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Multi-level Quality Assessment of Retinal Fundus Images using Deep Convolution Neural Networks

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Abstract: Retinal fundus image quality assessment is one of the major steps in screening for retinal diseases, since the poor-quality retinal images do not allow an accurate medical diagnosis. In this paper, we first introduce a large multi-level Retinal Fundus Image Quality Assessment (RFIQA) dataset. It has six levels of quality grades, which are based on important regions to consider for diagnosing diabetic retinopathy (DR), Aged Macular Degeneration (AMD) and Glaucoma by ophthalmologists. Second, we propose a Convolution Neural Network (CNN) model to assess the quality of the retinal images with much fewer parameters than existing deep CNN models and finally we propose to combine deep and generic texture features, and using Random Forest classifier. Experiments show that combing both deep and generic features outperforms using any of the two feature types in isolation. This is confirmed on our new dataset as well as on other public datasets.

1 INTRODUCTION

The world Health Organization (WHO) estimates that 285 million people across the world are visually impaired (Mariotti and Pascolini, 2012). Retinal diseases are diagnosed through different imaging modalities such as Fundus Photography, Optical Coherence Tomography (OCT), Fluorescein Angiography, Scanning Laser Ophthalmoscopy (SLO) and B-scan ultrasonography (Salz and Witkin, 2015). Among these, fundus photography is the most common procedure to screen for multiple eye diseases including diabetic retinopathy (Raman et al., 2018), age related macular degeneration (AMD) (Grassmann et al., 2018), glaucoma (Nayak et al., 2009) and other anomalies associated with retinal diseases, and to monitor their progression. The fundus image of the retina is captured using a specialised camera called a fundus camera and the goal is to spot disease-related changes in the retina to treat them early and save vision/prevent blindness (Giancardo, 2011). It has been widely used in telemedicine, natural history studies, and to perform research studies on new treatment for eye disease (Salz and Witkin, 2015).

Retinal fundus image degradation often occurs during the image capturing process. Inadequate illumination, noticeable blur, unsharp and over-brightness are some of the artifacts responsible for image degradation, which makes medical diagnosis very difficult for ophthalmologists or automated systems (Fu et al., 2019). Therefore, it is very important to ensure a good quality of a fundus images. Traditionally the quality assessment is preformed manually by ophthalmologists and it is very time consuming. Therefore, automated assessment techniques are needed to assist the experts or an automatic system.

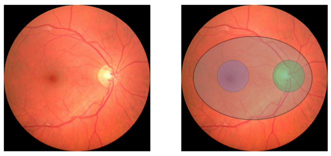


Figure 1: Retina fundus image showing the optical disk (OD) (green), macula (blue), region surrounding to macula (gray) and OD.

Several methods have been proposed for automated retinal fundus image quality assessment. They are broadly classified into three categories: structural, generic and combine feature based methods. Structural feature based methods segment the blood vessel structures to assess the quality of retinal images. In generic methods simple image features are extracted without segmenting the structures to asses the retinal image quality and in combination based methods, both generic and structural features are combined together for the quality assessment. An example is Paulus *et al.* (Paulus et al., 2010) who proposed a method which performs structural analysis by applying k-mean clustering on pixel intensities. Sharpness image contrast is computed and finally combined with Haarlick features to achieve quality assessment. A recent survey of the above discussed categories can be found in (Lin et al., 2019).

The recent advancements in deep learning techniques, which integrates multi-level feature representations, have shown significant performances in different medical imaging applications. In (Saha et al., 2018; ZAG, 2018), the authors use the pre-trained models and fine-tune on publicly available datasets to deal with the quality assessment task. Deep neural network based methods have solved the feature engineering problems of conventional methods. However, they need large datasets for training. There are several publicly available retinal fundus image quality assesement (RFIQA) datasets like DR2 (Pires et al., 2012), DRIMBD (Sevik et al., 2014), HRF (Köhler et al., 2013) and ELSA (Aquino et al., 2012), which consists of 920, 216, 18 and 842 fundus images, respectively, with two levels of grades 'Accept' and 'Reject'. Huazhu *et al.* (Fu et al., 2019) presented a general Multiple Color-space Fusion Network (MCF-Net) by integrating different color spaces at feature level and prediction for retinal image quality classification and created an Eye Quality (EyeQ) dataset by re-annotating from the EyePACS dataset (EyePACS, 2015), with three levels of grading 'Good', 'Usable' and 'Reject'. However, two or even three levels of grading are not sufficient to assess the quality. Instead of disregarding the entire image for grading, a retinal image can still be assessed for e.g. glaucoma if the optic nerve head is free of artefacts/shadows, while the macula area can be deemed inassessable due to artefacts on the same image. Moreover existing RFIQA datasets are limited in size and hence not sufficient to train deep learning methods. The research community therefore needs a fine grained multi-level graded and comprehensive dataset.

Our contributions in this paper are threefold. First, we create a large multi-level grades RFIQA dataset, which is annotated by experts (ophthalmologists). This detailed level of grading benefits fundus camera operator when an image should be retaken and provides an explanation as to why it should be retaken to improve grading possibility. Second, we propose a baseline CNN model to assess the quality of multi-level grades retina fundus images and finally we propose to combine generic and deep features together and trained with random forest learning methods. The rest of the paper is organized as follows. In Section 3 we describe the new RFIQA dataset. Section 4 describes the proposed deep learning based RFIQA methodology and combination of generic and deep features. Section 5 shows performance evaluation of our methods and comparisons of different deep models and finally, Section 6 provides concluding remarks.

2 RELATED WORK

In this section we introduce some of recent state of art methods of Retinal Fundus Image Quality Assessment. In (Costa et al.,), the authors proposed a Deep Learning based quality assessment method EyeQual by learning the patch classifier from a given set of eye fundus images and corresponding quality labels. This method classifies the quality of input image and also returns a heatmap which highlights the location of the high/low quality patches. The authors formalized the method by a graphical model view and they illustrated how to apply it to the image quality assessment problem. They also proposed a pooling function that suits the specific task of retinal image quality assessment better than the existing *Max* or *Average* Pooling.

(Jiménez-García et al., 2019) proposed an Retinal Image Quality Assessment (RIQA) method by combining novel generic quality features. Several features derived from the spatial and spectral entropy-based quality (SSEQ) and the natural images quality evaluator(NIQE) methods were extracted and combined with novel sharpness and luminosity measures based on the continuous wavelet transform (CWT) and the hue saturation value (HSV) color model, respectively. In addition to that a subset of non-redundant features was selected using the fast correlation-based filter (FCBF) method. Finally, a multilayer perceptron (MLP) neural network was trained to obtain the quality of images from the selected features.

In (Lamiaa Abdel-Hamid and Hornegger, 2016), the authors proposed a transform-based RIQA algorithm to assesses images based on five clarity and content quality issues namely sharpness, illumination, homogeneity, field definition, and content. The sharpness and overall illumination of the images were evaluated using wavelet-based features. A retinal saturation channel were used along with wavelet-based features for homogeneity assessment. The presented sharpness and illumination features were used to guarantee adequate field definition and finally color information was used to exclude non retinal images. (Lamiaa Abdel-Hamid and Hornegger, 2016) claim that transform-based RIQA algorithms have the advantage of considering retinal structures while being computationally very low.

The authors in (Fu et al., 2019) proposed a Multiple Color-space Fusion Network (MCF-NET) which combines the different color-spaces representations at a feature-level and prediction-level to predict image quality for RIQA and discussed about the influences of different color-spaces in deep networks on RIQA. They also re-annotated an Eye-Quality (EyeQ)

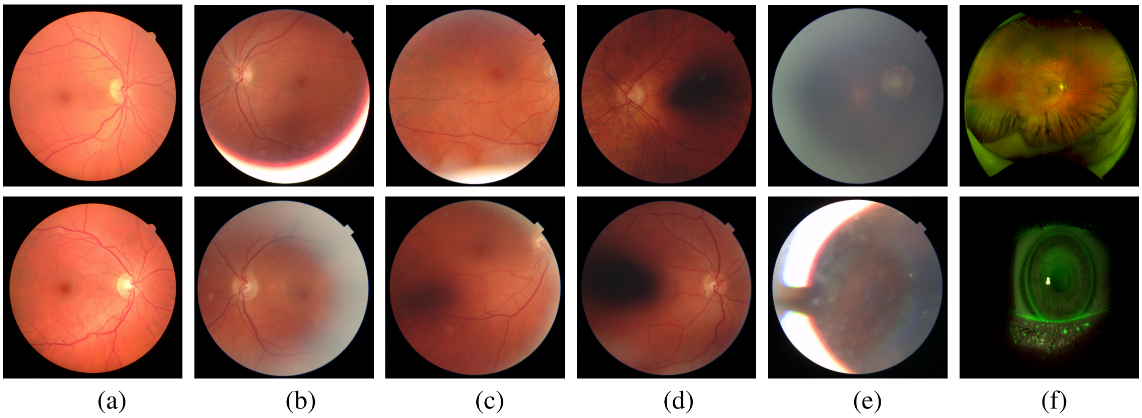


Figure 2: Examples of different quality grades of RFIQA dataset.(a) Grade0, (b) Grade1, (c) Grade2, (d) Grade3, (e) Grade4 (f) Grade5.

dataset with 28,792 retinal images selected from the EyePACS dataset (EyePACS, 2015), with three-level quality grading system (i.e., 'Good', 'Usable' and 'Reject'). EyeQ dataset has the advantages of a large-scale size, multi-level grading, and multi-modality. In (Saha et al., 2018) an automated method was developed to determine the image quality during acquisition in the context of diabetic retinopathy (DR). The method explicitly applied machine learning techniques to access the image and to determine 'accept' and 'reject' categories. 'Reject' category image requires a recapture. A deep convolution neural network was trained to grade the images automatically. A large set of 7000 colour fundus images was obtained from the EyePACS dataset (EyePACS, 2015). It is annotated by three retinal image experts to categorise these images into 'accept' and 'reject' classes based on the definition of image quality in the context of DR. (Fasih et al., 2014) proposed an algorithm for retinal image quality assessment based on generic features independent from segmentation methods. It computes the local sharpness and texture features by applying the cumulative probability of blur detection metric and run-length encoding algorithm, respectively. The quality features are combined to evaluate the image's quality for diagnosis purposes. Based on the recommendations of medical experts and experience. To classify images to 'gradable' and 'ungradable' classes, support vector machine with radial basis functions was used as a nonlinear classifier.

Most of the current existing approaches are based exclusively on generic features or structural features or a combination. These methods are designed and can work better for limited and specific set of retinal image dataset. Deep learning based methods have shown significant performance to overcome the problem. In this study we present an ensemble approach that combines CNN features and generic features such as texture and sharpness. The proposed method benefited by utilizing the domain knowledge of CNN and generic features and shown significant performance than using individual features as will be shown in the experimental results in Section 5

3 Retinal Fundus Image Quality Assessment (RFIQA) Dataset.

The existing state-of-the-art datasets DRIMBD (Sevik et al., 2014), DR2 (Pires et al., 2012), ELSA (Aquino et al., 2012), HRF (Köhler et al., 2013) and EyeQ (Fu et al., 2019) has only 2 or 3 categories of quality grades, which is not how opthomologist do when they assess whether or not the quality of an image is sufficient. Instead they use six categories of quality grades, which are rooted in the visibility of the major anatomic features in the fundus, namely the optical disk, the macula and the region surrounding to macula which is shown in Fig 1. Moreover when an image is found to have too low quality, it is important to understand *why*, so the appropriate action can be taken by the doctor and/or equipment when a new image is captured. To address these issues we introduce our new RFIQA dataset with six categories. The six categories are defined as follows, see Figure 2:

Grade 0 (Good): if all major areas such as the optical disc, the macula and the periphery are properly visible. It can be acceptable for medical analysis.

Grade 1 (Good; periphery not visible): if the periphery (border regions of the retina) is not clearly visible. Such images are still accepted for diagnosing diseases as the main structures such as the optical disc, the macula, and the regions near the macula are clear enough to be identified by ophthalmologist.

Grade 2 (Bad; Optical disc not clearly visible): if the optical disc of the retina is not clearly visible

Classes	No of Images
Grade0	5444
Grade1	1817
Grade2	158
Grade3	1058
Grade4	1449
Grade5	19

Table 1: Summary of our RFIQA dataset.

then the retinal image has a serious quality issue and cannot be used to provide a full and reliable diagnosis, even by ophthalmologists.

Grade 3 (Bad; Macula area not clearly visible): if the macula region of the retina is not clearly visible due to shadow on this region, it cannot be used for analysis as the macula region is considered as one of the important regions.

Grade 4 (Bad; unsharp, blinking, big reflections, over exposure): if the image is overexposed which is characterized by the milky-white layer from the periphery and towards the center. Apart from this if the image is unsharp and has reflections then it is also considered as bad quality grade 4.

Grade 5 (Bad; miscellaneous):if it is not containing the actual retina or if it is a different image modality such as SLO, OCT, etc.

For the new multi-grading dataset, we collected a large and diverse retinal image dataset with 9,945 fundus images captured by different types of fundus cameras and under a variety of imaging conditions from various patients with different retinal diseases. A summary of this RFIQA dataset is listed in Table 1 and sample images of the six levels of quality grading are shown in Fig 2.

4 METHODOLOGY

In this section, we introduce a baseline retinal fundus image quality assessment methodology based on a deep CNN model and generic features. The proposed CNN model is described in Section 4.1 and the proposed combined models is described in Section 4.3.

4.1 Deep CNN model

CNN has been very successful in visual object recognition (Russakovsky et al., 2015). Training deep existing CNN models from scratch requires huge amount of labeled data, which is often difficult to obtain for medical applications due to limited resources (experts) for annotating the data and patient privacy issues. Therefore, we propose a CNN model inspired by VGG16 (Simonyan and Zisserman, 2014) with about 29.3 million parameters - much fewer than complicated standard CNNs models (Szegedy et al., 2015; Szegedy et al., 2016). Our CNN model consists of totally 25 layers. Among these eighteen are convolution layers and five are max-pooling layers. A RELU non-linearity activation function is used for every convolution layer. A global average pooling layer(GAP) is added after the high level feature extraction convolution layer followed by Fully Connected (FC) soft-max layer. The input layer size for this network is 587×587. The number of filters used in our network are 32, 64, 128, 256, 512 and 1024, respectively. The convolution kernel sizes used in the model are 4×4 and 3×3 and Max-Pooling layers have kernel size of 3×3. A global average pooling is applied to last convolution layer. The final features are flattened before passing through the FC softmax layer. The architecture of the proposed baseline CNN is listed in Table 2. The training procedures are described in section 4.2.

4.2 Training

The proposed methodology is trained on our RFIQA dataset described in Section 3. The dataset is split into 80% training, 10% validation and 10% testing. Data augmentation is performed on the training samples. We apply image transformations such as random rotation, width shift, height shift, zooming, horizontal flipping and scaling to the RFIQA training subset to enlarge the dataset. The CNN model is trained over 120 epochs with batch size of 3. We use categorical cross entropy as a loss function and SGD as optimizer with learning rate 10^{-4} and momentum as 0.9. The proposed CNN model is initialized with random weights and trained on the RFIQA dataset. The framework is implemented on Tensorflow keras with GPU memory of $11GB$, Nvidia, RTX 2080Ti.

4.3 Combined model with CNN and Generic Features

In this section we describe our combined method which is illustrated in Fig 3. The proposed method retinal quality assessment method consists of three steps. In the first step we do pre-possessing for the input image. The features are extracted then concatenated in the second step and finally the concatenated features are given to a Random Forest classification algorithm in order to classify them.

4.3.1 Pre-processing

The prepossessing step can be further divided into regions of interest (ROI) detection and generating the mask for the retina. The ROI detection filters the background black region and the retinal mask is generated using Hough Circle Transform (Fu et al., 2019) and finally the cropped image and generated mask is

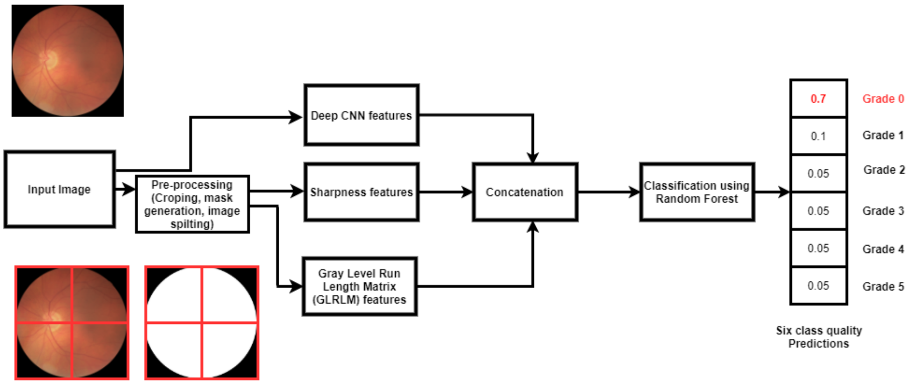


Figure 3: Proposed Combined Model with CNN and generic features.

divided into four patches shown in Fig 3. The features are then extracted on each image patch described in section 4.3.2.

4.3.2 Feature extractions

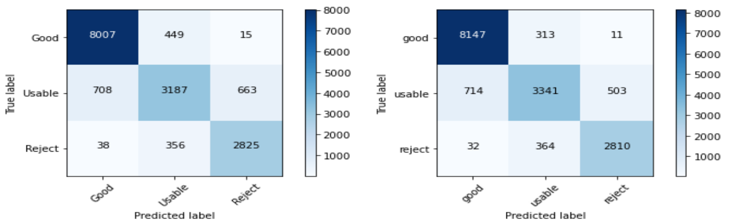
In this step, we first extract features from CNN model described in 4.1. For the given input image, the predictions are computed using trained CNN model and these predictions are used as CNN features. Generic features such as sharpness and textural features are extracted since these two features very important for retinal fundus image quality assessment. We extract the sharpness feature based on Cumulative Probability of Blur Detection (CPCD) (Narvekar, 2009). The steps involved in this method are edge detection followed by estimating the probability of detecting blur at the detected edges. A probability density function for the obtained probabilities is calculated from which the final cumulative probability of blur detection is obtained. The obtained CPCD values given the sharpness's of the image. We choose to use Gray Level Run Length Matrix (GLRLM) texture features in our method as they performed very well in medical image application (Florez et al., 2018). A Gray Level Run Length Matrix (GLRLM) measure gray level runs, which are defined as the length in number of pixels, of consecutive pixels that have the same gray level value. In a gray level run length matrix $\mathbf{P}(i, j|\theta)$, the $(i, j)^{th}$ element describes the number of runs with gray level i and length j occur in the image (ROI) along angle θ. The value of a feature is calculated on the GLRLM for each angle individually and finally the mean of these values is returned. The extracted sixteen GLRLM features are short run emphasis, long run emphasis, gray level non-uniformity, gray level non-uniformity normalized, run length non-uniformity, run length non-uniformity normalized, run percentage, gray level variance, run variance, run entropy, low gray level run emphasis, high gray level run emphasis, short run low gray level emphasis, short run high gray level emphasis, long run low gray level emphasis, long run high gray level emphasis. The GLRLM features are extracted after the dot product of original image patch and corresponding mask.

4.3.3 Classification

We choose Random Forest classifier to ensemble CNN and generic features. A Random Forest (RF) is an ensemble classifier that is widely used in the literature due to its capability to perform both classification and feature selection simultaneously (Breiman, 2001). It can be suitable for dealing with noisy, high dimensional and imbalanced data. It is robust against over-fitting, which is relevant when having small training sets. We train this classifier using our concatenated feature vector. RF is a ensemble of T decision trees which are learned from T examples that are randomly sampled with replacement from our training set S. Each node in a tree corresponds to a split made using the best of a randomly selected subset of $m = \sqrt{p}$ features, where p is the dimensionality of the feature vector. The quality of the split depends on the decrease in the Gini index that the split produces (Breiman, 2001).

5 EXPERIMENTAL RESULTS

In this section we evaluate the performance of the proposed CNN model and Combined model.The proposed CNN model is evaluated on our novel RFIQA dataset described in Section 2 and the publicly available EyeQ dataset (Fu et al., 2019) which has three classes 'Good','Usable' and 'Reject'. The retinal images in the two datasets have different characteristics



(a) (b)

Figure 4: Confusion Matrix of CNN and Combine model (CNN+GLRLM+SHARP) features on EyeQ dataset with three classes 'Good', 'Usable' and 'Reject'.(a) CNN Model, (b) Combined Model.

Layers	No of Filters	Size	Output
Conv1	32	4	294x294
Conv1	32	4	147x147
Conv1	32	3	147x147
Maxpool2	32	3	73x73
Conv2	64	4	73x73
Conv2	64	4	73x73
Conv2	64	3	73x73
Maxpool2	64	3	36x36
Conv3	128	4	36x36
Conv3	128	4	36x36
Conv3	128	3	36x36
Maxpool3	128	3	17x17
Conv4	256	4	17x17
Conv4	256	4	17x17
Conv4	256	3	17x17
Maxpool4	256	3	15x15
Conv5	512	4	15x15
Conv5	512	4	15x15
Conv5	512	3	15x15
Maxpool5	512	3	7x7
Conv5	1024	4	7x7
Conv5	1024	4	7x7
Conv5	1024	3	7x7
GAP	1024		1x1024
FC-Soft-max	6		1x6

Table 2: Proposed CNN model architecture.

Model	Val Acc	Test Accuracy
Resenet-50	0.82604	0.79
Inception-V3	0.84512	**0.80**
Inception-Resnet	0.83502	0.79
Proposed CNN	**0.84848**	**0.80**

Table 3: Evaluation of Deep learning models on RFIQA dataset.

collected from large number of patients with retinal diseases. Four measures recall, precision, accuracy and F1-score are used to evaluate the performance. we first compare the performance of the proposed CNN with three standard CNN models.

To perform the experimental evaluation, we conduct two experiments. First, we train the proposed CNN model described in Section 4 on RFIQA dataset which has six levels. Since this is the first work where a truly multi-level grading method is suggested, we cannot directly compare with the work of others. We therefore train the following more complicated standard CNN models ResNet-50(He et al., 2015), Inception-v3 (Szegedy et al., 2015), Inception-ResNet-v2 (Szegedy et al., 2016) and compare the results with the proposed CNN. For the standard CNN models we remove the fully connected layer and add additional layers such as GAP Layer and softmax layer. During the training of the models we initialize with ImageNet weights and train the whole model on our RFIQA dataset.

Class	Precision	Recall	F1-score
Grade0	**0.87**	**0.92**	**0.90**
Grade1	0.77	0.61	0.68
Grade2	0.50	0.06	0.11
Grade3	0.66	0.66	0.66
Grade4	0.69	0.80	0.74
Grade5	0.00	0.00	0.00

Table 4: Evaluation of different classes of RFIQA test dataset.

Table 3 summarizes the results obtained by different CNN models on our RFIQA dataset. We can observe that the best performances obtained are by the proposed CNN model and Inception-V3 (Szegedy et al., 2015).even though our model contains far fewer parameters compared to other models. Table 4. summarizes the results obtained on each class of the best performed model. Analyzing the classes individually 'Grade0' has high precision, recall, F1-score of 0.87, 0.92 and 0.90, respectively followed by 'Grade1','Grade4' and 'Grade3'. Whereas 'Grade5' and 'Grade2' achieve low precision, recall, F1-score values. This can be explained by the fact that 'Grade2' and 'Grade5' have insufficient data to train which is illustrated in Table 1 and it is not sufficient for the model to learn the features for that category/grade to classify. Therefore, when the training dataset is very small of any class of the dataset, test accuracy will penalize that class and it also shows impact on the overall accuracy of the model.

We conducted a second experiment to show the

Table 5: Evaluation of Features on RFIQA datset.

Features	Multilevel grades			Binary grades		
	Precision	Recall	F1-score	Precision	Recall	F1-score
GLRLM (Florez et al., 2018)	0.38968	0.55041	0.41944	0.60281	0.73459	0.64321
Sharpnesss (Narvekar, 2009)	0.55246	0.61728	0.57198	0.74102	0.76541	0.74512
CNN	0.74193	0.76358	0.74839	0.86927	0.86581	0.86725
Combined	**0.76150**	**0.78189**	**0.77084**	**0.90238**	**0.90358**	**0.90284**

Model	Precision	Recall	F1-score
Baseline (Wang et al., 2015)	0.740	0.694	0.699
ResNet-18-RGB (Fu et al., 2019)	0.804	0.816	0.808
ResNet-18-HSVB (Fu et al., 2019)	0.801	0.816	0.808
ResNet-50-RGBB (Fu et al., 2019)	0.812	0.807	0.810
Resenet-50-HSVB (Fu et al., 2019)	0.770	0.777	0.773
DenseNet121-RGBB (Fu et al., 2019)	0.819	0.811	0.815
DenseNet121-HSVB (Fu et al., 2019)	0.819	0.811	0.815
Proposed CNN-RGB	**0.860**	**0.862**	**0.860**
Proposed combined model	**0.878**	**0.880**	**0.878**

Table 6: Evaluation of different methods on the EyeQ dataset.

importance of combining CNN and generic features. The experiments are conducted on multi-level and binary grades. We created a binary grade dataset from the RFIQA dataset with two classes 'Good' and 'Bad' quality. We considered 'Grade0', 'Grade1' as 'Good' and the rest of the grades as 'Bad'. We initialize the model with the best weights of the first experiment and train the whole model. Table 5 summarizes the results obtained by proposed method for the single feature and multiple feature combining GLRLM (Florez et al., 2018), Sharpness (Narvekar, 2009) and CNN features on the multi-level and binary classification. Analyzing the results with a single feature, we can see that deep features gives better performance than GLRLM and Sharpness. From this table we can also observe that the proposed method using multiple features achieves higher performance than using any of the individual features alone.Thus the combination of generic features GLRLM, Sharpness and CNN features, provides a robust feature extraction for retinal image quality assessment.

In order to compare the proposed method against state-of-art quality assessment methods. We train our model on a public dataset (EyeQ) (Fu et al., 2019). Table 6 summarizes the results obtained by the proposed models and color space models from (Fu et al., 2019) and Fig 4 shows the confusion matrix plots of the proposed models. We can clearly observe the proposed combined model outperforms other methods in terms of precision, recall and F1-score. It should be noted that using multiple color spaces is likely to increase the performance further as seen in (Fu et al., 2019).

6 CONCLUDING REMARKS

In this paper, we proposed an novel retinal fundus image quality assessment (RFIQA) dataset with a six-level quality grading annotated by experts. It is based on important regions to consider for diagnosing DR, AMD and Glaucoma by ophthalmologist. Our RFIQA is the first of its kind with multi-level grading defined by experts and a large-scale size. We also proposed a CNN model with much fewer parameters for the purpose of RFIQA and a method which combines both deep features and generic features such as Gray Level Run Length Matrix (GLRLM) and sharpness. Experimental results using two different datasets with different characteristics shows that the combination of both generic and CNN features performs significantly better than using only one of them.

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