ABUNDANT DETECTION OF DIABETIC RETINOPATHY USING FUNDUS PHOTOGRAPHY AND IMAGE PROCESSING

Dr. V Vasanthi1, TVijayavarthini

[1] Assistant professor, [2]Student PG & Research, Department of Computer ApplicationHindusthan College of Arts and Science
Coimbatore, India.

Abstract: *The technique of dividing a digital image into different parts is called image segmentation (set of pixels also known as image objects). Segmentation's objective is to transform an image's representation into a more straight forward and meaningful form. More easily analyzed a typical clinical approach for capturing a retinal visualization is retinal imaging. The early identification of retinal disorders such hypertension, diabetes, and glaucoma uses segmentation of blood vessels in retinal pictures. An essential preprocessing step for the early diagnosis of retinal disorders is the segmentation of blood vessels. To diagnose and treat diabetic retinopathy early and avoid blindness, retinal vasculature extraction is used. Images of the retinal fundu's blood vessels serve as a crucial diagnostic tool for conditions like glaucoma, hypertension, and diabetic retinopathy. The eye condition known as diabetic retinopathy (DR) is brought on by long-term diabetes mellitus sickness and retinal damage. Many techniques have been put forth for the identification and diagnosis of DR. Pre- processing of color fundu's pictures, diagnostic feature extraction, and DR classification are the three processes in the diagnosis of diabetic retinopathy. As a result, we can evaluate a person's potential level of diabetes by looking at the thickness of their blood vessels using a variety of imaging algorithms.*

INTRODUCTION: Medicine is being revolutionized by the quick development and spread of medical imaging technology. With non-invasive viewing of the human body, medical imaging enables researchers and medical professionals to gather potentially life-saving information. Medical image analysis professionals are preoccupied with the difficult task of extracting, with the aid of computers, clinically useful information about anatomic structures imaged through various imaging modalities, including Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and others. This is because medical imaging is becoming more and more important in the diagnosis and treatment of disease. Understanding picture content is essential for searching and mining in medical image archives. Image segmentation, which tries to automate the extraction of object boundary characteristics, plays a key part in this process. Large scalar longitudinal projects frequently make manual segmentation unfeasible. In order to get beyond the drawbacks of manual segmentation, reliable picture segmentation techniques must be developed. The employment of computers to speed up their processing and analysis has become essential due to the growth in size and volume of medical pictures. A crucial element in helping and automating specialized radiological operations is the use of computer algorithms, namely those for the identification of anatomical structures and other locations of interest. Numerous biomedical imaging applications, including the quantification of tissue volumes, diagnosis, localization of pathology, study of anatomical structure, treatment planning, partial volume correction of functional imaging data, and computer integrated surgery, depend on these image segmentation algorithms. The requirement to segment retinal pictures is what inspired the automated techniques and methodologies disclosed in this paper. Nevertheless, the use of these technologies is appropriate for broader segmentation issues that may involve any imaging modalities or segmentation goals. The retinal blood vessels must be manually segmented, which is laborious and time-consuming. As a result, automated segmentation is useful since it requires less time and effort. The algorithms for segmenting retinal blood vessels primarily focus on automated identification of diabetic retinopathy, which is now known to be the leading cause of blindness. Yet, intensity data alone is frequently insufficient for an algorithm to provide 3 acceptable distinction of the target structure from its highly folded and interconnected neighbors.

REVIEW OF LITERATURE: The majority of the research on DR detection is split between classic and contemporary machine learning and image processing methods. The fundus pictures have previously undergone several image processing approaches for pre-processing and feature extraction. The categorization of the resulting feature extracted pictures was then performed using a variety of conventional machine learning techniques. The handmade characteristics that faithfully reflected the data had to be carefully extracted for these techniques, which had to be trained and evaluated on a smaller dataset. The feature extraction and classification of medical pictures using CNN, a subset of machine learning methods, has become quite popular due to the availability of powerful hardware with high processing capacity and vast image datasets. The authors of the study [23] employ transfer learning to classify fundus pictures from the blindness detection dataset from the Asia Pacific Tele-Ophthalmology Society (APTOS) by layering CNN on top of Res Net and Inception-based models. Resizing, blurring, and bounding box procedures are used to pre-process the photos while data augmentation is done to balance the data. For the APTOS dataset, the authors report a test accuracy of 82.18%. proposes a multiclass classification technique for several eye-related disorders. The technique classifies fundus images into various types of eye disorders using CNN architectures and transfer learning. The class labels for eight categories of ocular disorders include normal, diabetic, glaucoma, cataract, hypertension, myopia, AMD, and other diseases in the Ocular Disease Intelligent Recognition dataset published by Peking University. The authors suggest two Transfer Learning models (TL). The first one builds a parallel architecture with feature vectors that are merged before the pooling layer is applied at the end using the right and left fundus pictures of the eye. The second architecture classifies input using a concatenated picture of the right and left eyes. The second model, which uses transfer learning on the VGG CNN architecture, performs better on the concatenated picture input, according to the results. According to a suggested coarse-to- fine CNN architecture in , the input data is first binary classified into No DR and DR impacted pictures using a coarse network. In order to decrease background information and improve the lesion properties, the design adds attention gate modules to the CNN architecture. The last four phases of DR, mild, moderate, severe, and proliferative DR, are subsequently classified by the Fine Network from the DR classified pictures of the Coarse Network. The Eye PACS (a platform that offers DR pictures of the left and right eyes acquired from several types of cameras) and the Indian Diabetic Retinopathy Imaging Dataset are the datasets utilised in the article (IDRiD). Images from a Kowa VX-10 digital fundus camera from an eye clinic in India are included in the IDRiD collection.

EXISTING SYSTEM AND DISADVANTAGES:

Researchers working on the retinopathy detection problem ran across a few issues, some of which are inescapable and for which there is now no fix because deep learning is still a relatively unexplored subject and data collection is rife with issues. Data are hard to come by, and the majority of the ones that are aren't useful for one reason or another. Using CNN to segment the lesions, Fig. 1 illustrates the research gaps in retinopathy.

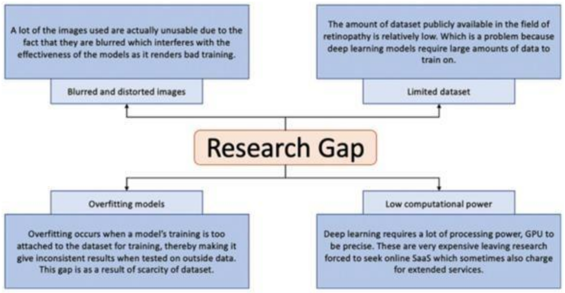

Fig : 1

The following are the key drawbacks of the standard methodologies and DL architectures that were used in the prior review of the existing literature:

1. Constrained dataset

2. Images that are twisted and blurred

3. Models that are over fit

4. Limited computational capacity

PROPOSED SYSTEM NAD ADVANTAGES:

There is a greater need than ever for a system that could automatically detect and identify people who have retinopathy since it is one of the illnesses for which there are few specialists. We started our work by gathering data, and we did this by using photos from the Indian Diabetic Retinopathy Imaging Dataset (IDRID) [1]. The next step was data preparation, which was very important since even though the dataset was typical, we still needed to modify it to meet the issue we were attempting to address. Finally, the data is fed into classification algorithms where it is taught to recognise retinopathy automatically. The segmentation of the lesions using the CNN experiment is shown in Fig. 2's pipeline.

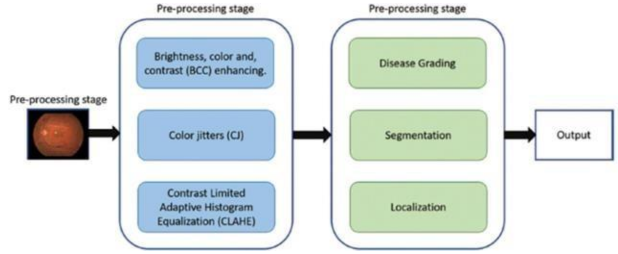

Fig : 2

METHODOLOGY:

The three tasks in the Indian Diabetic Retinopathy Image Dataset (IDRiD) are as follows:

1. Segmentation: This involves segmenting the four types of retinopathy— Microaneurysms (MA), Hemorrhages (HE), Hard Exudates (EX), and Soft Exudates— that each have a particular aetiology (SE). Images for segmenting the optic disc are also included (OD).

2. *Disease Grading:* This involves determining the extent of retinopathy in the eye and the likelihood of developing macular edoema as a result of retinopathy.

3. *Localization:* This comprises the location of the Fovea centre and the optic disc.

PRE-PROCESSING: Images were pre-processed and three additional datasets were created before beginning any activity. By improving the brightness, colour, and contrast (BCC) of the original photos, the first dataset was created. Applying colour jitters (CJ) to the original image produced the second dataset. Brightness, contrast, and saturation of pictures are modified at random in colour hiccups. Applying Contrast Limited Adaptive Histogram Equalization (CLAHE) to the original photos produced the third dataset.

DEEP-LEARNING: Artificial neural networks are the foundation of the Deep Learning (DL) family of artificial intelligence (AI) techniques, which are inspired by the structure of the human brain. DL essentially refers to techniques for automatically learning the mathematical representation of the latent and intrinsic relations of the data. Contrary to typical machine learning techniques, deep learning ones learn the proper features directly from the data instead of relying on the development of hand-crafted features, a procedure that may be highly time- consuming and labor-intensive. Also, when the volume of data grows, DL approaches scale significantly better than conventional ML methods. An outline of certain important DL ideas is given in this section.

NEURAL NETWORKS: An artificial neural network (ANN), which has three layers of neurons—an input layer, a hidden layer, and a final output layer—is the most basic type of neural network. As there is just one hidden layer in these networks, they are referred to as shallow (feed-forward) neural networks. A Deep (Feed-Forward) Neural Network (DNN), in contrast, has more hidden layers than two. Every input node and hidden neuron node is connected to every neuron in the following layer by a connection link, and each hidden and output layer is made up of many artificial neurons. Moreover, because these networks only accept a one-dimensional array as input, they cannot be utilized to process imaging data directly.

CNN ARCHITECTURE IN FUNDUS ANALYSIS:

Traditional CNN: Human vision served as the inspiration for convolution neural networks (CNN), which, unlike shallow neural networks, take 2D arrays as input and their idea is based on "convolution," a basic mathematical procedure. The primary distinction between a CNN and a DNN is that, unlike a CNN, a DNN does not require that all neurons at a particular layer participate to the calculation of each neuron's output at the subsequent layer. Rather, a CNN applies filters or kernels on a portion of the original picture to build a feature map, which is then used to compute convolutions. Hence, if the filter's size is X x X, only a window of x2 pixels will be used to calculate each unit's value in the feature map of the following layer. This has an immediate effect on the receptive field, which is defined as the area in the inputspace where a certain CNN feature ispresent.

UNet: Since UNet designs may keep the image's structural integrity, they are more suited for semantic segmentation than conventional CNNs. They are made up of a symmetric expanding path that enables correct segmentation as well as a contracting path to collect the pertinent context. Additionally, a UNet architecture processes the image in a single pass rather than processing various patches in a sliding window approach as a CNN would, which is why such architectures are referred to as "Fully Convolutional Networks" and have fewer parameters and are faster than conventional CNNs (FCN). The segmentation job, which is essential for medical image analysis since there are so few accessible data compared to other computer vision disciplines, requires substantially less data than typical CNNs.

Attention Modules: Human vision and perception are widely known to rely on attention processes to concentrate on particular elements of a scene or an item rather than processing the entire scene at once. Traditional CNNs, on the other hand, have not yet fully and effectively incorporated such a technique. In order to do this, several research have recently suggested these techniques, known as attention modules, in an effort to enhance the models' performance and resilience.

Generative Adversarial Networks: The Generative Adversarial Network (GAN) is a significant class of convolution neural networks . The generating network, which creates candidate samples based on the original data distribution, and the discriminator, which aims to separate the produced candidate samples from the actual data distribution, are the two independent models that make up a typical GAN. The generator is able to provide candidate samples that are quite similar to the real data distribution by using such a training technique. Image super-resolution (i.e., the generation of high resolution copies of the input picture), artistic creation, and image-

DATAFLOW DIAGRAM:

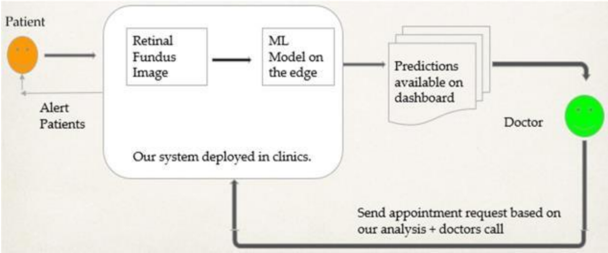

Fig : 3

BLOCK DIARAM:

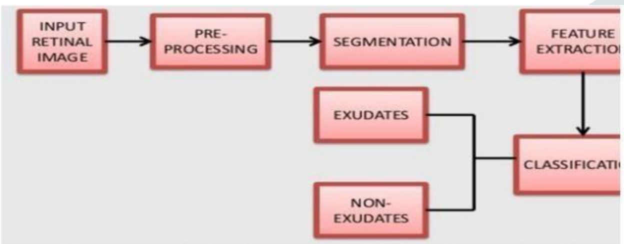

Fig: 4

ER DIAGRAM:

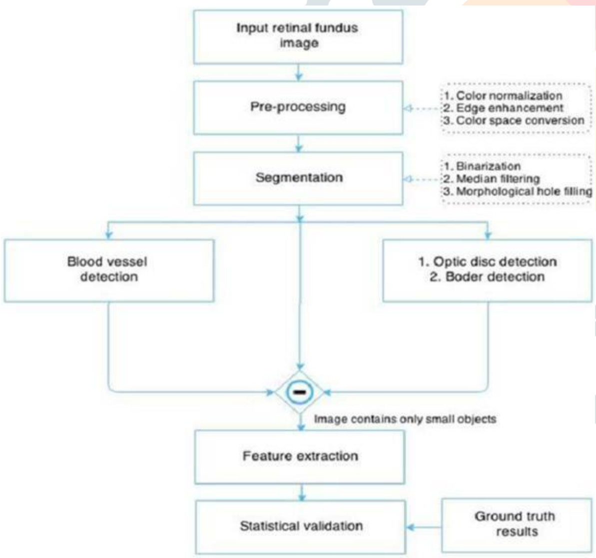

Fig:5

USECASE DIAGRAM:

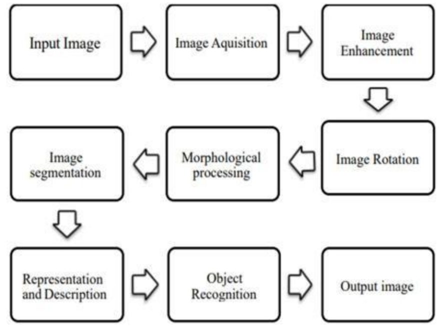

Fig:6

MODULE DESCRIPTION:

Process preparation: Pre-processing refers to actions taken on a picture at the most basic level of abstraction. If entropy is a measure of information, then these actions diminish rather than enhance the information content of the picture. Pre-processing is intended to improve the picture data by suppressing unwanted distortions or enhancing certain aspects that are important for further processing and analysis tasks.

Segmentation: Segmentation is the process of breaking up pictures into smaller, related parts that share characteristics like brightness, contrast, texture, and color. Depending on the issue being handled, the subdivision is carried out at several levels ofdetail.

It includes three parts and is based on mathematical morphology.

- Extraction of the blood vessels;
- Extraction of the hard exudates and theoptic disc.
- Finding the optic disc, this allows for exudates to be distinguished from it.

Identification of Disease Abnormalities: A method for spotting anomalies in a patient's medical imaging. The system consists of a learning engine, a detecting engine, and an examination bundle. At least one medical picture of the individual from the first modality and at least one medical image from the second modality are included in the examination bundle. In order to find anomalies in at least one of the medical pictures that make up the examination bundle, the detecting engines are used.

SCREENSHOTS:

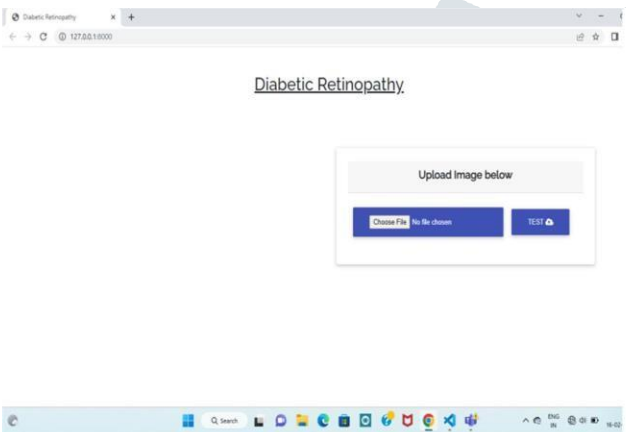

Fig:7 Home Page

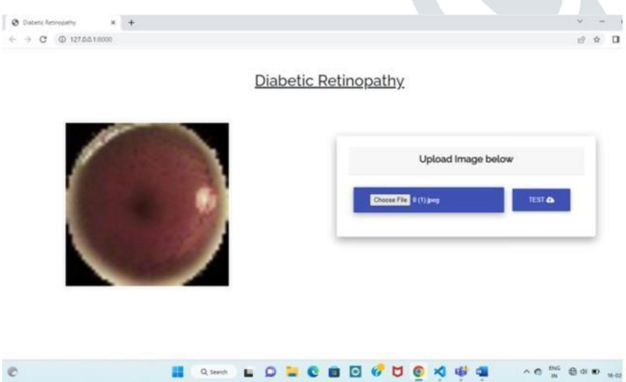

Fig: 8 Testing Page

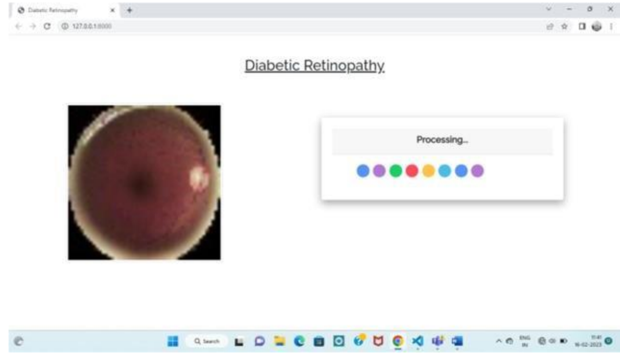

Fig:9 Processing

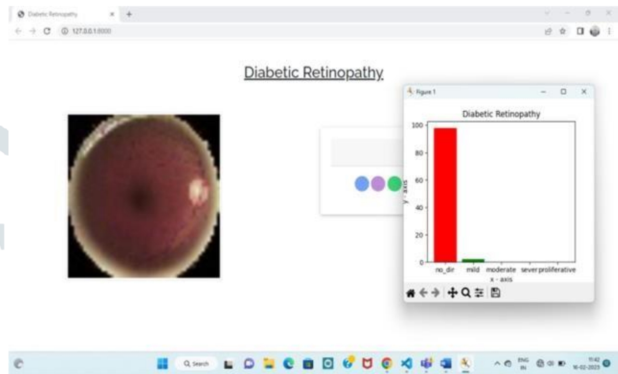

Fig:10 Graphical Plotting

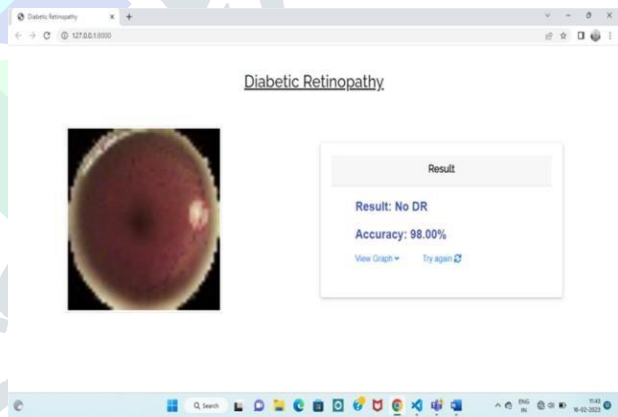

Fig: 11 Normal Detection

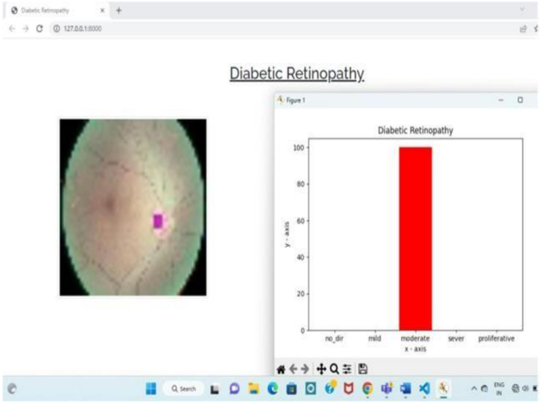

Fig 12 Infected Image

CONCLUSION: A major side effect of diabetes mellitus, diabetic retinopathy causes gradual retinal degeneration and can potentially result in blindness. Its early discovery and treatment are crucial to preventing it from deteriorating and causing retinal damage. Because numerous DL systems have evolved and been integrated into clinical practice, there has been a surge in interest in using them to diagnose diabetic retinopathy. This will help physicians treat patients more effectively and efficiently. This article summarizes the state of the art in studies on using deep learning to diagnose diabetic retinopathy. Although deep learning has paved the door for more precise diagnosis and therapy, more advancements in performance, interpretability, and ophthalmologist reliability are still required.

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