CHAPTER 2
LITERATURE SURVEY

2.1 INTRODUCTION

Presently, there is an expanding enthusiasm for setting up programmed frameworks that screen a huge number of individuals for vision weakening diseases like glaucoma and diabetic retinopathy and to give a computerized discovery of the illness. Picture handling is presently getting to be plainly pragmatic and a valuable apparatus for screening. Computerized imaging offers a fantastic changeless record of the fundus pictures, which are utilized by ophthalmologists for the observing of movement or reaction to the treatment. Computerized pictures can possibly be prepared via robotized examination frameworks. Fundus picture examination is an entangled undertaking, in the light of the fluctuation of the fundus pictures as far as shading or dark levels, the morphology of the anatomical structures of the retina the presence of specific components in various patients that may prompt a wrong elucidation. In the literature, various cases of the application of computerized imaging procedures utilized as a part of recognizable proof of diabetic retinopathy can be found. The increasing strength in the population affected by the vision threatening diseases diabetic retinopathy and glaucoma leads to the development of numerous image processing algorithms which become an effective and automated tool for the medical practitioners for screening and early detection. Moreover, the digital imaging techniques have the significance of patient’s record tracking resources which are used for consistent monitoring and decision making.

This chapter is organized as follows. Section 2.2, reviews the literature with respect to detection of glaucoma. Section 2.3 provides the
literature survey related to the detection of diabetic retinopathy. Shortcomings of the existing methods are discussed in Section 2.4, and the summary of the literature survey is described in Section 2.5.

2.2 DETECTION OF GLAUCOMA

World Health Organization anticipated that 79 million individuals in the world are probably going to be affected by the year 2020 because of glaucoma. Glaucoma is asymptomatic in the early stages and the related vision misfortune cannot be re-established. Michelson et al. (2008) called attention to early identification, and resulting treatment is basic to avert visual harm. With the new advances in advanced modalities for retinal imaging, there is a dynamic need of picture handling apparatuses that give quick and dependable division of retinal anatomical structures. Generally, glaucoma detection techniques are based on the following.

1. Localization of optic disc
2. Detection of optic cup
3. Assessment of glaucoma

2.2.1 Localization of Optic Disc

In the digital fundus image, the brightest region that appears is the Optic Disc (OD) which is in yellowish or white colour with the shape of irregular circular or oval structure. This is the main entry and exit of blood vessels in the human eye. Identification of optic disc is the key part in retinal disease diagnosis. The changes in the shape of OD and abnormality may be detected for early analysis and treatment. Several researchers have attempted to localize the anatomical structure of the OD. In this literature, the localization of OD is broadly classified into six different groups: (1) Intensity variation, (2) Model-based approach, (3) Based on vascular structure, (4) Region growing method, (5) Principal Component Analysis and (6) Morphological approach.
The algorithms developed based on intensity variation are trouble-
free for common images with less intensity variation. Goldbaum et al. (1996)
make use of three properties to locate the optic nerve. (1) By appearance of the
bright disc approximately 1500µm, (2) Blood vessels get into the nerve from
above and below, (3) Convergence of blood vessels. Sinthanayothin et al. (1999)
traced the OD by locating the area with the highest intensity variation of
adjacent pixels using a window whose size of 80x80 pixels as the size of OD.
The appearance was characterised by the rapid variation in intensity, and the
variance of the adjacent pixels was used for the recognition of OD. Walter and
Klein (2001) developed a technique to identify OD by pixel brightness,
watershed transformation in Hue Saturatio Luminance colour space. They also
calculated centroid as the maximum of discrete distance function and considered
as the approximation of OD localization. Park et al. (2006) presented a method
to automatically outline the OD in a retinal image. This method for finding the
OD is based upon simple image processing algorithms which include
thresholding, detection of object roundness and circle detection by Hough
transformation.

Chrastek et al. (2002) applied an average filter to the green channel
image to roughly locate the OD point as the highest average intensity. Zhu et al.
(2010) used the Hough transform to locate circles in which the best-fitting circle
for OD was chosen with the method of intensity-based selection. The detection
rate was successful with 90% on DRVIE and 44.4% on STARE dataset. Lu et al.
(2011) captured circular shape of OD and image variation across OD boundary,
simultaneously. The pixel variation within the retinal image was calculated
along multiple evenly-oriented radial line segments of specific length. The pixels
with the maximum variation along all radial line segments were determined,
which were then exploited to locate both the center and the OD boundary. Vivek
Kumar et al. (2013) developed intensity-based approach to detect OD boundary.
The points of maximum intensity variation both horizontally and vertically were
chosen as the candidate contour points. Yu et al. (2014) localized OD based on bright pixels removal, iteratively to overcome the existence of any other bright regions (exudate). The fundus image was softened using Gaussian filter, and RBV were removed using the morphological closing. Then, iterative algorithm was carried out, the brightest pixels were extracted and a binary candidate map was constructed. The proposed method detected OD in 95% of 40 images from STARE dataset.

Lalonde et al. (2001) detected optic disc using Hausdorff-based template matching and pyramidal decomposition. Multiresolution processing was employed through pyramidal decomposition which allowed large scale objects tracking; small bright retinal lesions (e.g. exudate) that vanished at lower resolutions, made easy the search for OD region with a few false candidates. A simple confidence value was calculated for all the OD candidate regions representing the ratio between the mean intensity inside the candidate region and in its neighbourhood. Model-based (template matching) approach was employed by Osareh et al. (2003) to locate the OD roughly. Initially, the images were normalized by applying histogram specification, and then the OD region from 25 colour normalized images was averaged to produce a gray-level template. The normalized correlation coefficient was then used to find the most perfect match between the template and all the candidate pixels in the given image. Lowell et al. (2004) developed a template for optic disc composed of a Laplacian of Gaussian filter with a vertical channel carved out of the middle corresponding to the major blood vessels exiting OD vertically. This template was then correlated to the intensity component of the fundus image using full Pearson-R correlation. Xu et al. (2007) presented deformable model-based approach to spot the boundaries of OD and OC. The method developed here is based on knowledge-based clustering and smoothing update. The contour deforms to the location with minimum energy, and then self clusters into edge point group and uncertain point group were updated with both local and global information. Aquino et al.
(2010) proposed template-based technique for OD segmentation. Initially, the OD containing sub-image is extracted, and then OD pixel with maximum intensity and its surrounding regions are selected. The OD boundary was extracted using morphological, edge detection method followed by circular Hough transform for boundary detection. The OD can be localized by considering the characteristics of the vascular structure.

Hoover et al. (2003) developed a method based on fuzzy convergence of the blood vessels that lead to the detection of OD area. OD centre is defined as the focal point of the vascular network. Foracchia M. et al. (2004) gave a description of the common direction of retinal blood vessels at any given position in the retinal image by constructing a geometrical parametric model, where the position coordinates of the OD center correspond to two parameters of the geometrical model. Youssif A. et al. (2008) located the OD area by filter matched with blood vessels direction. The vessels are segmented to build the structure map and a standard vessel directional filter is designed. Then, the minimum difference between the directions matched filter and the direction of the vessels around the OD area were found and OD candidates were estimated. Tagore et al. (2016) have proposed an OD Segmentation method that takes care of fuzzy boundaries and inhomogeneity present in the retinal images. This method uses vessel direction matched filter (VDMF) and signed pressure force (SPF) to detect OD and the detection is superior compared with state-of-the-art methods.

Li & Chutatape (2003 and 2004) created an OD model by applying Principal Component Analysis (PCA) that was physically cropped around the OD and modified ASM method. Li. & Chutatape (2001) suggest the PCA analysis to locate OD centre and the proposed method provides acceptable OD detection. Novo et al. (2009) presented OD localization by combining region-based and edge-based segmentation techniques. It works on the fundus images having noise, bright or dark lesions. Zubair et al. (2013) located OD by raising
its contrast using CLAHE, contrast stretching transformation, and extended minima transformation. With the use of contrasted image, the OD was then localized by using morphological erosion and dilation to remove non-OD areas, and finally the obtained OD yielded an accuracy rate of 98.65% on MESSIDOR dataset. Meindert Niemeijer et al. (2007) use a cost function, which is based on a combination of both global and local cues, to detect the optic disc. Abdel-Ghafar et al. (2007) detect the OD by finding the largest circular object using circular Hough transform technique. Adithya Kusuma Whardana et al. (2014) developed a simple method using K-means clustering to detect OD area with perfected adaptive morphology.

2.2.2 Detection of Optic Cup

The detection of optic cup plays a significant role in identifying the retinal disease glaucoma. The chronic eye disease glaucoma cannot be cured but its growth can be stopped by proper management. Abramoff et al. (2007) have implemented pixel-based feature classification on the stereo color photographs and optimal subset of 12 features are used to segment pixels as cup or non-cup and the linear cup to disc ratio estimates the glaucoma.

Liu et al. (2008) detected the optic cup area by deriving a region based on the orientation color from a manually selected point. Pixels are selected in the RGB channels only if their intensity values lie within 25% range from selected pixel intensities. Cup boundary is estimated using threshold techniques, and level set method is used to determine the cup contour. Threshold value is selected to segment out the pixels corresponding to the top one third of grayscale intensity. Cup boundary obtained via ellipse fitting yields only coarse cup boundary.

As the optic cup possesses just a little area of the whole retinal picture, an area of intrigue is initially extracted through pixel intensity.
Variational level-set technique is next used to detect the optic cup. Liu et al. (2009) have offered a multimodal approach with different methods for the extraction of optic cup, and an ellipse fitting is applied to the extracted optic cup. Neural network has been used to fuse the results obtained by various modes. An automatic cup to disc ratio measurement for glaucoma analysis using level set image processing (ARGALI) system developed automatically computes the CDR and provides fast and objective measurement.

Joshi et al. (2010) developed a deformable model guided by regional statistics for optic disc and cup boundary detection with the appearance of the pallor in Lab color space. The cup region that appears most continuous in the ‘a’ plane of Lab color space is utilized, and morphological opening is carried out for smoothing the blood vessels in the cup area. Then, pixels have been extracted using dynamic threshold to select pixels that fall inside the OD region. The method gives rise to fewer false positives and high specificity.

Yanwu Xu et al. (2011) proposed a machine learning framework-based sliding window of different sizes to obtain cup candidates. A support vector regression with non-linear radial basis function is used to rank each candidate. Yin et al. (2012) developed a deformable model-based approach, in which the initialization of the cup boundary is based on pallor combined with prior knowledge of cup. Cheng J et al. (2013) developed a superpixel classification-based optic cup segmentation where the OD is oversegmented into superpixels, and then mean, intensity, centre surround statistics and location features are extracted from each superpixel to classify into cup or non-cup. Andres Diaz et al. (2016) used anatomical structures like position of vessels and cup within optic nerve, and with the help of color space and water-shed transformation, different characteristics of optic nerve were analyzed for distinguishing normal and glaucomatous image.
2.2.3 Assessment of Glaucoma

Early treatment for glaucoma can diminish the rate of visual impairment by around half. Glaucoma portrayed by neurodegeneration of the optic nerve is one of the basic reasons for visual impairment. Existing works relevant to glaucoma detection in retinal images mainly focus on the cup to disc ratio features. However, this CDR is inconsistent in detecting OD damages caused due to glaucoma. This is predominantly contended to be because of confinements with the CDR parameter which cannot represent different designs of optic cup, neuroretinal edge and central scoring (neighborhood expansion of cup region). Thus, an alternate OD assessment system, called the disc damage likelihood scale, has been presented by Spaeth et al. (2002) to absolutely portray the measure of OD harm brought about by glaucoma.

Stapor et al. (2004) used morphological elements for the quantitative assessment of cup based on genetic algorithm. The computed features are then utilized as a part of order technique in view of Multi Layer Perceptron (MLP) with Back Propagation (BP) learning principle. Shape of cup and the numerical attributes relate to a specific degree with the advance of glaucoma and accomplished 90% sensitivity and 86% specificity. Cup features were chosen by (Stapor et al. 2006) utilizing genetic algorithm. Categorization of fundus images is accomplished utilizing Support Vector Machine (SVM) classifier. This paper introduces the enhanced form of the classification system for supporting glaucoma finding in ophthalmology utilizing support vector machine classifier and accomplishes 94% sensitivity and 97% specificity.

Mei-Ling Huang et al. (2007) utilized a computerized classifier in view of adaptive neuro fuzzy inference to separate normal and glaucomatous eyes from the quantitative assessment of synopsis information reports of OCT in Taiwan Chinese populace. With Stratus OCT parameters utilized as info, the outcomes from neuro fuzzy demonstrated promising results for segregating
amongst glaucomatous and normal eyes with 90% accuracy. Rajendra Acharya et al. (2011) built up a glaucoma diagnosis system utilizing a blend of texture and higher order spectral components with a random forest classifier and accomplished an accuracy of 91%. Ganesh Babu et al. (2014) presented an approach based on the spatially weighted fuzzy c-mean clustering and region of interest for detection of optic disc and optic cup. Superior side to area of blood vessels and neuro retinal rim in ISNT is combined with CDR for classification of fundus images using back propagation neural network and support vector machine.

Kurnika Choudhary et al. (2015) used artificial neural network for the detection and classification of Glaucoma disorder in diabetic patients. The authors used feed forward back propagation neural network for training and testing the retinal images for Glaucoma classifications. Prasad N Maldhure et al. (2015) used the technique of OD and OC segmentation for Glaucoma detection and diagnosis process. The super pixel classification approach was used to segment the OD and OC regions in retinal images. The severity of Glaucoma was classified based on Cup to disc ratio. The authors achieved 96% of average Optic disc segmentation for Glaucoma detection.

2.3 DETECTION OF DIABETIC RETINOPATHY

In recent years, consistently expanding the quantity of diabetic patients has to a great extent aroused the examination works in building up the methodologies to encourage the screening and assessment technique for diabetic retinopathy. Early determination and precise arranging are fundamental essentials for successful treatment of diabetic retinopathy and diminishment of visual incapacity hazard. The algorithms described in the literature for diabetic retinopathy are based on the following.

1. Segmentation of blood vessels
2. Segmentation of exudate
3. Segmentation of microaneurysms
4. Segmentation of hemorrhages
5. Assessment of diabetic retinopathy

2.3.1 Segmentation of Blood Vessels

Various methods have been projected for blood vessel segmentation in ocular images. Hoover et al. (2000) presented a class of popular approaches to vessel segmentation. Matched filter-based method uses a two-dimensional linear structural element that has a Gaussian cross-profile section, rotated into three dimensions to identify the cross-profile of the blood vessels. The resulted image is finally thresholded to produce a binary segmentation of the vasculature. However with this method, the junction points are not always detected, small vessels are missed and the validity of the detected vessels is not checked. Besides, the threshold selection is also critical. Xiaoyi et al. (2003) proposed a general framework of adaptive local thresholding on a verification-based multi threshold probing scheme. Object hypotheses are generated by binarization using hypothetic thresholds and accepted/rejected by verification procedure. Another technique for vessel extraction is the ridge-based method proposed by Staal et al. (2004) in which the image ridges are extracted, which coincide approximately with vessel center lines. The ridge detection is followed by ridge pixel grouping and classification using a kNN-classifier. Supervised methods are a class of machine learning-based methods. They exploit some prior labelling information to decide whether a pixel belongs to a vessel or not, while unsupervised methods do the vessel segmentation without any prior labelling knowledge. A simple and efficient method is proposed for segmentation using Gabor Wavelet and Gaussian mixture classifier (Joao et al. 2006). This method is conceptually simple and gives efficient results, but it does not perform well for large variations in lighting throughout an image, and it has the inability to capture some of the thinnest vessels that are barely perceived by the human observers.
Elisa et al. (2007) proposed a method for vessel segmentation using cellular neural networks. This method is easy to use and results in acceptable accuracy. In addition, Elisa et al. (2007) also proposed a method for vessel segmentation using line operators and support vector machine. Feature extraction is simple, but pixel-wise classification is not possible which results in the overestimation of well-contrasted pixel. A supervised algorithm for vessel segmentation in fundus images has been developed by Anzalone et al. (2008).

A classification mechanism is proposed for segmentation of blood vessels in retinal images by Chang et al. (2009). Both SVM and a combination of PCA and SVM are used for classification. PCA reduces the feature dimensionality and maintains accuracy above 90%. Lili Xu et al. (2009) presented a novel method of segmenting blood vessel using adaptive local thresholding to produce binary image and extract connected component as large vessels and classification is made by SVM. A new supervised method for vessel segmentation was proposed by Martin et al. (2011). This method uses a back propagation neural network scheme for pixel classification and computes a 7-D vector composed of gray-level and moment invariants-based features for pixel representation. Miri et al. (2011) proposed a new method for blood vessel segmentation. This method uses curvelet transform for image enhancement and morphological operators for detecting the blood vessels and has achieved better accuracy. Sun et al. (2012) presented an active contour model within the level set framework using local morphology fitting for automatic vascular segmentation on 2-D angiogram. The vessel and background were fitted to fuzzy morphology maximum and minimum opening separately, using linear structuring element with adaptive scale and orientation.

Xiao et al. (2013) have used spatial constraint-based Bayesian classifier for segmenting the blood vessels. The modified level set approach was used to extract the vessel boundaries in the retinal images. Siva Sundhara Raja et
al. (2014) used SVM classifier to detect and segment the retinal blood vessels. The absolute difference image was constructed by subtracting the green channel retinal image from the morphologically processed retinal images. Manvir Kaur et al. (2015) proposed a method for blood vessel segmentation using ANFIS classifier. Gabor features are extracted for classifying each pixel as vessel or non-vessel in DRIVE dataset. Vaibhavi et al. (2016) have proposed a texture-based segmentation of blood vessel where a bank of Gabor energy filters are used to analyze the texture features from which a vector is constructed for each pixel. The Fuzzy C-Means clustering algorithm classifies the feature vector as vessel or non-vessel.

### 2.3.2 Segmentation of Exudate

Several techniques have been developed for exudate detection in fundus images. Image processing techniques such as dynamic thresholding have been used for exudate segmentation by Liu et al. (1997). However, this technique does not contain any recognition models that are able to distinguish between visually similar symptoms. Li et al. (2000) proposed a method to detect exudate using Kirsch’s edges and morphological operators. Kirsch’s edges are applied to the different colour channels, and morphological operators are used to separate the blood vessels and exudate. Based on the colour characteristics of retinal images, a simple Bayesian classifier was used to detect the exudate by Wang et al. (2000). It is a novel approach that combines brightness adjustment procedure with statistical classification method and local-window-based verification strategy. Eong et al. (2001) demonstrated the role of domain knowledge in improving the accuracy and robustness of detection of hard exudate in retinal images. Extraction of exudate is done by computing the difference map and by k-means clustering.

Walter et al. (2002) have presented that the exudate are found using their high gray level variation, and their contours are determined by means of
morphological reconstruction techniques and the watershed transformation. This method resulted in a sensitivity of 92%. Fuzzy C-Means clustering and neural networks were used to detect the exudate in diabetic retinopathy images by Osareh et al. (2003). But the system works well only on LUV colour space, and in the case of non-uniform illumination, the detection accuracy is low. Mitra et al. (2005) have proposed a naive Bayes classifier for diagnosis of diseases from retinal image, and this can provide a good decision support to the ophthalmologist. Pre-processing techniques such as histogram specification and local contrast enhancement are integrated with dynamic thresholding (DT) and edge detection for exudate detection by Sagar et al. (2007), and it has achieved a mean predictivity of 93%. Contextual clustering algorithm is used to segment the retinal image and the detected candidate objects are classified as exudate or non-exudate using the fuzzy neural network as proposed by Jayakumari et al. (2007).

Hussain et al. (2010) have proposed an automated method for hard and soft exudate detection using coarse to fine segmentation principle. Fine exudate detection is done by adaptive local thresholding method. S.Kavitha et al. (2011) present an automatic detection system of exudate in colour fundus images. The colour fundus images are subjected to pre-processing for CIELab colour space conversion and Fundus region detection using binarization and mathematical morphology respectively. Exudates are detected with the aid of thresholding colour histogram, which is used to classify the hard and soft exudate pixels from the colour fundus retinal image.

Jayakumari et al. (2012) presented a technique for detection of exudate using contextual clustering technique. This technique uses pre-processing; contextual clustering algorithms to segment exudate. Standard deviation, mean, intensity, edge strength and compactness are the key features extracted and fed as inputs into Echo State Neural Network (ESNN) to discriminate between the normal and pathological image. Haniza et al. (2012)
presented an approach to locate exudate and OD in fundus images based on inverse surface thresholding. The methodology involves Fuzzy C-Means clustering, edge detection, otsu thresholding and inverse surface thresholding. Poonam et al. (2015) proposed an automatic detection of hard exudate using the Haar wavelet transform followed by KNN classifier. Manpreet kaur et al. (2015) have proposed a hybrid approach exudate detection with the help of un-sharp masking for pre-processing, and region-based segmentation is used for candidate detection, and then pixel-based classification is used to determine the severity level of the disease. Partovi et al. (2016) presented exudate detection using simple image processing techniques. The morphological function was applied on intensity components of Hue Saturation Intensity (HSI) space. To locate exudate area, thresholding was performed on ocular images.

2.3.3 Segmentation of Microaneurysms

Various methods for microaneurysm detection have been published. Kamel et al. (2001) implemented a learning vector quantization neural network to detect microaneurysms from fluorescein angiograms based on multi-stage training procedure. This approach effectively improved the accuracy rate. C.Sinthanayothin et al. (2002) proposed an automated system of detection of diabetic retinopathy using recursive region growing segmentation (RRGS). Usher et al. (2004) have employed a combination of RRGS and adaptive intensity thresholding to detect candidate lesion regions, and a back propagation neural network is used for classification. Serrano et al. (2004) proposed a method for detecting microaneurysms by the region growing technique in order to analyze fluorescein angiograms. Fleming et al. (2006) proposed a method for the detection of microaneurysms by using a watershed transform on fluorescein angiograms. Walter et al. (2007) proposed a method based on diameter closing and kernel density estimation for automatic classification.
Atsushi Mizutani et al. (2009) proposed detection of microaneurysms by applying double-ring filter on the green channel of the colour images; this was followed by the elimination of lesions in the blood vessels, which were false positives. Next, the shapes of the candidate lesions for an accurate determination of their image features were examined. B. Zhang et al. (2010) used multi-scale correlation coefficients (MSCF) for MA detection. Mathematical morphology has been used for the detection of MA by Sopharak et al. (2011). This has provided successful results in spite of missing some MA and false detections. Sarni Suhaila Rahim et al. (2016) proposed feature extraction methods and the circular Hough transform employed in the microaneurysm detection system, alongside the fuzzy histogram equalisation method. Syed et al. (2016) present an automated MA detection system for colour fundus image analysis based on curvelet transform. MA candidates were extracted in two stages. In stage one, blood vessels were removed, and preliminary MA candidates were selected by local thresholding technique. In the second stage, based on statistical features, the image background was estimated. The results of the two stages allowed identifying preliminary MA candidates which were also present in the image foreground. A collection set of features was fed to a rule-based classifier to classify candidates into MAs and non-MAs.

2.3.4 Segmentation of Hemorrhages

Detection of hemorrhages in ocular images plays a major role in clinical diagnosis of DR. It is the initial medical sign of DR, and detection of hemorrhages helps the ophthalmologists in screening retinal disease more precisely.

Sinthanayothin et al. (2002) apply the idea of region growing in their work. Moat Operator has been used to define the features of hemorrhage followed by adaptive intensity thresholding. The candidates go through the process of recursive region growing. Chutatape & Zhang (2005) presented a top-
down method for hemorrhage extraction, in which after pre-processing, the hemorrhages were located using Support Vector Machine (SVM) to compute pixel value. Combined Two-Dimensional Principal Component Analysis (Combined 2DPCA) was employed to take out features which were then fed to SVM classifier. Zhang et al. (2005) use colour normalization where the value for every pixel was calculated by SVM to locate the hemorrhages. The hemorrhage boundaries were sectioned by post-processing. Niemeijer et al. (2005) developed a hemorrhage lesion detection algorithm based on pixel classification. The red candidates were extracted by using mathematical morphology. The detected candidate objects were classified using all features and a k-nearest neighbour classifier. Fan & Zhang (2006) described a spot lesion detection algorithm using multi-scale morphological processing. Hatanaka et al. (2008) presented an improvement over HSV space to correct non-uniform brightness of ocular image. The p-tile thresholding technique was utilized to detect OD. Density analysis was used to extract hemorrhage candidates and to classify using rule-based method and three Mahalonobis distance classifiers. Shivaram et al. (2009) developed an algorithm for hemorrhage detection from DR pathological images. Fundus image was improved, and image subtraction was used to remove blood vessels and hemorrhages. Optimally adjusted morphological operators were employed to highlight only hemorrhages suppressing blood vessels.

Karnowski et al. (2008) proposed morphological reconstruction method for lesion detection. The segmentation was executed at different scales to fix on the hemorrhages using ground-truth data. Kande et al. (2009, 2010) described a method to detect microaneurysms and hemorrhage based on pixel classification and mathematical morphology. Support vector machine is applied to classify red lesion areas and non-red lesion areas in ocular images. Kande et al. (2009) also presented a technique to locate red lesions by relative entropy thresholding after pre-processing. Acharya et al. (2009) used morphological operations to detect various lesions. An image with RBV was removed using
‘ball’ shaped structuring elements, in addition to morphological operations. Then, abnormal image with RBV and hemorrhages was identified using the same technique with slightly increased ball size. The final location was obtained by subtracting the image with RBV alone from the RBV and hemorrhage image. Sadjedi & Langroudi (2010) used morphological operations and thresholding to detect OD, lesions and fovea in ocular image. Singh et al. (2010) proposed top hat transform and fuzzy clustering methods for RBV removal. Hemorrhages and microaneurysm were located by suppressing fovea and vessels.

Tang et al. (2011) described a huge hemorrhage detection based on splat feature classification. The retinal image was split into several splats of same colour based on the guess that the pixels of the same structure had like colour and were located spatially. Köse et al. (2012) have presented method, which focuses on the unhealthy regions. This method used inverse segmentation method to divide healthy region and unhealthy region. Based on the information that the texture of healthy region does not vary as much as the texture of the unhealthy region, it is more precise to extract the healthy region. Then, dark lesions are left after segmentation using the intensity value that is less than the background intensity value. Narasimhan et al. (2012) proposed a thresholding technique applied to enhance the image, and region growing method was used to extract features for the detection of microaneurysm and hemorrhage. Singh & Tripathi (2010), Shivaram et al. (2009) and Fleming et al. (2008) used morphological operators in their hemorrhage detection algorithms. Erosion, dilation, opening, closing and top-hat are some examples of operators utilized in these works. Esmaeili et al. (2010) proposed an algorithm based on multiscale approach called Digital Curvelet Transform (DCUT). Curvelet coefficients were defined in such a way that a red lesion, especially hemorrhage was easily differentiated from other image parts.
García et al. (2010) propose neural network-based classifiers to automatically segment the hemorrhage candidates using four neural network-based classifiers, namely Multilayer Perceptron (MLP), Radial Basis Function (RBF), Support Vector Machine (SVM) and Majority Voting (MV) schema. Bae et al. (2011) applied the template matching method in addition to region growing segmentation. The technique uses circular shaped template and a program performing template matching which performs hemorrhage candidate extraction called Normalized Cross-Correlation (NCC).

2.3.5 Assessment of Diabetic Retinopathy

Diabetic retinopathy is a quiet sickness since it might just be perceived by the patient when the changes in the retina have advanced to a level where treatment is confounded and almost unimaginable. The pervasiveness of retinopathy changes with the time of onset of diabetes and the span of the illness. Up until now, the best treatment for DR can be controlled just in the principal phases of the sickness. Hence early discovery through consistent screening is of fundamental significance. To bring down the cost of such screenings, computerized image catching technology must be utilized since this innovation empowers one to utilize state-of-the-art image processing methods which automate the discovery of abnormalities in retinal images.

Developing of automated screening system for analyzing the digital color fundus images is very much required to prevent loss of vision. Precise identification and early treatment prevent the vision loss. Previously developed automated systems were used to detect the major landmarks (optic disc, blood vessels and fovea) of retinal images (Sinthanayothin.C et al. 2002). The authors make use of new technique ‘Moat Operator’ used to automatically detect the features of NPDR. The features include microaneurysm and hemorrhage in one group and exudate in the other group. The system yielded a sensitivity of 80.21% and a specificity of 70.66%. Image handling can both decrease the
workload of screeners and assume a central role in quality assurance tasks. Thus, there has been an expansion in the utilization of computerized image processing techniques for automatic identification of DR (The Liverpool declaration. 2005). Samuel et al. (2005) developed an automated diagnosis of NPDR using lesions: hemorrhages, microaneurysms, hard exudate and cotton wool spots and were able to identify the NPDR with an accuracy of 81.7%.

In the course of the most recent two decades, there has been a quick advancement of computer-aided diagnosis (CAD). Using computers in diagnosing medical image is in more practice. However, the nature of these CAD frameworks expanded with more precise sensor information, all the more preparing power and better comprehension of the fundamental infection (Fujita et al. 2008). Normal, mild, moderate, severe and prolific DR stages were automatically classified using both area and perimeter of the RGB components of the blood vessels together with a feed forward neural network (Wong et al. 2008). Acharya et al. (2008) make use of bispectral invariant features for the support vector machine classifier to classify the fundus image into normal, mild, moderate, severe and prolific DR classes. Acharya et al. (2009) classify the DR severity based on the hemorrhages, microaneurysm, exudate and blood vessel area with support vector machine classifier. The system was able to identify the unknown class accurately with an efficiency of more than 85% and sensitivity of more than 82% and specificity of 86%.

An alternative DR seriousness evaluating strategy was proposed by Usman Akram et al. (2014) based on the type (RLs and EXs) and number of lesions detected. Images without lesions were viewed as ordinary images. In different reviews, Antal et al. (2014) proposed a four diverse seriousness grades. Level R0 (no DR) related to the situation where no RLs were found in an image. Furthermore, levels R1, R2, and R3 (DR images) related, individually, to the situations where a little, medium and substantial number of RLs showed up in
the image. The authors assessed the accuracy of their algorithm in recognizing normal (R0) from abnormal (R1, R2, R3) images. Roychowdhury et al. (2014) designed a framework based on machine learning systems. Images were delegated with or without DR as indicated by the quantity of RLs identified.

2.4 SHORTCOMINGS OF EXISTING TECHNIQUES

Methods described in the literature are related to the two retinal disease detection viz. glaucoma and diabetic retinopathy. Optic disc localization is aimed at recognizing the centre focal point of the optic disc or setting the circle inside a particular region. In either case, optic disc localization is confused by the nearness of noteworthy distracters. Blood vessels may cross the optic disc limit darkening the edge of the disc with the edges of the vessels going about as distracters. Normal variety in the qualities of OD incorporating the distinctions in pigmentation and myelineation of the nerve fiber layer are noteworthy issues in characterizing the shape of the disc. Broadly useful edge recognition algorithms frequently neglect to portion the optic disc because of fuzzy limits, conflicting image contrast or missing edge features. Algorithms which depend on intensity variation demonstrate simple and strong for optic disc localization in fundus images.

Notwithstanding, an optic disc darkened by blood vessels or just in part noticeable might be misidentified utilizing the techniques in the light of distinguishing the brightest areas. Such strategies are profoundly sensitive to distracters, for example, yellow or white lesions or bright features. Optic cup identified utilizing thresholding and level set strategy requires manual installation. Twisting of little vessels at the cup edge is utilized as a piece of information to measure the cup boundary. There is a high thickness of vascular structure crossing the cup boundary. This technique can just give a few purposes of cup boundary in the range where there are little vessels. For the region without little vessels, the cup border line is difficult to be assessed.
Despite the fact that numerous systems have been proposed in this field, the strategies are restricted by no less than one of the accompanying downsides. Client association is expected to choose region of interest, and the technique is not totally automated. Segmentation requires more computational endeavors. In the discovery of DR, basic thresholding methods utilized for the identification of lesions are very undesirable as the variation in background intensities makes it hard to locate a proper threshold. Region growing strategies are clear, yet choosing seed points are troublesome. Endeavors in view of particular components and morphological reconstruction methods are sensitive to image distinction. While the outcomes are empowering, existing methods are restricted by problematic feature selection and pixel grouping systems.

2.5 OVERVIEW OF THE PROPOSED WORK

From the shortcomings of the literature survey discussed, the flow diagram of the proposed segmentation and classification process for detection of retinal diseases Diabetic Retinopathy (DR) and Glaucoma are shown in Figure 2.1 illustrating the sequence of works carried out. The whole research work is divided into four parts. Pre-processing, Segmentation of anatomical and pathological retinal structures, feature extraction from the segmented image, classification and grading of retinal diseases.
2.6 SUMMARY

An overview of methods for the automatic identification of glaucoma and diabetic retinopathy has been introduced in this section. The proposed strategy includes two stages (i) detection of diabetic retinopathy and (ii) detection of glaucoma. A coordinated system is to be developed to begin with
for the detection of diabetic retinopathy and glaucoma, to upgrade the system execution by i) enhancing the results of different tasks, for example, the location of optic disc, optic cup, blood vessels, detection of microaneurysm, hemorrhages, exudate utilizing color and textural features and ii) to enhance the classification techniques using appropriate features. The overview of the proposed work investigates fundus images to recognize the anatomical and pathological structures and to grade the disease based on the severity level of the lesions which in turn support the ophthalmologist to provide decision support system.