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Retinal Blood Vessel Extraction using Lite U-Net Architecture

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ABSTRACT: The analysis of retinal images is a potent methodology for augmenting the precision of diagnosing retinal diseases. This methodology encompasses diverse techniques, including those that leverage deep learning algorithms and Convolutional Neural Networks (CNNs). Specifically, Lite U-Net, a CNN algorithm, is utilized in the analysis of retinal images. This recently proposed algorithm employs various pre-processing techniques to extract blood vessels from retinal fundus images before applying them to the Lite U-Net algorithm. The integration of these pre-processing techniques has resulted in a significant advancement in the accuracy (0.9659) and sensitivity (0.9913) of the retinal image analysis.

I.INTRODUCTION

Our eyes are crucial for our daily life, but some diseases can cause vision loss. One such disease is Diabetic Retinopathy, which can damage the retina and blood vessels. Detecting it early is essential to prevent permanent vision loss. During the model training process of a convolutional layer, the hyperparameters that can be adjusted are the number of filters used and the size of the filters.But it's not easy to identify blood vessels from these images, and it takes time and training to do so. To make it easier and faster, scientists have developed various techniques to extract blood vessels from retinal images, including image pre-processing and machine learning techniques.

II. WORK RELATED

A convolutional layer is a fundamental component of a Convolutional Neural Network (CNN) used for feature extraction, enabling the network to learn and identify significant features from the input data.
The convolutional layer applies a set of learnable filters (also known as kernels) to the input data, performing a mathematical operation called convolution. The filters are small matrices of weights that slide across the input data, and at each position, the dot product is taken between the filter and the corresponding portion of the input data. This operation produces a feature map, which highlights the presence of specific features in the input data.
During the model training process of a convolutional layer, the hyperparameters that can be adjusted are the number of filters used and the size of the filters. Typically, smaller filters (e.g., 3x3 or 5x5) are used, as they allow the network to capture finer-grained features. By dictating the number of feature maps generated, the depth of a convolutional layer is determined by the quantity of filters applied.
After the convolution operation, a non-linear activation function (such as ReLU) is applied to introduce non-linearity to the network. This helps to increase the expressive power of the model and enables it to learn complex patterns and representations.
Convolutional layers are a vital component of CNNs as they extract features from input data, and they have been effectively employed in diverse computer vision tasks such as image classification, object detection and segmentation.

III.IMAGE PRE-PROCESSING AND SEGMENTATION

Despite its significance in the field of medical science, image data segmentation processing remains a multifaceted and nuanced problem with no standard, one-size-fits-all solution. As such, practitioners often deploy a diverse range of tools and platforms such as Python, Keras and Tensorflow to pre-process images. In the context of machine learning

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and computer vision projects, the availability and quality of data are critical to achieving desired results. However, image data poses unique challenges, including complexity and inaccuracy that can hinder the effectiveness of the models constructed on them. To mitigate these challenges, image data must undergo pre-processing, a technique that entails cleaning and processing data to the desired format before constructing computer vision models. Image data pre-processing can be crucial in improving model accuracy and reducing complexity. A myriad of techniques exists for pre-processing image data, such as image resizing, grayscale conversion, histogram equalization, and image augmentation. In this particular project, we employed fourtypes of image pre-processing and segmentation techniques, which included edge detection, grayscale conversion, histogram equalization, and grayscale conversion.

IV. PROPOSED ALGORITHM

Lite U-net is a modified version of U-net, which is a popular deep learning architecture used for image segmentation. The Lite U-net architecture consists of five layers, each with a varying number of feature channels. The layers are designed to perform convolutions followed by activation function known as ReLu. However, to make the architecture more flexible, the Lite U-net was created with the goal of varying the difficulty and number of convolutions at each layer.

The Lite U-net works by taking an input image and applying convolutional operations, followed by a non-linear activation function. The output is then down-sampled using a max pooling operation and passed to the next layer. This process is repeated for each layer in the contraction path.

In the expansion path, instead of down-sampling, the architecture employs an up-sampling operation to re-establish the image. This allows the network to learn and represent the finer details of the image, resulting in more accurate segmentation. Overall, Lite U-net is a powerful and versatile deep learning architecture that can effectively segment images with varying complexities.

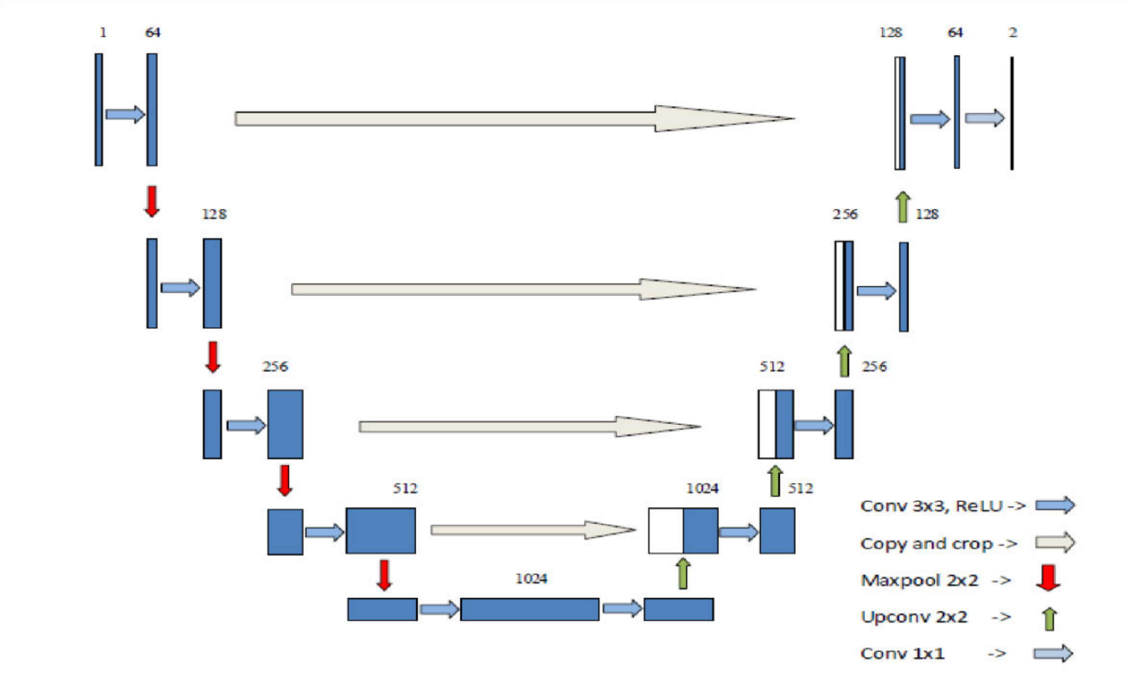

Figure1- Lite U-net Processing Architecture

V.EXPERIMENTATION

DRIVE and STARE are two commonly used datasets in the field of medical image analysis for evaluating the performance of algorithms used for the detection and diagnosis of retinal diseases.

There are 40 colour fundus images in the DRIVE (Digital Retinal Images for Vessel Extraction) dataset, each of which has been manually annotated with vessel segmentations. The images were captured using a fundus camera and have a resolution of 565 × 584 pixels. The DRIVE dataset is often used to evaluate the performance of algorithms that extract blood vessels from retinal images.

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The STARE (Structured Analysis of the Retina) dataset contains 20 colour fundus images that are manually annotated with lesion segmentations. The images were captured using a fundus camera and have a resolution of 700 × 605 pixels. The STARE dataset is often used to evaluate the performance of algorithms that detect and diagnose retinal diseases such as diabetic retinopathy, age-related macular degeneration, and glaucoma.

VI.RESULTS

Based on the table provided, it can be seen that the Lite U-net model achieved the highest accuracy and specificity on the DRIVE dataset compared to the other models. The Lite U-net model also achieved a high F1 score on both the DRIVE and STARE datasets. It's worth noting that different models may perform better on different datasets or specific tasks. Therefore, it's important to evaluate the model's performance based on the specific requirements of the task at hand. Additionally, visual inspection of the predicted images and ground truth can provide more insight into the performance of the model.

Models	Accuracy	Area Under Curve	Sensitivity	Specificity	F1 Score
U-net	0.8521	0.8735	0.7437	0.9821	0.7816
Lite U-net	**0.9569**	0.9786	0.7019	0.9912	0.8652

Table 1: Contrast betweenU-Net and Lite U-Net modelson DRIVE dataset

Models	Accuracy	Area Under Curve	Sensitivity	Specificity	F1 Score
U-net	0.8378	0.8572	0.8289	0.9711	0.7772
Lite U-net	0.9725	0.9875	0.7826	0.9894	0.8226

Table 2: Contrast between U-Net and Lite U-Net models on STARE dataset

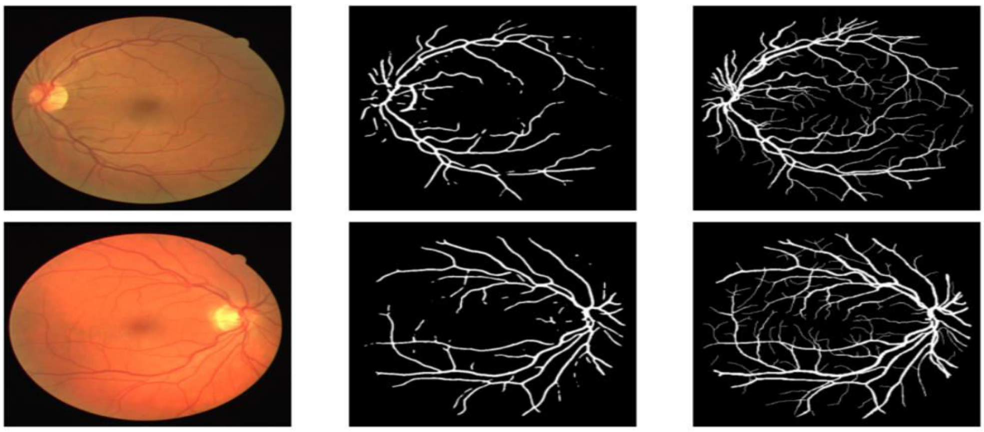

Fig2.Pre-processed and Tested output images in DRIVE Dataset of U-Net and Lite U-net

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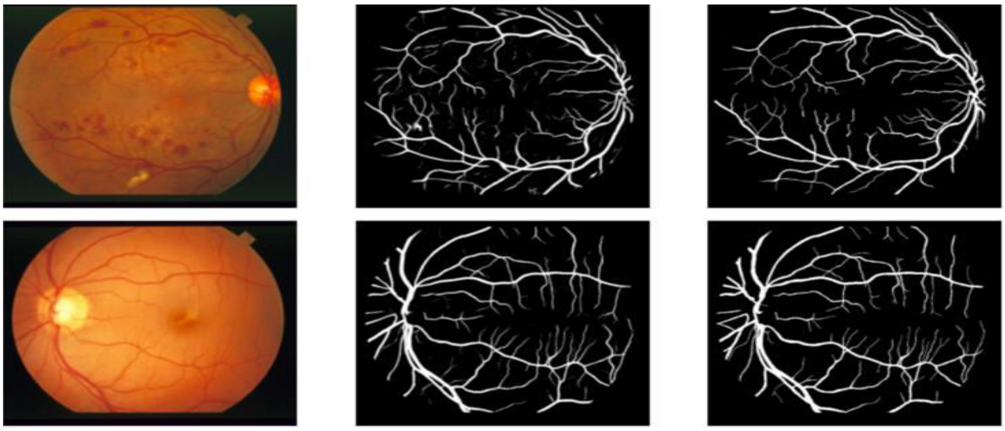

Fig3.Pre-processed and Tested output images in STARE Dataset of U-Net and Lite U-net

VII.CONCLUSION

The segmentation of retinal blood vessels is a crucial undertaking within the medical field, particularly in the early detection and diagnosis of eye diseases like diabetic retinopathy and glaucoma.The precise segmentation of retinal blood vessels helps identify the level of damage to the vessels, enabling medical professionals to provide prompt and effective treatment to patients. Accurate segmentation also allows for the monitoring of disease progression and treatment efficacy over time. In general, retinal blood vessel segmentation is an essential tool in securing the most favourable results for patients suffering from retinal diseases.

Traditionally, retinal blood vessel segmentation has been performed using various image processing techniques such as thresholding, morphological operations, and region growing. However, these techniques often rely on manual intervention and may not always produce accurate results.

In more recent times, promising results have been observed through the application of machine learning and deep learning algorithms to the task of retinal blood vessel segmentation. U-net is one of the most popular deep learning architectures used for this task. It is a type of convolutional neural network that was originally designed for biomedical image segmentation tasks, particularly for tasks where the input image and output image have the same size.

Inspired by the success of U-net, researchers have proposed various modifications and extensions to the architecture. One such modification is the Lite U-net architecture, which is a simplified version of the original U-net architecture with fewer convolutional layers.

When applied to the DRIVE and STARE datasets, Lite U-net has been shown to outperform existing methodologies in terms of parameters such as sensitivity and specificity. However, there are still some limitations to the model, such as the need for large amounts of annotated training data and the possibility of overfitting to the training data.

VIII.APPLICATIONS

U-Net is a sophisticated technique created particularly for biomedical applications, primarily for segmenting images. This technique is highly effective at identifying and accurately segmenting images with only a small amount of training data. Using automated U-Net techniques to analyse segmented images can be highly beneficial in identifying diseases and providing the appropriate treatment to patients. Our Lite U-Net model is a variant of the original U-Net architecture that has been optimized for even greater accuracy and segmentation results. Implementing our model can significantly reduce the time required for image analysis, allowing medical professionals to devote more time to patient care. Overall, Lite U-Net represents a powerful and innovative tool for biomedical image segmentation that can lead to improved patient outcomes.

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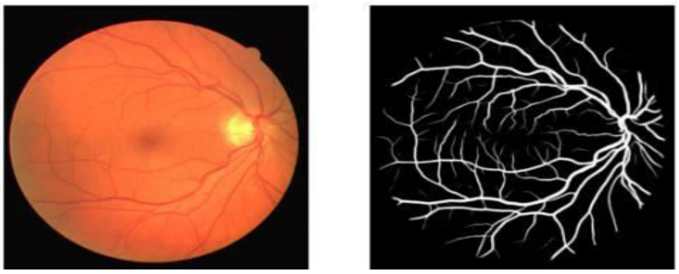

Fig 4.U-net representing of retina vessels segmentation with an Accuracy nearly equal to 0.9531

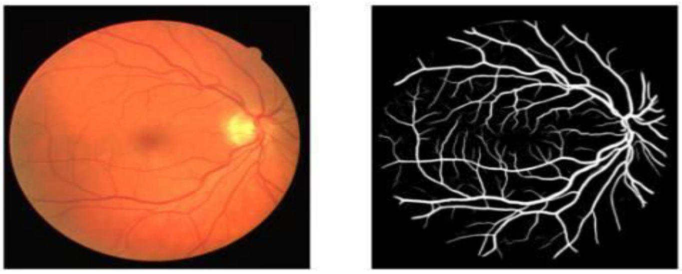

Fig 5. Lite U-net of representing retina vessels segmentation with an Accuracy equal to 0.9727

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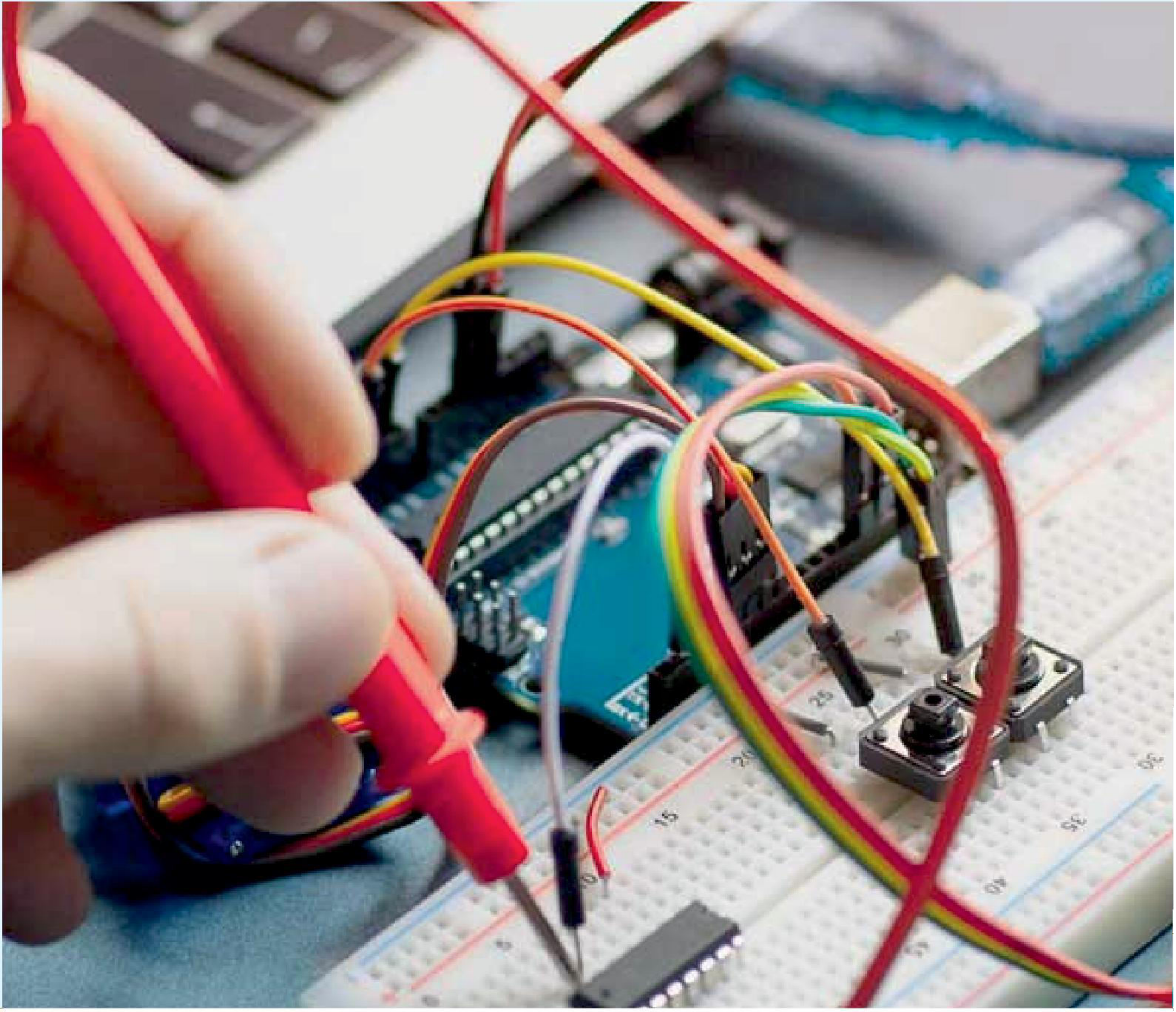

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