



RESEARCH ARTICLE

Deep-Ultraneet: Diabetic Retinopathy Grading System Using Ultra-Widefield Retinal Images

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Abstract

Diabetic Retinopathy (DR) is a complication due to diabetes that affects human vision. An automated and more accurate classification system is required for DR diagnosis to avoid blindness worldwide. This study presents a novel deep learning-based framework, Deep-UltraNet, designed for grading DR using Ultra-Wide Field (UWF) retinal images. The proposed system combines the strengths of dual colour space analysis (RGB and Lab) to enhance diagnostic precision. It integrates advanced preprocessing techniques, including bicubic interpolation and colour space conversion, followed by deep feature extraction through a custom Convolutional Neural Network (CNN) architecture. The custom CNN consists of four convolutional blocks using 3×3 kernels, max pooling layers, and fully connected layers for classification into four DR severity levels. The classification employs a neural network optimized with the Adam optimizer and trained via 10-fold cross-validation on the DeepDRiD dataset. The experimental results show that the proposed Deep-UltraNet provides 99.16% detection accuracy that surpasses state-of-the-art architectures such as VGG16, ResNet, and DeepUWF.

Keywords: Retinopathy, Retinal image analysis, ultra-wide field images, Deep neural network.

Introduction

DR is an eye disease that has almost no initial symptoms (mild vision problem) and if it is not treated earlier, blindness can occur. To grade the DR, many computerized algorithms are developed using recent advanced technologies such as deep learning. An early detection of DR is discussed in [1] using ultra wide-field images. It utilizes a Residual Network (ResNet), a deep neural network (DNN) for grading after detecting the optic disc and macular regions. Also, the undesired components such as hairs and eyelashes are removed by segmentation. A Deep Neural Network (DNN) for grading ultra wide field images is discussed in

[2]. The inception architecture is used, and various data augmentation for data scarcity is used. It utilizes a transfer learning approach to reduce the complexity while training. A multi-layer DNN is discussed in [3] for grading DR. It uses DenseNet architecture to perform the grading of DR from ultra wide-field images. The standard data augmentation and Gaussian noise augmentation also employed for the evaluation.

An automated lesion detection algorithm is described in [4] for grading DR. It extracts features by a Convolutional Neural Network (CNN) and classifies them using support vector machine classifier. The DR lesion such as exudates, haemorrhages, cotton wool spots and micro-aneurysms are detected from the ultra wide field images. Two custom classifiers are described in [5] for grading DR. It consists of two sub-systems; screening and diagnosis systems. Before applying DNN, different preprocessing approaches are employed such as histogram equalization, gamma correction, rescaling and sigmoid adjustment. The conventional fundus images are obtained from the ultra-wide field images in [6] for ophthalmological diagnosis. An attention aided generative adversarial network is utilized with the help of object detector and illumination estimation algorithms. An image fusion approach is discussed in [7] for effective retinal image analysis. It uses two different modalities such as fundus imaging and ultra-widefield images. It uses the common features from these images

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obtained from the same patient for image registration as well as image scaling.

A graph cut based approach is described in [8] for the classification of retinal vein to identify retinal diseases. It uses hand-crafted features to represent the graph, which discriminates the venular and arterial networks. Features are extracted based on the vascular morphology and local vessel intensity. A deep CNN based system is developed in [9] for detecting proliferative DR. It uses sixteen-layer visual geometric group architecture with transfer learning for the detection. A stochastic gradient optimization is employed for training with softmax activation in the output layer. A DNN approach based on residual network is discussed in [10]. It is a CNN that extracts the compact features for grading. Before applying the CNN for grading, the intensity of fundus images is normalized, and data augmentation is also employed. The early signs of DR are detected in [11] using a three dimensional CNN for extracting blood vessels and then classified using random forest classifier.

A new loss function is discussed in [12] for DR grading that increases the convergence rate while training the DNN. An efficient CNN is discussed in [13] using bilinear model for the identification of discriminative areas. A metric loss is introduced instead of categorical loss and uses soft labels instead of one-hot labels while training the CNN. The ultra-wide field imaging technology is not only used for DR grading but also used in detecting branch retinal vein occlusion [14] and central retinal vein occlusion in [15]. Colour based classification systems are developed for haemoglobin estimation using multilayer perceptron in [16] and vision transformer in [17]. The colour changes in the palm are captured by a smartphone and are used for DR classification. A CNN model is described in [18] for DR classification using foot monitoring.

Problem Statement

A wide range of automated methods have been developed using conventional techniques that rely only on textural characteristics, and their performances depend on the retrieved features and the specifically selected classifiers. The extracted textural characteristics for DR diagnosis may be compromised by the inadequate classifier and vice versa. Additionally, the development of a precise classification system requires the combination of two separate modules.

Proposed Solution

Numerous deep learning systems such as Visual Geometric Group (VGG), AlexNet and ResNet have emerged in recent years to address various applications, eliminating the need for a distinct feature extraction step in classification [19-21]. They have emerged as prominent contributors to the domain of computer vision. Each architecture has distinct characteristics and has played a crucial role in medical image classification. The primary aim of this study is to develop

a highly effective deep CNN architecture named Deep-UltraNet that can accurately and reliably classify different stages of DR using fundus images.

Results

The grading of DR can be obtained via a cautious study of clinical history and imaging with either fundus or ultra wide-field retinal images. Though the fundus images have been shown to be effective for DR grading, the proposed system uses ultra wide-field retinal images for grading DR. The proposed Deep-UltraNet architecture is evaluated on the Deep-Diabetic-Retinopathy-Image-Dataset (DeepDRiD) database where it achieves an average accuracy of 98.68% for DR grade classification using ultra wideband fund images.

In this paper, an approach for the DR grading system by Deep-UltraNet is proposed. The rest of the paper is organized as follows: The proposed Deep-UltraNet system is discussed in section 2. The performances of Deep-UltraNet are evaluated using DeepDRiD database in section 3 in terms of average classification accuracy and compared with conventional deep learning architectures. The conclusions are given in section 4 based on the obtained results of Deep-UltraNet.

Proposed System

The proposed Deep-UltraNet system consists of preprocessing, Deep Colour Features Extraction (DCFE) from two different colour spaces; Red, Green, Blue (RGB) and $L^*a^*b^*$ and classification by Neural Network (NN) in the Fully Connected Layer (FCL) with stochastic gradient optimization modules. In the preprocessing module, the UWF retinal images are resized and colour space conversion takes place from RGB to $L^*a^*b^*$. In the DCFE module, deep features from RGB and $L^*a^*b^*$ colour spaces are extracted using the Deep-UltraNet system and then grading of DR is achieved in the classification module.

The design of the proposed Deep-UltraNet architecture is based on its dual colour space feature extraction (RGB and $L^*a^*b^*$) combined with deep learning for improved grading of DR using UWF images. While the traditional models use ordinary fundus images, Deep-UltraNet analyses high-resolution UWF data to identify peripheral retinal characteristics enhancing diagnostic precision. The modular architecture integrates deep colour feature fusion, and a DNN classifier, resulting in exceptional performance.

UltraNet is essential for evaluating DR using UWF retinal images since it effectively manages high-resolution, intricate inputs while maintaining fine details. The multi-scale convolutional layers in the design extract information from several colour spaces, enhancing sensitivity to tiny colour variations. The design optimizes depth and parameter efficiency, mitigating overfitting on constrained medical data. UltraNet's comprehensive architecture facilitates

collaborative optimization for enhanced accuracy and resilience in DR classification.

Deep-UltraNet uses small 3x3 convolutional kernels to extract intricate retinal characteristics. Enhancing filter numbers in deeper layers facilitates the acquisition of intricate patterns. The max pooling reduces spatial dimensions, hence decreasing computational demands and enhancing resilience. Four convolutional blocks optimize depth and efficiency. Dense layers combine features for classification into four classes. This design enhances precision, allows high-resolution images, and prevents overfitting in DR assessment. Fig. 1 shows the diagrammatic overview of your proposed framework.

Preprocessing

Before extracting deep features, the images are rescaled to 256x256 pixels in the preprocessing stage. It uses bi-cubic interpolation for rescaling purposes. It interpolates pixels on a 2-dimensional rectangular grid. To determine the output or the estimate the pixels use 16- nearest neighbours while the

bi-linear uses only 4 neighbours. Fig. 2 shows the rescaled image and its corresponding RGB colour channels. Two different colour spaces, such as RGB and La*b*, are employed in the proposed system.

The definition of colour space conversion is as follows:

$$L = 11.6h\left(\frac{G}{G_w}\right) - 16 \tag{1}$$

$$a^* = 500 \times \left[h\left(\frac{R}{R_w}\right) - h\left(\frac{G}{G_w}\right) \right] \tag{2}$$

$$b^* = 200 \times \left[h\left(\frac{G}{G_w}\right) - h\left(\frac{B}{B_w}\right) \right] \tag{3}$$

where R_w , G_w , and B_w are reference white tri-stimulus values and h is defined as

$$h(q) = \begin{cases} q^{\frac{1}{3}} & q > 0.008856 \\ 7.7879q + \frac{16}{116} & q \leq 0.008856 \end{cases} \tag{4}$$

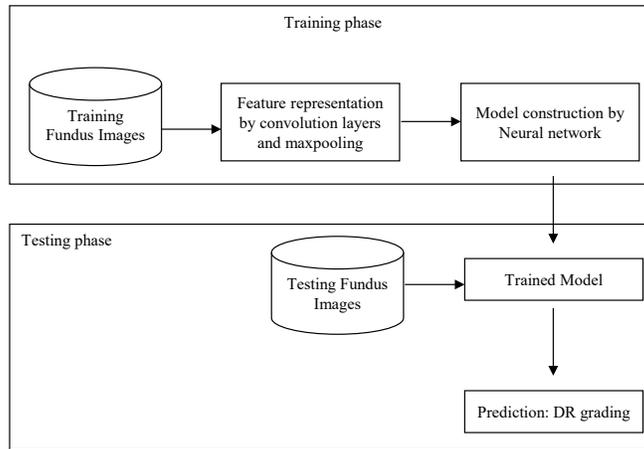


Fig. 1: Diagrammatic overview of your proposed framework

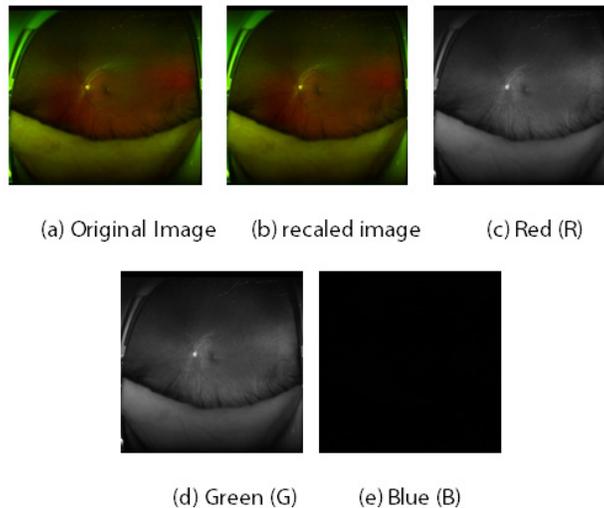


Fig. 2: Preprocessing: Rescaled and RGB Colour Channel Images

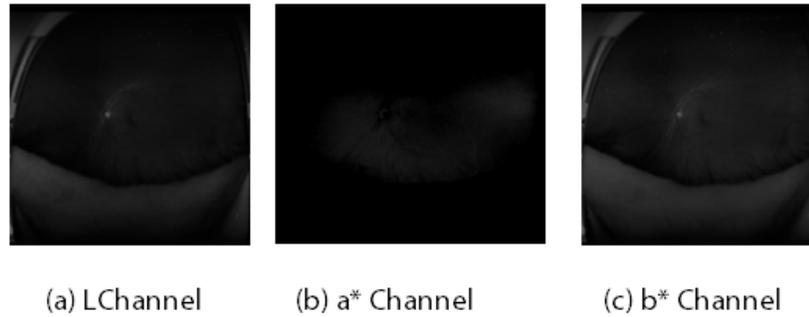


Fig. 3: Preprocessing: Individual Colour Channels from the La*b* Colour Space

Fig. 3 shows the individual colour channels from the La*b* colour space.

Deep-Ultraneet System

From the colour planes, deep features are extracted using the well designed Deep-UltraNet system. The combination of convolution layers with predefined filters [22-25] and a max pool layer is repeated to extract deep features in Deep-UltraNet which is shown in the middle section of Fig. 4. The two dimensional convolution is defined as.

$$y(p,q) = x(p,q) * h(p,q) = \sum_{i=-1}^1 \sum_{j=-1}^1 x(i,j) h(p-1,q-j) \tag{5}$$

where x and h are the inputs and convolution filter of size 3×3 and y is the convolution results of $x * h$. The Max Pool layer reduces the dimension of the extracted deep features, and their computation is shown in Fig. 5. It uses 2×2 filters with stride 2.

Deep features from the RGB and La*b* colour spaces are fused and fed to the two fully connected layers for DR diagnosis. Table 1 shows the structural summary of the proposed Deep-UltraNet architecture.

The classification uses a neural network consisting of many neurons in the input (X) and hidden layer (H) and four neurons (4 classes) in the output layer (O) for the classification. It uses a stochastic descend gradient optimization algorithm to fit the data for the prediction. Fig. 6 shows the simple feed forward neural network used in the FCL. The input layer of Deep-UltraNet system uses rectified linear unit as activation function and softmax (multi-class) at the output layer. These functions decide to activate the neurons in the network using simple mathematical operations and are also responsible for transmitting the summed weights between the nodes. For the back propagation with stochastic gradient, they are used to learn very fast and also vanishes gradient problem.

Classification is the assigning of a ultra wide field image into one of the given classes; normal, DR-1, DR-2 and DR-3. The supervised classifier that will be used in this work is the neural network classifier with deep features. The FCL in

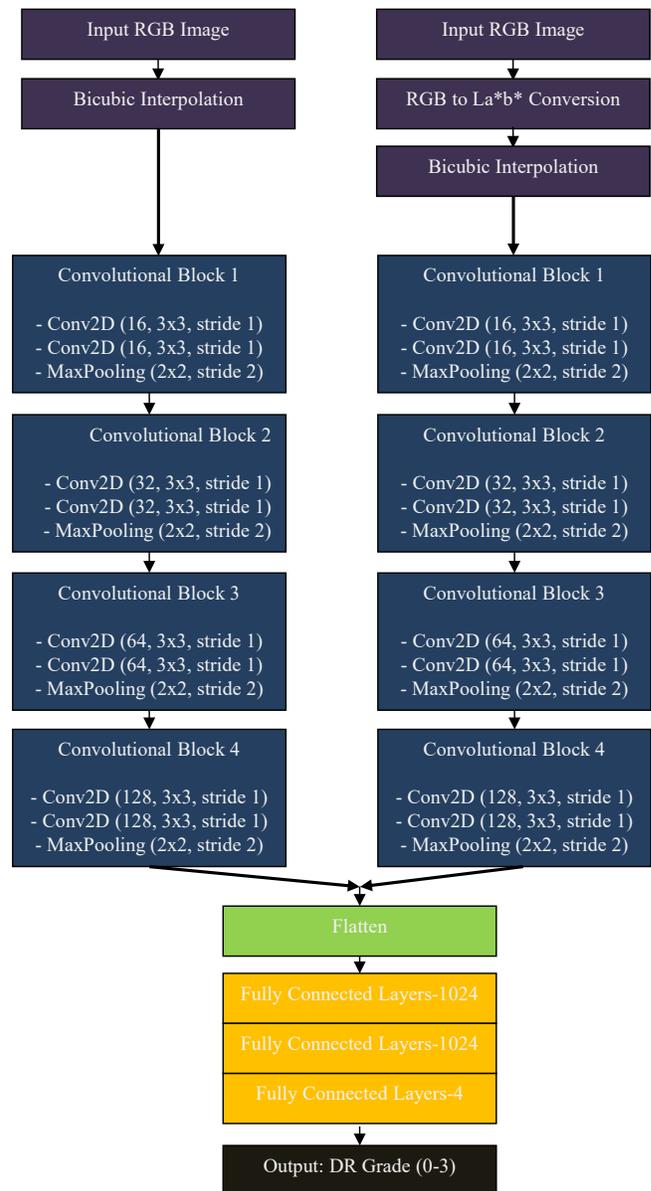


Fig. 4: Proposed Deep-Ultraneet System for DR Diagnosis

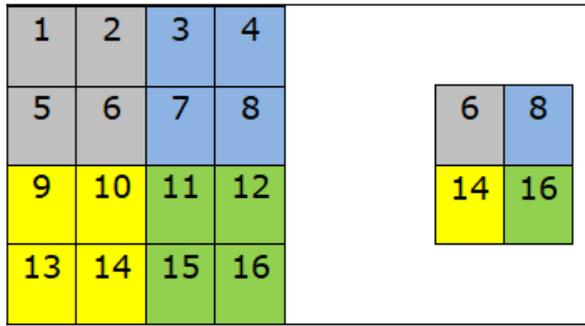


Fig. 5: Max Pool Layer Calculations

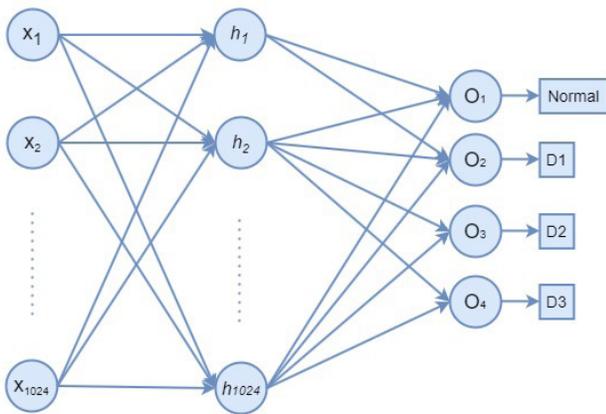


Fig. 6: Fully connected layer of the proposed Deep-UltraNet architecture

Table 1: Structural summary of the proposed Deep-UltraNet architecture

Block	Layers	Filters	Kernel Size	Stride
Conv Block 1	Conv2D	16	3×3	1
	Conv2D	16		
	MaxPooling	-	2×2	2
Conv Block 2	Conv2D	32	3×3	1
	Conv2D	32		
	MaxPooling	-	2×2	2
Conv Block 3	Conv2D	64	3×3	1
	Conv2D	64		
	MaxPooling	-	2×2	2
Conv Block 4	Conv2D	128	3×3	1
	Conv2D	128		
	MaxPooling	-	2×2	2
Dense Layers	Fully Connected-1024	-		
	Fully Connected-1024	-		
	Fully Connected-4	-		
Output	Softmax	4 (classes)		

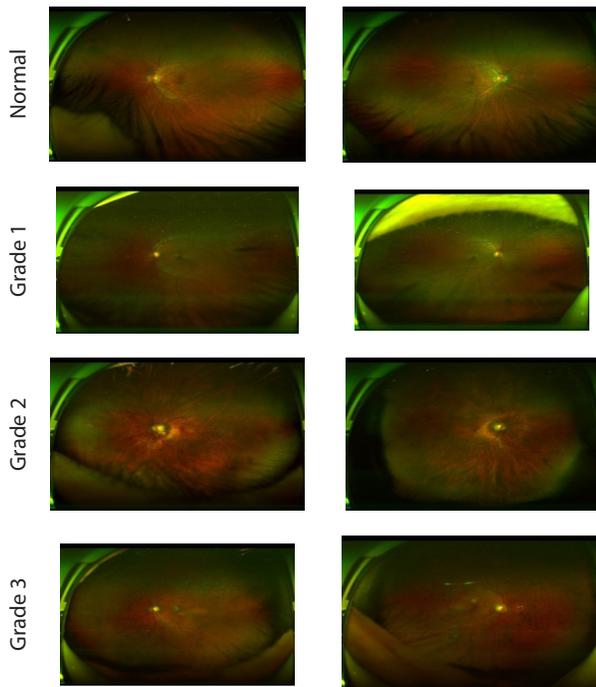
Fig. 4 acts as a classifier. The neural classification strategy is adopted over the other classifiers because the former is data-driven and that they can compute any desired function that captures the underlying structure of the data which formulates a model of the system that generated it. The decision spaces mapped out by the NN are used for assigning inputs it has not seen before but that are typical of patterns it has seen in the past. This process is called generalization, and it is what makes the NN attractive. The training in NN includes memorizing the data, a phenomenon associated with using too many hidden units during neural network training. The network begins to model noise if it is trained well beyond the stopping criteria, and this is called overtraining. When ambiguous data (similar input vectors given different labels) is used the NN learns the average of the ambiguous target values which leads to a wrong solution.

NNs are recommended where the input is high dimensional, discrete and real valued and where the training time is not critical. NN incur high computational costs especially where large inputs and outputs are involved. In addition, there is always noise in the data because real world data is probabilistic. Noise degrades the performance of a classifier. Furthermore, the performance of the NN suffers where there is insufficient input data because NN is a statistical method. Neural networks do not explain the computational process by which the network makes a decision. The key notion in NN is learning and not programming. Training many networks and then averaging can improve the results. The gradient descent method recalculates the error at each step. The line search method is computationally less expensive, and additionally, it does not use the momentum and the learning rate parameters which are used by the gradient descent method. The conjugate method constructs a sequence of successive search directions that are conjugate to all previous directions. It determines the step in each direction automatically. It combines the good attributes of the second order (historical information about where it has been) and that of the line search method. It is more efficient, faster, and easy to know what is going on. Thus, the gradient descent method has been used in many application areas.

The data set, in which one of the classes has for example, twice more samples than the other classes, is called an unbalanced set. In this set, the test samples will always give a wrong result. The NN with its backpropagation training algorithm are suitable for grading DR in this work. The use of error function Mean-Squared Error (MSE) is accompanied by longer learning times and also the change in MSE can occur before reaching the global minimum and this makes the NN solutions suboptimal. It is therefore profitable to have a classifier that incorporates a cost and at the same time optimizing learning. Thus, the proposed Deep UltraNet uses Adam optimizer for the classification task. Table 2 shows the

Table 2: Key Training Parameters for Deep-UltraNet

Parameter	Value
Optimizer	Adam
Learning Rate	0.001
Batch Size	32
Epochs	50
Loss Function	Categorical Cross-Entropy
Weight Initialization	Normal
Dropout Rate	0.2(to prevent overfitting)
Validation approach	10-fold stratified cross validation

**Figure 7:** Samples in the DeepDRiD Database

parameters for DNN training that regulate model learning efficiency and mitigate overfitting.

Results And Discussions

The performance of the proposed system using Deep-UltraNet for the diagnosis of DR is evaluated using the DeepDRiD Diabetic Retinopathy Image Dataset [26]. This dataset is intended to support the development of algorithms that can detect the presence and severity of DR. It has high-resolution fundus images and UWF retinal images of the inner surface of the eye, including the retina, optic disc, and blood vessels, therefore playing a crucial role in the diagnosis of DR. All images are in JPEG format with 3900x3972 pixels. Sample images are shown in Fig. 7.

Each image is annotated with one of the four grades of the standard grading system of DR. They are DR-0: Normal, DR-1: Mild, DR-2: Moderate, and DR-3: Severe. The Deep-

Table 3: Images in the DeepDRiD database

Category	Normal	DR-1	DR-2	DR-3
#samples	60	57	56	31
After data augmentation	420	399	392	217

UltraNet is executed using TensorFlow-2 with Keras libraries on a PC equipped with an i10, 12th generation CPU, 32 GB RAM running at 3.4 GHz, and NVIDIA GEFORCE 4080 GPU. In this work, only UWF retinal images are analyzed for DR with 256 images from 128 patients. All images are graded into 4 classes of DR: 0 (normal), DR-1, DR-2, and DR-3. Table 3 shows the number of images in the database. A total of only 204 images are available in the DeepDRiD database. Data augmentation is needed in deep learning to address the challenges of limited and imbalanced datasets, which can lead to poor model generalization and overfitting. It artificially increases the size and diversity of the training data by applying transformations such as rotation, flipping, scaling, and cropping. These variations help the model learn more robust and invariant features, enabling it to perform better on unseen data. It also acts as a regularization technique, reducing the risk of overfitting by preventing the model from memorizing the training data. As the samples are limited in the DeepDRiD database and the Deep UltraNet requires more images for proper training, data augmentation is employed. Deep UltraNet requires more images for proper training, data augmentation is employed to increase the size of the database into seven times by flipping and rotation.

Ten-fold stratified cross-validation is employed to analyze the performances of the proposed Deep Ultra-Net on the DeepDRiD database. It involves partitioning the dataset into 10 equal subsets while preserving the original class distribution and undergoing training and validation ten times. Each time, it uses a distinct fold as the test set, while the remaining nine folds serve for training purposes. Finally, the mean performance metric is computed to evaluate the model's efficacy. The discriminating capability of the original features could be improved by the combination of deep features. Deep-UltraNet is analyzed with the features obtained from individual colour spaces and their combination. The performance of the developed Deep-UltraNet is also tested with the images in the original database i.e., without augmentation. Fig. 8 and Fig. 9 show the performances of Deep Ultra-Net for grading DR.

From the confusion matrices in Figure 8 and Figure 9, the performance of Deep-UltraNet is evaluated in terms of classification accuracy. The definition of classification accuracy is

$$\text{classification accuracy} = \frac{\# \text{correct classification}}{\# \text{Total images}} \quad (6)$$

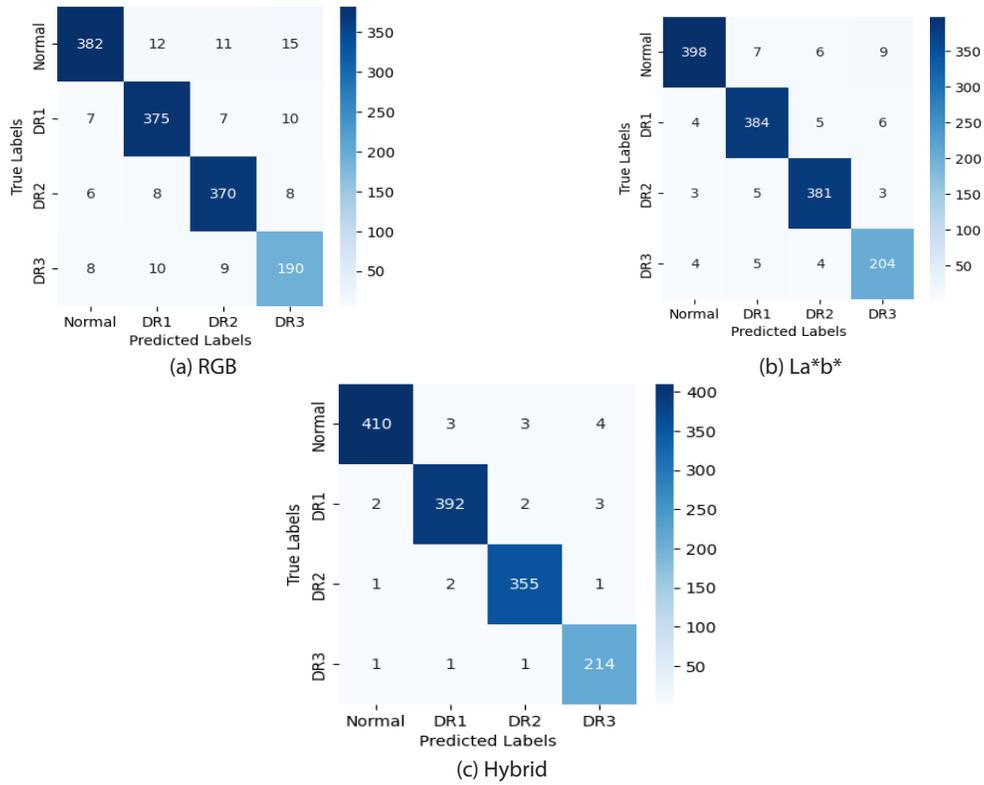


Figure 8: Confusion matrices of Deep Ultra-Net for grading DR with augmentation

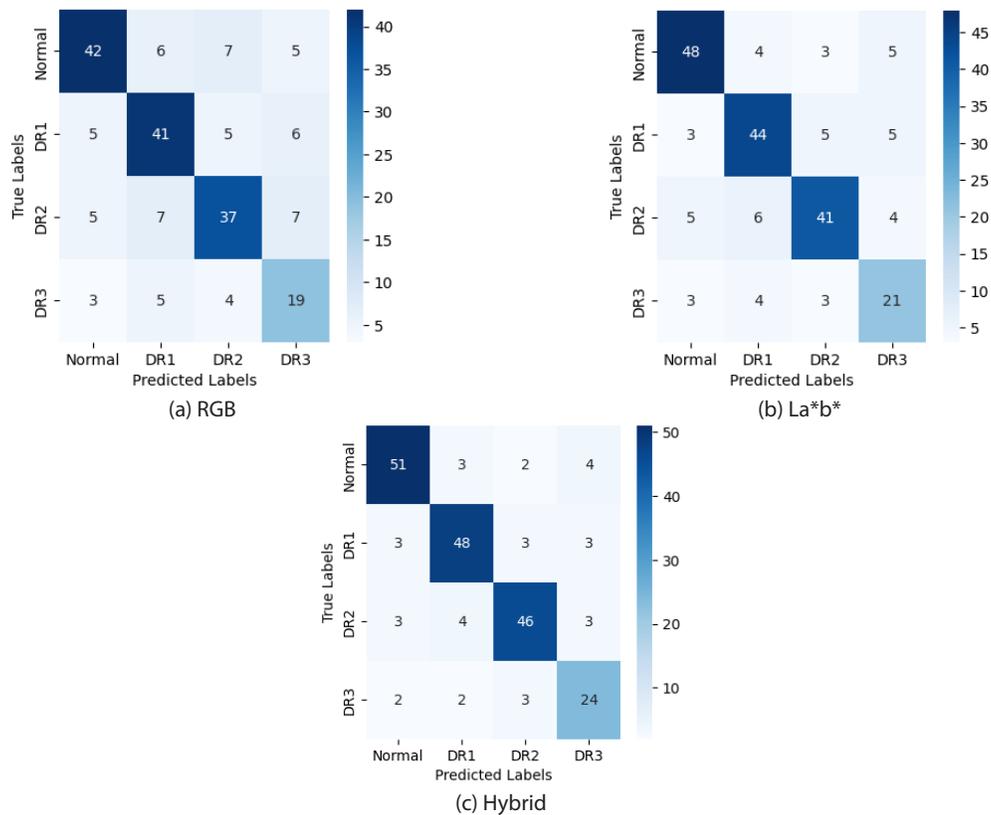
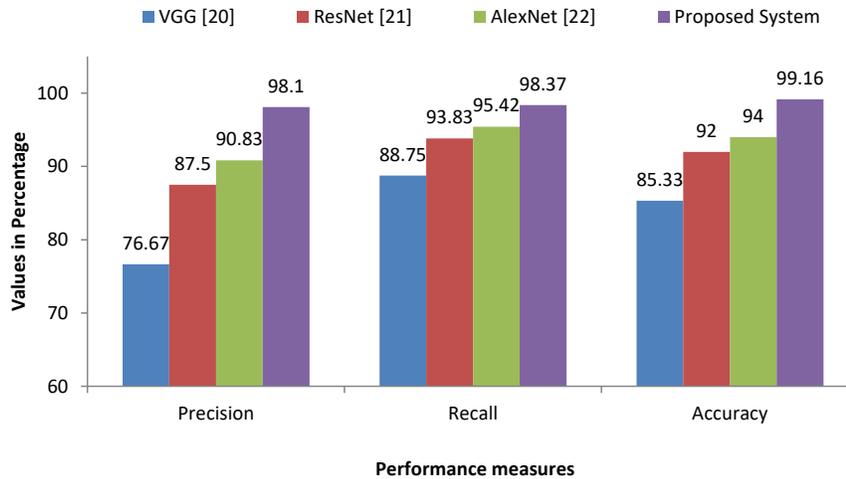


Figure 9: Confusion matrices of Deep Ultra-Net for grading DR without augmentation

Table 4: Classification accuracy or detection rate of the proposed Deep Ultra-Net architecture

Colour Space	Detection rate (%)									
	Without augmentation					With augmentation				
	Normal	DR1	DR2	DR3	Avg	Normal	DR1	DR2	DR3	Avg
RGB	84.80	83.33	82.84	85.29	84.07	95.87	96.22	96.57	95.80	96.11
La*b*	88.73	86.76	87.25	88.24	87.75	97.69	97.76	98.18	97.83	97.86
Hybrid	91.67	91.18	91.18	91.67	91.42	99.02	99.09	99.30	99.23	99.16

**Figure 10:** Comparisons between the proposed Deep-UltraNet and conventional architectures

Using Eqn. 6 and the correct classification of the proposed Deep-UltraNet system in the diagonal values in Fig. 8 and Fig. 9, the classification accuracy of the system is computed and shown in Table 4.

It can be seen from Table 3 that the data augmentation significantly enhances the detection performance in all colour spaces. The hybrid system consistently achieves the highest accuracy, with an impressive average detection rate of 99.16% under augmentation and 91.42% without it. This suggests that combining multiple colour spaces can lead to more robust feature extraction and improved classification. The performance of Deep-Ultra-Net using the original images in the database (without augmentation) is lower than the performance of the system with augmented images. This is due to the developed network having a greater number of images for training and hence trained well using the augmented images than the original images in the database. The La*b* space also performs better than RGB, achieving average rates of 97.86% (with augmentation) and 87.75% (without augmentation). In comparison, RGB yields the lowest accuracy, averaging 96.11% (with augmentation) and 84.07% (without). These results show the importance of the fusion of features and data augmentation in optimizing deep learning models for DR image analysis, with the Hybrid approach offering superior discriminative capability

and resilience. The performances of Deep-UltraNet are compared with the conventional deep learning architectures such as VGG, AlexNet and ResNet and the obtained results are shown in Fig. 10.

Fig. 10 clearly demonstrates that the proposed Deep-UltraNet has the maximum precision of 98.1%, with AlexNet closely following at 90.83%. Deep-UltraNet achieves a maximum recall of 98.37%, closely followed by AlexNet (95.42%). In comparison to VGG (85.33%), ResNet (92%) and AlexNet (94%), the proposed Deep-UltraNet has a notable improvement with 99.16% of accurate DR classification. These findings indicate that the Deep-UltraNet surpasses the previous models and is the top performer for DR classification.

The performances of the proposed system is further compared to the state-of-the-art techniques in the literature survey. Table 5 shows the comparative study of the proposed Deep-UltraNet system with other techniques.

It is inferred from Table 4 that traditional models like the Residual Network [10] achieved an accuracy of 86.67%, indicating a baseline performance. More advanced architectures such as VGG16 [9] and Inception-ResNet [2] improved accuracy to 96.9% and 97%, respectively, by using deeper and more complex feature extraction strategies. The DeepUWF [5], which combines Xception and Inception,

Table 4: Comparative analysis of the proposed Deep Ultra-Net architecture with other techniques in the literature

System	Architecture	Accuracy (%)
CNN [10]	Residual Network	86.67
Deep CNN[9]	VGG16	96.9
Inception-ResNet [2]	Hybrid	97
DeepUWF [5]	Xception and Inception	97.45
Proposed Deep-UltraNet	Custom CNN	99.16

further enhances accuracy to 97.45%, reflecting the benefits of hybrid architectural designs. However, the proposed Deep-UltraNet, a custom CNN architecture, outperforms all existing models with a remarkable 99.16% accuracy. This significant improvement demonstrates the effectiveness of the proposed architecture in capturing critical features by optimized design and the use of a hybrid colour space.

Conclusion

The proposed Deep-UltraNet framework offers a significant advancement in the automated detection and grading of DDR by utilizing UWF retinal images and a dual color space approach. Through the custom CNN design, the system captures minute and critical retinal features by integrating convolutional layers across both RGB and Lab color spaces. The fused features are processed by a densely connected neural network, leading to superior classification accuracy. Data augmentation is applied to address data imbalance and improve generalization. Experimental results reveal that Deep-UltraNet consistently outperforms existing deep learning models including VGG16, ResNet, and DeepUWF, achieving an outstanding 99.16% detection rate when trained with augmented data. These findings highlight the benefit of hybrid feature fusion, color space diversity, and data augmentation in improving classification robustness and resilience against overfitting. It is also observed that Deep-UltraNet maintains diagnostic consistency across all DR grades, addressing the challenges posed by class imbalance through data augmentation and stratified cross-validation. The proposed Deep-UltraNet can be extended to multi-modal retinal analysis for early intervention of DR.

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Nil.

Conflict of Interest

The authors declare that they have no conflicts of interest to report regarding the present study.

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