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Detection and Classification of Retinal Fundus in Diabetic Retinopathy Using Modern Artificial Intelligence and Machine Learning Approaches

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Abstract: *In recent years, automated computer systems have gained popularity as a means of diagnosing eye disorders such as glaucoma, age-related macular degeneration (AMD), and diabetic retinopathy(DR) in their early stages.But in reality, retinal picture quality is a major issue since automatic systems that don't account for deteriorated image quality are likely to produce inaccurate findings. The eye condition known as diabetic retinopathy (DR) is a direct result of diabetes, and its effects can range from mild impairment to total blindness. It has been noted that the diagnostic examination of ocular fundus pictures can be hampered by the presence of various types of color aberrations and irrelevant illuminations. Blindness is a possible outcome of diabetic retinopathy. Diabetic retinopathy can cause blurred vision and other consequences if not caught early. Fundus photographs are being used for the identification of diabetic retinopathy. However, this method is time-consuming & expensive because it requires the utilization of ophthalmic imaging equipment to capture fundus images and a thorough inspection of the stored photos. The main objective of this work is to develop user-friendly Artificial Intelligence and machine learning algorithms with electronic fundus imaging for the diagnosis of diabetic retinopathy. We have collected annotated fundus photos from open data sources and used them to train and test the proposed classification model*

Keywords*:* Text Encapsulation, Text Summarization, Extractive NLP, Text Extraction, Text Rank Algorithm.

I. INTRODUCTION

There are currently 528 million people with diabetes mellitus, a number that is expected to climb to seven hundred million by 2050 [1]. One third or more of people with diabetes also have a diabetic eye illness, in which Diabetic retinopathy stands out as the most common form. [2]. Progressive vascular abnormalities in the retina brought on by chronic hyperglycemia characterize DR, which can occur in any diabetic patient [3]. There are an estimated 93 million persons with DR globally [4], consequently, it accounts for the highest rate of disability among people of working age. This expected growth is partly attributable to the growing diabetes epidemic in developing Asian nations like Japan as well as India [5, 6].

Diabetic retinopathy's early phases are characterized by a lack of symptoms despite the fact that neural damage to the retina and clinically unseen micro vascular alterations are occurring [7]. Patients with diabetes should get routine eye exams since prompt diagnosis and treatment are crucial [8]. Early identification of DR is crucial because the sole method for prevention is the management of risk factors such as hyperglycemia, hyperlipidemia, and hypertension [7]. In addition, if diagnosed and treated early, proliferative retinopathy & diabetic maculopathy can be prevented in nearly all cases (up to 98%) [9]. This is due to the effectiveness of therapies such laser photocoagulation. It becomes clear that early detection and suitable treatment are crucial to delaying or preventing blindness in diabetic retinopathy [10].

The human eye is a delicate structure that plays a significant role in seeing. It has the shape of an irregular spherical hollow. Amazingly, it can translate the reflected light from the objects around us into visual representations [11]. The essential parts of the eye and its anatomy are shown in Figure 1 [12]. The cornea, a transparent dome covering the coloured iris and acting as a filter for incoming light, is located at the front of the eye. Light entering the eye is focused onto the retina via the lens, a transparent area located behind the iris. Light is converted into electrical impulses by the retina, which travel through the optic nerve and into the intelligence [13].

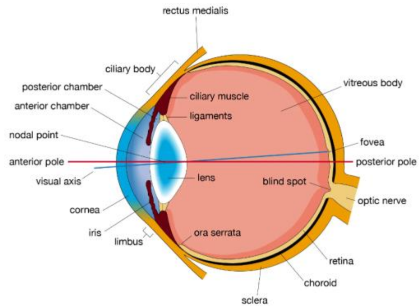

Figure 1. Anatomy of Human Eye

It has been suggested that electro retinography (ERG), retinal blood circulation, & retinal vessel capacity can all play a role in the initial diagnosis of DR [14], however fundus inspection is the preferred method for early identification in medical practice [15]. One of the most common approaches to evaluating DR severity is fundus photography [16], which is popular because it is quick, painless, generally well-tolerated, and easily accessible. Ophthalmologists use fundus photographs to analyse retinal abnormalities at higher resolutions in order to diagnose and assess the seriousness of diabetic retinopathy. There will likely be a huge increase in the number of patients with diabetes and DR in the coming years, but there are a disproportionately small number of ophthalmologists to treat them. This presents a significant problem in highly occupied areas like Africa & India. Because of this, scientists are working on CAD systems that will make DR diagnosis more efficient and less costly for healthcare providers to implement. Machine Learning (ML) and Deep Learning (DL) methods for precise DR detection & categorization have become possible thanks to recent developments in AI & a rise in computer capacity and resources.

The Remaining paper is structured as follows: In Section 2, we give a comprehensive literature review of recent AI and ML techniques that can be used to treat diabetic retinopathy. In Section 3, we present an in-depth analysis of the Proposed Methodology; in Section 4, we apply the Proposed methodology to many well-known datasets; and in Section 5, we draw conclusions and present our findings.

II. LITERATURE SURVEY

Researchers have proposed a variety of methods for dealing with the critical issues of computer-aided diagnostics, balancing brightness distribution, restoring contrast, & retinal image standardization. This study's literature review provides a comprehensive overview by focusing on two broad types of DR texts. The experimental design as well as information patterns are presented, the works in every group were evaluated using a variety of performance measures and design features.

The brightness adjustment technique created by Zhou et al. [17] involves altering gamma of a channel in the HSV colour space. To improve contrast, we used a contrast limited adaptive histogram equalisation (CLAHE) strategy, which involves equalising the histogram of picture pixels using a kernel-based iterative procedure while avoiding pixel congestion within a predetermined range. In [18], the authors offer a CNN model for categorization and a Fundus image processing founded on histogram equalization. Using only 400 photos, they were able to increase the sensitivity to 96.67% and the specificity to 93.33%. Fundus pictures' contrast and brightness were proposed to be normalized by Bhaskar and Kumar [19], who assumed that all neighboring pixels were the same. Using the Tyler-coy algorithm and the accelerated adaptive contrast enhancement algorithm, a method for improving the retina was proposed in [20]. The SAUCE approach use a principal component analysis to generate a picture with grayscale, which is then fed into the Tyler-coy technique to enhance prediction precision. Employing a combination of a low-pass with a Gaussian filter, [21] demonstrated an illumination correction approach in 2015. Before superimposing the results of the Gaussian filter, the low pass filter is applied to standardize the image's background, cancelling out any previous foreground noise.

Singh et al. [22] improved normalization results by using the standard histogram equalization method for low-radiance images, where the median value of the image is used as a threshold to cut pixel values. They checked their forecasting accuracy using the structural relationship index and Euclidean distance. Although many methods have been offered for improving picture contrast, none of them have concentrated on de-saturating images in order to create a DR system.

In the second, we see the many AI-based deep/machine learning approaches to DR early detection that have been proposed. Most of the prior research was devoted to the improvement of canonical machine learning methods and collective deep learning approaches. Multiple instance learning, a poorly supervised method, was recently developed for identifying DR in fundus images by Zhou et al. [23]. Before extracting features from an image, standard image processing techniques including scaling and Gaussian smoothing were applied. There were two aspects to their detection model. They started by assembling a collection of patches of image for use in spotting tumors. Second, automatic feature extraction was achieved with a trained Alex net model. The model obtained an AUC of 93.4%. An ensemble method for DR detection based on deep models of transfer learning was proposed in [24]. Extensive tuning of hyper parameters was performed on models such as ResNet [25], Dense net [26], Frontier [27], & Xception [28] for feature extraction. They reported metrics on a per-class basis, with the most unbalanced class having an AUC of 97%, but they didn't take into account any sort of pre-processing to normalize the photos. In order to acquire accurate results, The scientists used a collection of images modified to include blurring, darker corners, and other spatial noise and abnormalities.

In 2017 they saw the introduction of yet another enhanced ensemble method, this time from the minds of Somasundaram & Muhammad [29]. For the purpose of DR prediction, a machine learning tagging ensemble classifier was taken into account. Saleh et al. [30] provided a team approach for DR risk evaluation, which provides evidence for the presence or lack of the disease by grouping images into identical and different pairings using the t-distributed Stochastic neighbor embedding algorithm. They compared the random forest classifier to their own work, It entailed developing a set of balanced rules determined by leadership. The highest attainable level of sensitivity was close to 80%. In a similar vein, many different DR detection techniques have been introduced to the community. However, none of these approaches deal with the fact a significant influence in the detection of both proliferative and no proliferative DR can be played by non-uniform illuminations..

III. METHODOLOGY

Figure 2 depicts the proposed technique used to complete this study and how that methodology flows. The following sections outline the steps taken prior to analyzing retinal fundus pictures for the purpose of identifying and rating diabetic retinopathy.

3.1 Data Acquisition Phase:

High-resolution fundus photos captured in a wide range of imaging settings are available on an online platform (kaggle). Each image in the dataset was evaluated for the existence of diabetic retinopathy using the following scale, and the results were recorded by a qualified pathologist:

0- No DR   1-gentle   2- Reasonable

3-Dangerous 4-Proliferative DR

The images were captured by a wide range of camera makes and models. As a result, some of the pictures can be blurry or dark. There are a total of 55 photos in the data set, 55 of which are of normal retinas and 55 of which are of diabetic retinopathy. The information in this dataset is useful for determining the relative importance of the various factors under discussion. Following the guidelines laid out in the previous review section, we have taken into account 20 different features

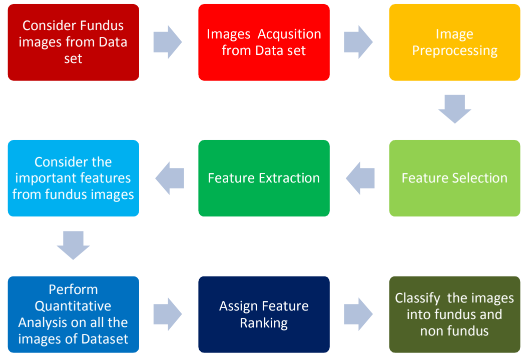

Figure 2 Proposed Methodology Step wise

3.2 Feature selection

In feature selection, the data features that contribute the most to the predictive variable or output of interest are automatically chosen. Data that contains attributes that do not contribute to the classifier's accuracy, or that are redundant, can be cleaned up with the help of feature selection. We are only going to be testing 10 of the possible 22 features.

3.3 Pre-processing

Preprocessing, segmentation, and feature ranking are all carried out in the search for diabetic retinopathy. The dataset needs to be preprocessed to make sure it presents only relevant features and is consistent throughout. This procedure is essential in lightening the load of subsequent actions. The photos must then be divided in order to identify aberrant from typical chemicals. Green The blood vessels, exudates, and haemorrhages contrast most clearly in the green channel, which is neither under-illuminated nor over-saturated as the other two channels in the image (red and blue). As a result, in Figure 3, for the purposes of analysis and classification, we selected only the green channel.

Adaptive histogram equalization with a contrast threshold is used to further improve the image's details. Histogram equalization is performed by slicing the image into smaller sections. Reducing and enlarging There was a need for standardization because the original photos' dimensions varied greatly and some were missing sections at both the top and bottom. Since the FOV of an image is circular, it is first clipped to a square with sides equal to the FOV's diameter. This is the area of the retina that is visible in the image. Some pictures don't include the top and bottom parts, therefore a patch is made to the ones that do so that they all seem the same. The resulting 1024 by 1024-pixel image is a down sampled version of the original 1024 by 1024 image.

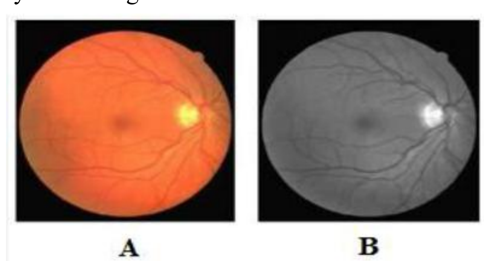

Figure 3. A) A common color retinal picture. B) Image A's green channel.

3.4 Feature Extraction and Classification

Detection of Exudates and Absence of Optical Discs The elimination of the optic disc prior to the development of exudate is the primary goal of exudate detection. It is crucial because it shares the same brightness, color, and contrast as the rest of the features in the fundus image. The optic disc stands out thanks to its high contrast round shapes. It's worth noting that blood vessels are also very visible. They are lesser in both size and quantity, however. The blood vessel within the optic disc can be removed using a grayscale closure operator (Ö). To do this, as given in Eq. (1), we employ a disc-shaped element with a fixed radius of (A1).

OP1 = µ (*A1*) (*f1*) -------(1)

In which case A1 serves as the morphological scaffolding. The last picture was a threshold at predetermined grayscale levels to remove the faint area. A flat disc-shaped element with a constant diameter of 8(A1) is employed to guarantee that all neighboring pixel of the threshold value were incorporated within the chosen region. Figure 4 depicts a possible outcome of doing away with optical discs.

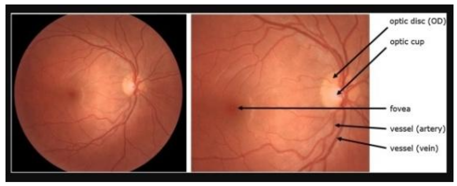

Figure 4. Optic Disc Elimination [31]

Haemorrhages and Micro aneurysms In order to detect haemorrhages and micro aneurysms, a classification technique must be used. The information obtained from Messidor is first subjected to picture segmentation for preprocessing. The next step is to select an image to classify using a support vector machine. We use a filter and a wrapper class to narrow down our options. Haemorrhages and micro aneurysms can be found after the data has been sorted. Vascular system Observing the grayscale image through the sub-image's red or green field Images R and G that include the OD suggest that blood vessels included inside the OD act as significant deviators and should be removed from the image in advance. The vasculature can be conceptualized as a structure made up of many similar linked linear structures that range in size from very short to very long.

IV. PREDICTION AND EVALUATION:

Dataset Description:

Multiple datasets of fundus images are used to test the proposed approach, including the Singapore Malay Eyes Study (SiMES) [32], the Singapore Chinese Eyes Study (SCES)[33], and the Blue Mountains Eyes Study (BMES). The retinal image recognition is also tested using non-fundus image databases, such as slit-lamp pictures, OCT pictures, Retcam images, and scenic photographs. The SiMES image database is used for further quality evaluations.

4.2 Discussion:

The identification algorithm for fundus images was trained with 689 photos, 439 of which were fundus images and 250 were not. The system has a testing set accuracy of 98.93% when classifying images as either fundus or non-fundus. Except for Accuracy Specificity, precision, and F1-score are the remaining criteria taken into account while assessing the proposed system. Table 1 displays an overview of the datasets used for training and for testing, as well as the experimental findings.

Table 1 . Results of Evaluating the Designed System on Several Data Sets

Data Bases	Accuracy	Specificity	Precision	F1-Score
SiMES	98.6	95.6	93.5	92.8
SCES	99.5	96.7	92.1	93.4
BMES	98.7	94.9	92.9	92.9

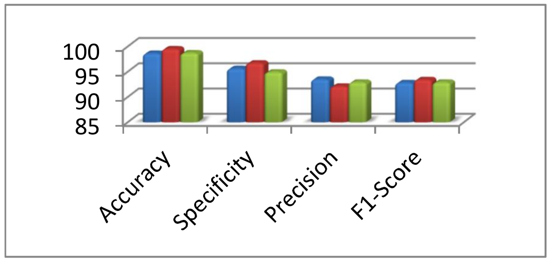

Figure 5. Evaluation Results Graph

Above you can see a comparison of our proposed system's performance on well-known benchmarks such as SiMEs, SCES, and BMES. The suggested system works well in all the examined parameters and accurately distinguishes fundus & non fundus images, as evidenced by the average results across all parameters being more than 93%. This demonstrates the superior performance of our suggested solution with respect to the measured criteria.

V. CONCLUSION

The increasing impairment and eventual loss of vision caused by diabetic retinopathy is a severe consequence of diabetes mellitus. In this study, we offer a system for evaluating images' quality that can detect and categorize fundus images of the retina from other types of images, as well as evaluate the entire retinal image and a selected zone around its most important features. To aid in the diagnosis of diabetic retinopathy, we additionally pre-processed and extracted features from the retinal fundus image. The comparison and ranking of the seven most critical elements retrieved from a typical and a diabetic the fundus picture is both straightforward and fundamental. Finally, a thorough analysis of the suggested approach has been on widely used data sets, demonstrating that it excels in every metric under consideration by a margin of at least 93%.

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