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Eye Diseases Detection and Classification in Fundus Image Database with Optimization Model in Machine Learning Architecture

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Abstract: In recent years, diabetes rates are increasing drastically due to elevated blood sugar in the human body. With the increase in diabetes rate, it impacts the eye it requires regular examination to prevent blindness. Eye diseases affects the person with a higher glucose rate in the blood. However, after certain duration blood sugar remains in the retina and affects the retina lead to damage in the eye. The presence of blood glucose in the vessels of the eye damages the eye vessels and causes leakage of fluid. Eye diseases' impact on working-age adults causes the loss of eyesight. Even though treatment can help but early intervention prevents loss of vision due to eye diseases such as Diabetic Retinopathy (DR), maculopathy, Glaucoma, Exudates, and Hemorrhage. This paper proposed an Entropy segmentation Survival Analysis Optimization (EsSO) for the classification of Diabetic Retinopathy (DR), maculopathy, Glaucoma, Exudates, and Hemorrhage. The proposed architecture performs segmentation based on the estimation of entropy. The feature extraction and classification are performed with the optimization of the GLCM features in the images. To perform image optimization GLCM features with the black widow are implemented. Through computed feature classification is performed with the conventional neural network model for classification. The classification is performed for estimation of different diseases in the eye Diabetic Retinopathy (DR), maculopathy, Glaucoma, Exudates and Hemorrhage. The proposed EsSO model concentrated highly on the intervention of eye diseases for diagnosis and treatment. The performance of the developed model is comparatively examined with the conventional technique. The proposed EsSO model provides an accuracy of 96% whereas the conventional classifiers SVM and RF provides the accuracy of 91% and 94% respectively. The evaluation expressed that the proposed EsSO model exhibits ~4% improvement than the conventional classifiers.

Keywords: *Eye diseases, Feature Extraction, Classification, Diabetic Retinopathy (DR), maculopathy, Glaucoma, Exudates and Hemorrhage, Optimization.*

1. Introduction

In the current scenario, about 250 million of people are affected by diabetes [1]. If humans are affected highly affected with diabetes, due to increases in the blood glucose level which leads to damage in the retina. This leads to blindness or loss of vision [2]. Eye diseases, glaucoma, age-related macular degeneration, and cataract are the major causes of blindness and visual impairment that affects human beings. Eye disease is commonly known as diabetic eye disease which leads to blindness [3]. This causes damage to the blood vessels in the retina and can be a source of losing vision. Nearly 4.1 million people have the same form of Eye disease, one in four of these people suffer from loss of vision [4].The National Eye Institute reports that Eye diseaseis a major cause of vision loss in people those are suffering from diabetes for vision impairment blindness among adults aged between 20 and 74. The increase in blood pressure damages the blood flow towards the retina and causes retinopathy [5]. The development of retinopathy causes bleeding in the eye, blurred vision or double vision, and complete loss of vision. This is the condition in which blood flow is completely blocked and damages the eye optic nerve.

Eye diseases impact themicrovasculature of the eye retina. The development of the microvasculature is due to diabetes mellitus. In case, if DR is not properly diagnosed and treated it leads to complete loss of vision [6]. In the initial case, need to evaluate the eye through regular checkups through manual fundus images. The capturing of the morphological changes in the DR occurred and was estimated with the aneurysms, internal bleeding, inflammations, macula errors, and defects in the blood vessels [7]. However, the checkup process consumes more complex. To withstand the limitation computer-aided system need to be developed to check variations in the fundus images of the eyes. Glaucoma is the term used to refer a group of eye disorders, which leads to the loss of vision. The primary cause of glaucoma is increased intraocular pressure in the anterior chamber of the eye. The fluid pressure in the anterior chamber is known as intraocular pressure (IOP).As presented in figure 1 different classification stages of the DR are presented.

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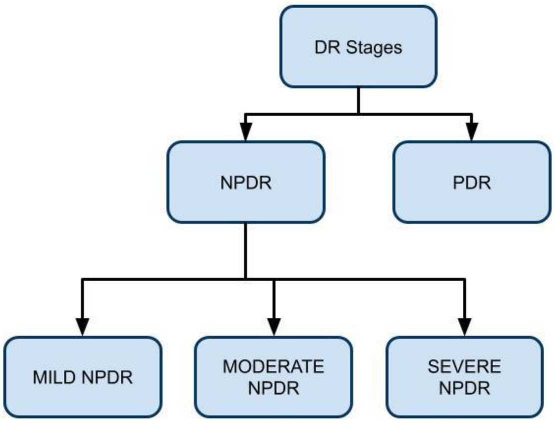


Figure 1: classification of DR

Eye diseases has two main stages as shown in Figure 1. They are i) NPDR (Non- Proliferative Eye diseases) ii) PDR (Proliferative Eye diseases) When the vessels of blood in the retina of eye get injured and it leaks the fluid from it, then the NPDR occurs [8].Other symptoms of NPDR include hard exudates, hemorrhages, cotton wool spots, drusens, etc. The NPDR is again classified into mild NPDR, moderate NPDR, and severe NPDR.To evaluate and perform classification Medical imaging is a type of diagnostic testing, used to generate images of organs and tissues inside the body for utilization in diagnosis and treatment [9]. Different types of medical imaging techniques are used for visualizing various parts within the human body. Analysis of medical images helps in the determination of a possible disease or disorder. Biomedical image processing is an interdisciplinary field of research drawing the attention of experts from mathematics, engineering, statistics, physics, biology and medicine [10]. Computer-aided processing for disease diagnosis has become an important part of the clinical routine. With the advancement of modern technologies and the exploitation of various imaging modalities, more challenges occur on how to process and examine large datasets of images that result in producing qualitative information for the diagnosis and treatment of diseases.

1.1 Contribution of the Research

This research aimed to develop an effective scheme for the classification of DR in the fundus images. The presented technique is termed EsSO for the segmentation, extraction, and classification. The specific contribution of this research is presented as follows:

1. Initially, pre-processing is performed with the normalization of the image pixels.
2. This paper incorporated an entropy model for estimation of the pixel value in the image for segmentation of the optic disk.
3. Feature extraction is performed with the computation of the GLCM features for the classification. The feature extraction is performed with the survival analysis those applied with the autoencoder model for evaluation.
4. The estimated image features are optimized with a black widow-based optimization model for effective classification.
5. Finally, the classification is performed for the estimation of different eye diseases.

This paper is organized as follows: the review related to fundus image processing is presented in section 2. The proposed EsSO model for segmentation, feature extraction, and classification are presented in section 3. The results obtained from the simulation environment and comparative analysis are presented in section 4. Finally, the overall conclusion for the proposed EsSO model for the developed model overall conclusion is presented in section 5.

2. Related Works

In existing literature vast range of classification techniques are evolved for the DA those are presented as follows: In [11] presented a technique for Eye diseases detection. The detection of the DR is based on the computer-aided design for processing and diagnosis.Eye diseases is long-term diabetes that ismost common and if untreated, itsimpactbecomes severe. It affects the retina and causes blindness. In DR, the microaneurysms are first detected, and localization of the retinal and fundus images is carried out. The image is processed with the dynamic thresholding and filtering with a correlation of multi-scale images. Two public datasets like retinopathy online challenge and standard Eye diseases are used. In [12] presented an automaticdetection mechanism for microaneurysms in medical image processing systems. Preprocessing and candidate extractors are considered to be the internal components of an ensemble-based framework. This framework is used to enhance the input image. The edge detection method is used to find the correct location of the optic disc which is affected by blood vessels. With the aid of edge detection techniques, various stages of Eye diseases can be analyzed.

In [13] proposed a neural network and fuzzy clustering for image segmentation. They proved that automatic detection of retinal images can be used to diagnose and screen Eye diseases easily. However, the developed model exhibits the limitation associated with the noisy regions as it becomes too bright it leading to incorrect image segmentation. In [14]constructed an automated Eye diseases scheme for screening with Kirch's edge detection model. The developed model involved in the extraction of the image blood vessels from the retina with the Kirsch template method. Upon the effective pre-processing of the retinal images for the blood vessels, extraction and classification is performed.

In [15]developed a hemorrhages fundus image processing through k-means color compression method scheme for minimization of the color dimension in the images. The evaluation is based on the consideration of the different image regions in the fundus images. Through the implementation of the fuzzy interface system Eye diseases are involved in the recognition of the features for the classification. The classification performance expressed that the proposed model exhibits an accuracy of 96.67%.

In [16] developed a hybrid classifier model for automated classification of Eye diseases. The developed model comprises the pre-processing of the fundus image for the extraction of the abnormal signs, exudates area, blood vessels, point, texture, and entropies in the image. The developed model uses the Hybrid Kernel Support Vector machine integrated with the global optimization techniques. The optimization technique used for the classification is the genetic algorithm (GA)and the particle swarm optimization (PSO). Similarly, [17] developed a model for earlier detection of Eye diseases. The evaluation is based on consideration of the color, gray level, and statistical features for the classification of the images. To improve the accuracy of the classification novel technique is implemented for processing.

In [18] developed an SVM classification model for retinal image processing. The developed model uses the image pre-processing with the median filter with the adaptive histogram equalization method. Upon the completion of the preprocessing images are segmented for classification. The segmentation process uses k-means clustering and classification is performed in the SVM classifier. In [19] developed an automated Eye diseases classification in the fundus images. The processed image comprises the sequential of steps such as pre-processing, feature extraction, and classification. The developed model is comparatively examined with the existing technique such as KNN, Gaussian Mixture (GMM) and SVM. The developed model KNN and GNN exhibits minimal computational complexity

In [20] present novel technique to classify the exudates. K-means clustering is used to detect the optic disc and kirsch's template edge detection algorithm is used for blood vessels segmentation. The intensity computation and features extraction are carried out. Here SVM classifier is used to classify the true or false exudates for high gray level variation in exudates. The detection and classification of exudates with an accuracy of 94.17% is obtained with the proposed method. In [21] proposed a technique to detect the presence of abnormalities in the retina by applying morphological processing to the fundus images so as to extract features, like blood vessels. With a large number of fundus images quickly processed, the cost gets drastically reduced resulting in an increase in productivity and efficiency. This does not require any user intervention and it can perform well in both normal and abnormal images. However, it becomes a failure if there are a large number of retinal images. In [22]proposed an auto-correlogram model for feature extraction in the fundus images is based on consideration of low dimensionality features. The analysis is based on the consideration of the multi-class, multiple-instance learning framework model for classification in the feature vector. The comparative analysis model framework exhibits the superior performance in the processing of the images and effective classification model.

3. Proposed Architecture

This research involved in classification of the different eye diseases in the fundus images. The proposed EsSO model is involved in the segmentation, feature extraction, and classification of the DA in the fundus images. In figure 2 the overall process involved in the developed model EsSO is presented for classification. Initially, fundus images of the retina are applied as the input those are pre-processed with the elimination of noise with an appropriate transformation scheme in fundus images. In the pre-processed image segmentation is performed with the entropy-based model for the identification of the optic disk. Upon the segmented model feature extraction is performed for the computation of GLCM features. The feature in the fundus images isapplied processed with the optimization model. Upon the extraction of the feature, vector classification is performed to differentiate various eye diseases such as Diabetic Retinopathy (DR), maculopathy, Glaucoma, Exudates and Hemorrhagein the retinal fundus images.

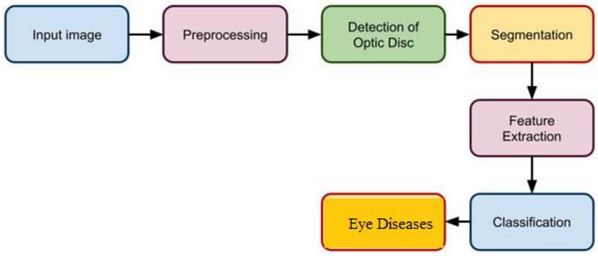


Figure 2: Process in EsSO

The proposed EsSO model perform segmentation of the nerves for the estimation of eye diseases and severity rate in the fundus images for Diabetic Retinopathy (DR), maculopathy, Glaucoma, Exudates and Hemorrhage. The process involved are segmentation, extraction and classification. The developed model architecture for the fundus images are presented on the figure 3.

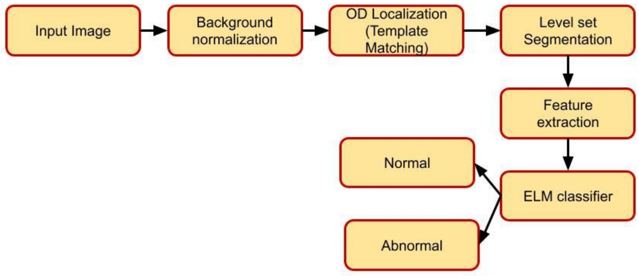


Figure 3: Process in proposed EsSO

The first pre-process stage involved in elimination of the artifacts those are generated with the acquisition of the fundus camera. The retinal images illumination part subjected to non-uniform optical aberration due to improper focus of light in the optical system. The localization of the optic disc illumination non-uniform values are evaluated for the accuracy of the estimation. In the non-uniform illumination smoothes in the background need to be normalized. Additionally, it improves the overall segmentation performance characteristics in the segmentation both foreground and background. The figure 4 (a) presents the input fundus image for pre-processing and figure 4 (b) provides the normalized output region of the fundus images.

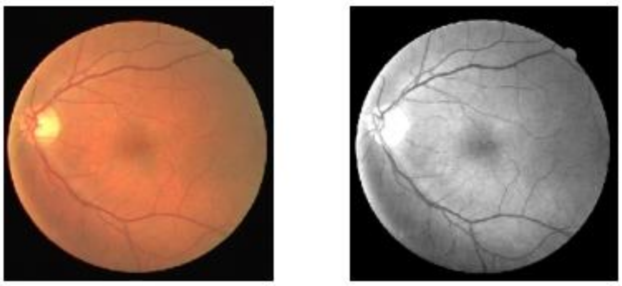


Figure 4: a) Input Image b) Normalized Image

3.2 Entropy based optic disk in the fundus image segmentation

Image segmentation plays an essential role in the analysis of retinal images as the extraction of the optic disc provides a vital signs for precise diagnosis of various eye-related diseases. Segmentation of the optic disc is the initial step for many computer-based methods used to assist the ophthalmologist in detecting Diabetic Retinopathy (DR), maculopathy, Glaucoma, Exudates and Hemorrhage. Consider an image volume size of X × Y × Z for a fundus image, where image height or row is denoted as X, image width or column is represented as Y, and pixels in the image are denoted as Z. Let's define fundus image tissues as C, which need to be segmented. Based on this consideration proposed EDMGL objective function is given in equation (1) as follows:

$$I_{EsSO} = \sum_{i=1}^{c}\sum_{l=1}^{z}\sum_{j=1}^{x}\sum_{k=1}^{y}\left[\alpha\mu_{ijkl}^{m}\left(d_{ijkl}\right)^{2} + (1-\alpha)u_{ijkl}^{m}\left(f_{ijkl}\right)^{-1}\left(\overline{d_{ijkl}}\right)^{2}\right] -\alpha\sum_{i=1}^{c}\sum_{l=1}^{z}\sum_{j=1}^{x}\sum_{k=1}^{y}\left[\mu_{ijkl}^{m}\, ln\left(\mu_{ijkl}^{m}\right)\right] - (1-\alpha)\sum_{i=1}^{c}\sum_{l=1}^{z}\sum_{j=1}^{x=}\sum_{k=1}^{y}\left[u_{ijkl}^{m}\, ln\left(u_{ijkl}^{m}\right)\right] \quad (1)$$

The proposed algorithm is based on two constraints which are presented $\sum_{i=1}^{c}\mu_{ijkl} = 1$ and $\sum_{i=1}^{c}u_{ijkl} = 1 \forall i,j,k,l$. Based on the above equation the parameters μ_{ijkl} are stated as global membership values and u_{ijkl} represented as local membership value of images. The membership estimation is based on the consideration of eye parameters $a_{i,j,k,l}$ for the image i^th cluster. The parameters m within the fuzzy cluster can be selected optimally which is defined as m>1.0. Through existing literature comparative analysis it is observed that the optimal value of m is utilized for regularization those values are between α (0.0 < α ≤ 1.0). The eye Euclidean distance for images is represented as $d_{i,j,k,l}$ with estimation of eye distances as $a_{i,j,k,l}$. The image i^th cluster center is represented as $t_i, \overline{d_{i,j,k,l}}$ which defines the Euclidean distance mean lies in neighbouring pixels of eye fundus images stated as $a_{i,j,k,l}$ with consideration of image i^th cluster $t_i, f_{i,j,k,l}$ for estimation of likelihood i^th cluster of image eye $a_{i,j,k,l}$ as estimation of local entropy. The image eye volumes $d_{i,j,k,l}$, $d_{i,j,k,l}$ and $f_{i,j,k,l}$ are presented as follows from equation (2) - (4):

$$\left(d_{i,j,k,l}\right)^{2} = \left\|a_{jkl} - t_i\right\|^{2} \forall i,j,k,l \quad (2)$$

$$\left(\bar{d}_{ijkl}\right)^{2} = \frac{1}{N}\sum_{x_{jkl}\in N_{jkl}}\left\|x_{jkl} - t_i\right\|^{2} \forall i,j,k,l \quad (3)$$

$$f_{ijkl} = \frac{\sum_{x_{jkl\in N_{jkl}}}\left(\mu_{ijkl}x_{ijkl}\right)}{\sum_{x_{jkl\in N_{jkl}}}x_{jkl}} \forall i,j,k,l \quad (4)$$

In the above equations, N and N_{jkl} denote total neighboring eye volume and constrained neighborhood estimated for the center of eye a_{jkl}. The corresponding neighboring eye is denoted as x_{jkl}. To minimize the time consumption products related to global and local membership need to be eliminated for this weighted fuzzifier and Euclidean distance of images are evaluated. The approximation in the segmentation of the optic disk in fundus images are based on consideration of the Lagrange multiplier and the final equation is obtained through iterative parameters into consideration such as μ_{ijkl} ,u_{ijkl} and t_i those can be performed with partial derivations based on μ_{ijkl} , u_{ijkl} and t_i, respectively those need to be equal to value of zero. The process of the iteration of the variables is presented in the equation (5) – equation (9)

$$\mu_{ijkl} = \frac{1}{\sum_{s=1}^{c}\left(\frac{\alpha\left[\left(d_{ijkl}\right)^{2} - ln\left(\mu_{ijkl}^{m}\right) - 1\right]}{\alpha\left[\left(d_{rjkl}\right)^{2} - ln\left(\mu_{rjkl}^{m}\right) - 1\right]}\right)^{\frac{1}{m-1}}} \forall i,j,k,l \quad (5)$$

$$u_{ijkl} = \frac{1}{\sum_{s=1}^{c}\left(\frac{(1-\alpha)\left[\left(f_{ijkl}\right)\left(\bar{d}_{ijkl}\right)^{2} - ln\left(u_{ijkl}^{m}\right) - 1\right]}{(1-\alpha)\left[\left(f_{ijkl}\right)\left(\bar{d}_{rjkl}\right)^{2} - ln\left(u_{rjkl}^{m}\right) - 1\right]}\right)^{\frac{1}{m-1}}} \forall i,j,k,l \quad (6)$$

$$t_i = \frac{\sum_{l=1}^{z}\sum_{j=1}^{x}\sum_{k=1}^{y}\left\{\alpha\mu_{ijkl}^{m}a_{jkl} + (1-\alpha)u_{ijkl}^{m}\left(f_{ijkl}\right)^{-1}\bar{a}_{jkl}\right\}}{\sum_{l=1}^{z}\sum_{j=1}^{x}\sum_{k=1}^{y}\left\{\alpha\mu_{ijkl}^{m} + (1-\alpha)u_{ijkl}^{m}\left(f_{ijkl}\right)^{-1}\right\}}\Bigg|\bar{a}_{jkl} \quad (7)$$

$$= \frac{1}{N}\sum_{x_{jkl}\in N_{jkl}}X_{jkl} \forall i \quad (8)$$

After the estimation of global and local membership estimation. The membership function for fuzzy is estimated the g_{ijkl} using consideration of weighted equation (9):

$$g_{ijkl} = \frac{\left(\mu_{ijkl}\right)^{p}\left(u_{ijkl}\right)^{q}}{\sum_{r=1}^{C}\left(\mu_{rjkl}\right)^{p}\left(u_{rjkl}\right)^{q}} \forall i,j,k,l \quad (9)$$

In the above equation (9), the weighted parameters are defined as (1 ≤ p, q ≤ 3) which impacts local and global membership values. The process of the segmentation model involved in estimation of the optical disk within the system for segmentation of the optic disk in the fundus images.

3.2 Survival Analysis for estimation of the image features

After the segmentation of the optic disk feature extraction is performed in the fundus images. The feature extraction stage survival analysis framework model in the auto-encoder based structure. Theautoencoder perform the survival analysis model based on the consideration of three layers for process the extracted GLCM features in the images. Here, X, H and X' denote the input, hidden and output layer respectively, and $X, X' \in R^{d}$. The encoder comprises of both $X \; and \; H$, and the decoder comprises of both X', H .

The encoder function is denoted as $\emptyset$, and it is represented in equation (10).

$$\emptyset: X \to H \quad (10)$$

The decoder function is denoted as φ, and it is represented in equation (11).

$$\varphi: H \to X \quad (11)$$

The encoder function is represented in equation (12). Here, W denoted the weight vector, σ denotes the activation function, and b denotes the bias vector.

$$H = \sigma(WX + b) \quad (12)$$

The decoder function is represented in equation (13). Here, W'denotes the weight vector, σ' denotes the activation function, and b'denotes the bias vector.

$$X' = \sigma'(W'H + b') \quad (13)$$

The loss function for auto encoders is denoted as $L(X, X')$, and it is represented in equation (14). The loss function represents the reconstruction error. The training of auto-encoders involves minimizing this loss function.

$$L(X, X') = ||X - X'||2 = ||X - \sigma'(W'(\sigma(WX+b)) + b')||2 \quad (14)$$

3.2.1 GLCM feature extraction model in EsSO with Survival Analysis Framework

The survival analysis model (SAF) concentrated on the extraction of features in the fundus images. In the proposed EsSO with SAF is to model the occurrence of an Event of Interest (EoI). The Survival Time is denoted as T , which represents the waiting time until EoI occurs. The density function of the random variable T is denoted as$f(t)$, and it is represented in equation (15).

$$f(t) = \lim_{dt\to 0}\left(\frac{p(t \le T \le t \le dt)}{dt}\right) \quad (15)$$

The Cumulative Distribution Function (CDF) of T is denoted as $F(t)$ and it is represented in equation (16).

$$F(t) = P(T < t) = \int_{x=0}^{x=t} f(x)dx \quad (16)$$

The survival function or survival probability is denoted as $S(t)$, and it is represented in equation 17. The survival function denotes the probability that EoI has not occurred by time t.

$$S(t) = P(T \ge t) = \int_{x=0}^{x=\infty} f(x)dx \quad (17)$$

The hazard function is denoted as $\gamma(t)$, and it represented in equation 18. The hazard function denotes the instantaneous probability of EoI, given that, the EoI has not occurred before t.

$$\gamma(t) = \lim_{dt\to 0}\left(\frac{p(t \le T \le t \le dt | T \ge t)}{dt}\right) = \frac{f(t)}{s(t)} \quad (18)$$

The $S(t)$ and $\gamma(t)$ are also related as represented in equation 19.

$$S(t) = e^{\left(-\int_{x=0}^{x=t} \gamma(x)dx\right)} \quad (19)$$

For discrete setting, $S(t)$ is represented in equation 20. Similarly, $\gamma(t)$ is represented in equation 20.

$$\gamma(t) = \gamma_t = \frac{f_t}{s_t} \quad (20)$$

The extracted GLCM features with auto-encoder based survival analysis framework optimizes the features for the classification. In figure 5 presented the overall process in the feature extraction.

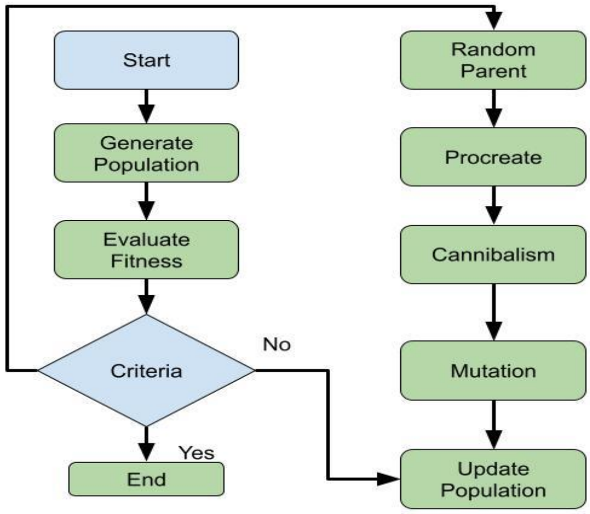


Figure 5: Overall Process in feature extraction

4. Results and Discussion

The performance of the proposed EsSO is evaluated in terms of the classification performance. As the proposed model comprises of the segmentation, feature extraction and classification performance characteristics. The evaluation is based on the analysis of the processed or extracted features in the fundus images.

4.1 DataSet for Analysis

The proposed EsSO model uses the fundus image in the jpeg format. The medical image format comprises of the colors such as Red, green and blue between the level of 256. The dataset images count of 400 that has been utilized for classification of the fundus images for DR. The data for analysis is collected from the different datasets such as STARE (STARE, 2008) which provides the fundus images of 20 with pathological structure. The DRIVE (DRIVE, 2008) database is acquired for computation of the ground truth value with the fundus images count of 40 colour. Also, the another dataset DIARETDB0 comprises of the 260 images and DIARETDB1 provides the 80 fundus images. The dataset related to maculopathy, Glaucoma, Exudates and Hemorrhage are collected from websites such as https://www.kaggle.com/datasets/andrewmvd/ocular-disease-recognition-odir5k,https://www.kaggle.com/datasets/andrewmvd/retinal-disease-classification, https://www.kaggle.com/datasets/sshikamaru/glaucoma-detection, The dataset comprises of the training images size of 6970 images and validation comprises of the 6326 images. The overall summary of the dataset collected for the analysis are presented in the table 1.

Table 1: Dataset Description

Dataset	Count
STARE	20
DRIVE	40
DIARETDB0	260
DIARETDB1	80
https://www.kaggle.com/datasets/andrewmvd/ocular-disease-recognition-odir5k	6970
https://www.kaggle.com/datasets/sshikamaru/glaucoma-detection	675
Total	**8,045**

4.2 Result Analysis

The proposed EsOSis highly concentrated on the processing and classification of the DR in the fundus images. The earlier diagnosis of the DR prevents the blindness in the patients. In figure 6(a) sample images for mild DR is presented b) moderate DR and c) Severe DR in the fundus image database.

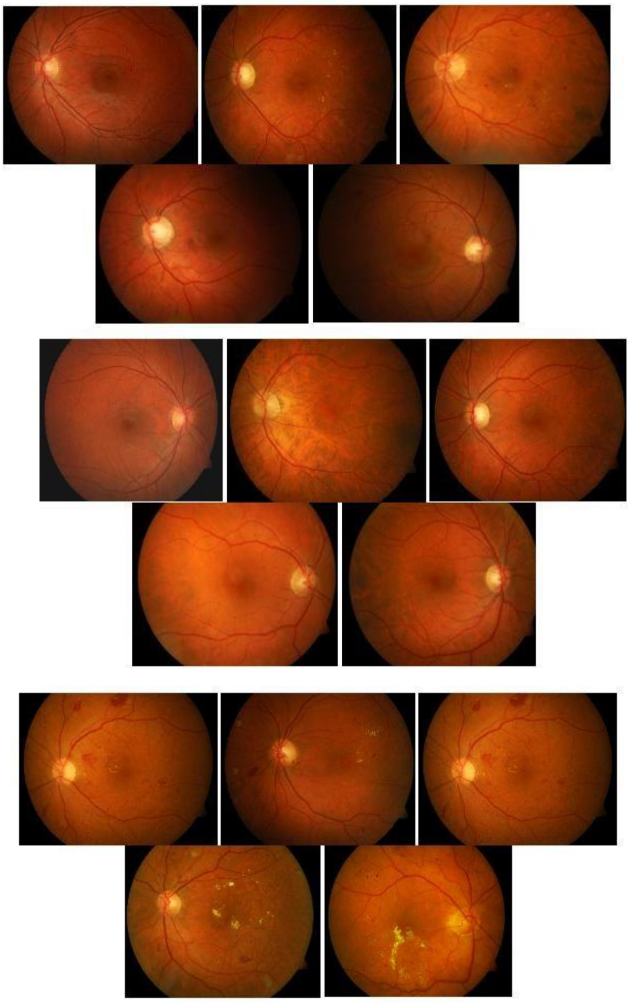


Figure 6: Sample images for a) DR b) Exudates c) Hemorrhage

In the above figure 4 illustrated them aculopathy, Glaucoma, Exudates, and Hemorrhage samples of Eye diseases images which are taken from the publically available DIARETDB 0 and DIARETDB 1 databases. These retina images are considered for the classification purpose on finding the stage of the disease. 30 samples of each category are taken but here 5 samples of each category outputs are shown in this chapter. These images are processed in the Python simulation software. The proposed EsSO comprises of the segmentation and feature extraction process. The feature extraction process involved in computation of the GLCM features in the fundus image. In the extracted features survival analysis is performed of the classification of the DR in the images. In the table 2 presented the extracted GLCM features for the fundus images.

Table 2: Test sample GLCM Features

Image No	GLCMFeature			
	Contrast	**Correlation**	**Energy**	**Homogeneity**
1	0.008556	0.97934	0.6123	0.995717
2	0.004687	0.978634	0.8163	0.997207
3	0.005238	0.985797	0.7487	0.997331
4	0.005214	0.976312	0.7746	0.997393
5	0.006642	0.973369	0.7439	0.996679
6	0.005742	0.983522	0.6463	0.997129
7	0.008752	0.956693	0.7892	0.995624
8	0.004593	0.969224	0.8461	0.997703
9	0.009621	0.976871	0.5744	0.995189
10	0.00748	0.982728	0.5598	0.99626

The above Table2 shows the GLCM features obtained from the Eye diseases images of test sample. In the GLCM, there are 24 features available. Here suitable features like contrast, correlation, energy and homogeneity are extracted for the apparent classification and identification of disease in the eye. To improve the performance characteristics of the fundus images classification for DR the features those stated as first order statistics are estimated and presented in table 3.

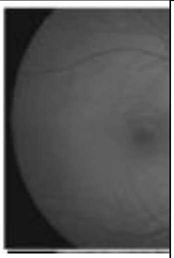
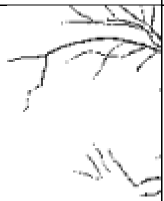
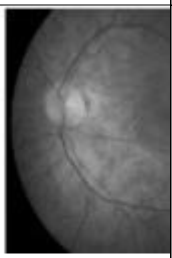
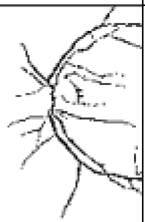
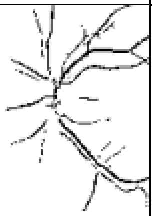
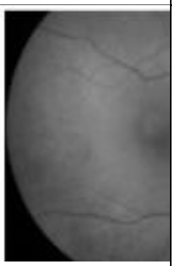
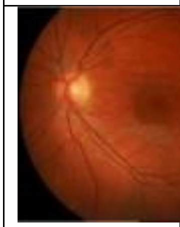
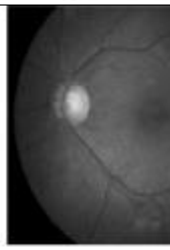
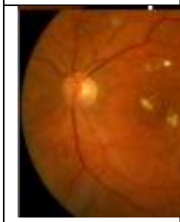
Table3: Sample Image FOS

ImageNo	FirstOrderStatistics(FOS)Feature				
	Mean	**Standard Deviation**	**Skewness**	**Kurtosis**	**Entropy**
1	0.016	0.023343	1.321097	3.09597	2.91838
2	0.011	0.014494	2.312048	8.31284	2.94016
3	0.018	0.024522	1.366714	3.99288	3.10470
4	0.007	0.011143	3.406844	18.0536	2.45109
5	0.008	0.015436	1.860908	5.39652	2.11470
6	0.011	0.012914	1.366733	4.45557	3.01829
7	0.014	0.017058	2.396754	10.4019	3.03849
8	0.02	0.023568	0.931389	2.72939	3.05869

9	0.016	0.023250	2.3052	9.94496	2.87536
10	0.017	0.032156	2.177116	7.20947	2.39905

The table 3 shows the FOS features obtained from the Eye diseases images of test sample. In the FOS, 5 features are available. They are Mean, Standard Deviation, Skewness, Kurtosis and Entropy features. From the extracted features, the apparent classification and identification of DR in the images are performed with proposed EsSO. The images performed for pre-procesing, segmentation and extraction are presented as follows in table 4:

Table 4: Processed image in the proposed EsSO

Input Image	**Pre-Processed Image**	**Segmented Image**	**Classification**
			Maclopathy
			Exudates
			Excudates
			Normal
			DR
			Hemorrhage
			Exudates

Comparative Analysis

The proposed EsSO model is evaluated for the classification of the fundus images under DR, maculopathy, Glaucoma, Exudates, and Hemorrhage. The performances are analyzed based on the sensitivity, specificity and accuracy. The SVM algorithms are used to train and test the 99 retinal images individually. The training dataset for a single classifier includes images from all the classes; in all classifiers the same dataset is used. In three classifiers, preprocessing method and procedure of feature extraction is implemented and then performance measures of each classifier are analyzed separately. The statistical measures of each classifier such as accuracy, sensitivity and specificity are analyzed. In table 5 the performance measures of the SVM classifier are presented. In figure 7 presented the performance metrices estimated for the SVM classifier.

Table 5: Confusion Matrix of EsSO

Classpredicted	Groundtruthclass				
	DR	Maculopathy	Glaucoma	Exudates	Hemorrhage
DR	330	2	1	135	97
Maculopathy	2	1230	1	73	103
Glaucoma	19	2	2670	41	43
Exudates	234	19	103	1985	87
Hemorrhage	118	78	86	67	983
Individualclassaccuracy	99.29%	97.87%	97.97%	98.47 %	97.89%
Overallclassificationaccuracy			98.298%		

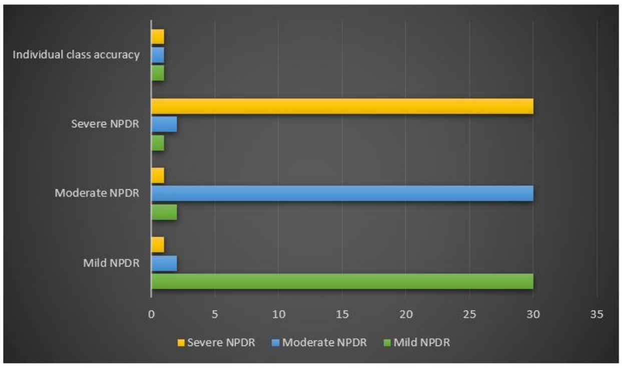


Figure 7: Performance of the EsSO

Table 5 shows the confusion matrix of Random Forest (RF). With different classifier estimated parameters are presented. The estimated parameters for the confusion matrix offers positive and negative rate for the classification of the retinal images at different categories. Similarly, in table 6 RF model for the estimation is presented. Similarly, in figure 8 characteristics measurement of the RF is presented.

Table 6: Performance measure of RF

Classpredicted	Sensitivity(%)	Specificity(%)	Accuracy(%)
DR	92.30	97.23	93.09
Maculopathy	88.57	97.16	95.03
Glaucoma	94.59	96.63	92.09
Exudates	88.67	79.33	90.34
Hemorrhage	86.92	90.46	89.71
Overall classification accuracy			91.13%

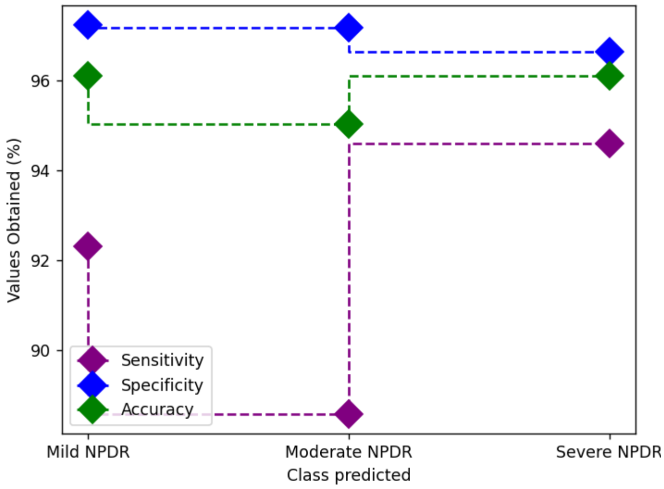


Figure 8: Performance of the RF

Table 7: Performance measure of SVM

Classpredicted	Sensitivity(%)	Specificity(%)	Accuracy (%)
DR	93.84	98.61	93.51
Maculopathy	92.85	97.64	96.45
Glaucoma	97.29	97.59	95.51
Exudates	95.93	95.84	92.69
Hemorrhage	94.89	96.86	95.83
Overallclassificationaccuracy			94.32%

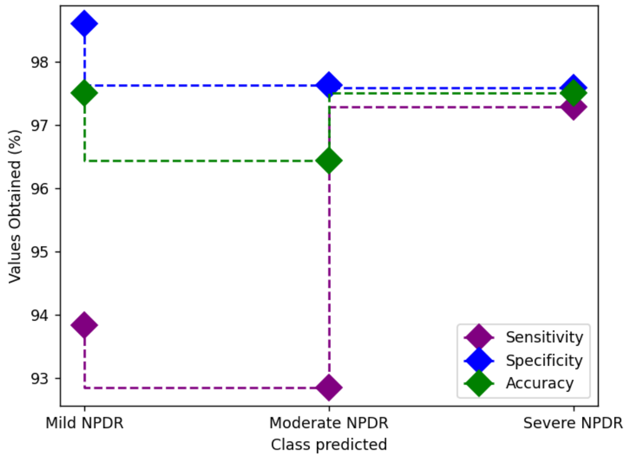


Figure 9: Performance of the SVM

Table 5 shows the classification accuracy of EsSOas96.09% of Mild DR, 95.03% of moderate DR and 96.09% of severe DR. The overall classification accuracy is calculated and the value obtained is 91.13% in RF. In figure 9 performance of the conventional SVM is presented. Table 6 shows the performance measure of SVM as 97.51% of mild DR, 96.45 % of Moderate DR and 97.51 % of severe DR. The overall classification accuracy of SVM is 94.32%.

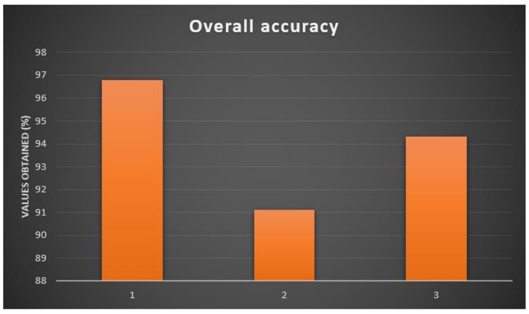


Figure 10: Overall Comparison of the Classifiers

Figure 10 shows the comparative analysis of various classification. In comparative analysis, the classification of Eye diseases stages arecompared with another neural networkmethod of RF and SVM. The proposed classification accuracy of EsSOis 96.80%,SVM is94.32%andRFis91.13%.The comparative analysis expressed that developed classifier exhibits significant performance that the other classifiers. In table 8 presented the overall comparison with the existing literature is presented.

Table 8: Comparison of Results

References	**Class**	**Approach**	**Accuracy**	**Sensitivity**	**Specificity**
[17]	4	Area of blood vessel	84	90	94
[18]	5	High order spectra	82	83	89
[19]	2	Single lesions	-	82	92
Proposed	3	Optic disc	96.66	96	95

The comparative analysis of the results expressed that the proposed EsSO model exhibits improved performance in the classification and detection of the DR in the fundus images.

5. Conclusion

People who have been affected with the diabetes requires prolonged monitoring to prevent the vision loss. Medical image processing comprises of the different methods and detection algorithms in the detection of abnormalities present in the retina. This paper presented the EsSOmodel for the fundus image utilized for the segmentation, feature extraction and classification. The developed model uses the entropy based segmentation, survival analysis based feature extraction and classification. The proposed EsSO model performance is comparatively examined with the existing classifier to detect and diagnosis the DR, macropathy, glaucoma, exudates and Hemorrhage in the fundus images. The proposed EsSO model comparative analysis expressed that the performance of the proposedEsSO is effective compared with the other technique in the classification of the eye diseases in the fundus images.

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