

# Automated Fundoscopy for Glaucoma Detection and Classification



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**Abstract:** *glaucoma is leading chronic eye diseases in the world that leads to vision lost. The main cause of Glaucoma is intrinsic deterioration of the optic nerve which leads high intraocular pressure of the eye. Manually detection of glaucoma is tedious and costly. In our work we are providing automated system for glaucoma detection which is based on fully connected conditional random field (FC-CRF) model, it works on long and thin structure. Conditional random field provide a platform for structure prediction. Taking benefit of current results, validating assumption and parameters of our system learned automatically with the help of structured output support vector machine. Our system trained both quantitatively and qualitatively on publically existing data sets: DRIVE, STARE, CHASEDB1 and HRF. Once we obtain segmentation results further classification is done by SVM and K-NN classifier results of our proposed system is analyzed with gold standard labeling provided each data sets in terms of TP, TN, FP and FN. importance of our proposed system is it works for enlarge structure which can provide a platform to other biomedical and biological applications.*

**Keywords:** *-vessel segmentation, fundus image, k-NN, SOSVM, CRF.*

## I. INTRODUCTION

Retina is a part of central nervous system resides in peripheral location represents the neural portion of human eye. Detecting macular degeneration (ARMD) which may result total vision lost or blurred vision, diabetic Eye or diabetic Retinopathy (DR) occurs due to diabetic mellitus, and retinopathy of prematurity (ROP) occurs due to unwanted growth of retinal vessels, segmentation of blood vessels contains elementary role in diagnosis of eye syndromes. Segmentation is an important step in visualization of programs for primary detection of eye syndrome. The development of Automated detection system is beneficial it simply means the system combine all screening programs in a single system to provide accurate results. The idea behind developing automated system is ophthalmologist unable to detect exact results in a single screening hence it is not feasible to get results in time [1]. These systems usually perform morphological operations on retinal structure of blood vessels this immense information will help us for further examination and treatment [1]. For diabetic retinopathy early detection plays a vital role to avoid vision lost [2].

Segmentation process plays important part for the analysis of retinal vessels. Earlier this process perform manually by experts but it is tedious due to low contrast nature of fundus images, uneven width of vessels, shape which affects analyst to get accurate results hence it is time consuming and ambiguous [3]. These facts encourage us for building an automated fundoscopic system for blood vessel segmentation without manual efforts [1]. Many research persons working in this field of automated detection and classification of vessel segmentation but still it is open for all to get accurate results. Generally for classification of presented approaches, there are number of classifiers, classification techniques contain two types, supervised and unsupervised. To learn a model Supervised techniques need trained samples. In this case these samples are nothing but picture cells and their features with analysis. We studied several classifiers in literature survey they are k-NN [4], Bayesian [5], SVM [6]-[7], NN [8]-[9], decision tree [10]-[11], Gaussian Mixture Model [3], Adaptive boosting [12]. A recently introduced B-COSFIRE trainable filter highlights the retinal vasculature [13]. Even if the method is unsupervised in term of training a classifier, it adopts parameters which are mainly based on trained data. In unsupervised learning method system doesn't require labeled classes and annotations; hence this technique had lower accuracy, unsupervised learning technique involved thresholding, vessel tracking [14] region growing [15]-[17], active contours [18]-[19] – morphological operations performed this task [20], matched filter responses [21]-[22], wavelet transform [23]-[24]. This study purposes supervised methods. Conditional random fields (CRFs) are discriminative statistical modeling technique means it is has been used when class levels are dependant. Earlier segmentation using fully connected CRFs is applied to detect tumor of liver and brain through CAT and MRI scanning. [25]- [26]. In our work we are working on thin retinal two dimensional structures. Local classification unable to classify while incorporates previous information regarding contours of the preferred patterns for learning stage. CRFs obtain this information using pairwise potential. SOSVM used for learning phase prior to learn local neighborhood based CRFs [27]-[28]. Here we use fully connected CRFs for learning by skipping SOSVM, as its computational complexity it requires multiple calls during training algorithm on other side dense CRFs slow in nature [29]. In this study, we carry

Out our prior effort with more advanced research information and performance throughput. We also adapt the policy of estimation and set new parameters to improve performance of training phase.

Manuscript published on January 30, 2020.

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Additionally, we validate our results, quantitatively and qualitatively on freely existing standard datasets (DRIVE, STARE, CHASEDB1 and HRF). Our system performs on multiple quality measures to obtain accurate results.

**II. METHODOLOGY**

In our proposed work we are providing automated fundoscopic system for glaucoma detection by discriminatively fully connected conditional random field (FC-CRF) model. It can graphically plot retinal images, it means we used pixel as node having connection with an edge to its very closest neighbors. Using this technique we are able to get detailed information of neighbor pixels as well as interface between elongated pixels. Using this technique we obtain exact segmentation result but it is time consuming because it is computationally complex at the training phase. This problem is overcome by defining pairwise edge potential in the form of linear combination of Gaussian kernels [30], it means it uses approximate mean arena of the primary CRF, capable towards exact segmentations within fraction of second.

• **FC-CRF Segmentation of retinal vessels**

To understand this technique we are having certain mathematical formulations as we know here we are going to apply energy minimization on conditional random field. This process is carried out using features of unary and pair wise potentials. Simply unary potential encode local information of pixel and pair wise potential assign labels to two neighbor pixels in our case it define inference.

$$E(y) = \sum_i \psi_u(y_i, x_i) + \sum_{i < j} \psi_p(y_i, y_j, f_i, f_j) \dots\dots\dots(1)$$

E(y) is energy function

$$\psi_u(y_i, x_i) = -\langle w_{u_{y_i}}, x_i \rangle - \beta_{y_i} \dots\dots\dots(2)$$

$\Psi_u$  is unary energy.

$$\psi_p(y_i, y_j, f_i, f_j) = \mu(y_i, y_j) \sum_{m=1}^M w_p^{(m)} k^{(m)}(f_i^{(m)}, f_j^{(m)}) \dots\dots\dots(3)$$

$\Psi_p$  is pairwise energy.

By adding equation (2) and (3) we get energy function.

Where  $w_{u_{y_i}}$  weighted vector  $\beta_{y_i}$  biased function related with label  $y_i$ .

After getting energy function we need pixels those differs form mean value of the group to obtain this we use Gaussian kernel which is mathematically depicted as follows.

$$k^{(m)}(f_i^{(m)}, f_j^{(m)}) = \exp\left(-\frac{|p_i - p_j|^2}{2\theta_p^2} - \frac{|f_i^{(m)} - f_j^{(m)}|^2}{2\theta_{(m)}^2}\right) \dots\dots\dots(4)$$

Where  $k^{(m)}$  is kernel  $f^{(m)}$  is random feature  $w_p^{(m)}$  group of linear weight and  $\mu(y_i, y_j)$  label compatible function.

**A. Learning of Structured support SVM through conditional random field**

It is a machine learning algorithm mostly used in binary classification. SVM works on linearly separable points (features), means it contain a hyperplane that separate the

points (features) in the single category. In our case this condition doesn't satisfied because we are having multiple features, to overcome this we apply 1-slack formulation (slack variables are responsible for measuring distance between point to its marginal hyperplane.). Using this technique we learn vector W having different unary features with respect to bias and pairwise kernels. By using mathematical formulation we calculate weights W.

$$\min_{w, \xi \geq 0} \frac{1}{2} \|w\|^2 + C\xi \dots\dots\dots(5)$$

Where C can defined as regularization constant.

**B. Classification**

In this work we are having two types of classifiers SVM and k-NN for classification.

• **SVM**

In our work we can define support vector machine as a support vector classifier. Here kernels (similarity quantifier) extend the feature space. It is supervised learning technique classification and regression analysis is done by analyzed data. In our case we need non-linear classification to deal high dimensions for this purpose we tune the following parameters.

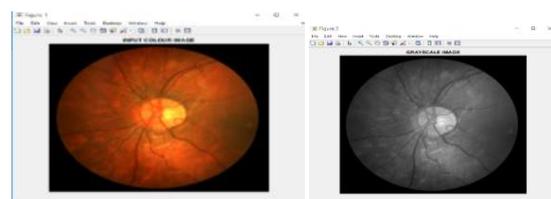
- a) Kernel parameter:-responsible for linear or non-linear separation.
- b) Regularization parameter:-Responsible for svm optimization in training phase by measuring the quantity of misclassifying avoided points.
- c) Gamma parameter:-defines the low (far), high (close) influence in training phase.
- d) Margin parameter:-line separation for high class points.

• **k-NN**

It is distribution free means depends on observations means here we don't know target variable. Related identified neighbors are defined by number K .we get closest training samples using K factor, when k=1 we call it nearest neighbor algorithm.

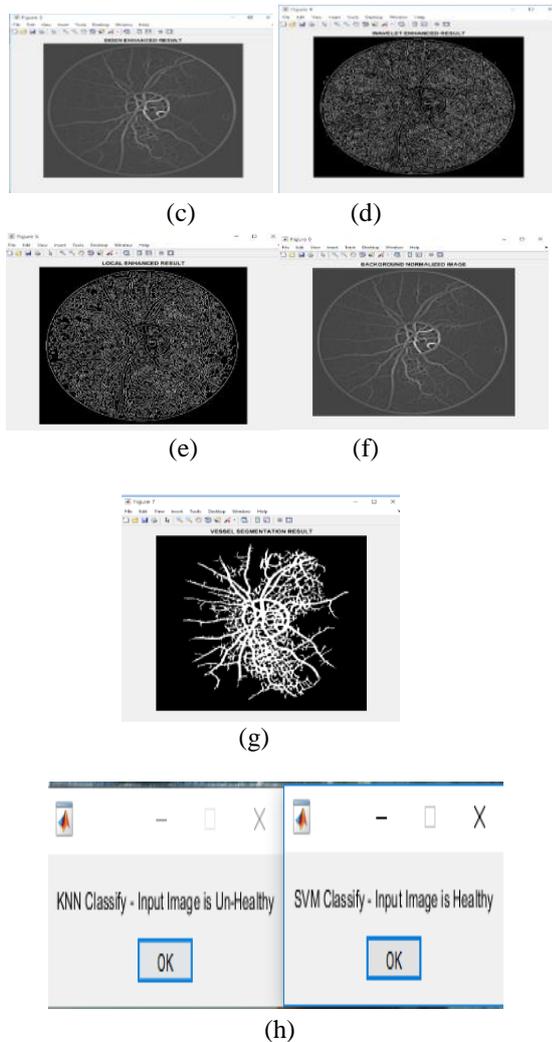
- a) Implementation of k-NN model
  - Step1: data loading.
  - Step2: initialization of k factor.
  - Step3: class prediction.
  - Step4: distance calculation between test and training data.
  - Step5: ascending order sorting of calculated distance values.
  - Step6: find highest k rows.
  - Step6: find recurrent class of k rows.
  - Step7: return the predicted class.

**III. EXPERIMENTAL RESULTS**



(a)

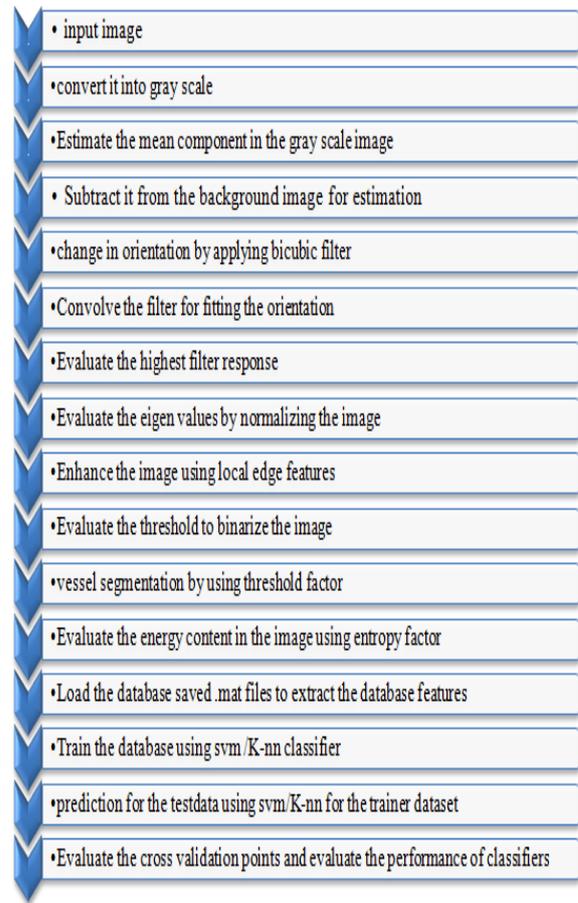
(b)



**Fig.1.(a)input image (b)gray scale image (c)complemented Eigen image (d)complemented wavelet output (e)complemented local output (f)background normalize image (g)vessel segmentation result (h)svm and k-nn classification result.**

In our system we select one image from CHASEDB1 database our system converts that image into grayscale image then after for image enhancement our system apply Eigen vector .after that system can take mean to remove noise from a image by subtracting background of enhanced image using filters in the last system apply wavelet transformation using canny edge transformation to get normalization of image finally our system obtain segmentation using FC-CRF and using SVM and K-NN features we get results if any injury or daises occurs we get bulged pattern of nerves.

To better understand our experimental results we have to go through operational flow diagram of our system which is shown in figure 2.



**Fig.2.Operational flow diagram**

• Validation of results

We compare our segmentation results quantitatively with respect to accuracy, specificity and sensitivity in terms of TP, TN, FP and FN.

$$S_e = \frac{TP}{TP+FN} , S_p = \frac{TN}{TN+FP} , P_r = \frac{TP}{TP+FP}$$

$$Acc = (TP+TN) / (TP+FN+FP+TN)$$

$S_e$ : defines sensitivity  $S_p$ : defines specificity

$P_r$ : defines precision respectively Acc: defines accuracy. We can also use several other performance measurements like G-mean, F1-score and MCC (Mathew’s correlation coefficient).

$$F1 = \frac{2 \cdot P_r \cdot R_e}{P_r + R_e}$$

$$G = \sqrt{S_e \cdot S_p}$$

$$MCC = \frac{TP/N - S \cdot P}{\sqrt{P \cdot S \cdot (1 - S) \cdot (1 - P)}}$$

Table: I performance analysis for SVM

Images	S <sub>e</sub>	S <sub>p</sub>	Acc	Result
1-Test	.9333	.909	.856	Unhealthy
02-Test	.9333	.918	.872	Unhealthy
03-Test	.9333	.909	.84	Unhealthy
04-Test	.9333	.909	.856	Unhealthy
05-Test	.9333	.909	.856	Unhealthy
06-Test	.9333	.90	.848	Unhealthy
07-Test	.9333	.909	.84	Unhealthy
08-Test	.9333	.90	.848	Unhealthy
09-Test	.9333	.881	.832	Unhealthy
10-Test	.9333	.918	.864	Unhealthy
11-Test	.9333	.909	.864	Unhealthy
12-Test	.9333	.909	.856	Unhealthy
Image01-L	.9333	.890	.84	Healthy

Table: II performance analysis for k-NN

Images	S <sub>e</sub>	S <sub>p</sub>	Acc	Result
1-Test	.466	.781	.80	Unhealthy
02-Test	.533	.981	.80	Unhealthy
03-Test	.533	.772	.792	Unhealthy
04-Test	.466	.781	.80	Unhealthy
05-Test	.466	.781	.80	Unhealthy
06-Test	.466	.781	.80	Unhealthy
07-Test	.333	.781	.80	Unhealthy
08-Test	.466	.781	.80	Unhealthy
09-Test	.466	.781	.80	Unhealthy
10-Test	.466	.781	.80	Unhealthy
11-Test	.533	.781	.80	Unhealthy
12-Test	.466	.781	.80	Unhealthy
Image01-L	.466	.781	.80	Unhealthy

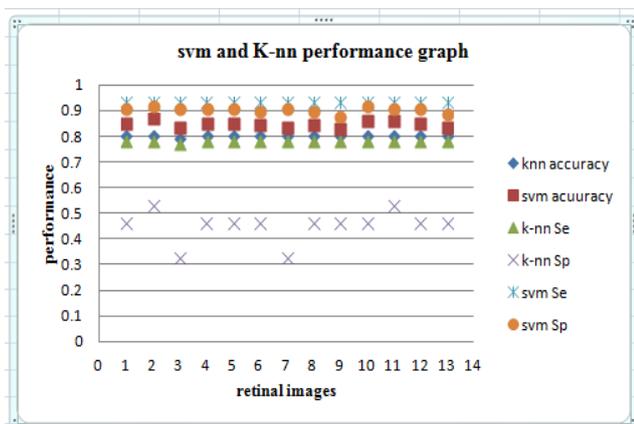


Fig.3.performance graph of classifiers

IV. CONCLUSION

This study proposes a blood vessel segmentation system to detect different eye diseases our system performs segmentation and classification for segmentation we use FC-CRF model the advantage of FC-CRF is we get retinal vasculature accurately then unary potential .we use two classifiers K-NN and SVM for best results. The benefit of our system is it works under dense potential it also benefit other biomedical and biological applications.

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