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PERFORMANCE ANALYSIS OF RETINAL BLOOD VESSEL IMAGE SEGMENTATION USING DEEP LEARNING TECHNIQUES

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Abstract : The state of the human eye's vascular network is an essential diagnostic element in ophthalmology. The properties of retinal vessels reflect a patient's health condition and aid in the diagnosis of certain disorders such as diabetic maculopathy, diabetic retinopathy, and hypertension. In practice, retinal image data has a high dimensionality, resulting in data of tremendous magnitude. Deep Learning (DL) approaches are assisting in the development of intelligent retinal image analysis tools because morphological retinal image datasets may be evaluated in a broad and non-invasive manner. Accurate identification and treatment of these disorders can help people avoid total blindness. Because of their improved efficiency and accuracy, deep learning techniques have recently been quickly used to retinal vascular segmentation. By measuring the performance of various techniques, the better deep learning technique will be decided by doing the analysis of various parameters like accuracy, F1-score, sensitivity, specificity.

***IndexTerms* - Fundus image, Dataset, Deep learning , CNN , U-net.**

I. INTRODUCTION

The most advanced human sense is vision. So pictures play the most significant function in visual perception, and human visual perception is also highly crucial since image processing techniques are chosen solely on the basis of human visual perception visual judgements. There are some of the main parts in the eye such as cornea, retina, choroid as shown in the figure 1.1

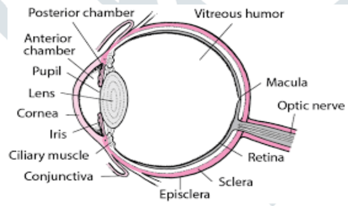

Fig1.1.Structure of eye

The tissue layer at the rear of the eyeball that is light-sensitive is called the retina. The retina receives the sharpest images that pass through the lens of the eye. These images are subsequently converted by the retina into electric signals, which are ultimately transmitted to the brain by the optical nerves. The ophthalmologist uses retinal blood vessels for the detection of vascular and related diseases such as diabetic retinopathy, maculopathy, hypertension. These diseases may leads to global blindness. Diameter of the vessels, length of the vessels are the characteristics which are useful to identify the diseases easily. The examination of retinal images have developed an major step for the recognization of retinal anatomy for the ophthalmologist.

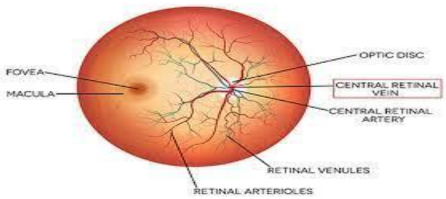

Fig1.2.Structure of retina

The retinal fundus picture depicts retinal structure like retinal arterioles, retinal venules, optic disk (OD), fovea, macula, central retinal vein, central retinal artery as shown in Figure 1.2. To prevent blindness, there should be three major steps to be followed.

- Identification that is precise
- Findings regarding eye abnormalities
- Adequate medication

The digital image processing method such as Image segmentation accustomed to recognize the retinal blood vessels in the retina. Deep learning approaches may be used to analyse metrics like as accuracy, specificity, sensitivity, and F1-score (Dice coefficient) for various samples. By evaluating the above metrics earlier the problem can identified easily and can be prevented before without affecting any individual. The DRIVE dataset is used to identify the different evaluation metrics for various image samples.

Convolutional Neural Network is one of various ways that have been employed to combat retinal issues. A deep learning approach based on artificial neural networks is included in the CNN method. Deep learning has been introduced in the field of medical image identification, has become popular now a days due to the performance analysis of various evaluation metrics. Convolutional Neural Networks (CNN) are deep learning approaches that have the capacity to handle challenging processes and perform pattern recognition using pictures. This research compares the best model by training multiple CNN models to predict retinal vasculature using assessment measures such as accuracy, specificity, sensitivity, and F1-score.

2 Abbreviations and Acronyms

CNN	:	Convolution Neural Network
DRIVE	:	Digital Retinal Images for Vessel Extraction
DU-net	:	Deformable U-Net
AUC	:	Area under curve

3. Theoretical framework

3.1 In 2018,Guo, et al. developed a Convolution Neural Network with Using six layers and a reinforcement sample learning technique, the network was trained using subpar samples. The suggested model consists of two convolution layers, two pooling layers, one dropout layer, and one loss layer. The algorithm makes two distinct contributions. First, a new CNN model with six layers was developed, along with a sample learning strategy that taught the network on poor-performing examples. 2 convolution layers, 2 pooling levels, dropout layer, and loss layer make up the proposed model. The algorithm makes two distinct contributions. To begin, a new CNN model is being developed to extract characteristics and identify the retinal vascular area. It is totally automated and does not require preprocessing as compared to typical classification processes. With 92% accuracy and 0.96 AUC score (area under the receiver operating characteristic) on the DRIVE data set and 92% accuracy and 0.94 AUC value on the STARE data set, respectively[1].

3.2 In 2019, Q.Jin proposed a deformable network for segmenting retinal vessels The automatic sub division of retinal vessels in fundus pictures aids in the detection of certain disorders such as diabetes and hypertension. In this study, we present Deformable U-Net (DUNet), which uses the retinal vessels' local properties with a U-shape structure for retinal vascular segmentation from start to finish. Our models are tested using public datasets such as DRIVE, STARE, CHASE DB1, and HRF. In our study, we compare the proposed network in-depth to the deformable neural network U-Net. The findings show that DUNet has cutting-edge performance for retinal vascular segmentation, with global accuracy of 0.95 and AUC of 0.98 on DRIVE, STARE, CHASE DB1 and HRF. It can also extract more precise veins. Furthermore, to demonstrate the DU-Net's generalisation capacity, we employ two additional retinal vascular data sets, WIDE and SYNTHE, to subjectively and statistically examine and compare with other approaches[2].

4 RESEARCH METHODOLOGY

This section consists of different methods that are used to identify retinal blood vessels. In the health care industry, deep learning has played a big role. Data is fed to an algorithm using deep learning so it can comprehend the relationship between input and output. Some of the steps are involved to identify the vessels as shown in fig 4.1.

Fig.4.1.Block Diagram

4.1 Image Segmentation:

The technique of breaking an image up into smaller segments is called picture segmentation. These created pieces or numerous segments will aid in the calculation of picture segmentation tasks. Another necessity for image segmentation jobs is the usage of masks.

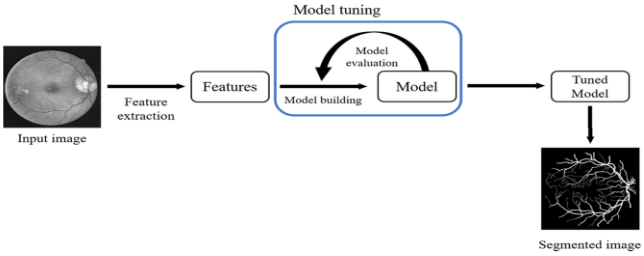

Fig.4.1.Block diagram of Image Segmentation process

As shown in the fig 4.2, the desired outcome for the segmentation problem by using masking, which is essentially a binary picture consisting of zero or non-zero values and may do a variety of future actions using pictures and their related masks after characterising the most important parts of the image produced during image segmentation. Machine vision, object identification, medical image segmentation, machine vision, face recognition, and many more applications rely on image segmentation.

4.2 Methods

4.2.1 Convolutional Neural Network

CNNs are neural networks with convolutional layers (and some other layers). A convolutional layer consists of many filters that perform convolutional operations. As shown in the figure 4.2.1, A well-known model is the convolutional neural network (CNN) created by combining deep learning with technique for processing images, which includes picture extraction and classification of features, as well as pattern recognition. The convolutional neural network is a supervised learning deep model. An input layer and an output layer are just a few of the hidden layers that make up CNN. Each layer of a hidden layer carries out a particular function, like activation, pooling, or convolution.

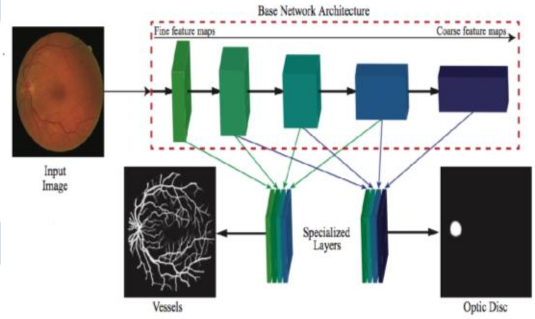

Fig.4.2.1.CNN architecture

The middle convolutional layer extracts features from the input information using a convolution operation to generate an outline map. Convolutionary operation's output is determined by parameters set throughout the convolution kernel.. All neurons in the previous layer are completely integrated through the fully connected layer. The final value acquired is passed to the classifier, who then generates the outcome.

4.2.2 U-Net

As shown in the figure 4.2.2, the network has a u-shaped design because it has a path that expands and one that contracts. Consisting of repeated convolutional application, a max pooling operation and a rectified linear activation unit, the contracting route is a conventional convolutional network.

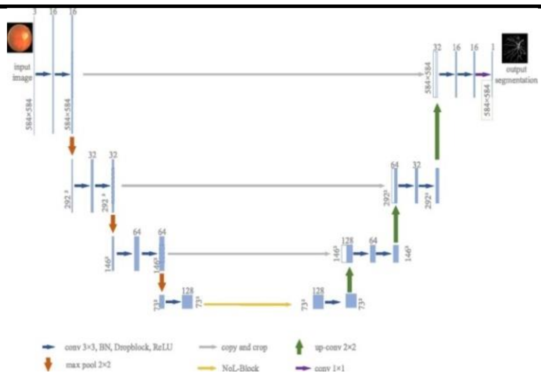

Fig.4.2.2.Architecture of U-net

The geographic data is lowered while the feature information is boosted during the contraction. Utilising a series of concatenations and up-convolutions employing high-resolution features from the contracting path, the expansive pathway integrates information about features and spaces.

4.3 Project Dataset

As shown in the figure 4.3, for identifying the retinal blood vessels in a fundus images, there requires a more number of fundus images. Both models were trained with certain fundus images to identify the retinal blood vessels and analyzing the performance of retinal image using various parameters. This model takes two epochs to measure the accuracy, specificity, sensitivity and F1-score.There is a collection of these databases through online in kaggle. There is a collection of 20 samples, ten samples are utilised to train, and ten more are used to test.

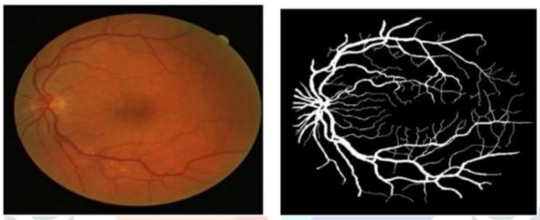

Fig 4.3.Fundus image and retinal blood vessels

5 Model Analysis:

Evaluation Metrics:

An evaluation of the classifier's performance typically involves utilizing a confusion matrix. In the confusion matrix, four different terminologies are used. False positives and False negatives are present, as well as True positives and True negatives. With the help of a confusion matrix, these parameters are calculated for each algorithm.

1.) Accuracy:

Accuracy is used to assess model performance by calculating the ratio of true positives to true negatives based on all predictions produced.

$$Accuracy = Sensitivity+Specificity$$

2.) Sensitivity:

It is the degree to which a model can forecast true positives for each accessible category.

$$Sensitivity = \frac{True\ Positive}{True\ Positive+False\ Negative}$$

3.) Specificity:

The degree to which a model can forecast true negatives for each accessible category is known as its specificity.

$$Specificity = \frac{True\ Negative}{True\ Negative+False\ Positive}$$

4.) F1-score:

It is the mean of accuracy and recall and is used to grade performance statistically.

$$F1\text{-}score = \frac{2*True\ Positive}{2*True\ Positive+False\ Positive+False\ Negative}$$

6 RESULTS AND DISCUSSION

Table 6.1: Descriptive Statics

This experiment has done with two deep learning models, CNN and U-net. The evaluation metrics are described in the sections below.

METHOD	ACCURACY	SPECIFICITY	SENSITIVITY	F1-SCORE
CNN	0.592	0.246	0.602	0.041
U-NET	0.704	0.144	0.696	0.019

Table 6.1:Evaluation metric values for both the models

As shown in the table 6.1, In CNN model we have taken 20 image samples,10 samples used to train and another 10 samples is used to test. We got the average accuracy of 60%,specificity of 25%,sensitivity of 60% and dice coefficient of 4%.Similarily for U-net, the accuracy level of 70%, specificity of 14%, sensitivity of 70% and dice coefficient of 2%.

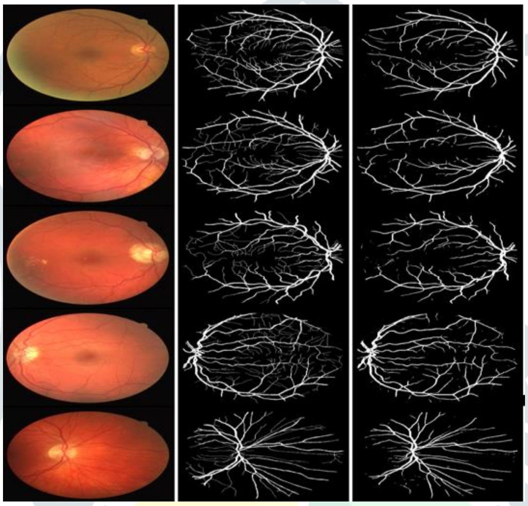

Fig.6.2. Extraction of Features in both CNN and U-net from retina fundus images

As shown in the figure 6.3, by comparing the assessment criteria of several models, we can conclude that U-net is a far superior model to CNN.

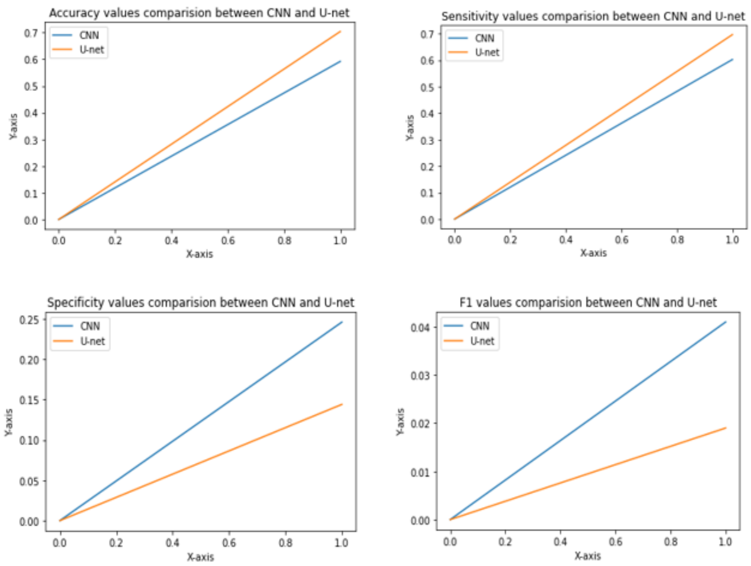

Fig.6.3.Comparision between the various models by different parameters

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