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Automated Glaucoma Detection from Fundus Eye Images Using Grey Level based Feature Extraction Methods and Supervised Learning Classification

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Abstract

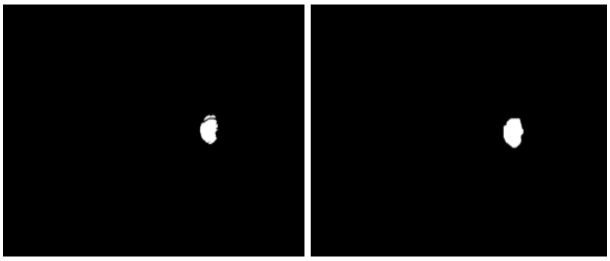
Over 60 years, health organization’s survey exposed that glaucoma leads to permanent vision disorder in human eye. Although 79 million of people were affected by this second major cause in 2020, glaucoma detection technique exploits preventing scheme at the earlier stage and reducing the necessary disease treatment cost. This research is trained probe a best analysis for glaucoma prediction in segmented retinal fundus images to assist an ophthalmologist. Our model utilizes a many feature extraction approach to detect glaucoma from digital fundus image using a fusion feature set. Along-with extraction way, Gray Level Coherence Matrix, Gray Level Run Length Matrix, Gray Level Difference Method approaches are used to extract texture based features. The contributions of extracted spatial domain from these approaches are expected to formulate higher efficiency of fusion feature set using classification. Thus, proposed work is presented with the comparison of four machine learning algorithms like support vector machine (SVM), k-nearest neighbors (kNN), Decision Tree (DT) and Naive Bayes (NB). Diagnosis methodology is clearly demonstrated a way to detect glaucoma in early stage from fundus image. Performance of the classifier is analyzed by computing the accuracy value. Then effectiveness of the system is improved by the combination of texture with supervised learning techniques.

Keywords: Glaucoma, Feature Extraction, Gray level, Supervised learning

1. Introduction

Glaucoma is an unhealthy disorder in human eye that front to chronic problem, which can change vision into vision loss by damaging the optic nerve structure. Hence, there is a possibility of irreversible vision loss can caused by glaucoma [1]. This model projected a mechanism for treatment screening to reduce the blindness probability at earlier in an effective manner. So the availability of automatic detection system is used to detect eye disorder from fundus images. Basically, there are two main categories of analysis in glaucoma diagnosis methods based on its types called clinical based analysis, feature based analysis [2]. The combination of these two subsystems produced glaucoma detection with improved independent result. In this work, an automated detection tool to diagnose glaucoma from fundus images which have been retained from trained and tested data set using feature based analysis.

The feature based system applies feature extraction techniques to extract their textual and statistical features. Feature extraction is the process involved in analyzing image texture. The results gives a better understanding of texture and object shape determination of segmented image as shown in Fig.1.



When the algorithm has more input data set, it is to be converted to a smaller dimension for better handling. Converting input image into a standard set of features is termed as feature extraction. By employing feature extraction procedure on the segmented images under normal, glaucoma category, the grouped pixels were converted to numerical data by the process of feature extraction [3]. The features considered in this research are mainly Gray Level Co-occurrence Matrix (GLCM) for extracting statistical features, Gray-Level Run-Length Matrix (GLRM) is to extracting run length features and Gray level Difference Method (GLDM) applied for extracting statistical texture features using Probability Density Functions for the given image.

Also, this automated system considers machine learning algorithms in extracted feature set to detect glaucoma from input images. These algorithms have some patterns to handle the huge data set and to simplify data problem. Beside this, supervised learning is used to extract relevant data. All supervised algorithms can have dataset which is trained or tested for classification. In this work, we have discussed four supervised machine learning algorithms such as Support Vector Machine(SVM), K Nearest Neighbor (K-NN)Decision Tree (DT), and Naive Bayes (NB) with statistical performance, the measure is considered to evaluate. The concluded result has improved the detection system by distinguishing positive and negative cases from glaucomatous image [4].

1.1.Contribution of this research:

To recognize the glaucoma, different methods have been evaluated with computational complexity and long system configuration that endures performance of those methods. So, selecting a method that can detect glaucoma corresponds to necessary features with accurate result. Thus the aim of this research is to explore feature extraction based Machine learning algorithm. Regarding to that, the proposed method uses GLCM, GLRM, and GLDM feature extractor to extracting a features from glaucomatous image dataset. The perfect accurate result is produced with less computational time by proposed extraction algorithms. Finally, the contribution of this study is to get applicable accuracy rate by comparing the extracting result with machine learning algorithms.In Addition to that supervised learning methods such as NB, k-NN,SVM,DTis utilized by their performance measures and obtained to find out the best result with supervised classifier. The combination of efficient feature extraction techniques with supervised classifier yields appropriate outcome in our proposed scheme.

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2. Background

Fan Guo et al., differentiate their model with increasing field of view (IFOV) from the existing ones. This novel screening method has taken place with the combination of clinical based dimension and image texture features. Clinical features are extracted from OD and OC segmentation measurement. Image based features are followed by IFOV to extract features like texture and Gabor transform features. So the range of the visual field was defined by cup region of fundus image with four different scales including hidden visual features such as Gray Level Co-occurrence Matrix (GLCM) and Gabor transform. Theextracted invisible features from the identified region are to produce image transformation for glaucoma detection. Hence the automatic glaucoma detection was improved with expected accuracy. [5]

Neda Ahmadi et al., focused with human iris tissue and extracted features precisely from fundus tissue image. In this study, preprocessing is to identify iris tissue of individual image carried out by region of interest (ROI). Besides, features extraction was achieved by applying Gray-level difference method (GLDM) technique. It was implemented with the problem that to identify iris recognition by a hybrid classifier model called Multi-layer perceptron Neural Network(MLPNN) and Imperialist competitive algorithm(ICA).In order to achieve highaccuracy rate, trained hybrid model classifier are recognized to classify a iris tissue.[6]

Abhishek Dey et al.,developed a extraction of statistical feature with Support Vector Machine classification system for glaucoma detection in fundus images. In this model, fundus images are preprocessed by feature extraction techniques such as GLRLM and GLCM.The outcome of extraction is consisted with large amount of texture features, so it may encounter computational overhead problem. This model utilized RBF kernel approach, which can overcome the classifiers overload by producing as a small training set.[7]

To get expected feature value, there exist combinations of methods which provide feature extraction in glaucoma is Gray Level Co-occurrence Matrix,Principle Component Analysis. These are implemented with the classification methodswhich have similarkernel functionality of gaussian or Radial Basis Function (RBF)as OAA, OAO. Alongside the classification, Dinda Aulia Gustian et al., suggested a multiclass Support Vector Machine (SVM) to classify troso fabric images of 480x480 pixels with GLCM. Result have been analyzed with an accuracy of 90% and 86.7 corresponding to SVM with OAA, SVM with OAO.[8]

Than Than Htay et al., focused a feature extraction based on GLCM first order statisticaltechnique with textureproperties. It has been developed to classify mammograms abnormalities in breast cancer detection system. Beside the feature, texture characteristics are extracted using thresholding of the images after region segmentation. To representing a low-dimensional image, the classification technique is used with the feature types like compressed thresholding value. According to k-Nearest Neighbor (k-NN) classifier, this model identifies the classification of extracted objects as normal or abnormal.[9]

Qaisar Abbas stated the automatic method to extract features of OD region of a fundus image for glaucoma detection. This model considered pre-assumption changes of OD corresponding to disease cause and relate with morphological encoding. Hence accurate removal of cup and disc borders is recognized by statistical image features. Automatically it has been extract with base features using deep learning. Beside extraction of features, there numbers of classifiers are used in deep-learning without a understanding knowledge of a domain expert. Glaucoma can detected by high specificity through this technology, it can only detect a predefined functional error.[10]

For feature extraction process, region of Retina nerve fibre layer (RNFL) also considered as input image. Maria Ulfa Muthmainah et al., proposed statistical-based feature extraction to extract RNFL features by GLCM and GLRM. RNFL image region is comprised with grayscale image, from which textures features are retrieved. Beside the region of retina, ONH (Optic Nerve Head) features are proposed with morphological measurement. These features are measured by OD(Optic Disc) and OC(Optic Cup) segmentation. In this model, SVM and kNN methods are used to find well known hyper plane to make a one or more classification based on class type. It means that finding optimum distances to classify a class from the other with voting scheme [11].

The detailed study of the related work encompasses the importance of extraction and classification techniques that are used to detect glaucoma of a color fundus image. Each of the work demonstrates its difficulty in extracting a texture feature according to abnormalities of fundus image may result in unsuccessful classification. In order to evaluate these challenges, we developed method to classify glaucoma. Features of a fundus image are extracted based on texture by GLCM, GLDM, GLRM techniques. Totally it provides a statistical measure of 33 features of the segmented image. The outcome of feature extraction is added to process the classification results with four types of classifier scheme to predict normal or abnormal. Finally, types of features are gained to form one finest classifier's glaucoma prediction result in supervised manner[25]. The orientation of this paper is structured as follows. Section 3 presented a details of feature extraction technique, Section 4 describes about supervised classification methodology, and the proposed system for feature engineering is discussed in Section 5.In section 6 results and discussion are drawn and session is ended with conclusion.

3. Overview of Feature Extraction

Feature extraction is the process involved in analyzing imagetexture. The results gives a better understanding of texture and object shapedetermination. When the algorithm has more input data set, it is to beconverted to a smaller dimension for better handling. Converting input image into a standard set of features is termed as feature extraction. By employing feature extraction process on the fundus images under normal and glaucoma category, the grouped pixels wereconverted to numerical data by the process of feature extraction.Most of the featuresconsidered in this research work are Gray Level Co-occurrence Matrix(GLCM) for extracting the statistical features, Gray-Level Run-LengthMatrix (GRLM) for extracting the run length features [12] and Gray Level Difference Matrix (GLDM) for extracting the probability of gray level usingdensity function. The functionality of each method is given below.

3.1 Gray Level Co-Occurrence Matrix (GLCM) Technique:

The Gray Level Co-Occurrence Matrix (GLCM) method extracts texture features and maintains arelationship among pixels by calculating the gray level co-occurrence values.Here the probability value of GLCM is obtained by density functionp(a, b | dist, ɵ) on specified direction of ɵ = 0, 45, 90, 135°, etc., and 'dist' varying from 1 to 5 distance. The function p (a, b | dist, ɵ) denotes probability between any pair ofpixels 'a' and 'b', that are located at distance 'dist' and a direction 'ɵ' ofgray level. Thus distance is defined a spatial relationship is known as inter sample distance. All images are assigned to have number of intensity 'N_{di}at discrete level.The features of GLCM method is described below,

1. ***Autocorrelation (AU):*** It is anaccurate calculation of the scale/magnitude of the distinction as well as thickness of input image texture, a higher value indicates a texture with more pairs with high gray levels.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)ij$$

2. ***Contrast:*** It is an exact difference of the local intensity values of the input images, choosing p (i, j) pixel values left from the diagonal (i = j) part. A greater value associates with a larger difference in pixel intensity values between adjacent voxels.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i-j)^2 p(i,j)$$

3. ***Correlation:*** This value lies among the 0 (represented as uncorrelated) and 1 (represented as exactly correlated) showing the linear dependency of gray level values to their respective voxels in the GLCM

$$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)ij - \mu_x(i)\mu_y(j)}{\sigma_x(i)\sigma_y(j)}$$

4. ***Cluster Prominence (CP):*** Skewness and asymmetry of the GLCM are used to calculate the Cluster Prominence value. Asymmetry indicates the larger variation and Skewness indicates the lower variation values near the mean value.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(i+j-\mu_x(i)-\mu_y(j))^4 p(i,j)$$

5. ***Cluster Shade (CS):*** Skewness and uniformity values of the GLCM are used to calculate the Cluster Shade feature. The highest value of asymmetry nearby the mean represent the higher cluster shade.

$$\sum^{N_g}\sum^{N_g}(i+j-\mu_x(i)-\mu_y(j))^3 p(i,j)$$

6. ***Dissimilarity:*** The mean absolute variance among the adjacent pairs represented as a dissimilarity value. A greater value associates with a larger difference in pixel intensity values between adjacent voxels.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}|i-j|p(i,j)$$

7. ***Energy:*** From the input mage, homogeneous patterns are used to measure the energy value.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}(p(i,j))^2$$

8. ***Entropy:*** The randomness in region/object intensity pixel values are used to calculate the entropy value.

$$-\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} p(i,j)\log_2(p(i,j)+\epsilon)$$

9. ***Homogeneity1 (H1):***Relationship among the pixel intensity values of adjacent voxels in the input image is used to calculate the homogeneity1 value.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{p(i,j)}{1+|i-j|}$$

10. ***Homogeneity2 (H2):***Resemblance in intensity values for adjoining voxels are used to measure the homogeneity2 value.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g} \frac{p(i,j)}{1+|i-j|^2}$$

11. ***Maximum probability (MP):*** Maximum Probability is the occurrence of the most predominant pair of neighboring intensity values.

$$\max(p(i,j))$$

12. ***Sum of squares (Variance):*** Variance (also known as Sum of Squares) is the average value of the aligned distances value of the every intensity after the average value.

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(\mathbf{X}(i)-\overline{X})^2$$

13. ***Sum Average (SA):*** Sum Average measures the correlation among existences of input pixel pairs with lower values of intensity also greater values of intensity.

$$\sum_{k=2}^{2N_g} p_{x+y}(k)k$$

14. ***Sum Variance (SV):*** Sum Variance is a ration of heterogeneity value, which places the greater weights on adjacent intensity value level pixel pairs.

$$\sum_{k=2}^{2N_g}(k-SE)^2 p_{x+y}(k)$$

15. ***Sum Entropy (SE):***It is a total value of adjacent pixels intensity Variations.

$$\sum_{k=2}^{2N_g} p_{x+y}(k)\log_2(p_{x+y}(k)+\epsilon)$$

16. Difference Variance (DV):It is a ratio of heterogeneity value, which places greater weights on conflicting input pixel intensity level pairs.

$$\sum_{k=0}^{N_g-1} (1 - DA)^2 p_{x-y}(k)$$

17. Difference Entropy (DE):Variability in adjacent pixel intensity value is termed as difference entropy.

$$\sum_{k=0}^{N_g-1} p_{x-y}(k) \log_2(p_{x-y}(k) + \epsilon)$$

18. Information Measure of Correlation1 (IMC1):This feature is a ratio of linear dependences of gray tone value in the input image.

$$\frac{HXY - HXY1}{\max\{HX, HY\}}$$

19. Information Measure of Correlation2 (IMC2):

$$\sqrt{1 - e^{-2(HXY2 - HXY)}}$$

20. Inverse Difference (ID):

It is alternative ratio of the confined area homogeneity of an input image.

$$\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{p(i,j)}{1 + |i - j|}$$

21. Inverse Difference Normalized (IDN):

It regularizes the variance among the adjacent intensity values of input pixels byisolating above the total number of discrete/disconnected intensity values.

$$\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{p(i,j)}{1 + \left(\frac{|i - j|}{N_g}\right)}$$

22. Inverse Difference Moment Normalized (IDMN):

This features values is calculated from the local/object region homogeneity of an input image. The square of the 2 adjacent pixel intensity difference values are calculated by dividing square of the total number of disconnected/discrete intensityvalues

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_g}\frac{p(i,j)}{1+\left(\frac{|i-j|^2}{N_g^2}\right)}$$

3.2 Gray Level Run Length Matrix (GRLM) Technique

According to specified direction GRLM is representing a features' geometrical values the form of a row and column. During a run length process, intensity of a pixel is measured at a given direction in two dimensional forms. So each element is represented as 'j' number of pixel elements withthe intensity 'i' in the direction ɵ. At a given direction, the run-length matrix estimates total occurrence time of each pixel intensityvalue. It will continue by enlarge a consecutive pixel selection by the same intensity value of pixel [14]. The length of the run is the number of pixelpoints in execution. The following features are extracted by GLRM:

1. **SRE (Short Run Emphasis):** SRE feature value is a calculated from the distribution of short run lengths of pixels, with a larger value of shorter run lengths of pixels as well as sufficient textural textures of pixels.

$$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\frac{\mathbf{P}(i,j|\theta)}{i^2}}{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\mathbf{P}(i,j|\theta)}$$

2. **LRE (Long Run Emphasis):** LRE feature value is a calculated from the distribution of long run lengths of pixels, with a larger value of longer run lengths of pixels and rough structural textures of pixels.

$$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\mathbf{P}(i,j|\theta)j^2}{\sum_{i=1}^{g}\sum_{j=1}^{N_r}\mathbf{P}(i,j|\theta)}$$

3. **GLN(Gray Level Non-uniformity):** GLN feature value is calculated from the resemblance of gray level intensity values of the input image, where a lesser GLN value associates with a larger resemblance in pixel intensity value.

$$\frac{\sum_{i=1}^{N_g}\left(\sum_{j=1}^{N_r}\mathbf{P}(i,j|\theta)\right)^2}{\sum_{i=1}^{N_g}\sum_{j=1}^{N}\mathbf{P}(i,j|\theta)}$$

4. **RP (Run Percentage):** RP feature value is calculated with the roughness of the texture by getting the ratio of number of rounds also total number of voxels in the object/ROI.

$$\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\frac{\mathbf{P}(i,j|\theta)}{N_p}$$

5. **RLN(Run Length Non-uniformity):** RLN feature value is calculated with the resemblance of run length values of the whole input image, with a lesser value of the pixel representing additional homogeneity between run lengths in the given image.

$$\frac{\sum_{j=1}^{N_r}\left(\sum_{i=1}^{N_g}\mathbf{P}(i,j|\theta)\right)^2}{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\mathbf{P}(i,j|\theta)}$$

6. **LGRE (Low Gray Level Run Emphasis):** LGLRE feature value is calculated with the distribution of small gray level value of the input image in this higher value representing a larger absorption of small gray level values of the input image.

$$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\frac{\mathbf{P}(i,j|\theta)}{i^2}}{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\mathbf{P}(i,j|\theta)}$$

7. **HGRE (High Gray Level Run Emphasis):** HGLRE measures the distribution of the higher gray-level values, with a higher value indicating a greater concentration of high gray-level values in the image.

$$\frac{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\mathbf{P}(i,j|\theta)i^2}{\sum_{i=1}^{N_g}\sum_{j=1}^{N_r}\mathbf{P}(i,j|\theta)}$$

Totally twenty nine features were extracted for each types of segmented image separately.The result fromthe above two methods of feature extractionprocedure is input to the classifierdirectly.

3.3 Gray Level Difference Matrix (GLDM)

The GLDM is a process to calculate gray level probability of a segmented image using density function. It is used to distinguish any two pixels which are provided with absolute gray level that has beendisplaced by a precise separation. For a given image, density value of new feature is classified using the below equation:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} PDF(i)$$

where PDF (i) is total probability value ofpixel’s gray level, ‘N’denotes number of image graylevels in the particular image pixel ‘i’ [15].

4. Supervised Classification

Supervised learning is a mapping process to predict the result for unseen data by applying mapping between a set of input variable X and output variable Y. The majority of practical ML techniques use supervised learning. The output values are indicated by label representation corresponding to each input value. The proposed model applies the ML classification algorithms like

Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT) and Naive Bayes (NB). Based on the performance of extracted features, the classification accuracy is demonstrated.

In this research, supervised learning algorithms use extracted texture feature of a segmented image are classified into two classes as normal and abnormal. The supervised learning methods followed the labeled instances in the training data set that aids the learning models to train proficiently [16].

4.1 Support Vector Machine (SVM)

SVM is a supervised learning model that is generated for binary classification in both linear and nonlinear forms. Usually, datasets are nonlinearly inseparable, thus the main goal of the SVM method is to catch the finest available surface to make a separation among positive and negative training feature samples depend on experimental threats (training set, test set error) reduction principal. This method can try to describe a decision boundary with the hyper-planes in a high dimensional feature space. These hyper-planes distinct the vectorized data into 2 classes and also finds an outcome to take a decision depend on this support vector. The working method of SVM can be described as follows.

Given ‘N’ linearly separable training set with feature vector ‘x’ of dimension D. For dual optimization,

Then the outcome of SVMs can be described as follows:

$$\vec{\alpha}^* = argmin\left\{-\sum_{i=1}^{n}\alpha_i + \sum_{i=1}^{n}\sum_{j=1}^{n}\alpha_i\alpha_j y_i\, y_j \langle\vec{x_i}\,,\vec{x_j}\rangle\right\}$$

Where, $\alpha \epsilon D^N$ and $y \epsilon \{1, -1\}$

$$\sum_{i=1}^{n}\alpha_i\, y_i = 0; \qquad 0 \le \alpha_i \le C$$

In SVM classification, it separates the linear dataset with a single hyper-plane of given feature subset into two classes. Further, nonlinear dataset separates more than two classes by utilizing a kernel functions. It stateshigher dimensional space layout of data in a linear orientation.Fig.2illustratesbasic idea of SVM;this algorithm can be viewed as thetask of separating two classes positive and negative in featurespace. The main problem is to find out a hyper-plane, which separates those classes effectively depending on maximalmargin.

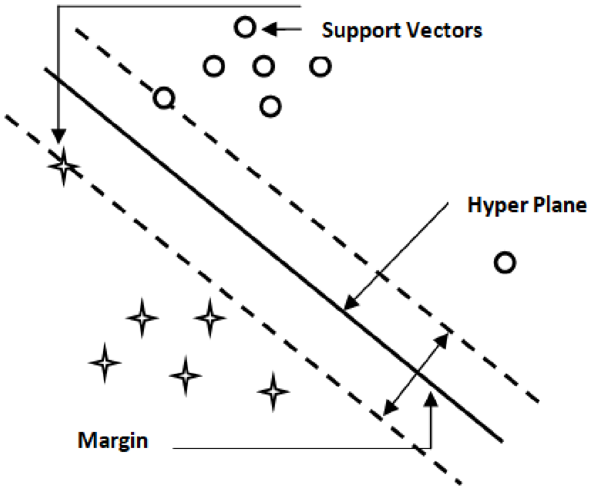

Fig.2Functioning of SVM

As shown inFig.2, SVM presents a linear separable of data points in two dimensional form.The data pointsare distinguished as positive or negative, where the issue is to identify a hyper-plane that acts as separator between twotypes of feature points.Basically, the hyper-plane that shown above is the expecteddecision boundary for linear support vector machine [17].The pseudo code of theimplemented algorithm is described below,

Algorithm: SVM classifier
Input:Texture features
Output: Accuracy

- *Step1:* Start
- *Step2:*Extracted feature dataset given as input
- *Step3:*Labeling the features for training
- *Step4:* the SVM algorithm is applied with kernel function (Radial Basis Function)
- *Step5:* Identify the Hyper-plane of the SVM
- *Step6:* If attained accuracy values is not satisfied then go to step 4
- *Step7:* End

By applying SVM with RBF kernel, classification is to extract a feature from a specified Hyper-plane. Then it checks the obtained accuracy [17].

4.2 K-Nearest Neighbour(KNN)

Another supervised technique used particularly for the classification purpose is KNN. The idea behind this method captures a similarity in finding a distance between nearest samples. For the input population nearest value is identified and is ready to assign classes to all or any the samples.

Consider $X_i = \{x_1, x_2, \dots, x_{iN}\}$ and $X_j = \{x_1, x_2, \dots, x_{jN}\}$ the sample population and similarity, distance of sample is given as.

$$\mathrm{Dist}(X_i, X_j) = \sqrt{\sum_{m=1}^{N} (x_{im} - x_{jm})^2}$$

In the above equation, Euclidean distance is described by evaluating a similarity between two pixel points. Hence, the pixels obtain the category to which a number of pixels that are existswith commonresemble.In KNN, k is the quantity of closest neighbors. The quantity of neighbors is considered as center factor to make a classification[18]. The below figure illustratesclassification of samples within the feature space.

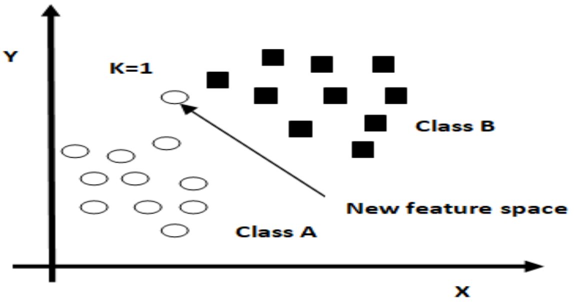

Fig.3 Functioning of KNN

Algorithm:KNN classifier
Input:Texture features
Output: Accuracy

Classify (X,Y,x)//X:Training data;Y:Class labels of X, x:Unknown sample

Step1: Start
Step2: Select the K (number of the neighbors) value
Step2: For i=1 to m do
Step3: Compute distance d (X_i, x)
Step4: end for
Step5: Compute set I containing indices for the k smallest distances d (X_i, x)
Step6: Return majority label for {Y_i where i ∈ I}
Step7: End

Drawbacks:

- The value of K needs to be determined every time and it can be sometimes complex
- For every training sample, the distance between every data point is calculated and it increases the computational cost [18].

4.3 Decision Tree (DT)

The DT classifier generatestree-structured classifier along withtwo nodes called ‘decision nodes’ and‘leaf nodes’. In which features of a datasetis represented in internal nodes, decision rules are represented as branches and each leaf node represents the output. On the basis of feature of a given dataset, test is performed.Each decision node tested ‘X’ element of the input data and features of branches, then each branch holds a result of ‘X’. Every leaf node signifies a group to make an effective decision.

A fundamental method of building a 'DT' is a split procedure by dividing a feature space into number of sub classes. A training feature set 'T' can holds data of 'k' classes (c_1, $c_2 \ldots c_k$) or onlycontains single class. If 'T' restrains no data, assignedas leaf node and its connected class is going to act as main class of its parent node. If 'T' holds the cases of mixed classes, a test hold some attribute 'a_i' of the training data are accepted and can be split into 'n' subsets (T_1, T_2,…..,T_n), where 'n' is the number of results of the test over attribute 'a_i'. A corresponding process of constructing 'DT' is recursively executed over every T_i, where T_i ranges from 1 to n, till every subset fits into one class [19].The Fig.4shows Classification method using Decision Tree within the feature space.

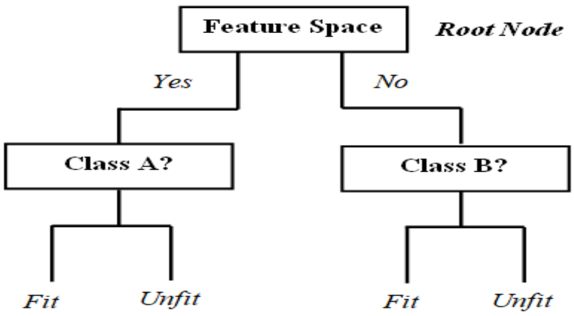

Fig.4Functioning of DT

The algorithm starts the whole process of classification at a root node of the tree. The root divides the feature space into more sub classes of feature set. The classes are assigned by weights. Based on features weights are computedduring the learning process and these weights are used to classify testing (unknown) data.

Algorithm:DT classifier
Input:Texture features
Output: Accuracy

tree - Training Set; T - Input Feature Set; y - Target Feature

Step1: Start
*Step2:*Create a new tree T (feature space) with a single root node
*Step3:*Let tree be the set of training instances
*Step4:*If tree instances (y-> tree) are A (Positive),
: return leaf node 'Class A'
*Step6:*Else if tree instance (y-> tree) are B (Negative)
return leaf node 'Class B'
*Step8:*end if
Step9: End

Drawbacks:

- It can be unstable, meaning that a small change in data points can translate into a big change in classification model.
- It tends to over fit, which means low bias but high variance: i.e., might not perform as well on unknown data even if the score on the train data is great.
- There is a high probability of over fitting in Decision Tree [19].

4.4 Naive Bayes (NB) Algorithm

This method is sustained from Bayes theorem constructed with predictive modeling on the independence theory. In machine learning algorithm there is a possibility to define hypothesis on given data. The best way to select a probable hypothesis is carried over by prior knowledge about the problem.Hence the Bayes's theorem represents a way to calculate the hypothesis probability with prior knowledge and it is stated as

$$P(hyp|d) = (P(d|hyp) * P(hyp)) / P(d)$$

where,

P(hyp|d) is the probability of hypothesis hyp given the data d. This is called the posterior probability.
P(d|hyp) is the probability of data d given that the hypothesis hyp was true.
P(h) is the probability of hypothesis hyp being true (regardless of the data). This is called the prior probability of hyp.
P(d) is the probability of the data (regardless of the hypothesis).

Wherein, the classifier is applied to map prospects of features to the hypothesis from specified feature subsets. Through which,approximate probability score is computed. This classifier applies the simple probabilistic classifier, which is assist to classifying a data 'd_r' from a classes $c_i \in C$ ($C_{i=1}^{m}$ = c_1, c_2,…..c_m). The finest class returns Maximum Posterior (MAP) class in NB classification as follows

$$C_{map} = \text{argmax} (P(c_i) * P(d_r|c_i)) \quad \text{where } c_i \in C$$

Here, the class '$P(c_i)$' can be calculated by dividing the total number of features in class 'c_i' by the entire number of features. P (d_r |c_i) denoted the number of occurrence of the feature in data 'dr' belongsto class 'c_i'. The probability value will be calculated for every new class, but '$P(d_r)$' doesn't change for every class. It chooses the maximum probable classes 'c_{map}'of given data 'd' by computing the posterior probability of every class [20]. The below figure illustrate the working mechanism NB classifier in the feature space,

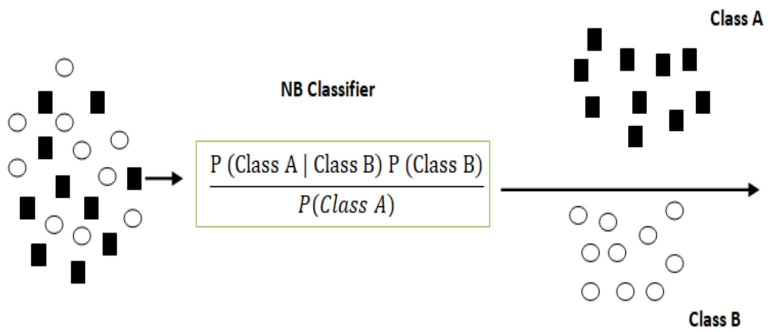

Fig.5. Functioning of NB

Naïve Bayes classifiers are a family of simple "probabilistic classifiers" based on applying Bayes' theorem with strong independence assumptions between the features.The steps of Naive Bayes's Algorithm in the classification are as follows:

- *Step 1:* Calculate the prior probability for given class labels
- *Step 2:* Find Likelihood probability with each attribute for each class

- *Step 3:* Put these value in Bayes Formula and calculate posterior probability.
- *Step 4:* See which class has a higher probability, given the input belongs to the higher probability class.

Drawbacks:

- The assumption of independent features. In training, it is almost impossible that model will get a set of predictors which are entirely independent.

- If there is no training tuple of a particular class, this causes zero posterior probability. In this case, the model is unable to make predictions. This problem is known as Zero Probability/Frequency Problem [20].

5. Proposed system for Feature Engineering

This section deals with the extraction of feature along with classification. To discuss the working mechanism of the proposed scheme focus the preliminary background of extraction technique and classification algorithms as presented in the Figure.6.

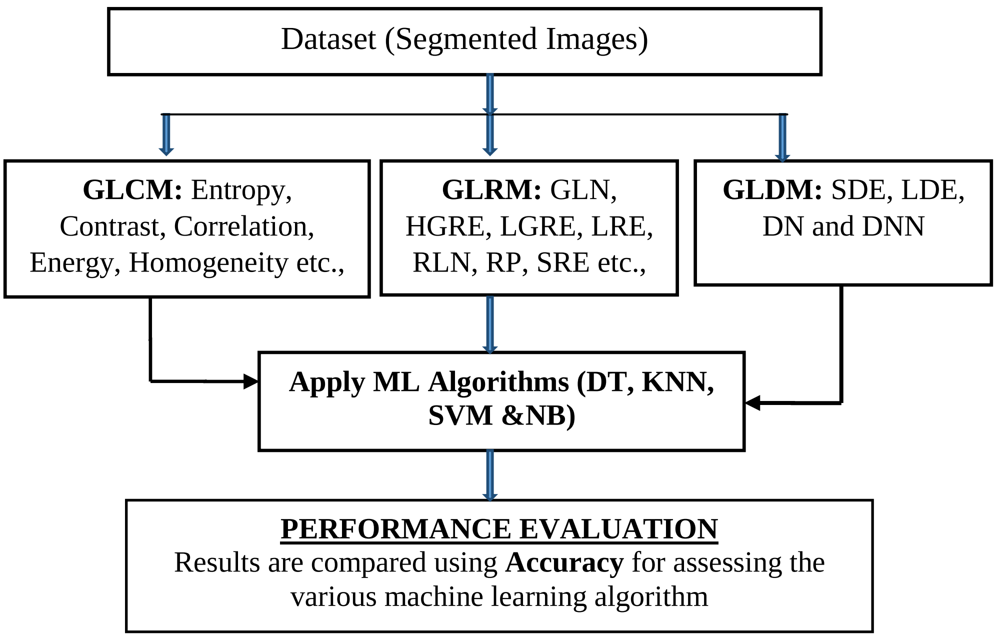

Fig.6.Feature Extraction system

The featuresconsidered in this research were used to increase the significance differencebetween the class areas. The features generated by GLCM and GLRM and GLDM werelisted in Section 3. The Overall features werelisted in below Table 1.

Table.1. Overall features

Methods	Features
GLCM Based Features	Autocorrelation, Contrast, Correlation, Cluster Prominence, Cluster Shade Dissimilarity, Energy, Entropy, Homogeneity1, Homogeneity, Maximum probability, Sum of

	squares (Variance),Sum average, Sum variance, Sum entropy, Difference variance, Difference entropy, Information measure of correlation1, Information measure of correlation2, Inverse difference, Inverse difference normalized, Inverse difference moment normalized.
GLRM Based Features	SRE, LRE, RLU, GLN, RP, LGLRE and HGLRE
GLDM Based Features	SDE, LDE, DN and DNN

Totally 33 features were extracted for each normal and abnormal images separately.

TotalNumber of Features = (22 GLCM Features **+7** GLRM Features + 4 GLDM Features)

Basically, extracting feature is focused with intensity characters of image pixel.Thus the extracted features provide vital informationabout the image intensity, shape, texture and location. So, the spatialdependencies of the grey levels on different angles are given by GLCM andthe GLRM gives the coarse characters of the images. The GLRMsignificantly boost the intensity of the class area by giving the higher orderstatistical information. GLDM identifies the feature with gray level density.The feature from a data set imagesare generated into two types of classes. Then this researchutilized the various machine learning algorithms to classify the normal and glaucoma images. Meanwhile, these algorithms have been compared in terms of accuracy.

6. Results and Discussion

As presented in Fig.1, we illustrated a processing procedure for feature extraction and classification to assess a glaucoma of a given input fundus image. Totally 221 images were taken from the data sets [21][22], in which normal image image is labeled as “0” and glaucomatous image is labeled as “1”. The evaluation scheme contains two-stage classification and number of parameters to obtain feature space with single probability. Beside, performance of the proposed method is analyzed with distinguished classifier comparison. In this way, a MATLAB code has been programmed for successful identification and classification of glaucoma disease.

6.1 Performance Parameters

The features which are selected from the datasets are used for training and testing process. For evaluation, 80% of data were used for training and 20% of data were used for testing. The evaluation is carried out for the different algorithms with the following parameters such asTP, FP, TN, FN, and Accuracy [23].

- TP - Number of normal feature is correctly classified as normalfeatures
- TN - Number of abnormal feature is correctly classified as glaucoma features
- FP - Number of feature is wrongly classified as glaucomafeatures

- FN - Number of abnormal feature is wrongly classified as normal features
- Accuracy value predicts correct of number proportion to generate accurate result.The proportion is determined by a equation:

$$\text{Accuracy} = \frac{(TP + TN)}{(\text{TP} + \text{TN} + \text{FP} + \text{FN})}$$

In this research, performance parameters of the feature extraction algorithms have been declared by a well known representation (confusion matrix) as in Fig.7. Hencevisualization of algorithm execution is belonging to recognition of uncertainty between classes as predicted in Fig 7.

True Positive (TP)	**False Negative (FN)**
False Positive (FP)	**True Negative (TN)**

Fig 7. Confusion Matrix

The objective isto assess the overall performance of machine learning procedure with the extracted features as follows.

GLRM

GLRM technique is employed in feature extraction process to extract optimal feature from the segmented images. This process is employed to enhance the classification process of machine leaning model. These extracted features are often used to trained machine-learning algorithms. The features set are described in section 3.1. Sample imaging features extracted in this work are listed in below table.

Table.2. GLRM Features

SRE	LRE	GLN	RP	RLN	LGRE	HGRE
0.428784	548.3424	33762.1	0.498039	30109.51	50.21015	33762.1
0.407549	540.8012	32098.62	0.495193	27567.25	53.13468	32098.62
0.44007	431.4176	32395.84	0.596945	38304.35	64.43315	32395.84
0.415768	583.8721	35920.95	0.480013	27493.41	83.9845	35920.95
0.425313	539.4079	39769.16	0.506892	30244.1	78.18947	39769.16
0.428784	548.3424	33762.1	0.498039	30109.51	50.21015	33762.1
0.431559	458.5914	34629.22	0.570154	35373.46	84.21521	34629.22
0.415543	585.6968	24961.02	0.467078	26500.33	53.59368	24961.02
0.447853	427.4349	44183.57	0.586335	38259.98	61.36647	44183.57
0.407879	593.8338	29050.85	0.46619	25816.08	84.07849	29050.85
0.419495	575.2562	32058.94	0.475249	27609.84	92.0174	32058.94
0.44007	431.4176	32395.84	0.596945	38304.35	64.43315	32395.84
0.415768	583.8721	35920.95	0.480013	27493.41	83.9845	35920.95
0.425313	539.4079	39769.16	0.506892	30244.1	78.18947	39769.16
0.359994	10989.64	135859.5	0.184619	111178.6	40.07823	135859.5

0.396792	10788.06	115052.1	0.184618	128383.3	65.748	115052.1
0.402738	12311.82	100362.1	0.167456	120281.9	42.53416	100362.1
0.446135	13117.61	115862	0.16106	138102.5	49.83659	115862
0.432363	13661.18	116979.5	0.160312	131810.4	40.30907	116979.5

From the tables, the GLRM features were extracted from the glaucoma fundus image datasets, which are used as an input files for machine learning techniques.The performance of the proposed algorithms has been assessed by various cases.

GLCM

The GLCM function characterizesspatial relation between two pixels its texture with necessary values in a specified image. It displays the matrix representation ofextracted statistical measures for an image.The features set are described in section 3.1. Below Table shows extracted imaging features of this work.

Table.3. GLCM Features

AutoCorrelation	Contrast	corrm	corrp	cprom	cshad	dissi	energ	entro	homom	homop
7.636242	0.060187	0.976478	0.976478	47.99116	-3.22449	0.059579	0.32634	1.369968	0.970312	0.970271
10.22294	0.0544	0.98594	0.98594	120.4206	-5.59161	0.052463	0.295798	1.456097	0.974091	0.973962
11.12381	0.070023	0.984285	0.984285	140.4938	-5.84609	0.067655	0.243092	1.640159	0.966567	0.966409
15.62253	0.060223	0.9906	0.9906	274.8017	-24.5234	0.052955	0.307565	1.399938	0.974653	0.974249
11.46239	0.050064	0.987971	0.987971	113.9928	-14.9619	0.044964	0.42896	1.151049	0.978355	0.978028
7.636242	0.060187	0.976478	0.976478	47.99116	-3.22449	0.059579	0.32634	1.369968	0.970312	0.970271
14.21182	0.061875	0.9892	0.9892	214.4146	-19.5188	0.057065	0.285296	1.461448	0.972238	0.971948
8.899173	0.051169	0.984473	0.984473	77.64847	-3.25002	0.050599	0.272994	1.523112	0.974796	0.974758
6.415859	0.03503	0.980983	0.980983	23.57287	-3.62848	0.032729	0.461867	1.032615	0.984009	0.983866
15.40749	0.059883	0.990499	0.990499	258.2727	-24.2601	0.049749	0.30794	1.412243	0.976444	0.976105
17.01271	0.067588	0.990473	0.990473	333.9398	-29.9797	0.05715	0.325727	1.433161	0.972953	0.972466
11.12381	0.070023	0.984285	0.984285	140.4938	-5.84609	0.067655	0.243092	1.640159	0.966567	0.966409
15.62253	0.060223	0.9906	0.9906	274.8017	-24.5234	0.052955	0.307565	1.399938	0.974653	0.974249
11.46239	0.050064	0.987971	0.987971	113.9928	-14.9619	0.044964	0.42896	1.151049	0.978355	0.978028
5.431042	0.025314	0.99105	0.99105	96.09495	11.08662	0.025314	0.357036	1.334577	0.987343	0.987343
8.351557	0.025301	0.995029	0.995029	198.5769	17.56629	0.024387	0.340484	1.418975	0.987946	0.987898
5.106206	0.01587	0.994076	0.994076	89.69807	11.9364	0.015868	0.343691	1.351677	0.992066	0.992066
5.723697	0.015512	0.995085	0.995085	133.4999	15.4577	0.014592	0.35554	1.34498	0.992845	0.992796
6.077256	0.017937	0.99487	0.99487	179.7199	18.93735	0.017909	0.342426	1.39096	0.99105	0.991048

maxpr	sosvh	savgh	svarh	senth	dvarh	denth	inf1h	inf2h	indnc	idmnc
0.449714	7.587604	5.054485	18.94746	1.327539	0.060187	0.226874	-0.80789	0.918604	0.993387	0.999075
0.391984	10.16027	5.767336	26.6041	1.417612	0.0544	0.207705	-0.83651	0.936364	0.994192	0.999166
0.314589	11.06568	5.976944	28.07467	1.591371	0.070023	0.250356	-0.81702	0.946691	0.992509	0.998926
0.402683	15.54263	7.056701	45.20891	1.359722	0.060223	0.20978	-0.83692	0.930936	0.994195	0.999086
0.572574	11.39182	6.133968	33.47767	1.113648	0.050064	0.185314	-0.83125	0.897496	0.99506	0.999237
0.449714	7.587604	5.054485	18.94746	1.327539	0.060187	0.226874	-0.80789	0.918604	0.993387	0.999075
0.324477	14.13759	6.746339	39.79439	1.417329	0.061875	0.221934	-0.82757	0.934317	0.993712	0.999055
0.314674	8.840702	5.395202	21.81616	1.486685	0.051169	0.201197	-0.84315	0.944145	0.994384	0.999214
0.601018	6.360248	4.695673	17.27385	1.004505	0.03503	0.14517	-0.85457	0.886447	0.996389	0.999464
0.404522	15.32815	7.010256	44.33977	1.371675	0.059883	0.198622	-0.84527	0.934616	0.994575	0.999105
0.459284	16.93194	7.348265	49.64631	1.387991	0.067588	0.221598	-0.82852	0.931824	0.993761	0.99898
0.314589	11.06568	5.976944	28.07467	1.591371	0.070023	0.250356	-0.81702	0.946691	0.992509	0.998926
0.402683	15.54263	7.056701	45.20891	1.359722	0.060223	0.20978	-0.83692	0.930936	0.994195	0.999086
0.572574	11.39182	6.133968	33.47767	1.113648	0.050064	0.185314	-0.83125	0.897496	0.99506	0.999237
0.521662	5.381213	4.01472	12.90903	1.317031	0.025314	0.118056	-0.91055	0.944755	0.997187	0.999611
0.519182	8.289065	4.824772	21.88421	1.399701	0.025301	0.115156	-0.91586	0.953441	0.9973	0.999612
0.521594	5.053671	3.885699	11.81921	1.34067	0.01587	0.081495	-0.93781	0.952931	0.998237	0.999756
0.520641	5.66801	4.076043	13.82291	1.332554	0.015512	0.076267	-0.94198	0.953321	0.998389	0.999763
0.521949	6.021381	4.165627	14.74303	1.378422	0.017937	0.089842	-0.93367	0.955236	0.99801	0.999724

GLDM

This method differentiatestwo pixels which are provided with absolute gray level that has been displaced by a precise separation. The features set are described in section 3.1. The sample imaging features extractedin this work are listed in below table.

Table.4. GLDM Features

SDE	LDE	DN	DNN
103957.7	103552	104583.8	103495.7
235773	235026.9	236720.2	235088.9
204272.5	203322.5	204718.5	203341.2
174028.5	173803	175475.2	173708.8
174028.5	173803	175475.2	173708.8
235773	235026.9	236720.2	235088.9
103957.7	103552	104583.8	103495.7
174028.5	173803	175475.2	173708.8
235773	235026.9	236720.2	235088.9
204272.5	203322.5	204718.5	203341.2
174028.5	173803	175475.2	173708.8
235773	235026.9	236720.2	235088.9
235773	235026.9	236720.2	235088.9
103957.7	103552	104583.8	103495.7
174028.5	173803	175475.2	173708.8
4437204	4428881	4436657	4428483
4429011	4418180	4428942	4414360
4444174	4436343	4444542	4437012
4436233	4429394	4440595	4423854
4446012	4437947	4446347	4438869

After the completion of the features extraction methods,those features are given as input to the ML classifiers forclassification isevaluated. Below tables shows the classification accuracy ofvariousclassifier with different features set like GLCM (22), GLRM (7), GLDM (4) and ALL (33). It isobserved that, classification accuracy withDecisionTree (DT) shows considerableimprovement.

Table.5. Performance Evaluationwith Accuracy (%)

ML Algorithm	GLCM (22)	GLRM (7)	GLDM (4)	ALL (33)
Decision tree (DT)	80.5	78.9	89.3	94
K-Nearest Neighbor (KNN)	67.7	70.9	80.2	83
Support Vector Machines (SVM)	77.7	77.7	81.4	69.5
Navie Bayes (NB)	74.5	74.5	80.5	78

From the above results, the DT classifier yields the best result for all features while compare with other algorithms. This classification process determines the normal and glucomaimages under two categories.

Most of the ML algorithms gives best result while combining all features (GLCM, GLRM& GLDM). The feature extraction and ML algorithm provided by the MATLAB machine-learning toolbox is utilized for assessing the effort of the proposed methodology and calculates the number of normal and abnormal features present in the testing dataset. Among that, 20% of images from testing data and the 80% from training data. With this the accuracy percentage of DT algorithm has been reached with 94% of accuracy for all (33) features.

Conclusion

The presented methodology ensures reliable texture based feature extraction to detect glaucoma with supervised classification [24]. The model focuses on extracting various features using efficient feature extraction methods which improves the result of classification accuracy from segmented fundus eye images. Saliency based segme4nted fundus image is considered for extraction of texture features byusing both (first&second) statistical order and probability techniques like GLCM, GLRMand GLDM. The results obtained by these methods indicate the potential advantages of using feature extraction techniques to improve the classification accuracy with maximum number of feature subset.The proposed classification scheme enables to include four classifiers to reduce the dimensionality of feature with robust.From the result, given detection method conclude that the performance of combined features is superior to DT classification. The probabilistic design of the feature extraction and classification is given by compressed discriminating image dataset features.Further, this research will provide a better understanding of AI in medical science.

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