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Retinal Disease Identification Using Anchor-Free Modified Faster Region-Based Convolutional Neural Network for Eye Fundus Image

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ABSTRACT- Major Improvements in diagnostic methods are providing previously insight into the condition of the retina and other conditions outside of ocular disease. Infections of the retinal tissue, as well as delayed or untreated therapy, may result in visual loss. Furthermore, when a large dataset is involved, the diagnosis is prone to inaccuracies. As a consequence, a completely automated model of retinal illness diagnosis is presented to get rid of human input while maintaining high accuracy classification findings. ODALAs (Optimal Deep Assimilation Learning Algorithms) are unable to handle zero errors or covariance or linearity and normalcy. DLTs (Deep Learning Techniques) such as GANs (Generative Adversarial Networks) or CNNs might replace the numerical solution of dynamic systems (Convolution Neural Networks), in order to speed up the runs. With this objective, this research proposes a completely automated multi-class retina disorders prediction system in which pictures from the Fundus image dataset are upgraded using RSWHEs (Recursive Separated Weighted Histogram Equalizations) to boost contrast and noise is eliminated using the Wiener filter. The enhanced picture is used for segmentation, which is done using clustering and the optimum threshold. The suggested EFFCM is used for clustering (Enriched Fast Fuzzy C Means) The suggested AOO (Adaptive optimum Otsu) threshold technique is used for clustering and picture optimal thresholding. This paper suggests AMF-RCNNs (anchor-free modified faster region-based CNNs) that integrate AFRPNs (anchor free regions proposal generation networks) with Improved Fast R-CNNs into single networks for detecting retinal problem exactly. The performances of the suggested method illustrate improved outcome when compare with other related techniques or methods.

Keywords: Retinal disease, Fundus image dataset, contrast enhancement, Fast Fuzzy C Means, Adaptive optimal Otsu and faster region-based convolutional neural network.

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1. INTRODUCTION

Human's vision is a crucial sense and lack of which impacts independence and productivities in humans. Retinal illnesses affect millions of humans resulting in visual losses when not identified or treated in early stages of vision loss. DRs (Diabetic retinopathies), glaucoma and other eye defects are macular degenerations which crop up as humans age [1] where early therapies can arrest or eliminate the disease's progressions. Despite the fact that there are many hospitals and eye clinics in India's cities, the doctor-to-patient ratio remains low. There is a paucity of both infrastructure and ophthalmologists in rural locations [2]. Even community outreach activities are hampered by a lack of qualified professionals in remote locations to appropriately assess patients. With advancements in technology and image processing, it is feasible to automate disease identification and refer patients to doctors for additional evaluation. Ophthalmologists can use retinal fundus imaging to diagnose retinal abnormalities. Early detection can boost treatment chances and avoid blindness [3].

Medical specialists can use retinal fundus images to identify retinal diseases including DRs and retinitis pigmentosa. Studies using MLTs (Machine learning techniques) have been recently focusing on identification of retinal disorders including DRs by categorizing fundus images based on extracted features [5]. The main aspire of this paper is to differentiate automatically abnormalities in the retina without segmentations or feature extractions from their images and use DLTs to automatically categorize retinal images as healthy or sick. Many of these models use the retinal picture to identify, extract, and evaluate disease-specific characteristics. This necessitates a thorough understanding of the illness as well as considerable work in developing the characteristics for the classifiers. Without being taught where to look, MLTs utilize data to uncover hidden

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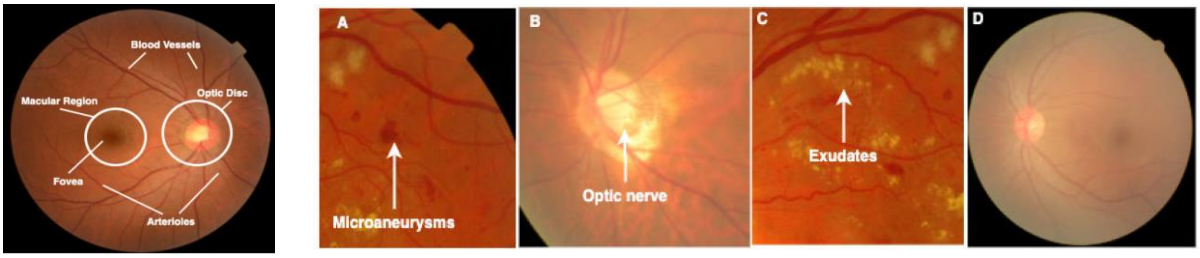
patterns and have gained traction in disease diagnostics. These algorithms identify patterns and qualities in images at multiple levels and relate them to recognized disease classes. Guided learning have assisted in early detections and categorizations of eye disorders including cataract, conjunctivitis, and DRs. Various MLTs have been found equivalent to that of human specialists for certain eye conditions in studies. ANNs (Artificial Neuronal Networks) are mathematical models that reproduce neuronal organizations of cerebral cortex [6].



(a) (b)

Fig.1. (a) Normal anatomical structures of the retina. (b) Illustrates a complication of eye disease in a retina: A. Microaneurysms, narrow bulges (DRs), B. Optic nerve damage (Glaucoma), C. Exudates with retinal thickening (Diabetic Macular Edema), D. Degeneration of lens (Cataract) [4].

Input layers are followed by one or more hidden layers where patterns are processed using system of weights 'connections' for recognizing patterns. These hidden layers get connected to output layers, creating patterns of retinal images. Most ANNs include learning rules which alter weights of neurons in response to input patterns. A typical neural network, on the other hand, is incapable of analyzing patterns in different positions. Specifically, unlike traditional ANNs, the layers of DLTs, such as CNNs and DNNs (Deep Neural Networks) [7], contain neurons organized in three dimensions: width, height, and depth. Certain neurons may sense the margins while others detect the centre. Using a certain stride and ensuring that various neurons acquire distinct data on pattern localization. Thus, unlike standard NNs, these networks learn more about patterns in images instead of plain detections. Information obtained by first layer's neurons are forwarded to corresponding hidden layers, with neurons contributing vital information about distinct image parts. The last layers use multi-class classification functions that count number of units as output class counts. This research work's contributions include developing DLTs based on CNNs for identifying retinal eye diseases from fundus images and are listed below: RSWHEs are used to boost the contrast of input pictures. Detecting diabetes-related eye disorders areas early and automatically using cluster-based segmentation is a difficult challenge. The EFFCM-based approach was applied in the described methodology for disease area localization.

The suggested AMF-RCNNs can identify illness symptoms, including early warning indications, and have no difficulty learning to recognize an image of a healthy eye. Finally, we compared the strategy to the most recent cutting-edge methodologies and obtained better performance results. The overall research technique and Relate work is shown in (*Section 2*). Implementation methodology describes the clustering method and proposed classification method for classifying the retinal disease (*Section 3*). Then the results of the experiment with discussion is projected in experimental and results (*Section 4*). Finally concludes the paper with future study in conclusion and future work (*Section 5*).

2. RELATED WORK

This section provides a thorough examination of the principles and applications of DLTs in retinal image processing. Machine learning, particularly DLTs, has lately been successfully utilized in this field. This section examines current developments in DLTs approaches for retinal image processing. Pan et al. [8] use DLTs to identify and categorize DRs Lesions in pictures of FFAs (fundus fluoresce in angiographies) by comparing three CNNs: DenseNet, ResNet50, and VGG16. In [9] author developed a DLTs-based DC-Gnets (disc cup segmentation glaucoma networks) for glaucoma diagnosis using structural characteristics like cup-to-disc ratios, probability scales of disc damages, inferior/superior nasal temporal regions using RIM-One and Drishti-GS datasets for segmentations. In [10] present a method for detecting the existence of neovascularization that includes image resizes, filtering green channels, Gaussian filters, and morphological methods like erosions and dilations in processing of images. The several layers of CNNs were employed and modeled combined in a VGG-16 net architecture for classification. The method was tested and trained on over 2200 photos from the Kaggle database. In [11] suggested a two-stage approach for detecting and localizing the optic disc before classifying it as healthy or glaucomatous. The first stage utilizes Regions of CNNs to locate and extract optic discs from fundus images while in the second stage DCNNs (Deep CNNs) classify extracted discs as healthy or glaucomatous. Unfortunately, none of the publicly obtainable retinal fundus image datasets could provide much needed bounding boxes localization of discs.

In [12] offered modified U-Net topologies that included block squeeze and excitations as well as usages of attention gates in datasets to segment demarcation lines/ridges and vessels. These changes were verified and confirm by ROP experts. All three networks (AG U-Net, U-Net and SE U-Net) showed good results with ranges in the dice coefficients ranging from 1 to 6% for the HVDROPDB datasets. In [13] author suggested architecture employs a dilated convolution filters to obtain bigger receptive fields, resulting in near-human accuracy in segmenting retinal blood vessels. The popular datasets were used to train the CNNs. In [13] introduced the DL-CAEF (DLT

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Assisted Convolution Auto-Encoders Frameworks) to diagnose glaucoma and recognize AVPs (Anterior Visual Pathways) from retinal fundus pictures. In [15] identified CWS, HE on retinal images using super iterative clustering approach which comprised of CNNs and encoders with encoder structures. To convert red, blue and green images into ideal grayscale images devoid of noises, FBMIR dataset's data were combined with histogram filters and subsequently categorized using DALAs (deep assimilation learning algorithms). In [16] proposed presenting a mixture of losses in DNNs model to enhance recognition performances in biomedical data for classifiers.

3. PROPOSED WORK

The suggested AMF-RCNN for classifying retinal fundus pictures was examined. BDR Backgrounds for PDR stands for Proliferative DRs, CRVOs stand for Central Retinal Vein Occlusions, CNVs stand for Choroidal Neo-vascularization, HISTs stands for Histoplasmoses, and Normal stand for Normal eyes. Fig. 2 depicts the broad framework of the primary sequential procedures for classifying DR pictures in the suggested technique. To begin, DR pictures were acquired, graded, and tagged. The STARE (Structured Analysis of the Retina) web-database was used to obtain the dataset. The collection contains 400 raw funduscopic pictures from various instances, including 13 illnesses and normal cases [17]. After that, the appropriate image pre-processing techniques were used to capture images for better training for the planned learning. The improved picture is used for segmentation, which is done using clustering and the optimum threshold. The suggested method gathered features from multiple sample photos with ground truth labels and automatically changed its hyper parameters to get the greatest classification accuracy. The identification outcome might help ophthalmologists decide whether or not to refer patients.

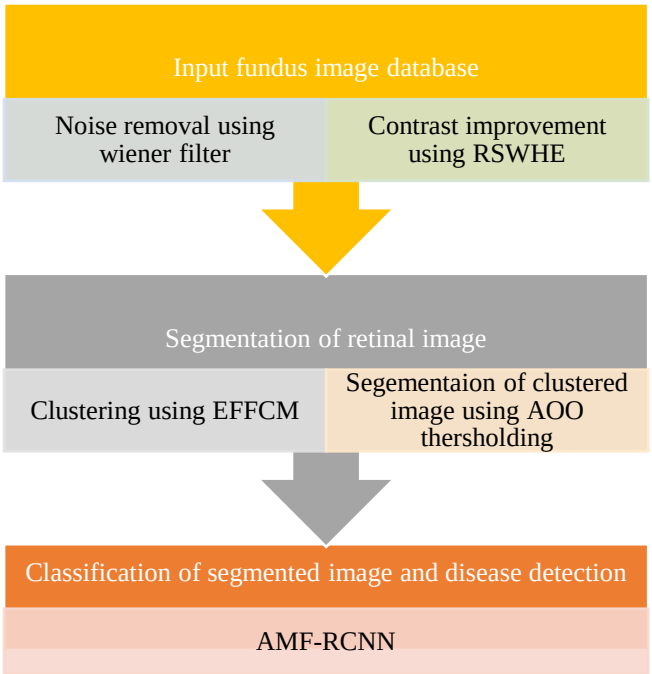

Fig.2. The general Framework of proposed methodology

3.1 Image pre-processing

The suggested approaches aid in the identification of eye diseases by enhancing picture quality and clarity. Here, two ways for improving the contrast and quality of retina fundus pictures have been developed: RSWHEs boost picture contrast, whereas Wiener filters reduce noise. RSWHEs: RSWHEs work by recursively segment input histograms into sub-histograms and modify sub-histograms with weights based normalized power law function procedures and histogram equalizations on weighted sub-histograms separately. It improves the contrast of a picture in three phases [18]: First, take the picture I and calculate the histogram *H(I)*, which is then split into the number of sub-histograms. A second histogram weighting is used to modify the sub-histograms using a normalized power law. Finally, histogram equalization is performed, in which the weighted sub-histograms are equalized separately over the modified sub-histograms. Wiener filters: Wiener filters are non-adaptive additional predefined patterns that incorporate linear approximations of predicted signal organization on or after a non-adaptive extra predetermined pattern. A typical Wiener filter is a convolution filter that computes the shape and size of the neighborhood using only a frame. It may be more effective to filter with more really large Viennese masks and fewer blurry masks. A fundus photograph of size (*ij*) must have each pixel representing the strength of a single stationary point in front of the camera. The Wiener filter is used to remove noise from a signal that has been tampered with by statistical analysis. The Wiener filter is a type of filter that is used to reduce assuming that signal and noise processes are second-order picture derivate. Consider the following *equation 1* to demonstrate and transform to 2D:

$$ob(i,j) = ir(i,j) * I(i,j) + un(i,j) \qquad (1)$$

Where * represents *I* is the unknown real ovarian cyst picture with *ij* pixel value, *ir* is the impulse response of a linear, time-invariant filter, un is incremental unknown noise independent of *I*, and *ob* is the observed image. Then, as given in *equation 2*, a de-convolution filter dc must be found to evaluate *I*:

$$\widehat{I}(i,j) = dc(i,j) * o(i,j) \qquad (2)$$

Where $\widehat{I}$ indicates the value of *I* that reduces the mean square error. The transition function of Tr, in the frequency domain, given in *equation 3*,

$$Tr(x,y) = \frac{ir * (x,y)PS(x,y)}{|ir(x,y)|^2 PS(x,y) + NSP(x,y)} \qquad (3)$$

Tr (*x,y*) is the Fourier transform of the probability mass equation, PS is the power spectrum of the signal process used to acquire the Fourier transform of the signal co-linearity, and NSP(*u,v*) is the power spectrum of the noise (*N*) practice acquire by generating the Fourier transform of the noise autocorrelation.

3.2 Segmentation Process using EFFCM Clustering and AOO Method

The improved picture is used for segmentation, which is done using clustering and the optimum threshold. The suggested

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EFFCMC Algorithm is used for clustering, while the proposed AAO threshold with ALOs is used for optimum thresholding (Ant Lion Optimizations). Real-time photos are used to collect materials for processing. FCMC is a widely used approach for picture segmentation since it is more efficient than other machine learning algorithms. The biggest disadvantage of this approach was its slowness. The Fast Fuzzy C Means Clustering technique was applied to increase the speed of this technique. The primary distinction in this approach was that an image histogram was employed instead of raw picture pixels. The objective function OF of the Fast Fuzzy C Means Clustering method is given by,

$$OF = \sum_{i=0}^{n} \sum_{C=1}^{c} hist_i * \mu_{iC} * dis(i, \theta_C) \quad (4)$$

Here, $hist_i$refers to the histogram,μ_{iC}refers to the fuzzy membership between pixel $x_i$and histogram of cluster with centerθ_C,$dis(i, \theta_C)$refers to the distance between pixel $x_i, i = 1,2, \dots, n, \forall n = 255$and histogram of cluster with centerθ_C, Let C=1,2,...c represent each centroid. Then, the mean of the pixels in every centroid is given asv_C. The mahalanobis distance between the data point $x_i$with each $v_C$is then calculate. This term is added to the objective function in the present EFFCMC plan. Thus, the new objective function is given as,

$$OF = \sum_{i=0}^{n} \sum_{C=1}^{c} hist_i * \mu_{iC} * dis(i, v_C) * mahalan(x_i, v_C) \quad (5)$$

Otsu thresholds are common image segmentation techniques that use global thresholds to divide images into two categories: foreground and background. Pixel values in images are compared using thresholds. When values of pixels exceed threshold values they are classified as foregrounds; else they are classified as backgrounds. The initial threshold determines Otsu algorithm's efficacy. As a result, the authors suggest an adaptive Otsu thresholding method (AOTA) in which optimal threshold selection is performed using a ALOs that adaptively select best starting threshold values. In this part, the variable threshold influences the AOTA output, and the goal of any optimizer is to find values for these variables that provide the best segmentation rate and accuracy. The Ant Lion Optimizer (AOO) is used to increase the performance of AOTA. AOO is a strategy that disallows the local minima and maxima in order to obtain an optimal solution. To compute the input for the AOO method, the ALO [17] algorithm is employed. The suggested algorithm AOTA system is adjusted utilizing the ALO optimizer using the provided fundus image pre-processed data set. This raises the bar for learning from the model. ALO is used to modify the incidence of local minima and maxima. The AOTAs through ALOs is illustrated in *fig 3*.

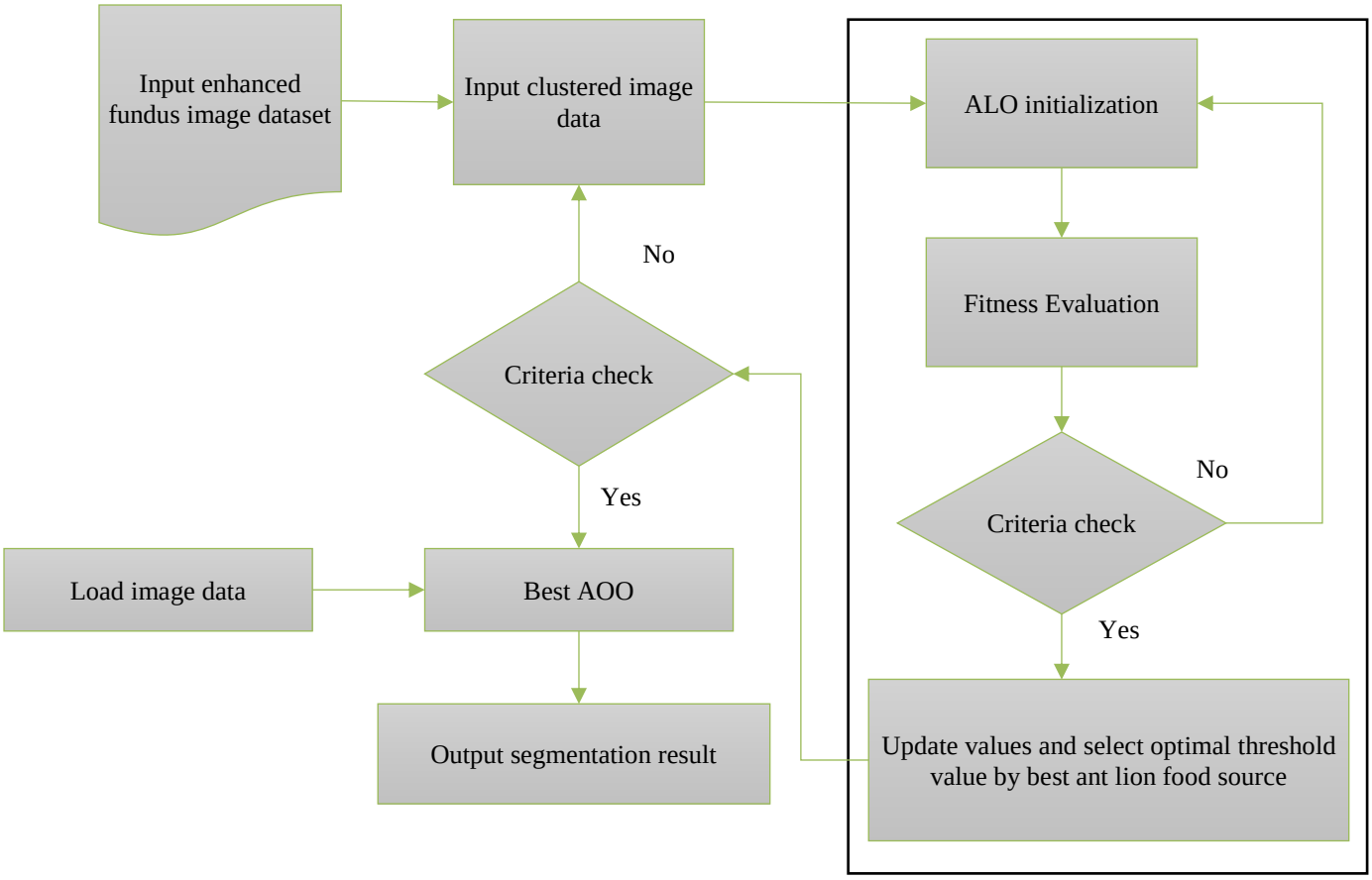

Fig 3. Flowchart of proposed AOO Method

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Early data quality segmentation is a necessary step since classifying early phases of eye illnesses includes uncertainties that govern disease predictions, and progressions caused by aspects of image data which necessitate strong models to reliably predict outcomes. The segmentation region of eye disease. In this study, AOO is used for segmentation with the weaker domain identification among the major 4 domains.

Step 1. Initialize: random initialization of the positions of input variables of the features as Ant lion selected from preprocessed image dataset
Step 2. Calculate the cumulative total of a maximum number of iterations, where iteration represents the steps in a random walk. One matrix stores the position of each input's value. Another matrix stores the relevant objective values. Another matrix is generated in order to save the position and fitness value as accuracy.
Step 3. Use a random threshold value to update the location of the input value.
Step 4. Create Traps: Make two vectors, one with a minimum of all variables from a single input source and the other with a maximum of all variables from the same input source. This provides the input weight for the fitter for the intended output value.
Step 5. Entrapment of Ants in Traps: If it gets fitter, replace the position of all input variables with the appropriate fit of the other input variables.
Step 6. Finally, change the threshold value based on Ant Lion's location.
Step 7. Rebuilding Traps: Check the termination requirements; if the termination conditions are met, return the ideal solution; otherwise, proceed to updating Ant Lion's location.

Following inference, Otsu is used to provide automated threshold selection for segmentation. Elitism, or remembering the best solution discovered, is an important feature of a nature-inspired algorithm that allows for the preservation of the best solution achieved at any point of the optimization process. The best result generated in each iteration is kept and considered Elite in this investigation. Because the Elite is the fittest output, it will influence the movements of all other variable thresholds throughout iteration.

3.3 Eye disease image detection model using AMF-RCNN model

As illustrated in *fig.4*, the proposed eye disease image detection model, AMF-RCNN, consists of eye disease images. Area of interest extraction network, a features extraction network, and an eye illness picture detection network are all examples of networks. To begin, CNNs are used to extract characteristics and get fusion features from an image of an eye ailment. Second, the AFRPN receives the fused feature map produce by the feature fusion methods and creates a series of eye sickness image suggestions. The top sorted are reduced to the similar size ROI vector using the ROI Align layer [12]. The classification layer predicts the image category of an eye condition, and the bounding box regression layer refines class-specific suggestion box offsets, using these fixed vectors.

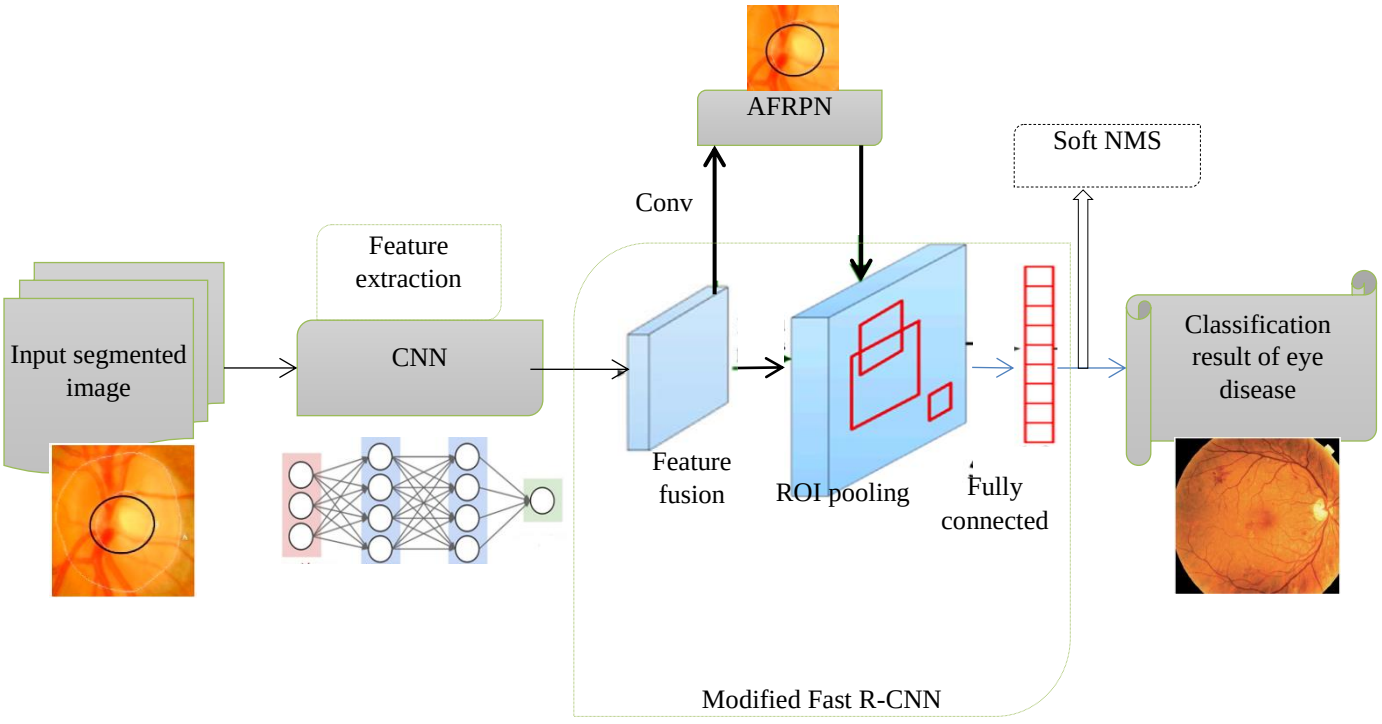

Fig.4. Block diagram of AMF-RCNN

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Feature Extraction Network: Automatically extracting target features from eye disease pictures and integrating feature depiction and goal for "joint learning" were accomplished using the CNN-based approach. Depending on the optimization goal, the parameters of eye sickness picture features can be changed adaptively during network training. The feature extraction network is made up of four layers: convolution, pooling, activation, and feature fusion. In conclusion, the new feature fusion module creates a more compact feature map with strong semantic characteristics and fine-grained details ideal for micro item identification. AFRPNs are full convolution networks that enable compute sharing with multi-class detection networks. This tiny network employs a 33 spatial window on the input feature map, and the feature extract by every sliding window is translated to a 512-dimensional feature vector using a 33kernel convolutional operation with 512 channels, which is then transmitted to two simultaneous complete convolutional networks. For classification, one branch generates two probabilities of being objects or not, while another generates four box coordinates for localizations.

This study integrates AFRPN and modified Fast R-CNNs into one network, *i.e.* AMF-RCNN, to identify the multi-categories eye illness picture, where AMF-RCNN is trained end-to-end via back-propagation and stochastic GDs (SGD), allowing for shared convolutional layers. Each SGD mini-batch is created for AMF-RPN training from a single eye illness imaging image containing 256 data. Positive and negative samples are chosen at random for each mini-batch, so that the ratio of positive to negative samples is 1:1. The regression layers and classification start with a zero-mean Gaussian distribution with standard deviations of 0.01. Backward propagation occurs as normal, and the backward propagated signals for the shared convolutional layer originate from a mix of AFRPN loss and modified Fast R-CNNs loss. The fundus image scale varies substantially during the real eye disease detection procedure. The original quicker RCNN typically uses a set size for all training pictures. As a result, the generalization performance of object identification with varying sizes is low. This work employs multi-scale training; before being uploaded to the network, the photographs will be scaled at random. After that, the various scale photographs will be taught. For joint training, loss function LF is widely used. Furthermore, enhancing localization exactness can get better the overall finding rate of airports. As a result, we get better the classification loss, which is defined as the integral of the classification loss $Loss_{cl}$ under IoU threshold th. The final loss function is:

$$\int_{50}^{100} Loss_{cl}(pr_{th}, clp_{th}) \approx \sum_{50} \frac{Loss_{cl}(pr_{th}, clp_{th})}{n} \qquad (6)$$

Where n = 4, $th \in \{50,60,70,80\}$, the predicted probability of the final output of the network model is the average value of different thresholds. The feature map corresponding to the suggestion box is input to the full connection layer, and finally, output from two same output layers. One output is the set of predicted probabilities for the background and $k$classes objects, namely, $= (pr_0, pr_1 \cdots p_k)$, clp_{th}represents the class prediction value when the threshold value is th. pr_{th}Represents the prediction probability and$n$is the equal number in definite integral interval. When many types of eye illness images are detected during the testing stage, duplicate boxes are frequently predicted for the same eye disease image. Traditionally, a recommendation box SB with the highest score is chosen, but its adjacent boxes are suppressed depending based on a preset overlap threshold if the suppressed boxes include extra items, however, the suppression will cause some items to be overlooked. To solve this problem, instead of forcing class scores to be zero, give them penalty weight. The following is an example of how a Gaussian penalty function (GPF) is used:

$$GPF = cs_i e^{-\frac{IoU(SB,nb_i)^2}{th}} \qquad (7)$$

$$IoU(BB, nb_i) = \frac{area(SB \cap nb_i)}{area(SB \cup nb_i)} \qquad (8)$$

Where cs_i is the confidence score for the ith detection box, $IoU(SB, nb_i)$ denotes IoU (Intersection over Unit) ratio between boxes with highest scores SB and their neighboring boxes nb_i and th is threshold is set to 0.5. Following the above stages, sharper eye disease image identification results will be obtained. When we find multi-category pest items during the testing stage, duplicate boxes are frequently anticipated for the same bug. To suppress these redundant boxes, a class specific NMS is traditionally used: picking a bounding box with the highest score but suppressing its nearby boxes depending on a pre-defined overlap level. However, if the suppressed boxes include additional items, the suppression will result in some things being missed. To remedy this issue, we provide penalty weight to class scores instead of forcing them to be zero. A Gaussian penalty function is used specifically:

$$cs_i = e^{\frac{IoU(SB,nb_i)^2}{\delta}} \qquad (9)$$

Where δ is set to 0.5 and after the above soft-NMS suppression method, can obtain finer eye disease detection results.

4. RESULTS AND DISCUSSION

To validate the effectiveness of the proposed approach, the proposed AMF-RCNN method is used to identify eye diseases and is compared to several current detection methods based on CNNs [8, DL-CAEF [14], and ODALAs. The fundus pictures were arbitrarily divided into training (70%) and test (70%). There were 650 training photos and 280 validation images from five illness categories used. The results showed that the outputs provided by the proposed single CNNs model, which was meant to categorize pairs of distinct retina diseases BDRs (Background DRs), CRVOs CNVs, HISTs: PDRs: Proliferative DRs and Normal were accurate, sensitivity, and specificity. In the context of classification presentation, a true positive value (TP)" is a result that properly predicts the positive class. A true negative value (TN) is a result that forecasts the negative class appropriately. False negative (FN) and false positive (FP) values are used to reflect misclassified samples. Using accuracies, precisions, F1-scores, and MCCs as parameters (Mathew Correlation-coefficients), specificities, and sensitivities, their equations may be represented as follows:

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Accuracies of models show overall performances of models and computed by the formula given below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} * 100$$

Precisions are ratios of actual positive scores and positive predicted scores by classification models/algorithms. Precisions are computed by the following formula:

$$Precision = \frac{TP}{TP + FP} * 100$$

F1-scores are weighted measures of both recalls and precisions. They range between 0 and 1 where 1 implies good performances of classification algorithms while 0 stands for bad performances.

$$F1\ score = \frac{2 * Precision * Recall}{Precision + Recall}$$

MCCs are correlation coefficients between actual and predicted results. MCCs give resultant values between − 1 and + 1. Where − 1 represents completely wrong predictions of classifiers while 0 implies classifiers generate random predictions and + 1 represents ideal predictions of classification models. The formula for calculating MCCs are given below:

$$MCC = \frac{TP * TN - FP * FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

Specificities are ratios of recently classified healthy people to total counts of healthy people. It implies the predictions are negative and persons are healthy. The formula for calculating specificity is given as follows:

$$Specificity = \frac{TN}{TN + FP} * 100$$

Sensitivity is the ratio of recently classified heart patients to the total patients having heart disease. It means the model prediction is positive and the person has heart disease. The formula for calculating sensitivity is given below:

$$Sensitivity = \frac{TP}{TP + FN} * 100$$

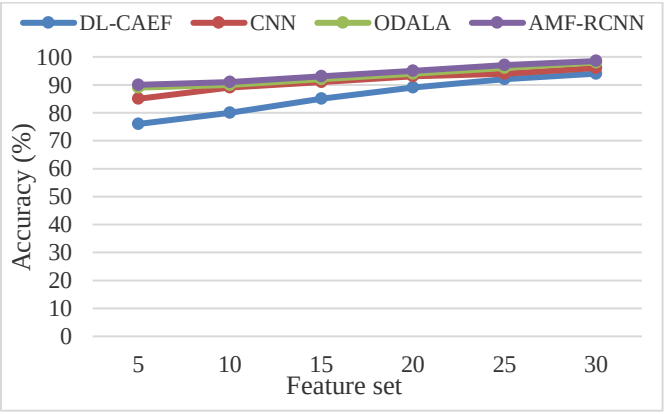

Fig.5. Accuracy performance of methods on different subsets of feature

From *fig.5*, it gives the accuracy of proposed and existing models for the amount of features in a given database. The AMF-RCNN increases the accuracy while reducing the processing time. The AMF-RCNN attains the accuracy of 98.5% compared to all other models since the high quality generated by the proposed AFRPN can be applied to improve the disease detection. The results of existing methods such as DL-CAEF, CNNs and ODALAs are 94%, 96% and 98% respectively. Thus the proposed algorithm is greater to the existing algorithms in terms of better good validation results for predicting DR disease.

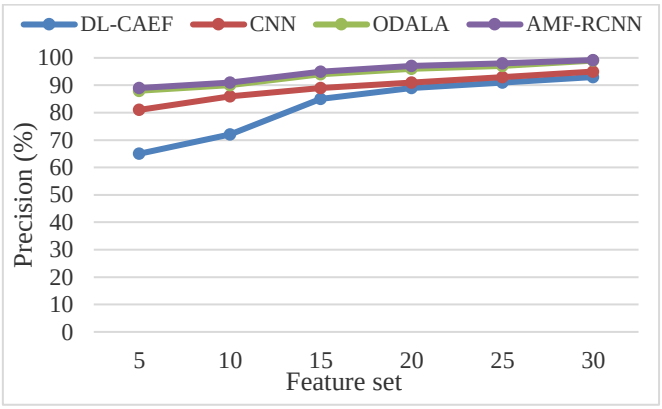

Fig.6. Precision performance of methods on different subsets of feature

From *fig.6*, it indicates the precision of proposed and existing models for the amount of features in a given database. As increasing the amount of features, the precision is also maximized. The AMF-RCNN attains a recall of 99.2%. This may be due to the benefit of our sample selection approach, which is based on an effective region of RFs and allows more tiny objects to participate in training the eye illness detection module. Existing approaches such as DL-CAEF, CNNs, and ODALAs achieve 93 percent, 95 percent, and 99 percent accuracy, respectively. Existing approaches cannot yield good detection findings when blood vessels are thickly scattered. In comparison to these three approaches, the suggested method is capable of successfully overcoming blood vessel interference and obtaining the best eye disease detection result.

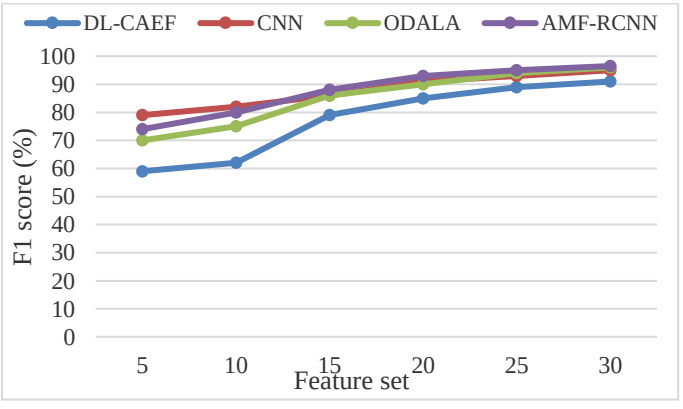

Fig.7. F1-score performance of methods on different subsets of feature

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From *fig.7*, it indicates that the F1-sore of proposed and existing models for the amount of features in given databases. While maximizing the amount of features, the f-measure is also maximized. For e.g., the AMF-RCNN provides an f-measure of 96.5% compared to the all other models such as DL-CAEF, CNNs and ODALAs. The results of existing methods such as DL-CAEF, CNNs and ODALAs are 91%, 95% and 96% respectively. The DL-CAEF approach clearly fails to capture the limits of the eye illness adequately, resulting in a fitted ellipse that deviates significantly from the ground truth. The CNNs approach is sensitive to weak edges and produces the lowest results for detecting eye diseases. The ODALAs approach detects the brightest section of the eye illness zone, resulting in incorrect detection findings. Instead, the suggested technique, which takes use of the deep features recovered from the pre-trained AFRPN, is a smaller amount influenced by blurred eye disease borders and poor contrast and achieves the desired eye illness identification results.

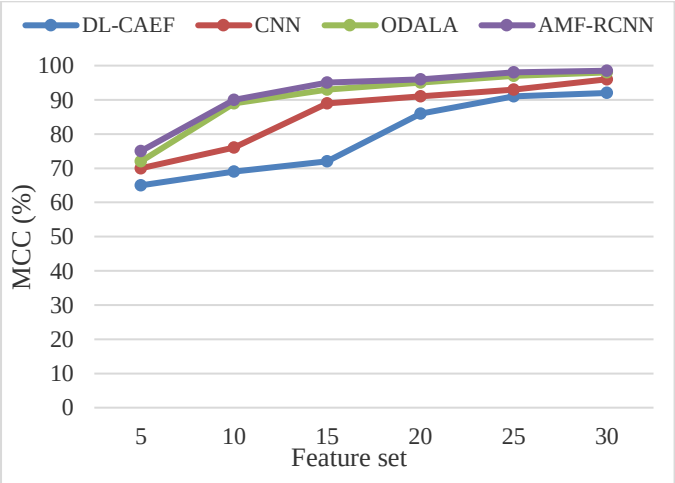

Fig.8. MCC performance of methods on different subsets of feature

From *fig.8*, it indicates the MCC of proposed and existing models for the amount of features in a given database. As increasing the amount of features, the MCC is also maximized. For e.g., the AMF-RCNN attains a recall of 98.5% compared to the DL-CAEF, CNNs and ODALAs. The performance of existing approaches is as follows, based on the examination of experimental findings. The available approaches are substantially hampered by the interference of lesions. When the intensities of the eye illness region and lesions are near, the system cannot identify them accurately. In comparison to the preceding techniques, the suggested method may resist the impact of lesion interference to an assured amount and take out the eye disease borders more precisely using an efficient clustering method.

From *fig.9*, it indicates the recall of proposed and existing models for the amount of features in a given database. As increasing the amount of features, the recall is also maximized.

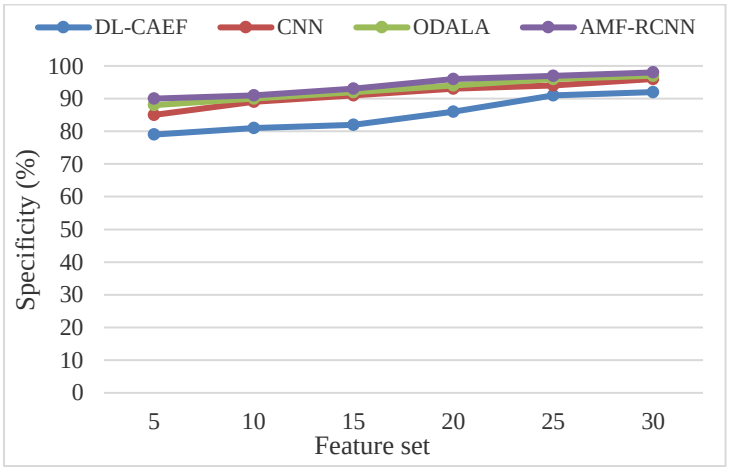

Fig.9. Specificity performance of methods on different subsets of feature

For e.g., the AMF-RCNN attains a recall of 98% compared to the DL-CAEF, CNNs and ODALAs. By observing the results, the proposed method has attain alike results and is superior than the other methods, because of effective EFFCM and adaptive OTSU threshold with ALO segmentation method could achieve prior eye disease detection.

5. CONCLUSION AND FUTURE WORK

In this work, we describe a novel unsupervised learning strategy for detecting eye diseases in retinal fundus pictures using AMF-RCNN and EFFCM-AOO segmentation. In addition, pay attention to the precise extraction of the illness region in the presence of vascular structures, lesion regions, and intensity in homogeneity. The EFFCM-AOO-based segmentation detection approach is used first to pre localize the eye disease region. On this premise, the AMF-RCNN model is developed to extract the correct optic disc area by including the deep features generated from pre-trained AFRPNs into the original framework. The experimental findings and quantitative analysis show that the suggested technique is capable of precisely detecting eye disease areas and outperforms several current methods. AMF-RCNNs have shown promising results in the identification of eye diseases, but the complexity of regulating is unknown and regarded a black box. In the future, for example, research should focus on fine-tuning the restrictions of the existing AMF-RCNN approach in order to improve classification efficiency. As a result, determining the efficient model and ideal values for the number of hidden layers and modules in various levels remains difficult.

Conflict Of Interest: The Author(s) declare no conflict of interests.

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