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Enrichment of Retinal Fundus Images using EN-CLAHE and Auto-CLAHE Methods

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Abstract

Retinal imaging techniques are commonly used to diagnose various eye diseases. These methods, such as fundus photography, play a crucial role in detecting the impact of lifestyle conditions like diabetes and hypertension for retina. They helps to identify retinal complications at an early stage, such as micro aneurysms, exudates, and haemorrhages, which are often difficult to detect through regular clinical evaluation. By detecting these issues early on, the prevalence of retinal diseases worldwide can be reduced. One commonly used method to enhance retinal images is called Contrast Limited Adaptive Histogram Equalization (CLAHE). However, the effectiveness of this approach depends on selecting the right clip limit (CL) and sub-images (N). These choices can present challenges and limit the outcomes of the conventional approach. To address these limitations, updated versions of CLAHE have been introduced, known as Enhanced-CLAHE (EN-CLAHE) and Automated-CLAHE (Auto-CLAHE). These techniques have shown significant improvement in enhancing the contrast between different retinal landmarks. By employing a newly developed approach, clinicians can now perform screenings for conditions like diabetic retinopathy, glaucoma, and hsypertensive retinopathy in hospitals and remote locations. This approach enables direct examination of delicate details present in retinal images. Researchers have explored various image-enhancing methods and compared their results using quality evaluation tools like Peak Signal-to-Noise Ratio (PSNR). These evaluations help assess the extent of contrast enhancement and the overall richness of the image.

Keywords*: CLAHE; Enhanced CLAHE; Automated CLAHE; Glaucoma; Fundus Photography; Retinal fundus Images**

1.Introduction

The use of automated disease analysis in eye screening devices has made it feasible to provide prompt therapy to individuals with retinopathies like glaucoma and hypertension. Non-invasive fundus photography is now a need for automated retinopathy identification, which has improved convenience for ophthalmologists and retina care specialists. Ophthalmologists may send images associated with Glaucomatic or hypertensive retinopathy syndromes for further disease investigation [1,2].

The burden on ophthalmology doctors would be reduced globally if abnormalities that are typically not visible by the clinical investigation were discovered early. The optic disc, blood vessels, macula, and lesions including haemorrhages etc. may all be recognized and separated using image processing and deep learning algorithms. The quantitative examination of these anomalies will aid in the more accurate identification of retinal diseases [3].

On a human retina, it has been possible to spot numerous lesions that may have been brought on by diabetes, a chronic illness. From moderate diabetic issues to severe Proliferative Diabetic Retinopathy (PDR), the illness progresses [4]. Microaneurysms, which are microscopic capillary dilations or minor haemorrhages that appear as little red spots, are often the typical early indicators. When lipids build and cause exudates from the retinal capillaries of patients with severe illness, these lesions appear in photographs as brilliant white or yellow spots. The existence of macular oedema is indicated if the exudates occur around the macula [5]. Most of the research has focused on the classification and segmentation of retinal lesions, but little emphasis has been paid to pre-processing these pictures to highlight the lesions under evaluation. Appropriate strategies for their amplification are crucial since the lesions are deep in the retina [6].

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1.1. Need of Glaucoma Detection Using Ml

Early detection of glaucoma is made possible by machine learning algorithms, which allow prompt intervention & treatment to avoid permanent visual loss. These methods—pattern recognition algorithms in particular—are excellent at identifying minute structural alterations in retinal pictures and optic nerve heads, which improves diagnostic precision. It makes it easier to analyse massive retinal imaging collections effectively, which enables systematic glaucoma screening and diagnosis in a variety of patient groups. With ML, glaucoma diagnosis may be made objectively and consistently, minimising subjectivity in evaluations and guaranteeing consistency across various healthcare environments. By automating the first screening procedure, ML-driven glaucoma diagnosis maximises healthcare resources and frees up ophthalmologists to concentrate on complicated patient care and confirmed cases. Since machine learning algorithms can grow and adapt to ever-larger amounts of medical imaging info, they are a good fit for broad programmes to screen for glaucoma in a variety of healthcare settings.

1.2. Limitations of Glaucoma with ML

ML models for Glaucoma may suffer data imbalance difficulties, where the amount of healthy data greatly outnumbers Glaucomatous samples, thereby leading to biased outcomes. Because ML algorithms might perform differently across models, it's critical to test findings on a variety of datasets and take model-specific quirks into consideration. Glaucoma datasets lack uniform imaging techniques and data formats, which might make machine learning (ML) models less consistent and less generalizable amongst various healthcare facilities. It is important to train machine learning algorithms on representative datasets since they could not generalise effectively across different ethnic and demographic groupings. Some datasets may not have enough longitudinal data available, which might make it difficult for machine learning models to accurately depict how glaucoma progresses over time. It may be difficult to explain how and why a certain diagnosis was made since ML models, especially deep learning architectures, sometimes lack transparency in their decision-making.

1.3. Need of Glaucoma Detection Using CNN

In order to avoid permanent vision loss, CNNs are essential for the early identification of glaucoma and for prompt intervention and therapy. It provides the capacity to automate the screening procedure, making it possible to analyse massive retinal image collections effectively and to support mass screening programmes for early detection. CNNs' scalability makes them ideal for managing the growing amount of medical imaging data, offering a dependable and quick fix for glaucoma screening across a range of demographics. It offers impartial and standardised evaluations, reducing subjectivity in the diagnostic procedure and guaranteeing trustworthy outcomes in many medical contexts. By automating the preliminary screening, this maximises the use of healthcare resources by freeing up ophthalmologists to concentrate on verified cases and provide more effective patient treatment. CNN-based glaucoma detection facilitates telemedicine programmes by enabling remote screening & early risk identification, especially in underprivileged areas

2 . Related Work

The two types of image-enhancing techniques are time domain and frequency domain techniques. The pre-processing, or enhancing of contrast in a picture, is what determines the final processed outcome. For this, high-pass filters with edge detection techniques like the Laplacian of Gaussian are typically used. Edges are often discovered using a few simple techniques, such as Sobel, Prewitt, or the Laplacian of Gaussian operators [8].

Noise is present in real-time medical applications, noise enhancement is a concern with these filters since noise and edges are both high-frequency components of a picture. In comparison to HPF masks like Prewitt and Sobel, morphological operations that deal with the shape and size of objects appear to be more sophisticated. For example, morphological opening and closing transform work well to clear away noise from both inside and outside of the object, respectively [9–11], and choosing the right masks, like discs or lines, based on the shape of the object helps to enhance the chosen object of interest.

Wavelet transform is another technique for enhancing photographs from the medical area. Here, a wavelet is utilized to separate a picture into its high-frequency components. High-frequency parts of the spectrum are subjected to soft thresholding to reduce noise. Later, the inverse wavelet transform is employed to create an upgraded version of a picture [12].

Gamma correction is one technique for enhancing medical images [13]. Here, local gamma optimization is achieved by reducing the homogeneity with the co-occurrence matrix with the input picture. By using this technique, the range of pixel values is increased, and the image quality is enhanced.

Adaptive Histogram Equalization techniques with variable contrast limits are explored in [14]. The limitations imposed by CL and N are lessened by these approaches, which adjust the clip limit and number of sub-images dependent on the picture.

The bi and multi-histogram method was suggested by [15]. In contrast to a typical display, which is ruined by the bi-histogram approach, an image's brightness is kept by raising the contrast. The Multi Histogram Equalization technique, on the other hand, keeps the display as-is but is unable to keep the contrast or intensity.

For irregular and low-contrast pictures, [16] proposed an approach based on fuzzy logic. This technique separates the bright and dark areas of the picture. This approach outperforms more established strategies like the power law transform. In comparison to previous approaches, this process takes less time and produces brighter images.

To increase the contrast of color photographs, a quick solution using a histogram and fuzzy basis was presented in [17]. Only images with low contrast provide good results with this technique. From a given RGB image, the HSV image is generated, and only the V factor is improved using the K and M parameters. Comparing the outcomes of several Histogram equalization methods with the fuzzy constructed technique.

Anshul et al [22] has developed a couple of technologies CNN and MobileNetV2 for the detection of eye disease before attacking. The objective of the OHTS is to prevent or postpone visual field loss in people with increased IOP, especially in those who are moderately at risk of glaucoma. It is a forward-looking, multicenter study. The dataset (phases 1 & 2) covers around 16 years, which makes it possible to create algorithms that predict glaucoma before the condition manifests. Glaucoma labeling requirements include the reading center needing two repeated aberrant visual fields, which are then reviewed by a separate endpoint committee. Because of its effectiveness in situations with limited training data and computing resources, MobileNetV2, a highly efficient CNN, is selected. The ImageNet dataset's pre-trained weights are used to initialize MobileNetV2 via the use of transfer learning. With the use of OHTS fundus photos, models are refined. Class imbalance is addressed by balanced data sampling and data augmentation using methods including random turns, rotations, and color, saturation, and contrast alterations. Regions in fundus photos that affect the model's categorization are found using gradient-weighted class activation maps.

Mamta Juneja et al [23] has implemented a CNN, and G-Net methodology for the identification of glaucoma. There are 101 photos in the DRISHTI-GS collection. Ground facts are given for both sets for the optic disc, optical cup, & notching. Images of patients with glaucoma or normal eyesight have been obtained from Aravind Eye Hospital in Madurai, India. The optic disc was the main focus of the cropped original fundus photos. The optic disc and optic cup were precisely segmented using a modified G-net. Using all RGB channel for the cup and the red signal for the disc, two different CNNs were trained for the segmentation of the disc. There are 31 layers in total for both segmentation models. While the second model divides the cup using photos cropped in accordance with the form of the segmented disc, the first model analyses cropped retinal fundus images. By calculating the ratio between the cup and disc regions in the segmented masks, CDR is achieved. The suggested method's accuracy depends on a precise CDR estimation, which is essential for glaucoma identification. The accuracy of optic disc & cup delineation is improved by the use of models for segmentation such as G-net.

Yongli Xu et al [24] has proposed a HDLS methodology for the identification of glaucoma. The Beijing Tongren Hospital IRB approved the research, which followed the Declaration of Helsinki. Pre-diagnostic, picture division, and final diagnosis are the three components that make up the HDLS. For pre-diagnosis and picture segmentation, Inception-v3 & U-shaped convol DNN were used, respectively. Based on the segmentation of OD and OC, features such as MCDR and ISNT score were derived. The anatomy of the neuroretinal rim was mirrored in the ISNT score. SVM was used to create a two-dimensional classification line, and a decision tree structure was used to determine the final diagnosis, which included the existence of RNFLD. For the first global diagnostic, the HDLS used a PDCN, concentrating on the whole fundus picture. Annotated locations were used to train segmented network for OD, OC, & RNFLD. The diagnostic procedure was concluded using SVM & a decision tree structure. A threshold of 0.8 was established for the classification network's softmax output in order to handle pre-diagnosis aberrations. With validation datasets, this modification attempted to strike a compromise between both specificity and sensitivity in the final diagnosis of the patient.

Fatima Ghani et al [25] has focused on CNN, InceptionV3 and VGG16 methodologies for the identification of glaucoma. A collection of 508 fundus photos from 25 different classes is gathered from the Joint Shantou International Eye Centre. The dataset has been tagged and split into testing and training sets. A CNN ignores text and is built with numerous layers to interpret pictures. The CNN model is tested after development to make sure it satisfies criteria. The CNN ignores text in favour of producing outcome in the shape of a picture using GPU processing. Resizing is the process of changing the pixel count by enlarging and contracting the pixels. An approach used in Inception-V3 & Vgg-16 to increase the size of the training dataset is data augmentation. For the purpose of augmenting picture data, Keras is used for operations such as covering, cutting, & horizontal flipping. For image identification, the Inception-V3 model consists of a CNN-based feature extraction section and a SoftMax & FC layers-based classification section. The model is modified for glaucoma detection and used for object recognition in general.

Ajitha S et al [26] has developed Softmax, and CNN methodologies for the identification of glaucoma. The photos gathered at Little Flower Hospital and open data sets (HRF, Origa, and Drishti) are the sources of the dataset. Ten convolutional layers and three fully linked layers make up the CNN model. By stabilizing input pictures, batch normalization speeds up the learning process. Images input are down sampled using max pooling, and overfitting is avoided via dropout layers. Class probabilities are assessed by the final fully linked layers with SoftMax activation. Nonlinearity is introduced by applying ReLU layers to convolution and fully linked layers. Spatial dimensions are reduced via max pooling using a 3 * 3 filter & two layers' stride lengths. The Max pooling layer and RELU layer are used to train the model. In addition to introducing nonlinearity, the RELU layer guarantees convergence learning. Feeding a dataset is part of the training process to determine if a picture is part of the glaucomatous. In order to forecast whether a picture corresponds to the glaucomatous or healthy class, a dataset is fed into the training process. Using a 0.001 default learning rate and a batch size of 32, the model is trained utilising the Adam Optimizer. The loss function used in the error computation is categorical cross-entropy.

Ramgopal Kashyap et al [27] has implemented a U-Net, DenseNet-201 with DCNN methodologies for the identification of glaucoma. 650 retinal fundus photos from the SiMES make up the glaucoma dataset. For feature extraction, a pre-trained model called Densenet-201 is used. The model performs well on a number of datasets, including CIFAR-100 and ImageNet. An important part of glaucoma detection is optical cup segmentation, which is accomplished using U-Net architecture. Preprocessing, creating ground-truth masks, and applying the U-Net architecture to the segmentation process are all part of optical cup segmentation. Disc double & cup double equations are used to produce the masks. The DenseNet-201 design is shown with direct connections between layers to show how connected it is. Using feature maps, the network adjusts to shifting environments. DenseNet-201 uses transfer learning, which makes use of information from big datasets such as ImageNet. TL speeds up model training and decreases the need for large amounts of data. In order to determine the final classification, sigmoid activation is used to make a binary choice for glaucoma risk evaluation. The neuron's output is represented by value between 0 & 1 that are produced by the sigmoid function.

Lucas Pascal et al [28] has proposed a MTL-IO methodology for the identification of glaucoma. The

dataset REFUGE was used. adoption of a VGG-16 structured U-Net architecture for MTL. The segmentation, regression, and classification tasks are covered by this architecture. Following the common decoder, a convolutional layer yields the OD & OC segmentation masks. By using ground truth coordinates to create a map, fovea localization is approached as a segmentation job. After training the network to suit these maps, the saliency map's centre of mass is anticipated to be located at the fovea coordinates. The process of detecting glaucoma consists of two stages: first, a LR classification prediction that incorporates the visual class distribution from segmentation tasks, and then an FC classifier prediction. When classifying cases of glaucoma, focal loss is used to address the disparity between positive & negative samples. Introduction of a separate gradient descent technique for MTL that involves alternating steps on several task-specific goals. The employment of unique optimizers for every job is emphasized by designating the whole pipeline as MTL-IO. This method helps to keep tasks from interfering with one another while optimizing.
Syna Sreng et al [29] has focused on Encoder with DCNN, SVM, TL, Ensemble models for the identification of glaucoma. The system consists of two stages: the categorization of normal & glaucoma utilizing 3 different forms of deep CNNs, and the OD segmentation using DeepLabv3+. DeepLabv3+ is used for an encoder & a decoder in OD segmentation. The decoder retrieves object boundaries while the encoder extracts features using four simultaneous atrous convolutions. Three techniques for glaucoma prediction using deep CNNs. Eleven pre-trained CNNs are used in transfer learning to replace the final fully connected layer in the categorization of glaucoma. Pre-trained models customized for glaucoma prediction using ImageNet. optimization of cross-entropy loss for every iteration. Deeply activated features are extracted by using CNNs that have been trained as feature descriptors. While deeper layers collect bigger, more complex data, early convolutional layers catch little, low-level characteristics. Retrieving deep active features by flattening the last level before categorization and the completely linked layer. SVM classifier is used to identify glaucoma. constructing two ensemble classifiers by fusing the individual learners' predictions from Methods P1 and P2. The estimated probabilities of each individual classifier are averaged to provide predictions from ensemble classifiers. Table X discusses the overall analysis of the existing approaches.

Table X: Comparative Analysis on Traditional Approaches

Author	**Algorithm**	**Merits**	**Demerits**	**Accuracy**
Anshul Thakur et al	CNN, MobileNetV2	Hybrid model has high efficiency.	The datasets was not real.	
Mamta Juneja et al	CNN, G-Net	Because of multiple layers the images are easily classified.	Compared to OD OC has less performances.	95.8%
Yongli Xu et al	HDLS	This model was built in three modes for easy and early detection.	Several methods are used where it may be difficult while building.	95%
Fatima Ghani et al	CNN, Inception V3 and VGG-16	Even the layers are less the prediction was appropriate.	The dataset contains less data.	90.1%
Ajitha S et al	Softmax, CNN	Several layers are used where the data is easily detected.	Combining with DL. ML has high performances.	95.6%
Ramgopal Kashyap et al	U-Net, DenseNet-201 with DCNN	For every layer high technologies are utilized.	The testing has less accuracy.	98.8%
Lucas Pascal et al	MTL-IO	Time complexity is less.	The images should have high quality.	97.0%
Syna Sreng et al	Encoder with DCNN, SVM, TL, Ensemble models	The models are efficient while creating ensemble models.	Difficult for creating this method.	95.5%

3.Methodology

3.1 Introduction

High-Resolution Fundus (HRF)- The dataset was made available by a collaborative research team to do a comparative study on automatic segmentation methods on retinal fundus images. The images were taken using a Canon EOS 20D camera at a resolution of 3504x2336. The online-accessible collection consists of 45 images in total, 15 of each kind representing the normal human retina, diabetic retina, and glaucoma-affected retina. For each picture in the collection, the masks, together with the FOV and segmented vessel tree, are made accessible as a ground truth standard. The group of professionals in the analysis of retinal pictures and trained specialists from ophthalmology clinics provide the gold standards for segmentation [18].

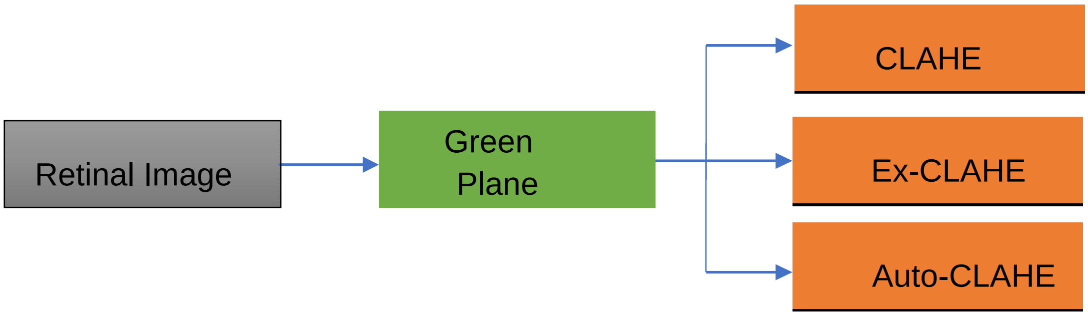

Fig1: Pre-processing flow chart

3.2 Methodology

In the pre-processing procedure depicted in Figure 1, the effects of three enhancement approaches—conventional CLAHE, AC-CLAHE, and FA-CLAHE [14]—on retinal fundus pictures are investigated. Based on the results, a comparison of the techniques was made.

3.3 Contrast Limited Adaptive Histogram Equalization

CLAHE is an adaptation of the classical HE technique that redistributes pixel intensities to enhance the apparent amount of details in photographs. It makes sure that the enhancement is tailored for specific characteristics and structures by adjusting its contrast enhancement procedure to the properties of various areas inside a picture. Each of the tiny tiles that make up the picture has its own individual application of the histogram equalization. This lessens the likelihood that noise in areas with poor contrast will be over-amplification. by adding a contrast limiting option to stop noise from being amplified in areas with high contrast. By doing this, it is ensured that the augmentation is under control and doesn't produce inflated or unrealistic details. CLAHE often includes overlapping between adjoining tiles to prevent erroneous borders between them. This facilitates a more seamless shift in contrast improvement across various places. For low-contrast areas, it usually uses a non-linear adjustment to map the pixel intensities' cumulative distribution function, making the augmentation more noticeable.

Increased contrast between the image's foreground and background is an advantage of CLAHE. It prevents the issue of oversaturation in related locations and reduces the difficulty of noise and contrast intensification. The number of sub-images and clip limit play a major role in the CLAHE method's outcomes. The input photos are split up into a variety of smaller images, or "tiles," and the contrast transform function is generated for each tile with the contrast factor "Clip Limit." The Rayleigh, Exponential, or Uniform distributions are used to create the contrast transform function. The CLAHE is utilized according to [21] and we employed an exponential distribution in this case to achieve superior results.

Contrast Limited Adaptive Histogram Equalization (CLAHE) is used to equalize images. In order to overcome the problem of contrast over-amplification, CLAHE is an adaption of Adaptive Histogram Equalization (AHE). CLAHE operates with separate regions known as tiles rather than the entire image. Bilinear interpolation is used to combine the neighbouring tiles in order to remove the fake borders. This technique can be applied to improve contrast in photos.

We may also use CLAHE on colour photos; typically, it is performed on the luminance channel, and the outcomes are considerably better for an HSVrather than for a BGR image by adjusting all the channels.

3.4. Enhanced Contrast Limited Adaptive Histogram Equalization

A more flexible and adaptable enhancement is possible with enhanced CLAHE, which dynamically modifies the contrast limiting value depending on the local properties of picture areas. In order to ensure that the enhancement method is responsive to changes in local gradient magnitude, it could combine data on gradients to better capture picture structures. Multi-scale processing, in which the method is performed at many scales to enable the augmentation of characteristics at various degrees of detail, is often used in enhanced CLAHE. This version could include controls for boosting certain aspects of the image—like edges or textures—selectively so as to prevent over-amplification of undesirable details. Post-processing measures may be used in improved CLAHE approaches to further improve the appearance of the enhanced picture and minimize artefacts. Depending on the features of the local picture content, the process may dynamically modify the size that it processes tiles in order to optimize the trade-off between improving detail and reducing noise.

The choice of the clip limit value and the number of sub-images is particularly important in the heuristic CLAHE strategy to control the best possible picture quality. For CLAHE, the value of the clip limit in CLAHE is determined by the size of bins in the local histogram of a sub-image. The number of tiles (N X N sub-images) in the recommended Auto Clipped CLAHE technique should be determined by user based on the objects of interest. The maximum height of the bin 'n' local histogram for the selected tile, is used to determine the clip limit value. All the pixels in the sub-image that are over the clip limit are reallocated evenly [14]. The algorithmic definition of the EN-CLAHE is as follows:

Algorithm1: EN-CLAHE

Step 1. Import retinal fundus image.

Step2. Green plane extraction from the image.

Step 3. Create N × N subsections from the supplied image.

Step 4. Complete the instructions for each subsection.

- *a) Find each tile's histogram and the greatest intensity value for each tile.*
- *b) Determine the Clip Limit (CL) value using the half-interval search method.*
- *c) Equalize the histogram by evenly distributing the pixels with values greater than CL throughout all the histogram bins of a tile.*

Step 5. To acquire the best image processing quality, map each pixel in the provided picture to the weighted sum of four neighbours, two neighbours, or the pixel itself depending on its placement as an Internal Region, Border Region, or Corner Region.

3.5. Automated Contrast Limited Adaptive Histogram Equalization

Automatic CLAHE uses algorithms to dynamically modify contrast limiting settings according to the statistical properties of the input picture, therefore it may be used to a variety of material. The programme is able to determine the appropriate level of enhancement in various places by using automated image analysis techniques to evaluate local contrast fluctuations. In order to avoid over-amplification of noise and other artefacts, the algorithm may use feature-sensitive techniques to selectively improve certain picture structures. In order to optimize the trade-off between computational efficiency and local contrast enhancement, automated CLAHE cleverly arranges and sizes processing tiles according to the content. In some implementations, the method is trained on a variety of datasets using machine learning techniques, which enables it to generalize and adjust to a broad range of pictures and events. Real-time processing might be included in CLAHE automation, allowing for quick and spontaneous parameter adjustments for changing visual surroundings.

The approach suggested in EN-CLAHE still depends on the user's selection of the number of tiles or sub-images, or "n," and is still arbitrary. While the constant value of "n" might not be appropriate for all photos, even those from the same database, or for various image kinds captured using various sensors. We have suggested a fully automated CLAHE considering the EN-CLAHE method's flaw. Based on the input picture's overall and sectional entropy values, the approach separates the input image into sub-images. Here, "n" is changed from 2 to 12, and the value of "n" will be chosen to divide the input picture into sub-images for which the associated entropy will be at its highest. Here, the number of tiles and clip limit is automatically selected.

Algorithm 2: Auto-CLAHE
STEPS:
Step 1. Enter an image.
Step 2. Green plane extraction from the image.
Step 3. Obtain the entropy values as described by Equation 1 from the smallest to the largest value of "N" and store them in an array as "entropy[n]".
Step 4. Select the N value that matches the highest possible entropy[n] value.
Step 5. The total number of photos equals N x N.
Step 6. Repetition of steps 3 through 5 from the EN-CLAHE method described in this paper's section "D".

3.6. Integration of Automated Contrast Limited Adaptive Histogram Equalization with CNN

The CNN receives the input pictures after they have undergone automated CLAHE pre-processing, which dynamically modifies contrast and highlights local characteristics. Because CLAHE is automated, contrast is adaptively changed, which helps CNNs concentrate on pertinent information and lessens the effect of varying lighting conditions in a variety of datasets. By highlighting the important aspects in photos, CLAHE improves feature localization. This gives the CNN better input representations, which enable more precise feature extraction. CNN robustness may be improved in particular by using CLAHE's adaptive nature to lessen the influence of noise and increase the proportion of signal to noise in the pictures. The integration enables automatic adaptation to various imaging domains, guaranteeing that the CNN is capable of managing contrast and illumination fluctuations over a wide range of datasets. Adaptive contrast enhancement improves the CNN's ability to generalize across various pictures, which improves model performance on tasks like object detection and segmentation.

4. Results

The dataset HRF (High-Resolution Fundus) is used to test the proposed algorithms. Here, the results are shown on photos from a single dataset, HRF, to help with comprehension. Figures 2(a-d) display the outcomes of the healthy fundus under HSV and BGR-plane CLAHE algorithms while figures 3(a-d) display the outcomes of glaucomatous fundus under HSV and BGR-image CLAHE algorithm. Figures (a, c) are used for the clip limit value=2.0 while figures (b, d) are used for the clip limit=0.8. The resultant images are the findings from a single original healthy fundus(2a-2d) and a single original glaucomatous fundus(3a-3d).

CLIP LIMIT= 2.0; NUMBER OF TILES=8

CLIP LIMIT= 0.8; NUMBER OF TILES=8

HSV

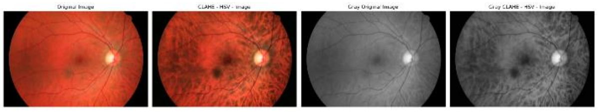

FIG 2a:HEALTHY EYES

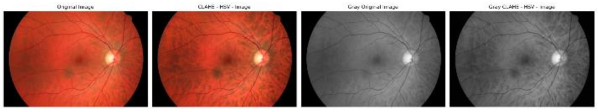

FIG 2b: HEALTHY EYES

FIG 3a: GLAUCOMATOUS EYES

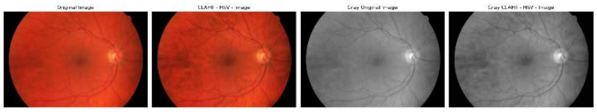

FIG 3b: GLAUCOMATOUS EYES

BGR

FIG 2c: HEALTHY EYES

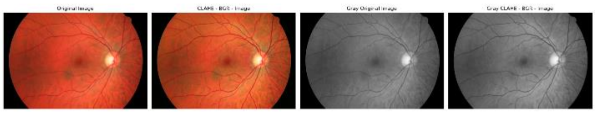

FIG 2d: HEALTHY EYES

FIG 3c: GLAUCOMATOUS EYES

FIG 3d: GLAUCOMATOUS EYES

Figures 2(a-d); Figures 3(a-d)

EN-CLAHE BASED OBSERVATIONS:-

Here, the number of tiles used are 8. The figure (4a) displays the outcome of the healthy fundus under the proposed algorithm of EN-CLAHE. The figure (4b) displays the outcome of the glaucomatous fundus under the proposed algorithm of EN-CLAHE.

FIG: 4a

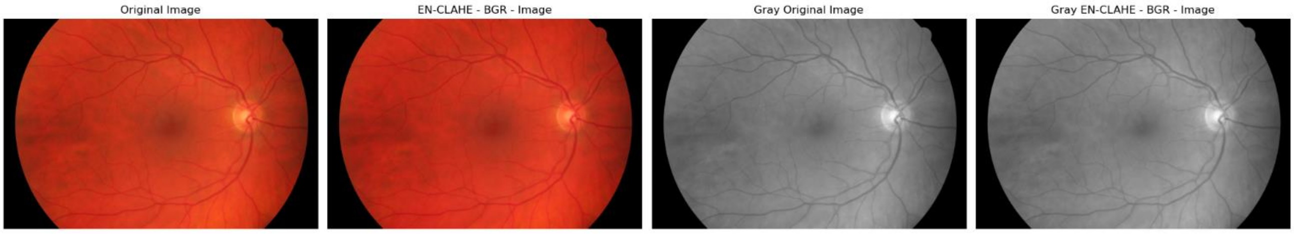

FIG: 4b

AUTO-CLAHE BASED OBSERVATIONS:-

The figure (5a) displays the outcome of the healthy fundus under the proposed algorithm of AUTO-CLAHE. The figure (5b) displays the outcome of the glaucomatous fundus under the proposed algorithm of AUTO-CLAHE.

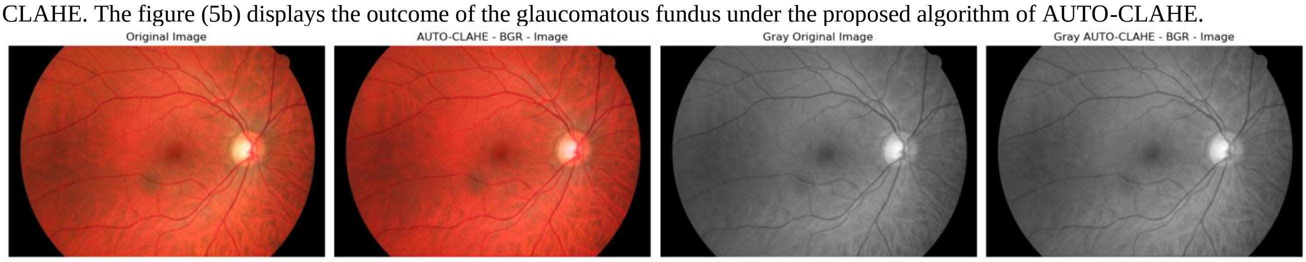

FIG: 5a

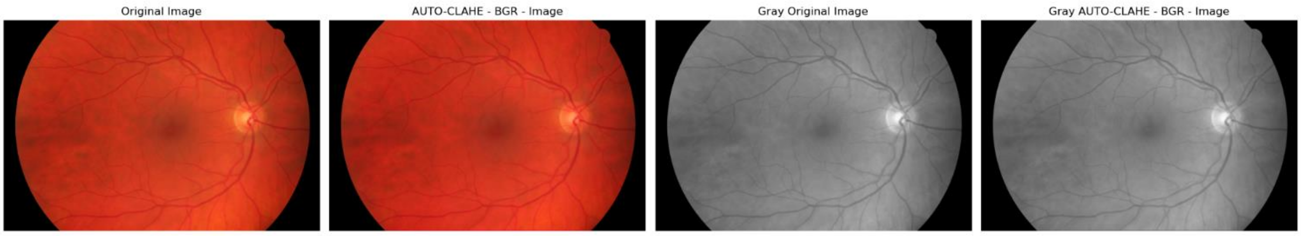

FIG: 5b

5. Findings and Analysis

On a PC running PYTHON 3.9 and equipped with an Intel Core i5 CPU running at 2.40GHz and 8GB of RAM, experiments are conducted.

The CLAHE algorithm is implemented in two steps: first, the number of tiles is fixed at 8, and the clip limit is changed from 0.8 to 2.0 because higher clip limit values result in saturation in terms of enhancement, as well as undesirable effects like noise and uneven lighting being added to the image. Similar to the first part, the second portion's clip restriction is maintained but the number of tiles varies. It has been shown that even for photos in the same database, a constant clip limit and number of tiles value do not work well.

The CLAHE findings show that choosing the right clip limit value was essential to achieving the best potential improvement. The answer to this issue is provided by EN-CLAHE, which selects the clip limit adaptively depending on the histogram of a sub image. When testing with the EN-CLAHE method, the number of tiles (n) was equal. The results were seen on both high-contrast and low-contrast photos. Selecting 'n' too high can often add noise and exacerbate the issue of uneven illuminations, while selecting 'n' too low does not improve the quality of all objects in a picture. A method that chooses "n" and "clip limit" depending on the kind and contents of a picture is therefore necessary.

By varying the value of "n" from 2 to 12, we have looked for the input image's highest entropy (randomness) and have picked the value of "n" for which the associated entropy is largest. Once the number of sub-images has been established, the EN-CLAHE technique is used to find the clip limit value for each sub image. Although the approach strives for adaptable 'n' and 'L' values, the issue of non-uniform lighting still persists for many of the input photos. On the aforementioned equipment, the Auto-CLAHE process requires 1 to 2 minutes.

In the below table, Img1 and Img2 denote healthy fundus while Img3 and Img4 denote glaucomatous fundus. Peak Signal-to-Noise Ratio (PSNR) comparison between suggested art and literary strategies. A high value denotes excellent image quality.

Methods	Img1	Img2	Img3	Img4
CLAHE under HSV	30.450	30.494	32.100	32.332
CLAHE under BGR	33.446	33.421	33.337	33.381
EN-CLAHE	35.595	35.382	37.491	37.419
Auto-CLAHE	35.588	35.375	37.480	37.407

6. Conclusion

Traditional CLAHE techniques produce results that depends number of sub-images (N) and also clipping limit (CL) that we select initially. A higher number of tiles unnecessarily adds to the computational load, while a smaller number of tiles-subsections does not raise the image quality to the necessary level. The another issue with this type of approach is selection of the clipping limit; a higher clip limit value enhances noise, whereas a single clip limit value applied to the whole image yields subpar results. Because EN-CLAHE selects the clip limit based on the sub picture intensities, it overcomes the issue of noise amplification and, as a result, performs better than CLAHE. Due to the fixed amount of sub images used in EN-CLAHE, it nevertheless remains subjective. The number of tiles and clip limits are automatically selected in Auto-CLAHE as it provides more results.

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