COMPUTER AIDED DIAGNOSIS OF DIABETIC RETINOPATHY DISEASE USING IMAGE PROCESSING AND DEEP LEARNING TECHNIQUES

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Summary

Diabetic Retinopathy (DR) is the most common microvascular complication of diabetes, an important public health problem in Turkey, and is one of the leading causes of blindness in the 20-65 age group. The 20-65 age group is the working part of the society, and this disease causes great damage to the human resources and production of the country. Our Goal is to diagnose the disease early and to prevent permanent damage.

In this study, it is aimed to use different color channels and color spaces during preprocessing, and to process images through image processing and find the most efficient method, resulting in a more consistent and successful result than other deep learning applications at the end of the experiments.

The application to be made with these methods will reduce the workload and human error in the detection of the disease, and will reduce the loss of workforce, especially in the working sector, and will positively affect the welfare of the society. It will reduce the burden of technicians working in the field and increase their productivity and happiness.

Method

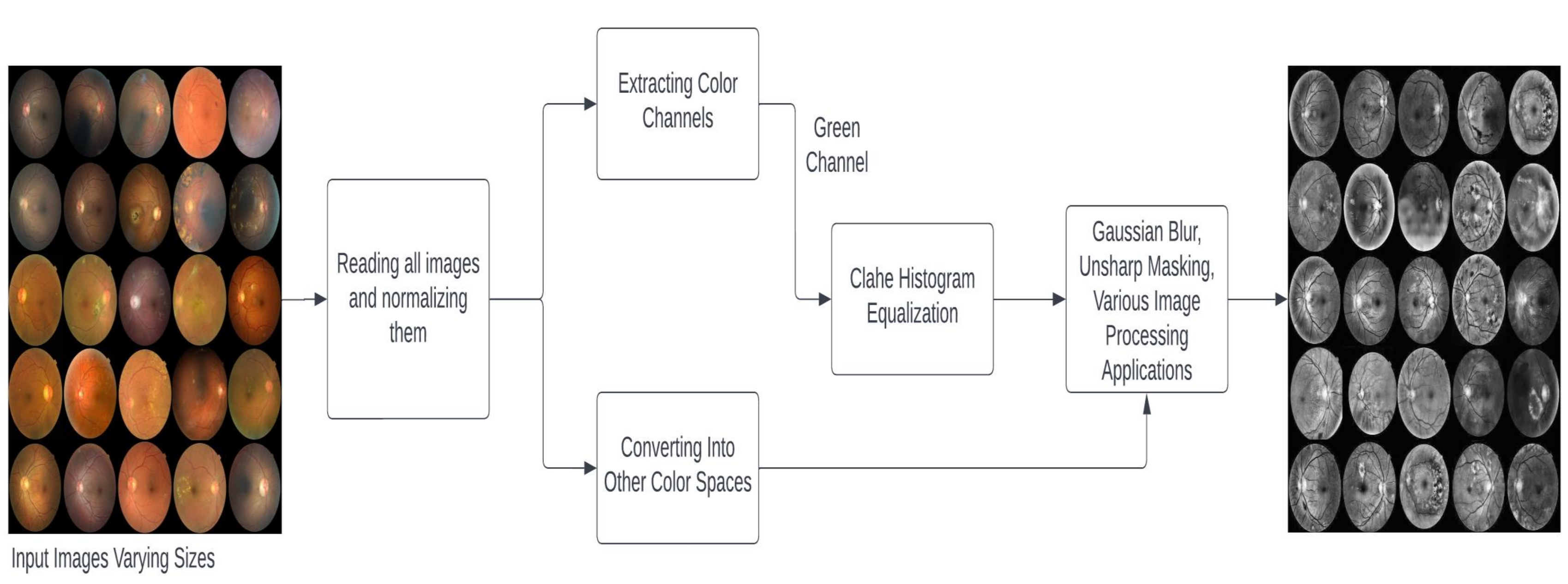

Figure 1. Dataset Processing Diagram

1) Preprocessing

Kaggle EyePACS retina dataset, which is the dataset to be used in the study, consists of high resolution retinal images obtained under different conditions. The data set consists of 35,126 labeled images in JPEG format.

In this study, several pre-processing methods has been used and most importantly CLAHE histogram equalization method to make most out of our data. In this method, the image is divided into sub-images and a separate histogram is calculated for each. The histograms are then cropped and arranged according to the contrast boundary.

For each, their contrast is enhanced using the histogram equalization method, and then the image is combined. Various operations such as noise removal and sharpening on the above operations will be applied to the images to be obtained from the algorithms, and the performance of the proposed method will be tried to be increased by rearranging the data set.

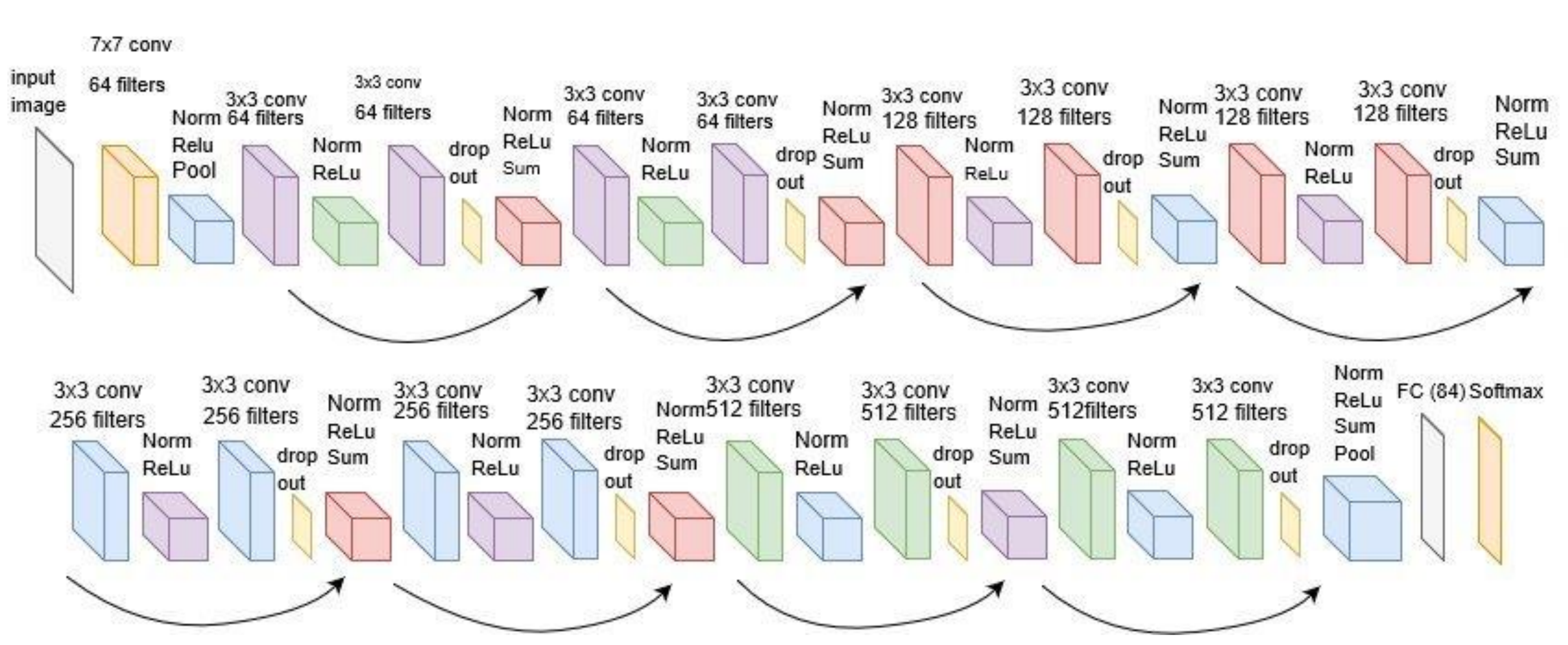

Figure 2. ResNet-18 Convolutional Neural Network Diagram

2) Transfer Learning

Convolutional neural networks, a sub-title of deep learning, are widely used in image processing. The convolutional neural network does classification directly on images with minimum processing and best performance.

Trying to build a neural network from scratch requires a lot of data and time to train and validate. In this case, transfer learning comes into play. Transfer learning is the storage of the information learned by the artificial learning systems during the training phase and using that information when a different or similar problem is encountered.

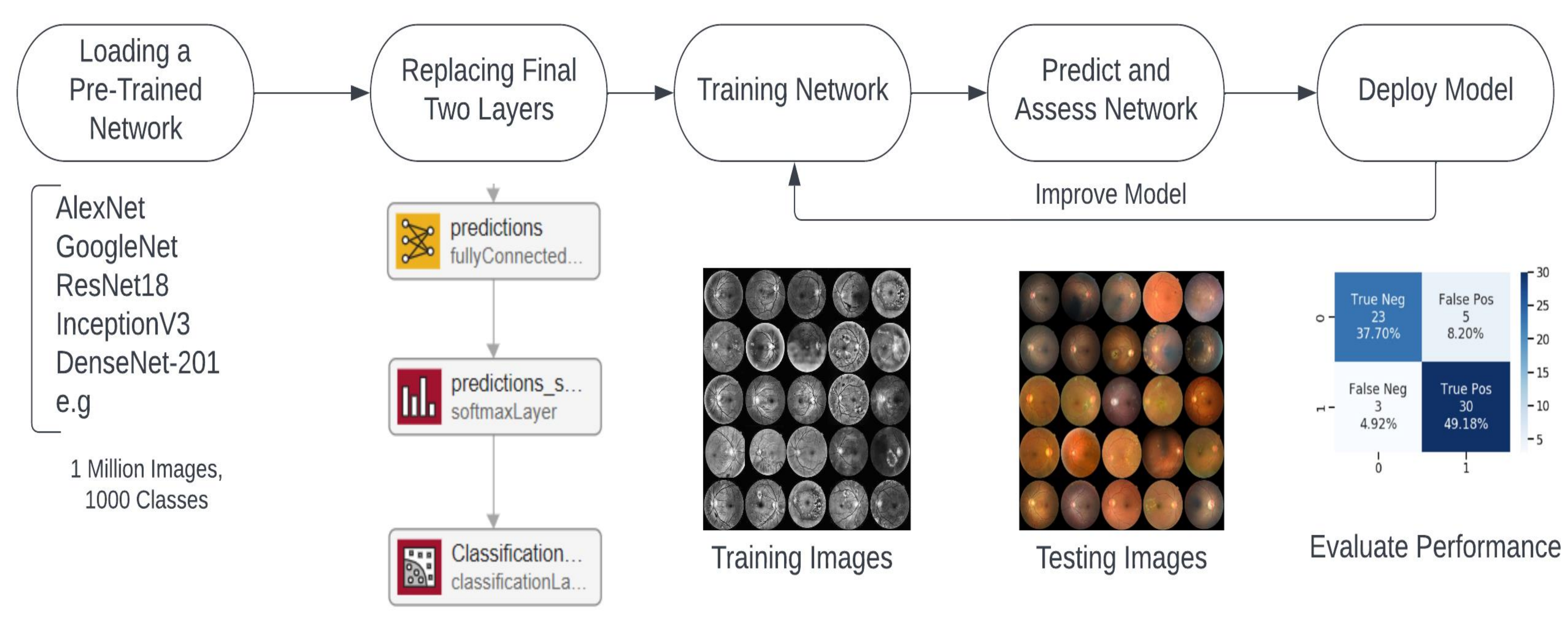

Figure 3. Transfer Learning Diagram

With transfer learning, features, weights, etc. obtained from previously trained models. used for a new application.The advantages of using transfer learning instead of training deep learning methods from scratch can be listed as follows:

• Pre-trained models contain a lot of information. By fine-tuning this information, the new model is trained faster.

• The disadvantage of models created from scratch is that a large-scale dataset is required for training. High performance is achieved with less data by using pre-trained models.

Accuracy of Networks

#	Original	Grayscale	Red	Green	Blue	Clahe	HSV
AlexNet	0.7625	0.7950	0.7650	0.7900	0.6850	0.7800	0.6200
GoogleNet	0.7950	0.8350	0.7950	0.8225	0.7950	0.8375	0.6400
DenseNet-201	0.7950	0.7950	0.7825	0.8125	0.7725	0.8300	0.6725
InceptionV3	0.7925	0.7725	0.7850	0.7850	0.7575	0.7975	0.6250
ResNet18	0.7525	0.7900	0.7625	0.7775	0.7175	0.7900	0.6550

Figure 4. Accuracies of Several Networks on Different Preprocessing Methods

Example Confusion Matrix of %83 Accuracy

Confusion Matrix	Positive	Negative
Predicted Positive	185	15
Predicted Negative	53	147

Figure 5. Confusion Matrix

Conclusion

Pre-trained deep neural networks require different sizes of input images. Therefore, in this study, all images in the dataset will be resized according to the input image size required by the network used after processing separately with various preprocessing techniques and combinations of these techniques, as well as their original versions.

The performances of different pre-trained deep neural networks on the original images will be compared with the performances obtained by using the preprocessed images using different image processing methods and their individual combinations as inputs. Thus, the effect of preprocessing techniques and color spaces on performance will be observed in the computer aided diagnosis of diabetic retinopathy, and a method with higher performance in terms of speed and accuracy will be obtained.

15. PROJE FUARI ve YARIŞMASI (2022)