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ARTIFICIAL INTELLIGENCE IN DIABETIC RETINOPATHY FOR NORMAL RETINAL IMAGES

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ABSTRACT

Introduction: *The field of computer science research that is considered to be one of the most important new frontiers is artificial intelligence (AI).*

Aim of the study: *the main aim of the study is to Artificial Intelligence In Diabetic Retinopathy For Normal Retinal Images*

Material and method: *The patient was seated in a relaxed position in front of the OCT, with their chin supported by the chin rest.*

Conclusion: *It is not the purpose of this research to identify a region design that produces the most significant findings; rather, it is to ensure that each area more accurately represents the retinal thickness of its corresponding anatomical equivalent.*

INTRODUCTION

ARTIFICIAL INTELLIGENCE IN DIABETIC RETINOPATHY

The field of computer science research that is considered to be one of the most important new frontiers is artificial intelligence (AI). Utilizing this technology may improve not just the cost but also the quality and accessibility of medical treatment. AI, or artificial intelligence, refers to the completion of a job mostly via the use of a computer or a robot, with the participation of humans being kept to a minimum. To put it another way, artificial intelligence (AI) is the replication of human intellect by software or a computer. In its most basic form, it refers to the capacity of a computer system to demonstrate cognitive skills. In the same way that people learn, artificial intelligence systems need to have access to a database that teaches them basic information about an illness or discovery before they can be considered to have "learned" anything.

However, artificial intelligence is comprised of a great deal more than just a massive database. After going through the first stages of education, the system or machine is then instructed to "improve," or develop further based on its previous education so that it may become more precise and effective. In order for the system to comprehend the nonlinear interactions that exist between various variables by means of a flow of information known as "neural networks," it must first master difficult mathematical equations.

LITERATURE REVIEW

Zang, Pengxiao & Hormel (2022) This is because deep learning classifiers are trained to learn from examples (OCTA). The effectiveness of these models may be attributed, at least in part, to the incorporation of secret layers that provide the necessary level of complexity to accomplish a sought-after goal. On the other hand, hidden layers make it more difficult to comprehend the results of an algorithm. Clinicians now have the ability to check and comprehend the decision-making process of classifiers thanks to an unique biomarker activation map (BAM) framework that was developed here and is based on generative adversarial learning. On the basis of the most recent clinical criteria, a data set that had 456 macular scans was categorised as having either non-referable or referable DR. This data set was first utilised for the training of a DR classifier, which was then used to the evaluation of our BAM. This training took place before the generator was deployed. After that, the BAM is formed by taking the picture that results from subtracting the output from the input of the main generator. This was done to guarantee that the BAM only focuses on highlighting biomarkers that are employed by the classifier. The produced BAMs brought attention to recognised pathologic characteristics such as areas of nonperfusion and retinal fluid. Clinicians may be able to more effectively employ and validate automated DR diagnosis with the aid of a classifier that is completely interpretable and is based on these features.

Zang, Pengxiao & Hormel (2022) With the goal of drawing attention to the regions of interest identified by the DR classification framework, three-dimensional class activation maps were created for scans that were ultimately classified as rDR or vtDR. Expert-level DR classification may be possible with just one imaging modality using an OCT/OCTA-based deep learning architecture. Because of the expert-level performance that was shown in this research, the framework that was suggested may be used to construct a clinically useful automated DR detection system. This has important implications for translation.

Abas Hasan, Dathar & Zeebaree (2021) Diabetes mellitus is a long-term condition that is rapidly increasing in prevalence all over the globe. The condition arises as a consequence of an elevated glucose level in the blood and leads to difficulties in the organs responsible for vision, heart function, and kidney function. In order to provide the proper medical therapy, earlier diagnosis and categorization of DR patients is an essential step that must be taken. As a result of the rapid advancement in its algorithms, machine learning has recently begun to play an important and useful function in the field of medical applications and computer-assisted diagnostics. In this research, our objective is to investigate the performance of many different DR detection and classification systems that are based on machine learning methods. These algorithms are trained and evaluated utilising huge volumes of retina fundus and thermal pictures taken from a variety of datasets that are accessible to the public. These methods demonstrated their effectiveness in locating the warning indicators and determining the degree to which the DR was severe. The Resnet50 is equipped with a collection of feature extraction kernels that can examine photographs of the retina in order to derive information about wealth. Our findings lead us to the conclusion that algorithms for machine learning may provide the physician with assistance in making accurate diagnosis and treating DR patients.

Tsiknakis, Nikos & Theodoropoulos (2021) Vision loss and degradation may be delayed or avoided entirely with proper diagnosis and treatment in the early stages of the condition. The scientific community has come up with a number of different approaches that are driven by artificial intelligence in order to accomplish this goal. This review paper provides an in-depth analysis of how deep learning techniques are being applied at various stages of the fundus image-based diabetic retinopathy diagnostic pipeline. A review article format is used for the analysis. Here, we discuss the most popular datasets used in the academic world, the preparation methods that are put into practise, and how these factors contribute to faster and better performance. In addition to this, we go through a few models that have been used in actual clinical environments. At last, we bring the discussion to a close with a few significant takeaways and outline potential routes for further study.

Cano-Hidalgo, Rene & Urrea-Victoria, Tatiana (2021) Retinal microvasculature might be detected in vivo without the use of contrast dye. This has allowed for improved diagnosis and evaluation of diabetic macular edoema (DME)-related microvascular retinal changes, retinal ischemia, and neovascularization. The goal of this study is to offer a synopsis of the current state of knowledge about diagnostic interpretation of OCT angiography results in DME.

METHODOLOGY

The patient was seated in a relaxed position in front of the OCT, with their chin supported by the chin rest. They were given the instruction to concentrate on the goal. The internal fixation target was by far the most common kind of target to be employed (green colour lights). Patients who were unable to fixate on a particular object were given the task of focusing on an alternate target with their other eye. Following the completion of the necessary repairs, both the eye and the device were prepared to do the rapid macular thickness scans. As a result, the monitor displayed both the fundus picture and the scan beam.

RESULTS

FEATURE EXTRACTION AND CLASSIFICATION USING ARTIFICIAL INTELLIGENCE

In order to put the suggested model for retinal image categorization into action, MATLAB-2020 was the programming language of choice. The fundus photos were extracted from a larger collection of around 6,000 shots that is available to the public. In order to train and validate the recommended model, the ResNet-101 transfer learning framework was used. At the present, ResNet-101 is one of the finest pre-trained models available for classifying the many different kinds of medical imaging that are available. The CL, pool5, and FC layers are used in this work to extract features from pictures. The FC layer is upgraded in this study by modifying the weights in accordance with the dataset in order to facilitate more effective training. There are a total of 2048 distinct characteristics that may be extracted from each picture. Figure 4.1 illustrates the architecture of ResNet after it has been updated. The suggested model has an accuracy of 98.72 percent, which is quite high and virtually accurate in all circumstances, in contrast to other approaches that are already in existence.

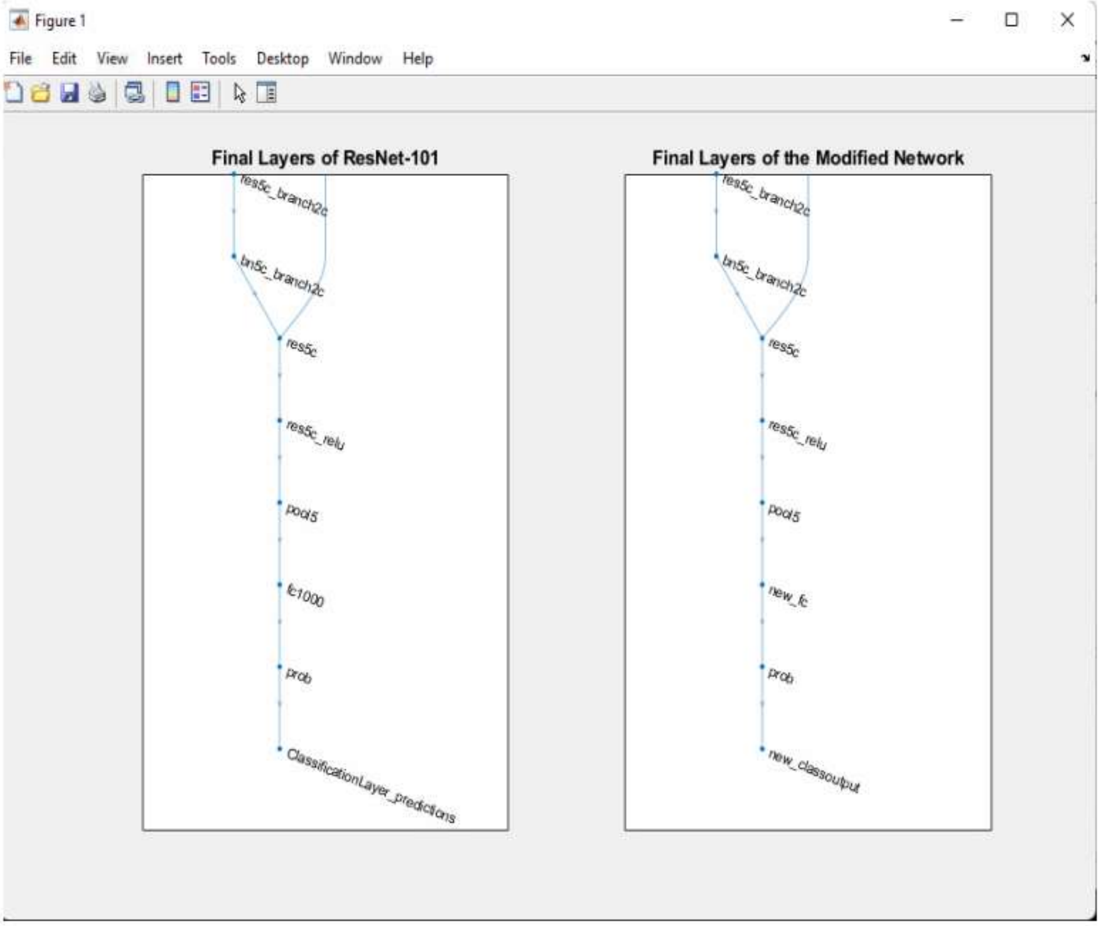


Figure 4.1 Modified ResNet 101 architecture in MATLAB

Table 4.1 Accuracy of diverse transfer learning models.

Technique	**Performance**
RESNET 50 and Random Forest	96
CNN512 and YOLOv3	89
DenseHyper	95
CNN	94.44
Modified Dense Net and Xception	85
ResNet and Modified Inception v4	90.7
ResNet 101	98.72

The correctness of the approach that was suggested may be determined by utilising these data. Accuracy levels of 98.72% were attained using the strategy that was presented.

The retinal images of diabetic patients may be difficult to scan and recognise in the early stages of the disease, and as the illness progresses, the patient's vision may become more impaired. In this study, a model of the retina that consists of three stages is provided. During the first stage, the pictures of the retina are improved such that there is less noise visible. After then, the segmentation of the blood artery has been completed. The recommended model, which is trained using the segmented pictures and is based on the architecture of ResNet-101, is then evaluated. The model has been developed to carry out a job that is analogous to the real thing. The fully connected layer of the network is trained using the dataset that was used by the pool5 layer of the network to extract the 2048 features from each picture. In reaction to the output, the weights will automatically adjust themselves and undergo dynamic changes. The recommended method achieved an accuracy of 98.72 percent when it came to classifying retinal images as normal, mild diabetic, moderate diabetic, severe diabetic, or hypertension. In the future, the authors are able to adapt the suggested approach to a variety of additional medical datasets.

1. Phase 1: Pre-processing

Original photographs are often subjected to a variety of noises, each of which has the potential to diminish the image's overall quality. It is necessary to do pre-processing on the pictures of retinopathy in order to exclude undesired induced signal. In order to convert an RGB picture into a grey image, the RGB component of the original photos must first be extracted from those images. After applying the edge-distance function to distinguish between the foreground and background of the image, the A-CLAHE algorithm is applied on the picture.

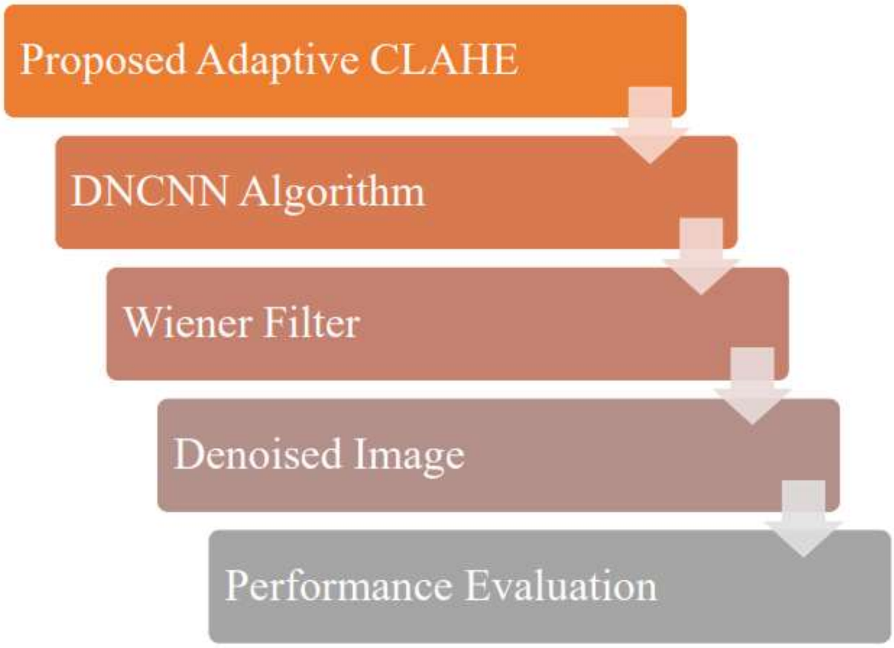
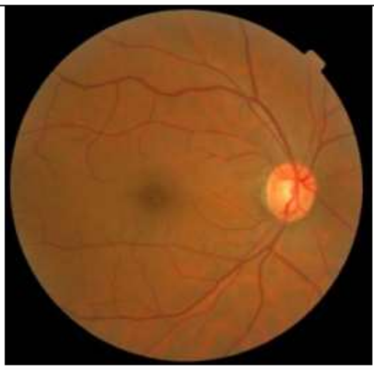
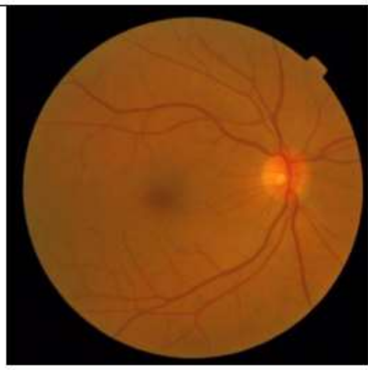
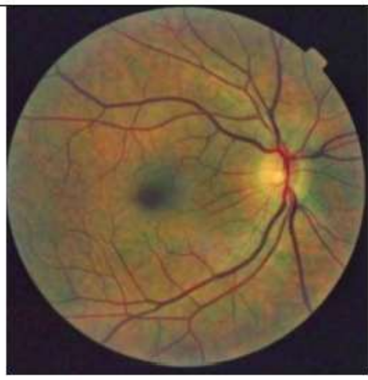


Figure 4.2 Pre-processing methodology

Based on the PSNR ratio, an evaluation of the pre-processing that was done on the datasets of MESSIDOR and ODIR (Ocular disease intelligent recognition) has been completed. The results of applying image enhancement to retinal images are shown in Tables 4.1 respectively. Figure 4.3 presents a chart that illustrates a comparison of the pre-processing approach that has been suggested with the pre-existing procedures.

Vol. 5, Issue IV, Oct-Dec, 2022 http://bharatpublication.com/current-issue.php?jID=29/IJAE

Table 4.2 Output of image enhancement on normal retinal Images

Input Image	Sample Image 1	Sample Image 2
Input Image		
CLAHE		

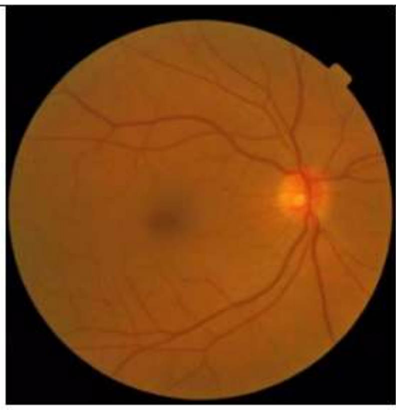
DNCNN		
Wiener Filter		

Figure 4.3 how pre-processing using alternative techniques performed

2. Phase 2: Segmentation

The segmentation step is essential in any image analysis that you do. The remainder of the picture analysis will be more difficult if the segmentation is not performed accurately. In addition, the OD segmentation in the retinal picture is an essential part of the diagnostic process for determining the presence of certain ophthalmological disorders. The process of classifying data based on the similarity of its pixels is called segmentation. The pixels in the surrounding area have varying values with regard to grayscale, colour, and intensity. These differences may be seen. When it comes to the automated categorization of diseases, accurate segmentation is one of the most important factors. Any error in the segmentation step will result in a misclassification, which will make it impossible to correctly diagnose the abnormal indication.

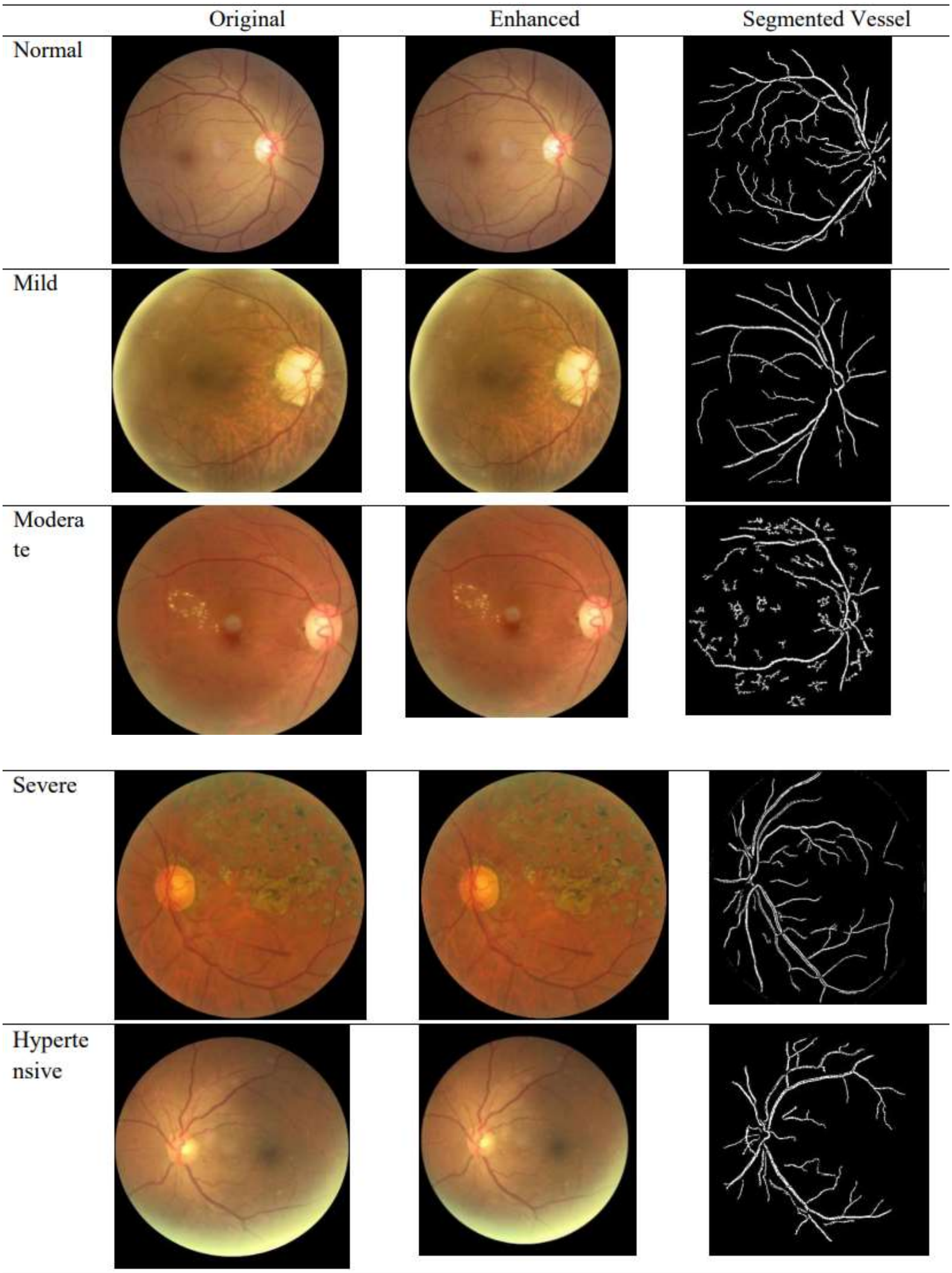
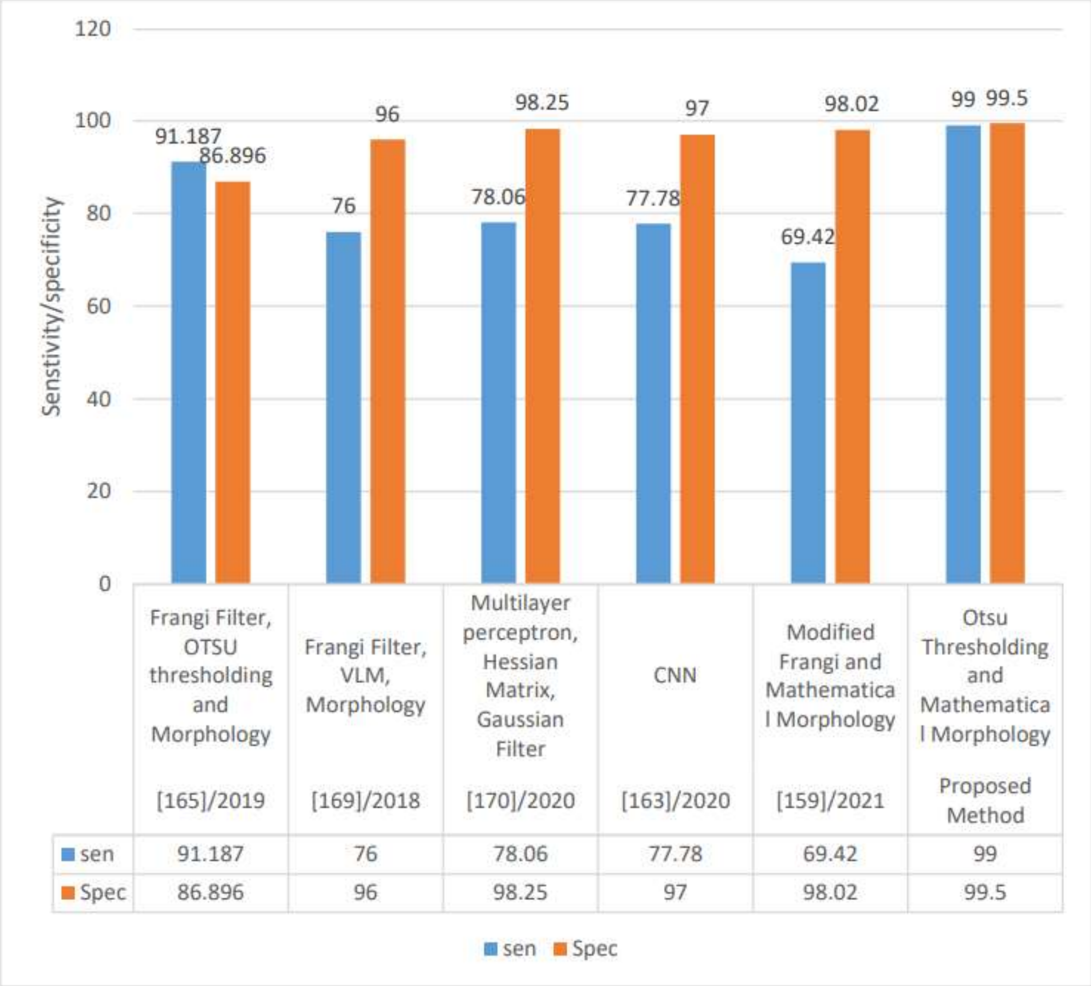


Figure 4.4 The output of Blood vessel segmentation



	Frangi Filter, OTSU thresholding and Morphology [165]/2019	Frangi Filter, VLM, Morphology [169]/2018	Multilayer perceptron, Hessian Matrix, Gaussian Filter [170]/2020	CNN [163]/2020	Modified Frangi and Mathematica l Morphology [159]/2021	Otsu Thresholding and Mathematica l Morphology Proposed Method
sen	91.187	76	78.06	77.78	69.42	99
Spec	86.896	96	98.25	97	98.02	99.5

Figure 4.5 Blood vessel segmentation analysis

CONCLUSION

It is not the purpose of this research to identify a region design that produces the most significant findings; rather, it is to ensure that each area more accurately represents the retinal thickness of its corresponding anatomical equivalent. Finding a region design that is better at recognising retinal thickness abnormalities and that is also connected with retinal architecture would be intriguing for me. If retinal thickness abnormalities are detected in certain places, then the benefit of studying the anatomy of those regions lies in the fact that it may provide light on the reasons why those particular portions of the retina are more prone to retinal thickness irregularities within a retinal layer.

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