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EMPLOYING LIGHTWEIGHT COMPUTATIONAL MODELS TO ANALYSE AND CLASSIFY DIABETIC RETINOPATHY IMAGES

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Abstract

This research proposes a hybrid strategy that combines light weight models of deep learning with extensive pre-processing methodologies to improve the categorization and identification of diabetic retinopathy (DR). DR images have been resized during the pr-processing stages and suitable filters algorithms have been used to eliminate both salt-and-pepper Gaussian noise. The selected filtering method ensures effective smoothing of homogeneous regions while preserving critical edge details, with its performance evaluated using Structure and Edge Preservation Indices. A lightweight pre-trained network is employed for classification, ensuring computational efficiency without compromising Accuracy. Extensive experimentation demonstrates that Shuffle Net achieves a remarkable classification accuracy of 96.33% on a combined dataset. These findings highlight the potential impact of the proposed hybrid strategy for enhancing and automating DR detection, paving the way for scalable and accurate diagnostic tools in medical imaging, and potentially improving the lives of millions affected by diabetic Retinopathy.

Keywords:

Pre-Processing, Soft Max, Pre-trained network, Lightweight Network

1. INTRODUCTION

The most Prevalent eye disorder that can result in blindness or Decreased vision are Age-related Muscular Degeneration (AMD), Cataracts, Diabetic Retinopathy, the most common disease is diabetes, and it is ranked seventh all over the world. Diabetic Retinopathy is a medical ailment of diabetes due to which the retina is effected severely and potentially results in blindness. Nearly 62 million Indians aged between 25 and 75 have currently been diagnosed with Diabetic Retinopathy, with projections estimating this number will reach 102 million by 2030 [1] [5] [28].

NPDP (Non-Proliferative Diabetic Retinopathy) and PDP (Proliferative Diabetic Retinopathy) are the two stages of categorisations of Diabetic Retinopathy. Early identification of Diabetic Retinopathy relies on the analysis and classification, the rising prevalence of diabetes and the need for reliable, scalable screening techniques are driving further advancement in the domain of diabetic retinopathy imaging research. Researchers strive to develop accurate, accessible, and practical solutions for timely detection and intervention of diabetic retinopathy by integrating various disciplines and leveraging advanced technologies.

Numerous studies suggest transfer learning approach for pre-trained network using deep learning models for classifying images of diabetic retinopathy [5]-[18] [28]. Further, detection of abnormalities of diabetic retinopathy is usually done through Fundus retina images. In this work, a Comprehensive DR dataset has been compiled for binary class classification of images [19]-[22]. Both NPDP (Non-Proliferative Diabetic Retinopathy) as well as PDP (Proliferative Diabetic Retinopathy) are contemplated to be unhealthy eye conditions, whereas the healthy eye Fundus images are considered to Non-diabetic Retinopathy [28]. Retinal vessels exhibit irregularities in Diameter, size, and shape in case of unhealthy eye images, in comparison to healthy eye images [20]-[28].

For the experiment, three robust datasets of diabetic retinopathy images namely, DRD- EyePACS, APTOS-2019 and IDRiD, have been selected. Additionally, for exhaustive experiments, a consolidated images of diabetic retinopathy image dataset have been created. The datasets have been then subsequently split into training, testing, and validation sets. Classification, Precision, Accuracy, Specificity, Sensitivity and F1-score were employed to assessment the model’s efficiency. In the present work, eight distinct pre-trained networks from the lightweight category have been chosen, highlighting the comprehensiveness and rigor of our experimentation, these three Standard differences of diabetic retinopathy images have been considered

Accuracy, which can be defined as the ratio of the total number of True Negative (T_N) and True Positive (T_P) images to the Total number of images taken for the classification, are the key metrics in our study.

Here, sensitivity is defined as the measure of the patients correctness True Positive (T_P), which is the total number of patients with diabetic Retinopathy, to the total number of Patients [28] The formula used for sensitivity is given in Eq.(1).

$$Sensitivity = T_P/(F_N+T_P) \tag{1}$$

Accuracy which is defined as the ratio of the total number of Images with true negative (T_P) and true positive (T_N) to the total number of Images Formula is shown in Equation.2.

$$Accuracy = (T_N+T_P)/(F_N+F_P+T_N+T_P) \tag{2}$$

Precision is the ratio of DR images classified correctly to the total number detected DR images, including NDR images detected wrongly as DR images. The formulas for Precision in described in Eq.(3).

$$Precision = T_P/(F_P+T_P) \tag{3}$$

Specificity refers to ratio that identifies if a person is impacted by the DR disease or remains unaffected. The Specificity formula is shown in Eq.(4).

$$Specificity = T_N/(F_P+T_N) \tag{4}$$

$$Recall = T_P/(F_N+T_P) \tag{5}$$

The F-Score (F1-Score), used to evaluate binary classification systems, is a measure of accuracy of a model is on a given dataset.

$$F\text{-}Score = 2\times(Precision \times Recall)/(Precision+Recall) \tag{6}$$

2. DIABETIC RETINOPATHY DATASET COLLECTION

The diabetic Retinopathy Dataset (DRD-EyePACS) available at Kaggle is a significant resource for our research, as it contains 2750 DR images, of size 256x256, with1750 unhealthy classes and 1000 healthy classes. This dataset provides a diverse range of images for our experiments. APTOS (Asia Pacific Tele-Ophthalmology Society)-2019, includes 3662 DR images are compiled by India's Aravind Eye Hospital collected from numerous participants in rural India, with the fundus images taken over a prolonged period in diverse settings and condition within the field of medical. Third data set, Indian Diabetic Retinopathy Image Dataset (IDRiD) has total count of DR images 513 of size 4288×2848, in which 103 unhealthy class of images and 413 healthy images.

In this work, datasets ATOS -2019, IDRiD and DRD EyePacs are combined, resulting in a consolidated dataset comprising 6,928 images of which 2973 are healthy and 3955 are unhealthy classified into healthy and Unheathy Images In this four experiment are performed and the Fourth experiments is based performed by the consolidating all the of three data set from these three sources as the data sets utilized by medical professionals are not inherently robust .The details of the DR are presented in Table.1.

Table.1. Diabetic Retinopathy Datasets Details

Class	IDRiD	ATOS -2019	DRD-EyePACS	Combined Dataset
Healthy (Not Diabetic Retinopathy)	168	1805	1000	2973
Unhealthy (Diabetic Retinopathy)	348	1857	1750	3955
Total	**516**	**3662**	**2750**	**6928**

3. DENOISING ALGORITHM FOR IMAGE ENHANCEMENT

In the present work, pre-processing stem was utilised to enhance the quality of DR images. A comprehensive review of research published illustrates wide application of contrast adjustment, denoising and sharpening for the purpose of enhancement of the quality of DR images [1]-[20]. This study explores comprehensive selection of large of filtering and enhancement algorithms which has been selected for the various categories: (a) contrast b) enhancement c) linear, (b) non-linear, (d) edge-preserving [7] [21]-[28]. It has been seen out of all the methods and techniques used for these categories, Gaussian filter has shown the best performance in all categories, demonstrating its effectiveness in image quality and thus, has been used as a pre-processing step for Diabetic Retinopathy (DR) [7].

3.1 IMPLEMENTING DATA AUGMENTATION AND SPLITTING OF THE DATASET

Data augmentation (involving translation, flipping and rotation transformation) has been employed to balance class subsets, to ensure unform distribution of diabetic retinopathy images across these subsets in this work. The dataset description as shown in Table.2. In these 24053 images are used for the Validation and training and 900 data sets are used for the Testing of the Images. Validation total of 3053 images are considers and for training 21000 images are taken into consideration including healthy and unhealthy retinal images.

Table.2. The dataset description

Dataset	**Combined Dataset**		
Total No. of Images	**24053**		**900**
Class	**Validation**	**Training**	**Testing**
Healthy (Not Diabetic Retinopathy)	1524	10500	450
Unhealthy (Diabetic Retinopathy)	1529	10500	450
Total	3053	21000	900

3.2 PARAMETERS USED FOR EVALUATING CLASSIFICATION OF DR IMAGES

The evaluation for the detection of Diabetic Retinopathy from an exhaustive literature survey, it is noted that performance matrices sensitivity, precision, F1-Score, overlapping error, Accuracy, Specificity, log loss, boundary-based evaluation, etc., used by several researchers. The performance matrix used to calculate assessment parameters of DR images for the classification are sensitivity, F1-Score, precision, specificity Accuracy in this work.

3.2.1 Selection of Hyperparameters:

The selected hyperparameter used for the implementation of experiments is shown in Table.3.

Table.3. Selected hyperparameter and used machine for the implementation of experiments

Hyper Parameter	**Details**
Mini Batch Size	32
Optimizer	Adam
Maximum Epochs	30
Learning Rate	10^{-4}

3.3 CLASSIFICATION MODULE AND PRETRAINED NETWORK SELECTION

It is noted that total 8 pre-trained networks have been chosen from the lightweight category. The intensity of these pre-trained networks is considered vital for ensuring the accurate classification of the DR images [28]. Compact categories for selecting a pre-trained network are shown in Table 4.

Table.4. Compact category for selecting a pre-trained network

Name of the Pre-trained Networks	Type of Categories	Image Dimension	Number of Parameters (Million)	Depth of the Network
Googlenet-places365	Light weight Networks	224×224×3	7.0	22
mobilenetv2		224×224×3	3.5	53
Resnet18		224×224×3	11.7	18
nasnetmobile		224×224×3	5.3	-
GoogleNet		224×224×3	7.0	22
efficientnetb0		224×224×3	5.3	82
shufflenet		224×224×3	1.4	50
SqueezeNet		227×227×3	1.24	18

4. RESULT AND DISCUSSION

In this study, images of Diabetic Retinopathy are classified using pre-trained eight Lightweight models named Squeeze Net, mobilenetv2, shufflenet, nasnetmobile, efficientnetb0, GoogleNet, Googlenet-places365 and Resnet18.These images are chosen to the distinguish effectively between the healthy and unhealthy classes by utilising Collective data sets of DRD-EyePACS, APTOS-2019 and IDRiD, This innovative methodology has significantly improved the precision and the efficiency of detecting Diabetic Retinopathy(DR). The performance without Augmentation and after Augmentation using collective datasets of original DR Pre-processed Images in Table.5 (before augmentation) and Table.6 (after augmentation) The pre-trained network from the lightweight category has demonstrated exceptional performance, achieving the highest classification accuracy with the Collective dataset. 96.66% Accuracy was reached after the augmentation of the consolidated dataset using the Shufflenet network. The individual class accuracy using the series based Shufflenet for healthy and unhealthy is 439 and 431 respectively The Evaluation matrix for the network is 0.96 for Sensitivity, 0.98 for Specificity, 0.98 for Precision, and F1-Score 0.97 The best outcome are marked in blue as in Table.5. To address overfitting problems, this research applies normalization as well as pre-processed data augmentation Based on extensive experiments, the most effective pre-trained model was chosen since classification of accuracy. Shuffle Net trained model offers an efficient method for accurately detecting diabetic retinopathy in radiological images across different scenarios.

Table.5. Performance of Lightweight pre-trained networks based on without augmentation

Network Name	Confusion Matrix		Without Augmentation				
			F1	Sens.	Spec.	Pre.	Acc (%)
Squeeze Net	338	112	0.70	0.68	0.75	0.73	71.3
	146	304					
mobilenetv2	351	99	0.72	0.69	0.78	0.76	73.3
	141	309					
shuffle net	358	92	0.74	0.70	0.80	0.78	75
	133	317					
nasnetmobile	343	107	0.71	0.68	0.76	0.74	72.3
	142	308					
efficientnetb0	326	124	0.67	0.65	0.72	0.70	68.6
	158	292					
GoogleNet	317	133	0.66	0.64	0.70	0.68	67.1
	163	287					
Googlenet-places365	335	115	0.70	0.68	0.74	0.73	71.1
	145	305					
resnet18	331	119	0.67	0.63	0.74	0.71	68.4
	165	285					

Table.6. The performance of Lightweight pre-trained networks based after augmentation

Network Name	Confusion Matrix		After Augmentation				
			F1	Sens.	Spe.	Pre.	Acc (%)
Squeeze Net	408	42	0.87	0.84	0.91	0.90	87.33
	72	378					
mobilenetv2	411	39	0.90	0.89	0.91	0.91	90
	51	399					
shuffle net	439	11	0.97	0.96	0.98	0.98	96.66
	19	431					
nasnetmobile	415	35	0.89	0.87	0.92	0.92	89.66
	58	392					
efficientnetb0	397	53	0.85	0.83	0.88	0.88	85.77
	75	375					
GoogleNet	395	55	0.85	0.83	0.88	0.87	85.44
	76	374					
Googlenet-places365	407	43	0.88	0.86	0.90	0.90	88.44
	61	389					
resnet18	396	54	0.88	0.87	0.88	0.88	87.55
	58	392					

5. CONCLUSION

From the comprehensive experiments, it is concluded that the utmost accuracy is achieved by ShuffleNet-based pre-trained network using collective dataset**.** The proposed method holds potential for application in routine clinical practice. Shufflenet would strike a balance between accuracy, depth and computing efficiency, accuracy. Additionally, within the lightweight category this network demonstrates efficiency, high accuracy and robustness for making it a highly effective approach for classifying and diagnosing diabetic retinopathy. It is also observed that implementing and training ShuffleNet demands more processing in comparison to other networks and requires high-quality labelled data. It is also observed that ShuffleNet achieved an accuracy of 96.66%. this outcome can represent a step towards the early detection of DR in patients and has the potential to be applied in real-time clinical practice.

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