Machine learning and Deep Learning models for Diabetic Retinopathy

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Abstract:
Diabetes Mellitus, an increasingly prevalent endocrine disorder, presents a formidable challenge worldwide. Numerous nations diligently attempt to alleviate the impact of this ailment by employing various methodologies to predict its symptoms. Among the countless complications that affect individuals with diabetes, one particularly insidious indicator is diabetic retinopathy, a condition that detrimentally affects the eyes. This study aims to employ cutting-edge deep learning techniques, specifically convolutional neural networks (CNN), to construct a predictive model for diabetic retinopathy. Researchers have precisely analyzed and compared a plethora of scholarly articles pertaining to deep learning methodologies employed in the diagnosis of this visual affliction. These approaches have been accurately validated using data samples, with the model's efficacy being evaluated using accuracy metrics for datasets both with and without instances of diabetic retinopathy.

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1. INTRODUCTION

Retinal ailment, specifically “diabetic retinopathy (DR)”, is a pervasive predicament of global proportions. Astonishingly, about one-third of the estimated 285 million individuals afflicted with diabetes exhibit indications of DR, with an additional one-third enduring the distressing prospect of vision-threatening DR [1]. As alarming as these figures may be, the prevalence of this affliction continues to surge. Projections indicate that by the year 2040, an estimated 288 million individuals will be plagued by age-related macular degeneration (AMD), while the number of cases of DR will triple by the year 2050.

The perils of diabetes mellitus extend beyond the realm of blood sugar control, significantly escalating the risk of grave health complications. These complications can be broadly classified into two categories: “microvascular and macrovascular”. The former ensues from damage inflicted upon the delicate network of small blood vessels, while the latter results from the impairment of larger blood vessels (as per the World Health Organization) [2]. Among the microvascular complications, retinopathy, a pernicious affliction that ravages the eyes and can lead to irreversible blindness, takes center stage. In addition, diabetes-induced nephropathy, which impairs the proper functioning of the kidneys and may ultimately culminate in renal failure, as well as neuropathy, a debilitating condition characterized by nerve damage, including the potential for impotence, further exemplify the far-reaching consequences of this insidious disease [3].

"Artificial intelligence (AI)" [4], "Machine Learning (ML)" [5], and "Deep Learning (DL)" [6] have already demonstrated their efficacy in various medical domains that bear remarkable resemblances to ophthalmology, given the intricate nature of diagnostic imaging, which represents the foremost application of AI in healthcare [7]. The numerous advantages of AI in the realm of medicine are extensive. Specifically modified to navigate the complexities of 21st-century ophthalmology, AI can proficiently assist clinical practitioners by employing efficient algorithms to discern and prognosticate features derived from imaging data. This, in turn, contributes to the mitigation of diagnostic and therapeutic inaccuracies. Moreover, AI, ML, and DL possess the capacity to identify disease-specific patterns and establish correlations between novel features, thus fostering innovative scientific insights. For ophthalmologists to secure mastery over their professional destinies, it becomes imperative that they readily adopt intelligent algorithms and actively equip themselves with the knowledge necessary to evaluate and effectively implement AI in a constructive manner.

2. Literature Review

The DR is a serious complication of diabetes that affects the retina and can lead to vision loss if not detected and treated earlyand AI techniques have been applied to various aspects of DR detection, diagnosis, and management, such as fundus image analysis, lesion segmentation, grading, screening, and prediction [1]. In this literature review, I will summarize the recent advances and challenges of AI-based methods for DR and provide some suggestions for future research directions [2].

The main sources of data for AI-based DR detection are fundus images, which are captured by a fundus camera and show the details of the retina, such as blood vessels, optic disc, macula, and lesions [3]. Fundus images can be classified into different types, such as color, red-free, fluorescein angiography, and optical coherence tomography (OCT) [4]. Each type of fundus image has its own advantages and limitations for DR detection. For example, color fundus images are widely available and easy to acquire, but they may suffer from low contrast, noise, and illumination variations [5]. Red-free fundus images can enhance the visibility of blood vessels and hemorrhages, but they may miss other lesions, such as exudates and microaneurysms and fluorescein angiography fundus images can show the leakage and occlusion of blood vessels, but they require the injection of a dye and may cause allergic reactions [6].

AI techniques can be broadly divided into two categories: Ml and DL, Mlrequire manual feature extraction and selection from fundus images, such as blood vessel segmentation, optic disc detection, lesion localization, and texture analysis [7]. ML methods also need to design and train classifiersto distinguish between normal and abnormal fundus images, or to grade the severity of DR according to different scales, such as the "International Clinical Diabetic Retinopathy (ICDR)" scale [8]. DL methods can automatically learn features and classifiers from fundus images, without the need for manual intervention by using "convolutional neural networks (CNNs)", which are composed of multiple layers of neurons that can extract hierarchical and abstract features from fundus images [9]. CNNs can be trained end-to-end, or fine-tuned from pre-trained models, to perform various tasks for DR detection, such as image classification [10], lesion segmentation[11], grading [12], screening and prediction [13].

Asystematic literature review on DR detection using an AI approach, and discussed the basics of diabetes, its prevalence, complications, and AI techniques for DR detection. They also reviewed the existing datasets, screening systems, performance measurements, biomarkers, potential issues, and future scope of AI for DR detection [14].

Another literature review of early-stage DR detection using DL and evolutionary computing techniques, such as particle swarm optimization, genetic algorithm, fuzzy logic, and neural network [15]. Theadvantages and disadvantages of different fundus image types, and the challenges and future directions of soft computing for DR detectionin retinal images, and covered the different aspects of DR and its detection methods [16]. Further they are compared the performance of different methods and datasets and suggested some improvements and recommendations for DR detection [17]. Another systematic review is conducted on DR detection using DL and fundus image segmentation (RFIS) of blood vessels, lesions, optic disc, and optic cup [18]. Futuredirections and challenges of deep learning and RFIS for non-proliferative DR diagnosis relationship between DR and cardiovascular disease (CVD) and discussed the common risk factors and pathophysiological mechanisms of DR and CVD, the new progress of diagnostic techniques for DR, and the biomarkers for early screening of DR [18].

Developing more robust and efficient methods for fundus image preprocessing, enhancement, and augmentation, to improve the quality and quantity of data for AI-based DR detection [19].Exploring more advanced and novel deep learning architectures and techniques, such as generative adversarial networks, domain adaptation, multitask learning, and explainable AI, to improve the accuracy and interpretability of AI-based DR detection [20].Integrating multiple sources and modalities of data, such as fundus images, OCT images, clinical records, and genetic information, to provide a comprehensive and personalized diagnosis and management of DR [21].Evaluating and validating the performance and reliability of AI-based DR detection methods in real-world scenarios and addressing the ethical and social issues related to the use of AI for DR detection [22].

3. Diabetic Retinopathy

When the human body fails to adequately store and utilize glucose, commonly known as sugar, it results in a condition called Diabetes Mellitus, or diabetes [23]. Elevated levels of blood sugar associated with diabetes can lead to damage in nerve cells known as diabetic neuropathy, as well as damage to the tiny blood vessels in the retina, known as diabetic retinopathy (DR) [24]. The retina's primary function is to detect light, which is then converted into signals that are transmitted through the optic nerve to the brain [25]. Diabetic retinopathy (Fig 1) can cause fluid leakage or hemorrhaging in the blood vessels of the retina, leading to vision distortions. In the most advanced stage of diabetic retinopathy, abnormal new blood vessels proliferate on the surface of the retina, resulting in scarring and loss of cells in the retina [26].

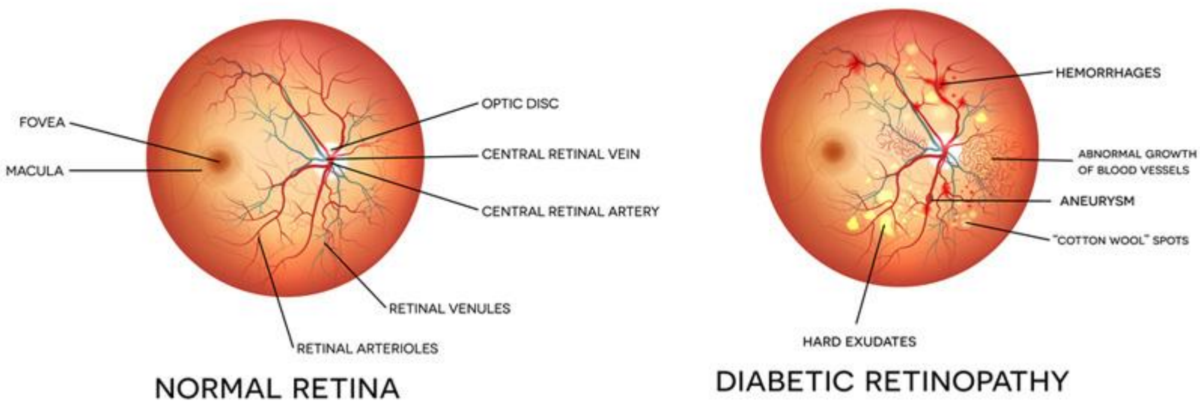

Figure 1. Diabetic retinopathy and Normal Retina

Diabetic retinopathy has the propensity to advance across four distinct stages: the initial stage being mild non-proliferative retinopathy, followed by the intermediate stage of moderate non-proliferative retinopathy. As the condition intensifies, it reaches the severe non-proliferative retinopathy phase, ultimately culminating in the most advanced stage, known as proliferative diabetic retinopathy.

4. Proposed Methodology

For creating the proposed DL modelwe used FastAI libraries by implementing the following steps:

- **Image Classification utilizing the FastAI Library**:The unparalleled convenience of constructing models with minimal code is facilitated by the FastAI library. It is imperative to note that FastAI is not just any ordinary library, but rather a pioneering research lab committed to democratizing the field of artificial intelligence. By furnishing a user-friendly library founded on PyTorch, complemented by exceptionally high-caliber educational courses, FastAI empowers individuals to engage with AI effortlessly. Operating as an elevated-level library established on PyTorch, FastAIexpedites the process of prototyping and grants users access to a plethora of contemporary methodologies. This study employs the esteemed 'Diabetic Retinopathy Detection' dataset procured from Kaggle, training the machine to discern between images depicting a normal retina and those exhibiting the presence of diabetic retinopathy.
- **Google Colaboratory**: is an innovation stemming from Jupyter Notebook, serves as a cutting-edge technology which is an open-source and web-based tool that seamlessly integrates various programming languages, libraries, and visualization tools. A Jupyter notebook can be utilized either on a cloud platform or locally as its main objective revolves around the dissemination of knowledge and research within the realm of ML. Remarkably, Colaboratory notebooks function as dynamic objects akin to Google Docs, enabling seamless sharing and collaboration among users. Furthermore, Colaboratory offers pre-configured Python 2 and 3 runtimes, equipped with essential libraries for machine learning and artificial intelligence, including but not limited to TensorFlow, Matplotlib, and Keras. By creation of a model that is capable of accurate image classification, a critical requirement is the utilization of a cloud GPU provider that has the fastai library readily available. This platform empowers developers in the field of deep learning, enabling them to leverage popular libraries such as Keras, TensorFlow, PyTorch, and OpenCV. However, it is essential to note that the virtual machine associated with the runtime is deactivated after a certain period of inactivity, leading to the loss of all user data and configurations. To address this limitation, Google offers a GPU-accelerated runtime, enhancing the computational capabilities of the platform.
- **CNN Utilizing FastAI**: The proposed deep learning framework for classification comprises a “convolutional neural network (CNN)” adorned with pooling layers and fully connected layers, culminating in a binary classification output: diabetic retinopathy (DR) or normal retina, denoted as no diabetic retinopathy (NODR). The CNNcomprises of a fully connected head containing hidden layers to serve as the classifierto predict the presence of diabetic retinopathy or a healthy retina. In this study, a dataset consisting of fundus images of the human retina, boasting dimensions of over 2000×3000 pixels, is utilized. The dataset is sourced from Kaggle, a website offering free access to datasets [27]. Specifically, the dataset encompasses over 800 images for training purposes and 200 images for testing. It is important to note that the resolution of the dataset fluctuates across different images. Thus, for this investigation, a subset of 1000 images was selected, adhering to an 8:2 training-to-testing ratio. The primary objective of this model is to acquire the ability to

discern between a normal retina and a diabetic retina. The utilization of the fastai library facilitates streamlined training, as it possesses swift and accurate image processing capabilities [28].

To construct the image classification model, the author avails FastAI in conjunction with the cloud GPU provider Google Colaboratory. The following steps were undertaken in the image classification process:

- **Downloading the Image Dataset**: The remarkable FastAI library exhibits an exceptional capability to effortlessly load an array of diverse datasets. Furthermore, it possesses an impressive functionality that empowers users to effortlessly procure an assortment of images by leveraging a file that encapsulates the URLs associated with said images. To acquire this invaluable URLs file, the dataset in question must be meticulously stored on a personal server.
- **Loading and Visualizing the Data**: FastAI utilizes specialized data structures known as "databunches" to facilitate the training of ML models. These data bunches can be generated using problem-specific techniques, such as the "Image Data Bunch.from_folder" method, which proves particularly useful for data loading purposes (as depicted in Figure 2 and Figure 4).


```
[ ]  data.classes

['diabretina', 'normalretina']
```

Figure 2. Data Classes

- **Creating and Training a Model**: The FastAI framework is a powerful tool that empowers users to effortlessly design and construct models, referred to as "learners," with minimal lines of code.

epoch	train_loss	valid_loss	error_rate	accuracy	time
0	0.240868	0.621682	0.210526	0.789474	00:01
1	0.196123	0.644820	0.157895	0.842105	00:01
2	0.203185	0.662209	0.157895	0.842105	00:01
3	0.185842	0.667164	0.157895	0.842105	00:01
4	0.199340	0.659575	0.157895	0.842105	00:01

Figure 3. creation of training model

They offer a technique named "create_cnn" which facilitates the creation of a CNN with a specific model employs the resnet34 architecture and is equipped with pre-trained weights derived from the dataset. Notably, only the fully connected layers situated at the summit of the network are amenable to training. To impart knowledge to these layers, the author expertly utilizes the "fit_one_cycle" method. As opposed to a conventional training approach, the "fit" method ensures a consistent learning rate throughout. On the other hand, the "fit_one_cycle" method adheres to the principles of the one cycle policy, wherein the learning rate undergoes temporal modifications with the aim of achieving heightened efficacy and performance.

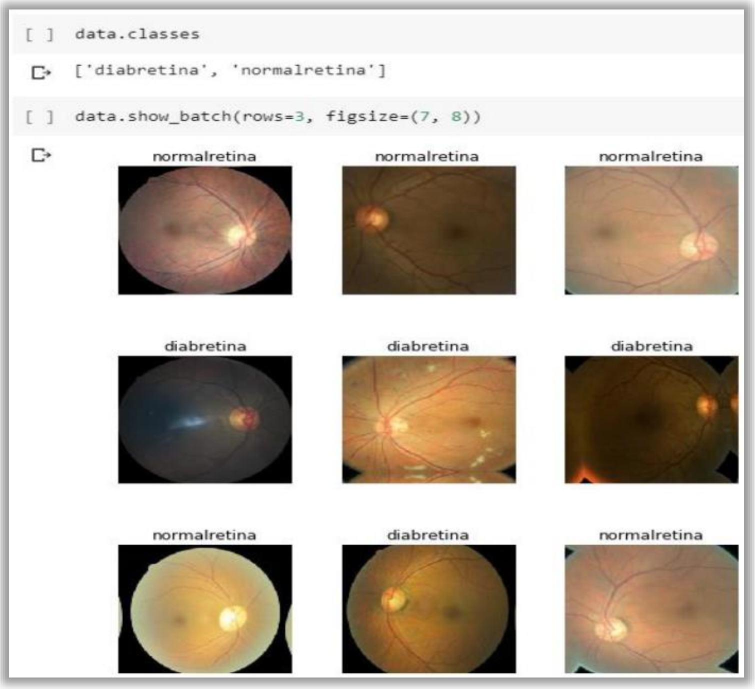

Figure 4. Loading of all classes

- **Cleaning the Data**: Fast AI offers a range of features to facilitate data cleaning through the utilization of Jupyter widgets. One such feature is the ImageCleaner class, which presents users with the ability to review and make decisions regarding the deletion or relabeling of images. The author of this tool opted to employ the Dataset Formatter().from_toplosses function to obtain a collection of misclassified images identified as top losses (Figure 5).

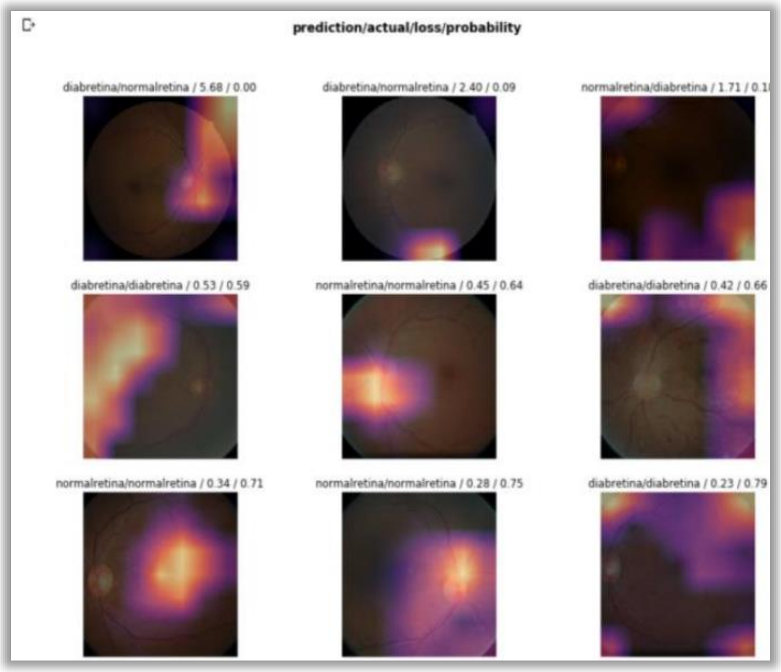

Figure 5. Generation of Top Loss

- **Interpreting the Results**: the Classification Interpretation class is employed for the purpose of interpreting the outcomes. To generate an interpretation object, scholars are required to invoke the from_learner function and provide it with our esteemed learner model (Figure 6).

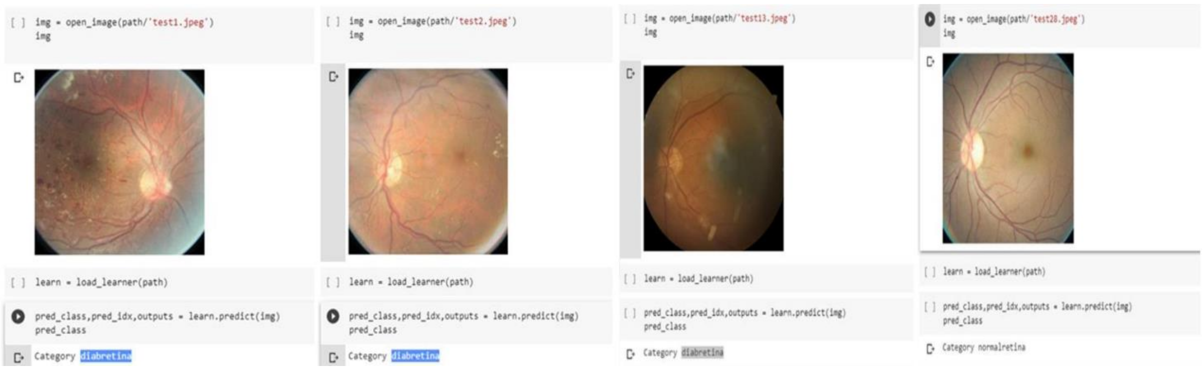

Figure 6. prediction of all types of categories considered

5. Results and Discussion

In the field of Diabetic Retinopathy and ML domains have witnessed the proposal and implementation of diverse ML techniques. With the availability of DL libraries, these libraries have become a crucial factor contributing to the model's performance. The growing utilization of digital information presents opportunities for the creation of comprehensive and extensive healthcare datasets, which can be analyzed for improved healthcare outcomes. This study showcases the effectiveness of a deep learning neural network in accurately distinguishing between fundus images of Diabetic Retinopathy and normal retina images. The utilization of fastAI libraries and the Google colab GPU in this novel application of deep learning algorithms contributes to the classification of retinopathy in the field of ophthalmology.

A detailed survey of algorithms and results utilized for the automated identification of different stages of Diabetic Retinopathy using fundus images. The development of a robust screening tool for Diabetic Retinopathy will significantly alleviate the workload of ophthalmologists and medical graders in clinical settings. We have employed a DL based approach for the classification of retinal images. The tool that assists ophthalmologists in the early detection of glaucoma, even at its mild stage has achieved outstanding accuracy, sensitivity, and specificity rates of 98.13%, 98%, and 98.30%, respectively, when tested on a substantial number of images.

While performing binary classification scenario, the count of accurately identified images belonging to the diabetic retina (diabretina) and normal retina (normalretina) obtained. The ultimate outcome of the meticulously trained neural network resulted in an accuracy rate of 85.5%. The remarkable advantage of employing the FastAI Convolutional Neural Network lies in its capacity to adeptly classify myriad images. This proficiently trained CNN enables swift diagnosis and immediate response to patients. It is worth noting that the accuracy rate can be further enhanced as it depends on the quality and diversity of the training dataset. Herein lies the essence of the ingenious innovation, employing the swift and efficient FastAI libraries, which significantly diminishes the compilation time of the neural network.

In the realm of computer-aided detection to identify retinal abnormalities by scrutinizing retinal fundus images, the model focuses on augmenting images, filtering out noise, discerning blood vessels, identifying the optic disc, extracting exudates and micro aneurysms, and ultimately classifying various stages of diabetic retinopathy utilizing machine learning techniques. Similarly, an optimal model for detecting diabetic retinopathyemphasized the significance of image pre-processing and statistical calculations, recognizing that the training time of the CNNcan be influenced by the GPU rather than through CPU system with an extensive dataset to attain higher accuracy.

The image analysis techniques for the automated and early detection of diabetic retinopathy, employing image processing alongside various other analysis are compared using DL enhanced algorithm for automated diabetic retinopathy detection with previously published results. They utilized the consensus reference standard for referable diabetic retinopathy, and the model that incorporates an image enhancement technique based on morphological operations, accompanied by a proposed threshold-centered static wavelet transforms for retinal fundus images, and Contrast Limited Adaptive Histogram Equalization for vessel enhancement gained better results.

The model that tackles the task of discerning the prevalent diabetic characteristics embedded within fundus images, while concurrently juxtaposing the performance of the neural network against the ophthalmologist's screening dataset of said images. Their pioneering work demonstrated commendable proficiency in detecting hemorrhages, exudates, and vessels. In a comparative analysis with the ophthalmologist, their network exhibited superior accuracy in identifying the presence of Diabetic Retinopathy. Anapproach centered around a hybrid classifier, which encompasses a series of stages encompassing preprocessing, lesion extraction from candidates, and feature formulation. Their innovative methodology paves the way for an augmented modeling technique rooted in m-Medoids, harmoniously fused with the Gaussian Mixture Model. This concoction gives rise to a hybrid classifier that effectively enhances the accuracy of classification.

A survey is conducted focusing on algorithms specifically designed for digital color retinal images have been classified into five distinct stages: preprocessing, localization and segmentation of the optic disk, segmentation of the retinal vasculature, localization of the macula and fovea, and finally, localization and segmentation of retinopathy.

Another approach has incorporated morphological operations in conjunction with segmentation techniques to effectively detect blood vessels and micro aneurysms which showcase their commitment to achieving accurate and reliable results.

A CNN architecture has been implementedto perform data augmentations in a network to demonstrate its prowess in classifying various features of retinal abnormalities, including micro-aneurysms, exudates, and hemorrhages, with remarkable precision. Notably, this automated diagnostic system does not require any user input. To train the network, the researchers harnessed the power of a high-performance graphics processor unit (GPU), utilizing the publicly available Kaggle dataset. The results obtained from their diligent efforts are undeniably impressive.

In the forthcoming era, it is conceivable that investigations shall be conducted whereby a specialized classifier is trained with utmost precision to discern particular attributes. It is imperative to acknowledge that our study possesses a multitude of constraints. Our study's predetermined criteria, and the neural network was exclusively trained on said mages possessing the desirable dimensions. In order to advance the field, future studies would encompass an expansive array of diagnoses, incorporating images from diverse institutions. Our application has the potential to facilitate the development of deep learning models that can be applied across a wide spectrum of retinal or choroidal pathologies. This automated classification system could be seamlessly integrated into the majority of computerized medical systems presently in use.

6. Conclusion

Deep learning methodologies are evidently assuming control over the sector and are progressively triumphant in the field of image-based diagnosis, illness prognosis, and risk evaluation. This paper aims to put forth a proposition for the identification of diabetic retinopathy by employing the FastAI framework, which grants us the ability to construct models with minimal lines of code. The CNN model utilized in this study proves to be highly efficacious in terms of image processing. To train the model, a GPU system provided by Google Colab is employed, ensuring a speedy and precise outcome. This proposed model effectively discerns between images depicting diabetic retinopathy and those presenting a healthy retina. In the future, an enhanced model can be devised, incorporating a more expansive dataset to detect all stages of diabetic retinopathy. Consequently, this model has the potential to serve as a valuable tool for ophthalmologists, enabling them to corroborate their clinical diagnosis.

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