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A Research on Glaucoma and Neuronal Image Disease Detection Using Various Techniques

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Article Info
Volume 82
Page Number: 9152 – 9167
Publication Issue:
January-February 2020

Article History
Article Received*: 18 May 2019*
Revised*: 14 July 2019*
Accepted*: 22 December 2019*
Publication*: 09 February 2020*

Abstract:
Prolonged Glaucoma can affect human vision either directly or indirectly, which results in a particular disorder which is said to be Neurological Disorders (ND). In early stage this ND is asymptomatic but if it's diagnosed later it leads to loss of vision which cannot be treated. The N D is aided by medical images for timely and precise therapy. This analysis describes various state of the art methods offered till now for ND of finding filamentary structures in Glaucoma and neuronal images. The article highlights worth & mass contrast with the prevailing literature with restrictions for exploration of both Glaucoma and neuronal images. This is a challenge to formalize the obtainable collection of methods for a simple assembles and help for investigators in this field for upcoming investigation.

Keywords: *Neurological disorders, Glaucoma and neuronal images, medical imaging, diabetes, image processing, classification..*

I. INTRODUCTION

Diseases namely Parkinson's and Alzheimer's are caused by the neurons loss and itslinks to the central nervous system. It is significant to perform high-performance screens of microscopic neuronal images to recognize the drugs needed to treat these diseases and which naturally demand automated neural tracers. Existing systems in the semiautomatic require human-guided monitoring during operation. Nevertheless, neurons cannot be reliably detected in the occurrence of crossovers i.e., overlapping or moving neurites. A similar situation can be viewed in a Glaucoma blood vessel through the fundus images. The valued clinical details obtained by diagnosing certain diseases like retinopathy, hypertensive retinopathy and glaucoma is presented by the topological and Geometric characteristics of Glaucoma vessel trees.

The chiefrole of this paper is:

- The detailed evaluation of the prevailing works for the neurological disorder recognition of locating filamentary structures in images of neuronal and Glaucoma using the image processing methods.
- The quantitative evaluation is made possible by, qualitative determination in the existing methods and recognizes the prevailing breaks.
- Identification of potential inspection areas and desired improvement to eliminate the breaks in the screening algorithms.

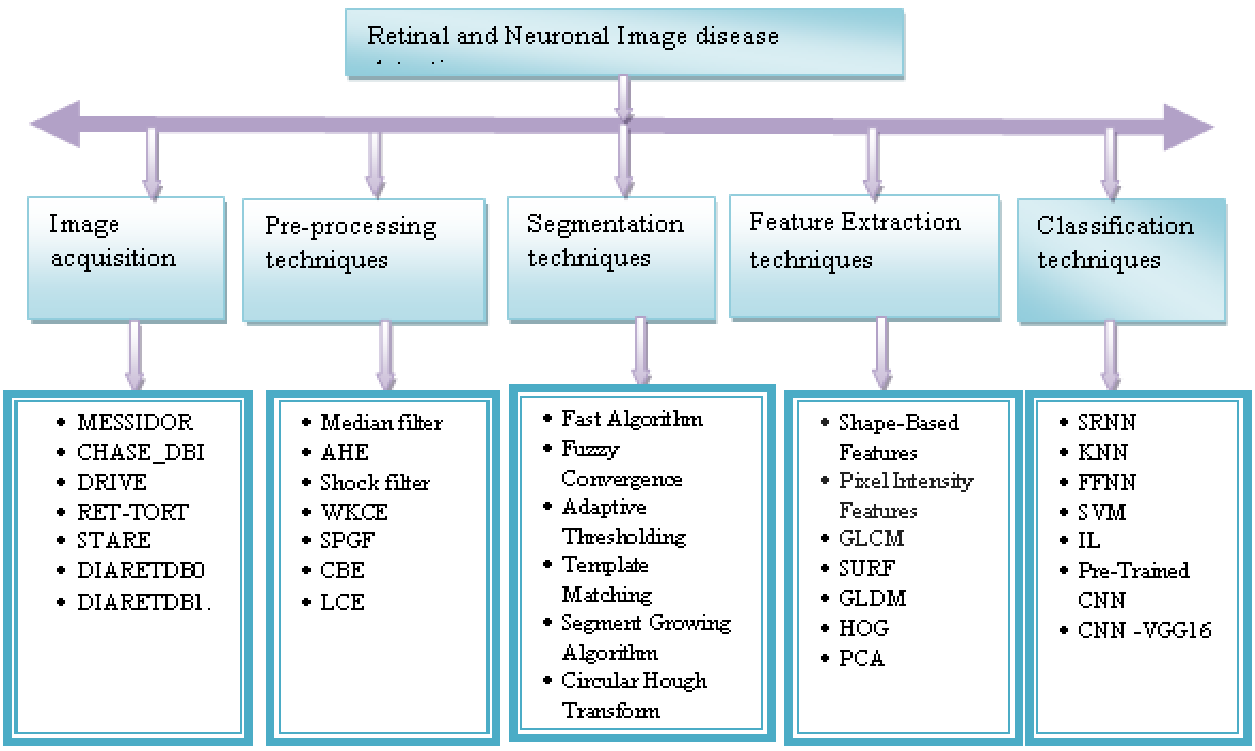
Numerous schemes have been prolonged to analyse prevailing techniques for computer-assisted screening of neurological disorders. Extensive investigations and research have been performed to classify neurological disorders from glaucoma and neural images.

This review paper contains itself to the latest articles available in last 15 years, including the latest techniques for ND depending on the retina and neuronal images. This paper is ordered as follows: Section II covers the entirety of the literature survey. Section 2.1 deals with various image databases. Section 2.2 includes pre-processing methods, section 2.3 covers segmentation methods, section 2.4 describes feature extraction, and section 2.5 describes the classification stages for detecting the current disease events in the retina. The conclusion is explained in the final section

II. LITERATURE SURVEY

A limited significant approaches and methods projected for glaucoma and neuronal images are discussed in this part. Further it discussed about the techniques such as review of pre-processing, segmentation, feature extraction and classification. Moreover, it highlights the methods accompanied by the merits and limitations, as projected by various authors. A many of those have been detailed below,

Figure 1: Various methods of Neurological disorders detection in Glaucoma and neuronal



2.1 Review of Image Database

The initial stage, the neurological disorders detection process is to analyze both the retina and the neutron image. The collection of images through original image shooting and a publicly presented database. The following databases are available for glaucoma image processing.

Aquino et al. (2010) have proposed mesidor, which is the biggest database of 1200

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retina images. 3 dissimilar ophthalmological units with resolutions of 1440x960, 2240x1488 and 2304x1536 pixels are used to collect images. This database images are kept in TIFF format. C.G. Owen et al. (2012) have proposed ARIA online database was registered 2006 in investigation association amid the Hospital named as Royal Liverpool, Liverpool, UK and the Department of Medical Sciences, University of Liverpool, UK. This database contains three groups that are age-based macular degeneration collection, diabetic collection and control collection. This database RGB images are kept in TIFF format. C.G. Owen et al. (2012) proposed ROC micro aneurysm database, which contains 100 color fundus images. These images are 768x576, 1058x1061, and 1389x1383 pixels in JPEG format. M.M. Frazet al. (2012) proposed CHASE_DBI database. The 28 Colorglaucoma fund images in the CHASE_DBI dataset in the England collected from study programs.U.T.V. Nguyen et al. (2013) proposed Review database. The blood vessel width is accessed by the glaucoma blood vessel images and is in the review database. Department of Computing and Informatics, University of Lincoln, Lincoln, UK in 2008 U.T.V. made this database. S. Chhabra et al. (2014) proposed drive database, which is a fundus image database that made available to the public. This collection of fundus images in this database through the Diabetes Retinopathy Screening Program is in the Netherlands. D. Relan, et al. (2014) proposed VICAVR database, which comprised of glaucoma images utilized for Artery to Vena ratio. 768x584 pixelsresolutions are found in the database with 58 images. Lisowskaet al. (2014) proposed RET-TORT database. RET-TORT dataset contains glaucoma image information and manually evaluated tortuosity of a usual and people suffering from hypertensive problem. There are 20 images of segmented blood vessel in the STARE database projected by Ravi, T et al. (2015). The image size in this database is 700x605 pixels, 8 bit for a color channel. Wisaenget al. (2019) proposed two sub databases namely, DIARETDB0 and DIARETDB1. DIARETDB0 has normal images 20 and 110 images diabetic retinopathy pictures. DIARETDB1 contains 5 healthy images, 89 glaucoma and 84 diabetic retinopathy images. Image size on the database is 1500x1152 in PNG format.

2.2 Review of Pre-Processing Techniques

The pre-processing stage is preferred to eliminate noise or changes available in the glaucoma image along with this it also improves the contrast and quality of the fundus image. Dissimilar types of cameras are preferred to take photographs from various patients. The image should have different characteristics such as size, color, quality etc. since its intensity variation within the retinal images can faces more challenges to develop methods in theimage-processing field. Consequently, pre-processing is essential for original glaucoma images.

Fleming et al. (2006) have proposed image contrast normalization (ICN). It shows how ICN improve their capability to distinguish between MAs and other points in the retina. The green plane is filtered by means of using 3X3 median filter, which is periodically eliminate salt & pepper noise. The difficulty is that MAs appear in clusters hence the individual MAs no longer have the features of the isolated point. Therefore, this mechanism for MA recognition is also problematic. Swierczet al. (2006) have proposed CWM filter for noise elimination and the FF filter for more uniform images. Youssifet al. (2007) have proposed illumination equalization & adaptive histogram equalization. Both methods are normalizing the brightness and contrast throughout the image. Kumar et al. (2009) proposed to Extract Blood Vascular Network for Retinopathy Screening System. Hence the proposed shock filter in order to eradicate the mosaic noise. The computational feasibility, gigantic scale properties of vessels are disregarded and in a way slim vessel, endings and bifurcations are missedin the inconvenience of this algorithm. Zhang et al. (2009) propose an adapted matched filter for vessel detection. It utilizes the shape of a Gaussian function is found in the slice of vessels in a glaucoma image. To "match" the vessels, a Gaussian-shaped filter can be utilized. The merits of using Gaussian shaped matched filter are that it widely reduces the noise. Osarehet al. (2009) have proposed two pre-processing steps. In the initial stage, the histogram specification method was used independently for each RGB channel to equalize the patterns of three exact histograms image. Following stages comprises the local contrast enhancement, which distributes the pixels values approximately the local average. The spatial relation amid the detected exudates and central macular area (fovea) does not established by this method. Niemeijeret al. (2011) have proposed to eradicate the gradient about the Field-Of-View (FOV) boundary and slow intensity changes are being eliminated in the image. FOV Mirroring and Background Removal technique is performed in the image. The huge gradient can disrupt measurements of features close to the border of FOV. It is eliminated by implementing a mirroring technique. The Gaussian filter performs huge standard deviation operation to solve a blurred images which slow down the background behaviour from the original images. The drawback is that, in Gaussian filter the estimation of the standard deviation is genuinely not an essential parameter as long as it is enormous enough to ensure the blurred images have no recognizable structures, for instance, vessels. Antalet al. (2012) projects an ensemble-based outline to progress the micro aneurysm recognition. The WKCE method to advance the contrast in the images of the fundus by implementing a gray level transformation. CLAHE method is very useful for visualizing salient parts in the fundus image. The image is separated into asynchronous regions and each region undergoes local histogram approach equation. Amongst the region's boundaries are eradicated by bilinear interpolation. The Illumination Equalization method tries to decrease the vignette consequence caused by random illumination. These methods have some drawbacks. Other elements must be inbuilt in the proper screening system; these elements are normal to increase the effectiveness of this approach. Kanthet al. (2013) propose to distinguish between dissimilar phases of DR. They are NPDR and PDR where available for examining fundus images it distinguish from the ordinary eye. The image which is with various color must be converted into gray scale image because it carries the details of the intensity alone and the each pixel value is a particular sample. For this transformation, it first obtains the RGB components values, and then combines 30% of red, 59% of green, 11% of blue respectively. Contrast adjustment caused by histogram equalisation is brought about after the gray scale conversion. With this intensities are best distributed in the histogram, which is accomplished by successfully distribution from the intensity values which is being repeated. Also, finding edges for blood vessels and morrhages is very important. But this is not possible with this method. Franklin et al. (2014) propose to automatically identify the exudates from the DR patient's glaucoma images. Initially, the original image of fundus in RGB format is converted into Lab color space. These space need to eradicate the grey scale approach for high correlation amongst the components.The luminosity layer is being substituted with the processed data and then the original colorspace is recovered and then mean filtering is being applied. Hence, for contrast enhancement of these glaucoma images, CLAHE operates over minute part in the tiles, was implemented. Kasurdeet al. (2015) an effective new vessel recognition process depending on line tracing and quantity of vessel pixel to investigate morphology of local glaucoma vasculature is

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being executed. The GC shows the excellent background contrast. Median filter is utilized to lessen salt and pepper noise. CLAHE gives local contrast enhancement. The demerits of this method yet there is noise in its edges. Kar (2017) has proposed curvelet-based enhancement, which is preferred to separate dark lesions from the worst illumination ofglaucoma background. Simultaneously, the variation between bright lesions and background is improved by the band pass filter. The supreme matched filter response interactions and the extreme Laplacian of the Gaussian response are jointly improved. Yu et al. (2017) have proposed toattain the intensity background image by mean filter, whichfilters the original image. Besides the illumination correction, the main vessels present in the image are being detected by the usage of the non-local algorithm filter and eliminate the fine characters. Zhou et al. (2017) et al. proposed a worldwideimprovement approach is adapted to trackbrightness and contrast variation inside the retina image by decaying RGB channels into YIQ. The increment of global luminosity and contrast of the image is adapted by worldwide improvement method but the quality brightness and contrast does not have any variation. Consequently, for the global enhanced image is produced if the statistical based model of the image approach is implemented, the local brightness and contrast of the image is enhanced. Palavalasaet al. (2018) have proposed the CLAHE technique in turn improves the image contrast. The main pro of CLAHE is to avoid the excess noise, which can be result of application of adaptive histogram equalization. Cheng et al. (2018) propose that by boththe human-lens attenuation & scattering the approximation of glaucoma images degradation is done. Depending on the resolution and scattering model the restoration of images are accomplished in the SGRIF. The glaucoma images contrast is enhanced in this method by measuring the histogram flatness, histogram spread, and variation of local illumination. Using this method in glaucoma imaging, it becomes difficult to eliminate the cloud effect due to lens scattering. Wisaenget al. (2019) presented CLAHEmethod in which intensity adjustments provides the excellent outcome and vessel is eliminated. In addition to propose the local contrast improvement, this progresses the quality of theglaucoma image.

Table 1 Pro and Cons of Different Pre-processing Algorithms

S.No	Author and Year	Method	Pros	Cons
1	Fleming et al. (2006)	Median filter	When the filter crosses an edge this does not generate recent unrealistic pixel values.	It difficult to treat analytically the effect.
2	Youssifet al. (2007)	Adaptive Histogram Equalization	AHE is to avoid excessive noise, which can increase variability.	The disadvantages of this method is operates only on small region, quite complex and expensive.
3	Kumar et al. (2009)	Shock filter	The shock filter well enhances the edges, turning a sine wave into a square-wave signal, in the	shock filter does not enhance the edges at all,

			noisy case	
4	Antalet al. (2012)	Walter–Klein Contrast Enhancement method	The backgrounds and foregrounds of the images are bright or dark	This may increase the variability of background noise while reducing the transient signal.
5	Franklin et al. (2014)	Mean filtering	Impulse is used to remove noise and implementation is simple	Image details are not preserved. Mean filter eradicates certain details of the image.
6	Kar (2017)	Curvelet-based enhancement	It is used to eradicate the noise fast in an image	This procedure allows denonise the sequence while preserving low-contrasted structures, but does not improve their contrast.
7	Cheng et al. (2018)	Structure-preserving guided filtering of glaucoma image	Edge preserving filtering	No gradient distortion
8	Wisaenget al. (2019)	Local Contrast Enhancement	Can be applied in low contrast and low bright color image	Can produce undesired result cause of gray level.

2.3 Review of Segmentation Techniques

Segmentation process is the core process in detection of blood vessel on the glaucoma fundus image. In this process, blood vessel will be detected on eye glaucoma fundus image. Detected blood vessel in this segmentation process can be helpful for further research. Various techniques for performing segmentation are covered in this part.

Spencer et al. (1996) have described the recognition& quantification of microaneurysms in digitized fluorescein angiograms. Regional Growing Method to confineevery binary object in a candidate-microanurysm image, original image is taken to affordgrey-level data, defining the field of the feature provides a binary object representation. The disadvantage of these processed images is that they entered a grey level, which is, in general, a compromise between all the microaneurysms being too low to detect and any bad features to be detected.Soloumaet al. (2002) have proposed that by detecting the centre of the vessel and are extracted. First, edge thresholding techniques detect vessel edges. In second, the Gaussian profile was observed to be along the blood vessel. The fast process is implemented to identify the lowermost value of points along with the incorrect points. Hoover et al. (2003) have defined an automated system to find the optic nerve in the fundus images. Multiple vessel segmentations are utilized to detect focal points. Fuzzy convergence method is preferred to identify vessel networkconvergence.This method

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accomplished 89% perfectrecognition. Narasimha-Iyeret al. (2007) have proposed that the vessel tracking mechanism could detect glaucoma vasculature.Connected pairs of parallel margins of blood vessels can be found again using directional edge templates. Hoover's fuzzy connected is required to identify the optic disc. Fovea viewing is detected using the position of the optic disk.Tobin et al. (2007) have proposed that the optic nerve the automatically detected and localization of the macula. Probabilistic approaches for defining the probability of an image position being connectedwith the help of Bayesian probability function. A method to determine the positionof the estimated macula centredepending on the empirical geometric associationsamid the construction of the vascular arcade & the optic nerveposition. The mathematical morphology technique was to section the vessels present in the retina. Al-Diriet al. (2009) have proposed the tramline algorithm which is preferred fortracing the first set of potential vessel segment center line pixels. By the removalof false positive pixelsthrough additional segment growing algorithm the conversion of the tramline pixel map into a segments set takes place. This method causes some difficulties in identifyingcertain diseases. Aquino et al. (2010) have segmented the OD from digital glaucoma images by inserting a new template-based method. This method prefers the usage of morphological & edge detection methodsalong with the CHT to achieve a circular OD boundary estimate. It necessitates a pixel positionedinside the OD as originalevidence. A location methodology depending on a voting-type algorithm is also projected to accomplish the objective. Xuet al. (2011) have used a graph-based algorithm to section both vessel edges instantaneously in order to quantity the thickness of vessels of the retina. Multicolumn model is preferred to find the vessel growing direction. Raja et al. (2014) have proposed dilation and erosion process which detect the glaucoma blood vessels. It is the very old technique of the image processing platform. Richa et al. (2014) have used two alternative methods for segmenting the optic disc. By eliminating vessels in the optic disc areathe MRF image reconstruction techniquesections the optic disc and the optic disc segmented using Compensation Factor method using formernative intensity information of the vessels. These two methods uses the initial stageby the graph cut method which performs retina vascular tree extraction. To cut the graph and find the optimal segmentation the Max-Flow algorithm is favoured. Ngo, L.et al.have been enhanced spontaneous segmentation of blood vessel in the glaucoma fundus images using a multi-level CNN model. In order to reduce the image resolution which in turn improves the simplification of the training progress? To eliminate over fitting problem the spatial-dropout layer and a dropout layer is being implemented.Novoselet al.(2017) have used a lightlyjoined level sets outline in eyes with topology-disrupting diseases in the retina to section glaucoma layers and lesions. When eyes are infected by central serous retinopathy andgrowth-related macular deterioration such eyes undergo assessment of the mentioned layer & lesion segmentation methods. In eyes the layer segmentation method was evaluated. Almotiriet al. (2018) have proposed two algorithms that are adaptive local thresholding and spatial local information-based thresholding. This method consists of fuzzy modelling, fuzzy model aggregation and binarization phases. Dai et al. (2018) projected the improvement of the efficiency of computation, images of fundus are sectored into super pixels depending on the comparison between nearby pixels withSLIC, where pixels belonging to the similar super pixel are presumed to take the identical label. Yueet al. (2018) suggests a fresh saliency-based process for the recognition of leakage in fluorescei angiography. The SLIC method is preferred to represent the given images at different positions. An enhanced multi-scale line indicator is used to

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find the glaucoma vessels segment. The SLIC iscapableof allocating every pixel to a super pixel based on its intensity and spatial location. Bekaloet al. (2019) have proposed a fully automated 3D method glaucoma layerssegmentation &NRDrelated sub glaucoma fluid from a SD-OCT image. The fluid segmentation; and layer segmentation are used to segment the glaucoma layer and this is performed using graph search and graph cut techniques. The NRD related sub-glaucoma fluid Segmentation was evaluateddepending on the dice coefficient and attainedby means of 90.78% and 92.04%

Table 2 Pros and Cons Of Different Segmentation Algorithms

S.No	Author and Year	Method	Pros	Cons
1	Soloumaet al. (2002)	fast algorithm	Commonly used an implemented	Not identify outliers and noise
2	Narasimha-Iyeret al. (2007)	fuzzy convergence, adaptive thresholding and template matching algorithms	Unsupervised and always converges	Long computational time
3	Al-Diriet al. (2009)	segment growing algorithm	Well developed	Missing information or causing potential errors from smoothing procedures.
4	Aquino et al. (2010)	Circular Hough Transform	Conceptually simple technique	Large storage space is required
5	Richa et al. (2014)	Markov Random Field (MRF)	More robust against noise and preserve fine structure to extend.	It is computationally expensive.
6	Ngo, L., and J-H. Han (2017)	multi-level CNN	Faster segmentation	Large number of parameters to be setup
7	Yueet al. (2018)	Simple linear iterative clustering	Less complex method	Results vary in the presence of outlier.
8	Bekaloet al. (2019)	Automated three-dimensional (3D) method uses fluid segmentation and layer segmentation	Exploits nature of the MRI volume directly. Acquires implicit contextual information.	Computationally expensive

2.4 Review of Feature Extraction Techniques

Segmentation process with classification technique requires the features extraction. It is necessary for performing an efficient segmentation process. Every pixels in the image are not segmented but only certain features in an image. The procedure of defining the features or features of the image that most efficient or more meaningful, which represents important information for analysis and classification. This stage extracts features of pixels in image.

Deco et al. (1997) have proposed the learning paradigm for a recurrent stochastic NN that executes feature extraction in nonlinear and factorial form. Frame et al. (1998) have proposed forrecognition of interested features in an image depends on the traditional model of computer visualisation. Thirteen features are spontaneously

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computed that features are area, perimeter, aspect ratio, circularity, intensity 1,2, normalized intensity 1,2, mean intensity 1,2, normalized mean intensity 1,2, matched filter seed value. Binary representation of each candidate object is used to originate four shape-based features. The new and shade-corrected images is used to derive the grey-scale intensity of the contender which is helpful for next eight measurements. Niemeijeret al. (2005) have offered a detection method named as red lesion recognition technique. Frame et al. (1998) suggests anentire 13 dissimilarcontestant object features to use it with the Spencer–Frame system. Two groups are being categorised from the features: shape features 1)–4) and pixel intensity features 5)–13). Gaussian filterbank outcomesfeature 19were provide for the set of feature at the same time a feature used todefine if an object is on an extendedarrangement feature 20. Photograph color is the additional source of information hence 15)–18) were extra. To remove elongated structures the extra shape feature is selected as feature 14. Large circular objects were determined successfully using feature 21. Marínet al. (2010) have proposed NN scheme for calculates a 7-D vector made of gray-level and moment invariants-based features for pixel representation. Succeeding features sets are invited. The gray-level in the candidate pixel is being subtracted from a statistical value illustrative of its backgrounds which in turn results in gray-level features. Moment invariants features which are depending upon the moment not varying for relating small image regions made by the gray-scale range of a window centred on the signified pixels. Tang et al. (2012) have proposed a dualclassesof feature extraction for splat-based haemorrhage recognition that are splat features gathered from pixel-based reactions and splat wise features. Pixel-Based Feature Responses are using following features. Color insideevery splat RGB color space extraction and dark-bright, red-green, and blue-yellow oppo nency images, which contain six color constituents in splat feature space. Local texture filters include local range filter, local standard deviation filter and local entropy filter, which compute the intensity range, standard deviation and entropy of one pixel of theneighbourhood or region. Splat features combined from pixel-based responses, we also concentrate splat canny features which ought not to be gathered. Shape features, for instance, splat area, degree, course and quality, are induced based on individual splat dispersal. Surface features are isolated by the statistics of GLCM and Tamura signatures. Franklin et al. (2014) have proposed to identify the proximity of spontaneouslyexudates and this aids the ophthalmologists in the analysis and follow-up of DR. The candidate sections were categorised features likecolor, size, shape, edge strength and texture which are being fed as input to NN. RGB, HIS and Luv, are being investigated and identified that separation of luminance from the chrominance values is accurate when luv color space is used. Morales Et al. (2015) have projected a process to distinguish healthy images and diseased image by investigating discrimination abilities in the texture onto the images of the fundus. LBP are aninfluentialgrey-scale texture operator utilized in numerous computer visualization applications due to its simple calculation. Imaniet al. (2015) have affordsthe capacity of glaucoma quality valuation of the image. These proposed method, the extremely high extensible structures set which are allocated to every block. The values of inhomogeneity are then regularizedbased on the sub-image size. Li et l (2015) have proposed DNN it determine the relations amid the image of the retina and the vessel map. Enough intermediate layers of the extracted features present in the network in order to extract all the vessel map of the input glaucoma image. Each layer detects the various features concurrently. Pireset al. (2015) proposed bypass lesion area, and really train a classifier for DR referral. For low-level component extraction, the lesion-based system

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used the SURF computation pre-tuned to recognize and depict a pre-chosen number of PoIs, e.g., 400. Mid-level part extraction targets evolving low-level local descriptors (e.g., SURF) into a worldwide and increasingly unrestrained picture representation of middle multifaceted nature. BoVW is the most standard mid-level representation in Computer Vision, depicts an image as a histogram of quantized local descriptors. It might be comprehended as the application of two steps. First step is coding, which converts the native descriptors into a code modified for the task, and second is pooling, which précises the codes gained into anonly feature vector. Patil et al. (2017) have concentrated on finding the glaucoma infection utilizing the images of the fundus. Feature Extraction is performed by Gray Level Difference Method, Stochastic watershed method and Pearson R Correlation Method. The GLDM is the most persuasive method for statistical texture clarification in restorative imaging, Ultrasonic, MR and CT image examination. Stochastic watershed method thought is to appraise a PDF for the contours of the image, wherein border changes without huge are filtered out. Dashtbozorget al. (2018) have proposed the combined features setwhich is provided to a hybrid boosting classifier to distinguish the MAs from non-MAs candidates. Classification of Microaneurysmvs non- Micro aneurysm patches was performed using three sets of features. The second feature is shape-based features. The extraction following parameters including Area, Convex area, Solidity, Extent, Perimeter, Circularity, Ellipticity, Eccentricity and Euler number shape-based features for each candidate region is being developed. The disadvantages such as detect of low contrast MAs and easy lossof background noise can be completely eradicated using LCF features which depends on gradient convergence and not intensity. Das et al. (2018) have proposed following feature extraction techniques. HOG is a characteristic descriptor and SURF will be a nearby characteristic extractor and descriptor. Next feature is a Haar Wavelets which an organizing square shaped function are combined to develop wavelet beginning with a wavelet family. Color histogram feature is a graphical representational of the quantity of pixels over a picture. Dai et al. (2018) Dai et al. (2018) have concentrated an interleaved deep mining procedure to adjust insightfully to the inconsistent microaneurysm area issue. Features are moreover isolated from super pixels. Cao et al. (2018) have used SSAE for MA detection by leveraging the use of deep learning. The raw pixel intensities, rasterized from the image patches are presented in the feature set. For the classification purpose it requires to lessen the dimensionality. The original feature set is being processed by dual dimensionality decline techniques which arePCA and RF features. Aslaniet al. (2019) have projected deep learning architecture. We construct a pipeline of parallel ResNets without weights sharing in order to activate the MRI multi-modality investigation. Furthermore, a MMFF and a MSFU were projected to join and upsample the features from dissimilar modalities and dissimilar resolutions, correspondingly.

Table 3 Pros And Cons Of Different Feature Extraction Algorithms

S.No	Author and Year	Method	Pros	Cons
1	Frameet al. (1998)	shape-based features	Easy, straightforward and speedy	Sensitive to noisy edge
2	Niemeijeret al. (2005)	pixel intensity features	Flexible to plate rotation. Simple and straight technique.	Cannot deal with joint or broken characters.

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3	Tanget al. (2012)	gray-level co-occurrence matrix (GLCM	By using features such as eccentricity, roundness, dispersion to the cope the shape of leaves can be eliminated.	Blur image is not detected
4	Pireset al. (2015)	Speeded-Up Robust Features (SURF) algorithm	Applicable to all 2D and 3D surfaces.	Difficult to stay up to date with developments.
5	Patilet al. (2017)	Grey Level Difference Method (GLDM)	Easy to implement	For image classification purposes, selecting the distance may be crucial
6	Daset al. (2018)	HOG	Work well for small resolutions	It does not able to handle occlusion and overlaps
7	Daiet al. (2018)	principal component analysis (PCA)		
8	Aslaniet al. (2019)	MMFF block and a multi-scale feature up sampling block (MSFU) resolutions, respectively.	Providing structural and functional information in the same image.	Reading efficiency is very poor.

2.5 Review of Classification Techniques

The classification of pixels as new vessel is significant in conforming the advanced stage of glaucoma and neuronal image detection to various diseases. Based on the correctness and optimalselection of features the performance of classification is evaluated. Before classification all the features should be normalized.

Frame et al. (1998) have proposed to identify the microaneurysms on digitised angiographic retinal image. The three dissimilar classification methods are used to determine the above problem: a statistical classifier that is LDA a neural classifier that is LVQ and an expert system that is rule-base (RBS). The RBS was executed with the sensitivity and specificity values chosen to be 84% and 85%, respectively. Kuyelet al. (1999) have proposed the human eye to computer image classification. The SRNN classifier make use ofaarrangement of rising resolutions till a last class choice is completed. In classification there must be a rise in the limited sample performance hence a distance weighted five-nearest neighbours classifier is preferred. The implementation approach for the "no decision" class is said to be significant for SRNN classification accurateness and speediness. Grisanet al. (2003) have established a fresh algorithm in order toclassify the vessels, which achieves the peculiarities of glaucoma images. Classification of the vessels it developed to using A/V classification technique. The main vessels have been properly classified 93%. Acharyaet al. (2008) uses SVM classifier to perform classification of five types of eye classes. Five dissimilar types of eye disease circumstances are included in 300 subjects which are necessary for this protocol. This demonstrates 82% of sensitivity and 88%specificity for the preferred classifier. Goatmanet al. (2010) have validated an automated system which is capable to distinguishusual and unusual vasculature on the optic disc. A SVM was chosen as the classifier for its rapid training phase and good classification performance. 38 images with new vessels and 71 normal images from two diabetic glaucoma screening centres and one hospital eye clinic are

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used for training and testing the system by using cross-validation process. Operating point which provides sensitivity of 84.2% and specificity of 85.9% is used to obtain highest accurateness. A substitute operating point provides a sensitivity of 92.1% and a specificity of 73.2%. Roychowdhuryet al. (2013) have presented a computer-aided screening system (DREAM) that investigates fundus pictures with variable light and fields of view, and makes a reality grade for DR using AI. A novel two-step hierarchical classification method is planned where the non-lesions or false positives are prohibited in the initial step. In the next step, classification is performed on the bright lesions. Abbasi-Sureshjaniet al. (2015) have proposed feed forward NN is trained using two datasets. The feed-forward NN classifier results in the highest performance such as sensitivity (0.7332), specificity (0.9782) and accuracy (0.9466). Maher et al. (2015) have detected adiabetic retinopathy in a fundus images with the help of computer based method. SVM classifier is chosen for automatic classification of 130 images which is initially tested and classified into 3 types which include microaneurysms, hemorrhages, and texture. Classification sensitivity of 96.43%, specificity of 95.9 % and accuracy of 99.27 % is being established. Manivannanet al. (2017) have foreseen a different event learning system to survey the visibility of the RNFL in fundus images trapped in the camera. Classification of the images and restriction of the RNFL evident regions is performed using image-level labels. Pellegriniet al. (2017) have presented a novel technique for vessel classification using a scanning laser ophthalmoscope to acquire ultra-wide-field-of-view images of the glaucoma fundus. Classification of funds images utilized for artery/vein (AV) classifier. The projectedtechnique was estimated in terms of accurateness of AV classification at dissimilarphases of the pipeline and in terms of development in the categorisation of graph n-edges. Tripledissimilar datasets was allowed for a testing process using the artery/vein classification technique and an average classification accurateness of 0.883 in the largest dataset has been acquired. Wu et al. (2017) have projected a system for automatic detection of MAs in fundus images. For our extracted features perfect classifier must be chosen out of three classifiers namelyKNN, NB and Adaboost hence all these classifiers must be tested to perform the perfect classification. Naïve Bayes classifier shows a different result whereas the other two classifiers KNN and Adaboost provides the similar outcome. Cao et al. (2018) have been projected for MA detection. The proposed classifiers are RF, a NN, and a SVM. NNs are dominant classifiers, but huge training datasets and well tuning of classifier parameters is necessary. Xuet al. (2018) have proposed an investigation of image to categorize MAs throughput, by joining the lesion coordinate detection and the image registration together. Additional proposal of a SVM based method on classifying MAs turnover in which the variance are noted for pathological risk factors that is intermediateeveryperiod, and further predict the weight of each pathological risk factor leading to the MAs turnover. Sensitivity of 89% &specificity of 88%, correspondingly is achieved by evaluating the classification model. Wang et al. (2018) have three state-of-the-art illustrativeCNN architectures, AlexNet, VGG16 and Inception Net V3, for DR stage classification. Architecture and explanation of dissimilaralignments to influence these CNNs for DR stage classification of image. The optimal accuracy of AlexNet, VGG16, and Inception Net V3 are 37.43%, 50.03%, and 63.23%, correspondingly. Khan et al. (2019) Identification of Diabetic Retinopathy using an automated system with fundus images. DR pictures is collected for CNN approach in this paper. Previously trained CNN models is utilized for instance AlexNet, VGG-16 and SqueezeNet, which gave the congregation accurateness of 93.46%, 91.82% and 94.49% exclusively. In like

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manner, a changed 5 layered CNN model is proposed which involves 2 convolution layers and 3 totally connected neural layers, this procedure has shown promising eventual outcome of sensitivity, specificity and accuracy with amounts of 98.94%, 97.87% and 98.15% separately. Harunet al. (2019) utilizes artificial NN such as MLP trained by LM and BR in order to perform classification fundus image which can hold signs of MR or sometimes they don't. It is known that MLP trained with BR gives a better classification with 72.11% (training) and 67.47% (testing) when comparing it while using LM.

Table 4 Pros and Cons Of Different Classification Algorithms

S.No	Author and Year	Method	Pros	Cons
1	Frameet al. (1998)	SRNN classifier	Non parametric	Classification time is long
2	Roychowdhuryet al. (2013)	k-nearest neighbour (kNN),	Training is done in faster manner	Sensitive to noise and testing is slow.
3	Abbasi-Sureshjaniet al. (2015)	Feed-forward neural network (FFNN)	It can be implemented in any application and without any problem.	Requires high processing time for large neural networks.
4	Maher et al. (2015)	Support Vector Machine(SVM)	Easily handle complex nonlinear data points	The main problem is the selection of the right kernel function. For every dataset different kernel function shows different results.
5	Manivannanet al. (2017)	Instance-Level (IL) classifier	Easy to understand	May suffer from over fitting
6	Wuet al. (2017)	Naïve Bayes classifier	Robust to irrelevant attributes	Independence without expectations for some attribute
7	Wanget al. (2018)	Convolutional neural network-VGG16	The model can be travelled by numerous data	Non linear time complexity
8	Khanet al. (2019)	Pre-trained CNN	Highest accuracy of image classification amongst all algorithms	Need abundant data

III. Conclusion:

Currentstatus in processing of medical image are supplementary in a simple and computeriseddisease screening. We have conversednumerous algorithms projected in literature for the computerized screening of Neurological disorders. For any screening method high sensitivity and specificity are required adequately. The British Diabetic Association projected that everyprogramme of screening for Neurological disorders must preserve 80% sensitivity and 95% specificity. During the authentication of automated screening of Neurological disorders the major problem analysed is recognition and creation of ground truth. Numerousinvestigation councils in associationwith aiding agencies are implementingcreativities for formation of ground fact database. Few algorithms are present in the literature thatsupports the ophthalmologist in a

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simple screening assisted by computer of ND. A quick, cost-effective and accurate method is always appreciated to be the finest but if all these are fulfilled then the time consumed will be obviously greater. Thus finding out the best and an efficient throughput method is really a challenging task to all the researchers. To achieve the maximum FROC scores and accuracy a strongest classifier with excellent features in less training time and dictionary learning for particular lesions must be accomplished by young researchers through deep learning.

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