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Artificial Intelligence based Early Recognition of Diabetic Retinopathy

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Abstract: *Diabetic retinopathy (DR), a prevalent outcome of diabetes mellitus, causes lesions of the back of the eye that impair vision. If it fails to be detected in time, paralysis could follow. Unfortunately, there is presently no known treatment for DR; the only choice is avoidance. Rapidly reducing the risk of vision loss involves early identification and treatment of DR. DR retina fundus pictures must be manually diagnosed by ophthalmologist, which is more costly, time-consuming, and error-prone than computer- aided diagnosis techniques. Deep learning has recently risen to the top of the list of preferred methods for improving performance, particularly when it comes to classification and decoding of medical images. Convolutional artificial neural networks are being employed in the interpretation of healthcare pictures since they are such an effective learning technique using Artificial Intelligence. The most sophisticated methods for classifying and identifying DR colour images of the fundus using algorithms based on deep learning have been examined and analyzed for the reason of this research. Additionally, the colour the fundus retinal DR data have been examined. Additionally, certain difficult problems requiring more research are dealt with.*

Keywords: Computer-aided diagnosis, Artificial Intelligence, Diabetic retinopathy, stages Retinal fundus images etc

I. INTRODUCTION

The leading cause of vision loss in people of working age in industrialized and developing nations is diabetic retinopathy. people with diabetes have a 25 times higher risk of going blind than people without diabetes [1]. A retinal consequence of diabetes is called diabetic retinopathy. Early on, the disease is largely asymptomatic, but if left untreated for an extended period of time, it could result in permanent eyesight loss. The issue here is that the patients might not be aware of it until it has progressed to an advanced stage. Once the condition has advanced, vision loss is unavoidable. It is urgently necessary because diabetes-related retinopathy is the third biggest cause of deafness, particularly in India, it is essential to develop efficient diagnosis methods to treat this issue [1].

High blood sugar levels cause the walls of microscopic blood arteries to swell, which leads to the development of micro-aneurysms. Micro-aneurysms will burst as the condition worsens. This causes retinal hemorrhages in the retina's outer layers or deeper layers [1] (Fig. 1(a)). Along with leaking blood, the arteries also let lipids and proteins out, which contributes to the development of tiny. Diabetes Mellitus (DM) is a medical disorder that can lead to diabetic retinopathy (DR). As a result of the human retina being damaged, it results in vision issues and blindness. Statistics show that DR affects 80% of diabetes patients who have had the disease for 15 to 20 years or longer. As a result, it now poses a serious threat to people's lives and health.

The disease can be manually diagnosed, but doing so would be difficult and time-consuming, making a novel approach necessary to treat DR. Therefore, early detection and diagnosis are necessary to stop DR from progressing into severe stages and to stop blindness. Numerous Machine Learning (ML) methods have been presented by academics from all over the world to do this. Numerous extracted feature algorithms are available for the collection of DR characteristics for early identification. Traditional ML models, however, either exhibit poor generalization during feature extraction and classification for use with smaller datasets or use more training time for poor prediction performance when used with larger datasets. Deep Learning (DL), a new area of machine learning, is thus introduced.

A smaller dataset can be handled by DL models with the aid of effective data processing methods. They do, however, Deep architecture often use larger datasets to enhance the accuracy of feature extraction and classification of images.

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This study provides a thorough analysis of DR, including its characteristics, root causes, modern DL models, problems, comparisons, and future approaches for DR early detection.

II. PROBLEM IDENTIFICATION

DR infection associated diabetic retinal edoema (EDM) have lately been diagnosed in a sizable percentage of diabetic patients. The most deadly eye disorder, diabetic retinopathy (DR), is brought on by enlarged and fluid- leaking blood vessels in the eyes. Additionally, blood vessels may clog, preventing the fluid from flowing through and leading to the formation of a typical aberrant growth of blood vessels on the cornea. Finally, all of these modifications result in vision loss or possibly blindness.

Ophthalmologists can treat or slow the progression of retinal eye illness by identifying it in its early stages. This prevents patients from losing their vision. The iris, cornea, retina, sclera, nerve fibres, optic nerve, The primary elements of the eye are, etc. Diabetes patients run the risk of developing a condition called retinopathy caused by diabetes, cataracts, obstructions in the retina arteries, and obstructions in the retinal veins, among other disorders. The benign or pre-final phase (NPDR) and are proliferative or final phase (PDR) are the two distinct clinical stages of DR infection. NPDR refers to the initial stage in diabetic fundus disease. When there is NPDR, blood vessels leak, forcing the retina to expand.

The main cause of vision blur and occasional vision loss is this. The second stage of diabetic fundus disease is known as proliferative retinopathy (PDR), and it is the most severe condition. It happens when additional blood vessels start to rise on the cornea. In this instance, it is referred to as the formation of n If the patient bleeds a bit, they might see a few hazy floaters. They could lose all vision if they bleed profusely. The newest blood vessels supplying the eyes in the ocular system can produce tissue scarring.

Central and peripheral vision can be stolen by PDR. As a result, it is essential to find DR as quickly as feasible. A manual detection of DR disease is a significant undertaking that is normally performed by ophthalmologists. The findings of manual identification are difficult to repeat when needed and are subject to human mistake. The suggested framework has the capability of extracting the region of concern and automatically identifying DR in the initial phase, supporting eye doctors in screening patients and clinical studies in addition to reducing human mistakes and processing time as well as enabling quick and highly precise replication of the findings whenever necessary.

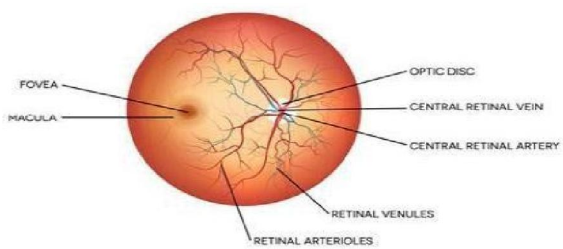

Fig.1. Healthy human retina

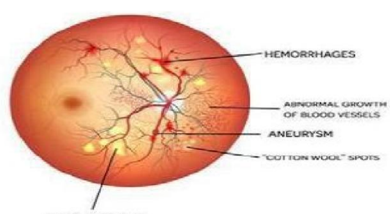

Fig. 2. Affected with DR

III. METHODOLOGY

Exudate feature extraction and classification are the two subsequent processes that most existing DR classification techniques follow. Image preprocessing is needed in the first stage to boost contrast and reduce noise. The possible

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candidate for exudates is then represented by segmenting and removing the white region of the image. Then, using feature analysis—which includes extraction of features and feature selection—DR is discovered. Using a classification method, these characteristics are separated into the various DR levels, such as typical and abnormal (mild, mild, severe). The general methods for fluid detection and DR categorization are summarized in Fig. 3.

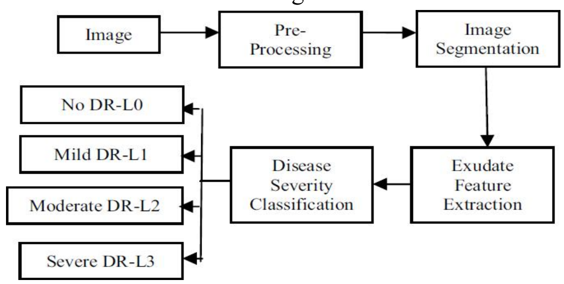

Fig. 3. The processes of DR Classification system

IV. TOOLS / PLATFORM TO BE USED

Learning is the practice of acquiring knowledge through study, as stated in its definition. In the specific instance of machine learning, a computer performs this learning process, making it possible to create computer programs that automatically get better over time. The three applications of machine learning.

Data mining: These systems are designed to use vast amounts of data that people cannot process on their own to make better decisions. Since it enables the generation of medical knowledge based on medical records, this offers, for instance, a particularly beneficial application in the field of medicine.

Software applications: As absurd as it may seem, humans cannot programme everything in the world. However, these frontiers can be expanded with the help of machine learning algorithms. In the case of this project, Automatic Number Generation, for example, these kinds of approaches are currently being successfully implemented in sectors like autonomous driving, speech recognition, picture recognition.

Self-customizing programmers: Even though most individuals might not be aware of it, practically everyone often interacts with this last specialty. In actuality, it is this type of technology that underlies the news feeds that consumers typically receive based on their individual interests when they browse the Internet.

By using an assortment of marked training examples, the algorithms have the ability to create broad target functions this, when used on a brand-new dataset which wasn't used before, accurately forecast the expected outcome. This is how machine learning algorithms actually work. The samples with label training make up the training dataset, whereas fresh, unused data make up the testing dataset. A sufficient good and comprehensive training dataset is necessary in these types of applications because a poor train always produces poor outcomes.

The GUI window displays the final output, which is represented in the html page connected to the main system. There is a "Load Data" button on the output page. After clicking the "Like" button, a script that extracts values from the dataset is run.

Aside from the fundamentals that have just been described, there isn't much that Machine Learning algorithms have in common. In reality, an algorithm for machine learning can be created in an endless number of different ways. Consequently, choosing the best design requires a thorough review, which is typically done using a variety of data.

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V. FLOW DIAGRAM

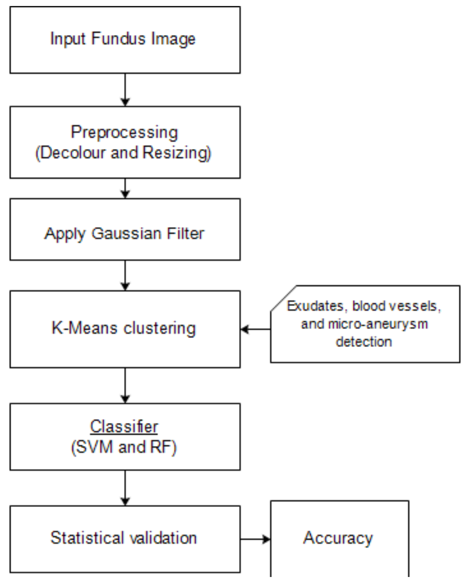

Fig. 4. Flow Chart

VI. RESULT AND ANALYSIS

In order to evaluate the performance of pattern classification systems the binary classification performance has to be measured. The performance of a binary classifier can be best described in terms of its sensitivity and specificity, quantifying its performance to false positive and false negative (FN) instances.

The performance will be evaluated using the following parameters

True Positive (TP): it is defined as the number of exudates correctly identified as exudates.

True Negative (TN): it is defined as the number of non- exudates correctly identified as non-exudates.

False Negative (FN): it is defined as the number of exudates identified as non-exudates.

False Positive (FP): it is defined as the number of non- exudates identified as exudates.

From these parameters, the sensitivity, specificity and Accuracy are computed using Equation 1, 2 and 3 respectively. These metrics are as follows: Specificity is the percentage of non-exudates pixels that are correctly classified as non exudates pixels, given by:

$$Specificity = \frac{\text{Negatives correctly classified}}{\text{Total Negatives}} = \frac{T_N}{T_N + F_P} \qquad (1)$$

Sensitivity is the percentage of the actual exudates pixels that are detected given by:

$$Sensitivity = \frac{\text{Positives correctly classified}}{\text{Total Positives}} = \frac{T_P}{T_P + F_N} \qquad (2)$$

The overall Accuracy is the ratio between the total numbers of correctly classified instances and the test size, given by:

$$Accuracy = \frac{\text{Instances correctly classified}}{\text{Total instances}} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \qquad (3)$$

Measurement of Classification Performance of KNN :

Performance is measured by determining various parameters like Specificity, Sensitivity, and Accuracy. From MESSIDOR dataset, 45 images were used for training and 20 images are used for testing. The systems accuracy is 95 percent, where 19 out of the total 20 tested, images that are correctly classified by KNN. Since the specificity is 0.83

and sensitivity is 1, performance of classifier system may be accepted. Table 1 indicates calculated values of different performance metrics for MESSIDOR dataset.

Table 1: Binary classification performance metrics using KNN for MESSIDOR dataset,

Performance Metrics	Value
TP	14
FP	1
FN	0
TN	5
Sensitivity	100%
Specificity	83%
Accuracy	95%

From DIARETDB0 dataset, 30 images were used for training and 15 images are used for testing. The systems accuracy is 93 percent, where 14 out of the total 15 tested, images that are correctly classified by KNN. Since the sensitivity and specificity is greater than 0.9 (90 percent) hence, classifier's performance may be accepted. Table 2 indicates calculated values of different performance metrics for DIARETDB0 dataset.

Table 2: Binary classification performance metrics using KNN for DIARETDB0 dataset images are used for testing.

Performance Metrics	Value
TP	9
FP	0
FN	1
TN	5
Sensitivity	90%
Specificity	100%
Accuracy	93%

The systems accuracy is figured utilizing equation 3, which is found to be 88 percent, where 13 out of the total 15 tested, images that are correctly classified by KNN. Since the sensitivity and specificity is greater than 0.83 (83 percent) thus, the performance of classifier system may be accepted. Table 3 indicates calculated values of different performance metrics for local dataset.

Table 3: Binary classification performance metrics using KNN for Local Dataset

Performance Metrics	Value
TP	5
FP	1
FN	1
TN	8
Sensitivity	83%
Specificity	88%
Accuracy	87%

The effects of the eye abnormalities are mostly gradual in nature which shows the necessity for an accurate abnormality identification system. Abnormality in retina is one among them. Most of the ophthalmologists depend on the visual interpretation for the identification of the types of diseases. But, inaccurate diagnosis will change the course of treatment planning which leads to fatal results. Hence, there is a requirement for a bias free automated system which yields highly accurate results. In this project, we are classifying DR stages.

We first present the summary of diabetic retinopathy and its causes. The DR classification system starts by\ automatically detecting the anatomical structure of the retina: optic disc. Then, it identifies abnormality like exudates present in the retina. The system grades diabetic retinopathy based on the detection of the exudates such that an ophthalmologist can make a detailed diagnosis.

This system presents encouraging results in identifying and grading images having diabetic retinopathy. The proposed CAD system has achieved classification accuracy of more than 90 percent for MESSIDOR, DIARETDB0 and local datasets. As the proposed system achieved high sensitivity and reasonable specificity, it can be used to assist ophthalmologists in the screening and treatment of diabetic retinopathy.

In this work, we establish a competency approach for automatic recognition of surplus blood vessels, exudates dots, from fundus illustrations. The ocular picture is preprocessed via the HE approach and the modified picture is segmented

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by k-means clustering. SVM and RF are valuable for the categorization of the usual and unusual part of the ocular picture and also plummeting human mistake that diminishes false recognition and acquires a high precision rate.

The recognition rate of RF is 96.62% that expresses a great and stable outcome as compared to the SVM. The profit of the established approach is that it holds the highest precision and also capable of initial phase recognition of DR automatically to overcome human mistakes and diminish the false identification rate that offers the progression which is more truthful, easy, and unproblematic. In the future, we extend our work on different datasets to prove a more general conclusion and exterminate false recognition rate.

VII. CONCLUSION

Diabetic retinopathy is a very common medical condition of the human eye, affecting almost 400 million people worldwide, and around 32 million cases in India itself. Treatment of this medical condition on time is very important to avoid chances of total blindness. Detection of diabetic retinopathy during its early stages is very necessary in order to give the patient appropriate treatment on time to avoid the chances of the patient losing his eyesight completely. The current manual procedures followed by the doctors are sufficient and cause problems due to being time consuming. So, to overcome this problem a good amount of research carried in automating the detection of diabetic retinopathy has been done using machine learning. For this, we have presented a system to perform automated detection of diabetic mellitus by making use of image processing and machine learning.

The automated process of detection gives the opportunity to the patient to avoid a significant vision loss. Various machine learning algorithms like the Support Vector Machine, K means algorithm and Convolution Neural Networks have been used in the project to train and test the system by feeding sample images, so that it can detect the presence of diabetic retinopathy in a given patients retinal images that will be supplied to it. The system learns from the sample images, and then detects the medical condition in the new input images of the patient, hence cutting down on the overall time consumed exponentially. One of the challenges that we faced during the project was the constraint of the computational resources available with us. The deep CNN models were time consuming in terms of training, which is an important step that eventually becomes expensive with time. Since the use of this project will help the doctors detect the diabetic mellitus at the early stages, the patient can be given appropriate treatment on time, slowing down the degeneration of his eyes and possibly avoiding complete blindness.

VIII. FUTURE ENHANCEMENT

The system has a scope for future enhancement. The next addition that will make the system better would be adding a function that will determine the stage at which the diabetic mellitus is present. That is, the system will be able to differentiate between the mellitus stages 0,1,2 and 3; and giving the output. This will help the doctor move forward with appropriate treatments for the patient based on the severity of this retinopathy condition. The continuing developments in convolution neural networks will help for deeper networks that would learn the fine details and elaborate features the present system faced trouble with.

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