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Glaucoma detecting and Classification in Funds Images using Automated Image Processing and machine learning Techniques

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Abstract
Glaucoma is an eye related disease which is hard to detect and treat at an initial stage. There is a need for multicenter trials, a more comprehensive approach to documentation at all levels, and the need to recognize potentially preventable risk factors associated with Glaucoma disease. Late detection of the disease is a significant cause of this since no reliable early detection techniques are available. Fundus scan imaging has now proven to be the safest diagnostic tool for the identification of glaucoma in eyes. CAD system can also be useful for physicians to correctly classify disease. Many computer-aided techniques using image processing, machine learning have been investigated and executed from the literature survey. The main goal of this research is to analyze the different computer-aided methods, find out the limitations and disadvantages, and eventually recommend changes to the current model. To this end, this research proposes a computer aided diagnosis (CAD) system for glaucoma disease detection on Fundus images.
Keywords: Glaucoma, Denoising, segmentation, features, classification

1. Introduction

Glaucoma is one of the leading causes of irreversible vision loss, it progresses gradually without easily noticeable symptoms. The detection of glaucoma in the early stage is crucial as it may help to decelerate the progress. The traditional instrument methods are manual, time-consuming and less accurate. Hence, the automated diagnosis of glaucoma is needed for detection of glaucoma in the early stage with high accuracy. The flexible Adaptive median filter method has been applied for denoising Retinal Fundus Images. In the research method, Grow cut segmentation method has been used to decompose the preprocessed images into various sub-band images [1].

Then, the fundus image is segmented the various entropies and fractal dimension (FD) based features, respectively. Further, the extracted feature values are ranked using Fisher's linear discriminant analysis (LDA) dimensionally reduction. Finally, the higher rank features have been used for the classification of glaucoma stages using least squares-support vector machine (LS-SVM) classifier. The proposed method has been evaluated on publicly available large and diverse glaucoma database. The classification accuracy of the proposed method is 93.40% using tenfold cross-validation. The proposed method has demonstrated better performance for glaucoma classification as compared to the existing methods. The proposed method is ready to help the ophthalmologist in their daily screening for glaucoma detection.

This Research Methodology proposes an optimized feature-based framework to discover the optimal solution for research objective. The solutions provided in this research are more feasible and discriminative. Whale Optimized feature based selection is applied to extract the finest features for optimization. Here, different classification algorithms are analyzed and a technique is suggested to reach the optimum solution and maximum accuracy. Proposed Research contribution and Enhanced technique is shown in the below figure. The research process is based on the following stages.

Pre-Processing (Adaptive Medain Filtering)
Segmentation (Grow Cut Algorithm)
Feature Extraction (GLCM,GLRM)
Classification (SVM)

Fig.1 Proposed Research Design

2. Literature Review

Deepak Parashar used 2D-DWT method to decompose the preprocessed images into various sub-band images (SBIs). Further, the significant grey level co-occurrence matrix (GLCM) features have been computed from SBIs. Then, the ReliefF algorithm has been utilized to select the relevant features from the extracted feature set. Finally, these robust features have been used for classification using the K-nearest neighbor (KNN) classifier. The developed framework obtained the maximum accuracy of 92.10% with a tenfold cross-validation process [2].

E. Deepika et al., aimed to detect the glaucoma in the retinal image and classify them based on their severity. To detect the abnormality, preprocessing methods such as filtering, green channel extraction and CLAHE are proposed and for feature extraction namely optic disc ratio, active contour and blood vessel segmentation are proposed. Extracted Features are given as the input for classification based on ANFIS and SVM. Then sensitivity, specificity and accuracy of two classifiers are compared to attest an efficient diagnosis system for screening the Glaucoma disorder [3].

Ying Quan et al., presented a platform which provides automatic glaucoma screening service based on hybrid cloud framework. A novel pattern classification technique was proposed for cup to disc ratio (CDR) assessment using 2-D retinal fundus images and it uses the reconstruction coefficients from SDC to compute the CDR. The proposed technique is used in the glaucoma screening diagnosis module of the remote hybrid cloud system. The scalability and flexibility of hybrid cloud framework enable the platform to work as moving connectivity between patients and ophthalmologists. The system enables the patients to get remote diagnostics from distance with low-cost and blindness and visual loss can be prevented through early detection and timely management [4].

M. Abdullah et al., presented a robust methodology for optic disc detection and boundary segmentation, which can be seen as the preliminary step in the development of computer-assisted diagnostic system for glaucoma in retinal images. The proposed method is based on morphological operations, Circular Hough transform and grow cut algorithm. The morphological operators are used to enhance the optic disc and remove the retinal vasculature and other pathologies. The optic disc center is approximated using the Circular Hough Transform, and grow cut algorithm is employed to precisely segment the optic disc boundary. The method is quantitatively evaluated on publicly available retinal image databases DRIVE, DIARETDB1 and CHASE_DB1 and has shown significant improvement over existing methods in terms of detection and boundary extraction of the optic disc. The proposed method has optic disc detection success rate of 100% for these databases. The optic disc boundary detection achieved an average spatial overlap of 77.10%, 85.12% and 83.23% for these databases, respectively, which are higher than currents algorithms [5].

3. Materials Methods

3.1 Dataset Collection

Data used in this research were obtained on a Fundus scanner. Totally, 101 Fundus eyes images confined from 2018 to 2020 were used to early detection of glaucoma disease. During this research, two equally limited labels were considered (i) normal, i.e. images that do not present any irregularities; (ii) ab-normal, i.e. images stated as glaucoma constituents. These images are of dimension 512 × 512 × 178. This dataset totally has 101 images of which 31 are normal and 70 are abnormal (illness).

3.2 Pre-processing by Adaptive Median (AM) filtering

The adaptive Median filter carries out spatial processing to find out which pixels in an image have been affected by noise. It classifies pixels as noise by comparing every pixel in the image to its neighbor pixels. A pixel which is dissimilar from a majority of its neighbor pixels and being not structurally aligned with those pixels, to which it is similar that labeled as noisy pixel. Finally, the noise pixels are then replaced by the median pixel value. The AM filter works on a rectangular region S_{xy}. This filter changes the size of S_{xy} during the filtering process depending on some conditions [6]. The methodology of AM filter is as follows,

$$Z_{min} = \text{minimum pixel value in } S_{xy}$$
$$Z_{max} = \text{maximum pixel value in } S_{xy}$$
$$Z_{med} = \text{median pixel value in } S_{xy}$$
$$xy = \text{pixel value at coordinates } (x, y)$$
$$S_{max} = \text{maximum allowed size of } S_{xy}$$

The AM filtering algorithm works in two levels. It can be denote by level A and level B.

Level A:

IF ($Z_{min} < Z_{med} < Z_{max}$) then

Z_{med} is not a noise go to level B to test if Z_{xy} is a noise

ELSE

Z_{med} is a noise

1. Increase the window size
2. Repeat Level A until...

(a) Zmed is not a noise

Level B:

IF ($Z_{min} < Z_{xy} < Z_{max}$) then

Z_{xy} is not a noise

1. Output is Zxy

ELSE

Z_{xy} is a noise

1. Output is Zmed

3.3 Segmentation of ROI by Grow Cut Algorithm

Segmentation is the process of subdividing the images with different values of textures and pixels. Several methods have been produced for segmenting the images. Here best methodology has been applied which is called as Grow cut algorithm. It completely decomposes the respective images into compact and heterogeneous elements [7]. There will be a subtraction of unnecessary components in the images.

i. Grow Cut Algorithm

The Grow Cut algorithm is based on the cellular automata theory. A cellular automation is an algorithm discrete in both time and space, which operates on a lattice of sites n $\forall p \in P \subset Z^n$ (pixels or voxels in image processing). A cellular automaton is a quad-tuple (Z^n,S,N,δ), where Z^n is the cell space, S is an state set, N is a neighborhood system, and δ is the local state transition function, which defines the rule of calculating the cell's state at t+1 time step based on the states of the neighborhood cells at previous time step t and its typical style is $\delta : S^N \rightarrow S$. The common used neighborhood systems N are the von Neumann and Moore neighborhoods:

1) Von Neumann neighborhood

$$N(p) = \{q \in Z^n : \| p - q \|_1 := \sum_{i=1}^{n} | p_i - q_i | = 1\}$$

2) Moore neighborhood

$$N(p) = \{q \in Z^n : \| p - q \|_\infty := \max_{i=1,n} | p_i - q_i | = 1\}$$

The state S_p of the cell p in our case is actually triplet (l_p, θ_p, C_p), where l_p is the label of the current cell p, θ_p is the strength of the current cell p, and C_p is the feature vector. In the original Grow Cut, an image can be considered as a particular configuration state of a cellular automation, where cellular space is defined by the pixels of the image. For every unlabeled pixels of the image p, the initial states for $\forall_p \in P$ are set to:

$$l_p = 0, \theta_p = 0, C_p = RGB_p$$

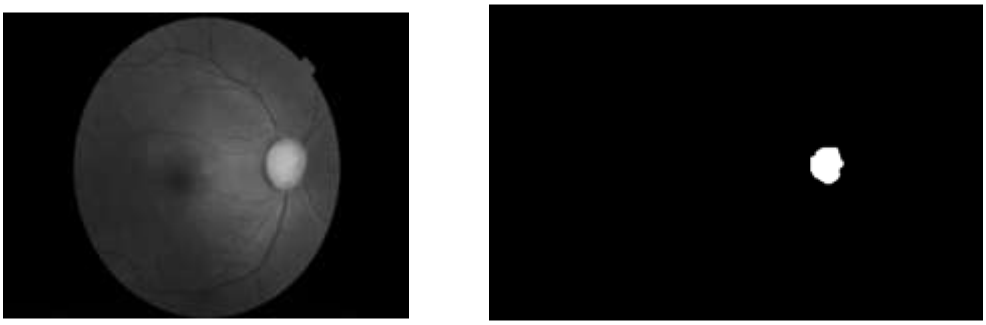
When user specify the segmentation seeds by mouse, the seeded cells labels are set accordingly. The initial states of the foreground seed pixels are set to:

$$l_p = 1, \theta_p = 1, C_p = RGB_p$$

The initial states of the background seed pixels are set to:

$$l_p = -1, \theta_p = 1, C_p = RGB_p$$

Where l_p =1 denotes foreground, -1 denotes background. At time step t+1, the cell labels l_p^{t+1} and strengths θ_p^{t+1} are updated as algorithm. The above equation is used for segment the glaucoma region from preprocessed image which are shown in the below,



(a) **(b)**

Fig.2. (a) Before Segmentation (b) After Segmentation

The process of the segmentation and feature extraction are intimately related to the design of the rest of the image analysis system [8]. Features are extracted from the segmented image using various methods which is described as follows,

3.4 Feature extraction

By employing feature extraction procedure on the segmented images under normal, glaucoma diseases category, the grouped pixels were converted to numerical data by the process of feature extraction. In this research, Features of a fundus image are extracted based on texture and statistical properties by Grey Level Co-occurrence Matrix (GLCM) and Gray-Level Run-Length Matrix (GLRM) techniques. Totally it provides a statistical measure of 29 features of the segmented image and its procedure is given below.

Totally 29 features were extracted for each normal and abnormal images separately.

Total Number of Features = (22 GLCM Features **+7** GLRM Features)

Basically, extracting feature is focused with intensity characters of image pixel. Thus the extracted features provide vital information about the image intensity, shape, texture and location. So, the spatial dependencies of the grey levels on different angles are given by GLCM and the GLRM gives the coarse characters of the images. The GLRM significantly boost the intensity of the class area by giving the higher order statistical information. The feature from a data set images are generated into two types of classes [19]. Then this research utilized the various machine learning algorithm to classify the normal and glaucoma images. Meanwhile, accuracy of these algorithm has been compared with various training stages.

The features considered in this research were used to increase the significance difference between the class areas. The features generated by GLCM and GLRM were listed below,

GLCM: 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: SRE, LRE, RLU, GLN, RP, LGLRE and HGLRE

The features extracted for this research work is listed above. In this step, every segmented images are utilized for feature extraction. Analyzing and extracting features from requirement specifications is a crucial action to support classification process.

3.5 Classification

After feature extraction, classification is carried out with extracted features. Supervised classification (KNN) method is applied in this research for glaucoma classification [12].

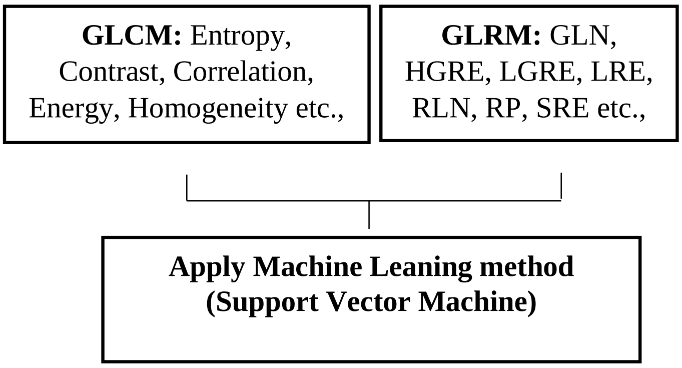


Fig.3. Classification system

i. K-Nearest Neighbour(KNN)

Another supervised technique used particularly for the classification purpose is KNN. The most idea for this method is that it is similar output for similar training samples. For the input population nearest value is identified and is ready to assign classes to all or any the samples [10].

Consider $X_i = \{x_1, x_2, \dots, x_{iN}\}$ and $X_j = \{x_1, x_2, \dots, x_{jN}\}$ the sample population, thus to measure the similarity between them and the distance is calculated as given.

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

In the above equation, Euclidean distance is described that evaluates similarity between two pixel points. Hence, the pixels obtain the category to which a number of them commonly resemble. In KNN, K is the quantity of closest neighbors. The quantity of neighbors is the center central factor. K is commonly an odd number if the quantity of classes is 2. When K=1, at that point the calculation is known as the closest neighbor calculation. This is the most straightforward case. The below figure is an illustration on how the KNN works in classification task within the feature space.

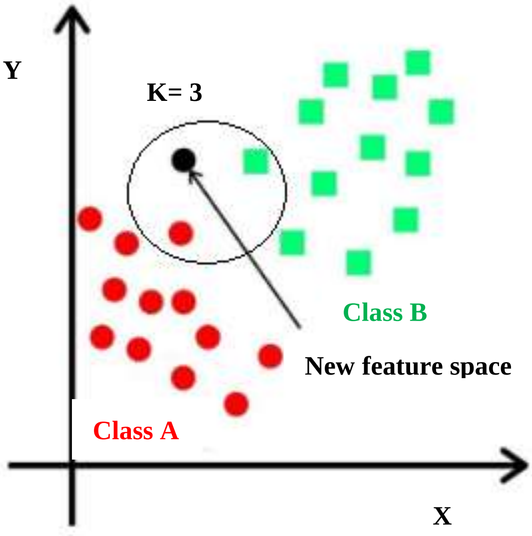


Fig.4. Functioning of KNN

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 (Xi, x)
- *Step6:* Return majority label for {Y_i where i ∈ I}
- *Step7:* End

4. Experimental Analysis

In order to testing and assess the proposed system, totally 221 images of patients are taken as an input images, going to the two types such as normal (101) and then glaucoma (120). The label is numbered as ‘1’ for diseased images and normal is numbered as ‘0’. In this way, MATLAB codes has been programmed for successful identification and classification of glaucoma disease.

4.1 Performance Measures 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 as TP, FP, TN, FN, Precision, Recall, F1-Score, and classification Accuracy [16].

- TP - Number of normal feature is correctly classified as normal features
- TN - Number of glaucoma feature is correctly classified as glaucoma features
- FP - Number of normal features is wrongly classified as glaucoma features
- FN - Number of glaucoma features is wrongly classified as normal features

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

Fig.5. Confusion Matrix Format

- Accuracy value is the proportion of the accurate number of predictions. It can be determined using the below equation:

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

To describe the performance of the FS algorithms, confusion matrix has been used in this research. It permits envisioning of the execution of an algorithm. It also permits easy recognition of uncertainty between classes. The objective of this process is to assess the performance of PSO and WOA by using SVM algorithm.

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 for training machine-learning algorithms. Some sample imaging features extracted in this work are listed in below table.

Table.1. 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

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 functions characterize the texture of an image by calculating how often pairs of pixel with specific values and in a specified spatial relationship occur in an image, creating a GLCM, and then extracting statistical measures from this matrix. Some sample imaging features extracted in this work are listed in below table.

Table.2. 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

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

After the completion of the features extraction methods, those features are given as input to the ML classifiers for classification and the performance of the classifier is evaluated. Below tables shows the classification accuracy of the various classifier with different features set like GLCM (22), GLRM (7) and ALL (29). It is observed that, classification accuracy with KNN shows considerable improvement [11].

Table.3. Performance Evaluation with Accuracy (%)

Training levels	GLCM (22)	GLRM (7)	ALL (29)
70%	67.7	70.9	81.4
85%	74.5	74.5	82.3
80%	80.5	78.9	84.2

- Precision is the ratio of predicted positive examples which really are positive

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{TN}}$$

- Recall also called hit rate or sensitivity; it measures how much a classifier can recognize positive examples

$$\text{Recall} = \frac{\text{TN}}{\text{TP} + \text{TN}}$$

- 'F1_Score' is the 'Harmonic Mean' of recall with precision.

$$\text{F1\_Score} = \frac{(2 \times \text{Precision} \times \text{Recall})}{(\text{Precision} \times \text{Recall})}$$

FE Methods	Precision	Recall	F1-Score
GLCM	0.79	0.75	0.77
GLRM	0.86	0.80	0.83
ALL	0.90	0.90	0.86

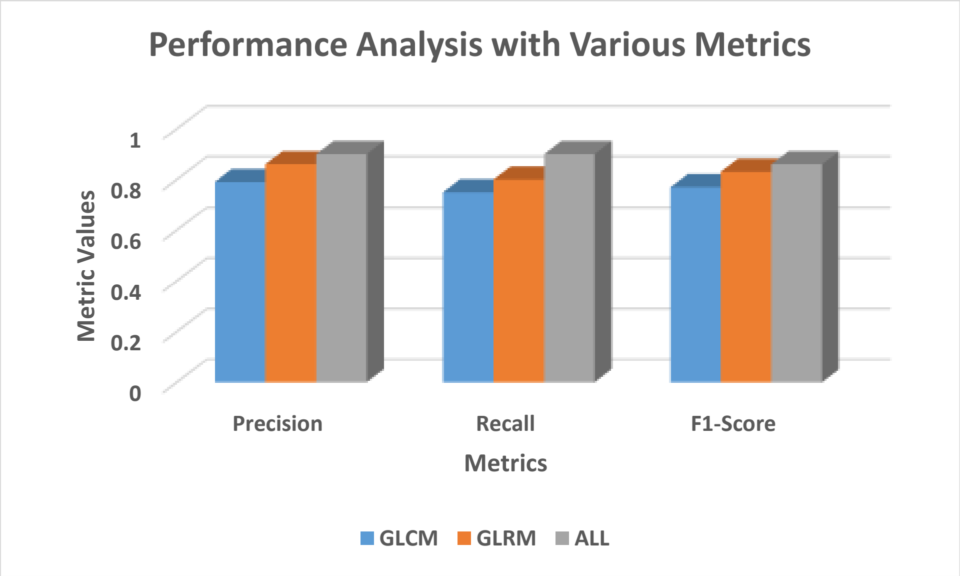


Fig.6. Comparative analysis with various metrics

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

The above diagram clearly shows that most of the ML algorithms gives best result while combining all features (GLCM and GLRM). The feature extraction and ML algorithm provided by the python 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% has been taken as testing data and the 80% has been taken as training data. With this the accuracy percentage of KNN algorithm has been reached with 84.2% of accuracy for all (27) features [13].

5. Conclusion

Computerized medical image classification is an increasingly significant tool for physicians in their daily work. The proposed research work aimed to design and develop an optimal feature engineering approach for the classification of glaucoma disease in fundus images with 4 major steps, as described above. The classification efficiency was increased and the proposed novel algorithms have increased the detection rate of glaucoma disease. This chapter entirely analyses the overall research design of the proposed methodology in each phase. In the next chapter, segmentation of glaucoma images is discussed.

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