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Classification of Diabetic Retinopathy Images through Deep Learning Models - Color Channel Approach: A Review

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Abstract

On a global scale diabetic retinopathy, or DR, is the most common cause of vision loss. Blindness can be prevented with prompt treatment and early identification with retinal screening. Automated analysis of fundus imagery is growing prominently as a means of increasing screening efficiency, thanks to the development of deep learning. This work focuses on deep learning methods for automatic DR severity grading using color channel information. First, we give some basic information on the etiology and color features of DR lesions. Next, a novel support for deep learning technique that use unprocessed color photos as input for comprehensive feature learning. A review is mentioned on color space encodings, data augmentation methods. A summary of the evaluation parameters and public databases that were utilized to benchmark DR techniques are provided. The objective of how color channel information in retinal pictures can be efficiently utilized by deep learning models for automated DR screening has been discussed with statistical support.

A. Introduction

Diabetes's quick evolution is one of the biggest problems facing modern medicine [1][2][3]The disease's patient population is increasing at an alarming rate.The World Health Organization predicts a rise in diabetes population from 130 million to 350 million over the next 25 years, with only 50% of patients aware. Medical complications include retinopathy, heart disease, and renal issues. Diabetes ranks as the fifth most deadly illness in the US, with no treatment available. Diabetes is a dreadful ailment that, particularly in western countries, affects many facets of life. Heart failures that occur during hospital stays and as a result of inadequate differentiation between symptom intensities represent a significant portion of the affected people. The goal of a competent diagnosis is to avoid the unpredictable and recurrent admissions. Beyond clinical and demographic variables, the models are influenced by a plethora of patient-specific characteristics [4][5]. Technically speaking, interviewing patients about their health state, adherences, and psychosocial traits is not part of the plan for developing predictive models, and not all experts agree on how important these criteria are. Epidemiological survey data further demonstrate that diabetes is a hereditary and ethnic condition. Diabetic diseases are caused by extremely unfavorable food choices and lifestyle alterations. Diabetes is more common in urban populations than in rural ones [6][7][8].

Diabetes mellitus is a prevalent medical condition that can lead to irreversible health complications, including diabetic retinopathy, neuropathy, and renal disease [9][10][11]. It is particularly common in urban India, with the number of patients in these countries expected to reach 100 million by 2030. Retinopathy of prematurity (RoP) is the main cause of blindness in infants, and research is needed to raise awareness and prevent the risk in infants [12][13]. In India, the National Survey on Blindness (NSB) found cataract as the principal cause of visual impairments, with senile cataract and glaucoma being the main causes [14][15][16].

It has been demonstrated that diabetic people can avoid blindness and visual loss by receiving prompt diagnosis and treatment. A large percentage of fundi that appear normal are predicted in patients who have recently been diagnosed with diabetes; only 5–20% may show funduscopically apparent diabetic retinopathy [17][18][19]. It has been demonstrated that digital photography of the retina, reviewed by knowledgeable readers, is sensitive and specific in identifying the initial symptoms of retinopathy. Lesions associated with early diabetic retinopathy can be categorized as either bright or red. Examples of brilliant lesions include lipid or lipoprotein exudates, superficial retinal infarcts (cotton-wool spots), haemorrhages, and microaneurysms.

The evaluation of retinal fundus pictures for Diabetic Retinopathy (DR) screenings is a task for ophthalmologists, and as the number of people with diabetes rises [20][21][22], providing comprehensive eye care to all has become increasingly challenging [23][24][25]. However, as the number of diabetes patients rises, screening for DR must be done on a regular basis for these individuals. This puts a great deal of duty on the specialists and delays the diagnosis and treatment of DR. The need for automated DR screening systems and processes was spurred by the widening gap [26][27]. As a result of technological advancements,

automated grading has emerged as a viable option for DR screening. It offers several benefits, such as increased efficiency, reproducibility, and scalability, as accurate evaluations of retinal images are required to supplement the already extensive and laborious manual screening process, which can be prone to errors [28][29].

Thus, an automated approach for evaluating psychological distress (DR) is required for the purpose to examine the patterns underlying traits of various degrees of DR severity without subjectivity or unconscious bias [30]. Scholars have employed diverse techniques to address issues associated to diabetes, including identification, categorization, and forecasting.

Additional methods for automating DR diagnosis, like decision trees, random forests, and feature selection, are being developed over time. Machine learning techniques such as decision trees and random forests have been extensively employed in the medical diagnosis of diabetes [31][32][33].

According to the principles of physiology, the retina is a light-sensitive layer rendered up of four primary sublayers: the outer neural layer, which is made up of blood vessels and nerve cells; the photo receptor layer, which is a single layer made up of rods and cones that sense light; the pigmented retinal epithelium (PRE); and lastly, the choroid, which is made up of connective tissue and capsular laminae. A barrier called the blood-retinal barrier (BRB) delicately separates the retina from the bloodstream. The PRE is the outer region of the BRB and is responsible for controlling the flow of nutrients and other solutes through the retinal sublayers. Vascular endothelium of the inner retina and tight junction create the inner border of the blood vessel bed. Given the high metabolic demand of the retinal vasculature, pathologic diseases like persistent diabetes can cause oxidative stress, which can damage the vasculature.

Two stages are distinguished in clinical DR [34]: (i) the initial phase non-proliferative diabetic retinopathy (NPDR) is a representation of DR, and (ii) the advanced stage of DR is represented by diabetes-related proliferative retinopathy (PDR) [35][36]. Fundus imaging can identify microaneurysms, haemorrhages, and hard exudates in the retinal vasculature throughout the NPDR stage, even though the patients may be asymptotic. These observations concentrate on the increased vascular permeability and capillary occlusion. There are three categories of non-proliferative diabetic retinopathy: mild, moderate, and severe. Neovascularization, or aberrant new vessels, can be categorized as new vessels on the optic disc or elsewhere, particularly in tissues where trauma or illness has compromised circulation. This is the definition of PDR.

Deep learning models like convolutional neural networks (CNNs) are ideal for analyzing retinal images for diabetic retinopathy screening [37][38]. These models learn discriminative features automatically, and can be fine-tuned using transfer learning. Data augmentation techniques are used to expand training data and prevent overfitting. Multi-scale approaches classify lesions and abnormalities at different resolutions. Combining deep learning with traditional image processing and machine learning techniques [39][40] improves performance. Recent deep learning models have reported accuracies over 90% for 5-class DR grading.

B. Related Works

The most crucial predictive outcomes for medical image studies are classification and annotation among deep learning tasks on images. Diabetic retinopathy (DR) is a primary cause of blindness in both young and old [41][42]. Even with sufficient competence, managing the enormous number of potential patients is extremely difficult for the medical and healthcare systems because DR can cause serious blindness if it is not recognised in a timely manner. Experts are lacking, the issue with medical image analysis has reached a crucial degree of understanding, and technology is behind [43][44]. This situation drives the creation of automated diagnosis tools to support professionals in making timely decisions. The research spectrum has provided numerous procedures and methods for medical image analysis, ranging from automation to manual engineering, and has demonstrated efficacy in DR detection.

Expert assessments and consultations are made easier with the use of funduscope-supported cameras to produce images electronically [45][46][47]. To obtain a high-quality image of the retina when obtaining a manual fundus image, first dilate your pupil. A dilated pupil receives many light ray paths, producing a variety of fundus observations. Numerous excellent traits are found, including pupil darkening, focus issues, and other surface abnormalities. Using a thorough tissue examination of the pictures, ophthalmologists identify different characteristics of diabetic retinopathy [48][49].

Computer vision approaches for image processing help automation specialists create computer-assisted diagnostic systems (CADSs) [50] that improve diagnosis accuracy in contemporary ophthalmology [51][52][53]. Standard processes must therefore be developed in order to ease into conventional ways because computer algorithms and methods are used in imaging analysis.

To facilitate consultations and reviews, images from a range of funduscope-compatible camera models and types are electronically generated and stored. Dilated pupils provide high-quality retinal pictures. Multiple attempts are made to capture the image in order to minimize quality flaws like focusing issues, darkness, etc. [54][55]. Ophthalmologists use a deep tissue imaging analysis to identify diabetic retinopathy. CADSs, or computer-assisted diagnostic systems [56][57][58], which makes use of computer vision and image processing, helps the experts in modern ophthalmology refine the diagnosis. Thus, in order to facilitate the best possible disease diagnosis, a few requirements must be met in order to guarantee efficient imaging.

One method for assessing both proliferative and non-proliferative diabetic retinopathy is fluorescein angiography imaging. Fluorescein angiography is the standard imaging method for proliferative DR. It shows the existence and location of capillary drop as well as the presence of small new vessel formations that are linked to a guiding laser, specifically the macular laser for oedema.

Basis for diabetic eyes, colour fundus imaging is created. Traditionally, this is done with a film, but it is now formally approved in medical documentation when done digitally [59][60][61]. Digital photos make analysis simple and aid in quick correction. It is helpful to regularly gather fundus photos using specialized fundus photography in order to track the progression of diabetic retinopathy over time.

The three varieties of fundus photography currently in use are stereoscopic, wide field, and standard.

Deep learning techniques and approaches come in a variety of robust forms that can handle picture characteristics. The characteristics are essentially the same as the blobs, clouds, ridges, edges, and corners that make up the blocks of lesions in the retinal areas. The feature, which consists of a collection of attributes, is an intrinsic property of the procedure used for research in the field of diabetic retinopathy. The qualities in imaging are the same as those of the corresponding physical picture and pixels [62]. Numerous techniques are created and evaluated scientifically, then used on photos using cutting-edge machine learning models. Image processing techniques including binary pattern methods, matrix methods, and histogram methods, among many more, are used to extract characteristics from images as pixel properties.

C. Methods

Lesion-based detection and total-image-based detection are the two main stages of DR detection. Lesion-based detection is evaluated at the low level and image-based detection at the high level. Image level is used from a screening perspective in order to assess the high level indicators of diabetic retinopathy. The measurement of lesions at different locations and their quantity is known as the "lesion level," and it is crucial in determining the degree of diabetic retinopathy's severity. Additionally, it entails two more stages: lesion categorization and segmentation. Lesions include haemorrhages, microaneurysms, and exudates. There are two types of exudates: soft and hard. All false positives are included in the detection phase, which targets prospective regions of interest. False positives are eliminated by the lesion classification. The initial step in diagnosing diabetic retinopathy involves analyzing fundus images to see if they are classed as healthy or with diabetic retinopathy. Numerous noteworthy advancements are documented in the literature on the automated identification of DR in fundus pictures.

Specific processes like preprocessing, noise reduction/correction, feature extraction, and classification are all part of the general framework for detection, segmentation, and classification. Both supervised and unsupervised learning techniques are available for the classification techniques used in the diabetic retinopathy images. In supervised learning, the system is trained to operate on functional mapping using labeled data. Unsupervised learning is the process of automatically identifying patterns from the existing properties from the unlabeled instances and determining how similar they are.

The method classifies diabetic retinopathy severity in retinal fundus images using deep learning models focusing on color channels. This involves preprocessing the dataset, extracting distinct red, green, and blue color channels, training channel-specific CNNs, and ensemble modeling. The final severity rating is obtained by averaging predictions from the CNNs in the channels. This strategy improves color information, focuses on specific color aspects, and blends features from various channels. However, using multiple CNNs increases training and inference times.

Data Sets

The Standard Diabetic Retinopathy Database, or DIARETDB1 [63][64], is a publicly accessible database that is used to benchmark the identification and diagnosis of diabetic retinopathy using digital retinal fundus images. Public databases, like the MESSIDOR [65][66] database, are crucial for researchers, providing data for developing new methods and enabling quantitative comparisons between approaches, especially in diabetic retinopathy screening and diagnosis. DRIONS-DB [67] Database for Retinal Images There are 110 eye fundus photos in the dataset, each with a 600 × 400 resolution. There are two sets of ground-truth annotations for the optic disc. Training and assessment are frequently conducted using the first set. A library of color fundus photos called e-Ophtha [68] was created specifically for scientific studies on diabetic retinopathy (DR). It has been developed from the OPHDIAT© Tele-medical network for DR screening, under the framework of the ANR-TECSAN-TELEOPHTA project supported by the French Research Agency (ANR). Clarifying a testing procedure and database that can be utilised to compare various diabetic retinopathy detection methods was the main objective of the design. It is possible to compare the results from different methods with this database and the prescribed testing procedure. The working manuals provide more extensive applications of operative protocols. An image database and an assessment approach for the automated diagnosis of diabetic retinopathy from digital fundus images. The benchmarking algorithm database is openly accessible in Kaggle, facilitating the comparison and evaluation of algorithms' maturity for the purpose of transferring technology from research labs to clinical settings.

Color Channel Approaches

Color content-based image classification uses color histograms, color moments, color coherence vectors, and color correlograms to classify images [69]. These features are useful for distinct color patterns in different image classes, like outdoor scenes. However, they are less effective for images with less color information. Color features are often combined with other visual features like texture and shape for improved classification performance. Classification algorithms like k-nearest neighbors, support vector machines, and neural networks can impact algorithm performance.

Color features are crucial for content-based image classification of diabetic retinopathy images. They detect lesions and abnormalities, using color spaces like RGB, HSV, and LAB. Color channels can be used individually for different types of lesions, and local color descriptors like color coherence vectors help distinguish lesions from normal retina regions [70][71]. Color features are often combined with texture features, and classification algorithms like k-NN, Random Forests, SVMs, and neural networks use color information. Pre-processing is essential for accurate detection against variable retina backgrounds.

Histogram Equalization

Histogram equalization is a technique used to improve the contrast and quality of diabetic retinopathy images by stretching out the intensity distribution. It works by remapping pixel intensities, revealing lesions and abnormalities. It is applied to individual color channels, with contrast-limited adaptive histogram equalization (CLAHE) being preferred for retinal images. Pre-processing steps like background subtraction and masking the FOV can limit artifacts. Histogram equalization is often combined with other techniques for enhanced visualization and automated analysis.

The method to improve the contrast characteristics of the images in order to identify specific details by changing the intensity values. The intensity values are guided by the information drawn as intensity range in the image. Histogram is computed from the cumulative distribution function of each pixel in the image. Consider an example of a gray scale image, if the gray levels of the image are from 0 to 7 then the cumulative distribution function values are as shown below.

Table 1. An Example Illustration of CDF values of Gray Level pixels values

Gray Level Value	0	1	2	3	4	5	6	7
CDF Value	0.11	0.22	0.55	0.66	0.77	0.88	0.99	1

The probability distribution function (PDF) is a crucial concept in color medical image classification. It provides an approximation of the PDF of pixel intensities, describing the probability of different color values occurring. The PDF can be obtained separately for red, green, and blue channels, and can be fitted with parametric PDFs for smooth analytic models. The PDF captures the overall color distribution, providing useful feature vectors for classification and assessing image similarity for retrieval/recognition applications.

The images of the DIARETDB1[72][73][74] data set are collected and preprocessed for the experiment. The repository consists of all curated images ready for the experiment. The images were also collected from the expert ophthalmologists and were processed with the similar lines of curation and preservation as done with the DIARETDB1. The images from the sources are 1500 dpi with a dimension of 1500 x 1152. The size is very huge to be processed by the Sequential model of CNN, therefore, they are reduced to reasonable size. The collection of images data contains that of which is classified to contain the properties of macular retinopathy. In order to determine the image consisting of macular retinopathy the image is constructed by the pixels with the density and color range ranging RGB(255,178,102) to RGB(255,128,0) i.e., or in hexadecimal notations as from #ffcc99 to #ff8800, thus determined as image contain signs of exudates.

Further the images selected from the repository are converted to the small sizes into various dimensions based on the requirements. The images are converted into three categories with different resolutions / sizes, viz., 720 x 720, 480 x 480 and 360 x 360, whereas the 360 x 360 resolution images state the abstract information about the images, 480 x 480 resolutions images state the component information about the images and 720 x 720 resolutions images state the status of the components in the images.

The datasets consists of calibration level 1 of color fundus images of 89 samples, where 84 are considered to contain very least or mild-proliferative signs of microaneurysms of the diabetic retinopathy.

Contrast Ratios

Images collected from the repository consist of various contrast levels when seen in raw formats. In order to identify the cotton woolly areas of the proliferative signs in the images the contrast levels from the sampled images are identified as 16, 21, 22, 26, 28 and are also applied in order to explore the macular details.

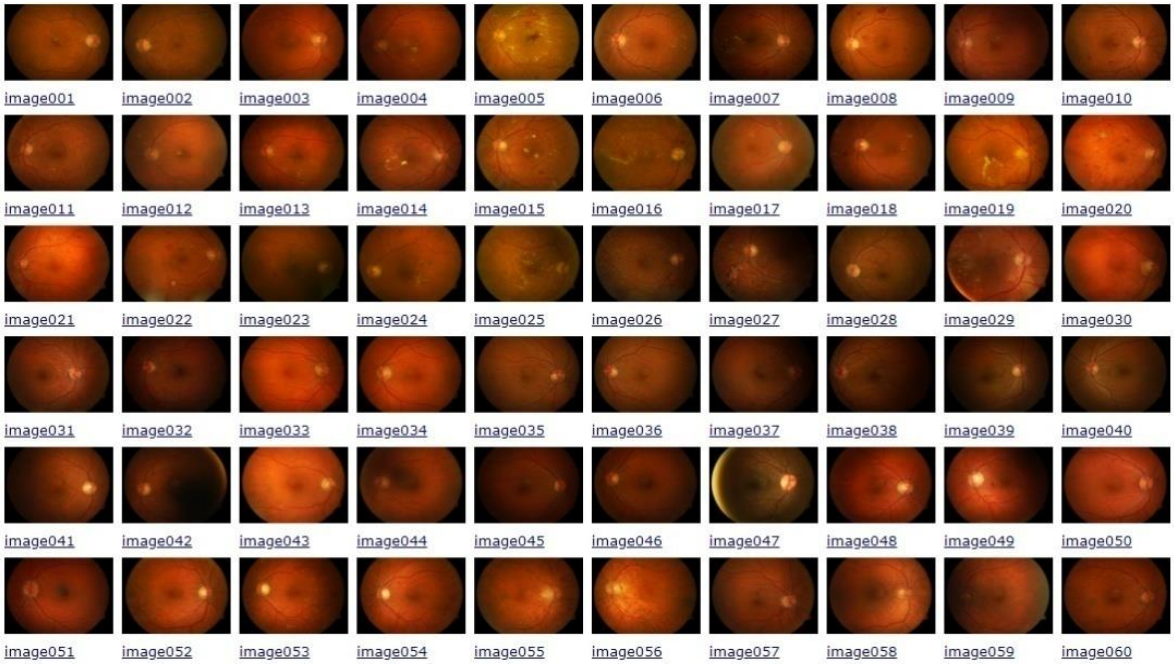

Figure 1. Collection of images from DIARETDB1 used for CLAHE

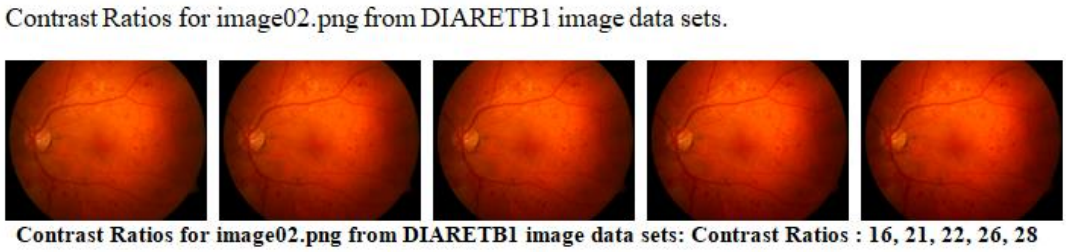

Figure 2. A Selected image of DIARETDB1 consists of contrast ratios

Table 2. Number of Images shown with various activation functions from samples

Description of Sample Selection (Contrast Ratio, Color after contrast)	No. of Fundus Images	Sample Size	Images in Classified Samples containing Exudates with respect to implemented activation function				
			Sigmoid	Tanh	ReLU	Leaky ReLU	GMPReLU
Contrast Ratio : 16 Color : RGB(255, 128, 0)	30	12	8	9	8	7	10
Contrast Ratio : 21 Color : RGB(255, 152, 42)	60	12	10	10	9	8	11
Contrast Ratio : 22 Color : RGB(255, 160, 58)	65	15	8	10	8	7	12
Contrast Ratio : 26 Color : RGB(255, 172, 86)	70	8	5	8	6	5	7
Contrast Ratio : 28 Color : RGB(255, 178, 102)	75	12	8	10	8	7	12

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Histograms

Histograms are statistical graphs indicating the distribution of pixel qualities, which represents the colors in the x-axis and distribution of RGB colors and Luminosity of image on the y-axis. A gross statistic of the image histogram represents a gray-scale version of luminosity and it is calculated with the formula 0.2126*R+0.7152*G+0.0722*B for each pixel [80].
The histograms of the selected images containing the contrast ratios are shown below.

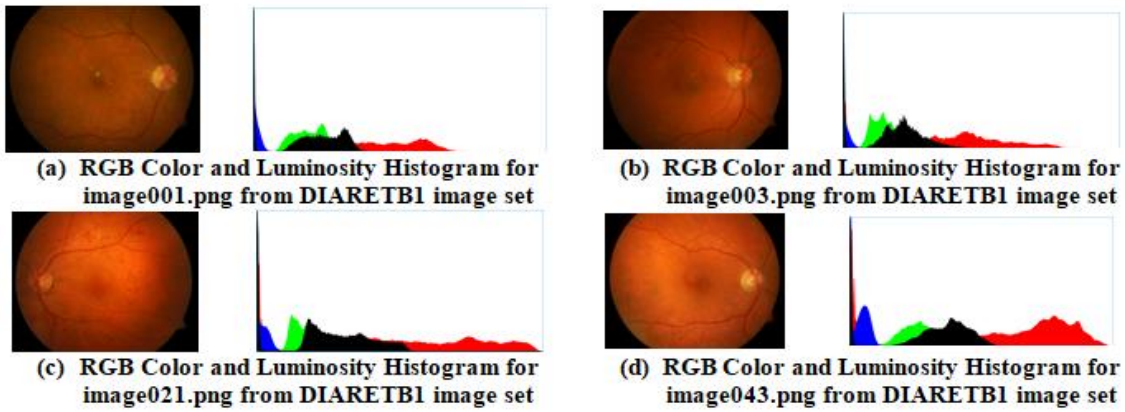


Figure 3. Color Histograms of the selected images with specified contrast ratios

Colors Analysis

Most of the fundus images drawn from the dataset contain pixels considering the hue values of 25 to 50, and saturation and luminosity values set up at constant 76% and 62% respectively in the regions notified as exudates. The regions look as

cotton-wooly areas which contain no crispy borders to locate the size and shape of exudates. Whether images contain features of exudates or not, it is very effortful to identify based on the colors, thus the Contrast Limited Adaptive Histogram Equalization method for the selected RGB density values of such areas are considered to supply as input to the classification process to ascertain the presence of proliferative exudates. From the selected images containing suitable densities of pixels, as shown in the following table, a Sequential Model of CNN with kernel values as densities are iterated using various types of activation functions. The table shows number of images that arrive satisfactorily in the experiment for each activation function.

Figures 1, 2 and 3 represents DR images DIARETDB1, which are treated by IBCA algorithm mentioned in Figure 5 for the application of CLAHE. Contrast Limited Adaptive Histogram Equalization with RGB Saturations is applied on images of diabetic retinopathy. The method is useful in extracting the signs of diabetic retinopathy. The images are resampled to generate into a tiles.

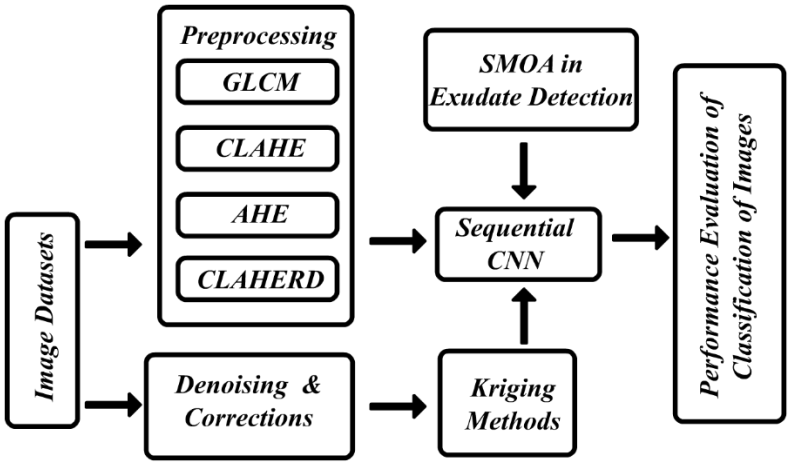


Figure 4. A map showing overall view of methods implemented for comparison and performance evaluation in Classification of Retinal Fundus Images of Diabetic Retinopathy for the detection Exudates

Table 3. Sample Sizes of Images with respect to the Contrast Ratio

Contrast Ratio (∗)	RGB Values			Number of Fundus Images	Sample Size
	R	G	B		
	255	128-175	0-102	Total:89	Avg.Size:10
16	255	128	0	30	12
18	255	136	14	40	8
20	255	144	28	50	10
21	255	152	42	60	12
22	255	160	58	65	15
24	255	166	72	65	8

26	255	172	86	70	8
28	255	178	102	80	12

The contrast ratios are selected from samples which represent more cohesive to the process related to color analysis.

The tile images are observed with relevant contrast ratios. Images with the specified interval or set of contrast ratios are filtered and the characteristics of the colors are learned by the sequential model of the CNN. The above mentioned algorithm explains the process of the YUV images converted into RGB in order to bring out the luminance values and apply the adaptive histogram equalization method. Bands of green, blue values are considered in order to determine the tile image contains exudate relevant colors.

Algorithm (Identification using Basic Contrast Analysis) – IBCA

```
begin
  Collect RGB Image of Same Dimension
  Convert RGB Images to Arrays
  Initialize the Exudate Color Values
  Apply YUV on RGB to Get Values of 'V'
  Generate Histograms for all YUV Converted Images
  On Respective RGB Images with High Contrast
  Compute Average of a Specific Color Band
  If averages are in the range of Exudate Colors
    Then
      Image contains Exudates
    Else
      Image does not contain Exudates
  End If
end
```

Figure 5. High level pseudo code for separating images with exudates

The RGB images are converted to high contrast and tested with histogram equalization for the presence of the exudate relevant colors. The experiment is connected with convolution neural network with a Rectified Linear Unit, which accelerates the learning of the presence of the colors supplied as weights.

Rectified Linear Unit

The fundamental of the activation function introduces the property of non-linearity.The Rectified Linear Unit, or ReLU [75], is not a separate component of the convolutional neural network process. The purpose of applying the rectifier function is to increase the non-linearity in the retinal fundus images of diabetic retinopathy. Non-linearity in the images comprises of representation of borders, colors and transition between pixels.

$$Sigmoid(Z) = \frac{1}{1+e^{-z}} \quad \ldots \quad (1)$$

$$Tanh(z) = \frac{2}{1+e^{-2z}} - 1 \quad \ldots \quad (2)$$

$$ReLU(z) = \max(0, z) \quad \ldots \quad (3)$$

$$LeakyReLU(z) = \max(\alpha z, z) \quad \ldots \quad (4)$$
$$GMPReLU(z) = \max(pz, z) \quad \ldots \quad (5)$$

Figure 6. Activation Functions used in CNN

The rectifier serves the job of imposing the non-linearity by breaking up the linearity, such that it can be defined as a tensor input for the intermediate operations of the convolution neural network. The only essential variation between the rectified and non-rectified versions fundus images is the progression of colors. In a typical CNN the dropout layer is used after the ReLU is implemented in the hidden layers.

The cloudy areas in the fundus image represent exudates, the said color densities with contrast of 1% to 100% are considered in as a geometric progression. The reason of using geometric progression in the experiment is the nature of the exponential spread style of the colored pixels. A pixel (p) is selected as a seed point of the random walk in the fundus image; the next pixel is detected with the same color with a distance (d). Thus, the infinite sum of the pixels is computed in geometric progression as:

$$\sum_{k=0}^{\infty} (p.d^k) = p.\left(\frac{1}{1-d}\right) \quad \ldots \quad (6)$$

For a sample window of the pixel values a series of contrast ratios accounted for the computation of the Geometric Progression sum, which may be considered as a parameter for the PReLU as the first case.Alternative case for Parametric ReLU is computed with value of α determined from a predefined value of pixel intensity with background knowledge, which is equivalent to the standard deviation of selected contrast ratios i.e., 16, 21, 22, 26, 28 is the value called 'p' which is replaced with α. The geometric progression of the min and max values of the selected contrast ratios of samples in an instance of observation is considered as an ideal value for the parameter. The statistical mean, sum and variance of the selected contrast ratio from the sampled images is 22.6, 113 and 17.44 respectively.

The standard deviation of the contrast ratios is computed as

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x-\mu)^2} = 4.1761226035642. \quad \ldots \quad (7)$$

a) Margin of Error (Confidence Interval)

Margin of Error elucidates the number of points that yield as results, shall differ from the original population. Mean is computed on the sample which is in normal distribution, therefore, standard error of the mean (SEM) is computed as follows:

The computation of the standard deviation

$$\sigma_x = \frac{\sigma}{\sqrt{Number of Contrast Ratios}} = 1.867618804 \quad \ldots \quad (8)$$

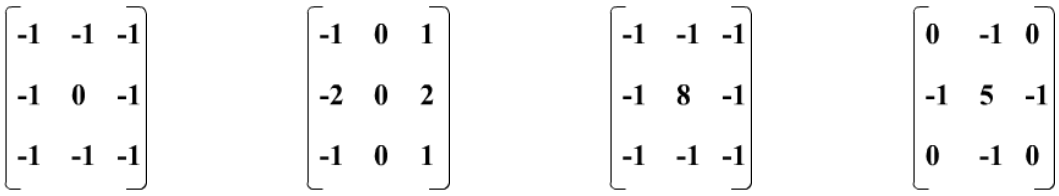
Thus, from the above observation of an instance of experimentation, the value of parameter 'p' is still corrected to p = σ_x ± SEM, where, if the confidence is considered as 95% of samples possess exudates p1 = σ_x + SEM and for less than 95% samples σ_x = sd – SEM. Probability of success always lies between 90% to 99%, optimistically the heuristic is to select the 95%, this is by mimicking the feature heuristic used in [76][77][78] and by Yuen et al. The 95% is not a fixed value for the confidence, a heuristically selected value which represents the highest of the percentage probabilities in the scale of 1 to 100.

Table 4. Number of Images found with exudates based on the samples and values of p_1 and p_2

Description of Sample Selection (Contrast Ratio, Color after contrast)	**No. of Fundus Images**	**Sample Size**	**Images in Classified Samples containing Exudates with respect to implemented activation function GMP-PReLU**		
			p_1	**p_2**	**average**
Contrast Ratio : 16 Color : RGB(255, 128, 0)	30	12	12	8	10
Contrast Ratio : 21 Color : RGB(255, 152, 42)	60	12	12	10	11
Contrast Ratio : 22 Color : RGB(255, 160, 58)	65	15	14	10	12
Contrast Ratio : 26 Color : RGB(255, 172, 86)	70	8	8	6	7
Contrast Ratio : 28 Color : RGB(255, 178, 102)	75	12	12	12	12

Convolution Filter

The convolution layer of the 2-Layer Sequential Model of the CNN does the filtering and classification task. The diabetic retinopathy features in the images lie in a non-linear form, connected, scattered or with sparse areas. Detecting these features is challenging as they are not found in specific spatial positions in the image. The convolution is performed on the various spatial areas of the image to determine whether it is an exudate. In contrast to traditional neural network, the image has to transform into a tensor rather into a vector in order to proceed with convolutions. DIARETDB1 contains images of 1500 x 1152 sizes.



(a) border detection with low contrast. | (b) object detection with low contrast | (c) border detection with high contrast | (d) object detection with high contrast

Figure 7. Convolution Filters used in the Sequential Models of CNN

All the 89 images represent vulnerable images to DR containing features microaneurysm, hemorrhages, soft exudates and hard exudates. Each of these features contains specific properties, where exudates are cotton wooly areas with no specific border and scattered with various sizes on the retina. The concept of convolution filter has been discussed in the section 2.2.3. A convolution filter is prepared, as a thumb rule the convolution filter is a matrix of size 3x3 or 5x5. The 3x3 convolution filtersapplied in the experiments are illustrated in Fig. 7:

Inferred from the above mentioned Fig. 7, the convolution filters are applied to detect the presence of the specific image components in the image scapes. The filterin 7(a) to detect the border of the image component in the image patches of retinal fundus images of DR which contain low contrast pixels. The filter in 7(b) is applied to detect the object of the image component in the image patches of retinal fundus images of DR which contain low contrast pixels. The 7(c) is applied to detect the border of the image component in the image patches of retinal fundus images of DR which contain high contrast pixels. The 7(d) is applied to detect the object of the image component in the image patches of retinal fundus images of DR which contain high contrast pixels.

Comparisons

In this article, the comparison of deep learning models for automated detection of diabetic retinopathy from fundus images as been accomplished. Various deep learning models for automated detection of diabetic retinopathy from fundus images[79][80][81]. The models tested include VGGNet, ResNet, Inception-v3, Inception-ResNet-v2, DenseNet, and MobileNet-v2. They were trained on public datasets of graded fundus images. Evaluation metrics included accuracy, sensitivity, specificity, AUC, and F1-score [79][80]. All models achieved accuracy over 90%, indicating deep learning's effectiveness in this application. Inception-ResNet-v2 and DenseNet were the top performers, capturing multi-scale features well suited for medical imaging. MobileNet-v2 was best for efficient detection on resource-constrained devices. The results demonstrate deep learning can accurately classify fundus images and improve clinical workflows and vision outcomes.

Table 4. Classification Accuracy and F1-Score on the datasets achieved by various Deep Learning methods

rchitecture	Classification Accuracy	F1-score			
		MESSIDOR	E-Ophtha	DRIONS-DB	DIARETDB1
VGGNet	87%	0.841	0.942	0.801	0.883
ResNet	83%	0.854	0.951	0.812	0.894
Inception-v3	72%	0.872	0.961	0.822	0.924
Inception-ResNet-v2	76%	0.891	0.967	0.842	0.938
DenseNet	72%	0.893	0.962	0.837	0.942
MobileNet-v2	66%	0.812	0.921	0.779	0.812

D. Discussions

Compared to other models like ResNet, Inception-v3, and DenseNet, VGGNet had lower overall F1-scores on most datasets. The authors attribute the lower F1-score of VGGNet to its relatively simpler architecture. Other models like DenseNet performed better because they incorporated multi-scale feature maps. Still, VGGNet achieved reasonably good F1-scores well above 0.8 on most datasets. This indicates it can accurately detect different stages of diabetic retinopathy from fundus images. VGGNet competitively achieves F1-scores for diabetic retinopathy detection across multiple public datasets in the comparative study. ResNet outperforms VGGNet on F1-score in this diabetic retinopathy detection task. But other deep learning networks edge out ResNet slightly, as they capture multi-scale features most relevant for medical imaging. The comparative results highlight ResNet's strengths and limitations. Inception-v3 outperformed earlier CNN architectures in terms of F1-score for this task, benefiting from its advanced multi-scale feature extraction. But deeper networks optimized for medical imaging can achieve slightly better performance. The scenario depicts, that the combinations of Inception architecture with residual connections results in optimal multi-scale feature learning for medical imaging tasks like diabetic retinopathy detection. The high F1-scores consistently above 0.84 indicate Inception-ResNet-v2's strong skill in accurately detecting and grading diabetic retinopathy from fundus images.

The results validate Inception-ResNet-v2 as the top performer for automated screening of diabetic retinopathy compared to other standard CNN models. Hence, Inception-ResNet-v2 achieved the highest F1-scores across datasets in this diabetic retinopathy detection task, demonstrating the advantages of fusing Inception with residual learning for enhanced performance. DenseNet achieved very strong F1-scores that were comparable or only slightly lower than Inception-ResNet-v2. This highlights the advantages of DenseNet's dense connections and multi-scale feature maps for medical imaging applications.

Table 5. Performance Metrics on the datasets achieved by various Deep Learning methods

Architecture	MESSIDOR			
	Accuracy	Sensitivity	Specificity	AUC
VGGNet	86	87	89	0.92
ResNet	86.05	87.04	89.05	0.92
Inception-v3	86.21	87.18	90.48	0.96
Inception-ResNet-v2	86.16	87.13	90	0.98
DenseNet	86.1	87.09	89.53	0.91

(a)

Architecture	E-Ophtha			
	Accuracy	Sensitivity	Specificity	AUC
VGGNet	86.52	82	87	0.83
ResNet	86.56	82.02	87.01	0.86
Inception-v3	87.04	83.05	87.89	0.79
Inception-ResNet-v2	86.88	82.71	87.6	0.56
DenseNet	86.72	82.37	87.31	0.38

(b)

Architecture	DRIONS-DB			
	Accuracy	Sensitivity	Specificity	AUC
VGGNet	85.32	86.52	87	0.87
ResNet	85.35	86.55	87.04	0.88
Inception-v3	85.85	86.7	88.25	0.89
Inception-ResNet-v2	85.68	86.65	87.85	0.87
DenseNet	85.52	86.6	87.44	0.92

(c)

Architecture	DIARETDB1			
	Accuracy	Sensitivity	Specificity	AUC
VGGNet	86.36	85.82	86.76	0.87
ResNet	86.39	85.87	86.78	0.87
Inception-v3	86.94	86.2	88.05	0.92
Inception-ResNet-v2	86.76	86.09	87.63	0.94
DenseNet	86.57	85.98	87.2	0.95

(d)

With F1-scores mostly above 0.85, DenseNet demonstrates reliable skill in detecting and classifying different stages of diabetic retinopathy. Along with Inception-ResNet-v2, DenseNet emerged as one of the top models suited for automated screening for diabetic retinopathy. DenseNet achieved overall top-tier F1-score performance, reflecting its strengths in learning discriminative features for diabetic retinopathy detection from fundus images. Its dense connections allow effective feature reuse.

E. Conclusion

Deep networks can identify lesions like microaneurysms, exudates and hemorrhages by learning color patterns from RGB images. Encoding color information in different spaces improves model performance. Data augmentation techniques and combining color inputs with other modalities boost model accuracy. Tuning color space and pre-processing techniques is crucial. Encoding color information in different color spaces like HSV, Lab, YUV as separate channels in the input layer has been shown to improve model performance compared to just RGB. Advanced CNN architectures and ensembles have achieved expert-level accuracy in detecting DR severity from color fundus images.

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