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Detection of Diabetic Retinopathy using ResNet50

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Abstract: Diabetic retinopathy, caused by damage to the retina from diabetes mellitus, is diagnosed through coloured fundus images that require trained clinicians to identify various small characteristics, making it a time-consuming task. In this research, we present a CNN-based method to detect diabetic retinopathy in fundus images. Our novel segmentation strategy using Gabor filters prepares the data for training the model, and data augmentation is used to gather enough data due to the limited dataset. Our segmentation approach identifies intricate properties in fundus images and also detects the presence of diabetic retinopathy. We utilize the ResNet50 algorithm for training the model, which is efficiently trained using a high-end Graphics Processor Unit (GPU). Our proposed method shows promising results in the detection of diabetic retinopathy, indicating its potential for use in clinical practice. On training the dataset we achieved an accuracy of 71.51 percent.

***Index Terms* - Deep learning, Segmentation, Augmentation, CNN**

I. Introduction

Diabetic Retinopathy is a complication that arises from diabetes, resulting in damage to the blood vessels of the light-sensitive tissue located at the back of the eye, which affects the eyes Initially, Diabetic Retinopathy can be asymptomatic or may manifest as mild vision problems. But this turns out to be a major cause of blindness. The occurrence of this condition is possible in individuals with either type 1 or type 2 diabetes. When a patient experiences chronic diabetes and irregular blood sugar control, the likelihood of developing these eye-related complications rises. Patients most likely have this condition which damages the blood vessels in the retina(light-sensitive tissues). Regular screening of diabetic patients for DR has shown to be a costly, effective, and important aspect of their care. Early detection of diabetes allows for timely and crucial treatment of Diabetic Retinopathy, underscoring the significance of this process.

The main purpose of our research is to reduce diagnosis time effort According to reports it provides accurate medical aid for the diagnosis of severe and proliferative DR and it reduces the uncertainty of DR blindness. Especially in rural areas such type of treatment is very helpful where there is a lack of awareness about diabetic treatment. We are spreading awareness through our research. The fundus camera, also known as the retinal camera, holds great importance in the field of human health as it aids in the detection of Diabetic Retinopathy. It is a specialized microscope with an integrated camera that is specifically designed to capture images of the inside of the eye, such as the retina, retinal vessels, optic disc, macula, and posterior pole (which is also referred to as the fundus). Our research aims to focus on the use of a deep learning-based Convolutional Neural Network approach to grade Diabetic Retinopathy using fundus images.

Convolutional Neural Networks (CNNs) hold great importance in the field of deep learning, boasting a rich and successful track record in image processing and interpretation, especially in the realm of medical imaging. We use deep learning-based CNN and ResNet50 algorithms for detecting DR using fundus camera images in this research. The deep architecture of CNNs has been instrumental in providing finesse and high performance to trained models by learning patterns for raw images. The dataset includes five classification categories i.e

NO DR, Mild DR, Moderate DR, Severe DR, and Proliferative DR. State-of-the-art deep learning models, specifically large convolutional neural networks (CNNs), are effectively addressing complex visual recognition problems that involve identifying multiple object classes.

To improve the training of these models, a novel approach for segmenting blood vessels has been developed, which has been a subject of interest in previous research due to its diagnostic importance in medical imaging. The image augmentation technique is employed on the photographs to expand the dataset and compensate for the limited number of images present in the training dataset. An increased number of photographs also led to better training outcomes.

In our system, we utilize training, testing, and validation datasets to make predictions on whether the subject has Diabetic Retinopathy or not. The resultant outcomes will be examined through various performance examined metrics that include accuracy and specificity. The aim of this study is to demonstrate superior performance compared to existing approaches. In the future test model other image classification models and try another blood vessel segmentation technique which can lead to better results. If possible then try to gather more images to train the model on a better dataset.

II. LITERATURE REVIEW

The detection of diabetic retinopathy (DR) from medical data is an interdisciplinary field that involves ophthalmology, endocrinology, and machine learning. In this section, we review the current literature and recent advancements in DR detection, starting from traditional methods in the early period to the present day of using machine learning algorithms on medical imaging data.

A. Traditional Diabetic Retinopathy Detection

Traditional diabetic retinopathy detection involves a comprehensive eye exam by an ophthalmologist or optometrist. The exam includes:

- Visual acuity test: The eye care professional will assess the patient's visual acuity by evaluating their ability to see clearly at different distances.
- Pupil dilation: The eye care professional will use eye drops to dilate the pupils, which allows them to see the back of the eye more clearly.
- Fundus examination: The eye care professional will examine the retina at the back of the eye for signs of diabetic retinopathy, such as swelling, blood vessel changes, or abnormal growth of new blood vessels.
- Optical coherence tomography (OCT): OCT (Optical Coherence Tomography) is a non-invasive imaging test that employs light waves to capture cross-sectional images of the retina. It can help detect diabetic retinopathy and other eye diseases.
- Based on the results of the exam, the eye care professional will diagnose diabetic retinopathy and recommend a treatment plan, which may include close monitoring, laser treatment, medication, or surgery.

B.Traditional Diabetic Retinopathy Detection versus Current Diabetic Retinopathy Detection

- Current diabetic retinopathy detection methods also use traditional techniques but also incorporate new technological advancements and methods, such as telemedicine and artificial intelligence (AI).

Compared to traditional diabetic retinopathy detection, current methods offer the following advantages:

- Increased access: Telemedicine allows for diabetic retinopathy screening and monitoring outside of clinical settings, providing increased access to eye care for individuals who may not have access to traditional evaluation methods.
- More objective data: AI algorithms can analyze retinal images to provide objective data on the presence and severity of diabetic retinopathy, complementing the subjective information gathered during the eye exam.
- Early detection: By leveraging AI algorithms, it is possible to analyze extensive datasets of retinal images to detect initial indications of diabetic retinopathy. This enables early intervention and the prevention of vision loss.

C. AI for Diabetic Retinopathy Detection

- AI algorithms have demonstrated considerable potential in the detection of diabetic retinopathy from retinal images. Deep learning algorithms, such as convolutional neural networks (CNNs), can be trained on large datasets of retinal images to accurately detect diabetic retinopathy. Transfer learning, which involves adapting pre-trained models to new datasets, can also improve the performance of AI algorithms for diabetic retinopathy detection.
- Research has shown that AI algorithms can achieve high sensitivity and specificity in detecting diabetic retinopathy. For example, one study found that a CNN model achieved a sensitivity of 91.7% and a specificity of 98.5% in detecting diabetic retinopathy from retinal images.

Overall, AI-based diabetic retinopathy detection holds promise as a complementary tool to traditional methods for identifying individuals who may be at risk for diabetic retinopathy. However, it's important to note that there are limitations to using AI algorithms for diabetic retinopathy detection, including issues with data quality and potential biases in the data. Therefore, it's important to approach these methods with caution and in conjunction with traditional methods of diabetic retinopathy detection

III. PROPOSED METHOD

The implemented work incorporates a proposed architecture primarily comprised of the following steps. The abovementioned steps for system architecture have been shown in the following flowchart in Fig. 1.

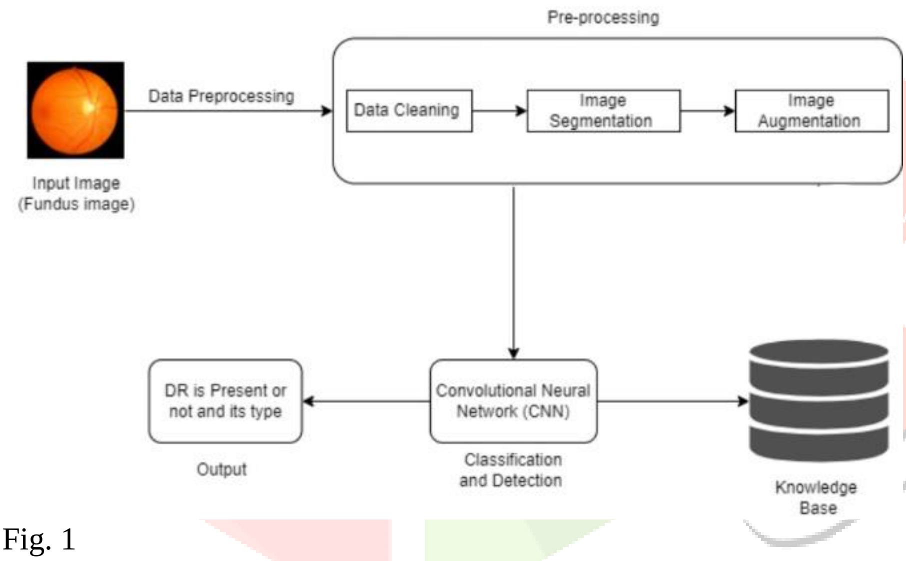

Fig. 1

1. Data collection: Collect the data from Kaggle which have various dataset for diabetic retinopathy available.
2. Pre-processing: Clean and pre-process the image, removing any irrelevant information and converting the image for suitable analysis. This step consists of data cleaning, segmentation, and augmentation.
3. Model training: This step involves running the algorithm of CNNs, use of activation function (Softmax)
4. Result: This step gives us an output of whether DR is present or not

A. Data collection:

The dataset was provided by the APTOS 2019 Blindness Detection Challenge organizers on Kaggle. The dataset we used includes 2794 fundus images, which are divided into a training set and a validation set images. The dataset consists of retinal images, with each image being assigned a severity score for diabetic retinopathy, ranging from 0 to 4.

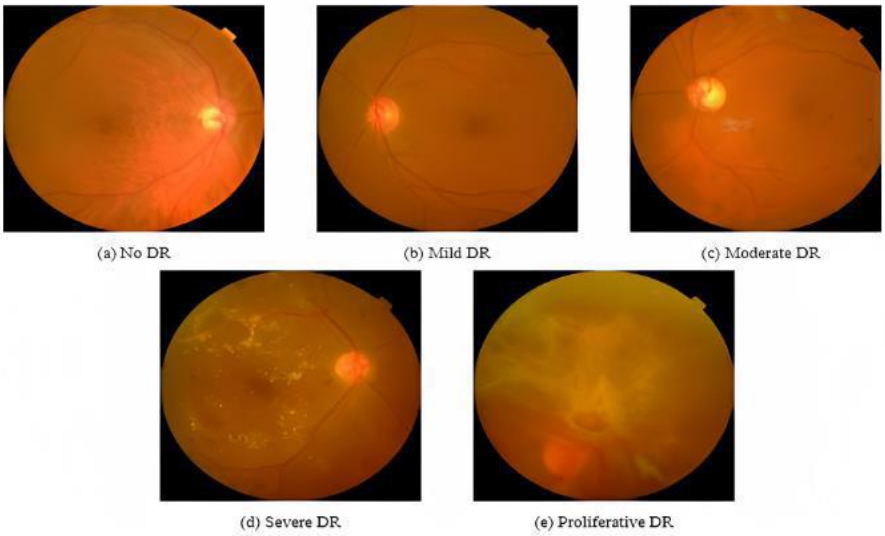

Fig. 2

B. Image segmentation:

The role of blood vessels in identifying Diabetic Retinopathy in the retina has been acknowledged for some time. However, before implementing a computer-aided diagnosis approach, it is essential to segment the retinal vascular tree. The segmentation process is performed using a specialized module that enhances the blood vessel anatomy in the retina. This module highlights the blood vessels in the image, leading to a more accurate classification by the model.

Segmentation is an essential pre-processing step in any image classification problem, as it helps improve the performance of the classification model. By segmenting the image and isolating the areas of interest, the model can train and classify the data more effectively. In diagnosing Diabetic Retinopathy, the segmentation module plays a crucial role in enhancing the model's accuracy by emphasizing the blood vessels in the retina.

In prior research, U-NET, a specific type of Convolutional Neural Network, was employed to segment blood vessels in the retina [3]. However, this network cannot be applied in the current study because the dataset does not contain segmented retinal photos for training. Moreover, manually segmenting the images is a laborious and time-consuming task, which is not practical for this study. As a result, alternative methods for blood vessel segmentation will be investigated to achieve precise and efficient DR detection.

Our study proposes an architecture for segmenting blood vessels in the retina using fundus images. We employ a combination of filters and transformations to achieve a high-quality segmentation that can be used to train the model. To perform these modifications, we utilize the Open-Source Computer Vision Library (CV2) in Python.

The segmentation module follows the below-mentioned steps and the results are illustrated in the accompanying figure.

- First, the original image, which is typically in color and three-dimensional, is converted into grayscale to simplify the image and reduce its complexity. This results in a one-dimensional image.
- Gabor Filters are then applied to the grayscale image. These filters are used to detect specific frequency pixels in the image and are commonly employed in image texture analysis [7].
- After the Gabor filtering, thresholding is applied to create binary pixels. Thresholding is a technique for converting grayscale images to binary images by applying a certain value of the threshold. This process helps to distinguish between foreground and background pixels.
- Finally, opening morphological transformations are applied to reduce noise in the final image. This transformation involves two steps: erosion and dilation. Erosion removes small foreground pixels while dilation expands the remaining foreground pixels. Together, these steps help to remove noise and refine the segmentation result.

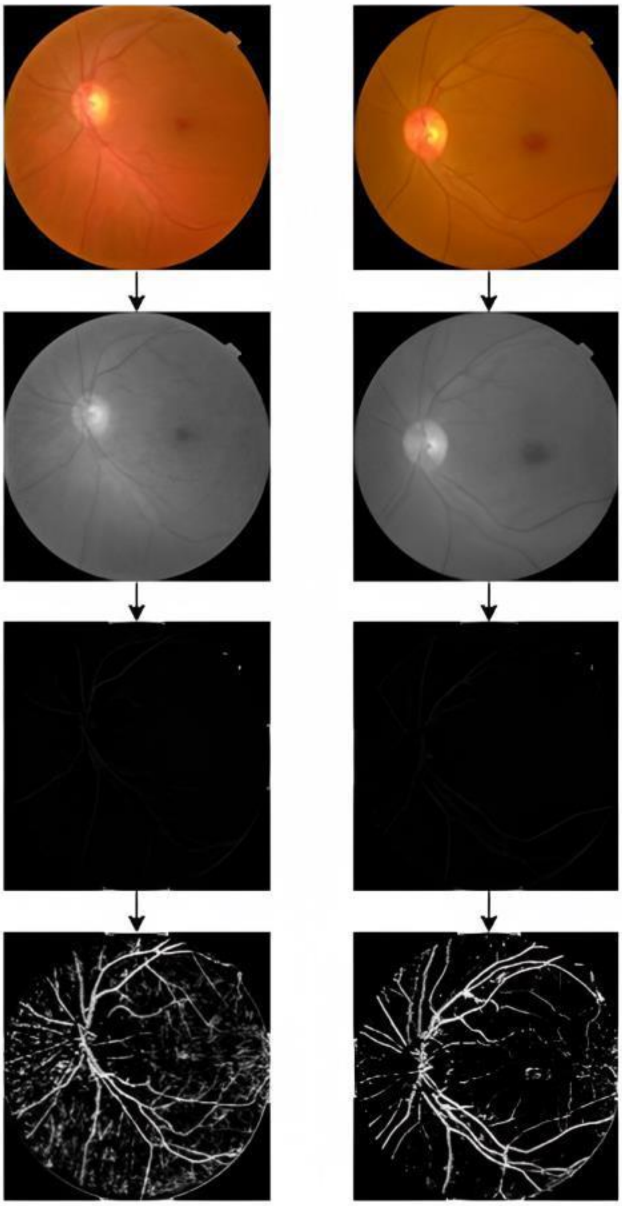

Fig. 3

C. Augmentation:

The original pre-processed images were found insufficient for proper training of the model. To overcome this, augmentation techniques such as rotation, zoom, horizontal and vertical flips, blurring, brightness, and saturation adjustments were applied to all images. The Keras Preprocessing Library's ImageDataGenerator was utilized to randomly generate all parameter values during the augmentation process. As a result of the data augmentation, the training dataset was expanded to more than 11,000 images, while the validation dataset now comprises 2,794 images.

D. Model training:

After exploring various CNN models, we opted to use ResNet50 architectures for our training, which is a multiclass model. We added more convolutional layers to enhance our neural network's capacity to learn deeper features. ResNet50, a widely recognized model for image recognition, has demonstrated exceptional accuracy when applied to the ImageNet dataset. The model consists of 48 layers and utilizes the SoftMax activation function for classification. Batch normalization was performed, and the learning rate was maintained at 0.0005. Gaussian initialization was used to decrease the initial training time. We trained the model for 200 epochs to attain the reported accuracy.

IV. RESULTS AND DISCUSSION

To classify images into five categories ranging from No DR to Proliferative DR, the neural network was trained and evaluated using a validation set of 2,794 images. Running the validation images on the network took 210 seconds. The accuracy of the final neural network was found to be 71.51%, which is calculated as the total number of images classified correctly for DR divided by the total number of images. The classification system used numerical labels, with 0 representing No DR, 1 for Mild DR, 2 for Moderate DR, 3 for Severe DR, and 4 for Proliferative DR.

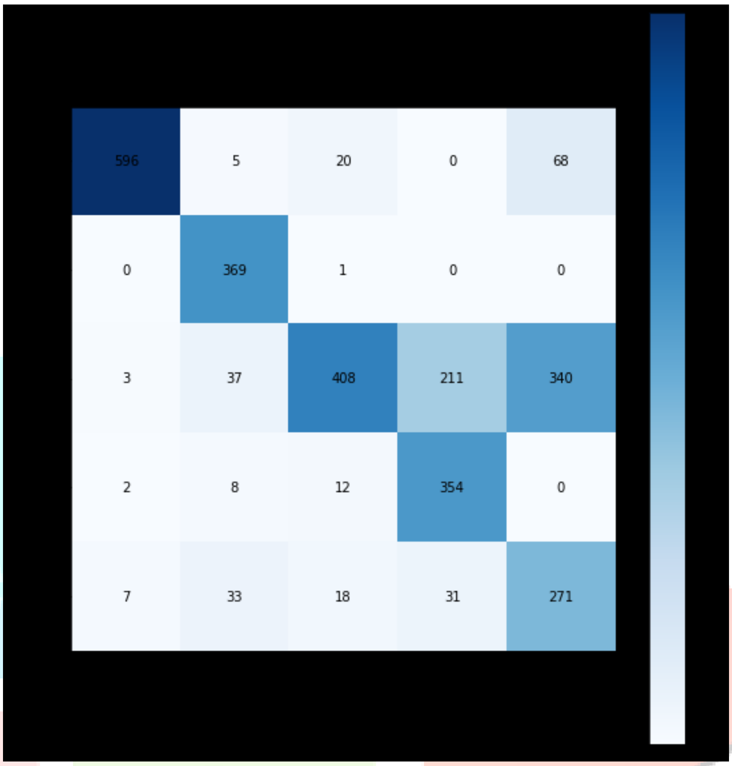

Fig. 4

V. CONCLUSION

The proposed research on using a system to identify and categorize fundus photos for diabetic retinopathy detection has the potential to revolutionize the healthcare industry by providing a reliable and accurate method of diagnosing DR. The suggested model will enable healthcare facilities and hospitals to quickly and accurately identify the severity of DR in patients, leading to earlier intervention and treatment. This could result in reduced healthcare costs and improved patient outcomes. The future work to evaluate other picture classification models and test different blood vessel segmentation methods may lead to even more accurate and efficient DR detection. The continued effort to collect more photos for training the model on a better dataset will improve the overall performance and reliability of the system. Early detection is an important benefit of the proposed research, as it allows for earlier intervention and treatment, potentially preventing or delaying the onset of blindness in diabetic patients. Overall, this research has the potential to significantly improve the diagnosis, treatment, and prevention of DR, resulting in better patient outcomes and a higher quality of life for those affected by this disease.

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