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Advancing Glaucoma Detection: Synthetic Image Generation via Generative Adversarial Networks and Classification with Pretrained MobileNetV2

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***Abstract* — Irreversible vision loss, generally insidious in start and lacking apparent symptoms, is usually attributed to glaucoma. Detecting glaucoma in its early stages is crucial since it may reduce disease progression. Conventional diagnostic approaches, depending on manual assessments, are notably prone to mistakes. Hence, automated glaucoma analysis acquires vital relevance for precise and prompt detection. Moreover, medical picture databases frequently display asymmetries, creating a problem. To solve these challenges, this paper presents a unique framework employing generative adversarial networks (GANs) to generate images, thus addressing dataset imbalances. Specifically, in the context of fundus images, standard approaches like image-to-image translation are applied to build synthetic fundus images and associated vascular networks, attempting to boost overall image quality and capture finer details. Gaussian filtering is originally done to pre-process the raw dataset, eliminating unwanted noise. Subsequently, GANs are applied for dataset balancing, providing synthetic images that boost classification accuracy. Optic cup segmentation is conducted using the Enhanced Level Set Algorithm. Finally, Pretrained MobileNetV2 permits accurate classification of glaucomatous images into normal and pathological categories. Experimental results illustrate the efficacy of our suggested framework, obtaining an accuracy of 98.9%, exceeding existing techniques.**

Keywords: Glaucoma detection, Generative Adversarial Networks, Fundus images, Optic cup segmentation, MobileNetV2, Image synthesis

I. Introduction

Glaucoma, now the leading cause of global disability, affected an estimated 85.9 million individuals in 2023 [1]. This condition culminates in irreversible vision loss due to optic nerve damage, disrupting the transmission of visual information to the brain [2]. Particularly challenging is its asymptomatic nature in early stages. Structural changes in the optic nerve head, or Optic Disc, signify glaucoma progression. Comprising the neuro-retinal rim and the optic cup, alterations manifest as thinning rims and enlarging cups. Monitoring these changes becomes imperative. However, automated optic cup identification proves more complex than disc identification [3]. Historically, glaucoma diagnosis relied on various instrument-based approaches like DCT, air puff tonometers, and tonometry [4]. Yet, these methods posed limitations such as lower accuracy, time-consuming procedures, and manual intervention. Consequently, there's been a shift towards computerized glaucoma diagnosis to streamline comprehensive examinations and address these challenges [5].

In recent years, a number of automated procedures have been established to simplify the automated identification of glaucoma. These techniques largely make use of pictures of the retinal fundus [6]. For the purpose of streamlining the diagnostic procedure, improving accuracy, and reducing reliance on approaches that are both time-consuming and manual, this improvement is being made [7-8].

The implementation of automated methods in determining the presence of glaucoma marks a big step forward in terms of enhancing the efficiency and precision with which this eye ailment is identified [9]. Computer-Aided Design (CAD) has the potential to become an invaluable instrument for the thorough investigation of illnesses across huge populations. It offers improvements over the conventional physical examinations that are carried out by medical personnel. The use of this technology has the potential to improve, refine, and support medical systems, especially in poor nations where there is a dearth of optometrist who are skilled and knowledgeable in their field [10-11].

II. Related Work

A new method called M-LAP has been created to improve the accuracy of glaucoma research by pulling features from different scales. By activating glaucoma in this way, this method also successfully bridges the gap between global semantic analysis and precise locations [12]. Also, it finds specific places in fundus images that are different, which is

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helpful for medically readable glaucoma analysis [13]. The results of the test of M-LAP's effectiveness, especially in terms of Area Under the Curve (AUC), are encouraging. The EAMNet method used in this case has a big advantage: it is very sensitive, which helps make it more accurate. However, it is pointed out that the optic cup needs to be approached with more attention, and GAP can't fully display high-resolution feature maps [14-15].

Through the application of computer vision algorithms to digital fundus images, a novel piece of research has contributed to the development of an effective imaging solution for automating the process of glaucoma identification [16]. In order to segment the optic disc, the approach that was created makes use of a geometric feature-oriented tactical model. This helps to improve the accuracy of the system during the recognition of noise and variations in light [17-18]. There is a significant disadvantage, which is the requirement to resolve class imbalance, despite the fact that it provides enhanced accuracy with high sensitivity. It has been determined that one of the most significant limitations is the varying intensity of pixels that are seen within the optic disc and blood vessels [19].

To diagnose glaucoma directly from mobile devices. The construction of Convolutional Neural Networks (CNNs) for classification and segmentation tasks is made possible by the integration of a variety of datasets [20]. The pipeline that has been provided for the evaluation of glaucoma offers complete segmentation and characterizes linked structures, which ultimately results in improved analysis. During the experimental study, the scheme displays minimal time consumption and complexity, hence enhancing accuracy and optimizing the F-score [21].

III. MATERIALS AND METHODS

Manual diagnosis of glaucoma is often time-consuming and expensive. While some automated diagnostic techniques exist, many either underperform or lack robust statistical validation. Therefore, our proposed work introduces an enhanced Convolutional Neural Network (CNN) detection model, meticulously detailed in the subsequent sections, illustrated in Figure 1.

In Figure 1 provides a graphical illustration of the complete workflow. We delineate the architecture and components of our CNN model. The model comprises multiple layers designed to extract features from retinal fundus images crucial for glaucoma detection. These layers include convolutional, pooling, and fully connected layers, each serving a specific function in processing image data. The convolutional layers apply filters to the input image, detecting various patterns and features. Subsequently, pooling layers reduce the spatial dimensions of the feature maps, preserving important information while decreasing computational complexity. Finally, fully connected layers integrate extracted features to make predictions about the presence of glaucoma. Furthermore, our model incorporates robust statistical validation techniques to ensure its reliability and accuracy. This includes rigorous testing on diverse datasets, cross-validation procedures, and performance evaluation metrics such as sensitivity, specificity, and area under the ROC curve.

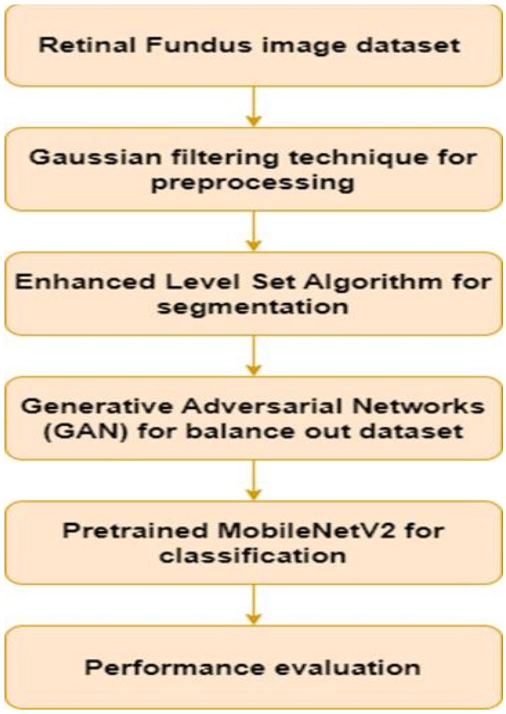

Fig 1. Workflow of Proposed Work

By employing this improved CNN model, we aim to overcome the limitations of existing automated glaucoma diagnostic techniques, providing a more efficient, accurate, and cost-effective solution for early glaucoma detection.

IV. PRE-PROCESSING PHASE

The initial step involves pre-processing the image using Gaussian filtering, a critical operation aimed at enhancing image quality. Gaussian filtering is employed to effectively clean up blurred images by removing noise and blur introduced by the attenuation of higher frequencies within an image.This filtering technique is particularly beneficial for reducing Gaussian noise in scenarios such as speckle noise or brain MR images in ultrasound imagery. In this method, the Gaussian filter replaces noisy pixels with the average value of adjacent pixels. A window size of 5 x 5 is commonly utilized for Gaussian denoising.

V. GENERATIVE ADVERSARIAL NETWORKS (GAN)

Within the context of game theory, the Generative Adversarial Nets (GAN) functions according to the principles of Nash equilibrium [22]. There are two components that make up the fundamental structure of the model, and these are G and D. G's primary objective is to get an understanding of the mapping relationship that exists between the retinal picture x and the optic disc and optic cup that correspond to it. In D directs G to reduce this discrepancy as much as possible, which ultimately results in an improvement in the precision of the partitioned optic disc and optic cup. In the course of model training, it is essential to perform periodic optimization of G and D in order to enhance their capacity of segmentation and discrimination. The ultimate objective of the architecture is to achieve the below objective function which was given in Equation (1).

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$$\min_{G}\max_{D}\{\mathbb{E}_{x\in T,y\in L}[\log D(x,y)] + \mathbb{E}_{x\in T,y\in L}\left[\log\left(1-D\left(x,G(x)\right)\right)\right]\} \quad (1)$$

VI. GENERATOR NETWORK (GE)

The G is a complete convolutional network framework with 19 layers. In Figure 2 shows the structure of its network. The retinal picture x is fed into this model. In this study, we set H = W = 512 and C1 = 3. There is an encoder (on the left) and a decoder (on the right) in the network layout. To get characteristics from the retinal image, the encoder uses the VGG16 network layout. Even though the original VGG16 network that has a downsampling ratio of 32, we found that too much downsampling causes important characteristic data to be lost, especially in areas that are smaller than 32 pixels, like the optic disc. To fix this, we got rid of the last two downsampling levels and raised the reduction factor to 16. This cut down on data loss, model settings, and computations. The forecasted probability map shows which group has the highest chance of occurring for each pixel. This makes it possible to separate the optic disc and optic cup at the same time [23].

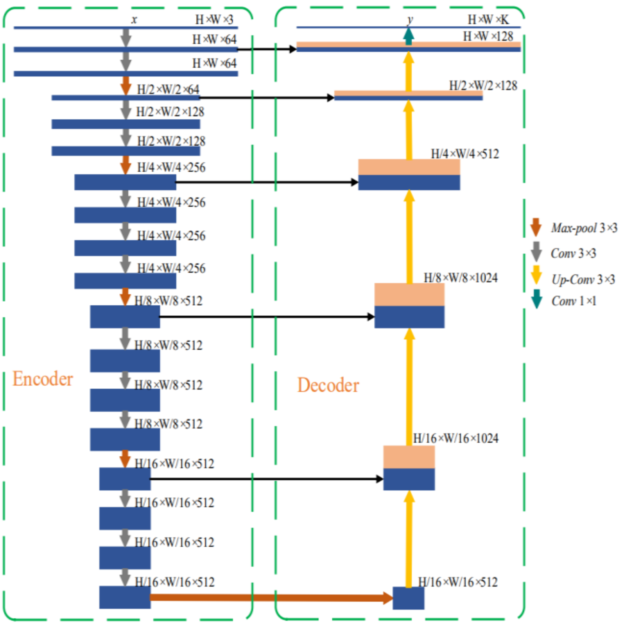

Fig 2. Structure of Generator

VII. SEGMENTATION OF OPTIC CUP USING ENHANCED LEVEL SET ALGORITHM

Prior techniques have, historically speaking, primarily been classified as belonging to an edge-oriented framework [24]. These approaches mainly rely on the picture gradient in order to develop an edge-detecting function. An illustration of the mathematical definition of a level set model can be found in Equation (2).

$$\frac{\partial\phi}{\partial t} = IG|\nabla\phi|\left(\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)+u\right) \quad (2)$$

From Equation (2), $\mathrm{div}\left(\frac{\nabla\phi}{|\nabla\phi|}\right)$ forecasts curvature of the mean, u denotes the forces with respect to ballon and ϕ indicates the different levels of set operation. When it comes to level set schemes, the reliability, which is represented by the symbol φ, plays a significant role in ensuring that constant advancement and accurate computations are achieved. A formula for a rapid-level set has been developed in order to handle this difficulty. Equation (3) is the representation of this formula.

$$\frac{\partial\phi}{\partial t} = \mu P(\phi) + \eta(IG,\phi) \quad (3)$$

The penalizing function, which is denoted by the symbol $P(\varphi)$, places an emphasis on the difference between the sign separation operation and the deviation of φ during its evolution. As shown in Equation (4), the succeeding function $\eta(IG,\varphi)$ is responsible for integrating the data pertaining to the image gradient.

$$\eta(IG,\phi) = \lambda\delta(\phi)\,\mathrm{div}\left(IG\frac{\nabla\phi}{|\nabla\phi|}\right) + uIG\delta(\phi) \quad (4)$$

For the Dirac functioning, the symbol δ(φ) is used to symbolize it. In order to determine the individual implications of the restrictions, parameters such as λ,u,and μ are utilized.

VIII. ACCURATE CLASSIFICATION OF GLAUCOMA USING MOBILENETV2 PRETRAINED MODEL

The MobileNetV2 network, which has been pre-trained on the ImageNet dataset, is the basis for this methodology. It acts as the foundation. Within the framework of the proposed method, we augment the convolutional layers of MobileNetV2 by incorporating a collection of calculations that are referred to as the head model. A feature map with dimensions of 7x7x1280 pixels is produced as a consequence of the results from the base model being directed into the first layer of the topmost model, which is a global pooling layer. A pooling operation is carried out by the global pooling layer, which results in the production of a one-dimensional feature vector. This is done in order to greatly reduce the dimensionality of the data. In the overall pooling layer, the suggested method makes use of an average pooling technique with a kernel size of 7x7 pixels. This results in the generation of an output feature map that is 1x1x1280 pixels in size [25-26].

The global pooling layer is followed by the implementation of two fully linked layers, both of which are fully connected to one another. Within these entirely interconnected layers, the ReLU activation function is responsible for activating 128 and 64 nodes respectively. When the two subclasses of the dataset (glaucoma and non-glaucoma) and the application of one-hot encoding are taken into consideration, the output layer is made up of two nodes that are activated by softmax technology. Particularly noteworthy is the fact that the 1x1 convolutional layer diverges from the standard by not having a layer for batch normalization and an activation function (ReLU6). This is due to the fact that its low-dimensional output is only subjected to batch normalization.

IX. RESULTS AND DISCUSSION

To assess our method's dimensional stability in identifying and categorizing glaucoma patients, we used the open-source ORIGA database, which is built in MATLAB. Out of 650 samples included in the ORIGA database, 168 show areas of human eyes damaged by glaucoma and 482 show healthy eyes. Artifacts in the ORIGA dataset make glaucoma

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categorization difficult. These artifacts include large variability in optic disc (OD) and optic cup (OC) size, color, location, and texture. The dataset is a complicated testbed for detection of glaucoma since it contains varied picture aberrations such noise, blurring, and fluctuations in hue and intensity. The output of GAN is given in Figure 3, which was taken after input has been passed. Followed by this segmentation process has been done using enhanced level set algorithm, which helps to accurately segregates the foreground and background of the glaucomatous fundus images and the respective result was given in Figure 4.

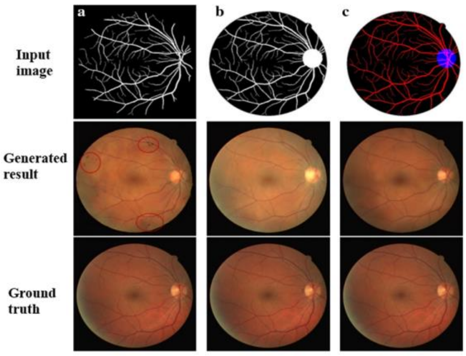

Fig 3. Synthetic Output after GAN Applied

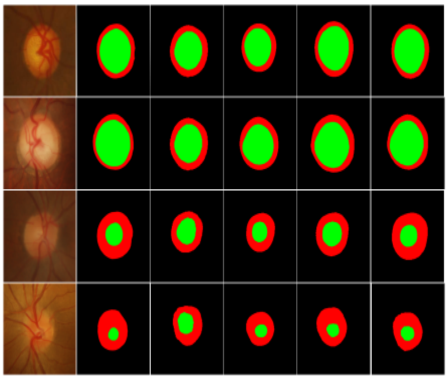

Fig 4. Segmented Output

The comparison is presented in Table 1, which includes quantitative measures that were derived from the comparison. This allows for a comprehensive evaluation of the effectiveness and superiority of the options that are now available.

TABLE 1. PERFORMANCE COMPARISON OF PROPOSED APPROACH OVER EXISTING TECHNIQUE

Methods	**Accuracy (%)**	**Precision (%)**	**Recall (%)**
Deep CNN [20]	92.5	92.3	91.3
Graph CNN [21]	92.9	92.9	91.2
Ensembling [22]	93.1	93.2	92.3
U-Net + Inception V3 [23]	93.6	94.9	93.7
ODGNet [24]	95.2	95.1	94.6
U-Net + EfficientNet [25]	96.5	95.3	95.7
Proposed Model (GAN+PTMNV2)	98.9	98.4	96.4

The relevant comparative graph is shown in Figure 5 and Figure 6, which can be found here.

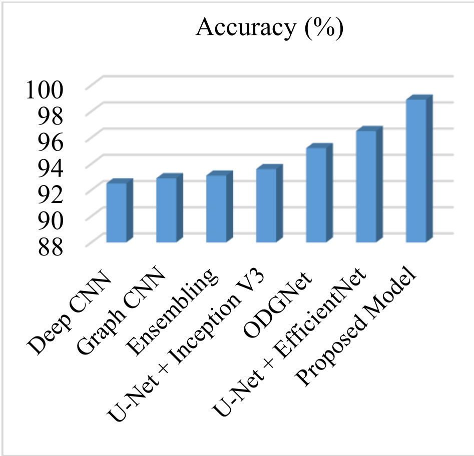

Fig 5. Accuracy

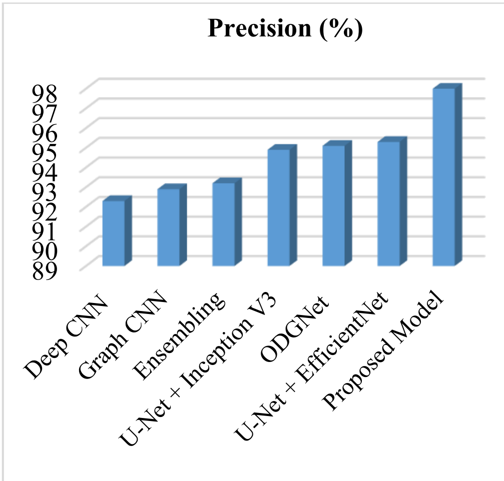

Fig 6. Precision

X. CONCLUSION

Our study effectively addresses the challenge of early glaucoma detection with high precision. Glaucoma, a leading cause of permanent vision loss, often evades early diagnosis due to the limitations of traditional, manual methods. By leveraging Generative Adversarial Networks (GANs) to synthesize balanced, high-quality fundus images, our framework overcomes the inherent dataset imbalance in medical imaging. Image-to-image translation and Gaussian filtering enhance the quality and detail of synthetic images, contributing to more accurate diagnoses. Additionally, the Enhanced Level Set Algorithm ensures precise segmentation of the optic cup, refining the accuracy of subsequent glaucoma classifications. The Pretrained MobileNetV2

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model facilitates the accurate classification of images into normal and pathological categories, achieving an impressive accuracy of 98.9%. This result surpasses existing approaches, highlighting the framework's potential to revolutionize automated glaucoma analysis. Our method paves the way for improved diagnostic precision, enabling timely intervention and more effective management of glaucoma, ultimately helping to prevent irreversible vision loss of these mobile applications in enhancing patient care.

REFERENCES

[1] Sarhan, Abdullah, Jon Rokne, and Reda Alhajj. "Glaucoma detection using image processing techniques: A literature review", Computerized Medical Imaging and Graphics Vol. 78, pp: 101657, 2019.

[2] S. Anindita and H. Agus, “Automatic glaucoma detection based on the type of features used: a review”, Journal of Theoretical and Applied Information Technology, vol. 72, no. 3, pp. 366–375, 2015.

[3] Abbas, Qaisar. "Glaucoma-deep: detection of glaucoma eye disease on retinal fundus images using deep learning", International Journal of Advanced Computer Science and Applications Vol. 8, no. 6, 2017.

[4] Dey, Abhishek, and Samir K. Bandyopadhyay. "Automated glaucoma detection using support vector machine classification method." British Journal of Medicine and Medical Research Vol. 11, no. 12, 2016.

[5] Claro, Maíla, Leonardo Santos,et al "Automatic glaucoma detection based on optic disc segmentation and texture feature extraction." clei electronic journal Vol. 19, no. 2, pp: 5-5, 2016.

[6] I. Govindharaj, S. Chattopadhyay, K. Joshi, V. Kukreja and R. Sharma, "Improving Beech Bark Disease Classification: A Multiclass Approach with CNN-MLP Fusion," 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET), pp. 1-4, 2024.

[7] Odstrcilik, Jan, et al. "Thickness related textural properties of retinal nerve fiber layer in color fundus images." Computerized Medical Imaging and Graphics Vol. 38, no. 6, pp: 508-516, 2014.

[8] Zilly, Julian, Joachim M. Buhmann, and Dwarikanath Mahapatra. "Glaucoma detection using entropy sampling and ensemble learning for automatic optic cup and disc segmentation." Computerized Medical Imaging and Graphics vol. 55 pp: 28-41, 2017.

[9] Fu, Huazhu, Jun Cheng, et al. "Disc-aware ensemble network for glaucoma screening from fundus image." IEEE transactions on medical imaging Vol. 37, no. 11 pp: 2493-2501, 2018.

[10] Chen, Xiangyu, et.at., "Glaucoma detection based on deep convolutional neural network". In 2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC), pp. 715-718. IEEE, 2015.

[11] I. Govindharaj, K. Rajput, N. Garg, V. Kukreja and R. Sharma, "Enhancing Rice Crop Health Assessment: Evaluating Disease Identification with a CNN-RF Hybrid Approach," 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET), pp. 1-5, 2024.

[12] P. H. Prastyo, A. S. Sumi, and A. Nuraini, “Optic cup segmentation using U-net architecture on retinal fundus image,” Journal of Information Technology and Computer Engineering, vol. 4, no. 2, pp. 105–109, 2020.

[13] L. Li, M. Xu, H. Liu et al., “A large-scale database and a CNN model for attention-based glaucoma detection,” IEEE Transactions on Medical Imaging, vol. 39, no. 2, pp. 413–424, 2020.

[14] El‐Hag, Noha A.et al,. "Classification of retinal images based on convolutional neural network." Microscopy Research and Technique Vol. 84, no. 3 pp: 394-414, 2021.

[15] Zhang, Guanghua, et al "Hybrid graph convolutional network for semi-supervised retinal image classification." IEEE Access Vol. 9 pp: 35778-35789, 2021.

[16] Sikder, Niloy,et al, "Severity classification of diabetic retinopathy using an ensemble learning algorithm through analyzing retinal images." Symmetry Vol. 13, no. 4 pp: 670, 2021.

[17] Bilal, Anas, et.at., "AI-Based Automatic Detection and Classification of Diabetic Retinopathy Using U-Net and Deep Learning." Symmetry Vol. 14, no. 7 pp: 1427, 2022.

[18] Latif, Jahanzaib, Shanshan Tu, Chuangbai Xiao, Sadaqat Ur Rehman, Azhar Imran, and Yousaf Latif. "ODGNet: a deep learning model for automated optic disc localization and glaucoma classification using fundus images." SN Applied Sciences Vol. 4, no. 4 pp: 98, 2022.

[19] Islam, Mir Tanvir, et.al., "Deep learning-based glaucoma detection with cropped optic cup and disc and blood vessel segmentation." IEEE Access Vol. 10 pp: 2828-2841, 2021.

[20] O. Ronneberger, P. Fischer, and T. Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation,” in Proceedings of the Medical Image Computing and Computer-Assisted Intervention, pp:234-241, 2015.

[21] I. Govindharaj, N. Thapliyal, M. Manwal, V. Kukreja and R. Sharma, "Enhancing Mango Quality Evaluation: Utilizing an MLP Model for Five-Class Severity Grading," 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET), pp. 1-4, 2024.

[22] J. Long, E. Shelhamer, and T. Darrell, “Fully Convolutional Networks for Semantic Segmentation,” in proceedings of the IEEE conference on computer vision and pattern recognition, pp. 3431–3440, Boston, MA, USA, June 2015.

[23] Z. Zhou, M. M. R. Siddiquee, N. Tajbakhsh, and J. Liang, “UNet++: a nested U-net architecture for medical image segmentation,” Deep Learning in Medical Image Analysis and Multimodal Learning for Clinical Decision Support, vol. 11045, pp. 3–11, 2018.

[24] J. Chen, Y. Lu, Q. Yu et al., “TransUNet: Transformers Make Strong Encoders for Medical Image Segmentation,” 2021.

[25] Govindharaj, I., Karthick, G., and Micheal G., (2024), "Hybrid Approach for Effective Segmentation and Classification of Glaucoma Disease Using UNet++ and CapsNet", Revue d'IntelligenceArtificielle, Vol. 38, No. pp. 613-621.

[26] I. Govindharaj, N. Thapliyal, M. Aeri, V. Kukreja and R. Sharma, "Onion Purple Blotch Disease Severity Grading: Leveraging a CNN-VGG16 Hybrid Model for Multi-Level Assessment," 2024 International Conference on Innovations and Challenges in Emerging Technologies (ICICET), pp. 1-5, 2024.