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SURROUND DIVERGENCE SELF ASSESSED LINEAR REGRESSIVE AND HAMMERSLEY-CLIFFORD DEEP CLASSIFICATION FOR EARLY GLAUCOMA RECOGNITION

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ABSTRACT

Glaucoma is an eye disorder that leads to blindness. Most of the research works conducted for early glaucoma detection in the eye fundus images and correspondingly obtain statistical values for early glaucoma detection. However, these statistical based methods rely heavily on optic disc and optic cup ignoring certain fine-tuned (i.e. salient) visual features. In this work, a method called, Self-assessed Linear Regressive segmentation and Hammersley-Clifford Deep Classification (SLR-HCDC)is presented to extract fine-tuned visual features so that glaucoma detection is fastened along with higher rate of sensitivity. First, pre-processing is performed with input retinal fundus images. Second, with pre-processed input retinal images, a Center Surround Divergence Feature extraction model is applied for fine-tuned feature extraction. With the more fine-tuned features extracted, glaucoma detection is said to be fastened. Next, a Self-assessed Linear Regressive segmentation model is applied to the fine-tuned features extracted for performing image segmentation. Here a linear regression is formed between the fine-tuned features to measure self-assessed score for its optic disc segmentation result. Then, the best fit is obtained by applying a self-assessed score with the objective of improving the sensitivity. Finally, Hammersley-Clifford Deep Classification model is applied to the segmented images for early glaucoma detection. Learning of segmented image features are done based on the Gibbs distribution that performs classification between three types of classification at an early stage. To evaluate the performance of the proposed method, three different factors are measured, sensitivity, specificity and accuracy using Digital Retinal Images collected from HRF image database.

KEY WORDS
Glaucoma Detection, Self-assessed, Linear Regressive segmentation, Hammersley-Clifford, Deep Learning

INTRODUCTION

One of the major root causes of blindness all over the world is glaucoma. Glaucoma is an optic neuropathy it correlated with predictable damage to the optic nerve, blindness and patterns of visual impairment which principally includes the loss of retinal ganglion cells (RGCs). The lamina cribrosa is the putative site of retinal ganglion cell axonal injury in glaucoma, where the initial damage appears to be an interruption of normal axoplasmic flow. This is go along with by progressive laminopathy and transsynaptic degeneration. Structural alteration to the RGCs and their axons can be notice clinically as changes in the retinal nerve fiber layer (RNFL) and optic nerve topography can be imaged by computerized devices such as spectral-domain optical coherence tomography (OCT) in the macula, RNFL, optic disc, and lamina, which facilitate diagnosis, monitoring, and treatment. Therefore, there are different types to evolution of computer vision algorithms designed for detecting glaucoma on the basis of the eye fundus images provided as input. But, these algorithms are failed to achieve efficient glaucoma detection in terms of minimum sensitivity and specificity. In order to these existing issues, the proposed Self-assessed Linear Regressive segmentation-based Hammersley-Clifford Deep Classification model is introduced for early glaucoma detection with higher sensitivity and specificity.

A more straightforward and genuine solution for glaucoma detection called, Modified U-Net neural network was presented in [1]. Despite improvement found in segmentation quality, with the optic cup recognition being challenging, the detection of glaucoma was not said to be fastened. Hybrid feature set [2] method provided a novel algorithm for glaucoma detection from digital fundus images. The method included an integration of structural and non-structural features to increase the glaucoma diagnosis accuracy. Though sensitivity and specificity were said to be addressed, early sensitivity with early glaucoma detection was not made.

In [3], glaucoma detection prediction based on statistical analysis was presented. These methods hence provide reliable mechanisms in assisting physicians in disease identification at an early stage. In [4], based on the Regions with Convolutional Neural Network (RCNN), localization and optic disc extraction from a retinal fundus image was made. With the basic consideration of intraocular pressure, a method based on Haralick features [5] were used to differentiate between normal and glaucoma affected retina. Yet another open angle glaucoma was also considered for diagnosis in [6] using a random forest model. In light of the modern achievements of fully convolutional networks (FCNs) tested to biomedical disease diagnosis, the potentiality in the purview of retinal artery-vein was assessed in [7] via deep learning. In [8], with the aid of clinical and technological aid, early glaucoma diagnosis was made using four different artificial intelligence classification methods, namely, multi-layer perceptron, support vector machine, K-nearest neighbor and decision tree. In [9], different Convolutional Neural Networks (CNN) mechanisms were applied to manifest the impact in the implementation of pertinent characteristics like the size of data, use of defined architectures and so on.

A novel deep learning method was introduced in [10] for ophthalmic diagnosing with help of retinal fundus images. However, the improvement of sensitivity and specificity are not sufficient in this method. A weighted path convolution neural network (WP-CNN) was implemented in [11] for diabetic retinopathy (DR)

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identification from eye fundus images. However, the deep learning method does not suitable for large datasets.

Optical coherence tomography evaluation in glaucoma was presented in [12]. Yet another joint method for optic disc and cup segmentation aiding glaucoma detection was presented in [13] using Region-based Convolutional Neural Network (Joint RCNN) towards improving the accuracy of glaucoma detection. Temporally modulated flicker were used in [14] for conducting glaucoma screening test. An automatic diagnosis system based on Pyramid Histogram of Oriented Gradients (PHOG) for glaucoma disease diagnosis was presented in [15]. A review of fundus image classification methods for glaucoma detection was proposed in [16]. However, the cost incurred in disease diagnosis was not concentrated. To address this issue, a cost efficient model based on the revised artificial neural network along with back propagation algorithm was presented in [17]. With higher rate of correlation, disease diagnosis is yet considered to be a tedious process. In [18], a ground truth and evaluation methodology was introduced for automatic detection of diabetic retinopathy.

However, the above mentioned existing methods are having some limitation such as minimum sensitivity, specificity and accuracy during glaucoma detection. Therefore, in this work Self-assessed Linear Regressive segmentation and Hammersley-Clifford Deep Classification (SLR-HCDC) method is designed for early glaucoma detection with higher accuracy.

In this work, instead of directly segmenting the optic disc and optic cup, we propose to extract the fine-tuned features. The extracted fine-tuned features are then segmented for early glaucoma detection based on the feature maps using trustworthiness score. Finally, we propose a Hammersley-Clifford theorem for deep classification using Gibbs distribution with respect to Markov random field for early detection. The main contributions of the proposed SLR-HCDC technique are as follows:

- To improve the specificity rate, Center Surround Divergence Feature extraction algorithm is utilized in the proposed SLR-HCDC technique. A Center Surround Divergence (CSD) operator is used to detect positions that stand out from their surroundings. Feature mapping is based on the center and surround level, statistical evaluation is performed for extracting fine-tuned features from the dataset.

- To increase the sensitivity, the proposed SLR-HCDC technique used the Self-assessed Linear Regressive segmentation model. With help of extracted fine-tuned feature, Self-assessed Linear Regressive image segmentation is performed. Based on the self-assessed trustworthiness score value, best fit is obtained (i.e., sensitivity improved segmented images).

- To enhance the accuracy, the proposed SLR-HCDC technique is introduced. In this technique, Hammersley-Clifford Deep Classification model is used to increase the accuracy of glaucoma disease diagnosis. Based on the Gibbs distribution, the segmented images are identified as normal or glaucoma.

MATERIALS AND METHODS

Self-assessed linear regressive segmentation and hammersley-clifford deep classification

Glaucoma is considered to be one of the most deadly disease whose progression results in permanent blindness. If only detected accurately at an early stage, the progression of glaucoma is said to be stopped. In this work, a Self-assessed Linear Regressive segmentation and Hammersley-Clifford Deep Classification method that enables the physicians in early diagnosis of glaucoma patients with high accuracy and minimum error and complexity is presented. Deep learning classification method is introduced in the proposed technique for accurate disease diagnosis. Deep learning is a category of machine learning algorithms which use deep neural networks to learn different tasks. Machine learning (ML) is a scientific study of algorithms and statistical models that computer systems used to perform a specific task without using explicit instructions, relying on patterns and inference instead. It is seen as a subset of artificial intelligence. [Fig. 1] shows the block diagram of the SLR-HCDC method.

The SLR-HCDC method obtains a raw input retinal fundus image and performs the color conversion. Followed by which Center Surround Divergence Feature extraction model is applied to extract fine-tune features, therefore fastening the glaucoma detection. Next, Self-assessed Linear Regressive segmentation model is applied to the fine-tuned features for obtaining sensitivity improved segmented image with minimum complexity. Finally, deep learning classification using Hammersley-Clifford theorem is performed to predict accurate glaucoma detection. This classification method classifies the images into three types such as glaucoma, non-glaucoma or early detection based on the Gibbs distribution.

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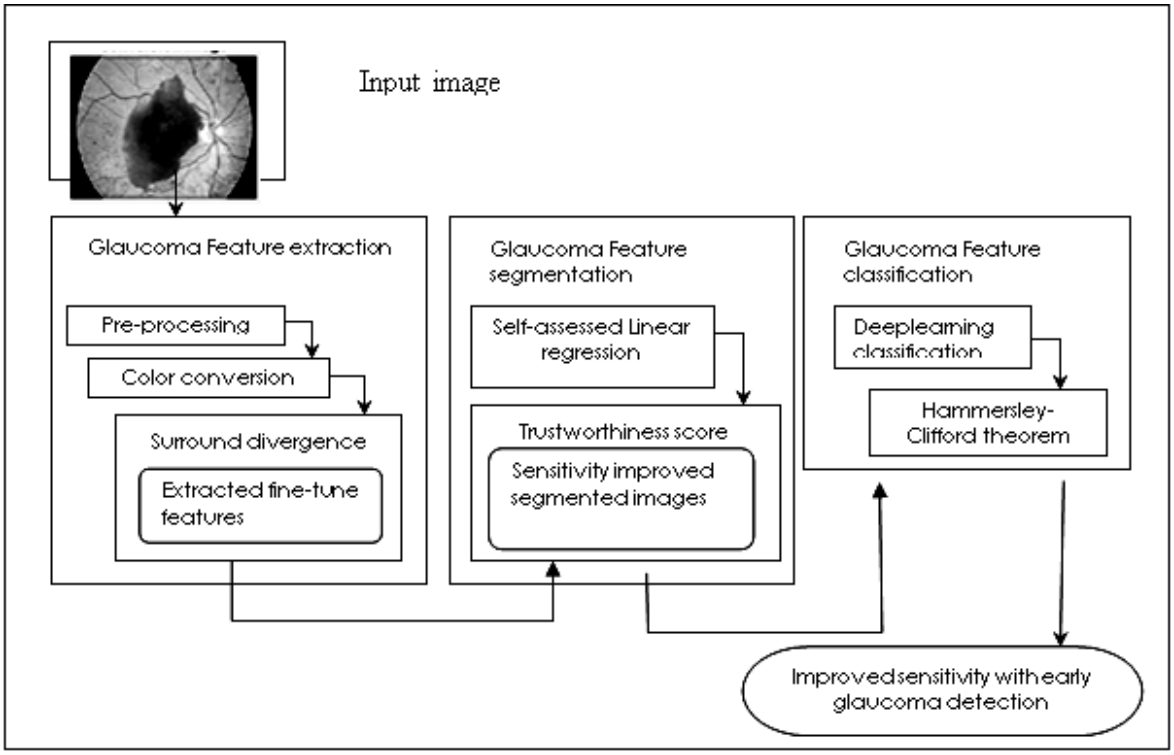

Fig. 1: Block diagram of self-assessed linear regressive segmentation and hammersley-clifford deep classification

Center surround divergence feature extraction model

At first, pre-processing is performed with input retinal fundus images, where color retinal fundus image is converted to corresponding gray image. Next, to the pre-processed retinal fundus image, a Center Surround Divergence Feature extraction model is applied with the objective of extracting fine-tuned features, therefore, fastening the glaucoma being detected.

The input retinal fundus images used for obtaining fine-tuning features were cropped in an automatic manner. To do this pre-processing, the input color retinal fundus image is converted to corresponding gray image. Image pre-processing is done around the optic disc in eye fundus image, it has a clinical reason, that is glaucoma disease affects specifically the optic disc and its surroundings. In this work, to extract fine-tuned features, a Center Surround Divergence (CSD) operator is used to detect positions that stand out from their surroundings.

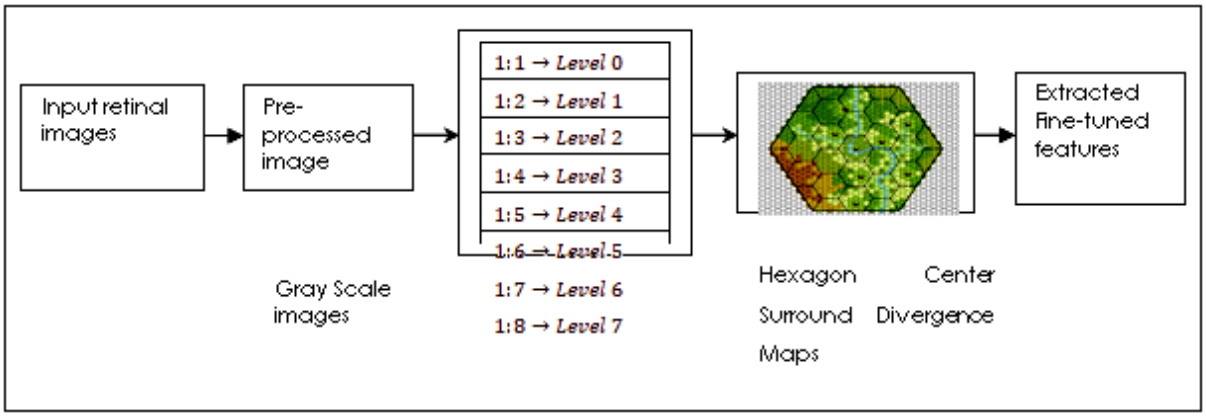

Fig. 2: Center Surround Divergence Feature extraction

The CSD operator is administered as the contrast between finer and coarser scales. [Fig.2] shows the Center Surround Divergence Feature extraction model for extracting fine-tuned features. The Center Surround Divergence Feature extraction involves two steps. The first step involves the intensity identification. The

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second step involves the statistical measurement. The pseudo code representation of Center Surround Divergence Feature extraction is given below.

Input: Retinal Fundus Image '$I = I_1, I_2, \ldots, I_n$'
Output: Fine-tuned feature extraction ''
1: **Initialize** finer 'c' and decimated values 'd' 2: **Begin** 3: **For** each Retinal Fundus Image '$I = I_1, I_2, \ldots, I_n$' 4: With finer and decimated values measure tuned level 5: Obtain feature map from surround level to center level 6: Obtain feature map from center level to surround level 7: Identify intensity based on feature maps 8: Measure Center Surround Divergence 9: Obtain statistical values for feature map within super pixel 10: **Return** (fine-tune feature 'FE') 11: **End for** 12: **End**

Algorithm 1: Center Surround Divergence Feature extraction algorithm

Let us assume that the center of the retinal fundus image is a pixel at range 'c ∈{2,3,4}' (i.e. c representing finer level) with 'd ∈{3,4}' (i.e. d representing the decimated value) then surround (i.e. s representing tuned level) being the analogous pixel at scales is mathematically expressed as given below.

$$s=c+d \quad (1)$$

With the above said fine-tuned decimated value, Hexagon maps are empirically obtained at levels

's=(2+3=5,2+4=6,3+3=6,3+4=7,4+3=7,4+4=8)', therefore, 's=2:5,2:6,3:6,3:7,4:7,4:8'. Let us further assume the feature map in center level 'c→FM(c)' and feature map in surround level 's→FM(s)', then Hexagon Center Interpolation 'HCI' map is mathematically written as given below.

$$HCI(s)\rightarrow \langle\!\langle FM \rangle\!\rangle\_(s\text{-}c)\ [FM(s)] \quad (2)$$
$$HCI(c)\rightarrow \langle\!\langle FM \rangle\!\rangle\_(c\text{-}s)\ [FM(c)] \quad (3)$$
$$HCI(c,s)\rightarrow [HCI(s)\ \cup HCI(c)] \quad (4)$$

From the above equation (2) and (3), '〖FM〗_(s-c)', represent the feature map from surround level 's', to the center level 'c' and '〖FM〗_(c-s)' represent the feature map from center level 'c' to the surround level 's' respectively. Finally, the intensity 'HCI(c,s)' is identified according to the union of hexagon center interpolation with respect to the surround and center level. The second step involves the identification of feature maps within super pixel. This is performed by applying statistical evaluation. To obtain the statistical evaluation, first, a Center Surround Divergence is measured as given below.

$$CSD\rightarrow FM(c)\text{-}HCI(s) \quad (5)$$

Followed by the evaluation of center surround divergence factor, the map values are measured from 'r', 'g', 'b', 'h' and 's' and channels to obtain resultant map values as '6*5=30 maps'. Here '6' represents the hexagon and '5' represents the RGB, HS values respectively, with maps represented as 'M_i,i=1,2,...,30'. The 'CSD' features as given above are then measured as the first and second instance of the center (finer) and surround (tune) feature maps within super pixel based on the mean and variance values. They are mathematically evaluated as given below.

$$\mu\_j\ (i)=CSD*\sum\_(p,q \in \langle\!\langle SP \rangle\!\rangle\_j) \langle\!\langle M\_i\ (p,q) \rangle\!\rangle \quad (6)$$
$$\sigma(i)=CSD*\sum\_(p,q \in \langle\!\langle SP \rangle\!\rangle\_j) [M\_i\ (p,q)-\mu\_j\ (i)]^2 \quad (7)$$

From the above equation (6) and (7), 'μ_j' represents the mean of the feature maps and 'σ' represents the variance of the feature maps within super pixel 'SP' for the corresponding five channels '$RGBHS$'. By this way, the proposed SLR-HCDC technique extracts the fine-tuned features using center surround divergence factor.

Self-assessed linear regressive segmentation model

Next, a Self-assessed Linear Regressive segmentation model is applied to the fine-tuned features extracted. Between the fine-tuned features, a linear regression is formed. With this, self-assessed trustworthiness score is measured for its corresponding optic disc. Finally, the best fit is said to be obtained via a self-assessed score with the objective of improving the sensitivity. Figure 3 shows the Self-assessed Linear Regressive segmentation model.

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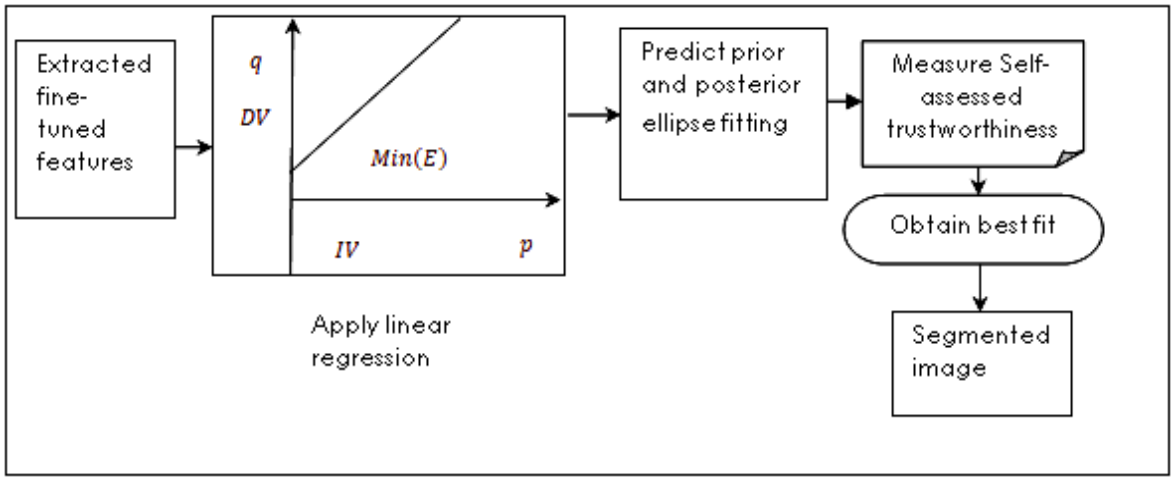

Fig. 3: Self-assessed linear regressive segmentation

As shown in the above figure, fine-tuned features extracted are provided as input. To start with, a linear regression is formed between the fine-tuned features. Here, the x axis or the independent variable 'IV' is represented as 'p' and the y axis or the dependent variable 'DV' is represented as 'q'. As the disc is usually very closer to an ellipse, the resultant boundary acquired prior and posterior ellipse fitting should be nearer if the super pixel based segmentation is nearer to the actual boundary. Otherwise, the result is likely to be less reliable. So first, a linear regressive value is identified to the extracted features so that resultant boundary acquired prior and posterior ellipse fitting are nearer to the actual boundary. Next, self-assessed trustworthiness score is measured with which the best fit obtained is the final segmented image. The algorithm representation of Self-assessed Linear Regressive model is given below.

Input: Fined-tuned Feature Extracted 'FE'
Output: Sensitivity improved segmented image 'SI'
1: Initialize 'b_0', 'b_1' **2: Begin** 3: Predict prior and posterior ellipse fitting nearer to actual boundary 4: Measure the error 5: Measure self-assessed trustworthiness score **6: Return** (Segmented Image 'SI') **7: End**

Algorithm 2: Self-assessed Linear Regressive segmentation

As given in the above Self-assessed Linear Regressive algorithm, the goal is to design a model that can fit nearer to the actual boundary with the given extracted features as input. Using the extracted features, a regression line is obtained that will given minimum error. That is if we give the features extracted as input, our model should predict the prior and posterior ellipse fitting nearer to the actual boundary with minimum error. This is measured as given below.

$$Pred= b\_0+b\_1*FE \quad (8)$$

From the above equation (8), the values 'b_0' and 'b_1' are selected in such a manner that they reduce the error. With the sum of squared error taken as a parameter to measure, then objective is to obtain the prior and posterior ellipse fitting that best reduces the error. This is measured as given below.

$$E= \sum\_(i=1)^n \left[\!\left[(A\_Output- P\_Output)**2\right]\!\right] \quad (9)$$

With the above predicted linear regressive value 'Pred' subject to minimum error 'E', self-assessed score is measured. To obtain the self-assessed trustworthiness score, initially, for each super pixel 'p' in 'P', the nearest feature in 'Q' and their distance is measured as given below.

$$\left[\!\left[Dis\right]\!\right]\_f(p)=INF\{Dis(p,q)\,|\,q \in Q\} \quad (10)$$

From the above equation (10), 'INF' denotes the infimum and 'Dis(p,q)' representing the distance between the super pixels 'p' and 'q'. Here, infimum refers to the greatest element of the containing set that is smaller than or equal to all elements of the subset. Then, the self-assessment trustworthiness outcome is computed as the ratio of the number of 'p' with ' $\left[\!\left[Dis\right]\!\right]\_f(p)<Th$' to the total number of 'p'. With the assumption that 'Th'

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refers to the neuro retinal rim (i.e. the tissue between the border of the cup and the disc), the trustworthiness score is measured as given below.

$$T(p)=Count\{(p|\ 〖Dis〗_f(p)<Th, p\in P)\}/Count(p) \quad (11)$$

Finally, with the above said self-assessed trustworthiness 'T(p)' score, the best fit is obtained for final segmented image. In this manner, segmented retinal image improving the sensitivity is said to be arrived at.

Hammersley-Clifford Deep Classification model

Image classification is the potentiality to distinguish glaucoma, non glaucoma region and early detection by applying feature based image extraction method. Classifiers attain significant results when the principal model applied for separation fits well with the sample distribution of retinal images. In this work, Hammersley-Clifford Deep Classification model is applied to the segmented images for early glaucoma detection. Learning of segmented image features are done based on the Gibbs distribution that performs classification between three types of classification at an early stage such as glaucoma, non glaucoma region and early detection. [Fig.4] shows the schematic diagram of Hammersley-Clifford Deep Classification model. The pseudo code representation of Hammersley-Clifford Deep Classification is given below.

Input: Segmented Images '*SI*'
Output: Early glaucoma detection
1: Begin **2:** **For** each Segmented Images '*SI*' 3: Measure the weight via Markov random field 4: Measure the step function via Gibbs distribution 5: Postulate Hammersley-Clifford theorem for classification 6: **End for** 7:**End**

Algorithm 3: Hammersley-Clifford Deep Classification

As given in the above classification algorithm, for each segmented images given as input, the objective here remains in early glaucoma detection with minimum errors. A Fully Connected Layer is a layer in which the neurons (i.e. pixels of segmented retinal images) is said to be connected to all the neurons ((i.e. pixels of remaining segmented retinal images) in the preceding layer. This fully connected layer integrates all the features learned by the preceding layers across the image to recognize the larger patterns. The last fully connected layer integrates the feature with the objective of classifying the segmented retinal images into three types.

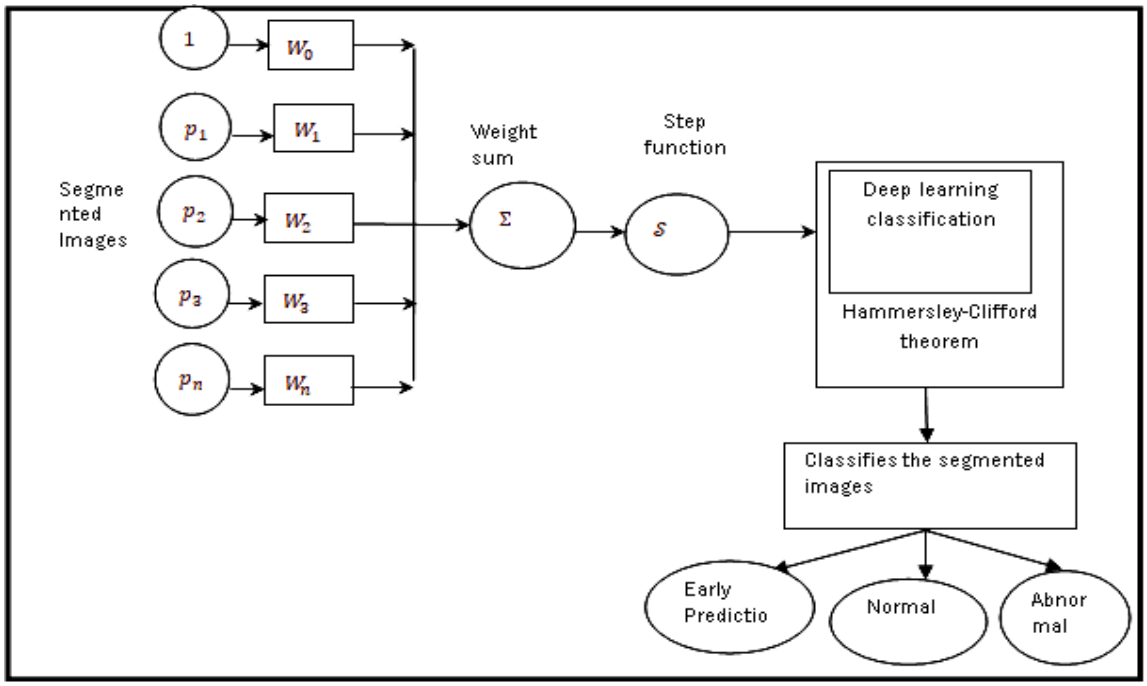

Fig. 4: Deep classification using Hammersley-Clifford theorem

As illustrated in the above [Fig. 4], for each segmented input images, the weights are calculated based on the Markov Random Field. This is mathematically expressed as given below for each center level 'c' and surround level 's'.

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$$W(\llbracket SI \rrbracket\_o) = Prob\{P\_s = p\_s \mid P\_c = p\_c, \text{for } s \neq c\} \quad (12)$$

From the above equation (12), the weights 'W' of the corresponding segmented images 'SI' are obtained based on the vector corresponding to center and surround level of each feature maps. The final layer is the classification layer. This classification layer utilizes the Gibbs distribution for each segmented retinal image input to assign the input to one of the mutually exclusive classes.

$$GD = \prod \llbracket V\_SI(p) \rrbracket \quad (13)$$

From the above equation (13), the Gibbs distribution 'GD' refers to a positive function 'V_SI' that depends on 'p' only through the coordinates '{P_s,P_c :s,c∈SI }'. Finally, the classification of three types namely, normal, abnormal or early detection of glaucoma is obtained based on the Hammersley-Clifford theorem. The Hammersley-Clifford Theorem postulates that the process '{P_s,P_c :s,c∈SI }' is a Markov random field if and only if the corresponding 'GD' is a Gibbs distribution. Then, the segmented images are said to be early detection. If the corresponding 'GD' does not forms a Gibbs distribution with respect to Markov random field, then, the segmented images are said to be abnormal. If the corresponding 'GD' is more equivalent with respect to Markov random field, then, the segmented images are said to be normal.

RESULTS

This section of the paper contains comparison between our solution Self-assessed Linear Regressive segmentation and Hammersley-Clifford Deep (SLR-HCDC) and existing methods Modified U-Net neural network [1] and Hybrid feature set [2]. Results are reported for publicly available DIARETDB0 - Standard Diabetic Retinopathy Database [18] obtained from http://www.it.lut.fi/project/imageret/diaretdb0/index.html. The current database comprises of 130 color fundus images, out of which 20 images are found to be normal and 110 images contain certain amount of signs of the diabetic retinopathy. Performances are evaluated for three different parameters, sensitivity, specificity and diagnosis accuracy. The hyper parameter for deep neural network is given as follows,

Table 1: Hyper parameter for deep neural network

Hyper parameter	Value
Learning rate	0.5
Weight	0.44
Hidden layer	5

Clinical tests are said to be evaluated based on the sensitivity and specificity rate. The sensitivity and specificity rate are independent of the population of interest (i.e. samples considered for experimentation) subjected to the test. To conduct the specificity and sensitivity test, both the positive and negative predictive values are useful when considering the value of a test to a clinician. These two rates are dependent on the retinal disease prevalence in the population of interest.

Performance evaluation of sensitivity, specificity and diagnosis accuracy

The sensitivity refers to the ability of the test to correctly identify glaucoma disease. In the example of a medical test used to identify a disease, the sensitivity of the test is the proportion of people who test positive for the disease among those who have the disease. Mathematically, this can be expressed as:

$$Sensitivity = TP/(TP+FN) \quad (14)$$

From the above equation (14), True Positive 'TP' refers to the number images detected as glaucoma, False Negative 'FN' refers to the number of images detected as glaucoma by an expert but detected as normal by the SLR-HCDC method.

Table 2: Tabulation for Sensitivity

Number of images	Sensitivity (%)		
	SLR-HCDC	Modified U-Net neural network	Hybrid feature set
10	0.8	0.7	0.6
20	0.8	0.7	0.6
30	0.8	0.7	0.6
40	0.7	0.6	0.6
50	0.7	0.6	0.6
60	0.7	0.6	0.7
70	0.6	0.6	0.6
80	0.6	0.7	0.6
90	0.7	0.6	0.6
100	0.8	0.7	0.6

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As shown in the above [Table.2] representing the sensitivity analysis, experiments are conducted with 100 different retinal fundus images. The reason behind the improvement of sensitivity is due to the application of Center Surround Divergence Feature extraction model. By applying this model, two different functions i.e., center and surround are said to be performed for feature mapping based on the intensity. With this, the sensitivity rate is said to be improved using SLR-HCDC method by 11% compared to [1] and 18% compared to [2].

The specificity refers to the ability of the test to correctly identify the normal retina. Consider the example of a medical test for diagnosing a disease. Specificity of a test is the proportion of healthy patients known not to have the disease, who will test negative for it. Mathematically, this can also be written as,

Specificity= TN/(TN+FP) (15)

From the above equation (15), True Negative 'TN' refers to the number of images detected as normal, False Positive 'FP' refers to the number of images detected as normal by an expert but detected as glaucoma the SLR-HCDC method.

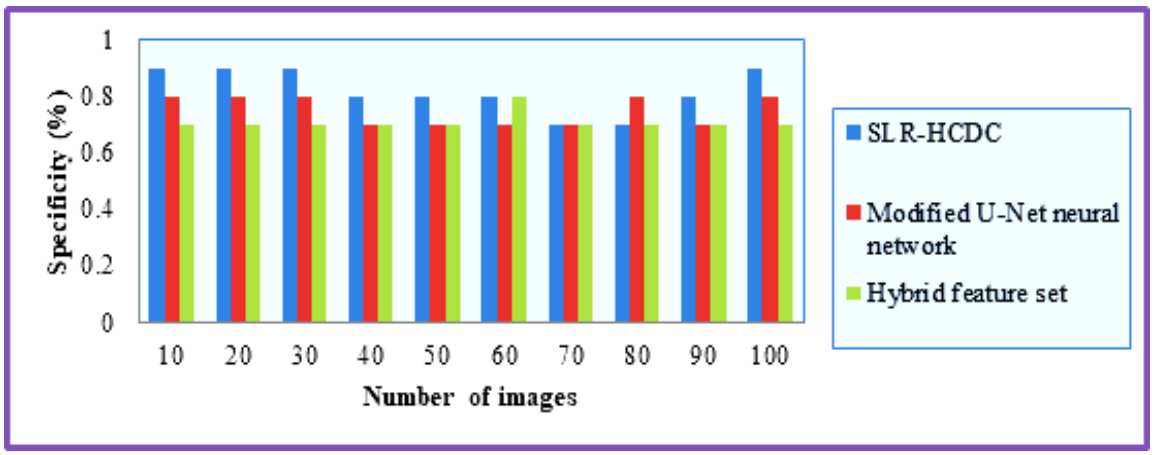

Fig. 5: Performance graph of specificity.

As shown in the above [Fig.5] representing the specificity analysis, experiments are conducted with 100 different retinal fundus images. The specificity rate in the above figure refers to the percentage of patients without having the glaucoma disease correctly identified as not having the condition. The reason behind the improvement of specificity is due to the application of Center Surround Divergence Feature extraction algorithm. By applying this algorithm, feature mapping is performed based on the center and surround level, statistical evaluation is also performed for extracting fine-tuned features. These fine-tuned features are then finally obtained via according to the Center Surround Divergence factor. With this, the specificity rate is said to be improved using SLR-HCDC method by 9% compared to [1] and 16% compared to [2].

The diagnosis accuracy 'A' refers to the percentage ratio of number of retinal images correctly diagnosed as glaucoma images '〖Correct〗_D' to the number of images 'I_i' provided as input for experimentation.

$$A=\sum_{i=1}^{n}[\ 〖Correct〗_D/I_i\ ]\ 100 \quad (16)$$

Table 3: Tabulation for diagnosis

Number of images	Accuracy (%)		
	SLR-HCDC	Modified U-Net neural network	Hybrid feature set
10	90	80	70
20	90	80	70
30	90	80	70
40	80	70	70
50	80	70	70
60	80	80	70
70	70	70	70
80	70	70	60
90	80	80	70
100	80	70	70

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[Table. 3] has given above shows the tabulation of diagnosis accuracy. The comparative analysis shows better diagnosis accuracy using SLR-HCDC method when compared to Modified U-Net neural network [1] and Hybrid feature set [2]. This is because of the application of Hammersley-Clifford Deep Classification. By applying this model, Hammersley-Clifford theorem was applied for Deep Classification that in term uses the Gibbs distribution for each segmented retinal image input to assign the input to one of the mutually exclusive classes. In this way, the diagnosis accuracy using the SLR-HCDC method is found to be better than [1] by 8% and 17% when compared to [2].

DISCUSSION

In this paper, Self-assessed Linear Regressive segmentation and Hammersley-Clifford Deep Classification method introduced for early diagnosis of glaucoma. With pre-processed retinal fundus image, a Center Surround Divergence Feature extraction model is performed in the SLR-HCDC method. Where, the fine-tuned features of pre-processed input image is extracted based on the Hexagon Center Interpolation mapping. Then, the extracted features are applied to the Self-assessed Linear Regressive segmentation model for improving sensitivity of glaucoma detection. In this model, prior and posterior ellipse fitting nearer to the actual boundary is measured for reducing error. Next, with this measured linear regressive value, self-assessed trustworthiness sore value is determined. Based on this score value, extracted features of images are segmented. Finally, Hammersley-Clifford Deep Classification model is used to the segmented images for early glaucoma detection. In this classification model, segmented images are classified into three types such as normal, abnormal and early detection of detection. By this way, the proposed SLR-HCDC method is achieves early glaucoma detection with higher sensitivity and accuracy. In the experimental evaluation, the performance of proposed SLR-HCDC method analyzed with two existing methods namely Modified U-Net neural network [1] and Hybrid feature set [2]. From the experimental analysis, the proposed SLR-HCDC method obtains 72% of sensitivity, 82% of specificity and 81% of accuracy. Similarly, 65% and 61% of sensitivity, 75% and 71% of specificity, 75% and 69% of diagnosis accuracy obtained by existing methods [1] and [2] respectively.

CONCLUSION

In this paper, a Self-assessed Linear Regressive segmentation and Hammersley-Clifford Deep (SLR-HCDC) is presented to detect the glaucoma in retinal fundus images. The proposed method that is based on Deep Classification demonstrated promising performance in diagnosing the glaucoma with considerably higher sensitivity and specificity as compared to existing equivalent methods. The raw images are directly applied to the Center Surround Divergence model to extract fine-tuned features to increase the specificity rate. Fine-tuned features of the glaucoma disease are extracted from center and surround level feature maps. The Self-assessed Linear Regressive used in this study has proved to be an effective strategy for obtaining sensitivity improved segmented image. Finally, by applying Hammersley-Clifford Deep Classification model, higher diagnosis accuracy was said to be achieved. In the experiment the proposed method successfully detected all normal retinal class images correctly and achieved a diagnosis accuracy of 90% Based on the high diagnosis accuracy achieved, the proposed method with a deep classification model can make a relevant improvement to medical science physicians and practitioners by assisting medical image analysis for glaucoma detection. In future, the proposed method is extended for early glaucoma detection with minimum time by using new developed algorithms.

CONFLICT OF INTEREST
There is no conflict of interest.

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FINANCIAL DISCLOSURE
None.

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