Towards explaining Classification Stages of Diabetic Retinopathy through localization and segmentation of Retinal Lesions

Technical Report for SPARC Project

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Abstract

Diabetic Retinopathy (DR) is a severe complication that provokes retinal vascular damage and is one of the leading causes vision impairment and blindness. DR broadly is classified into two stages – proliferative and non-proliferative, non-proliferative (NPDR) where there are almost no symptoms, except a few microaneurysms, while proliferative diabetic retinopathy (PDR) involves a huge number of microaneurysms and haemorrhages, soft and hard exudates, neo-vascularization, macular ischemia or a combination of these, making it easier to detect. This paper aims to detect NPDR in its early stages through a novel CNN based localization and segmentation procedure, which also makes the procedure more explainable and helps in supporting physicians at all stages of the diagnosis. This will be able to accurately classify all stages of DR.

1. Introduction:

Currently, detection of Diabetic Retinopathy is mostly carried out manually by ophthalmologists which involves checking fundus images and screening, to detect the lesions, which is time consuming, tiring and infeasible for a large number of images. It is crucial to devise an automated system for detection and treatment of DR in its early stages, so that it can prevented sooner and the process be made cheaper. Significant work has been done both in fields of localization and segmentation of various parts of the eye and also classification of the eye image as a whole. This paper brings together both of these approaches to not just make the CNN give an output but also to put bounding boxes around the retinal deformities to help the physician understand why the algorithm made the choices it made.

2. Literature Review

Segmentation of blood vessels and optic disc plays a significant role in lesion extraction as it reduces the chances of detecting false lesions. Sinthanayothin et al[1] used the intensity of the pixels to determine the areas with high variation to spot the optic disc. A multilayer perceptron neural network was employed for the extraction of blood vessels which involved Princple component analysis and edge detection. On the other hand, methods such as Pixel feature classification and vessel tree analysis were utilized for the detection of retinal vessels, as described by Michael D. Abramoff[2]. In the paper[3], Jebaseeli used the Tandem PCNN (TPCNN) for the blood vessel segmentation.

Enhancement of retinal images was an important step in every proposed method to increase the efficiency of classification. Extraction of the green channel from the image is seen as a common approach as it provides more intensity for the vessel pixels, as adopted by P Chudzik[4] and M Habib[5].

H Tan[6] exploited the procedure of converting RGB to LUV color space and removed the varying local contrast and uneven illumination.

Other enhancement techniques such as CLAHE were utilized for efficient extraction of lesions. P Khojasteh[7], for instance, adopted CLAHE and CE as a pre-processing layer for their 11 layered CNN.

Some of the work has been compared in Table 2.1 below.

Table 2.1 Table comparing some of the papers

PAPER	DATA PREP	ARCHITECTURE	LIMITATIONS	ACCURACY
The neural network of 1D CNN Yunlei Sun	• Min-Max scaling. • One-hot encoding. • Resized to 48*48. • Feature normalization	LENET-5 architecture with a 5*5 filter size and stride size of 1, It also consists of a LRN. ADA Grad, Sigmoid and ReLU	Lower efficiency as the dataset is small and so the BNCNN is not accurate	97.56% accuracy was achieved.
Automated Diabetic Retinopathy Detection on binocular-Siamese network Xianglong Zeng et al	• Scale down to 299*299 px • Subtract each pixel size and add 50% grayscale	Uses a Inception v5 network with a Siamese like Architecture and optimized by Adam optimizer.	Doesn't work well with other datasets.	Kappa score of 0.829
Introducing a Novel Layer in Convolutional Neural Network for Automatic Identification of Diabetic Retinopathy P. Khojasteh et al	• CLAHE and CE were used. • Bilinear interpolation	CNN architecture of 11 layers with 3 max pooling layers was used	No significant limitations mentioned.	90% was the highest accuracy achieved when using contrast enhancement

Automated detection of diabetic **Retinopathy on fundus images** C. Sinthanoyothin et al.	• HSV optimization was used • Moat operator was used for localization with excellent results	No architecture has been mentioned.	Significant errors may arise due to small dataset size and research results for detection aren't clear.	84.5% accuracy was achieved in localization tasks.
<u>CNN for Diabetic Retinopathy</u> Pratt H. et al	• Colour normalisation. • Resized to 512*512	10 layered CNN used and the features extracted were fed to SVM network	Dataset may possess a problem if not pre-processed properly.	Sensitivity of 95% and accuracy of 75%
Microaneurysm detection using fully CNN P Chudzik et al	• Green channel extraction, • Noise reduction, • Mask Generation	FCNN similar to convolutional Autoencoders, uses skip connections, Dice coefficient function was implemented.	No significant limitations appear to be present.	Score was found to be 0.562 ± 0.233
Segmentation of retinal blood vessels from ophthalmologic Diabetic Retin J Tan et al	• Converted RGB to LUV color space • Optimizations for color enhancement have been done.	Standard CNN architecture was used.	Their output was worse than expected but it gives us a useful	Sensitivity for hemorrhage detection was 0.87 and for MA it was 0.62
Segmentation of blood vessels T Jebaseeli et al	• CLAHE • Parameters were initialized using a tandem PCNN • DLBSVM	DLB SVM model was implemented in this paper	No limitations, the work done is of great quality.	>99% for segmentation

Color fundus image registration S Saha et al	Feature transformation done using SIFT, vessel detection and cross-over segmentation	This paper does not involve a CNN	No limitations exist.	This paper gives an extensive review of the performance of various methods.

3. Proposed Method

In this section, the dataset, pre-processing and architecture is discussed.

3.1. Datasets:

- Kaggle
- DIARETDB
- STARE
- IDRID
- DRIMDB
- MESSIDOR (macular edema)
- Retinopathy Online Challenge
- REVIEW (vessel width)
- VICAVR (vessel width)
- DRIVE (auto vessel extraction)
- STARE (auto vessel extraction)
- ARIA (auto vessel extraction)

3.2. Pre-processing:

Various pre-processing techniques have been used, which are described as follows.

3.2.1. Dataset manipulation:

Removal of images falling under a specific criterion will be removed, so as to get rid of extremely low-quality images, such as those disturbed by glare. On the other hand, images will be augmented through various techniques like cropping, rotation, flipping, etc, so as to make the model more robust. Batch size for data augmentation should be chosen according to the capacity of the system, this paper used a value of 4.

For eg, Fig 3.1 should never have made it to the database in the first place, as it involves a blinking artefact, and also the image has too much glare. These images have to be removed; else the eyelash shadow might be misclassified as blood vessels in G channel.

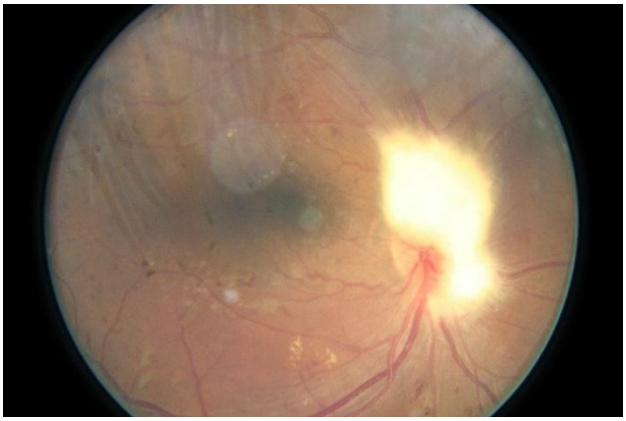

Fig 3.1

3.2.2. Choosing the appropriate channel

Green channel was found to be the best channel for training the neural network. It is also apparent to the naked eye how the green channel is superior to the other channels like R, B or L channels.

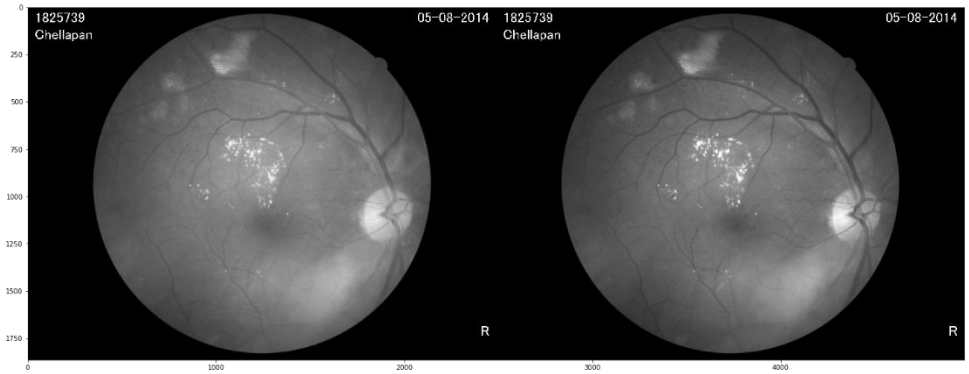

Fig 3.2 : Grayscale vs Green-channel image

3.2.3. Adaptive Equalization

CLAHE (Clip Limited Adaptive Histogram Equalization) has been used to get rid of some of the grain and improve contrast. Clip limit (an optimal value of 2 has been chosen) prevents the algorithm from adding extreme features or noise. This image is then sent to the next step.

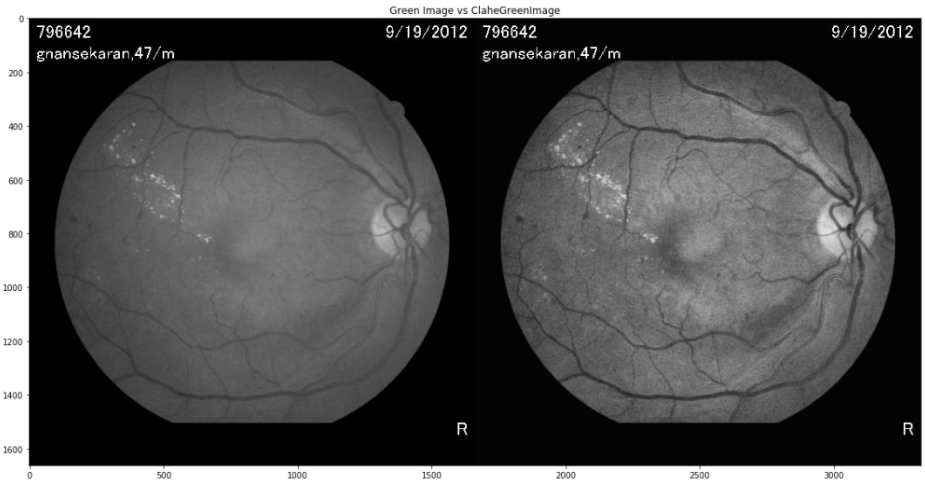

Fig 3.3 : Green-channel image before and after CLAHE

3.2.4. Improving Clarity

A blurred copy of the above image is created with a blur level of 40.

For each pixel p having intensity X_p from the histogram equalization step and the same pixel p in the blurred image having an intensity Y_p, X_p is updated accordingly.

$$X_p = 4 * X_p - 4 * Y_p + 128$$

The effect is clear in Fig 3.4 below.

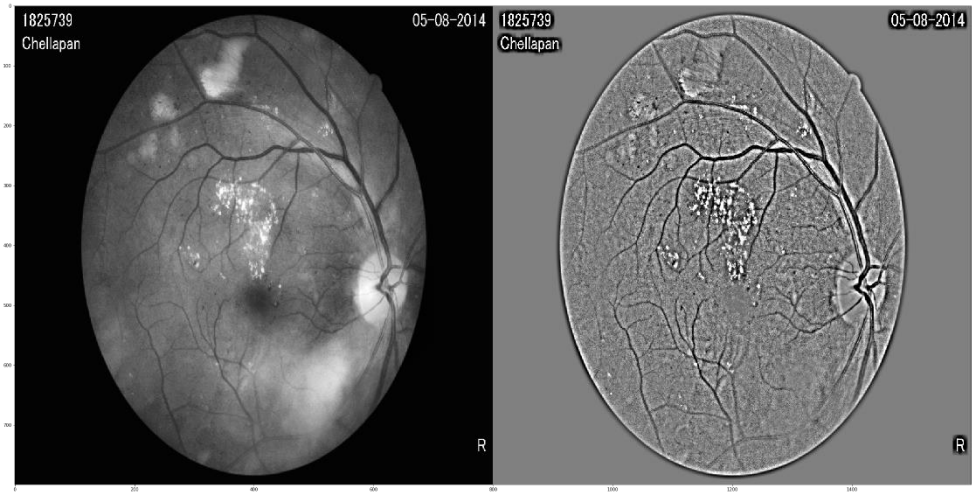

Fig 3.4 : Features become more prominent after applying the above method.

3.3. Localization

Localization of the optic disc will then be done on these images to identify the section of the eye containing the optic disc. Multiple ways of doing it are discussed in the references.

3.4. Feature extraction

Feature extraction enables the algorithm to obtain points of neovascularization, uneven thickness of the blood vessels etc., which are all good indicators of diabetic retinopathy. This can be achieved using SIFT, ANOVA etc preferably in frequency domain.

3.5. Segmentation

Segmentation needs to be done after feature extraction to make bounding boxes around the regions of interest, like haemorrhage, micro-aneurysm, exudates and neovascularization etc.

3.6. Classification

A standard CNN based model is used to classify the 800,800 G-channel images optimized by CLAHE currently and achieves about 35-50% accuracy. An overview of the architecture is given below.

3.6.1. Architecture

The architecture schema has been described below.

Layer (type) Output Shape Param #

==========

conv2d_1 (Conv2D) (None, 399, 399, 32) 320

---

batch_normalization_1 (Batch (None, 399, 399, 32) 128

---

leaky_re_lu_1 (LeakyReLU) (None, 399, 399, 32) 0

---

conv2d_2 (Conv2D) (None, 199, 199, 64) 18496

---

batch_normalization_2 (Batch (None, 199, 199, 64) 256

---

leaky_re_lu_2 (LeakyReLU) (None, 199, 199, 64) 0

---

conv2d_3 (Conv2D) (None, 99, 99, 128) 73856

---

batch_normalization_3 (Batch (None, 99, 99, 128) 512

---

leaky_re_lu_3 (LeakyReLU) (None, 99, 99, 128) 0

---

max_pooling2d_1 (MaxPooling2 (None, 49, 49, 128) 0

---

dropout_1 (Dropout) (None, 49, 49, 128) 0

---

conv2d_4 (Conv2D) (None, 24, 24, 256) 295168

---

batch_normalization_4 (Batch (None, 24, 24, 256) 1024

---

leaky_re_lu_4 (LeakyReLU) (None, 24, 24, 256) 0

---

max_pooling2d_2 (MaxPooling2 (None, 12, 12, 256) 0

---

conv2d_5 (Conv2D) (None, 5, 5, 512) 1180160

_____

batch_normalization_5 (Batch (None, 5, 5, 512) 2048

_____

leaky_re_lu_5 (LeakyReLU) (None, 5, 5, 512) 0

_____

dropout_2 (Dropout) (None, 5, 5, 512) 0

_____

conv2d_6 (Conv2D) (None, 2, 2, 512) 2359808

_____

batch_normalization_6 (Batch (None, 2, 2, 512) 2048

_____

leaky_re_lu_6 (LeakyReLU) (None, 2, 2, 512) 0

_____

dropout_3 (Dropout) (None, 2, 2, 512) 0

_____

flatten_1 (Flatten) (None, 2048) 0

_____

dense_1 (Dense) (None, 1024) 2098176

_____

batch_normalization_7 (Batch (None, 1024) 4096

_____

leaky_re_lu_7 (LeakyReLU) (None, 1024) 0

_____

dropout_4 (Dropout) (None, 1024) 0

_____

dense_2 (Dense) (None, 1024) 1049600

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leaky_re_lu_8 (LeakyReLU) (None, 1024) 0

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dense_3 (Dense) (None, 5) 5125

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activation_1 (Activation) (None, 5) 0

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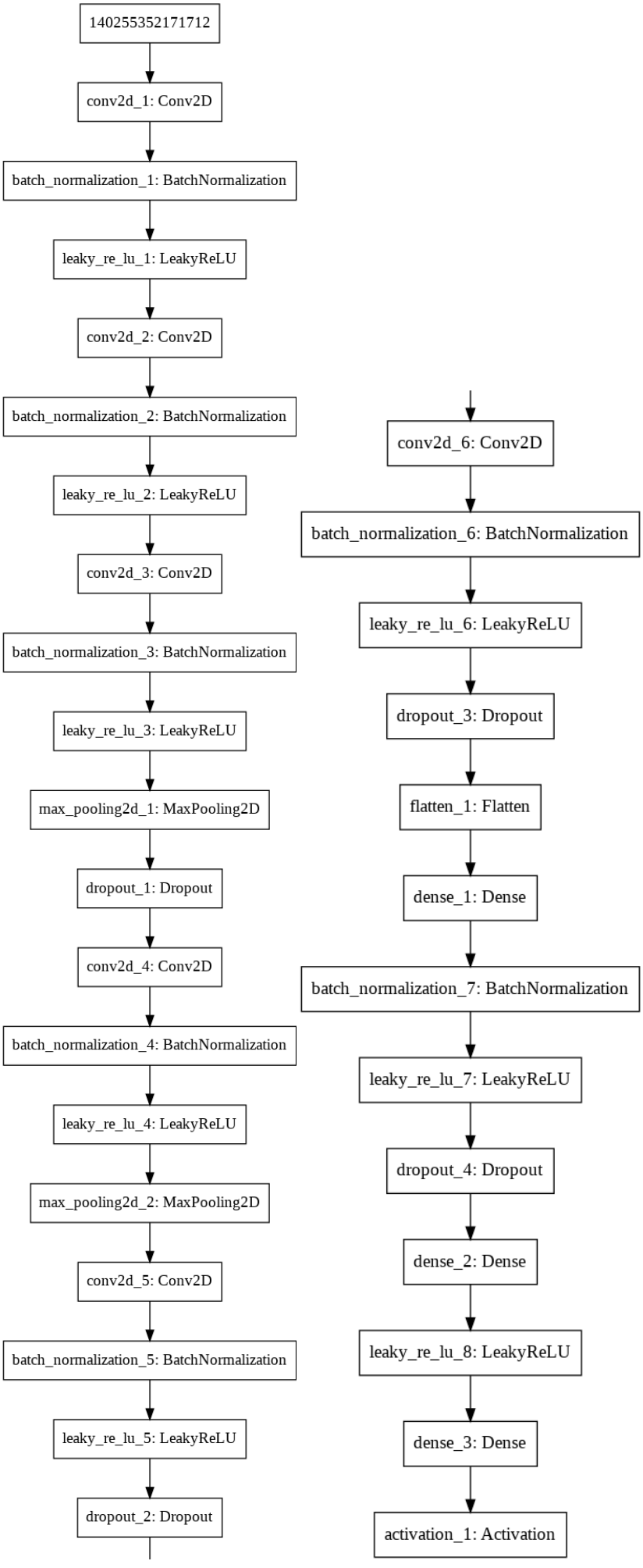
Total params: 7,090,821

Trainable params: 7,085,765

Non-trainable params: 5,056


140255352171712
conv2d_1: Conv2D
batch_normalization_1: BatchNormalization
leaky_re_lu_1: LeakyReLU
conv2d_2: Conv2D
batch_normalization_2: BatchNormalization
leaky_re_lu_2: LeakyReLU
conv2d_3: Conv2D
batch_normalization_3: BatchNormalization
leaky_re_lu_3: LeakyReLU
max_pooling2d_1: MaxPooling2D
dropout_1: Dropout
conv2d_4: Conv2D
batch_normalization_4: BatchNormalization
leaky_re_lu_4: LeakyReLU
max_pooling2d_2: MaxPooling2D
conv2d_5: Conv2D
batch_normalization_5: BatchNormalization
leaky_re_lu_5: LeakyReLU
dropout_2: Dropout
conv2d_6: Conv2D
batch_normalization_6: BatchNormalization
leaky_re_lu_6: LeakyReLU
dropout_3: Dropout
flatten_1: Flatten
dense_1: Dense
batch_normalization_7: BatchNormalization
leaky_re_lu_7: LeakyReLU
dropout_4: Dropout
dense_2: Dense
leaky_re_lu_8: LeakyReLU
dense_3: Dense
activation_1: Activation

3.6.2 ARCHITECTURE DESCRIPTION

The dataset used for training this model was taken from the kaggle database and it consists of approximately 88,000 images of different stages of DR and is of 88GB. The data was converted into 2 pickle file formats which holds different number of images. As any other dataset the kaggle dataset was highly biased and which resulted in overfitting of early model testing. The problem was solved by taking equal number of images from each stages of DR and adding them is a single dataframe which resulted in a total of 9574 images .

The model was made using keras library which consisted of tensorflow backend,the main model consists of 5 layers in which LEAKY_RELU was used in each layer with a learning rate of 0.01 .Batch Normalisation was also applied at each layer to prevent overfitting.At the last a dropout layer was added with a value of 0.5, a dense layer was also added at the end of the model .The activation function used was a softmax activation function and the loss function used was categorical_crossentory.The optimizer used was a ADAdelta optimizer to optimize the network .The model was run for only 2-5 epochs because of computational problems and the accuracy found was 50% .

4. Conclusion

This paper hopes to serve as a starting point for making CNN models for NPDR more explainable. This will help the model argue it's choice, and validate it's output instead of being just a black box algorithm with some weights.

5. References

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