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Multi-channel Convolutions Neural Network Based Diabetic Retinopathy Detection from Fundus Images

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Abstract

Diabetic Retinopathy (DR) is an eye medical condition usually found in patients suffering from diabetes. The initial stages of DR can either show no symptoms or cause mild vision problems but advanced stages of the disease can cause blindness. The main cause of DR is high blood sugar in diabetic patients that affect the blood vessels supplying blood to the retina and blocks them. The body tries to grow new vessels to supply the retina, however, they usually don't develop properly and can easily leak. DR Detection is an extremely challenging task due to the variation of retina change throughout the disease stages. In this paper, a multi-channel Convolutional Neural Network (CNN) is proposed for DR detection from fundus images of the eyes. The proposed system is tested on a DR Dataset consisting of 35,126 images provided by EyePACS. Experimental results indicate that the accuracy of 97.08% is achieved through the model that outperforms those achieved through other methods in recent studies.

Keywords: Diabetic Retinopathy Detection; Convolutional Neural Networks (CNN); Multi-Channel DR Detection; Fundus Images

1. Introduction

Diabetic Retinopathy (DR) is one of the major causes of blindness in patients affected from diabetes. DR affects the eye in many different ways that can eventually lead to vision loss. Early detection of DR is essential in providing proper treatment by the ophthalmologists. The major cause of DR is increased blood sugar that affects the blood vessels inside the tissues of the retina. This can happen due to insufficient insulin production or the cells not responding the insulin. The excessive blood sugar causes damage to the light blood vessels inside the tissues of the retina. Funduscopy

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is a medical imaging procedure which is used in the identification of these abnormal changes inside the eye. Images obtained through the funduscope reveal information about the fundus of the eye. These fundus images contain the internal structure of the retina and its optic disc section. The detection of DR is a manual process that requires careful examination by the clinician to grade the digital color fundus images of the retina. DR can cause various side effects to the retina of the eye. e.g. red lesions like microaneurysms and intra retinal hemorrhages, and white lesions like, exudates and cotton wool spots, etc. Various pixel classification and morphological base extraction methods have been proposed for extracting these lesions [1]. The progression of DR can be described in five stages according to the International Clinical Diabetic Retinopathy (ICDR) severity scale i.e. No DR, Mild DR, Moderate DR, Severe DR and proliferative DR. In the early stages of DR i.e. Mild DR, small balloon shaped areas appear in the fundus image of the eye that show the swelling in the tiny blood vessels of the retina. These are called microaneurysms. In the next stage, Moderate DR, the blood vessels inside the eye start to distort and lose their ability to supply blood throughout the retina. Severe DR occurs when the supply of blood to the retina is blocked causing the retina to grow new blood vessels. The most critical state of DR is proliferative DR which causes new blood vessels to be formed and grown into the vitreous gel of the retina. These new tissues can leak blood and cause retinal detachment which may result in permanent loss of vision. Fig. 1. shows the image as seen from a normal and DR affected eye.

Fig. 1. Image with healthy eye and DR affected eye.

Fig. 2. shows the DR lesions for a healthy patient and for a Diabetic patient. It can be observed that for a diabetic patient, the symptoms previously described such as new blood vessels, cotton wool spots and other appear clearly in the image.

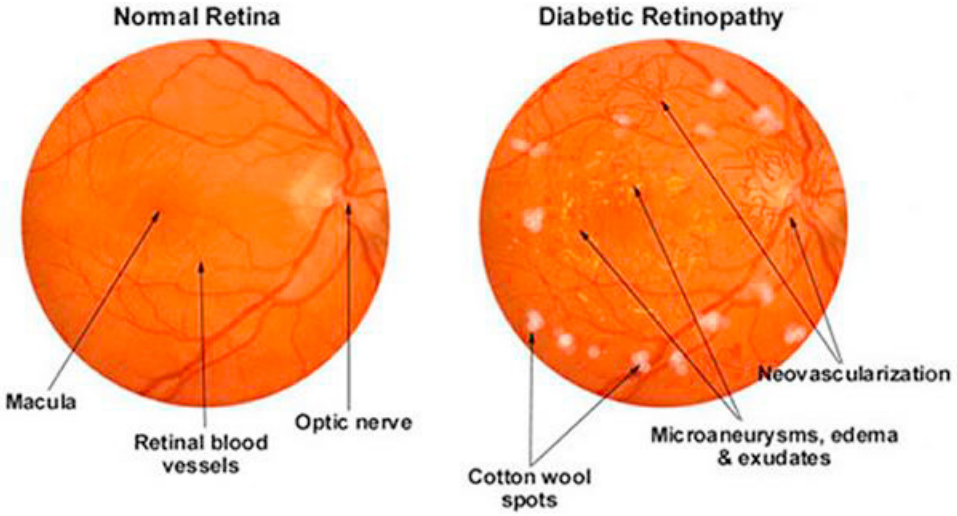

Fig. 2. DR Lesions: Microaneurysms, Exudates and Cotton-wool Spots.

2. Literature Review

Image processing methodologies techniques can be used to design Computer Aided Diagnosis (CAD) systems for diagnosing different medical conditions. Brain MR Images can be used in the design of an accurate tumor detection system. Similarly, automated Diabetic Retinopathy detection from fundus images is another useful application of image processing in which different structural properties of fundus images are used in the proper classification and detection of DR in its different stages.

A novel approach for the detection of different lesions caused by DR is proposed in [1]. The system first extracts the vessels from the retina and removes the optic disc. In the preprocessing stage, the dark lesions are highlighted from the lightly illuminated lesions using edge enhancement techniques. The contrast of the image between dark and light spots is further improved by a band pass filter. Genetic algorithms are then used in the next stage to extract the candidate lesions. In the last step, morphological operations are performed to remove any false positives.

An algorithm that uses deep learning is able to achieve high sensitivity and specificity for detecting referable Diabetic Retinopathy [2]. The CNN used in this work combines pixels into local and global features. The Incpetion-v3 architecture [3] is used to train the system. Stochastic gradient descent [4] algorithm is used to train the weights. A multiple binary classifier is achieved through the process. The performance of the algorithm is measured using the Area under the operating curve (AUC).

The authors of [5] use deep Convolutional Neural Networks (CNN) to classify the retinal fundus images into two classes i.e. No DR and Referable DR (rDR) having ICDR level 1-4. The sensitivity, specificity and Area under the curve (AUC) of their proposed system are compared with other algorithms for analysis. The system works by preprocessing the input image to remove any noise or artifacts. The data is then used to train a CNN that has 19 layers which is based on the VGGNet family of image classification challenge of 2014 [6] [7]. The results achieved are close to the recent models for DR detection.

Another work [8] uses 5 different combinations of convolutional layers for the classification of Diabetic retinopathy from retinal fundus images. The authors propose three models that use a quadratic kappa metrics to evaluate the performance of the results. A best kappa score of 0.3996 is achieved using their proposed methods.

In another study [9], the textural features of the fundus images are used for classification of diabetic retinopathy. The authors in [9] propose a modified version of Local Binary Pattern (LBP) [10] [11] feature extraction called Neighbor Mean – Local Binary Pattern (NM-LBP) and Global Mean – Local Binary Pattern (GM-LBP). The extracted features are classified using k-Nearest Neighbor (kNN) and Support Vector Machines (SVM). A binary and multiclass classification is presented. In binary class the fundus images are classified into normal and abnormal while in multiclass normal, mild medium and severe stages of the DR are identified. The accuracy achieved through these methods is approximately 90%.

In [12], the authors proposed multi-cell multi-task CNN for DR grading. Their method gradually increases the depth of the deep CNN and the resolution of the eye image which increases accuracy. The method also addresses multiclass classification of the different stages of DR. Used on the DR Dataset, the algorithm achieved a Kappa of 0.841. In [13], the authors proposed a deep CNN algorithm for pixel-wise exudate identification. A morphological candidate opening algorithm is utilized to extract potential educate candidate points. The candidate point with surrounding (64x64) image is input to the CNN model for classification. This method achieved a 91.92% accuracy on a small dataset E-Ophtha EX consisting of 82 images (47 exudate images and 35 normal images).

In [14], the authors propose a texture based method of the different lesions utilizing Gray Level Co-occurrence Matrix (GLCM) along with a 2-layer feed forward network along with sigmoid output neurons neural network. Their method achieved a 90% accuracy when tested on the MESSIDOR dataset (training) and DRIVE dataset (testing). In [15], the authors proposed a CNN method for diagnosing DR from fundus image as well as multiclass classification to determine severity. The DR Dataset provided by Kaggle was used in their work and achieved an accuracy of 75%.

In [16], the authors propose a method that extracts and isolates the blood vessels, microaneurysms and hard exudates from the image for the purpose of feature extraction. The contribution of their work on the feature extraction of the components included morphological operations, RGB to CMY representation, and binarization among others. Support Vector Machines (SVM) was then used for classification. Their method was tested on the MESSIDOR dataset consisting of 1200 images and achieved an accuracy of 92.4%. In [17], the authors propose a recognition pipeline

based on Deep CNN to detect DR. Their method was also tested on the Messidor dataset and achieved an accuracy of 90.5%.

3. Proposed Methodology

In this paper, the fundus images of the eye for DR affected patients are used to train a CNN that is able to classify the images into five different classes i.e. No DR, Mild DR, Moderate DR, Severe DR and proliferative DR. The input images are pre-processed and separated into gray scale and individual Red (R), Green (G) and Blue (B) channels. This data is used as an input to propose multiple CNN models that classify the images into various stages of DR. The results of using multiple channels (R, G, and B) and grayscale images to train CNN is examined and discussed in results section. The workflow of the proposed system is shown in Fig. 3.

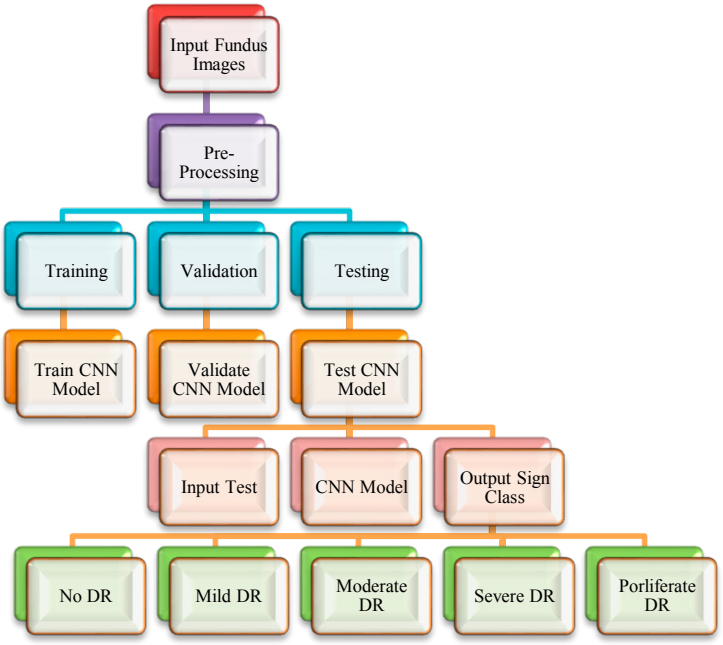

Fig. 3. Workflow of the Proposed System.

3.1. Data Description

For the data of color fundus images, we use the DR Dataset [18] which is provided by EyePACS. The data set contains 88,702 images of 44,351 patients for the left and right eye. This data is split into training and test set. The training set contains 35,126 images and an 80-20% split is used from this set to train and test the CNN. The image in the data set are rated from 0-4 with various stages of DR in accordance with the International Clinical Diabetic Retinopathy severity scale. i.e. No DR (0), Mild DR (1), Moderate DR (2), Severe DR (3), Proliferative DR(4).

3.2. Preprocessing

In the preprocessing stage, the input data is first separated into multiple channels i.e. R, G, and B, and gray scale images. The size of the input images in the DR dataset have a very high resolution which can cause the training process to be slow and can end up consuming and running out of memory during the training process. For this purpose, the images are resized into a resolution of 100 x 100 pixels before input into the CNN model.

3.3. Proposed CNN model

Three different CNN models are proposed in this work that have varying number of batch sizes and epochs sizes on which the experiments are performed. The selection of appropriate design parameters for CNN directly affect the performance of the model. The convolution layers perform the convolution operation between the input and different filters are used to extract important features from the image. Since, there are no linear relationship between the input images and output images in DR detection, a non-linear Rectified Linear Unit (ReLU) is utilized as the activation function. The pooling layers helps reduce the dimension of the input image to deal with the overfitting problems. In this paper, MAX pooling is used with varying size to reduce the dimension of the image and speed up the learning process. After the Convolution and pooling layers, fully connected layers are used to classify the image into various DR stages.

The first proposed CNN model (model 1) uses two convolution layers of 32 filters with kernel size 3 x 3 and ReLU activation. Each of the two convolutional layers are followed by MAX Pooling layers of size 3 x 3. Regularization is performed by using a 20% dropout in the next step. For classification, the images are flattened to one-dimensional vector followed by fully connected dense layers of 256 and 64 features with ReLU activation. The final dense layer uses softmax activation and transforms the result into 1 x 5 vector. The softmax function converts the output into a probability distribution. The images are classified to a certain class based on its probability distribution. Fig. 4. shows the proposed Model 1.

The second model (model 2), the model starts with a convolution layer having 32 filters with a kernel size of 5 x 5 and ReLU activation function. This is followed by a MAX pooling layer with kernel size 2 x 2. Next, another convolution layer with 32 filters and kernel size 3 x 3 is inserted using the ReLU activation. This is followed by another MAX pooling layer of 2 x 2 size. The last convolutional layer uses 16 filters with kernel size of 3 x 3 followed by the MAX pooling layer with size 2 x 2. For classification, the images are flattened to one-dimensional vector followed by fully connected dense layers of 128 and 64 features with ReLU activation. The final dense layer uses softmax activation and transforms the result into 1 x 5 vector. Fig. 5. shows the proposed Model 2.

The third proposed model (model 3) consists of four convolutional, four max pooling layers followed by the 3 dense layers as shown in the Fig. 6.

All three models are tested with batch sizes of 10, 20 and 40 with epochs varying from 8, 16, 32, 64 and 128 on the multi-channel and gray scale fundus images of the eye.

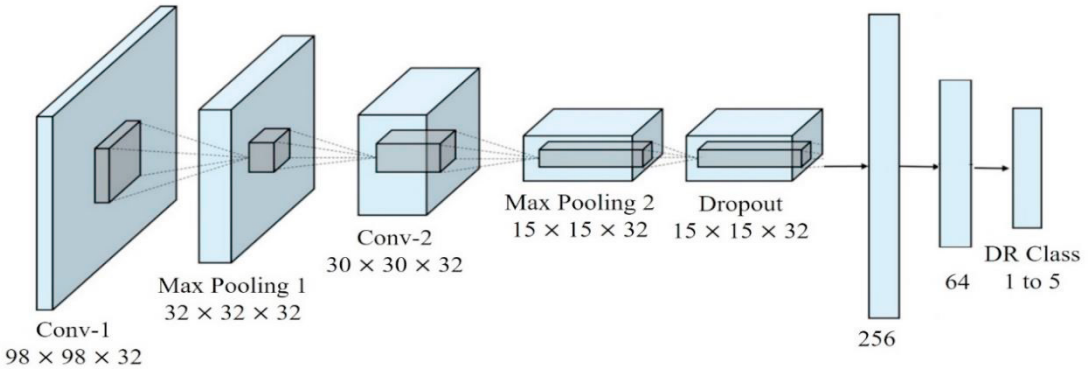

Fig. 4. Proposed basic CNN Model 1.

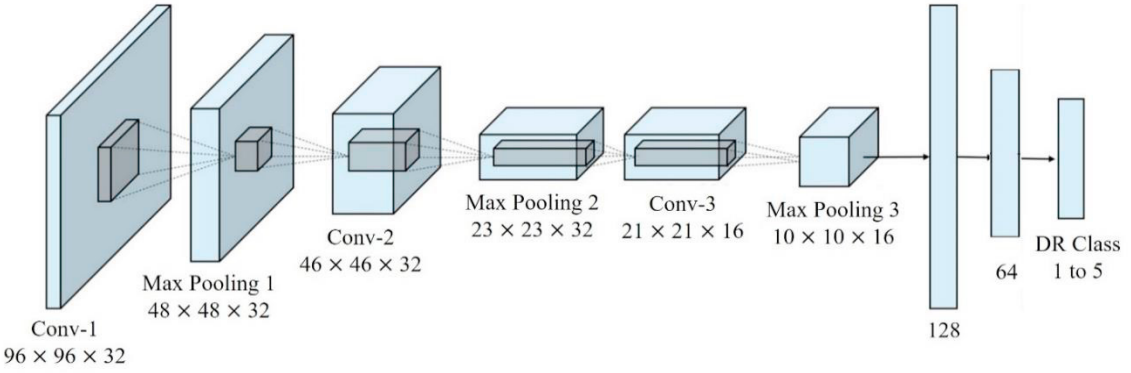

Fig. 5. Proposed basic CNN Model 2.

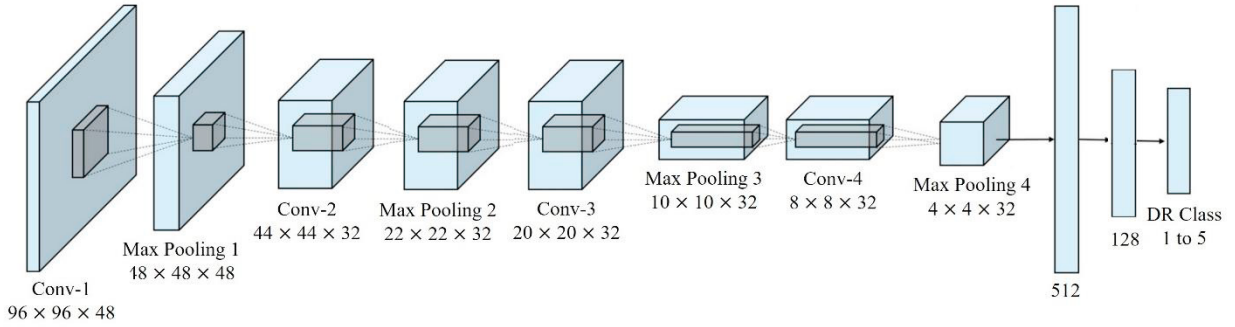

Fig. 6. Proposed basic CNN Model 3.

3.4. System Configuration

Experiments were performed on a system that utilizes the nVIDIA CUDA [19] architecture to train the CNN. The processor used in the system is AMD Ryzen 2700x having eight cores with sixteen threads and a system RAM of 32 GB. The system uses nVIDIA RTX 2080 Graphics Processing Unit (GPU) with 8GB of DDR6 Memory. The GPU has 2944 CUDA cores and 368 Tensor cores. Keras API running on top of tensor flow in python was used for training and evaluating the models.

4. Results and Discussions

Three models of Deep CNN have been proposed in this paper for the classification of DR into one of the five DR classes based on disease severity as follow: No DR, Mild DR, Moderate DR, Severe DR and proliferative DR. Table 1. shows the results obtained from all models on grey scale images, Table 2. shows the results obtained from all models by using the red channel of input images, Table 3. shows the results obtained from all models using the green channel of DR images, and Table 4. shows the results for the Blue channel.

It is also observed that for all models, significant changes in test accuracy occur only after epoch size 32 and above. So there is no linear relationship between epoch size and accuracy. The performance gets better at higher epoch sizes. It is also seen that the model 2 achieves the best accuracy overall. In Model 2, a maximum accuracy of 96.85% was observed for Grey Scale Images, 94.11% for Red Channel, 93.95% for Green Channel, and finally 97.08% accuracy for Blue Channel.

In comparing the three proposed models, model 2 achieved the best accuracy, followed by model 1 and then model 3. Model 3 attained the lowest accuracy. The accuracy rates relate to the proposed architecture and parameters set

for each model. Model 3 results indicate that increasing the number of convolutional and pooling layers in CNN architecture doesn't necessarily improve the performance of the system due to overfitting. The results obtained from Model 2 outperform those reported in recent literature.

Table 1. Proposed CNN Model results for Gray-Scale images.

Epochs	Batch Size	Grey Scale					
		Model 1		Model 2		Model 3	
		Test Acc.	Test Loss	Test Acc.	Test Loss	Test Acc.	Test Loss
8	10	73.24	0.8650	73.24	0.8606	73.24	0.8673
	20	73.24	0.8616	73.24	0.8579	73.24	0.8663
	40	73.24	0.8629	73.24	0.8587	73.24	0.8657
16	10	73.24	0.8567	73.31	0.8323	73.24	0.8716
	20	73.24	0.8557	73.59	0.8079	73.24	0.8723
	40	73.24	0.8497	73.42	0.8227	73.24	0.8582
32	10	73.45	0.8369	77.83	0.6415	73.24	0.8719
	20	74.13	0.7789	81.83	0.5064	73.26	0.8539
	40	73.83	0.8068	81.92	0.5132	73.32	0.8449
64	10	76.30	0.6892	86.96	0.3747	73.24	0.8716
	20	76.99	0.6960	87.91	0.3342	73.35	0.8368
	40	79.07	0.5985	90.18	0.2704	74.41	0.7812
128	10	86.77	0.3701	90.72	0.2641	73.27	0.8549
	20	91.11	0.2412	**96.85**	**0.0913**	76.38	0.6802
	40	87.98	0.3341	94.96	0.1415	76.88	0.6904

Table 2. Proposed CNN Model results for multi-channel images (Red Channel).

Epochs	Batch Size	Red Channel					
		Model 1		Model 2		Model 3	
		Test Acc.	Test Loss	Test Acc.	Test Loss	Test Acc.	Test Loss
8	10	73.36	0.8656	73.36	0.8611	73.36	0.8682
	20	73.36	0.8621	73.36	0.8604	73.36	0.8663
	40	73.36	0.8630	73.36	0.8592	73.36	0.8656
16	10	73.36	0.8580	73.36	0.8516	73.36	0.8607
	20	73.36	0.8559	73.37	0.8337	73.36	0.8589
	40	73.36	0.8498	73.46	0.8284	73.36	0.8577
32	10	73.40	0.8440	74.43	0.7708	73.36	0.8577
	20	74.14	0.8108	78.54	0.6401	73.36	0.8532
	40	73.48	0.8287	81.81	0.5368	73.39	0.8372
64	10	73.51	0.8330	89.92	0.2896	73.38	0.8574
	20	81.13	0.5239	85.95	0.4017	74.91	0.7814
	40	77.44	0.6736	87.92	0.3468	74.99	0.7600
128	10	78.16	0.6725	90.61	0.2673	73.41	0.8487
	20	88.80	0.3071	**94.11**	**0.1698**	76.89	0.7103
	40	86.08	0.3823	93.71	0.1794	80.86	0.5599

Table 3. Proposed CNN Model results for multi-channel images (Green Channel).

Epochs	Batch Size	Green Channel					
		Model 1		Model 2		Model 3	
		Test Acc.	Test Loss	Test Acc.	Test Loss	Test Acc.	Test Loss
8	10	73.48	0.8612	73.48	0.8612	73.48	0.8685
	20	73.48	0.8594	73.48	0.8594	73.48	0.8635
	40	73.48	0.8603	73.48	0.8603	73.48	0.8630
16	10	73.48	0.8542	73.48	0.8542	73.48	0.8682
	20	73.48	0.8544	73.48	0.8544	73.48	0.8684
	40	73.48	0.8458	73.48	0.8458	73.48	0.8550
32	10	73.49	0.8429	73.49	0.8429	73.47	0.8558
	20	73.61	0.8078	73.61	0.8078	73.54	0.8423
	40	73.72	0.8062	73.72	0.8062	73.54	0.8267
64	10	76.18	0.7238	76.18	0.7238	73.51	0.8525
	20	89.96	0.2664	89.96	0.2664	74.07	0.7881
	40	77.50	0.6489	77.50	0.6489	74.64	0.7722
128	10	93.95	0.1710	**93.95**	**0.1710**	73.46	0.8474
	20	87.01	0.3605	87.01	0.3605	73.48	0.8675
	40	92.06	0.2184	92.06	0.2184	84.57	0.4258

Table 4. Proposed CNN Model results for multi-channel images (Blue Channel).

Epochs	Batch Size	Blue Channel					
		Model 1		Model 2		Model 3	
		Test Acc.	Test Loss	Test Acc.	Test Loss	Test Acc.	Test Loss
8	10	73.57	0.8519	73.59	0.8347	73.57	0.8621
	20	73.57	0.8472	73.61	0.8365	73.57	0.8594
	40	73.57	0.8506	73.57	0.8373	73.57	0.8522
16	10	73.57	0.8269	74.29	0.7760	73.57	0.8541
	20	73.61	0.8301	74.76	0.7455	73.57	0.8513
	40	73.59	0.8286	74.06	0.7881	73.57	0.8351
32	10	74.82	0.7449	85.02	0.4196	73.57	0.8494
	20	74.72	0.7529	85.56	0.4000	73.80	0.8073
	40	74.95	0.7433	83.97	0.4470	73.88	0.7955
64	10	79.67	0.5853	91.66	0.2380	73.59	0.8383
	20	81.67	0.5206	94.81	0.1457	74.24	0.7926
	40	81.90	0.5027	94.12	0.1639	77.91	0.6213
128	10	84.76	0.4356	96.54	0.1040	73.82	0.8010
	20	88.81	0.2991	96.80	0.0545	76.91	0.6658
	40	91.12	0.2386	**97.08**	**0.0465**	85.54	0.3966

5. Conclusion

DR recognition and classification plays an important role diagnosing the early stages for DR. Doctors put patients under certain treatment to stop the disease from progressing and thus saving the patients eyesight. In this paper, three CNN models were proposed for the detection and classification of DR into the different classes according to disease severity. The proposed models contained different layers and parameters. Model 2 achieved the best accuracy that outperforms results reported in recent literature. The highest accuracy achieved was 97.08% by using the blue channel of the DR images. Future work will include identifying and proposing deep learning architectures that can combine probability distribution of the multi channels i.e. R, G, and B to improve the performance of the system.

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