Deep Learning based Analysis of Diabetic Retinopathy Datasets

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Abstract

Obtaining labeled image data has been a difficult task in many domains of healthcare. Deep learning has helped with automating tasks like early and automated detection of many diseases, with great accuracy. So acquiring good datasets with properly labeled images is a prime condition in deep learning because quality cannot be compromised when it comes to dealing with patients. Diabetic Retinopathy is becoming prevalent in many countries and the disease becomes nearly incurable after it reaches a severe condition and results in serious vision impairment and partial blindness in some cases. The disease can be cured properly if it is diagnosed early, but the analysis of the disease becomes costlier and complex if it gets severe. Computer-aided tools can help us in achieving early detection of Diabetic Retinopathy that helps in cutting down costs as well as curing the patients in a better way. Therefore, using deep learning can be useful in early detection of Diabetic Retinopathy. So in this paper, we would be discussing some good datasets available that could be used for understanding the lesions in the retina responsible for Diabetic Retinopathy and building deep learning models required for accurate analysis and early detection of the disease.

Keywords: Diabetic Retinopathy · Deep Learning · Datasets · Early Detection · Healthcare

1. Introduction

More and more patients suffering from diabetes are more prone to Diabetic Retinopathy. As mentioned in article [1], approximately 191 million people would be suffering from Diabetic Retinopathy by the year 2030 in which 56.3 million would be having severe vision problems including vision impairment. Analysis of Diabetic Retinopathy through images of retina requires many complicated instruments that are expensive because they are made with utmost precision and so research in this area is neglected in many low income countries, but since the problem is becoming worsening year after year, the need for automatic detection and analysis of Diabetic Retinopathy has become a necessity. Report [2] tells that the early detection of Diabetic Retinopathy is beneficial because it leads to less expensive treatment whereas late actions lead to costlier and more difficult treatments that require a lot of resources and that too it doesn't become entirely curable.

Using Deep learning for detection of Diabetic Retinopathy has proven to be useful due to better results achieved by Convolutional Neural Networks that are trained with images of the retina taken from the fundus camera. As mentioned in [4] fundus cameras are cost effective and can be used for detection of Diabetic Retinopathy in many good eye centres by ophthalmologists. As in [3] researchers have achieved sensitivity of 95.8% and specificity of 80.2% in detection of Diabetic Retinopathy using AI that is better than many of the eye specialists.

There are many datasets that are made by the ground truths provided by eye specialists in this field and they are really helpful in making models with convolutional neural networks. But for any modeling purposes the data must be interpretable along with perfect labeling that will help the model to learn many important features. Another significant thing is the quality of the dataset, the image quality highly matters in any kind of analysis because the lesions in the retina images are very small in some cases and if not captured clearly it could degrade the model accuracy.

2. Diabetic Retinopathy

Diabetic Retinopathy (DR) is a disease caused in individuals aged between 20-65 years having diabetes or those who are prone to habits causing strain in the eyes. Other reasons like trauma, hypertension, etc can also be the causes of non-proliferative DR. Whenever the glucose levels in an individual's body rise above the standard limit then the chances of DR increases. Microaneurysms, haemorrhages and other lesions get formed due to increased glucose levels in the body that reach up to the blood vessels of the retina.

Diabetic Retinopathy is defined by the lesions that get formed in the retina near the vessels, macula, optic disc or any other part being near the center or the surrounding boundary. Initially the problem starts due to the development of Microaneurysms(small red dots near the vessels). Microaneurysms are dot like structures varying from 25 μm to 120 μm in diameter and can be defined as saccular outpouchings in the capillary wall, and they generally are the first signs of the disease. As it gets a little ahead, haemorrhages are formed that are deep black spots bigger in size and they are caused due to the leakage of blood from the vessels. Generally steroids are given for treating haemorrhages and in more severe conditions' laser treatment is done. A small number of haemorrhages are generally seen in mild and moderate non-proliferative DR and if their number increases upto 20-25 haemorrhages along with microaneurysms then chances of severe nonproliferative DR are there.

As seen in [5], another type of lesions that are seen in nonproliferative DR are known as exudates. They are classified into hard and soft exudates. A group of yellow microaneurysms formed having sharp edges are categorised as a hard exudate. A soft exudate also known as cotton wool spot are pale yellow spots formed, that are responsible for the leakage of fluid from the vessels. Exudates can also become severe, that leads to loss of vision as time passes.

Proliferative Diabetic Retinopathy [6] is defined as retinal detachment or formation of vitreous haemorrhages that can result in neovascularization near the macula or anywhere else in the retina. This can be observed in fundus cameras as formation of irregular blood vessels that get incorporated on the retinal surfaces or the vitreoretinal surfaces.

There are other imaging techniques used for detection of Diabetic Retinopathy [6] like OCT(Optical Coherence Tomography) that is used for finding the cross-sectional imaging of the retina that shows macular edema in DR but OCT is not capable of visualizing the newly formed vessels. To overcome this there is another technique OCTA(Optical Coherence Tomography Angiography) that

gives 3D non-invasive chorioretinal vascular imaging that clearly visualizes the vascular structures in neovascularization.
FAF(Fundus AutoFluorescence) [7] is another imaging method that uses laser scanning ophthalmoscope for finding Diabeticmacular oedema, that is a severe condition of Diabetic Retinopathy where all the fluid leakage gets accumulated near the macula region which is responsible for making our vision clearer.

3. Datasets

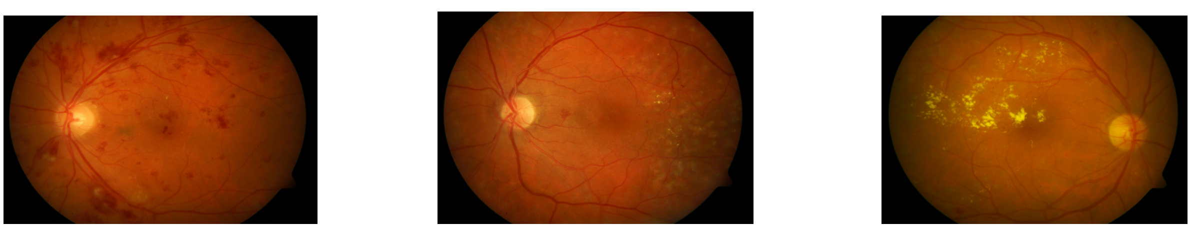
Some popular datasets discussed in this paper are:

3.1) ImageRet

ImageRet includes 2 datasets namely DiaretDB0 and DiaretDB1 that include markings of the lesions in the fundus images that help in grading the severity of the disease.

3.1.1) DiaretDB0

This [2] is a small dataset consisting of 130 images all having exactly the same width and height that were shot from a fundus camera having 50° wide view along with calibration level 0 and unknown lighting conditions. The most important point about diaretDB is that they have provided some of the initial images with ground truth markings given by specialists along with markings predicted by the screening methods. So this dataset can be useful for any researcher who is learning to examine the lesions responsible for non-proliferative and proliferative Diabetic Retinopathy. The dataset consists of a folder consisting of masked areas of the retinal images that represent the areas of the retina that could be used for further analysis. The images a, b, c are some samples from the dataset where we can clearly spot the lesions. Image 'a' consists of many microaneurysms and haemorrhages but no exudates. Image 'b' consists of a few hard exudates. Image 'c' consists of many exudates near the macula as well as some other parts.



(a) (b) (c)

Figure 1 : Sample images from DiaretDB0 that show different lesions in different areas of the retina.

3.1.2) DiaretDB1

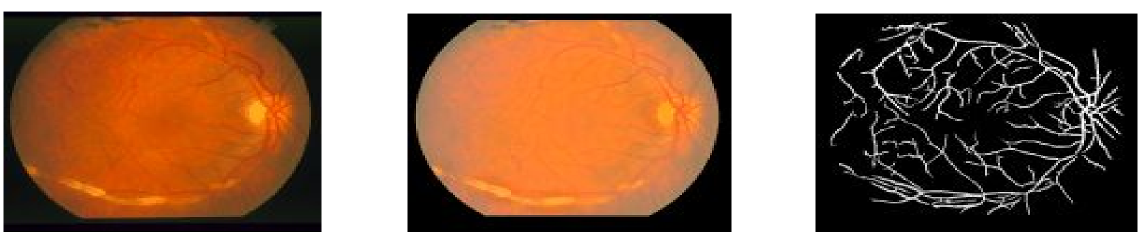
This [8] is an even smaller dataset consisting of 89 images all having the same width and height as in diaretDB0 and were shot from a fundus camera having 50° wide view along with calibration level 1 and known lighting conditions. In this dataset they have provided separate folders where all the 89 images are segmented according to the ground truth lesions present in the retina, and so this gives an understanding to segment the lesions and train our model by giving focus on those lesions using some thresholds to classify the normal and the infected regions. Due to the dataset being small it can be used for analysis and better understanding of the lesions in the retinal image and so it can be used by practitioners/developers new to this field. Images a, b, c are some samples from this dataset. As we can see, these images have better lighting and contrast than diaretdb0, hence diaretdb1 can be preferred over diaretdb0.

(a) (b) (c)

Figure 2 : Sample images from DiaretDB1 that show different lesions in different areas of the retina.

3.2) STARE

STructured Analysis of the Retina(STARE) provides a dataset that is generated by the Shiley Eye Center at the University of California, San Diego. The dataset consists of 400 images divided into batches along with annotations for the issues in all the images. The dataset mainly segments the images having haemorrhages, microaneurysms, macular edema, neovascularization, exudate, and many other things and the extent of all of these are mentioned in the annotations provided along with the database. In [9] we can see that authors have filtered the blood vessels in all the retinal images by using certain thresholding that helped in popping the vessels. In [10] they located/segmented the optic disc that achieved almost 92% accuracy in locating the nerve. This dataset contains ample information regarding various issues in the eye along with their severity index and masking of the raw images followed by equalizing the image pixels. Here image 'a1' is a fundus image, image 'b' is an equalized version(the fundus is masked to pop the retina portion and then the image pixels are subtracted with a certain threshold to get a balanced version of the image where lesions are popped out) of image 'a' and 'c' represents the blood vessel flow in the retina. The purpose of STARE was to enable automated analysis of retinal images so that they can be directly used by an ophthalmologist for further analysis/Retinopathy detection.



(a) (b) (c)

Figure 3 : Image (b) is an equalized version of (a). (c) represents the vessel flow in (a).

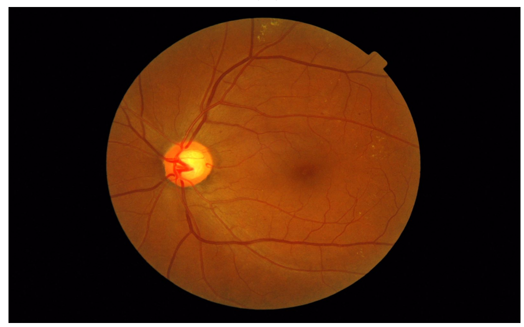
3.3) MESSIDOR

Messidor [11] is a research program that was started with a motto to help students/professionals in the field of Diabetic Retinopathy and their dataset was formulated with the purpose to help the community with early detection and segmentation of lesions in the retina for grading of the Retinopathy. The dataset consists of 1200 images obtained from a 45° wide view color camera under good lighting conditions where 800 images where taken with pupil dilation(pupil dilation aids the process of examining Retinopathy for the ophthalmologists and researchers and so it makes the process efficient and fast) and 400 images without pupil dilation. The dataset is bifurcated into 3 zipped folders each containing 400 images. The dataset belongs to supervised learning problem and so there are Excel sheets describing the Retinopathy severity(based upon number of microaneurysms, hemorrhages along with presence or absence of neovascularization) ranging from grade 0 to grade 3 along with chances of macular edema(based upon the concentration of exudates in the macula region that causes fluid leakage) ranging from grade 0 to grade 2 for each image. The dataset consists of high quality images with high resolutions and so the details regarding vessels, and lesions appear very clear. This database is very good for any research, modeling or analysis purposes and can also be used to train deep learning models for early detection of the disease. Here images ‘a’ and ‘b’ are taken randomly from the 1200 images and they are annotated with their respective Retinopathy and macular edema grades based on spread and number of lesions..

(a)

Retinopathy grade: 3 **Macular Edema grade: 2**

(b)



Retinopathy grade: 2 **Macular Edema grade: 1**

Figure 4 : Images (a) and (b) taken from Messidor along with their ground truth gradings.

3.4) DRIONS-DB

Drions-DB (Digital Retinal Images for Optic Nerve Segmentation) [12] is a dataset that was basically formulated for detecting glaucoma(problem caused in the optic nerve due to hypertension, diabetes and eye pressure) disease that is related to damage in optic nerve originating from the optic disc. The dataset like Drions-DB, DRIVE, RIM-ONE [18] all were specifically designed and used for a group of problems like glaucoma detection, Diabetic Retinopathy due to lesions formed and occurrence of macular edema. Drions-DB consists of 110 fundus images shot from a color fundus camera. There are ground truth labels to detect the optic disc in the retina(here image ‘a’ is the fundus image whose optic disc is detected by a contour plotted on the disc by an ophthalmologist and shown in ‘b’). The ground truth values for each image is of the form of a set of (x, y) coordinates that are plotted on the respective image to see the optic disc and can be used for training a model to detect optic disc and early detection of glaucoma. This is a small database that could be used for retinal analysis and optic disc detection.

(a) (b)

Figure 5 : (a) is a sample from DRIONS dataset and (b) is the same image with a contour plot for detecting the optic disc.

3.5) HRF

HRF(High Resolution Fundus Imaging Dataset) [13] is a dataset with a short amount of 45 images which are distributed into 3 groups of 15 images each for normal eye, eye having Diabetic Retinopathy, and glaucomatous eye. The group of researchers who published this dataset had an aim to promote the analysis and automated detection of lesions in the eye. The images(sample image 'a') in this database are taken with coloured fundus camera with a 60° wide field of view. The experts have also further annotated the distribution of arteries and vessels(as in image 'b') for all the images. This is a small dataset that can be used by developers to carry out glaucomatous analysis or DR lesion segmentation(mainly microaneurysms and hemorrhages).

(a) (b)

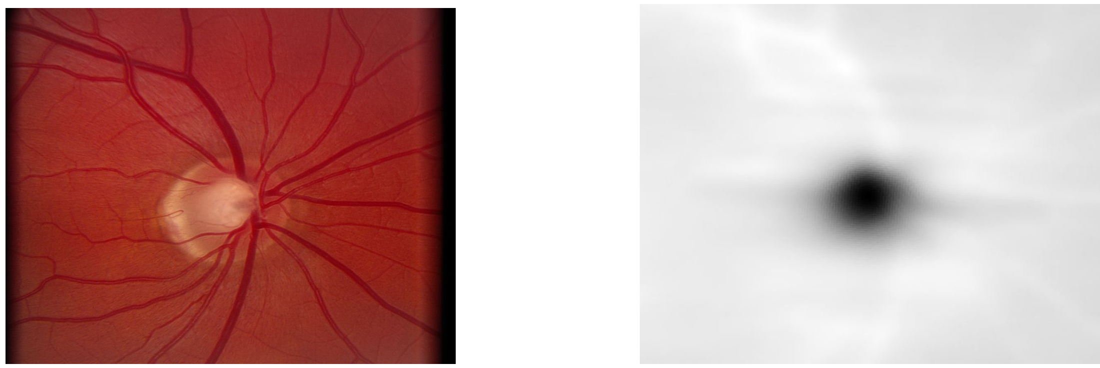
Figure 6 : (a) is an image from a wide view camera in HRF and (b) is the vessel flow in the retina

3.6) INSPIRE

Both of the datasets (STEREO and AVR) are based on lesions near the optic disc and the images are recorded from glaucoma patients.

3.6.1) INSPIRE-STEREO

This is a dataset [14] consisting of 30 images that are zoomed and concentrated around the optic disc. The uniqueness about this dataset is that each image is optic disc centered and includes its depth standard image that can show the depth reference of the optic disc. The images(sample image 'a') in this dataset is captured from patients having glaucoma and it is the first stereo dataset that captures the depth reference of the image(as in image 'b') that is considered in OCT(Optical Coherence Tomography).



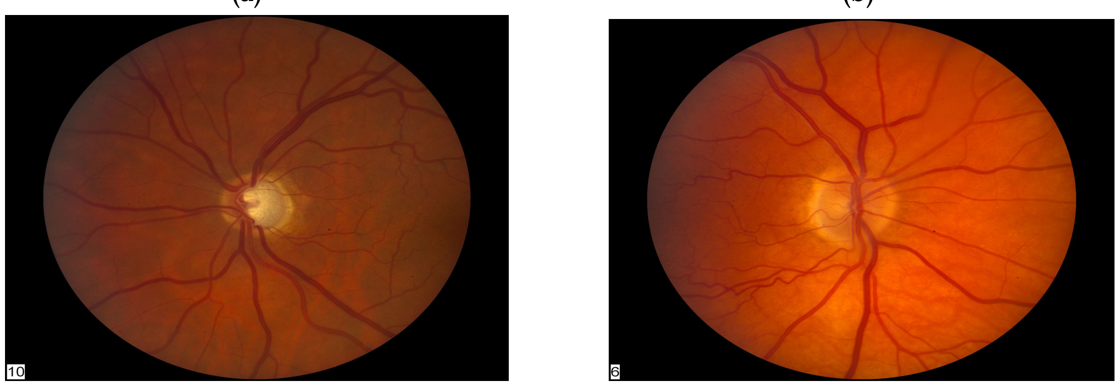
(a) (b)

Figure 7 : (a) is an image centered at the optic disc and (b) represents the depth reference of (a).

3.6.2) INSPIRE-AVR

This dataset described in [15] consists of 40 images each having optic disc at the center and there is a ground truth file describing an AVR(Arterio-Venous Ratio) according to 2 observations taken, AVR-1 and AVR-2 for each image given by experts by observing the optic disc and the vessel distribution in the images. 2 random images ‘a’ and ‘b’ are shown with their AVR ratios. This data is used mainly for analysing the vessel distribution and optic disc lesions.

(a) (b)



AVR-1: 0.57 AVR-2 : 0.62 AVR-1 : 0.65 AVR-2 : 0.64

Figure 8 : Both (a) and (b) are optic centered retinal images along with Arterio-Venous Ratio(AVR)

3.7) DRiDB

DRiDB(Diabetic Retinopathy Image DataBase) [16] is a dataset with 50 fundus images obtained with a 45° field of view RGB camera. This dataset was majorly constructed for Diabetic Retinopathy analysis and lesion detection and so it consists of ground truths for microaneurysms, haemorrhages, macula, hard and soft exudates and optic disc. This is a commonly used database that is widely used by many researchers and a dataset that can be considered for lesion segmentation and testing out the accuracy, sensitivity, and specificity of deep learning models.

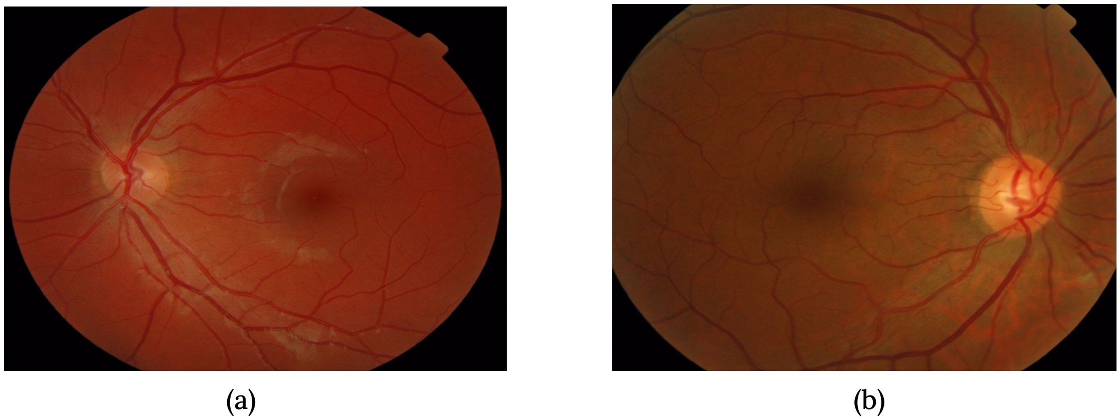


Figure 9 : (a) and (b) are samples from the DRiDB dataset.

3.8) HEI-MED

Hamilton Eye Institute provided the Macular Edema Dataset [17] that consisted of 169 good quality fundus images. The images were diagnosed for Diabetic Retinopathy and the expert graded them in terms of exudates, fluid regions, cotton wool spots, darker spots, and other lesions. Each image(sample image 'a' taken from database) consists of its blood vessel segmented image(as shown in image 'b'), ground truth for lesions and patient's metadata regarding type of diabetes, age, gender, and other basic details that could help in better analysis of the reports. The institute has also provided the matlab code for accessing all the possible options of analyzing the images. This data source can be considered for making early detection systems if we use data augmentation.

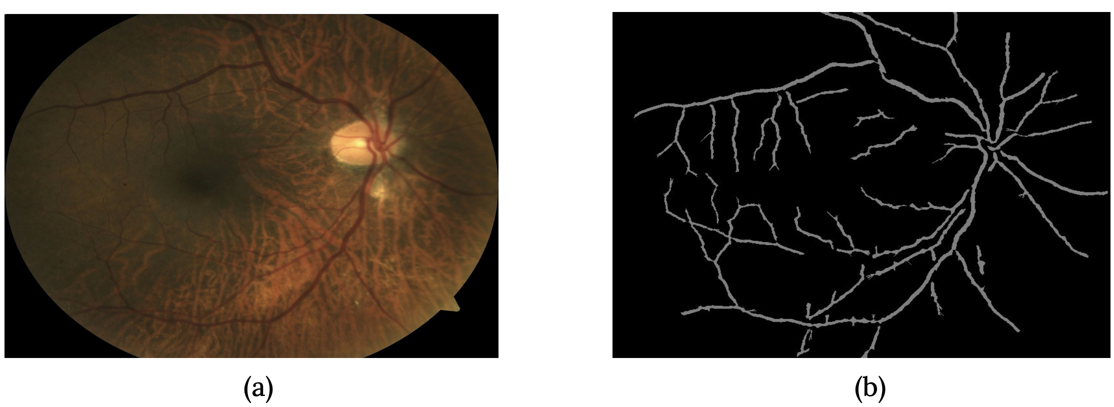


Figure 10 : (a) is a sample from HEI-MED dataset along with its vessel flow annotation in (b)

Datasets	Camera Used	Image Resolution	Diabetic Retinopathy Grading	Macular Edema Grading	Glaucoma Analysis Possible?
DiaretDB0	50° wide view fundus CAM	1500 * 1152 with 24 bit depth	Yes	No	No
DiaretDB1	50° wide view fundus CAM	1500 * 1152 with 24 bit depth	Yes	No	No
STARE	35° wide view TopCon TRV50 fundus CAM	605 * 700 with 24 bit depth	Yes	Yes	Yes
MESSIDOR	45° wide view 3CCD CAM	1440 * 960, 2240 * 1488, and 2304 * 1536 with 24 bit depth	Yes	Yes	No
DRIONS-DB	Analogical Fundus CAM	600 * 400 with 24 bit depth	No	No	Yes
HRF	45° wide view Canon CR-1 fundus CAM	3504 * 2336 with 24 bit depth	Yes	No	Yes
INSPIRE-STEREO	-	768 * 1019 with 24 bit depth of images and 32 bit depth of the depth reference	No	No	Yes
INSPIRE-AVR	-	2392 * 2048 with 24 bit depth	No	No	No
DRiDB	45° wide view ZEISS VISUCAM fundus CAM	720 * 576 with 24 bit depth	Yes	Yes	No
HEI-MED	45° wide view ZEISS VISUCAM PRO fundus CAM	2196 * 1958 with 24 bit depth	Yes	Yes	No
E-Ophtha-EX	-	1440 * 960, 2048 * 1360 and 2544 * 1696 with 24 bit depth	No (Can be used for segmenting exudates)	No	No
E-Ophtha-MA	-	1440 * 960, 2048 * 1360 and 2544 * 1696 with 24 bit depth	No (Can be used for segmenting microaneurysms)	No	No

Figure 11 : This table describes all the datasets

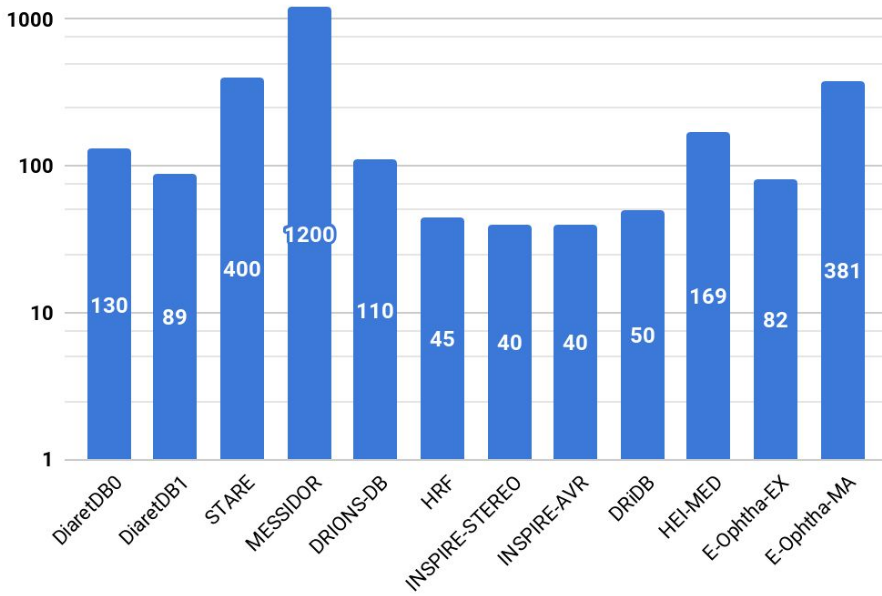


Figure 12 : Histogram describing the size of datasets (Number of images in each dataset)

4. Analysis

As we saw, there are many good datasets that are publicly available to be used for education and research purposes and even for building automated tools for diagnosing the disease.

ImageRet includes DiaretDB0 and DiaretDB1 and both of these datasets include ground truth markings for all the lesions in the retina and so both of these datasets should be considered for lesion analysis and performing lesion segmentation that helps in knowing the retina condition.

HRF(High Resolution Fundus Dataset) is a good dataset that has 3 groups of 15 images with different cases and hence a good dataset for optic nerve and lesion analysis.

After understanding the lesions and their impact on the retina now we can try to create a detection model that would help us in early detection of the disease and so MESSIDOR, STARE and the HEI-MED datasets can be combined and considered for making a model followed by data augmentation to make the model more generalised. All of these datasets would sum upto 1800 images which would be a good number to get satisfying performances.

Lastly the trained model can be tested upon images from some other datasets like the HRF or DRiDB so that we can get a confusion matrix for the trained model.

The 2 INSPIRE datasets along with DRIONS dataset can be used specifically for optic disc segmentation, vessel segmentation and glaucoma analysis.

Other 2 databases given by E-Ophtha [19] named E-Ophtha-EX and E-Ophtha-MA are provided with segmentations of Exudates and Microaneurysms respectively. They are small datasets that can be used for lesion segmentation algorithms and can be beneficial for faster analysis of Diabetic Retinopathy.

Among all the datasets, STARE is the only dataset including nearly 39 different complications in the retina that includes almost every single issue caused in the retina, so it is very useful for understanding different problems.

These are some considerations that can be thought upon before moving towards the depth of the disease for getting a good understanding of all the issues that occur in Diabetic Retinopathy.

5. Discussion and Conclusion

There have been a lot of different complications in Diabetic Retinopathy since it has evolved and ophthalmologists have concluded that the disease can't be cured properly if it isn't recognised at its early stages. Due to the advancements in deep learning and AI, many researchers have developed algorithms that are tuned and fed with images of the affected patients so that we can build automated tools and systems to analyse the disease with which we could reduce the adverse effects that used to happen due to late diagnosis of the disease. There are many models that are tuned by computer vision researchers that have even outperformed the accuracies of the specialists in the field due to their huge learning capacities. In this paper, we have summarized an approach that could be used for selecting a dataset for analysing the disease and building efficient models that could help in better diagnosis and early detection of the disease. In the future many new techniques and model improvements would be made that would give much better results in diagnosing and curing the disease effectively.

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