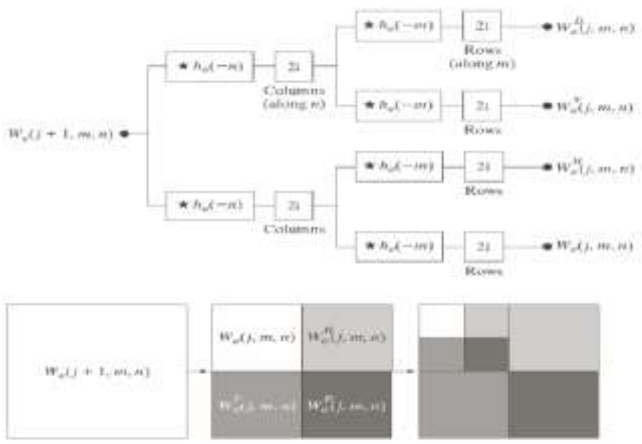
"Approximation" Coefficient

$$W_\emptyset(j_0.k) = \frac{1}{\sqrt{M}} \sum_x f(x)\emptyset_{j_0.k}(x) \quad (2)$$

"Detailed" Coefficient

$$W_\emptyset(j.k) = \frac{1}{\sqrt{M}} \sum_x f(x)\varphi_{j.k}(x) \quad (3)$$

Expanding to two dimension



Shearlet Transform

In applied mathematical analysis, shearlets are a multi-scale framework which allows efficient encoding anisotropic features in multivariate problem classes. Originally, shearlets were introduced in 2006 for the analysis as well as sparse approximation of functions. They are a natural extension of wavelets, to accommodate the fact that multivariate functions are typically governed by anisotropic features such as edges in images, since wavelets, as isotropic objects, are not capable of capturing such phenomena [13].

A discrete version of shearlet can be directly obtained from SHcont (φ) by discretizing the parameter set R>0 x R x R2. There are numerous approaches for this but the most popular one is given by,

$$\{(2^j, k, A_{2^j}^{-1} S_k^{-1} m) | j \in \mathbb{Z}, k \in \mathbb{Z}, m \in \mathbb{Z}^2\} \subseteq \mathrm{R}_{>0} \,\mathrm{x}\, \mathrm{R} \,\mathrm{x}\, \mathrm{R}^2 \quad (4)$$

From this, the discrete shearlet system associated with the shearlet generator φ is defined by

$$SH(\varphi) = \{\varphi_{j,k,m} = 2^{3j/4}\varphi(S_k A_{2^j} \cdot - m) | j \in \mathbb{Z}, k \in \mathbb{Z}, m \in \mathbb{Z}^2\} \quad (5)$$

And the associated discrete shearlet transform is defined by

$$f \mapsto SH_\varphi f(j,k,m) = (f, \varphi_{j,k,m}), f \in L^2(\mathbb{R}^2), (j,k,m) \in \mathbb{Z} \,X\, \mathbb{Z} \,X\, \mathbb{Z}^2 \quad (6)$$

3. Feature Reduction:
In machine learning and statistics, dimensionality reduction or feature reduction is the process of reducing the number of random variables under consideration, by obtaining a set of principal variables.

Information Gain
In information theory and machine learning, information gain is a synonym for Kullback–Leibler divergence. However, in the context of decision trees, the term is sometimes used synonymously with mutual information, which is the expected value of the Kullback–Leibler divergence of the

univariate probability distribution of one variable from the conditional distribution of this variable given the other one. In particular, the information gain about a random variable X obtained from an observation that a random variable A takes the value is the Kullback-Leibler divergence DKL(p(x | a) || p(x | I)) of the prior distribution p(x | I) for x from the posterior distribution p(x | a) for x given a. The expected value of the information gain is the mutual information of X and A – i.e. the reduction in the entropy of X achieved by learning the state of the random variable A [15] [16].

Classification

The Fundus images in the dataset are classified as normal and glaucomatus using a Support Vector Machine and K nearest neighbor classifier.

3. Results

Textural Feature Extraction:

Different types of spatial domain features have been extracted in this work. Details are given below.

- GLCM based Haralick features – 14
- GLDM based Haralick features – 13
- LBP features – 59
- HOG features – 81

Transform Domain Feature Extraction:

Two types of transforms domain features have been extracted. Details are given below.

- **Wavelet Transform**: Preprocessed images are decomposed into two levels by applying 2D Discrete Wavelet Transform. GLCM based Haralick features are extracted from all the resulting detail coefficient images. 2D DWT has been applied to images using four different types of wavelets namely, DB8, COIF1, SYM2 and BIOR1.1. Each wavelet results in 84 features.
- **Shearlet Transform**: Preprocessed images are decomposed using 2D shearlet transform as well. This results in 13 images. GLCM based Haralick features extracted from these 13 images has given 182 features.
- **Combined Features:** Features obtained by applying Wavelet transform and Shearlet transform has been combined to get 518 features.

Feature Reduction

Extraction of features by applying Shearlet transform and combining of transform domain features have resulted in large number of features. "Curse of Dimensionality" indicates that number of features and number of training images used should be optimized to get correct results. Therefore, feature reduction using Information Gain technique has been used to retain only the optimum number of features. This showed that only 168 out of 182 features in case of Shearlet and 378 features out of 518 in case of combined features are significant. Hence, only these significant features have been given to classifiers.

Classification Results

The classification of the images into normal and diseased is performed by using linear SVM and KNN classifier. SVM and KNN are supervised learning models used for data classification. The model is trained using a dataset with samples labeled with the class they belong to. Here, normal Fundus images belong to class 0 and Glaucoma affected Fundus images belong to class 1.

Following values are used for calculating the performance measures.

- True Negative (TN) is defined as the samples that are healthy and detected as a healthy image.
- False Positive (FP) is defined as the samples that are non-glaucomatous but detected as glaucoma.
- False Negative (FN) is defined as the samples that are glaucomatous but detected as non-glaucoma.
- True Positive (TP) is defined as the number of samples that are glaucomatous and also detected as glaucomatous images [10].

Performance measures like Accuracy, Sensitivity, Specificity, Positive Predictive Value and Negative Predictive value are used to check the ability of the features extracted to help in the disease detection.

Accuracy (A) is the proportion of the total number of predictions that were correct. It is determined using the equation-7 [10]

$$\text{Accuracy} = \frac{TN+TP}{TN+FN+FP+TP} \times 100 \qquad (7)$$

Sensitivity (Sn) or true positive rate (TPR) is the proportion of positive cases that were correctly identified, as calculated using the equation-8

$$\text{Sensitivity} = \frac{TP}{FN+TP} \times 100 \qquad (8)$$

Specificity (Sp) or true negative rate (TNR) is defined as the proportion of negatives cases that were classified correctly, as calculated using the equation-9

$$\text{Specificity} = \frac{TN}{TN+FP} \times 100 \qquad (9)$$

Positive Predictive Value (PPV) is the proportions of positive results in statistics and diagnostic tests that are true positive results, is calculated using equation-10

$$\text{PPV} = \frac{TP}{TP+FP} \times 100 \qquad (10)$$

Negative Predictive Value (NPV) is the proportions of negative results in statistics and diagnostic tests that are true negative results, is calculated using equation-11

$$NPV=\frac{TN}{TN+FP} \times 100 \quad (11)$$

Table 1: Spatial Domain Features with SVM classifier

SI. No.	Name of the Feature	No. of Features Used	Sn (%)	Sp (%)	PPV (%)	NPV (%)	A (%)
1	GLCM	14	77.77	88.88	80	87.50	83.33
2	GLDM	13	100	77.778	100	81.81	83.33
3	LBP	59	96.66	100	100	96.66	98
4	HOG	81	33.33	66.66	50	50	50

Table 2: Transform Domain Feature with SVM classifier

SI. No.	Name of the Feature	No. of Features Used	Sn (%)	Sp (%)	PPV (%)	NPV (%)	A (%)
1	Wavelet Transform						
	• DB8	84	100	96.67	100	97	97.5
	• COIF1	84	100	88.88	82.24	86.50	94.44
	• SYM2	84	100	88.88	82.22	86.50	94.44
	• BIOR1.1	84	100	55.55	77.77	100	62.45
2	Shearlet Transform	168	100	93.33	90	100	95.500
3	Combined	378	88.88	100	91.667	95	94.44

Table 3: Spatial Domain Feature with KNN classifier (City block)

SI. No.	Name of the Feature	No. of Features Used	Sn (%)	Sp (%)	PPV (%)	NPV (%)	A (%)
1	GLCM	14	70.00	56.66	61.67	65.38	66.66
2	GLDM	13	46.667	60.00	53.85	52.94	54.62
3	LBP	59	70	46.67	56.76	60.87	51.25
4	HOG	81	50.00	46.67	48.39	48.28	47.47

Table 4: Transform domain Feature Classification using KNN classifier (City block)

SI. No.	Name of the Feature	No. of Features Used	Sn (%)	Sp (%)	PPV (%)	NPV (%)	A (%)
1	Wavelet Transform						
	• DB8	84	53.33	56.67	55.17	54.84	53.76
	• COIF1	84	46.67	60.00	53.85	60.87	51.27
	• SYM2	84	53.33	80.00	72.73	63.16	63.64
	• BIOR1.1	84	36.67	50.00	42.31	44.12	41.73
2	Shearlet Transform	168	70.00	60.00	63.64	66.67	63.21
3	Combined	378	40	70	57	53	51.53

Classification results shows that different results are obtained by different type of features with SVM and KNN classifiers. It can be clearly seen that LBP with SVM has given excellent results. Similarly, best results obtained using transform domain features with SVM and KNN has been plotted. In this case, Wavelet transform using DB8 wavelet with SVM has performed well. Finally, comparing all the results obtained it is evident that LBP with SVM in spatial domain and Wavelet Transform (DB8) with SVM in transform domain is the best suitable combination for the detection of Glaucoma in fundus images. This is clearly shown in the plot given in Chart-1.

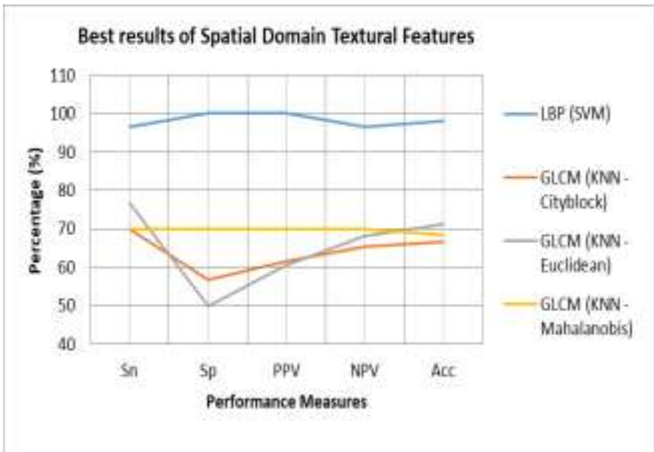


Chart - 1: Plot of Best Results obtained by Spatial Domain Features with different types of classifiers

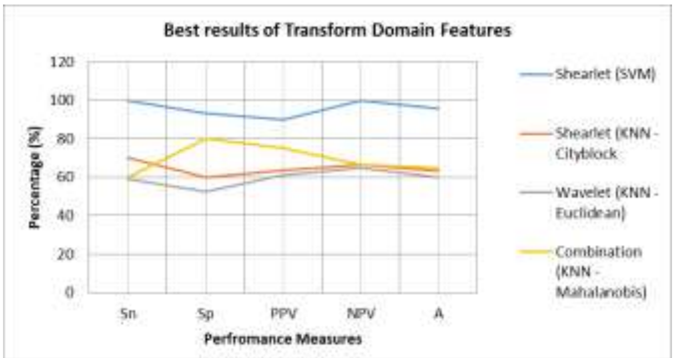


Chart - 2: Plot of Best Results obtained by Transform Domain Features with different types of classifiers

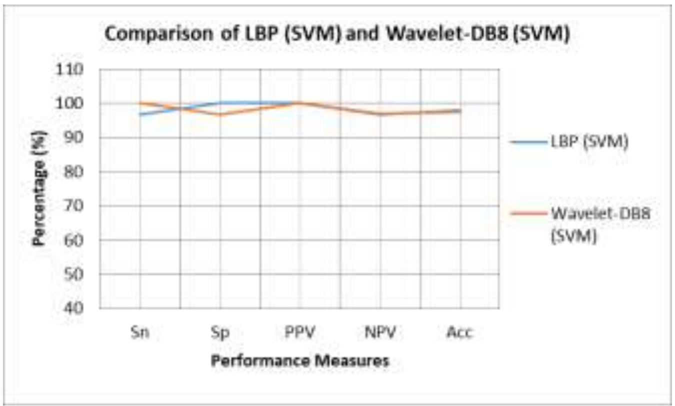


Chart - 3: Plot of best of spatial domain features and Transform domain features

4. CONCLUSIONS

In this work, different types of spatial domain textural features and transform domain features have been extracted. In spatial domain, GLCM, GLDM, LBP and HOG features have been extracted. Wavelet transform based features using DB8, COIF1, SYM2 and BIOR1.1 wavelet and Shearlet transform based features have been extracted in transform domain. All the features have been tested using SVM and KNN classifier.

A comparative study has been carried out. Results obtained shows that LBP gives best performance among spatial domain features giving with specificity of 96.66%, Specificity of 100%, Positive Predictive Value of 100%, Negative Predictive value of 96.66% and an accuracy of 98%. Wavelet Transform (DB8 wavelet) based features perform best in case of transform domain features achieving a 100% sensitivity, 96.67% specificity, 100% PPV, 97% NPV and 97.5% accuracy. Among the classifiers used, SVM outperforms KNN. Comparing all the results we can conclude that LBP features with SVM or Wavelet transform (DB8) features with SVM are the best suitable combination for the detection of Glaucoma in the set of fundus images we have used.

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