**Abstract:**

Glaucoma is a severe condition of the optic nerve, resulting in the loss of eyesight. The proposed methodology has introduced the extraction of HOG (histogram of oriented gradients) features from the retinal fundus image. After the removal of HOG features, we compare the performance of five different machine learning techniques like K-Nearest Neighbour (KNN), Support Vector Machine (SVM), Linear Discriminant Analysis (LDA), Naïve Bayes and Artificial Neural Network. The process of image classification is based on analyzing the numerical properties of the obtained image features and classifying the data into different categories. In the paper, we intend to classify whether the image belongs to the glaucomatous category or the healthy category. After the application of the different classification algorithms to the test data and further analysis of the results, we could conclude that the SVM classifier provided an accuracy of 90 %, KNN 86%, Naïve Bayes 96%, LDA 86% and ANN 96.90% on the dataset in hand.

**1. INTRODUCTION**

The Retina is defined as a layered tissue that forms a lining in the interior part of the eye, responsible for converting incoming light into a neuronic signal, which is then used for processing the brain’s visual cortex. Thereby it is often referred to as an extension for the brain. The facility of imaging the retina and developing a methodology to analyze these images is of great interest. The functionality of the retina requires it to see the outside world. So for image formation to take place,the optical transparency of ocular structures is required. The accessibility of imaging the retinal tissues and brain tissues noninvasively is because the retina is visible from outside.

Glaucoma is an eye disorder that is responsible for damaging the optic nerve that carries all the information for the eye towards the brain. It is the third major factor that leads to blindness in the United States(JTielsch, J. M., Katz, J., Singh, K., Quigley, H. A., Gottsch, J. D., Javitt, J., & Sommer, A.,1991). Optimal treatment and early detection have proven to reduce the risk of the development of glaucoma(Heijl, A., Leske, M. C., Bengtsson, B., Hyman, L., Bengtsson, B., & Hussein, M.,2002). Glaucoma is not mainly the part of retinopathy, but rather it is the part of neuropathy. Stereo color fundus photography and indirect stereo biomicroscopy can be used for imaging the optic disc two-dimensionally. The cup to disc ratio of retina acts as a structural indicator for detecting the progression and presence of glaucoma in humans. Ocular pressure-lowering drops and surgery forms to primary treatment for glaucoma.

The proposed paper explores the performance analysis for the detection of Glaucoma using different machine learning modal like K-Nearest Neighbour, Support Vector Machine, Naïve Bayes,Linear Discriminant Analysis, and Artificial Neural Network. The result is evaluated on 94 retinal images, in which 64 images used for training purposes and 30 images used for testing purposes.

Asan initial step, the retinal image is preprocessed by Histogram equalization and Median filter techniques. For the extracting of the optic disc, the Thresh holding, Ellipse fitting, and Morphological operation technique applied consecutively.The HOG features are extracted from the segmented optic disc image. After that, we trained the machine learning models and evaluated the performance. The shortlisted machine learning modelsthat are used in our proposed methodology are K-Nearest Neighbor, Support Vector Machine, Naïve Bayes, Linear Discriminant Analysis and Artificial Neural Network and the reported accuracy were 86.0,90.0,96.0,86.0 and 96.90 percent respectively.

The rest of the paper is organized as follows. Section 2 focuses on relevant prior published studies of the same area. Section 3 presents the proposed methodology in detail. Section 4 concentrates on the result and its discussion. Finally,Section 5 illustrates the conclusion as well as depicts the future work and limitations.

**2. LITERATURE SURVEY**

For this section, we have shortlisted some of the prominent prior studies published in this domain, and we have discussed their major contribution as below.

(Claro, M., Santos, L., Silva, W., Araújo, F., Moura, N., &Macedo, A.,2016)supports for the automatic detection of diseases, the application of digital image processing (DIP) methodology is important in medicinal scenarios. Therefore authors aimed to explore a methodology that would grant us with automatic detection of Glaucoma. Firstly the required database is acquired, next optic disc segmentation is performed, after that texture features are extracted in different color models, and finally classification is performed, which helps us in differentiating between glaucomatous and nonglaucomatous eyes. The proposed method gave an accuracy of 93%.

(Ahmad, H., Yamin, A., Shakeel, A., Gillani, S. O., & Ansari, U.,2014)in their paper focuses on the methodology of processing an image for the recognition of glaucoma that specifically hinders the (OD) optic disc. The hindrance is caused due to enhancements in the dimensions of the cup. The glaucoma was classified based on the features that are being extricated from fundus images of the retina. Various features involved are Cup to Disc Ratio (CDR) and Ratio of Neuroretinal Rim in (ISNT quadrants). The technique gave an accuracy of 97.5% when being performed on 80 retinal images, and the process on an average took a processing time of about 0.8141 seconds.

(Acharya, U. R., Dua, S., Du, X., & Chua, C. K.,2011)in theirstudy paper,the main focus is on the automated detection of glaucoma by using a technique that requires combining the textural composition and HOS features that are received from the fundus images. Classification is performed by using SVM, Naïve Bayesian,minimal sequential optimization, and random forest classifier. The required texture and HOS based features are provided from the result acquired after performing the z-score normalization and feature selection.On integrating these features with random forest classifier, the performance obtained is stronger than all the other classifiers.An accuracy of 91% is measured from this technique.

(Inoue, N., Yanashima, K., Magatani, K., &Kurihara, T. A. K. T.,2006) in their paper aims to develop a system for the automatic recognition of glaucoma with the assistance of fundus image. In this approach, a personal computer is used for testing the digitally obtained fundus image, and then the automatic assessment for the calculated ratio of the optic disk area to the optic disk cup area (C/D ratio) is performed.A database consisting of 650 images with defined margins for optic disc and optic cup is used. It reveals an over-lapping error of 9.5% in the optic disc and 24% in optic cup.

For normalizing the contrast and luminosity of the image, (Youssif, A. A. H. A. R., Ghalwash, A. Z., &Ghoneim, A. A. S. A. R.,2007)introduced a matched filter method which used adaptive histogram equalization and illumination equalization methods as preprocessing techniques for glaucoma analysis.For detecting optic disc, this algorithm requires matching of the expected directional pattern of the blood vessels of the retina with a matched filter so as to match the direction of retinal blood vessels around the region of the optic disc. A 2-D Gaussian matched filter is used to segment the blood vessels of the retina. Consequently, the same segmentation algorithm is used to attain a vessel map indicating the direction of the segmented vessels of the retina.Then, in order to recognize the OD center candidates, the local intensity is used as an aid for segmenting and thinning of the blood vessels. The difference within the introduced matched filter is further resized into four different sizes, and a rough estimate is taken for the direction of the vessels in the domain of the OD center candidates. The minimum difference is the approximation to the center of the OD.

(Ma, Y., Fallahzadeh, R., &Ghasemzadeh, H.,2016) in their paper,focus onthe implementation required the use of 3 axis wearable sensors by the patients suffering from glaucoma.The input to the framework wasan acceleration signal, and it included the application of data analysis algorithms for identifying prominent gait features. The former includes signal pre-processing and process of segmentation, while the latter includes analysis classification and extraction of features. The separation of raw sensor signals into the gait segments occurs while processing the signal, and then the gait signals are sensed automatically.Statistical and sptio-temporal gait features are extracted from the segments by using the process of data analysis.

The purpose of the paper proposed by (Balasubramanian, M., Bowd, C., Weinreb, R. N., Vizzeri, G., Alencar, L. M., Sample, P. A., ... & Zangwill, L. M.,2010)was to detect glaucoma progression from the HRT topographies obtained from human subjects by evaluating a proper orthogonal decomposition (POD) framework.Further, the results are compared with HRT topographic change analysis (TCA).From this conclusion was drawn that the POD framework provides similar performance as that of TCA in differentiation progressors from subject showing normal characteristics and those showing no progress of glaucoma.POD and TCA showed an accuracy of 86% for differentiatingprogressors from normal subjects,whereas for differentiating progressors from non-progressors, an accuracy of 68% and 64% were shown respectively.The database consisted of 267 eyes from 187 patients with 4 good quality retinal tomographic examinations taken from the University of California,San Diego.

The main purpose of study proposed by (Burgansky-Eliash, Z., Wollstein, G., Chu, T., Ramsey, J. D., Glymour, C., Noecker, R. J., ... & Schuman, J. S.,2005) was to determine whether the application of machine learning classifiers namely LDA,SVM,Recursive partitioning,regression tree,generalized linear and additive model led to any improvement in the results obtained for the detection of glaucoma as compared to the outputs of OCT.They worked on a dataset consisting of 47 glaucomatous eyes and 42 healthy eye images.The best results were under SVM, wherein it obtained a sensitivity of 97.9% and 92.5% at a specificity of 80% and 95%, respectively.

The proposed methodology mentioned in (Carmona, E. J., Rincón, M., García-Feijoó, J., &Martínez-de-la-Casa, J. M.,2008)aims to lower the computational complexity and cost of locating and segmenting the optic nerve head from the fundus images of the eye.The image that is provided to the system is represented in the form of a Gaussian pyramid from which a sub-window is obtained centered at the ONH region.Thereafter,a set of IPs is obtained by the application of the Laplacian pyramid.Thenusing the Two-Phase Genetic Algorithm at each level of the pyramid,an ellipse is outlined containing the maximum number of IPs within its perimeter, leading to the ONH location.

In the empirical study proposed by (Chen, H. T., Wang, C. M., Chan, Y. K., Yang-Mao, S. F., Chen, Y. F., & Lin, S. F.,2013)an automatic method for localization and segmentation of the optic disc is proposed using template matching. The parameters used for template matching were the measure of BBS(Best Buddies Similarity) between the optic disc that has been hand-marked and parts of the input image under consideration.

(Koh, J. E., Ng, E. Y., Bhandary, S. V., Laude, A., & Acharya, U. R.,2018)differentiate automatically between healthy and glaucoma eyes, the usage of a retinal analysis framework has been focused in this paper. Extracted features from fundus images of the retina can be broadly classified into two categories namelyPHOG (pyramid histogram of oriented gradients) and SURF (speeded up robust features)

Using adaptive synthetic sampling, the number of data is equated into normal and abnormal classes. The further fusing of highly correlated features extracted from SURF and PHOG descriptors is performed with the help of a canonical correlation analysis mechanism. On the employment of a -Nearest Neighbor classifier author’s have acquired an accuracy rate of 96.21%, a sensitivity rate of 95.00%, and a specificity rate of 97.42%.

In one of the recently published study authors (Singh, L. K., Garg, H,&Pooja (2020)) primarily focus on the approach used by machine learning techniques for automatic detection of glaucoma. In another study by the same authors (Singh, L. K.,Pooja & Garg, H. (2020)) authors emphasize on glaucoma detection using differential evolution based multi-objective feature selection techniques to select a subset of features which minimize selected objectives. The performance of the selected subset of features has been evaluated using the KNN classification technique. In the next paper (Zilly, J., Buhmann, J. M., &Mahapatra, D. (2017)) detection of Glaucoma with the support of Entropy Sampling And Ensemble Learning For Automatic Optic Cup And Disc Segmentation was proposed and authors proved that their proposed method outperforms other existing methods on one of the public dataset. They highlighted a new method to segment retinal images using ensemble learning-based convolutional neural network (CNN) architectures.

On the other side as machine learning techniques have been applied to solve the problem in hand, so we have also focused on some latest studies (based on machine learning or deep learning), which prove that these techniques can successfully solvevarious class of problems. In a study just published by (Reddy, T., RM, S. P., Parimala, M., Chowdhary, C. L., Hakak, S., & Khan, W. Z. (2020)), authors proposed a deep neural networks based model for uninterrupted marine environment monitoring. The study focuses on developing a prediction model for predicting the life of the battery well ahead and alert the technologists so that the monitoring will not be interrupted using Principal Component Analysis and Deep Neural network . In the next recently published empirical study (Bhattacharya, S., Kaluri, R., Singh, S., Alazab, M., & Tariq, U. (2020))afresh PCA-Firefly Based XGBoost ClassificationModel for Intrusion Detection in Networks is proposed. The model initially performs One-Hot encoding for the transformation of the datasets. After that, the hybrid PCA-firefly algorithm is applied for dimensionality reduction. The XGBoost algorithm is implemented on the reduced dataset for classification. A comprehensive evaluation of the model is conducted with the state of the art machine learning approaches to justify dominance. In another empirical study,practitioners(Gadekallu, T. R., Khare, N., Bhattacharya, S., Singh, S., Reddy Maddikunta, P. K., Ra, I. H., &Alazab, M. (2020)) proposed a PCA-Firefly based deep learning model for early detection of Diabetic Retinopathy. The raw dataset is normalized using the Standard scalar technique, and then Principal Component Analysis is used to extract the most significant features in the dataset. Later on, the Firefly algorithm is implemented for dimensionality reduction. This reduced dataset is fed into a Deep Neural Network Model for classification. The results generated from the model are compared with other existing machine learning models. Further, during next study authors (Iwendi, C., Maddikunta, P. K. R., Gadekallu, T. R., Lakshmanna, K., Bashir, A. K., &Piran, M. J. (2020)) throw light on the application of metaheuristic approach (Whale Optimization Algorithm with Simulated Annealing) for energy efficiency in IoT networks. Authors focused on minimizing the energy consumption of sensors in the IoT network that will lead to an increase in the network lifetime. In the last shortlisted recently published empirical study researchers(Reddy, G. T., Reddy, M. P. K., Lakshmanna, K., Kaluri, R., Rajput, D. S., Srivastava, G., & Baker, T. (2020)) focuses on Analysis of Dimensionality Reduction Techniques on Big Data using machine learning techniques.In this work, two of the prominent dimensionality reduction techniques, Linear Discriminant Analysis and Principal Component Analysis, are investigated on four popular Machine Learning algorithms, Decision Tree Induction, Support Vector Machine, Naive Bayes Classifier, and Random Forest Classifier.

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**3. PROPOSED METHODOLOGY**

This section is divided into 7subsections (3.1 to 3.7).

**3.1 IMAGE ACQUISITION**

The dataset that we have used for the experiment consists of 94 images(64 training and 30 testings).The training database has been divided into parts, namely,Abnormal and Normal Images.The abnormal images consist of retinal fundus images of Glaucoma infected eyes while the Normal images consist of retinal fundus images of healthy people. The Abnormal images comprise 36 images (out of 94 images)for training purposes and take the remaining 15 images for testing purposesfrom the Drishti database.

The images in the Drishti-GS dataset has been gathered and analyzed by Aravind Eye Hospital, Madurai, India**.**It has two divisions - a training set and a testing set of images.The ground truths about the optic cup and disc segmentation,along with the notching information, has been provided for the training set. It also consists of the testing setfor which ground truth is available only upon registration.For the formation of the Drishti database,the clinical investigators performed the crucial task of selecting the patients based on their clinical findings.The age of patients who were finally selected ranged from 40 to 80 years, consisting of almost equal numbers of male and female candidates. The only imaging constraint imposed was the definition of the field of view to be 30 degrees centered at the Optic Disc and of dimensions 2896x1944 pixels.The images with low contrast were removed beforehand.The area is corresponding to the fundus pixels extracted from the original image by removing the black region before the release of this dataset, which resulted in images of dimensions 2049x1751 pixels.

We took a total of 51 infected eye images from this database, out of which 36 were used for Training, and 15 images were kept for testing purposes.

The normal images were obtained from the Ophthalmology Dept., Feiz Hospital, Isfahan, Iran.The database consisted of fundus images of both the right and the left eye of 50 healthy persons.The normal images have a dimension of 1612x1536 pixels and a resolution of 150dpi.These images were then cropped manually initially to keep only the region of interest consisting of the optic disc.From this dataset,we employed a total of 43 images,out of which 28 images were used for training, and 15 images were kept for testing purposes.

Using this dataset,we now intend to propose our methodology for the efficient analysis and detection of glaucoma.

**3.2 METHOD**

The basic aim of the proposed technique is the application of supervised learning approaches for the analysis and detection of glaucoma. We plan to compare the performance of different classifiers in determining whether a given fundus image is normal or abnormal,i.e., to determine whether the retinal image is healthy or glaucomatous, respectively. The method consists of two major stages, training and testing, the purpose of the training stage is to form a feature database consisting of rows and columns in which each row correspond to the feature of each image and its corresponding label class (glaucoma or normal). The formation of a feature database requires two input parameters, the first is the training fundus image, and the second being the corresponding label class.However, the testing stage requires only one input parameter, which is the testing fundus image, while its output is the label class.Both these stages perform similar operations on the input fundus image. The set of operations can be divided into the following phases, mainly preprocessing, feature extraction,and classification.

The preprocessing phase consisted of image enhancement and image segmentation, while the classification of the fundus image into normal or abnormal classes was performed using 5 different classifiers, K-Nearest Neighbor, Support Vector Machine, Naïve Bayes,Linear Discriminant Analysis and Artificial Neural Network.(Fig 1)

**3.2.1 PREPROCESSING**

The preprocessing phase deals with image enhancement followed by segmentation of the region of the optic disc.Both these processes together form the preprocessing phase of the proposed methodology.

**3.2.2 IMAGE ENHANCEMENT**

The input retinal image is first resized into dimensions of 50 x 50. The color fundus image is converted into a grayscale image consisting of only the luminance information. This grayscale image is then subjected to Histogram Equalization.

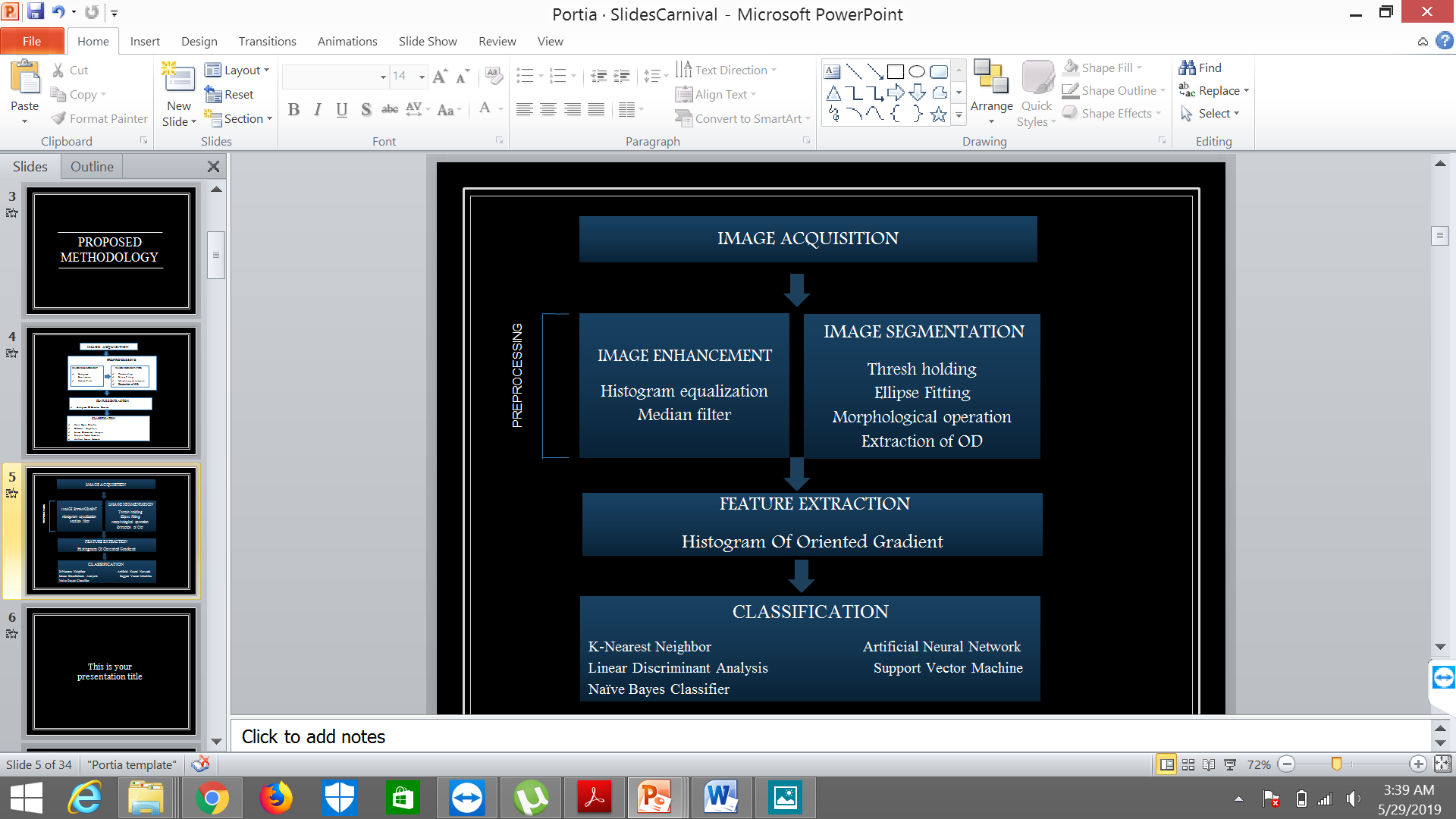


Fig 1.Proposed Methodology

**3.2.3 HISTOGRAM EQUALIZATION**

Histogram equalization finds its application in improving the contrast of retinal images and makes it better for further processing.Histogram equalization method is used for calculating the total number of obtained histograms where each histogram corresponds to a respective part of an image, and it is also used for redistributing the lightness value for the image. The main purpose of this method is to enhance the contrast between the image background and the exudates.

|  |  |
| --- | --- |
|  | (1) |

This histogram equalized image (Fig 2B) is passed through a median filter.

**3.2.4 MEDIAN FILTER**

The median filtering of an image manipulates the input image matrix such that each output pixel ion the output image matrix is the median value of the pixels in 3x3 neighborhoods around the corresponding center pixel in the input retinal image.A median filter smoothens the image and also prevents the blurring of the edges unlike the traditional low pass filters(Fig 2C)

**3.3 IMAGE SEGMENTATION**

Image segmentation is used to detect the optic disc region from the retinal fundus image.Segmentation of the foreground pixels from the background is dependent on the dominance of the features such as edges,ridges,color,etc.The more prominent are the features,the easier it is to segment the image.The detection of the optic disc cannot be achieved using traditional segmentation algorithms considering the fact that there is comparatively less difference between the optic disc and the other parts of the retina.Hence we performed the following set of processes to obtain a precisely more accurate optic nerve head region.

**3.3.1 THRESHOLDING**

Threshold operation is used for converting a multilevel image into a form of the binary image by selecting a proper threshold value called T, which is then used for dividing the pixels of an image into several regions in order to differentiate between the objects and their respective background.In this case,we have chosen the threshold value as 200.(Fig 2 D)Any pixel with an intensity value greater than 200 is assigned as the region of the optic disc while the rest of the pixels form the background of the black and white image(Youssif, A. A. H. A. R., Ghalwash, A. Z., &Ghoneim, A. A. S. A. R.,2007).

Let g(x,y) represent the gray level of an image then according to the concept of Thresholding;

g(x,y) = 255 ; g(x,y)>T

0 ; g(x,y)<T

**3.3.2 MORPHOLOGICAL OPERATION**

This image is subjected to the morphological operation of dilation by a flat disc shape structuring element.(Fig 2 E)The dilation operation removes the presence of any hole within the region as well as increases the boundary of the region of foreground pixels.The image appears brighter by the application of dilation.The bright spots in the image increase in size, whereas the black pixel region shrinks to a smaller area(Youssif, A. A. H. A. R., Ghalwash, A. Z., &Ghoneim, A. A. S. A. R.,2007).

If A is the image segment and B is the structuring element (flat shaped disc in our case) defined in Z^2,then the dilation of A by B is given by

|  |  |
| --- | --- |
| A⊕B={z|} | (2) |

t represents the set of all displacement points z,such that A and B have at least one overlapping element.Here represents the reflection of the structuring element B,about the origin. The next major step is to fit an ellipse over the optic disc region using the Ellipse fitting algorithm.

**3.4 ELLIPSE FITTING**

The Ellipse Fitting algorithm detects the optic disc contour, and further smoothens the optic disc boundary.(Fig 2 F)This algorithm is based on the least square fitting algorithm, which states that the best fit curve is the one that has the minimum sum of deviation square between the original set of points and the approximated curve. There are many popular ellipse fitting algorithms like the Taubin algorithm and the Bookstein algorithm.

Amongst the various available ellipse fitting algorithm, the most efficient algorithm designated to fit an ellipse over the region of the optic disk is the direct least-square fitting algorithm the various other algorithm has higher levels of complexity and are sensitive to noise (ocular blood vessels,drusen, hemorrhage).The direct square least fitting algorithm is not only efficient as it is ellipse specific but also minimizes the noise around the optic disc area.An Eigensystem can be used easily to solve this problem. (Liu, J., Wong, D. W. K., Lim, J. H., Li, H., Tan, N. M., Zhang, Z., ... &Lavanya, R.,2009).

In the fitting algorithm,in order to avoid unwanted and trivial solutions, we set a quadratic constraint on the parameters.The basic aim of this approach is to obtain a vector parameter consisting of the six major coefficients of the standard conic form.A general conic equation can be described as a second-order polynomial, as shown below.

|  |  |
| --- | --- |
|  | (3) |

For an ellipse specific conic,the following constraints are applied on the parameters

|  |  |
| --- | --- |
|  | (4) |

Where a,b,c,d,e,f are the coefficient of the ellipse and x,y are the coordinates of the point line on the ellipse.

By introducing vector

|  |  |
| --- | --- |
| A=[a,b,c,d,e,f]T | (5) |

|  |  |
| --- | --- |
|  | (6) |

It can be re-written to the vector form

|  |  |
| --- | --- |
|  | (7) |

The aim of this algorithm is to fit a general conic to a set a point () wherei= (1,2….N) this may be done by minimizing the sum of squared algebraic differences of the point to the conic coefficient (a)

|  |  |
| --- | --- |
|  | (8) |

The solution to the above problem can be obtained by the standard least approach of the resultant conic obtained may or may not be an ellipse. An ellipse may be ensured by the application of the appropriate constraints, as specified above. We may also obtain equality constraints from the inequality constraints by employing appropriate scaling.

**3.5 EXTRACTION OF OPTIC DISC**

Having fitted the ellipse over the optic nerve head, the set of connected components in a 2D binary image was obtained. We may either extract objects connected by 4-way connectivity or 8-way connectivity. However, in our approach, we have extracted the eight connected components. This is known as the technique of Connected Component Labeling.The method of connected component labeling scans the image from top to bottom and from left to right pixel by pixel,recognizing the regions that are connected by pixel s. These are the eightadjacent pixelregions having a common intensity value given by the set V.

The set v is defined as v={1} for the binary image while it is to contain a range of values (e.g.,v={51,52,53…….77,78,79,80}) for a grayscale image the output is an asset of labeled pixels where label e=1 indicates the first region,label=2 indicates the second region, and so on.

Obtaining the labeled pixels and the number of connected components, we remove the entire small object from the binary image. In other words, we define a threshold value P such that all the connected components that have greater than P pixel are cut in the image while the other is removed from the black and white image.The default connectivity that we use is 8 for two-dimensional images. This method is known as area opening.We then fit a rectangle over the resultant image.The obtained rectangular portion is cropped from the image giving us the final desired preprocessed image.(Fig 2 G)

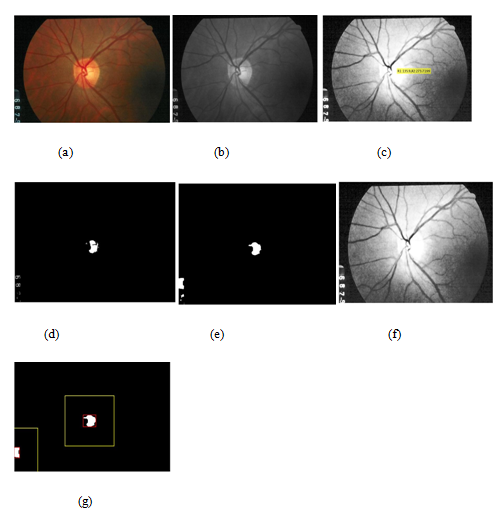


Fig 2.A:Original Image B:Histogram Equalized Image C:Median Filtered Image D:Application of Thresholding E:Application of Morphological Operation F:Application of Ellipse Fitting G:Extraction of Optic Disc

**3.6 FEATURE EXTRACTION**

The next step in forming the feature database is the extraction of the desired features from the preprocessed image.The purpose of feature extraction is to reduce the dimensions of the initial set of raw variables and reduce groups that are more manageable of processing we intend to derive a nonredundant and informative set of feature values that can further drive the supervised learning process that we aim to implement in the paper. These set of extracted features must contain information that is relevant to the input data.We must be able to describe a large set of data with the help of reduced resources such as memory and computation power. As per the belief of machine learning practitioners, and effective construction of the model is possible only by the application of an appropriate, optimize feature extraction technique.

The feature extraction technique that we are used in the paper is the HOG (histogram of oriented gradients) algorithm.

**3.6.1 HISTOGRAM OF ORIENTED GRADIENTS**

Histogram of oriented gradients is a widely used technique in image processing and computer vision. It was first implemented for pedestrian detection in stationary images. This algorithm is similar to edge oriented histograms but is more effective, considering its reduced computational complexity as well as diminished sensitivity to luminance and geometric changes. It is affected only by the orientation of the objective but is invariant to photometric changes and shadows. The basic purpose of this algorithm is object detection(Dalal, N., &Triggs, B.,2005). The main concept behind the introduction of the HOG Algorithm for object detection is the fact that the edge directions and the distribution of intensity values can very well approximate the appearance and shape of the various objects in an image. This technique computes the relative frequency of occurrence of different, various gradient orientations in the image.

This algorithm divides the entire image into small regions called cells that are connected to each other.We then compute the Histogram of oriented gradient directions for the pixels within each cell.All these histograms after concatenation form the feature descriptor for the input image.The accuracy of this Algorithm can be improved by computing the histograms over a larger portion of the image called block and thus using the measure of this intensity to normalize the contrast across all these blocks.

**3.6.2 ALGORITHM IMPLEMENTATION**

This algorithm divides the entire image into small parts called cells that are connected to each other.

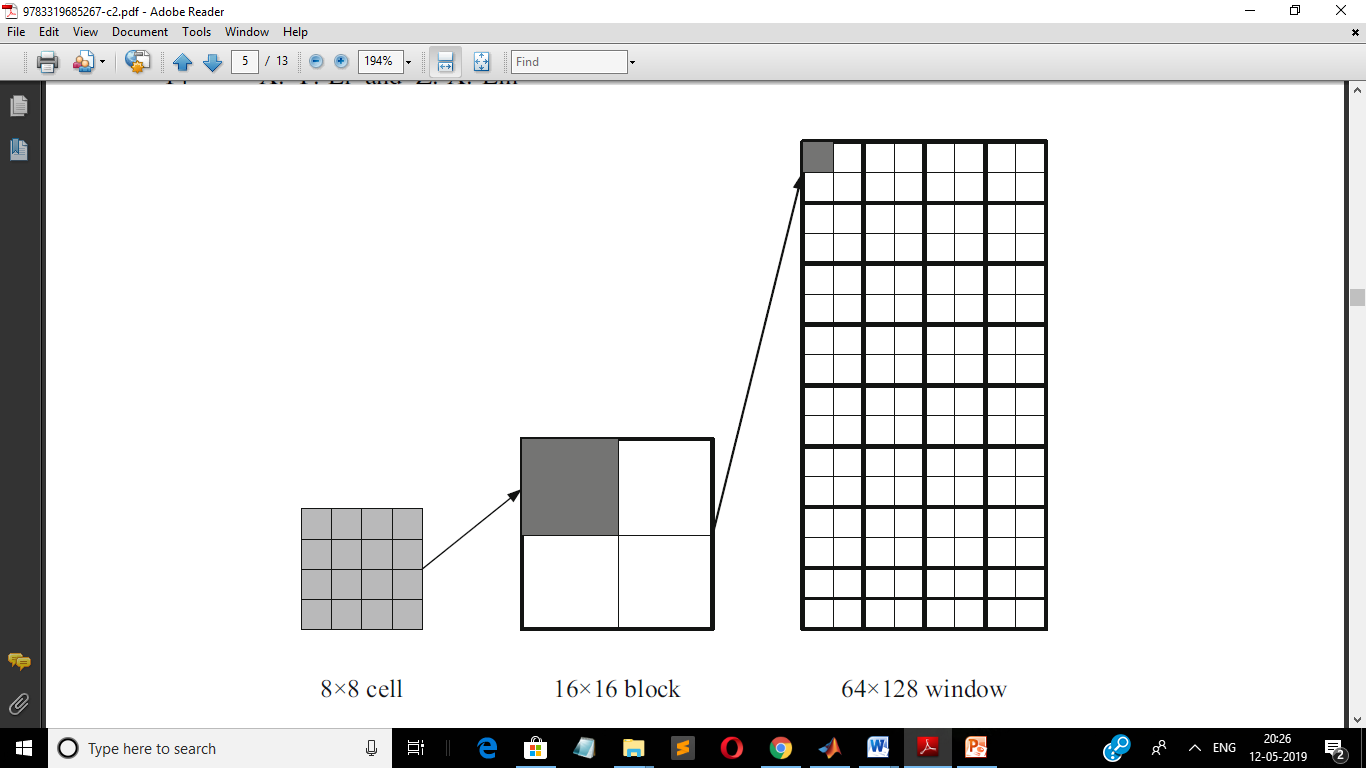


Fig 3.Division of an image into blocks of pixels

We then compute the Histogram of oriented gradient directions for the pixels within each cell.All these histograms after concatenation form the feature descriptor for the input image.The accuracy of this algorithm can be improved by computing the histograms over a larger portion of the image known as block and thus using the measure of this intensity to normalize the contrast across all these blocks.(Fig 3)As an example,we may divide the entire  64X128 pixel window into 8X8 pixel cells,resulting in a total of 8X16=128 pixel cells.

**3.6.3 GRADIENT COMPUTATION**

An advantage of this Algorithm over others is that it does away with the need to normalize the color and the gamma values of the object since the process of normalization of the feature descriptor is a part of this algorithm itself. Hence the first step of this Algorithm is the calculation of gradient values at each pixel coordinate (x,y).This is done by the convolution of the 1-D centers,point discrete derivative mask in both the horizontal as well as the vertical direction. In other words, we may filter the intensity values of the input image with the below-given filter kernels(Fig 4)

Fig 4 Kernel mask used for gradient computation

In x-direction : [-1,0,1]  
In y-direction : [-1,0,1]T

The performance of the algorithm is found best with these kernels compared to other complex masks such as the 3X3 Sobel operator,diagonal mask, and Gaussian smoothing.   
At,each point (x,y) we may calculate the gradient direction and the gradient magnitude in both the vertical and horizontal directions but the following formulas

|  |  |
| --- | --- |
|  | (9) |
|  | (10) |

The gradient magnitude is given by:

|  |  |
| --- | --- |
|  | (11) |
| The gradient direction is given by: | (12) |

**3.6.4 ORIENTATION BINNING**

The next step is the calculation of the Histogram for each cell.We define a set of orientation bins which may be spread from 0 to 360 degrees or 0 to 180 degrees.This depends on whether we employ signed or unsigned gradient values.However,it has been observed that unsigned gradient values, when used in association with 9 Histogram channels, provided the best results.We may either use rectangular or spatial cells from the image.Based on its computed gradient value,each pixel then casts a weight (equal to it's the gradient magnitude or a function of the gradient magnitude) to the orientation bin.However,the former is observed to produce better results.The vote weight may also be calculated as the square root of the gradient magnitude or any other clipped form of the gradient magnitude.  
Moving further on the above example, we divide the 360-degree block into orientation bins of 45-degree difference.We then calculate the gradient magnitude and direction at each pixel.  
Now,corresponding to each gradient direction,the respective gradient magnitude is added to the corresponding orientation bin to which it is closest. This gives us the set of real-valued orientation bin that will be further used for the computation of the HOG feature descriptor block.

**3.6.5 DESCRIPTOR BLOCKS**

In order to ensure that the computed feature descriptor is invariant to the shadowing and illumination,the cells need to group into larger connected Components called blocks for the normalization of the computer gradient strengths.The Histogram vector is then computed for all the cells in the block and further concatenated to produce the desired HOG descriptor.All these blocks are found to overlap each other as a result of which we observe a dual contribution by each cell in the block.The block may exist in two kinds of geometrical shapes,rectangular or circular.The rectangular blocks are represented by R-HOG, while the latter are represented by C-HOG.The optimal result was obtained using four 8X8 pixel cells per block along with 9 Histogram channels.

The circular Hog blocks, on the other hand, may either include a single central cell or an angularly divided cell. There are four parameters that can be used to completely describe a C-Hog block. These include the expansion factor for the radius of additional radial bins, the number of radials and angular bins and the radius of the center bin.

**3.6.6 BLOCK NORMALIZATION**

Block normalization can be performed by four different methods.

Let nonnormalized vector be represented by w consisting of all the histogram in a given block and let its corresponding k-form for k=1,2 be represented by , and e be some small constant. Then we may use any one of the following normalization factors:

|  |  |
| --- | --- |
|  | (13) |
|  | (14) |
|  | (15) |
|  |  |

3.6.7 **Object Detection**

The obtained HOG feature descriptor is then used as a parameter for the detection of an object. The feature vector forms the input of the different machine learning algorithms. They were first used with the support vector machine. However, its application is not limited to any specific classification algorithm. These features are used as a robust and effective measure of image description. In the proposed methodology, we have extracted 900 HOG features for each of the 64 training images. We obtained a feature vector of dimension 1x900 for each input image. The resultant feature database thus obtained consisted of 64x900 features. Hence, our objective of the first training phase was accomplished.

**3.7 CLASSIFICATION**

The objective of the process of the classification is to train the different learning models on the basis of the extracted features.There are two different approaches to the classification process.We may either provide the prior knowledge about the feature and there corresponding classes to the machine learning classifier (supervised classification) or the features may be automatically clustered into different prototype classes (unsupervised classification).The process of image classification is based on analyzing the numerical properties of the obtained image features and classifying the data into different categories.

In this study, we intend to classify the pixel as either normal or abnormal, that is whether the image belongs to the glaucomatous category or the healthy category.There are different machine learning classifiers that are available for performing the process of classification.

Some of the machine learning classifiers that we have applied have been listed below

**3.7.1 NAÏVE BAYES CLASSIFIER**

Naive Bayes classifier belongs to the category of probabilistic classifiers. It is an application of the Bayes theorem which assumes that the features are strongly independent of each other. Naive Bayes finds its use in the fields of medical analysis and text categorization. It saves resources as it does not implement the iterative approximation approach of its classification, unlike other classifiers. Naive Bayes classifier works very efficiently as a supervised learning approach(Nirmala, K., Venkateswaran, N., & Kumar, C. V. ,2017).The Naive Bayes classifier is based on the principle of conditional probability. Let us represent the test input that is to be classified as a set of n independent vectors given by   
We assign the probability  for each of the possible k categories of classes.  
However, this formula is not feasible in cases when the numbers of independent features are too large. Hence, the above formula is transformed to

|  |  |
| --- | --- |
|  | (16) |

Assuming the independence of features from each other, the conditional probability distribution of X over the category of class is given by

|  |  |
| --- | --- |
|  | (17) |

The training phase makes use of training data in order to estimate the parameter for the probability distribution, whereas the prediction phase makes use of unseen test data. This method is used for computing the posterior probability of the sample belonging to each class. The largest posterior probability is thus used for classifying the data efficiently.

After the features belonging to the training set are given to the classifier, the probabilities for each individual feature, as well as probabilities for each class is calculated. The classification of the input data set is performed by the following formula.

|  |  |
| --- | --- |
|  | (18) |

Where,

Represents the class as glaucomatous or normal

X represents the features obtained from the retinal input image

Represents the class conditional probability

Represents the posterior probability

In this study, the features and their corresponding class for each input image passed to the naïve Bayes classifier for its training purpose.The obtained output trained Naïve Bayes model had the following properties:

1. The number of classes, in this case, were two (normal and abnormal) .

2. The number of dimensions for the features was 900.

3. The posterior probabilities calculated for the abnormal and normal classes were 0.5625 and 0.4375,respectively.

**3.7.2 K-NEAREST NEIGHBOUR**

K-Nearest Neighbor is a supervised machine learning approach.It is also known as Lazy Learning,Instance-Based Learning,Example-Based Learning, and Memory-Based Learning.It is a non-parametric approach that can be applied to regression as well as classification (Huang, M. L., Chen, H. Y., Huang, W. C., & Tsai, Y. Y., 2010).When KNN is used for regression, it outputs the object value, which is the mean value of the k nearest neighbors.When KNN is applied to classification, it outputs a class corresponding to the input points. Each point in the feature space casts a vote for the class membership, and finally, the output class is the majority of all the classes in its k neighbors.When k=1,the output class is the same as that of the nearest neighboring both the cases, we use k nearest training samples as input to the KNN.KNN is of the simplest machine learning algorithms amongst all others as all the computation is performed only at the time of classification. It does not work upon the conventional method of building a model and then using it for consequent classification.The statistical arrangement for the application of the KNN algorithm must fulfill the following criteria

Let ,,…..be a set of points in the feature space defined from to 1,2}(binary classification) where Y is the corresponding class label to such that

for r={1,2}

Let there be given some norm ||.|| defined on  and a point x∈,then the training data may be reordered as ,….such that ……..

In this Algorithm,the training samples are plotted as vectors in the feature space where each point is associated with a class label.Though it does not require any explicit training, a prior step of storing the features of each input sample along with it's corresponding class is necessary.The value of the parameter k may be arbitrarily defined by the user depending upon the application.However,the generally used rule of thumb is to select k<√n where n is the number of training samples.

In the classification process,we provide two input parameters;the user-defined constant k and the unknown vector whose corresponding class has to be determined.The output class is defined as the one which is most common among the k training samples that are nearest to the testing sample.For continuous variables,the most commonly used measure of the distance between the training and the testing samples is the Euclidean distance.The two other popularly used distance measures are the Minkowski distance and the Manhattan distance.However,the discrete variables may employ the Hamming distance as a measure of the desired distance.The formulas for calculation of the different distance metrics have been described belowFor two n-dimensional points given by and where i=(1,2...n)The distance D between the training and the testing sample is given by

EUCLIDEAN DISTANCE

|  |  |
| --- | --- |
|  | (19) |

MINKOWSKI DISTANCE

|  |  |
| --- | --- |
|  | (20) |

MANHATTAN DISTANCE

|  |  |
| --- | --- |
|  | (21) |

In the paper, we have implemented the KNN Algorithm for the classification of the input retinal fundus image into one of the two classes (Normal and Abnormal).We provided the training HOG features and their corresponding classes as input to the KNN Classifier along with the testing sample. The value of k that we have used is 1.The distance measure used is Euclidean distance, and the majority rule used is ‘majority rule’. The other available rule that may be used is the ‘consensus’ rule in which the testing sample for which if all the classes do not agree on the same class, then the output class is assigned the value NAN for numerical values or undefined in case of strings.

The KNN classifier compares the extracted HOG features of the test input fundus image with each of the stored feature vectors. The class corresponding to the nearest feature vector is provided as output, which is Normal or Abnormal.

**3.7.3 LINEAR DISCRIMINANT ANALYSIS**

The linear discriminant analysis is a method used for classification as well as dimensionality reduction (Huang, M. L., Chen, H. Y., Huang, W. C., & Tsai, Y. Y. ,2010).This algorithm has been derived from the concept of Analysis of Variance(ANOVA).It uses the linear combination of the features belonging to both the classes as a linear classifier.LDA is also a supervised learning approach and requires prior knowledge of the features and their corresponding class labels.Letbe defined as the set of features or attributed belonging to each of the training samples and ybe its corresponding class label.Both x and y together form the training set.Then we can define LDA as a classifier, that given a set of another observation, can approximately predict the class of this unknown.

Linear Discriminant Analysis is based on the assumption that there exists a normal distribution of the conditional probability density functions and.The former is said to have the mean and covariance parameters as  and the latter has .Now the application of the principle of LDA predicts the points belonging to the second class by applying the following decision constraint on the threshold value T.



where;

|  |  |
| --- | --- |
|  | (22) |

|  |  |
| --- | --- |
|  | (23) |

Discriminant analysis is based on the production of Discriminant functions, which are defined as the linear combinations of the feature descriptors belonging to the two classes.Each discriminant function is assigned a latent variable.The number of Discriminant functions may either be equal to one less than the total number of groups or the number of predictors depending on which one is smaller.All these Discriminant functions have zero correlation between them.According to the Discriminant rule, let there be a group j containing sets of

samples,thenif,then,The aim is to find different regions of "good" such that the classification error is minimal.During this empirical study, we have trained an LDA classifier model using the feature database created in the prior steps.Thus X, this case,was the set of feature vectors, i.e., the 64x900 dimensioned array, while Y was the set of the corresponding groups. Therefore, it was a set of 64x1 sized array which consisted the class labels (1 for Abnormal and 2 for Normal)

**3.7.4 SUPPORT VECTOR MACHINE**

The support vector machine is a non-probabilistic linear classifier used for Binary classes. It is a supervised learning approach and requires prior knowledge about the feature vectors of the training data, and it's corresponding class labels. The SVM classifier builds a new model from the available training data and then employs this model for the classification of any new data sample. The SVM model strives to separate samples belonging to the two classes at a distance as large as possible. The new data samples are then plotted on the same feature distribution, and it is determined that the testing sample belongs to which side of the two classes(Huang, M. L., Chen, H. Y., Huang, W. C., & Tsai, Y. Y. ,2010).Let there be given a set of n-dimensional feature vectors of the training dataset. The support vector machine aims to determine an (n-1) dimensional hyperplane that can separate the samples belonging to the two classes with the maximum distance between them. Such a classifier is known as a linear hyperplane classifier.

There might be cases when it not feasible to linearly separate the samples belonging to the two classes. In such cases, we map the original feature vectors belonging to the lower dimension into a higher dimensional feature space so that the separation is computationally feasible in that dimension.The hyperplanes may be defined as a linear combination of the feature vectors xi that has been provided in the feature database. Thus the new sets of points defined from the original feature space to that of the hyperplane may be represented by. For the training of the SVM model, we provided the SVM classifier with the features of the training data along with their corresponding class labels(1 for Abnormal and 2 for Normal).The working can be more clearly understood with the help of the following given Linear SVM classifier.Let there be given a set of feature vectors from the training dataset defined as

  
Wheremay belong to either of the two classes 1 or 2.  
We want to compute the "maximum margin hyperplane," which can separate the samples belonging to the abnormal and the normal classes such that there exists a maximum Distance between the hyper plane and nearest the feature vector  belonging to each of the two classes.  
In general, ahyper plane can be defined as

|  |  |
| --- | --- |
|  | (24) |

for the set of points lying on the hyper plane.  
Where is the vector normal to the hyperplane.  
The offset of the hyperplane from the origin if given by the expression    along the direction of the normal vector.

**3.7.5 ARTIFICIAL NEURAL NETWORK**

An artificial neural network is defined as a processing system based on information that has working performance similar to that of the biological neural network. An analogy may be drawn between this algorithm and the neural system of human beings. The neural network “learns” with the time that is to say that it does not require a prior definition of the different features for classifying a given input sample into any of the separate categories. Withtime, as it encounters more and more number of samples, it itself generates the characteristic features of the different samples and their associated class.

A neural network can be used to perform a specific task by training it. The training of the neural network is performed by adjusting the weights associated with each connected node. In order for a particular input to reach a particular output, the neural network has to undergo various adjustments and training.

In this pragmatic study, we first designed an empty neural network with ten hidden layers.This neural network was then trained with the input layer formed by the set of training data consisting of the features of each of the 64 retinal fundus images and their corresponding class labels. For the training purpose, the total training data was divided into three sets,namely, the Training data, the Validation data, and the Testing data. The data was divided into these three categories in the ratio 70:15:15,i.e., out of the total 64 images 44 images were used as training data, ten were used as the validation data while the remaining 0 were used as testing data. The neural network was trained using this combination of data in conjunction with ten hidden layers. There are different algorithms of the neural network domain that can be applied to the learning problems. The one that we have applied in our approach is the BACKPROPOGATION ALGORITHM. In this approach, the weights of the nodes are updated iteratively and recursively, starting from the final output layer through the middle hidden layers down to the starting input layer. During each iteration, the weight of the neurons is updated with the objective of obtaining the least classification error.

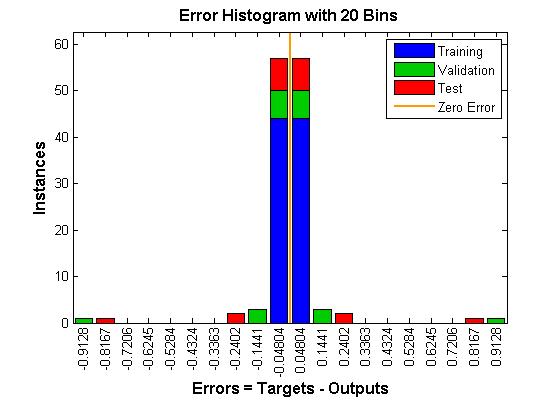
**4. RESULTS AND DISCUSSION**

One of the major performance metrics for supervised learning can be obtained by tabulating the confusion matrix (error matrix).The performance of the classification algorithm can be visualized through the layout of this table.  
Each row in this confusion matrix corresponds to the class of data samples as predicted by the proposed methodology, whereas each column corresponds to the actual class of the data samples. There are four parameters that are provided by the confusion matrix, namely  
**1.TRUEPOSITIVE**  
It consists of all the glaucomatous fundus images that were predicted to be Abnormal by the proposed methodology.  
**2. TRUE NEGATIVE**  
It consists of all the healthy fundus images that were predicted to be Normal by the proposed methodology.

**3.FALSE POSITIVE**  
It consists of all the healthy images that were predicted to belong to the Abnormal class by the proposed methodology. **4. FALSE NEGATIVE**  
It consists of all the glaucomatous fundus images that were classified into Normal class.The test data consisted of 15 glaucomatous and 15 nonglaucomatous images.The proposed methodology was applied to this test data.  
After preprocessing the image and applying the HOG feature extraction algorithm,the test data was classified on the basis of the extracted features to any one of the two classes using the different supervised learning algorithms.  
The input test data was applied to the models trained during the first phase.The output of the model corresponded to the class label of the category to which the fundus input image belonged.  
For KNN, though, we did not need a training model, and it classified the test data directly by comparing it with the feature dataset that we prepared during the first phase.

**4.1 ARTIFICIAL NEURAL NETWORK**

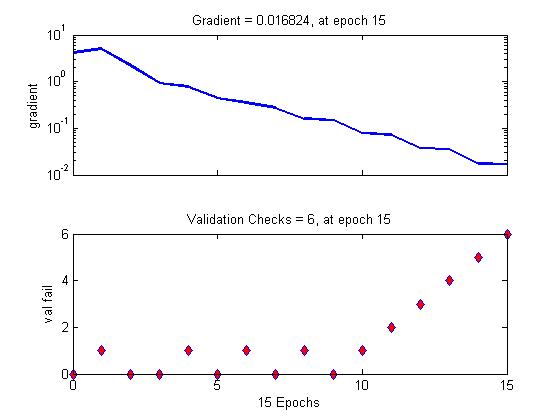
We divided the fundus data samples in the ratio 70:15:15 into the training data,validation data and test data respectively.During the training session,64 images were provided at the input layers which were mapped to their corresponding output classes and the error is calculated.The error signal determines the changes that are required in the synaptic weights.We repeated the process 15 times (epoch)to obtain the most appropriate values of weights.We obtained the following error Histogram from the trained neural network for the training validation and testing data.



**Fig 5 Error Histogram with 20 bins**

The Histogram clearly represents that as the no of instances are increased the error reduces almost tending to zero(Fig 5)

This can be more efficiently represented by the following plot of the number of failed validations against the number of epoch.As the epoch is increased,the number of failed validations first decreases and then tends to increase with the increase in the number of epoch.(Fig 6)



**Fig 6 Neural Training state**

Hence the best validation performance was provided at epoch =9

The parameters used for the training and testing of the ANN classifier have been listed below

|  |  |
| --- | --- |
| 1.Data Division | Random |
| 2.Training | Scaled Conjugate Gradient |
| 3.Performance | Cross Entropy |
| 4.Number of Validation checks | 6 |
| 5.Number of Features | 900 |
| 6.Number of Hidden Layers | 10 |
| 7.Number of epochs | 15 |

The results of the classifications and misclassifications of each supervised learning algorithm were presented in the form of the confusion matrix.Hence,we tabulated the values of true positive,true negative,false positive and false negative for each classifier result for the calculation of the different performance metrics as shown below

**Table 1 Confusion matrix for KNN classifier**

|  |  |  |
| --- | --- | --- |
| **KNN CLASSIFIER** | **DISEASE PRESENT** | **DISEASE ABSENT** |
| POSITIVE TEST | TP=15 | FP=0 |
| NEGATIVE TEST | FN=4 | TN=11 |

**Table 2 Confusion matrix for SVM classifier**

|  |  |  |
| --- | --- | --- |
| SVM CLASSIFIER | DISEASE PRESENT | DISEASE ABSENT |
| POSITIVE TEST | TP=15 | FP=0 |
| NEGATIVE TEST | FN=3 | TN=12 |

**Table 3 Confusion matrix for LDA classifier**

|  |  |  |
| --- | --- | --- |
| LDA CLASSIFIER | DISEASE PRESENT | DISEASE ABSENT |
| POSITIVE TEST | TP=14 | FP=1 |
| NEGATIVE TEST | FN=3 | TN=12 |

**Table 4 Confusion matrix for Naïve Bayes classifier**

|  |  |  |
| --- | --- | --- |
| NAÏVE BAYES CLASSIFIER | DISEASE PRESENT | DISEASE ABSENT |
| POSITIVE TEST | TP=15 | FP=0 |
| NEGATIVE TEST | FN=0 | TN=13 |

**Table 5 Confusion matrix for ANN classifier**

|  |  |  |
| --- | --- | --- |
| ANN CLASSIFIER | DISEASE PRESENT | DISEASE ABSENT |
| POSITIVE TEST | TP=34 | FP=0 |
| NEGATIVE TEST | FN=2 | TN=28 |

**ACCURACY**  
Accuracy is the measure of the correct classifications.It is the ratio of the number of data samples that were classified correctly into the classes to which they belonged to the total number of images that were used for testing.

Accuracy=(Number of correct classifications)/(Total number of classifications)

This can also be written as



The accuracy performance metric is useful only when the numbers of data samples in both classes are approximately equal.In cases when the number of data samples is unequal,the accuracy metric tends to give a false measure of the performance of the classifier.The results are biased towards the class with more number of samples.To overcome this,another performance metric that we use is Specificity and Sensitivity.

**SENSITIVITY**

Sensitivity is a measure of the number of actually glaucomatous fundus images that are classified correctly into their class.It is also known as True Positive Rate.It measures the percentage of the true classmeasured as positive.Here the term 'true' refers to the presence of glaucoma, and the term 'positive' refers to the detection of glaucoma as a positive test.Sensitivity= (Number of truly positive classifications)/ (Total number of classifications)In terms of the parameters of the confusion matrix, it can also be written as



**SPECIFICITY**

Sensitivity is a measure of .0the number of actually healthy fundus images that are classified correctly into their class. It is also known as True Negative Rate. It measures the percentage of the true class measured as positive.Here the term 'true' refers to the absence of glaucoma. And the term 'negative' refers to the detection of glaucomaas a negative test.Specificity= (Number of truly negative classifications)/(Total number of classifications)In terms of the parameters of the confusion matrix, it can also be written as



We have compared the values of these performance metrics from the different classifiers on the basis of the results obtained from them. After the tabulation of the confusion matrix and the determination of the four parameters,True Positive, TrueNegative, False Positive and False Negative, these performance metrics were compared, which provided us a visual representation of the performance of each of these classifiers. A comparison of the results has been tabulated below.

**Table 6 Comparison of the different classifiers based on their accuracy, specificity, and sensitivity**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **NAME OF THE CLASSIFIER** | **ACCURACY**  **(in %)** | **SPECIFICITY**  **(TNR) (in %)** | **SENSITIVITY**  **(TPR) (in %)** | **TP** | **TN** | **FP** | **FN** |
| SVM | 90.0 | 100.0 | 83.33 | 15 | 12 | 0 | 3 |
| KNN | 86.0 | 100.0 | 78.95 | 15 | 11 | 0 | 4 |
| NAÏVE BAYES | 96.0 | 96.0 | 96.0 | 15 | 13 | 0 | 0 |
| LDA | 86.0 | 92.31 | 82.35 | 14 | 12 | 1 | 3 |
| ANN | 96.90 | 93.3 | 94.4 | 34 | 28 | 0 | 2 |

An evaluation chart for the comparison of the performance of the applied classifiers has been shown in Fig 7.It clearly illustrates the better accuracies provided by Naive Bayes and ANN as compared to the other three classifiers.

**Fig 7 Evaluation chart for the different classifiers**

A comparison of these results obtained from our proposed methodology with the other results proclaimed in different literature texts that we reviewed; we could tabulate the analysis as follows.

**Table 7 Comparison of the proposed methodology with other methods used in the literature survey.**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **REFERENCE** | **YEAR** | **FEATURE EXTRACTION METHOD** | **CLASSIFIER** | **DATASETS** | **ACCURACY** |
| (Septiarini, A., Khairina, D. M., Kridalaksana, A. H., &Hamdani, H. ,2018) | 2018 | Statistical features (3rd moment smoothness and mean  ) | k-NN | 84 images (41 glaucoma and 43 normals  ) | 95.24 |
| ( Ali, M. A., Hurtut, T., Faucon, T., &Cheriet, F. ,2014) | 2014 | Local binary pattern | k-NN | 41 images (28 normal and  13 glaucoma) | 95.10 |
| (Bock, R., Meier, J., Nyúl, L. G., Hornegger, J., & Michelson, G. ,2010) | 2010 | Pixel intensity  values,  Texture and  Spectral  features | NB,  SVM,  KNN | 200  images | 86% |
| (Nirmala, K., Venkateswaran, N., & Kumar, C. V. ,2017) | 2017 | HOG features | Naïve Bayes | 101 | 94.4 |
| (Townsend, K. A., Wollstein, G., Danks, D., Sung, K. R., Ishikawa, H., Kagemann, L., ... & Schuman, J. S. ,2008) | 2008 | HRT based  detection of  glaucoma | SVM | 200  images | 87.5% |
| **PROPOSED METHODOLOGY** | 2020 | HOG feature extraction | SVM | 94 images  (51 glaucoma and 43 healthy images) | 90.0 |
| KNN | 86.0 |
| Naïve Bayes | 96.0 |
| LDA | 86.0 |
| ANN | 96.90 |

The above table clearly demonstrates that the combination of Naïve Bayes with HOG features provided better results as compared to (Nirmala, K., Venkateswaran, N., & Kumar, C. V.,2017).Moreover, the SVM classifier provided an accuracy of 90.0 is our proposed methodology compared to the 87.5% (Townsend, K. A., Wollstein, G., Danks, D., Sung, K. R., Ishikawa, H., Kagemann, L., ... & Schuman, J. S. (2008)obtained when HRT based detection of glaucoma was done using an SVM classifier.However,the results provided by KNN were not very impressive. The HOG-KNN in our proposed methodology provided an accuracy of 86.0 compared to the massive 95.24 in (Septiarini, A., Khairina, D. M., Kridalaksana, A. H., &Hamdani, H.,2018) and 95.10 in (Ali, M. A., Hurtut, T., Faucon, T., &Cheriet, F.,2014).

The best results were however provided by ANN and Naïve Bayes when it was used alongwith the features extracted using the HOG feature extraction algorithm which provided an accuracy of 96.90% and 96% respectively which was the highest among all the other combinations used.

The performance of a classifier can be represented graphically using the Receiver Operating Characteristic (ROC) Curve.

ROC is a Graphical plot between the True Positive Rate and False Positive Rate. This is the way through which we can show the performance of Machine learning models. Sensitivity is known as True Positive Rate, and the false-positive rate is calculated using (1-Specificity). .The ROC curve is a plot of the true positive rate(sensitivity) versus the false-positive rate at different values of threshold.It is an important measure of comparison between the different classifiers.It is a measure of calculating the ability of the classifier to differentiate between the glaucomatous and healthy classes.The area under the curve (AUC) is a measure of the classifier performance.Higher is the value of AUC;greater is the capacity of the classifiers to differentiate among the Fundus images belonging to the two classes.  
The False Positive Rate is plotted on the x-axis, while the True Positive Rate is plotted on the y-axis.  
The ROC curve was plotted for the two classifiers,namely SVM and ANN,both of which are shown below (Fig 8 and Fig 9)

|  |
| --- |
| Fig 8 ROC FOR ANN |
|  |
|  |
| Fig 9 ROC FOR SVM |

As discussed above that higher is the value of the area under the ROC curve,greater is the performance of the classifier,the above plotted ROC curves clearly demonstrate that the value of AUC is greater for the ANN classifier as compared to the SVM.Hence the Artificial Neural Network possesses a greater ability to distinguish between the fundus images of glaucoma and healthy classes as compared to SVM.This can be shown by the following plot of ROC of both SVM and ANN (Fig 10)

|  |
| --- |
|  |
| Fig 10 Comparison of SVM and ANN-based on ROC |

**5. CONCLUSION,LIMITATIONS AND FUTURE WORK**

As discussed in the above literature,there is a diversity of various techniques for the detection of Glaucoma. These techniques involve different features that bring up different aspects of Glaucoma detection methods. Every technique can be estimated on the basis of accuracy; time is taken, performance, and efficiency. Glaucoma is one of the primary causesof permanent vision loss in the world. Its detection and diagnosis must be made at an early stage. Studies in this field are being conducted. Here, we have made and attempt to learn and study a few techniques and methods used till date for the detection process of Glaucoma.

From a variety of techniques that that be used after the extraction of the region of interest for the detection of glaucoma,we used the HOG features for the classification of images into their classes.We then studied the application of 5 different classifiers to the test data, and the results obtained demonstrated the accuracy of the different classifiers wherein KNN and LDA gave us an accuracy of 86.0%, SVM 90%, ANN 96.90% and Naïve Bayes 96%.

The superlative generatedresults were, however, provided by ANN and Naïve Bayes when it was used alongwith the features extracted using the HOG feature extraction algorithm, which provided an accuracy of 96.90% and 96%, respectively which was the highest among all the other combinations used.

The results that we have obtained by the application of the different classifiers prove that the proposed methodology can be quite useful in distinguishing the glaucoma fundus retinal images from the healthy images and thus can be useful in the medical diagnosis of glaucoma patients.Early detection of glaucoma can prevent the loss of eyesight and blindness in more acute cases.

The classifiers that we have used have only been applied on a single dataset.The performance of the classifiers may vary when used with a different set of the dataset.

The results provided by the classifiers can be further improved by employing efficient feature selection techniques.We have computed 900 features for each retinal fundus image.By the application of a suitable feature selection technique, the performance of the classifier can be improved.Moreover,we have made a comparison of the aforementioned five classifiers.There can be many different classifies whose performance can be measured on the basis of HOG features.

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