Modelling of Retinal Images for Analysis of Diabetic Retinopathy Severity Levels

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Abstract. Synthetic data by various algorithms that resemble actual data in terms of statistical features. Computer-aided medical applications have been extensively applied to model specific scenarios, such as medical imaging of retinal images for diabetic retinopathy (DR) detection. The available data and annotated medical data are typically rare and costly due to the difficulties of conducting medical screening and rely on highly trained doctors to review and diagnose. The modelling of retinal images for DR analysis is essential since it will provide a model to guide and test DR detection algorithms. This paper aims to model normal retina and non-proliferative diabetic retinopathy (NPDR) stages (mild, moderate, and severe) data models with the variation of dynamic models.

The Digital Retinal Images for Vessel Extraction (DRIVE), The Standard Diabetic Retinopathy Database, Calibration Level 1 (DIARETDB1), and E-OPHTHA datasets are analyzed to obtain the specification of the human retina and DR lesions. In the data modelling phases, the model includes the bright and dark retinal lesions with the variation of dynamic parameters. 4100 synthetic images are used where 200 normal images and 3900 NPDR images to test the performance of DR detection algorithms over the full range of parameters.

1. Introduction

Synthetic data is data generated by various algorithms that mimic the statistical characteristics of the actual data but do not disclose any information about real individuals [1]. The ability to create meaningful synthetic information is highly desirable for many computer-aided medical applications, and the availability of vast amounts of annotated data is becoming increasingly crucial in medical image analysis applications. The amount of available data and computational resource constraints are blamed for the poor quality of synthetic data, not a problem inherent in the suggested technique. However, annotated medical data is typically rare and costly to obtain [2].

Diabetic Retinopathy (DR) is a condition in which the retina's micro-blood vessels are destroyed, and associated blood vessel (BV) damage is one of the diabetes's most serious repercussions. DR is a leading cause of blindness across the world [3], DR affects one out of every three diabetics and considers as the primary cause of blindness among working-age individuals [4]. According to the worldwide DR scale, DR is generally categorized as mild non-proliferative DR (NPDR), moderate NPDR, severe...
NPDR, or PDR [5], and it is classified based on the risk of progression [6]. The lesions that existed in the NPDR stages are Microaneurysms (MAs), Hemorrhages (HEM), Hard Exudates (EX), Soft Exudates (Cotton-wool spots) [7].

There are many databases include retina images, especially for DR, and we found out that three of them are the most extensive and frequently referred in the literature. These databases are DRIVE, DIARETDB1, and E-OPHTHA datasets. Therefore, in this work, we have referred to these three databases in developing our DR model. Firstly, the DRIVE database was developed to allow for comparative studies on retinal vascular segmentation and identification of morphological features of retinal vasculatures, such as length, width, tortuosity, branching patterns, and angles, which are used to diagnose, screen, treat, and evaluate DR. A total of 400 diabetic patients between the age of 25 to 90 years screened to provide the images for the DRIVE database [8]. Secondly, the DIARETDB1 consists of 89 colour fundus images where 84 contain the mild NPDR that including MAs only and 5 are normal retinal images that do not have any diabetic retinopathy lesions, according to all of the specialists who took part in the assessment [9]. Thirdly, the E-ophtha is a dataset of colour fundus DR images that designed for research purposes. e-ophtha is made of two sub-databases, one for MAs and another for EX [10].

Research conducted by Teresa et al. proposed a heuristic-based data augmentation technique compensating for the lack of PDR cases in DR-labeled datasets by synthesizing neovessel (NV)-like structures. The suggested neovessel synthesis technique is based on a broad understanding of these structures’ particular position and form. NVs are created and inserted into pre-existing retinal pictures, which may be applied to expand the training sets of deep neural networks [11]. Yi Zhou et al. proposed a diabetic retinopathy generative adversarial network (DR-GAN) to generate high-resolution fundus images. The structural and lesion masks and adaptive grading vectors collected from the latent grading space used to manage the synthesized grading severity [12].

Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) are two deep learning architectures that have been combined, where CNN is implemented to identify lesions on retinal fundus images, and LSTM is used to form description tag on those lesions [13]. Designed a lesion localization model using a deep network patch-based approach and trained the model on DIARETDB1 database and is tested on several databases (including Messidor) [14]. The primary feature of the model is that it proposes new ways for segmenting blood vessels and the optic disc. The DR lesions are classified using a radial basis function neural network [15].

The DR detection algorithm’s performance was validated on several tests that included using the FGADR dataset and Kaggle’s EyePACS dataset. Several failure situations still exist because of various restrictions. This synthetic sample demonstrates a low-illumination failure. Second, due to the cost of data annotation, the structural and lesion masks are inferred from the segmentation models rather than being true ground truths [12], while [13] used only the MESSIDOR data set. Most of the DR detection algorithms and their actual validity are unknown as they are not tested over the full range of parameters where it is only tested and compared with actual specific cases from publicly available databases. In this paper, DR data is modelled for normal and NPDR stages (mild, moderate, and severe) via computer vision under variations of retinal parameters and image parameters that reflect DR severity level over the full range of parameters.

2. Modelling of retinal images
The model of retinal images is based on a fundus camera, and different dynamic parameters will be changed to reflect the DR images. The modelling process steps of DR data is shown in Figure 1.
2.1. Develop image model
As a first step for developing an image model, the actual retinal images are analyzed in the grayscale version. Studying the real retinal images gives more information regarding the intensities range for each part in the retinal content. The analysis was done on the datasets of DRIVE, DIARETDB1, and E-OPHTHA after converting the colour images to grayscale, which depend on the weighted sum of the R, G, and B components as shown in equation (1) [16].

\[
Grayscale \ \text{pixel intensity} = (0.2989 \times R) + (0.5870 \times G) + (0.1140 \times B) \quad (1)
\]

Twenty images used to obtain the ground truth of BV in the DRIVE datasets. Figure 2 shows one sample from the ground truth of BV. The ground truth image did not show the difference between the retinal background (BG) within the field of view (FOV) and the outer pixels since it is a binary image that shows only BV. The next step is to localize the FOV pixels since not all the pixels in the image consider within the retina. In this step, the FOV pixels coordinates are stored for further processing. Within the FOV pixels (a circle of 270 pixels radius), localize the coordinates of BG pixels and BV pixels.

\[
BG \ \text{percentage} = (BG \ \text{pixels} \times (FOV \ \text{pixels})^{-1}) \times 100\% \quad (2)
\]
\[
BV \ \text{percentage} = (BV \ \text{pixels} \times (FOV \ \text{pixels})^{-1}) \times 100\% \quad (3)
\]
After calculating the BV and BG pixels percentage, all 20 images getting sorted based on lower percentage to the higher percentage. Only ten ground truth of BV images has been chosen in the image selection stage. The next step is to ensure that all the selected images have the same FOV center point and area, achieved through a standardized image FOV process. All the ten images have the size of 584×565 and the center point at coordinate (292,283).

2.2. Include DR lesion according to the severity level
This step includes retinal lesions to the image models separately, which are the bright lesion and dark lesion. The bright lesion consists of EX, while the dark lesion consists of MAs and HEM. The MAs have a sphere shape, while HEM and EX have a random shape. The next step is to generate random coordinates for the MAs, HEM, and EX and use those coordinates to model the DR of NPDR stages. Table 1 shows the DR of NPDR stages which are mild, moderate, and severe.

Table 1. The DR of NPDR stages [17]

| DR NPDR stage | Definition |
|---------------|------------|
| 0 (Normal)    | Mas=0, HEM=0, EX= BufferedReader.readLine(); } BufferedReader.close();

The models that have been created for NPDR stages consist of two different sets. The specification of NPDR stages for sets 1 and 2 is shown in Tables 2 and 3, respectively, showing the total number of retinal lesions for MAs, HEM, and EX in each stage.

Table 2. The specification of NPDR stages for set 1

| Lesion type | Mild | Moderate | Sever |
|-------------|------|----------|-------|
| MAs         | 3    | 10       | 20    |
| HEM         | 0    | 2        | 7     |
| EX          |      |          |       |

Table 3. The specification of NPDR stages for set 2

| Lesion type | Mild | Moderate | Sever |
|-------------|------|----------|-------|
| MAs         | 5    | 14       | 30    |
| HEM         | 0    | 4        | 10    |
| EX          |      |          |       |

The samples after modelling of NPDR stages for both set 1 and 2 are shown in Table 4, where (a) Mild, (b) Moderate, and (c) Severe. All those images are the results before variation of the dynamic parameters.
Table 4. Samples of NPDR stages for sets 1 and 2

| NPDR stage | Set 1 | Set 2 |
|------------|-------|-------|
| (a) Mild   | ![Sample Image](image1) | ![Sample Image](image2) |
| (b) Moderate | ![Sample Image](image3) | ![Sample Image](image4) |
| (c) Severe | ![Sample Image](image5) | ![Sample Image](image6) |

2.3. Dynamic parameters variation
The first parameter is intensities difference for both image and segment. The intensities difference percentage consists of five different stages for both sets 1 and 2. The specification of the intensities difference parameter for both image and segment (BG, BV, Dark lesions, and Bright lesions) implemented on data sets 1 and 2 is shown in Table 5.

Table 5. The specification of the intensities difference parameters

| Intensities difference | Stage 1 | Stage 2 | Stage 3 | Stage 4 | Stage 5 |
|------------------------|---------|---------|---------|---------|---------|
| BG to BV               | 3 %     | 10 %    | 20 %    | 30 %    | 40 %    |
| BV to Bright lesion    | 8 %     | 25 %    | 35 %    | 45 %    | 55 %    |
| BV to Dark lesion      | 3 %     | 5 %     | 10 %    | 15 %    | 20 %    |
The datasets studied to get the intensities difference are DRIVE, DIARETDB1, and E-OPHTHA datasets. The DRIVE datasets have been used to study BV, and the DIARETDB1 has been used to study HEM and EX. On the other hand, E-OPHTHA is used to study the MAs. First, the actual DR data is converted to a grayscale image for analysis. The intensity range for the BG of the retina is located between 80 to 210. According to the specification in Table 5, there are five stages for intensities difference where the intensities ranges are 80-106, 106-132, 132-158, 158-184, and 184-210, respectively. The intensity value for BG will be selected randomly within that range of intensities, and according to that value, the BV, Bright lesion (EX), and Dark lesions (MAs and HEM) intensities values will be set. Table 6 shows the samples of intensities difference for each stage for set 1.

**Table 6. Samples of intensities difference for each stage for set 1**

| Stage  | Mild          | Moderate       | Severe         |
|--------|---------------|----------------|----------------|
| Stage 1| ![Sample Image](image1) | ![Sample Image](image2) | ![Sample Image](image3) |
| Stage 2| ![Sample Image](image4) | ![Sample Image](image5) | ![Sample Image](image6) |
| Stage 3| ![Sample Image](image7) | ![Sample Image](image8) | ![Sample Image](image9) |
The following parameter implemented is the size. Three different sizes have been used on MAs. The sizes 1, 2, and 3 have three different radius lengths, which are 1, 2, and 3 pixels length, respectively. The total number of pixels for the three different sizes are 5, 13, and 29 pixels, respectively. After that, three different grades of noise based on Gaussian noise will be considered, which is Gaussian white noise with constant mean and variance. Each grade has a different noise density that is 0.0001, 0.0005, and 0.0009 for grade 1, grade 2, and grade 3, respectively [18][19]. Adding noise parameters makes the models more towards actual DR images where noise or artefacts make more difficulties on the segmentation of different lesions [20]. The total number of modelled DR data is 4100 where 1250 clear images without noise and another 2850 noisy images. The normal retinal images modelled are 200, while 3900 images for NPDR stages (mild, moderate, and severe).

3. Conclusion
In this paper, DR data is synthetically developed and modelled for normal and NPDR stages (mild, moderate, and severe) via computer vision under variations of the dynamic parameters. A total of 4100 DR data were modelled, including 1250 clear images without noise and another 2850 noisy images. The normal retinal category images produced are 200, while the NPDR stages modelled are 3900 images (mild, moderate, and severe). The model will provide synthetic data to guide and evaluate the DR detection algorithm over the full range of parameters. The advantages are that all the parameters are known compared to the real images, where some parameters are not entirely defined. In our future work, the model will be used to evaluate the performances of DR automatic detection systems and provide means for objective comparison.

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