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Deep Learing Technique for Diabetic Retinopath Classification

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***Abstract:** Strict control of blood glucose and blood pressure is critical for reduction of the incidence and progression of diabetic retinopathy (DR). Follow-up of patients with diabetes mellitus is protocol based and not based solely on the presence of symptoms. Staging of the level of DR (mild, moderate, or severe nonproliferative DR vs. proliferative DR, PDR) drives the follow-up interval. The most common cause of visual loss in diabetic patients is diabetic macular edema (DME). Detection of Eye Disorders Through Retinal Image Analysis Blood Vessel Segmentation, Optic Disc Segmentation and Fuzzy Logic Image Processing. Common Retinal Eye Disorders that has been solved in this project. The results of multicenter, randomized studies suggest that the best visual results for DME currently are achieved with intravitreal ranibizumab injections ± focal laser photocoagulation. Results using bevacizumab seem quite comparable to those with ranibizumab. In addition to treating DME, this approach also seems to reduce the likelihood of progression of DR. Selected patients also may benefit from intravitreal steroid treatment and focal laser therapy, but there is a relatively higher rate of glaucoma and cataract formation. An increase in intraocular pressure inside the retina led to the development of the neuro-degenerative eye condition known as glaucoma. Being the second largest cause of blindness worldwide, It can lead the person towards complete blindness if an early diagnosis does not take place. The architecture of CNN is cognate to that of the linking form of neurons in the brain of humans and was inspired by the suggestion of the visual cortex. The CNN algorithm has a faster prediction along with better accuracy.*
***Keywords:** DME (Diabetic Macular Edema), Glaucoma,DR (Diabetic Retinopathy), CNN (Convolutiona Neural Network).*

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I. INTRODUCTION

When damage to the retina results from diabetes, the condition is referred to as diabetic retinopathy or diabetic eye disease. Blindness may eventually result from it. Up to 80% of all people with diabetes who have had the condition for 20 years or more may experience this ocular manifestation of the systemic disease. There are frequently no early symptoms of diabetic retinopathy. Even macular edoema, which can cause a rapid loss of vision, may take some time before any symptoms appear. But, a person with macular edoema is typically going to have blurred vision, which makes it challenging to read or drive. The vision may occasionally improve better or worse over the day. Non-proliferative diabetic retinopathy (NPDR) is the first stage, and there are no symptoms in this stage. Patients will have 20/20 vision and the indicators won't be evident to the naked eye. Fundus photography, in which tiny blood-filled bulges in the artery walls can be observed, is the only method for identifying NPDR. Fluorescein angiography can be used to see the back of the eye if there is limited vision. Retinal ischemia is a condition in which the blood vessels of the retina are conspicuously narrowed or occluded (lack of blood flow). Any stage of NPDR can experience macular edoema, in which blood vessels spill their contents into the macular region. Vision blurriness and distorted or darkened images that differ in both eyes are signs of macular edoema.Ten percent (10%) of diabetic patients will have vision loss related to macular edema. Optical Coherence Tomography can show the areas of retinal thickening (due to fluid accumulation) of macular edema.

In the second stage, abnormal new blood vessels (neovascularisation) form at the back of the eye as part of proliferative diabetic retinopathy (PDR); these can burst and bleed (vitreous hemorrhage) and blur the vision, because these new blood vessels are fragile. The first time this bleeding occurs, it may not be very severe. Most of the time, it will only leave a few blood specks or spots floating in a person's field of vision, however the spots frequently disappear within a few hours.

These spots are often followed within a few days or weeks by a much greater leakage of blood, which blurs the vision. In extreme cases, a person may only be able to tell light from dark in that eye. The blood may take several days to drain from the interior of the eye, or it may take months or even years. In some circumstances, the blood may not clear at all. Large haemorrhages of this nature frequently occur during sleep and frequently occur multiple times.

A doctor will identify cotton wool spots, flame haemorrhages (similar lesions are also brought on by the alpha-toxin of Clostridium novyi), and dot-blot haemorrhages during a funduscopic examination.

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Both Type I and Type II diabetics are at risk, as are all patients with diabetes mellitus. A person's likelihood of experiencing some type of ocular issue increases with the duration of their diabetes. Between 40 and 45 percent of Persons with diabetes develop diabetic retinopathy in some stage. After 20 years of diabetes, nearly all patients with Type I diabetes and >60% of patients with Retinopathy is a condition associated with type II diabetes, however as these figures were published in 2002 using data from four years earlier, their applicability is constrained. Before modern quick acting insulin and at-home glucose testing, the late 1970s was when the subjects would have received their diabetes diagnosis. Microvascular alterations in the retina cause diabetic retinopathy.
Vascular walls become ineffective as a result of intramural pericyte loss and thickening of the basement membrane brought on by hyperglycemia. Both the blood-retinal barrier's development and the permeability of the retinal blood vessels are altered by these impairments. Hypoxia has been implicated as a causative factor in the degradation of the retina and some early investigations have supported this hypothesis. Small blood vessels – such as those in the eye – are especially vulnerable to poor blood sugar (blood glucose) control. An overaccumulation of glucose and/or fructose damages the tiny blood vessels in the retina. During the initial stage, called nonproliferative diabetic retinopathy (NPDR), most people do not notice any change in their vision. Early changes that are reversible and do not threaten central vision are sometimes termed simplex retinopathy or background retinopathy.
One of the most common chronic diseases that causes disability and one of the main reasons for avoidable blindness worldwide is diabetic retinopathy. Early detection of diabetic retinopathy allows for prompt treatment, hence screening programmes, particularly automated screening systems, will require significant investment if this goal is to be met.. For automated screening programs to work robustly efficient image processing and analysis algorithms have to be developed. This work examines recent literature on digital image processing in the field of early detection of diabetic retinopathy using fundus photographs. Algorithms were categorized into 5 groups (image preprocessing, localization and segmentation of the optic disk, segmentation of the retinal vasculature, localization of the macula and fovea, localization and segmentation of diabetic retinopathy pathologies). Diabetic retinopathy pathologies were further categorized into several groups. Glaucoma is a leading cause of irreversible vision impairment globally and cases are continuously rising worldwide. Early detection is essential because it enables prompt intervention, which can stop progressive deterioration of the visual field. With the assessment of the optic cup and retina at its core, fundus imaging of the optic nerve head can be used to detect glaucoma.assessment of the optic cup and disc boundaries. Fundus imaging is non-invasive and low-cost; In this project several different databases are presented and their characteristics discussed
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II. LITERATURE REVIEW

Literature survey is the most main step in software development process. Determine the time factor, economics, and company strength prior to developing the tool. Programmers require a lot of outside assistance once they start creating the tool. You can find this support online, in books, or from senior programmers. Before building the system the above examination are taken into account for developing the proposed system.

A. A Survey on Diabetic Retinopathy Disease Detection and Classification using Deep Learning Techniques (2021)

Diabetes can cause a number of problems to develop throughout the body if it is not addressed. Diabetes causes diabetic retinopathy (DR), an asymptomatic eye condition that affects the retinal blood vessels. Many automatic diagnostic systems with traditional handcrafted features have been created in the literature.With the development of Deep Learning (DL), particularly in medical imaging, more accurate and potential results are produced, as it performs automatic feature extraction. Convolutional Neural Networks (CNNs) are the most widely used deep learning method in medical image analysis. In this paper, several Deep Learning-based diabetic retinopathy disease detection and classification techniques are analyzed and reviewed for better understanding.

B. Automatic Glaucoma Diagnosis Based on Photo Segmentation with Fundus Images (2021)

Medical imaging is a process of creating images of internal parts of the human body for medical diagnosis. These images are used to help the doctors to quickly detect the most varieties of eye diseases which occur on the retina. The fundus camera is employed to capture the retinal images, and these images are called fundus images. Glaucoma is a leading disease in which eye vision is lost due to the destruction of the optic nerves. Early detection of glaucoma is noteworthy as recovering the damaged optic nerves is an especially complex task. Conventionally, the glaucoma disease detection using different machine learning techniques is very popular. The proposed photo segmentation approach is carried out the usage of a fundus picture database for qualitative and quantitative analysis. Experimental assessment is finished using a fundus photograph dataset with exceptional parameters along with peak sign to noise raetio, sickness detection accuracy, false-wonderful rate, and disorder detection time with recogniz to the variety of photographs.

C. *Glaucoma detection in retinal fundus images using U-Net and supervised machine learning algorithms (2021)*

This work proposes an offline Computer-Aided Diagnosis (CAD) system for glaucoma diagnosis using retinal fundus images. This application is developed using image processing, deep learning and machine learning approaches. Le-Net architecture is used for input image validation and Region of Interest (ROI) detection is done using brightest spot algorithm. Further, the optic disc and optic cup segmentation is performed with the help of U-Net architecture and classification is done using SVM, Neural Network and Adaboost classifiers.

D. *CANet: Cross-disease Attention Network for Joint Diabetic Retinopathy and Diabetic Macular Edema Grading (2020)*

Automated grading of DR and DME is crucial in clinical practise because it aids ophthalmologists in creating patient-specific therapy. The association between DR and its complication, i.e., DME, has not been taken into account in earlier publications, which either grade DR or DME. Furthermore, location data, such as macula and soft hard exhaust remarks, is frequently utilised as a prior for grading. Since getting these annotations is expensive, it would be ideal to create automatic grading systems that use image-level supervision. In this paper, we present a novel cross-disease attention network (CANet) to jointly grade DR and DME by exploring the internal relationship between the diseases with only image-level supervision. Our key contributions include illnesses with simply visual oversight. The disease-specific attention module, which we developed to selectively acquire useful features for certain diseases, and the disease-dependent attention module, which we developed to better understand the intrinsic relationships between the two diseases, are among our key contributions. In order to develop disease-specific and disease-dependent features and to jointly maximise the overall performance for grading DR and DME, we merge these two attention modules into a deep network. We test our network using two open benchmark datasets, namely the Messidor dataset and the ISBI 2018 IDRiD challenge dataset. The ISBI 2018 IDRiD challenge results in the best performance using our approach.

E. *Uncertainty-Aware Deep Learning Methods for Robust Diabetic Retinopathy Classification (2022)*

We present novel results for 9 BNNs by systematically investigating a clinical dataset and 5-class classification scheme, together with benchmark datasets and binary classification scheme. Moreover, we derive a connection between entropy- based uncertainty measure and classifier risk, from which we develop a novel uncertainty measure. We observe that the previously proposed entropy-based uncertainty measure improves performance on the clinical dataset for the binary classification scheme, but not to such an extent as on the benchmark datasets. It improves performance in the clinical 5-class classification scheme for the benchmark datasets, but not for the clinical dataset. The clinical dataset and one benchmark dataset are both broadly applicable to our new uncertainty measure.Our findings suggest that BNNs can be utilized for uncertainty estimation in classifying diabetic retinopathy on clinical data, though proper uncertainty measures are needed to optimize the desired performance measure. In addition, methods developed for benchmark datasets might not generalize to clinical datasets.

III. METHODOLOGY

A. *MATLAB*

A high-level language and interactive environment called MATLAB is used for programming, visualisation, and numerical computing. You can use MATLAB to analyse data, design algorithms, build models, and develop applications. You can explore several strategies and arrive at a solution more quickly with the language, tools, and built-in math functions than with spreadsheets or conventional programming.languages, such as C/C++ or Java You can use MATLAB for a range of applications, including signal processing and communications, image and video processing, control systems, test and measurement, computational finance, and computational biology. More than a million engineers and scientists in industry and academia use MATLAB, the language of technical computing.

B. *Key Features*

High-level language for numerical computation, visualization, and application development.

Interactive environment for iterative exploration, design, and problem solving.

Mathematical functions for linear algebra, statistics, Fourier analysis, filtering, optimization, numerical integration, and solving ordinary differential equations.

Built-in graphics for visualizing data and tools for creating custom plots.

Development tools for improving code quality and maintain ability and maximizing Performance

Tools for building applications with custom graphical interfaces.

Functions for integrating MATLAB based algorithms with external applications and Languages such as C, Java, .NET, and Microsoft Excel.

C. Convolutional Neural Network

When given inputs like images, voice, or audio, convolutional neural networks perform better than other neural networks, for instance. There are three basic categories of layers in them:

1) Pooling layer and Convolutional Layer

FC (fully-connected) layerA convolutional network's first layer is the convolutional layer. The fully-connected layer is the last layer, even though convolutional layers, further convolutional layers, or pooling layers, can come after it. With each layer, the CNN gets more complex, identifying greater portions of the image.

Early layers emphasise basic elements like colours and borders..

a) Convolutional Layer

The central component of a CNN is the convolutional layer, which is also where the majority of computation takes place. It needs input data, a filter, and a feature map, among other things. Assume that the input will be a colour image that is composed of a 3D pixel matrix. This means that the input will have three dimensions—a height, width, and depth—which correspond to RGB in an image. We also have a feature detector, also known as a kernel or a filter, which will move across the receptive fields of the image, checking if the feature is present. This process is known as a convolution. A section of the image is represented by the feature detector's two-dimensional (2-D) array of weights. Normally a 3x3 matrix, the filter size also determines the size of the receptive field but can vary in size. The dot product between the input pixels and the filter is calculated after the filter has been applied to a section of the image.The output array is then fed with this dot product. Once the kernel has swept through the entire image, the filter shifts by a stride and repeats the operation. A feature map, activation map, or convolved feature is the ultimate result of the series of dot products from the input and the filter. A CNN performs a Rectified Linear Unit (ReLU) adjustment on the feature map following each convolution operation, adding nonlinearity to the model. As was previously mentioned, the first convolution layer may be followed by another convolution layer.When this happens, the structure of the CNN can become hierarchical as the later layers can see the pixels within the receptive fields of prior layers. Let's use the case of trying to determine whether a bicycle is there in an image as an example. The bicycle can be viewed as a collection of components. It has a frame, handlebars, wheels, pedals, and other parts. A feature hierarchy is created within the CNN by the bicycle's component pieces, each of which represents a lower-level pattern in the neural network and the bicycle as a whole a higher-level pattern.

b) Pooling Layer

Downsampling, sometimes referred to as pooling layers, carries out dimensionality reduction and lowers the amount of parameters in the input. The pooling operation sweeps a filter across the entire input similarly to the convolutional layer, with the exception that this filter lacks weights. Instead, the kernel populates the output array by applying an aggregation function to the values in the receptive field. There are principally two forms of pooling:

- *Max Pooling:* The filter chooses the pixel with the highest value to send to the output array as it advances across the input. As a side note, this method is applied more frequently than average pooling.
- *Average Pooling:* The filter determines the internal average value the receptive field as it passes across the input and sends that value to the output array.

The pooling layer loses a lot of information, but it also offers the CNN a number of advantages. They lessen complexity, increase effectiveness, and lower the risk of overfitting.

c) Fully-Connected Layer

The full-connected layer is exactly what its name implies. As was already noted, partially connected layers do not have a direct connection between the input image's pixel values and the output layer. In contrast, every node in the output layer of the fully-connected layer is directly connected to a node in the layer above it.

Based on the features that were retrieved from the preceding layers and their various filters, this layer conducts the classification operation.While convolutional and pooling layers tend to use ReLu functions are frequently used by FC layers to categorise inputs accurately, yielding a probability ranging from 0 to 1. Vision with convolutional neural networks

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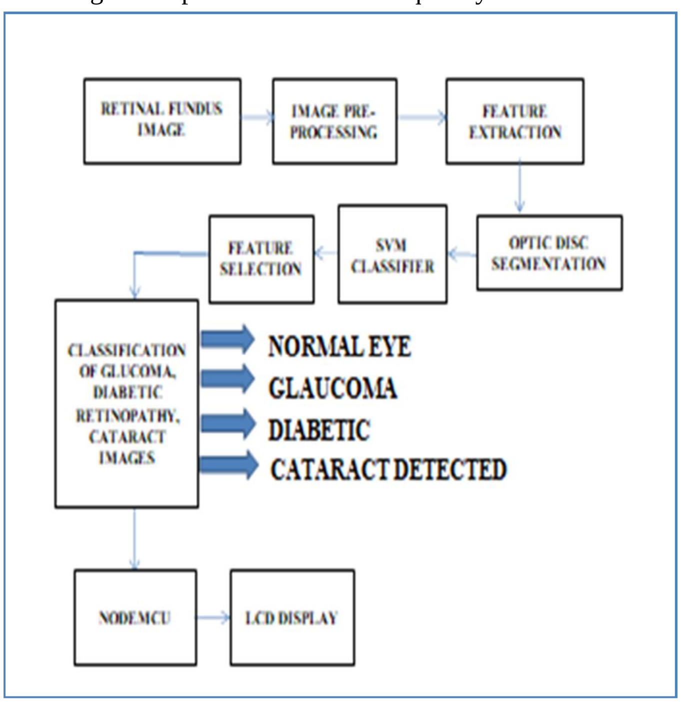
Computer vision and image recognition activities are powered by convolutional neural networks. Artificial intelligence (AIfield)'s of computer vision enables computers and systems to extract useful information from digital photos, movies, and other visual inputs, and based on those inputs, it may act. It differs from picture recognition jobs in that it can make recommendations. Currently, some widespread uses for this computer vision include:

- *Marketing:* Social media platforms provide suggestions on who might be in photograph that has been osted on a profile, making it easier to tag friends in photo albums.
- *Healthcare:* Medical technology has combined computer vision to improve the ability of clinicians to recognise malignant tumours in normal anatomy.
- *Retail:* Visual search has been incorporated into some e-commerce platforms, allowing brands to recommend items that would complement an existing wardrobe
- *Automotive:* While the age of driverless cars hasn't quite emerged, the underlying technology has started to make its way into cars, increasing the safety of the driver and passengers with features like lane line detection.

IV. PROPOSED METHODOLOGY

1) Diabetic Retinopathy cause changes in eye damage the blood vessel. Image will undergo a standard method of applying image processing which include image acquisition, pre-processing, feature extraction followed by exact identification of disease. In existing, the system can detect only one disease. We have proposed an algorithm which is capable of detecting all eye diseases in a single system.
2) Considering the fact that retinal image is one of the most important medical references that help to diagnose the cataract, DR, glaucoma this project proposes to use CNN algorithm for automatic eye disease detection based on the classification of retinal images.
3) There are many algorithms used for classification in deep learning but CNN is better than most of the other algorithms used as it has a better accuracy in results, and classification.
4) The Convolutional Neural Network Algorithm predicts events more quickly and more accurately.



Architecture of Proposed System

A. *Advantages*

1) Retinopathy Prediction is performed by using blood vessel segmentation and it gives better efficiency compared to existing method.
2) Accuracy, performance and evaluation of output is comparatively higher while using this algorithm.

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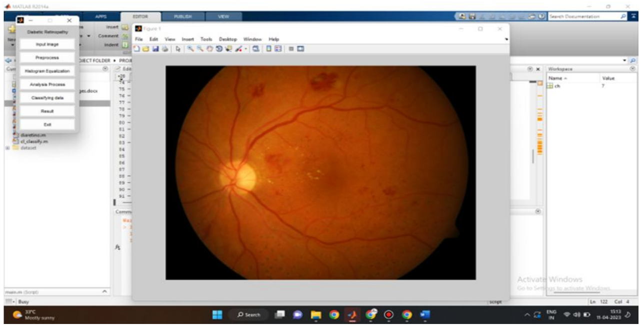
V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Description of Diabetic Retinopathy

1) Image Acquisition

There is a dataset consists four different types of retinopathy (Hard exudates, soft exudates, ,bleeding, and little red spots).Among those images select anyone of the image to classify.

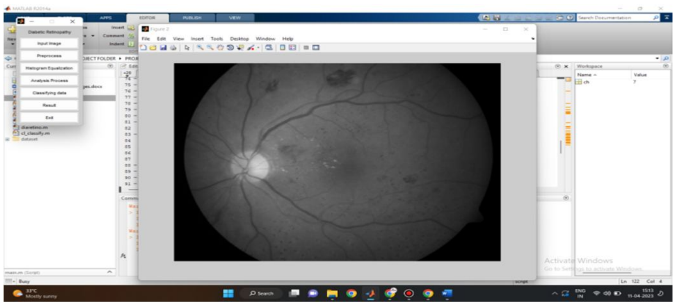
You may import photos and video captured by cameras and frame grabbers straight into MATLAB and SIMULINK using the image Acquisition Toolbox. You can configure hardware attributes and automatically detect hardware.Advanced workflows let you trigger acquisition while processing in-the-loop, perform background acquisition, and synchronize sampling across several multimodal devices. With support for multiple hardware vendors and industry standards, you can use imaging devices ranging from inexpensive Web cameras to high- end scientific and industrial devices that meet low-light, high-speed, and other challenging requirements.



Input Image

2) Preprocessing

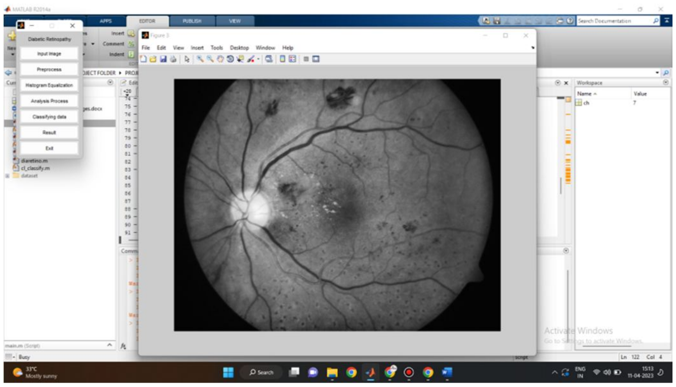
In preprocessing, two plane conversions is done by converting into gray format if the taken image as supposed to be three plane image.



Pr-Processing

3) Histogram Equalization

Histogram equalization is a technique for adjusting image intensities to enhance contrast. Because of this enhancement visual quality will be little bit better and easy to analysis. The values will be varied upto 256.



Histogram Image

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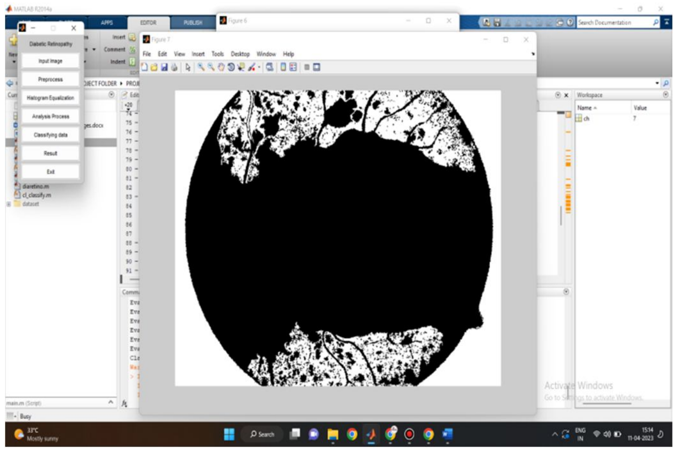
4) Algorithm Implementation

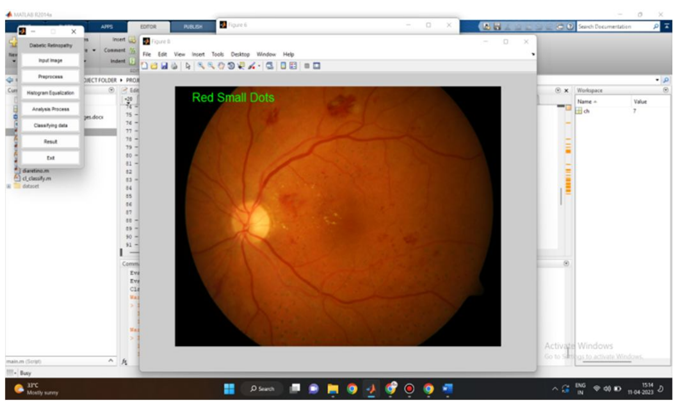
Algorithm is Color Histogram and Skin Locus modal used to classify the retinal images and features will be extracted.

5) Classifying Result

By using morphology technique the noises will be reduced for the classified images and we will obtain as desired one and text will be used to mention the classified type on images.



Classify Data



Prediction Result

VI. CONCLUSION

The automatic imaging method we created and prospectively evaluated for the detection of HEs. The system identifies HE lesions by classifying them based on colour and measuring the sharpness of their edges using a Kirsch operator. Our results demonstrate that the system is well suited to complement the screening of DR and may be use to help the ophthalmologists in their daily practice. Overall, these studies demonstrate the potential of Matlab-based systems for the detection and diagnosis of diabetic retinopathy. Such systems can help healthcare professionals to identify and treat the disease at an early stage, which can eventually result in improved patient outcomes.However, it is important to note that further research is needed to validate these findings and to develop more accurate and reliable Matlab-based systems for the detection of diabetic retinopathy.

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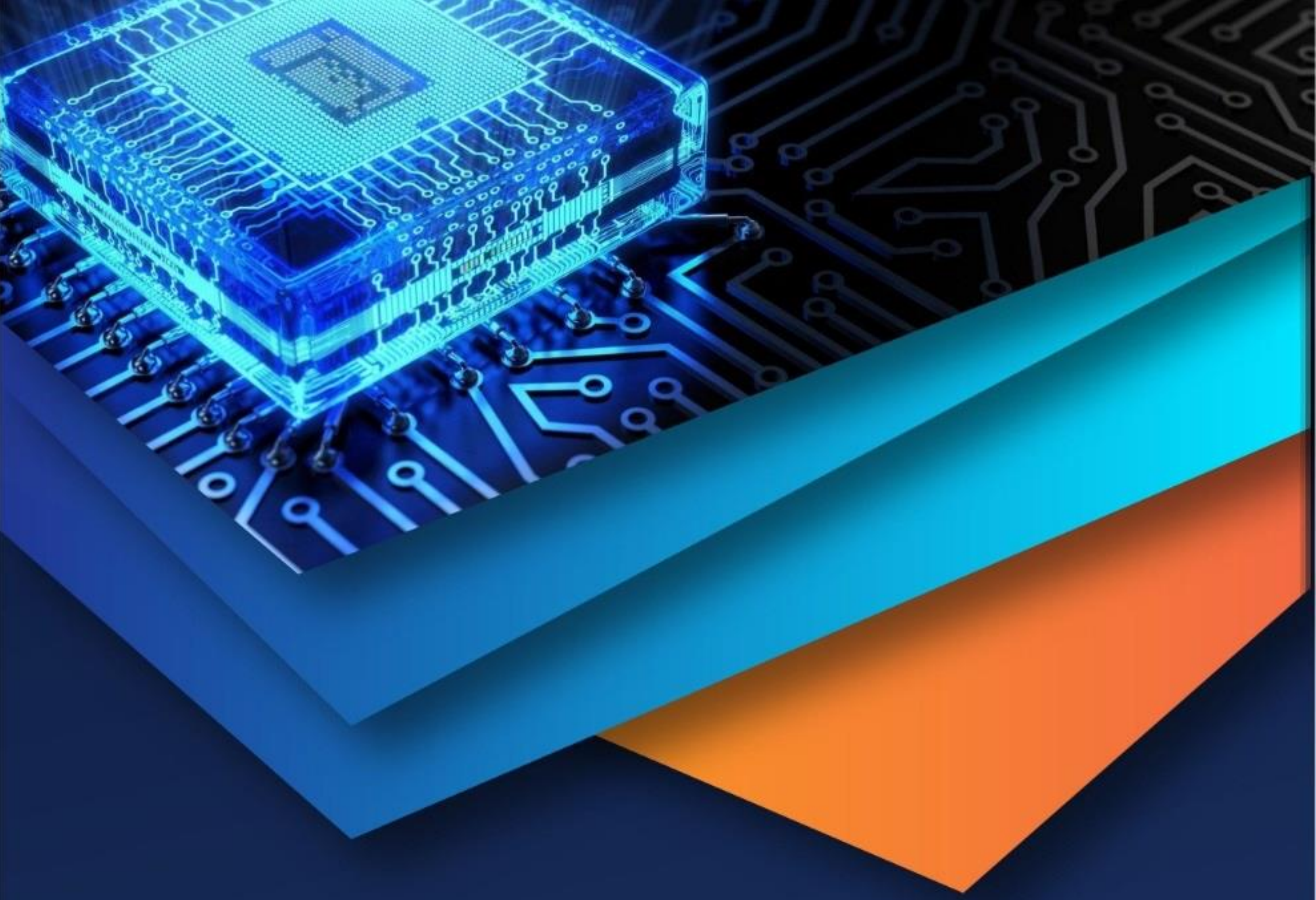

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