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Automated Detection of Diabetic Retinopathy Using Machine Learning in Ophthalmology

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Abstract: Diabetic retinopathy affects the retina and is the major cause of blindness among people with diabetes. Screening people on a regular basis to catch diseases early has traditionally required a lot of time and money. Therefore, it would be helpful if these illnesses could be automatically detected using computational approaches. Retina has several characteristics, such as exudates and micro aneurysms. Automatically detecting micro aneurysms (MAs) from colour retinal pictures is a challenging task, but their presence is an early indicator of diabetic retinopathy. To help with this, we are focusing on green Chanel images. The goal of this study is to use a classifier to identify retinal micro-aneurysms and exudates for automated DR screening. The ability to identify dark lesions and brilliant lesions in digital fundus pictures is essential for the creation of an automated DR screening system. Retinal fundus pictures from the Messidor dataset are used to identify micro-aneurysms and exudates. The characteristics are discovered using morphological processes after preprocessing.

Keywords*: *Exudates; Micro aneurysm; Green channel; Bright lesions; Red lesion

1. Introduction

Diabetic retinopathy, or DR, is a serious complication of diabetes that affects the retina of the eye. DR is a disorder of the retina's blood vessels. Long-term diabetic retinopathy is a common complication that affects those who have had the disease for some time. Regular DR screening is critical for early detection of the condition and prompt treatment. Diabetic patients often have digital retinal images taken as part of their regular checkups. The high prevalence of diabetes means that in-depth analysis of these images by trained professionals might take a long time and cost a lot of money. As a result, automated detection approaches will be invaluable in this field. Microaneurysms (MA), which are precursors of DR, are the primary focus of this study. Detecting microaneurysms at an early stage is the first and most crucial step in protecting against DR. The major objective is to provide an autonomous solution for diagnosing early-stage DR lesions (MAs) based on machine learning. There are two parts to the proposed study, and they are "Feature Selection Technique" and "DR Classifiers," respectively. The precision of machine learning algorithm output is heavily influenced by the features used in the analysis. In order to better train the algorithms, feature engineering is used. The goal of feature selection and optimisation is to narrow down the feature set to just those characteristics that contribute meaningfully to the prediction accuracy. The GA-NN feature selection method is designed to isolate the characteristics that make up the best possible collection of characteristics. Most notably, this strategy takes a two-pronged approach to collecting features for the optimal sub-set. Following the generation of several subsets using the weight by SVM method, an optimal subset is selected by GA-NN based on fitness function metrics and the number of iterations. Standard e-ophtha from the Diabetic Retinopathy Database have been used to test the suggested approach on fundus pictures. The SVM classifier achieves 92% recall, 81% specificity, and ROC-AUC of 0.89 with this optimised feature set consisting of GLCM and LBP features.

Diabetic retinopathy (DR) is one of the potential complications of diabetes. It's a leading cause of visual impairment and blindness. Regular eye examinations are critical for early detection of issues and prompt treatment. Diagnostic imaging in medicine relies on two factors to arrive at a correct diagnosis. Two parts make up this whole: the first is the picture itself, which was successfully acquired, and the second is the picture itself, which was correctly interpreted. Computers have undeniably had a major impact on how doctors get their hands on diagnostic images. They are crucial in the bulk of current imaging diagnostics. They are in charge of the

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imaging equipment, data reconstruction, post-processing, and archiving. However, computers have only had a negligible impact on the interpretation of medical images. The field of interpretation remains almost completely focused on humans. In recent years, researchers have shifted their focus to this topic. Numerous scientific and technological disciplines are quickly extending their use of image processing and computer vision methods. Recent developments in medicine using such methods have focused on improving the ability to detect health issues at their earliest stages. They achieve this by decreasing the time required for diagnosis, which in turn stops the disease's progression.

Diabetes Mellitus (DM), sometimes shortened to "diabetes," is on the rise around the world. From 2019's 9.3 percent prevalence to 2030's 10.2 percent and 2045's 10.9 percent, diabetes is expected to increase [1]. Damage to organs and tissues may occur as a result of diabetes's microvascular and macrovascular complications. These complications include diabetic retinopathy, nephropathy, neuropathy, ischaemic heart disease, peripheral vascular disease, and cerebral vascular disease. Diabetic retinopathy (DR) is one of the most severe consequences that may occur as a result of having type 2 diabetes. In developed countries, DR causes more blindness than any other condition, and its prevalence is rapidly expanding in less developed countries. The World Health Organisation estimates that DR causes 3.8 million cases of blindness globally. The risk of DR in SEA (South-East Asia Regions) nations is predicted to increase from 11.3% in 2019 to 12.2% in 2030 [2] by the International Development Foundation. Developing nations have seen a more dramatic surge. The expansion is happening much more in poorer countries [3]. Despite the fact that the prevalence of diabetes is higher in urban areas than in rural ones [4, DR fails to account for this fact]. Recent studies [5, 6] have shown that DM and DR are major non-communicable causes of ocular morbidity. Therefore, it is crucial to screen for DR in order to facilitate early diagnosis, treatment, and management of risk factors in order to reduce the possibility of problems. Both of them are essential for keeping DR-related problems at bay. Due to the lack of early symptoms, DR can only be diagnosed by a thorough eye exam conducted by a medical practitioner. There is a large selection of screening tools available for detecting and classifying DR. Ophthalmoscopy is widely used as a diagnostic tool. A recent clinical trial found that using non-mydriatic fundus cameras to diagnose illness is a very cost-effective method. Ophthalmologists use retinal image analysis in routine eye examinations to look for signs of this disease. As the number of people with diabetes increases, so does the amount of data that has to be manually analysed. As a result of the time and effort required to master image-based diagnosis, training unskilled practitioners may be a lengthy procedure. Computer-aided diagnosis (CAD) solutions may be efficient and cost-effective when ophthalmologists are only responsible for a small fraction of a larger screening programme. Computerised diagnostic methods may be used by ophthalmologists to aid in the evaluation of fundus pictures and the reduction of human error. Also, in areas where highly trained experts are in short supply, it might be used as a diagnostic tool by healthcare professionals. Given the worrying rate of DR expansion, this may assist shorten the duration of patients' waits. Medical imaging, and DR in particular, could benefit greatly from the introduction of autonomous diagnostic methods, as this would allow for greater efficiency and economy in medical imaging laboratories, lower costs, and better patient outcomes.

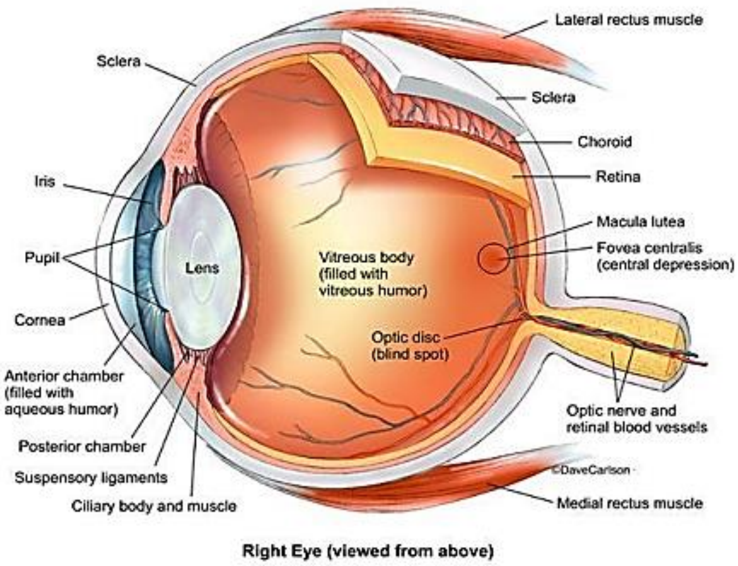


Fig 1: The human eye's internal structure [8]

Figure1 shows the several components of an eye, each of which has a unique function. Light from the outside world is transmitted via the cornea, iris, and lens to the retina at the back of the eye. Layers of the retina are responsible for its numerous functions, and the light-sensitive rods and cones are found in one of these layers. The retina and optic nerve form a single unit due to their close proximity. Stimulating the rods and cones in the retina sends a signal to the brain, which interprets it as an image. Diabetes is a metabolic disorder brought on by resistance to or inability to respond to the hormone insulin. The inability to adequately metabolise the carbs results in elevated blood sugar. High blood sugar may be harmful to blood vessels and nerves, increasing the likelihood that people with diabetes will develop complications related to the disease. DR

DR is a condition that often appears with diabetes. The breakdown of the small blood vessels in the retina is the underlying cause of this disorder. Retinal blood vessels may leak, become blocked, or break down as a result of the secondary effects of a diabetic disease. Over time, this causes vision loss by interfering with the retina's ability to receive its essential supplies of blood and oxygen. As a result of the obstructions, abnormal blood vessels may develop on the retina's outer layer. The risk of bleeding and fluid leakage may rise as a result of this expansion. These structural alterations to the eye may impair vision at first, and in advanced stages, they can cause the retina to separate from the back of the eye

Definitions of DR Subtypes

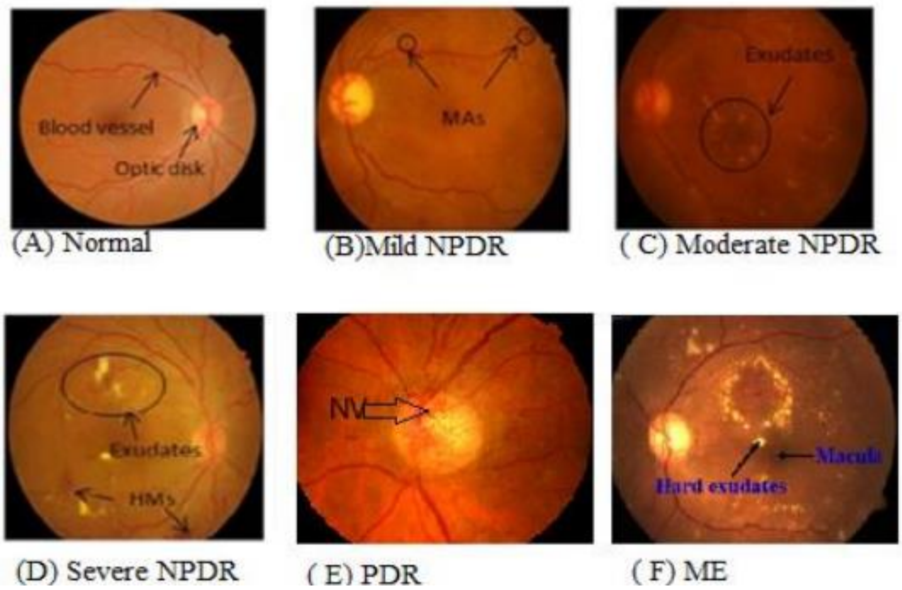


Fig 2 Stages of DR

2. Literature Review

Pranali Hatode et.al(2022) Artificial neural networks (or ANNs) are a common kind of machine learning algorithm. However, since they are based on artificial neurons rather than biological ones, their computational power is limited. Thanks to the advancement of graphic processing units, deep learning, also known as deep neural networks (DNNs), can now acquire massive amounts of data and perform complex computations. To better diagnose Diabetic Retinopathy (DR), this work is a pure investigation and assessment of the performances of the ML and DL algorithms, comparing the properties of the fundus pictures

K. Parthiban et.al(2021) Diabetic retinopathy (DR) is a leading cause of blindness and a prevalent condition among people with diabetes. Early identification of the condition is key to preventing the progression of DR. Retinal examination allows for the diagnosis and severity assessment of DR. Not only can ML models and IoT technologies aid in detecting and classifying DR, but they do it more efficiently and at lower cost. This research provides an IML-DRGC model for grading and classifying DR based on retinal fundus pictures. The purpose of the IML-DRGC model is to provide an accurate, automated diagnosis of DR.

Sonali Chaudhary et.al (2020) In this study, the authors suggest a reliable automated approach for identifying and categorising DR's several phases. Features are being retrieved from the segmented optic disc and retinal nerves using the Grey Level Co-occurrence Matrix (GLCM) technique. Fuzzy classifiers and Convolutional Neural Networks are used to categorise DR detection results. We use the STARE, DIARETDB0, and DIARETDB1 databases.

3. Experimental Results

Before beginning training, images are often filtered using a median filter to reduce noise. All pictures have been resized to a uniform 1024x1024. Each picture is reduced in size to 128 by 128, and then patched. In order to train and assess models for microaneurysms, sub-images of patches are used. From the 148 images in the e-ophtha dataset, 775 MA patches and the same number of non-MA patches were generated. Eighty percent of the photos are used for training the network, while the remaining twenty percent are used for testing its accuracy.

In Figure 3, we can see the confusion matrix created using the proposed method for patch recognition. As can be seen in Table 1, the SVM classifier is put to use when features from various GoogleNet layers are compiled and fed into it.Figure 3.: Generated confusion matrix for e-ophtha-ma dataset

Table 1: Performance measure for the features extracted at the different layers of GoogleNet

Features extracted from different layers	Accuracy	Sensitivity	Specificity	F1-Score
inception_5b-output	97.33%	98%	96%	0.97
inception_5a-output	97.33%	96%	98%	0.96
inception_4e-output	97%	96%	98%	0.96
inception_3a-output	73.67%	76.67%	70.67%	0.74

Table 1 shows that GoogLeNet performs well at the higher layers but drastically declines after the inception_3a-output layer. This illustrates that the network acquires few qualitatively distinct features during the introductory stages of its training. The classification result for MA lesion patch classification is shown in Figure 4.

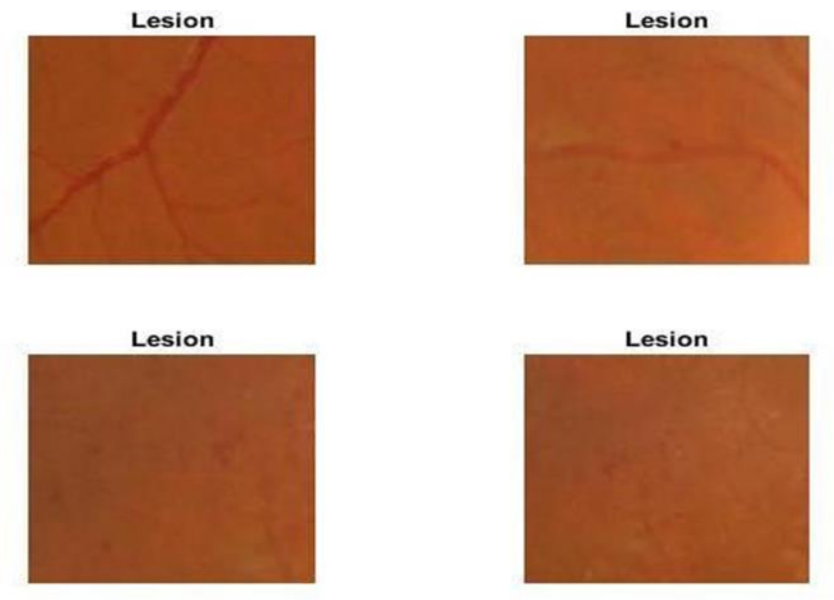


Fig 3: Model-classified MA Lesion Patches

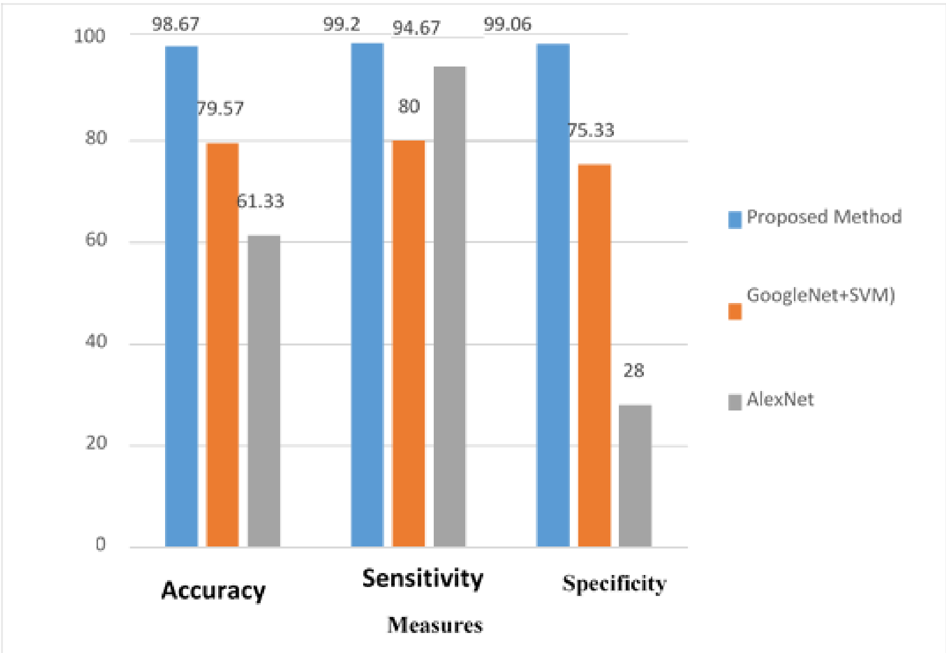


Fig 4. Comparison with different CNN architectures

Benchmark networks like GoogleNet and AlexNet are used to evaluate the proposed design. As can be seen in Figure 4, both AlexNet and GoogleNet yield substandard classifications. GoogleNet is somewhat better. An F1-score of 0.98, a hit rate of 99.2%, a specificity of 99.6%, and an ACC of 98.67% are the results of the proposed system's use of features extracted from GoogleNet's adjusted Loss3-classifier layer to feed the SVM classifier. Stochastic gradient descent is used to train each individual CNN module. They are all trained in batches of 8, at the same rate of 0.0001 across 50 iterations.

As can be seen in Figure 4, categorization error has reduced as GoogleNet's layer count has increased. With deeper CNN networks, feature extraction improves, which in turn leads to better categorization. An improved CNN model, such as GoogleNet or AlexNet, and the ability to stack more convolutional layers increase the likelihood that a CNN algorithm can identify the first symptoms of illness.

Model	Accuracy	Recall	Specificity	Precision	F1-Score
GoogleNet+SVM	70.6%	67.62%	73.58%	71.27%	0.69

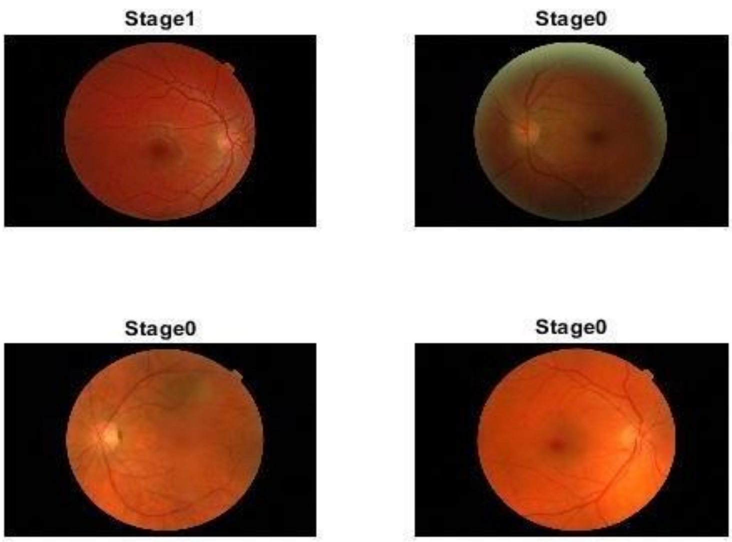
Table 2: Classification performance metrics for patch-level MA classification in the IDRiD dataset

Table 4: The MESSIDOR dataset's image distribution

Dataset Formation	Stage-0(Normal)	Stage-1(Mild)	Total
skewed	495	145	640
Up-sampled	495	495	990
Down-sampled	145	145	290

Table 5: Performance measure of different sample datasets

Dataset	Accuracy	Sensitivity (Recall)	Specificity	Precision	F1-Score
skewed	79.18%	84.12%	73.22%	76.1%	0.79
Up-sampled	89.39%	91.1%	77.88%	83.96%	0.87
Down-sampled	88.16%	88.62%	79.31%	89.44%	0.88



4. Conclusion

Experiments conducted on a benchmark dataset showed that using a combination of convolutional neural network (CNN)-based auto feature extraction and machine learning classification methods yielded statistically significant improvements over using either method alone. The proposed model outperforms state-of-the-art baseline CNN approaches in classifying MA patches. The E-ophtha and IDRiD datasets are used to show that this system outperforms AlexNet and GoogLeNet. When we evaluate how we came to our rankings of DR's austerity, we see a similar pattern. The proposed grading structure was designed to fit into pre-DR classification systems. The method has been tested on publicly available datasets like Messidor, where it has shown outstanding performance for early- stage DR evaluation, making it a good option for large-scale screening.

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