JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

RETINAL FUNDUS IMAGING SEGMENTATION AND CLASSIFICATION USING MODIFIED GAN ALGORITHM

Nikita Mahangade[1], Sonali Bhosale[2], Dhananjay Shirke[3], Sakshi Ghule[4]
Department of E&TC, SKNCOE,SPPU, Pune.

Abstract— **This Blood vessels are one of the most important indicators in retinal image analysis, which is becoming increasingly important for diagnosing eye diseases. A comprehensive review of deep learning-based retinal blood vessel segmentation and an automated and unsupervised method for segmenting retinal blood vessels from a fundus image are presented in this paper. In modern medicine, fundus images are one of the main ways to diagnose eye diseases. The patients' health status is reflected in the geometric characteristics of the retinal vessels, which also aid in the diagnosis of certain diseases like diabetic retinopathy, glaucoma and hypertension. Patients may avoid becoming completely blind if these conditions are correctly diagnosed and treated at the appropriate times. Due to their superior efficiency and accuracy over manual segmentation and other computer-aided diagnosis methods, deep learning algorithms have recently been rapidly applied to retinal vessel segmentation. M-GAN, a brand-new conditional generative adversarial network, is proposed in this paper for the purpose of balancing losses through stacked deep fully convolutional networks for precise retinal vessel segmentation. It consists of an M-discriminator with a deeper network for more effective adversarial model training and a newly designed M-generator with deep residual blocks for more robust segmentation. To clear up the retinal vessels in the input fundus image, we use automatic color equalization (ACE) to perform pre-processing. We compared the proposed M-GAN to other studies to verify the proposed method using the DRIVE, STARE, datasets. In order to conduct a comparison, we measured the accuracy, the intersection of union (IoU), the F1 score, and the Specificity, Sensitivity. Comparative results demonstrated that the proposed M-GAN performed better than other studies. In these paper different classifier is used, the classifier in the M-GAN algorithm helps to classify the diseases like diabetic retinopathy, glaucoma and hypertension. Researchers able to build more robust and advanced models with the help of this article.**

Keywords-- **Retinal blood vessel segmentation, fundus imaging, M-generative adversarial networks (M-GAN), convolutional networks, classification**

I. INTRODUCTION

Identification and separation of blood vessels in retinal pictures is a challenge in medical image processing known as retinal vessel blood segmentation. It is now feasible to identify diseases quickly because to the advancement of medical imaging technology. Also, several experiments have been done to automatically process medical pictures utilizing computer vision technology without the assistance of human professionals. In particular, the segmentation of retinal blood vessels is very important to retinal diseases such as diabetic retinopathy, glaucoma, Hypertension.

Retinal imaging can detect a variety of eye conditions, such as:-

One serious eye condition that diabetics may experience is diabetic retinopathy. It is brought on by injury to the retina's blood vessels, which, if left untreated and undiagnosed, can result in blindness and vision loss. Imaging of the retina can detect blood vessel anomalies that may be signs of diabetic retinopathy.

The optic nerve, which transmits visual information from the eye to the brain, is harmed by glaucoma, a condition. Although it can happen at normal or low intraocular pressures, high intraocular pressure is frequently a factor. Glaucoma is one of the leading causes of blindness worldwide, making early detection and treatment of the condition crucial for preventing vision loss.

Hypertension, or high blood pressure, is a common medical condition that can have negative effects on the body, including the eyes and retina. When uncontrolled or poorly managed, it can cause damage to the blood vessels in the retina, leading to hypertensive retinopathy, a potentially serious eye condition that can cause vision loss and other complications.

Using a Multi-scale GAN deep learning model is one strategy for completing this challenge (M-Gan). A generative adversarial network (GAN) called M-Gan is made to operate with multi-scale images. A generator network and a discriminator network make up its two primary parts. While the discriminator network attempts to tell actual images from produced ones, the generator network converts low-resolution photos into high-resolution images. The generator network is trained on a collection of retinal pictures and matching blood vessel segmentations in order to employ M-Gan for retinal vessel blood segmentation. The generator network creates artificial blood vessels during training.

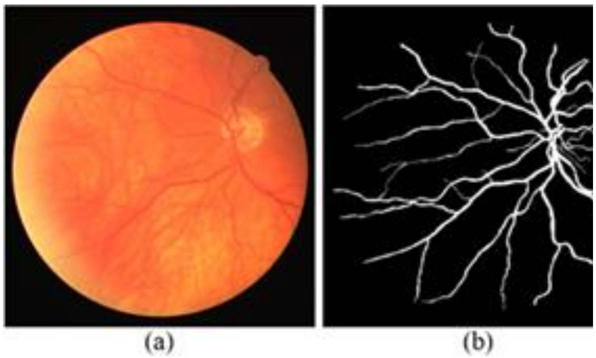


Fig.1 - Example of (a) fundus image (b) retinal blood vessel segmentation

The inner surface of the human eye, comprising the retina, vascular tree, fovea, and optic disc, is projected as the fundus picture, as shown in Figure 1(a). As illustrated in Figure 1(b), it is difficult to segment retinal blood vessel pictures robustly because the colour of the retinal surface is similar to that of the retinal blood vessel. Many research have been done to separate objects reliably and automatically using supervised or unsupervised machine learning techniques. Studies utilizing deep learning architectures, it should be noted, performed better than those using traditional approaches.

Artificial neural networks (ANNs) are used in deep learning, a branch of machine learning, to model and resolve complicated issues. They are particularly suited for applications like picture identification, natural language processing, and speech recognition because they have numerous layers of interconnected neurons that allow them to learn and extract hierarchical representations of data. Several kinds of deep learning algorithms exist.

GANs are deep learning models used for generative tasks, consisting of two neural networks that compete with each other during training to produce high-quality results.

From computer vision to natural language processing, deep learning has changed several industries. It is a potent branch of machine learning. Deep learning models can be tweaked and applied to a wide range of applications, and the choice of algorithm relies on the particular task at hand.

In this project, we employed the deep learning algorithm GAN. For generative tasks like producing realistic images or synthesizing new data, deep learning models called Generative Adversarial Networks (GANs) are used. GANs are composed of a discriminator and a generator, two neural networks that compete with one another during training to produce accurate results. The generator network uses random noise as input to produce fake data samples, including images. The discriminator network tries to tell real samples from a training dataset apart from produced false samples. The generator learns to generate more realistic samples by attempting to fool the discriminator, while the discriminator learns to identify with greater accuracy.

A Generative Adversarial Network (GAN) is a deep learning architecture that pits two neural networks against one another in the context of a zero-sum game. The purpose of GANs is to create new, artificial data that closely resembles a preexisting data distribution.

To verify the proposed approach, we employed publically accessible DRIVE, STARE, CHASE-DB1, and HRF datasets and compared the proposed M-GAN with prior works. We evaluated the area under the recall (sensitivity), precision, specificity, and accuracy for comparison analyses, the area under the curve (AUC), F1 score, sensitive, and specificity. Comparative assessments demonstrated the higher performance of the suggested M-GAN generated over other investigations.

The following contributions are made by the proposed approach.

1) By combining conditional GAN with deep residual blocks, a novel deep learning architecture called M-GAN is proposed to create the segmentation of retinal blood vessels more correctly and precisely. The M-generator is made up of two stacked deep FCNs, each containing short-term skip connections and long-term residual connections, as well as a multi-kernel pooling block to enable the scale-invariance of vessel properties between the two stacked FCNs. A deeper neural network is also present in the M-discriminator.

2) To achieve improved performance, we have redesigned loss functions that incorporate BCE, LS, and FN losses. In order to balance precision and memory, the FN loss function, in particular, can lower the false-negative rate of earlier research.

3) By doing pre- and post-processing utilizing computer vision algorithms before and after performing M-GAN, we have also enhanced the performance of the suggested technique.

4) A number of parameters, including accuracy, AUC, IoU, F1 score, and MCC, are compared between the proposed M-GAN and previous research. M-GAN outperformed other research, according to the comparison analysis.

II. LITERATURE SURVEY

Xiaoyu guo, Cheng chen, Yuanyuan lu, Ke meng, Hongyu chen Kangneng zhou, Zhiliang wang, AND Ruoxiu xiao They proposes a neural network design for segmenting retinal vessels based on Dense U-net and Inception module, with Dense Block replacing U-skip net connections and Generative Adversarial Networks (GAN) generating multilayer neural networks.[1] Chunhui chen, Joon huang chuah, (Senior Member, IEEE),Raza ali, (Member, IEEE), AND Yizhou wang,represent the segmentation of retinal blood vessels using deep learning algorithms. The shape of retinal vessels reflects a patient's overall health and aids in the diagnosis of several conditions, including diabetes and hypertension. Deep learning algorithms have recently been used to segment retinal vessels, and this study investigated these suggested techniques, particularly the network designs and network designs.[2] KYEONG Beom park, Sung ho choi, AND Jae yeol lee proposes a new conditional generative adversarial network called M-GAN to conduct accurate and precise retinal vessel segmentation by balancing losses through stacked deep fully convolutional networks. It consists of a newly designed M-generator with deep residual blocks for more robust segmentation and an M-discriminator with a deeper network for more efficient training of the adversarial model. To verify the proposed method, the authors used DRIVE, STARE and compared it with other studies. Results showed that the proposed M-GAN derived superior performance than other studies.[3] Jyotiprava Dash Nilamani Bhoi They presents a three-step thresholding-based technique for the extraction of blood vessels from retinal pictures. PCA and CLAHE are used to enhance the retinal pictures, global Otsu thresholding is used to remove the blood vessels, and morphological cleaning is used to eliminate extraneous details. The two freely accessible DRIVE and STARE databases are used to assess the effectiveness of the proposed technique. [4] E. Deepika; S. Maheswari They research aims to identify glaucoma in retinal images and categories it according to its severity. Preprocessing methods such as filtering, green channel extraction and CLAHE are proposed, and feature extraction is used for classification. Sensitivity, specificity and accuracy of two classifiers are compared to attest an efficient diagnosis system.[5] Yongmin Li, Xiaohui Liu, Djibril Kaba, Ana Salazar-Gonzalez, proposes a new method for segmenting the optic disc and blood vessels in fundus retinal images, which are becoming more and more popular as a noninvasive diagnostic procedure.[6]

Although the segmentation of retinal blood vessels in these earlier works performed well, it is still difficult to carry out more optimized segmentation in terms of accuracy, IoU, and overall F1 score.

DIFFERENT DATASETS FOR PROJECT

We used the publicly accessible DRIVE, STARE datasets to confirm the suggested method.

The DRIVE database has been constructed to compare the segmentation of blood vessels in retinal pictures. For the diagnosis, screening, treatment, and evaluation of various cardiovascular and ophthalmologic diseases, retinal vessel segmentation and delineation of morphological attributes such as length, width, tortuosity, branching patterns, and angles are used.

The STARE Study was funded by the American National Institutes of Health and supported by the Shiley Eye Clinic and San Diego Veterans Administration Medical Center, with expertise from engineering to science to medical.

III. PROPOSED SYSTEM

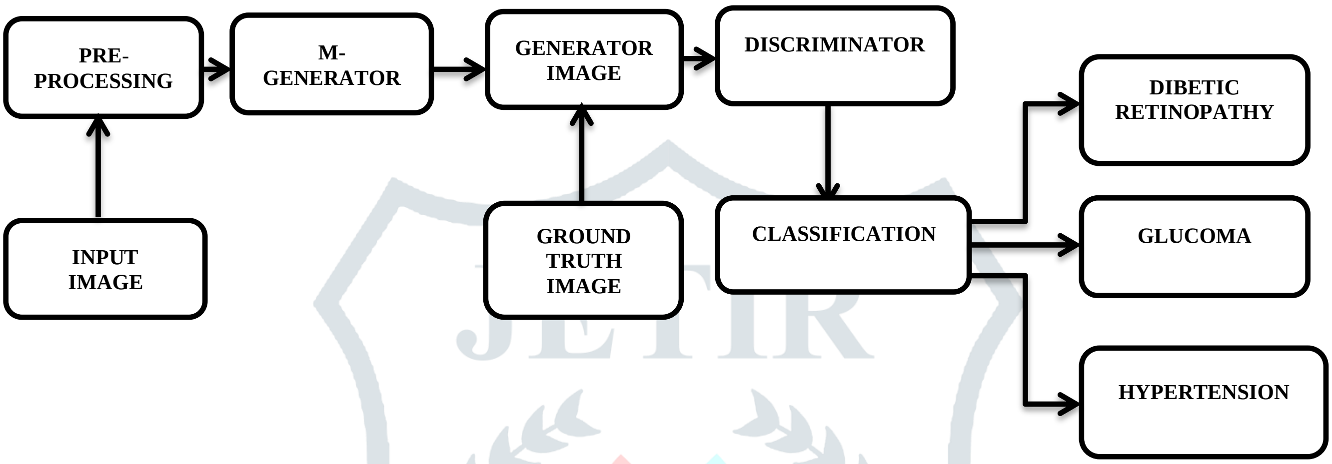


Fig. 2 -Proposed methodology of M-GAN

By balancing losses and using a stacked deep fully convolutional network, the M-GAN conditional GAN that this research proposes can segment retinal blood vessels more accurately and precisely. Figure depicts the proposed M-architectural GAN's layout.

INPUT IMAGE:-

The input image for retinal blood vessel segmentation is a fundus image, which includes the retina, vascular system, fovea, and optic disc. The fundus is the area of the inner eye that may be viewed through the pupil during an eye exam.

PRE PROCESSING:-

This paper introduces ACE for Automated Color Equalization, a novel technique for unsupervised enhancement of digital photographs. ACE imitates adaptive human visual system behaviors and recovers scene area appearance during the first visual encoding stage and normalizes values during the second display mapping stage

ACE is a novel computational methodology that combines equalization processes of the "Gray World" and "White Patch". It employs the adaptation mechanisms of the human visual system to extract visual data from its surroundings and adjust to a wide range of lighting conditions. ACE has demonstrated promising achievements in the solution of the color constancy problem. Preprocessing is a crucial stage in any deep learning or machine learning workflow, and retinal pictures can be preprocessed.

Preprocessing is a critical step in the M-GAN-based segmentation of retinal blood vessels and can enhance the model's functionality and accuracy.

M-GAN is a conditional GAN based on a "M" network topology with a freshly created M-generator and an M-discriminator to segment retinal blood vessels.

The M-generator consists of three convolutional layers, a short-term skip connection, and persistent connections between the up-sampling and down-sampling layers. These connections provide a deeper network that is longer and less prone to gradient vanishing.

M-GAN is a conditional GAN that combines up- and down-sampling of image characteristics to segment retinal blood vessels more accurately and precisely The M-generator has transposed convolutional layers for up-sampling to create segmented retinal blood vessel pictures. It has a two-stacked deep FCN "M" structure to support the scale-invariance of vessel segmentation, and a multi-kernel pooling (MKP) block is inserted between the stacked layers. The discriminator concatenates the created image with the original fundus image during training to identify it as a phoney label.

M-discriminator uses LSGAN loss function to solve gradient vanishing problem, combining ground truth fundus picture and image segmented by M-generator for training. The discriminator is a critical component of MGAN-based segmentation of retinal vascular blood, which uses the entire image to derive a scalar value.

The discriminator's task is to categories the input pictures as either created or fake, using a loss function to distinguish between the two types of pictures.

The discriminator helps the generator create more precise and realistic segmentations by assessing the generated segmentations and comparing them to the actual segmentations, leading to more accurate and reliable retinal vessel blood segmentations

MODIFIED ARCHITECTURE OF GAN:-

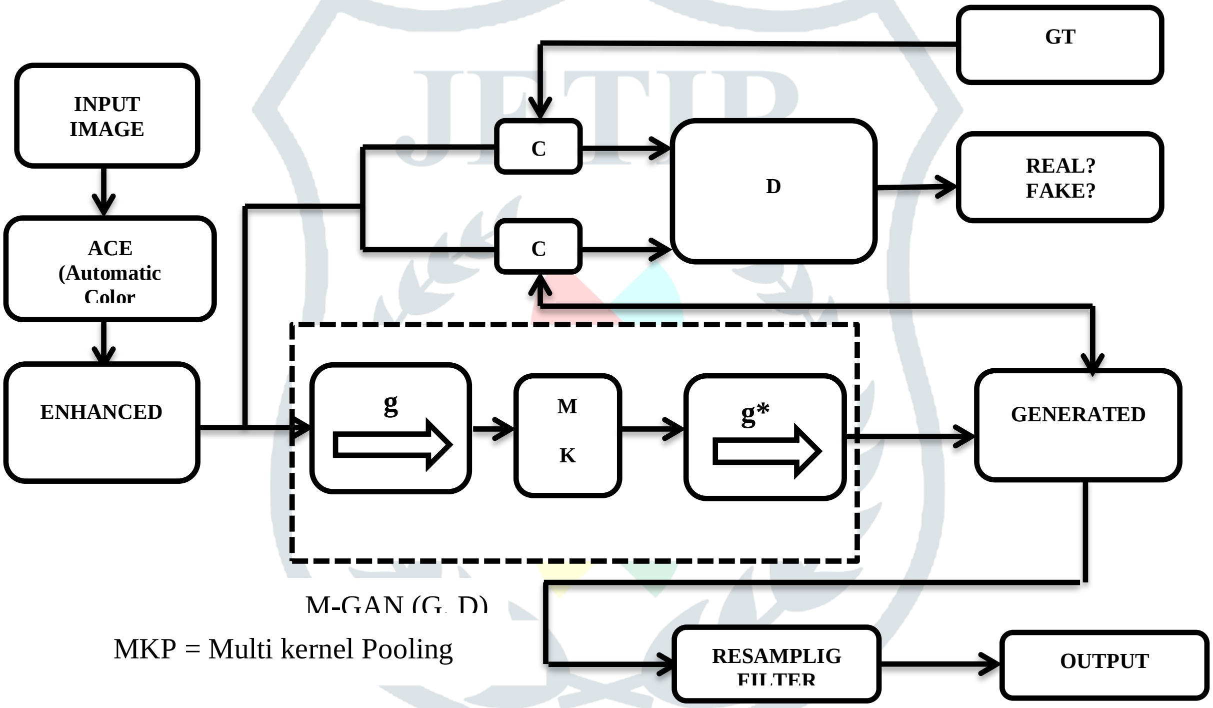


Fig. 3-Architecture of M-GAN

M-generator:-

The M-Generator in the M-GAN algorithm for retinal blood vessel segmentation is responsible for generating diverse segmentations of the input retinal fundus images. Each M-Generator is trained to generate a specific type of segmentation, such as a segmentation that focuses on the fine details of the blood vessels or emphasizes the overall structure of the vessels. During the training process, the M-Generators work together to generate a diverse set of segmentations of the input retinal fundus images. These segmentations are then passed through an M-Discriminator network, which is trained to distinguish between the real segmentations and the generated segmentations. The M-Generator's ability to generate diverse segmentations is essential for the M-GAN algorithm to produce accurate and comprehensive segmentations of the retinal blood vessels.

M-Discriminator:-

The M-Discriminator in the M-GAN algorithm for retinal blood vessel segmentation is responsible for distinguishing between the real segmentations of retinal blood vessels and the generated segmentations produced by the M-Generators. The M-Discriminator is a convolutional neural network that is trained on a dataset of both real and generated segmentations and learns to classify the segments as either real or generated based on their visual characteristics. The output of the M-Discriminator is used to compute the adversarial loss, which is a measure of how well the M-Generators are able to generate realistic segmentations. The M-Discriminator's ability to distinguish between real and generated segmentations is critical for the M-GAN algorithm to produce accurate and comprehensive segmentations of the retinal blood vessels. Overall, the M-Discriminator plays a crucial role in the M-GAN algorithm for retinal blood vessel segmentation, helping to ensure that the generated segmentations are realistic and diverse, leading to more accurate and reliable segmentation results.

IV.COMPARATIVE EVOLUTION

We measured sensitivity, specificity, IoU, F1 score, and ACC for comparative analysis as defined as follows.

$$\text{Se}=\text{Re}=\frac{TP}{TP+FN}$$

$$\text{Sp}=\frac{TN}{TP+FP}$$

$$\text{Acc}=\frac{TP+TN}{N}$$

$$\text{Mcc}=\frac{TP-SP}{\sqrt{\mathrm{P}\cdot\mathrm{S}\cdot(1-\mathrm{S})\cdot(1-\mathrm{P})}}$$

We must contrast the outcomes with/without the LS loss and FN loss functions in order to verify the efficacy and benefit of the proposed M-GAN architecture and its loss functions. The suggested deeper network must be contrasted with a shallow design devoid of leftover pieces. For comparison evaluation, we will assess performance metrics such as IoU, F1 score, and accuracy.

1 .INTERSECTION OVER UNION (IOU):-

IoU is a statistic used to assess how accurate a forecast is. It is a number that expresses how much two boxes overlap in numerical terms. It is used to assess the overlap of the Ground Truth and Prediction area in the context of object identification and segmentation.

$$IoU=\frac{Area\ of\ Overlap}{Area\ Of\ Unian}$$

2. F1 SCORE

The model score is represented by the F1 score, which depends on the accuracy and recall scores. A substitute for accuracy measures (it doesn't require us to know the entire number of observations), the F-score is a machine learning model performance statistic that equally weights precision and recall when assessing how accurate the model is.

F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Recall Score/)

3. ACCURACY

The ratio of true positives and true negatives to all positive and negative observations is the definition of model accuracy, a machine learning classification model performance statistic. It indicates how frequently the model can be expected to be accurate.

Accuracy Score = (TP + TN)/ (TP + FN + TN +FP)

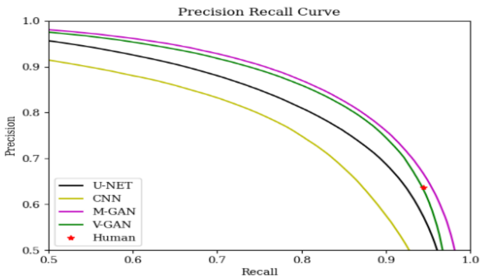


Fig.4-Precision Recall Curve of Drive Dataset

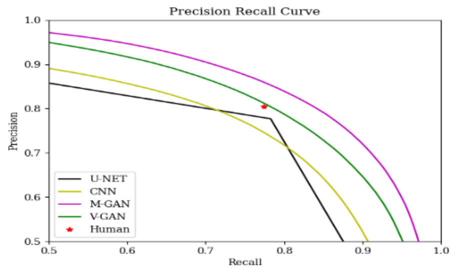


Figure.5.Precision Recall Curve of STARE Dataset

To evaluate the performance of the M-GAN algorithm, precision and recall can be calculated at different threshold levels and plotted on a precision-recall curve. The upper-right corner of the curve is typically the best area, with high precision and recall. When correctly separating pixels that are blood vessels from pixels that are not vessels, this point demonstrates the ideal precision/recall trade-off.

When segmenting retinal blood vessels, especially from retinal fundus images, the M-GAN algorithm can be evaluated in terms of precision and recall. M-GAN algorithm then exhibits strong performance across both data

Sensitivity and specificity are two frequently used metrics to evaluate the performance of binary classifiers, particularly in tasks involving medical image analysis. The sensitivity and specificity of a test can be evaluated.

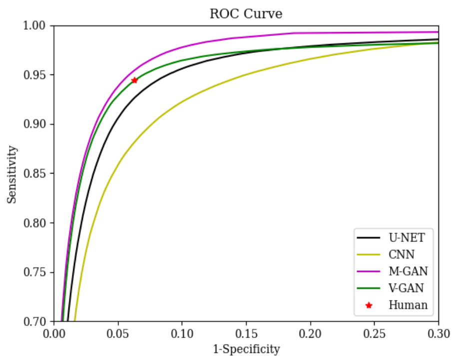


Fig.6.Sensitivity VS Specificity (ROC) Curve of DRIVE Dataset

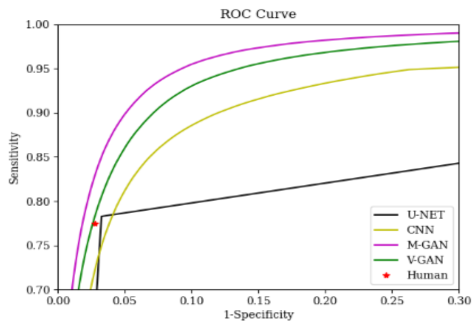
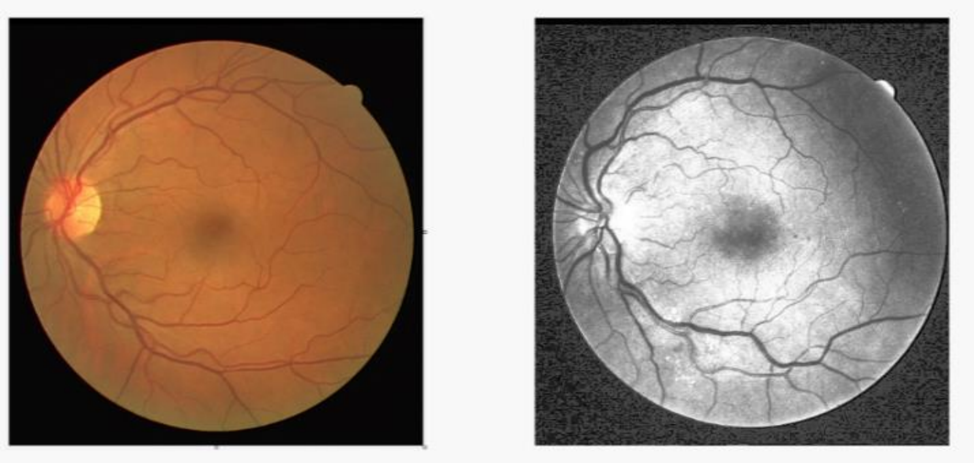


Fig.7.Sensitivity VS Specificity (ROC) Curve of STARE Dataset.

The percentage of true blood vessel pixels that are correctly identified by the M-GAN algorithm is known as sensitivity, also referred to as true positive(TP rate or recall. It evaluates how well the algorithm can identify blood vessels in the input image. On the other hand, the percentage of actual non-blood vessel pixels that the M-GAN algorithm correctly identifies is known as specificity. It evaluates how well the algorithm can recognize non-blood vessel regions in the input image.

Sensitivity and specificity can be calculated and plotted on a Receiver Operating Characteristic (ROC) curve to assess the effectiveness of the M-GAN algorithm in segmenting retinal blood vessels. The trade-off between sensitivity and specificity at various threshold levels is represented graphically by the ROC curve. One popular metric for assessing the algorithm's overall performance is the area under the ROC curve (AUC). The algorithm's overall performance in identifying blood vessels and non-blood vessel regions in retinal images is indicated by a high AUC

V.RESULT



A) Before Pre Proocessing (B) After Pre Proocessing

Fig.8. results of Pre and Post processing

Identifying eye diseases like glaucoma, hypertension, and diabetic retinopathy requires the use of retinal images. Preprocessing is a set of methods used to clean up unwanted artifacts like noise from retinal images. Contrast augmentation, image normalization, image registration, and noise reduction are typical preprocessing methods. Image normalization adjusts the brightness and contrast of the image to remove any uneven illumination, image registration aligns multiple images of the same eye to remove motion artifacts, and noise reduction removes noise from the image to make it clearer and simpler to analyze. Contrast enhancement increases the contrast of the image to make it easier to see details.

After preprocessing, a retinal image will be clearer, sharper, and easier to analyze. This can help to diagnose eye diseases more accurately and provide better treatment options for patients.

We comparative evaluation of the different methods, we include metrics such as precision, recall, F1 score, specificity, sensitivity, accuracy, and ACC. These metrics will help to quantify the quality of the generated synthetic data.

We compare different methods like U-net, CNN, V-GAN check the F1Score, precision, recall, F1score, specificity, sensitivity, accuracy, and ACC. The results of the comparative evolution are shown in Table II. M-GAN outperformed the other studies so that the retinal blood vessel segmentation was achieved with the best performance

We compared M-GAN with the other deep learning methods such as U-Net. M-GAN is a deep learning method that adds weights of the down-sampling network to the weights of the up-sampling network to reduce the vanishing gradient problem. Pix2Pix complements U-Net by using a generator that uses a pixel-wise objective function using the whole image, but its performance is poor due to its L1 loss function and its objective functions not suitable for image segmentation.

Regarding accuracy, IoU, F1 score, and MCC, the proposed approach performed better than previous studies. The fact that earlier studies divided the large fundus image into smaller patches and trained them made it particularly challenging to extract high-level features. The inference also took a long time. The proposed method, however, simply resizes the original image for the inference rather than segmenting it into smaller patches.

We perform the evolution architecture of the proposed GAN. Proposed Two-stacked deep architecture. The results of Two-Stacked deep FCN architecture are shown in table .The Two-Stacked deep FCN architecture derived the best results.

TABLE.I.PRECISION AND F1 SCORE VALUE OF M-GAN

Architecture	**precision**	**F1 score**
Two-Stacked	0.90638	0.88209

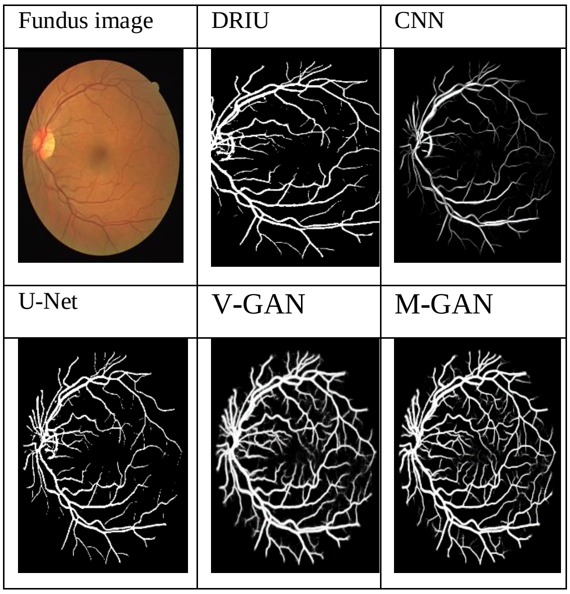


Fig 9. Segmentation results of an example in the DRIVE dataset.

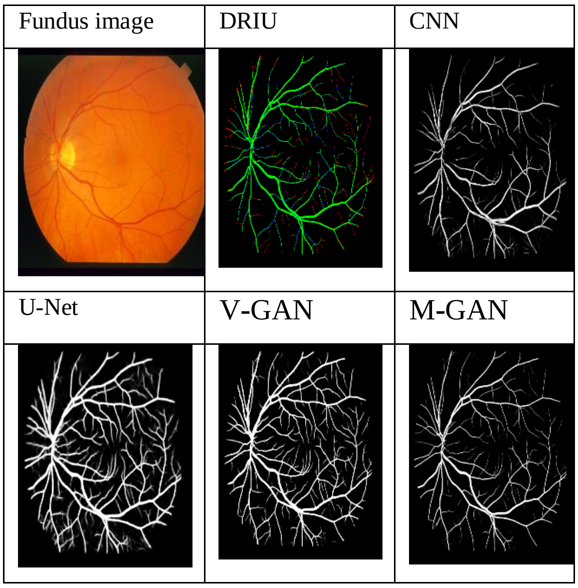


Fig 10.Segmentation results of an example in the STARE dataset.

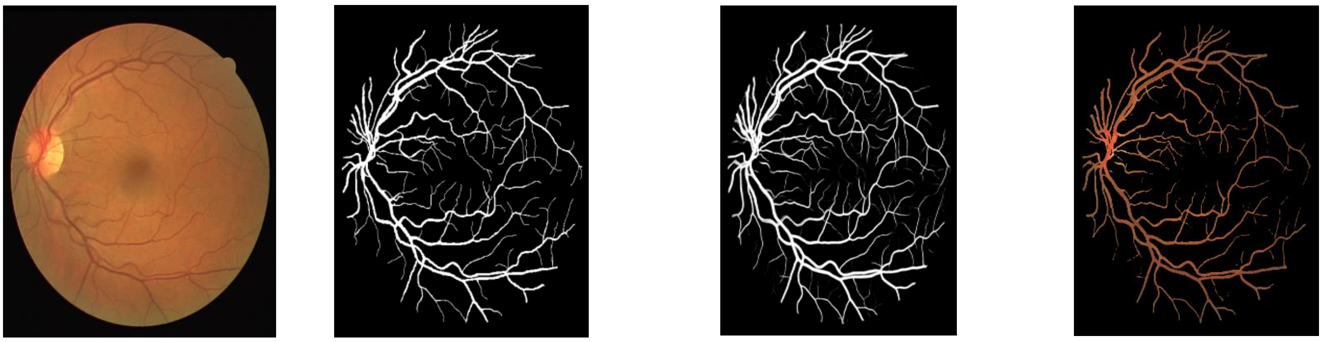
In the DRIVE dataset, a test image's segmentation results are displayed in Figure 9. M-GAN segmented images are also more accurate than images segmented using other algorithms like CNN, U-NET, and V-GAN, as shown in figure 10.Because factors like the performance metrics used to gauge segmentation accuracy can affect how accurately images are segmented. The ability of M-GAN to segment retinal images has been demonstrated, and it has the potential to produce segmented images that are incredibly realistic. Furthermore, M-GAN's multi-scale architecture enables it to recognize both local and global features of the input image, which can increase segmentation precision.

The segmentation of retinal blood vessels has shown promise when using the M-GAN (Multi-Generator Adversarial Network) algorithm. This algorithm uses a discriminator network to identify the difference between fake and real retinal fundus images and multiple generator networks to generate fake images that look like the real ones.

TABLE.II.. COMPARISON OF DIFFERENT METHODS RESULTS.

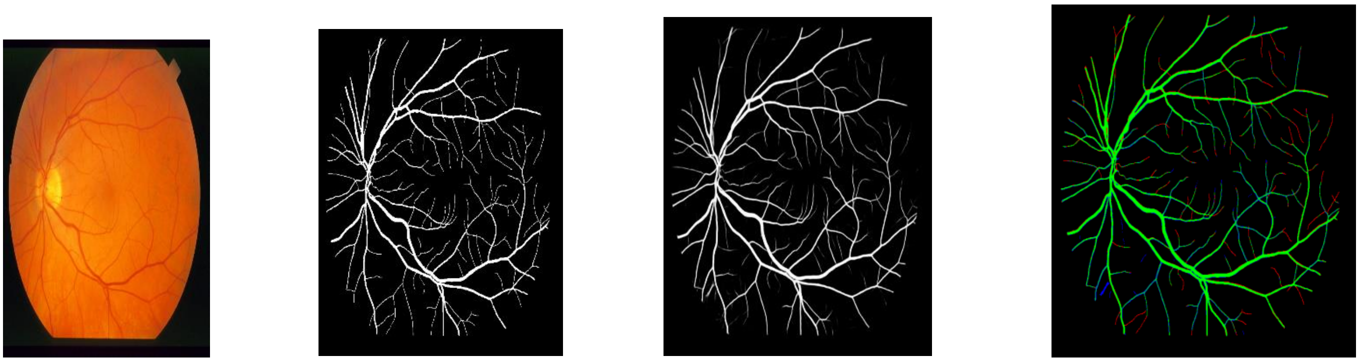
Methods	F1 Score	Accuracy	Specificity	Sesitivity	Auc	Precision
CNN	0.76008	0.93870	0.76282	0.96635	0.94364	0.81490
U-NET	0.77990	0.94375	0.82610	0.97281	0.87505	0.7937
V-GAN	0.79381	0.94747	0.79430	0.96981	0.96956	0.87729
M-GAN	**0.82099**	**0.95414**	**0.82610**	**0.97281**	**0.97929**	**0.90638**

The M-GAN algorithm has the potential to deliver segmentation results that are more precise and robust when compared to other conventional approaches, such as when the blood vessels have different sizes, shapes, and orientations. The M-GAN algorithm uses multiple generator networks to produce more varied and realistic synthetic images, which can increase the segmentation model's generalization and accuracy. Table no.2 shows that the accuracy,F1 score, Specificity, Sensitivity, Auc, Precision are higher than other methods.



(a) (b) (c) (d)

Fig.11. Segmentation results of an example in the DRIVE dataset: (a) original fundus image, (b) ground truth vessel image, (c) generated vessel image, and (d) generated M-GAN image



(a) (b) (c) (d)

Fig.12. Segmentation results of an example in the STARE dataset: (a) original fundus image, (b) ground truth vessel image, (c) generated vessel image, and (d) generated M-GAN image

IV CONCLUSION

This paper proposes a new generative adversarial network dubbed M-GAN for the exact and accurate segmentation of retinal blood vessels. It consists of an M-generator that uses deep residual blocks and an M-discriminator that has a deeper network for effectively training the adversarial model. To strengthen segmentation robustness and training efficiency, the proposed M-GAN includes the binary cross-entropy loss function and the false-negative loss function. To provide resilience in the segmentation of multiple datasets, the M-generator contains two layered deep FCNs that were created by copying and pasting the same network. The proposed M-GAN demonstrated superior performance on most of the measurements compared to the other methods, according to comparison analyses.It obtained the highest IoU and F1 score measurements in addition to the balanced precision and recall using the FN loss function. Additionally, it improved performance by applying a straightforward pre-processing step using the ACE algorithm and a post-processing step using the Lanczos resampling method. Finally, it will be used for various medical image segment.

ACKNOWLEDGMENT

With pleasure, the given concepts on "Retinal Fundus Imaging Segmentation and Classification Using Modified Gan Algorithm" are offered. Prof. S. S. Bhosale, who served as our internal guide, has our sincere gratitude for providing us with all the guidance and support we needed. We really appreciated their advice because it was so valuable. We also thank Dr. S. K. Jagtap, Head of the Electronics and Telecommunications Engineering Department at SKNCOE, for his invaluable assistance and counsel. Our principal, Dr. A. V. Deshpande, is to be thanked for his unwavering support and guidance, which were very helpful in getting this project done.

REFERENCES

[1] A. Khatami, A. Khosravi, T. Nguyen, C. P. Lim, and S. Nahavandi, ''Medical image analysis using wavelet transform and deep belief networks,'' xpert Syst. Appl., vol. 85, no. 15, pp. 190–198, Nov. 2017.

[2] L. C. Neto, G. L. B. Ramalho, J. F. S. R. Neto, R. M. S. Veras, and F. N. S. Medeiros, ''An unsupervised coarse-to-fine algorithm for blood vessel segmentation in fundus images,'' Expert Syst. Appl., vol. 78, pp. 182–192, Jul. 2017

[3] J. I. Orlando, E. Prokofyeva, and M. B. Blaschko, ''A discriminatively trained fully connected conditional random field model for blood vessel segmentation in fundus images,'' IEEE Trans. Biomed. Eng., vol. 64, no. 1, pp. 16–27, Jan. 2017

[4] X. Gao, Y. Cai, C. Qiu, and Y. Cui, ''Retinal blood vessel segmentation based on the Gaussian matched filter and U-net,'' in Proc. CISP-BMEI, Oct. 2017, "

[5] B. Zhang, S. Huang, and S. Hu, ''Multi-scale neural networks for retinal blood vessels segmentation,'' Apr. 2018,

[6] S. Thangaraj, V. Periyasamy, and R. Balaji, ''Retinal vessel segmentation using neural network,'' IET Image Process., vol. 12, no. 5, pp. 669–678, May 2018

[7] M. Z. Alom, C. Yakopcic, M. Hasan, T. M. Taha, and V. K. Asari, ''Recurrent residual U-net for medical image segmentation,'' J. Med. Imag., vol. 6, no. 1, Mar. 2019

[8] Q. Jin, Z. Meng, T. D. Pham, Q. Chen, L. Wei, and R. Su, ''DUNet: A deformable network for retinal vessel segmentation,'' Knowl.-Based Syst., vol. 178, pp. 149–162, Aug. 2019

[9] P. Xiuqin, Q. Zhang, H. Zhang, and S. Li, ‘‘A fundus retinal vessels segmentation scheme based on the improved deep learning U-Net model,’’ IEEE Access, vol. 7, pp. 122634–122643, 2019.

[10] Z. Zhang, H. Fu, H. Dai, J. Shen, Y. Pang, and L. Shao, ‘‘ET-net: A generic edge-attention guidance network for medical image segmentation,’’ in Proc. MICCAI, 2019

[11] T. A. Soomro, A. J. Afifi, J. Gao, O. Hellwich, L. Zheng, and M. Paul, ‘‘Strided fully convolutional neural network for boosting the sensitivity of retinal blood vessels segmentation,’’ Expert Syst. Appl., vol. 134, pp. 36–52, Nov. 2019

[12] Kyeong-Beom Park,Sung Ho Choi and Jae Yeol Lee “M-GAN: Retinal Blood Vessel Segmentation by Balancing Losses Through Stacked Deep Fully Convolutional Networks” August 20, 2020.