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RESEARCH ARTICLE

GD^2-EFFINET: GLAUCOMA DISEASE DETECTION AND SEGMENTATION OF DEEP LEARNING MODELS USING EFFICIENTNETB0

R. Shobana [1, *], Abitha V K Lija [2] and S. Shikky Marice [3]

[1] Assistant Professor, Computer Science and Engineering, S.A. Engineering college, Chennai, Tamil Nadu, India
[2] Assistant Professor Computer Science and Engineering Meenakshi College of Engineering, Chennai, Tamil Nadu, India.
[3] Research Scholar, Sri Krishna College of Engineering and Technology, Coimbatore, Tamil Nadu, India

Corresponding e-mail: rubanshobana@gmail.com

Abstract – Glaucoma is a major contributor to irreversible blindness, a condition marked caused by optic nerve injury, which is frequently brought on by high intraocular pressure. For vision loss to be effectively managed and prevented, early detection is essential. Conventional diagnostic techniques mostly rely on labor-intensive, error-prone manual analysis. To overcome these challenges, a novel deep learning based GD2-EffiNet model is proposed for the detecting of Glaucoma disease. Initially, images are pre-processed using the Gaussian Star Filter (GaSF) to enhance image quality and remove noise. EfficientNet-B0 is employed to extract deep features, enabling the classification of normal and abnormal glaucoma images. Finally, UNet is used to segment the abnormal regions, facilitating early diagnosis. The effectiveness of the proposed GD2-EffiNet method using metrics like F1 score, sensitivity, accuracy, and specificity. The classification accuracy of the proposed GD2-EffiNet model was 99.41%. The proposed model enhanced the total accuracy 0.03%, 1.56%, and 0.59% better than CG-EffiNet, ODGNet, SEG-UNet respectively. The proposed GD2-EffiNet model offers a reliable and efficient solution for automated Glaucoma disease detection, which is essential for early diagnosis and effective management of the condition.

Keywords – *Glaucoma disease, deep learning, Gaussian Star filter, EffientNetb0, UNet, Traditional diagnostic.*

1. INTRODUCTION

Glaucoma is a collection of disorders that affect the optic nerve in the eyes, a crucial component for vision. Intraocular pressure (IOP) refers to unusually high pressure inside the eye frequently the source of this injury [1]. Over time, elevated IOP can erode the optic nerve fibers, resulting in blindness or diminished vision if not treated. Glaucoma, which can afflict people of any age, is a leading cause of blindness globally, particularly in older persons [2]. Although there is other the two most prevalent Angle-closure and primary open-angle glaucoma are two types of glaucoma. It is difficult to identify early because it develops slowly and frequently shows no symptoms until considerable vision loss occurs [3]. In contrast, angle-closure glaucoma is less prevalent but can manifest rapidly with symptoms like headaches, nausea, blurred vision, and excruciating eye discomfort [4]. Other less common types include both congenital and normal-tension glaucoma, which can occur in infants. Treatment for Lowering intraocular pressure is usually necessary for glaucoma to prevent more harm to the optic nerve. Depending on how severe the disease is, this can be accomplished with surgery, laser treatment, or drugs such as eye drops. [5] Regular eye examinations are vital, especially for individuals are more susceptible, like those that have glaucoma in their family, older adults, or people of African, Hispanic, or Asian descent. Timely Preventing eyesight loss requires early detection and effective treatment caused by glaucoma.

In recent years, deep learning has revolutionized the early detection and diagnosis of glaucoma, offering promising solutions for analyzing medical images, such as fundus images and scans using optical coherence tomography [6]. CNN are a widely used deep learning architecture that can automatically identify if an image is glaucomatous or healthy by extracting pertinent information from it. [7] This approach enhances the precision and effectiveness of glaucoma diagnosis by minimizing the need for manual intervention and allowing for rapid, large-scale screening. [8] DL models have also shown potential in predicting disease progression and monitoring intraocular pressure trends, which are critical for managing glaucoma. The labeled medical data, these models can learn subtle patterns in eye structure changes over time, aiding clinicians in making informed decisions [9]. Despite these advancements, issues such model interpretability, the requirement for a variety of high-quality datasets, and data privacy remain key areas of focus in the ongoing research for deploying deep learning-based glaucoma diagnostics in clinical settings [10].

Glaucoma is a chronic, progressive illness that has an impact on the optic nerve irreparably and, if left untreated, can cause blindness or visual loss [11]. Traditional diagnostic methods depend on labor-intensive, human error-prone manual processing of ocular images, particularly during the initial phases of the illness when symptoms are subtle. [12] The growing global prevalence of glaucoma, especially in aging populations, there is an urgent the requirement for automated, effective, and precise diagnostic tools that can identify the illness early and monitor its progression effectively, reducing the risk of vision impairment [13]. Additionally, variability in image quality and lack of large, diverse datasets can hinder the robustness of these models. To overcome this problem, a novel GD2-EffiNet model has been proposed for Glaucoma disease classification. The major research contributions are mentioned below;

- The research aims to create a novel deep learning based GD2-EffiNet used for detection of Glaucoma disease.
- Initially, the input Glaucoma images are pre-processed using GaSF to enhance the image quality and remove the noises from Glaucoma images.
- Then the proposed method utilizes disease detection using EfficientNetb0 is used for extracting the deep features to classify Normal Glaucoma and Abnormal Glaucoma for Huntington images.
- Finally, UNet is used to segmentation for segmenting the abnormal Glaucoma images.
- The proposed GD2-EffiNet effectiveness was assessed using parameters like recall, specificity, accuracy, precision, and F1 score.

The remainder of the paper is arranged accordingly. Section 2 provides a summary of the literature review; Section 3 discusses about the proposed model and Section 4 focuses at the performance of the proposed approach and compares it to other methods. Finally, conclusion and future scope are explained in Section 5.

2. LITERATURE SURVEY

The researchers have recently released a number of advanced deep learning (DL) and machine learning (ML) designs to improve the reliability for the Glaucoma disease. Several of these techniques are investigated in the following section.

In 2022 Sudhan, M.B., et al., [14] devised a deep learning technique for early prediction of glaucoma. The output is contrasted with several DL models that are currently in use for CNN classification, including DenseNet-169, Inception ResNet, VGG-19, and ResNet 152v2. The recommended model's accuracy in testing was 96.90%, but in training it was 98.82%.

In 2020 Pandey, A., et al., [15] devised the deep learning approaches for the detection of image processing methods to treat glaucoma. The CNN model of DL, ML techniques, and image processing techniques are the three shared methods for detecting glaucoma disease. The K closest neighbor method yielded the accuracy of 99.6% of the deep learning model was the VVG-16 with the greatest accuracy of 98%.

In 2022 Joshi, S., et al., [16] introduced a CAD system to help with glaucoma early detection in order to screen for the condition and treat it. The DL model for diagnosing glaucoma is ensemble-based module of this approach. For the PSGIMSR data set, accuracy of 91.11% was attained, along with the suggested ensemble design, the sensitivity is 85.55% and the specificity is 95.20%.

In 2022 Latif, J., et al., [17] devised a transfer learning are employed for diagnosis of glaucoma. The transfer learning-based normal and glaucomatous images, models including Five publicly accessible retinal datasets are used to test the saliency maps that have been integrated into AlexNet, ResNet, and VGGNet. The suggested model's area under the curve, sensitivity, specificity, and accuracy are 95.75%, 94.90%, 94.75%, and 97.85%, respectively.

In 2022 Geetha, A. and Prakash, N.B., [18] introduced a deep learning model for Classification of retinal images of glaucoma utilizing EfficientnetB4. The current work's performance is contrasted with publicly available datasets, including ACRIMA, ORIGA, DRISHTI-GS1, HRF, and RIM-ONEV2 & V3 as well as other models, specifically VGG16, InceptionV3, and Exception. The suggested approach produced superior outcomes for several measures in addition to an accuracy of 99.38%.

In 2022 Kashyap, R., et al., [19] devised the deep learning to recognize and anticipate glaucoma symptoms prior to their occurrence. This deep learning system has been presented to analyze glaucoma images using the glaucoma dataset. The outcomes and CNN classification methods based on deep learning are compared. The recommended model achieves 98.82% accuracy of 96.90% during testing and accuracy for training.

In 2021 Ghani, F., et al., [20] introduce deep learning neural networks used to classifying and identifying for glaucoma in two distinct such as the Vgg-16 Model and the Inception-V3. According to the success findings gathered, the pre-trained better results are achieved by the Inception-V3 model in terms of classification accuracy than the Vgg-16 model with a 90.01 percent accuracy compared to 83.46 percent accuracy for the latter.

In the literature review, these existing techniques have several drawbacks include high computational costs, limited scalability, and labeled datasets. Additionally, variability in image quality and lack of large, diverse datasets can hinder the robustness of these models. To overcome these challenges, a novel GD2-EffiNet introduce for accurate classification of Glaucoma disease.

3. PROPOSED METHODOLOGY

In this research, a novel GD2-EffiNet model is proposed for detecting the Glaucoma images from the dataset. Figure 1 depicts the main workflow of the proposed GD2-EffiNet methodology.

3.1. Dataset Description

The ACRIMA dataset contains retinal fundus images aimed at developing machine learning models for glaucoma detection. It includes around 705 images, divided into glaucomatous and healthy classes. The images are in RGB format with a resolution of approximately 565 x 584 pixels. Each image is labeled based on clinical diagnosis. The dataset is used primarily for binary classification tasks in the study of medical images. It is utilized for building models to support automated glaucoma screening systems.

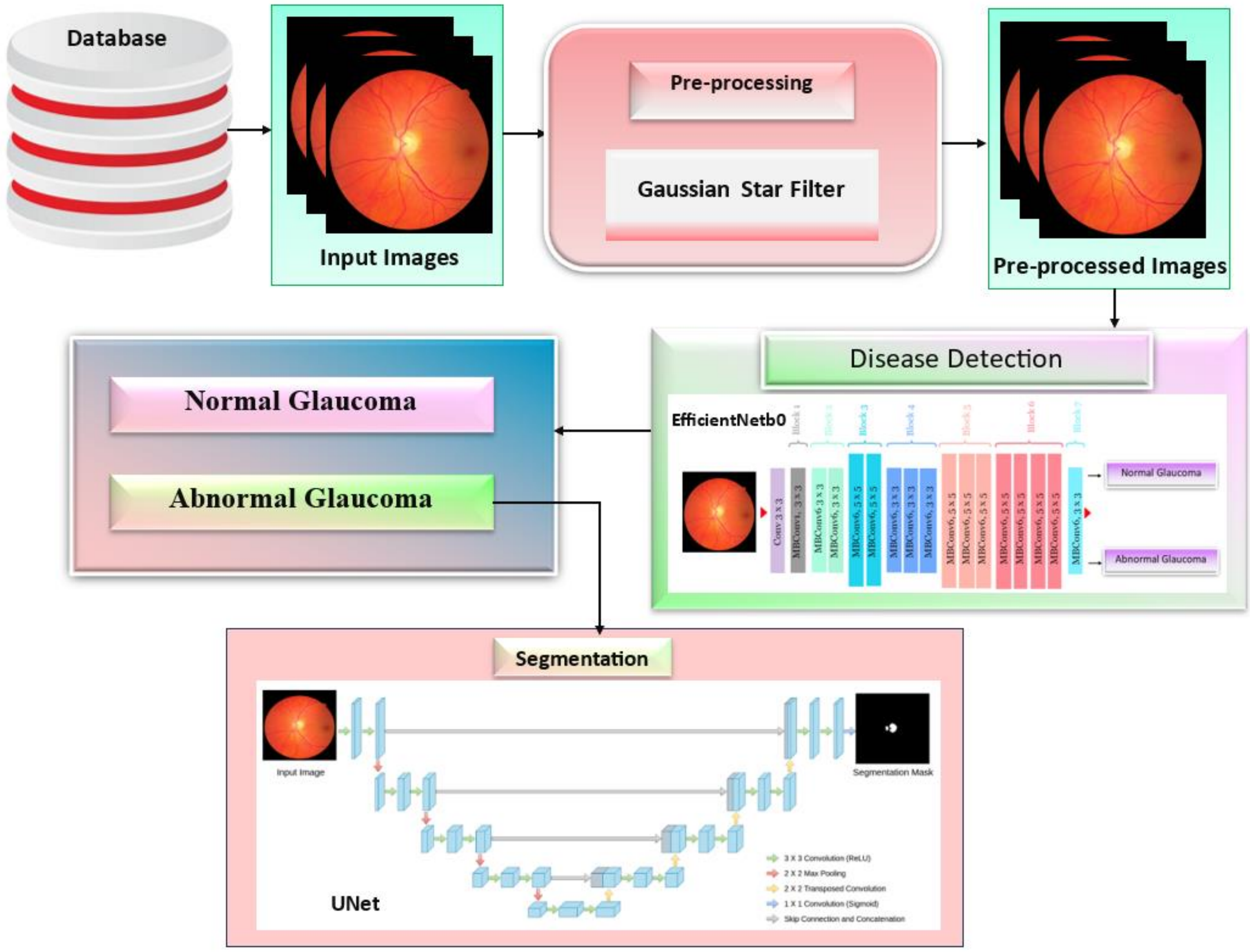

Figure 1. Proposed GD²-EffiNet method

3.2. Gaussian Star Filter

Gaussian Star Filter (GaSF) is used for pre-processing to enhance the image quality and remove the noises. This process is generally applied in scenarios where the Glaucoma image might contain noise that is periodic or quasi-periodic and is brought on by scanning artifacts, the environment, or other causes. The mathematical representation for the frequency domain representation of the Gaussian Star Low Pass Filter (GaSLF) is as follows:

$$GaSLF(a,b) = \begin{cases} max\big(S_1(a,b), S_2(a,b)\big) & if\ S_1(a,b) > 0\ and\ S_2(a,b) > 0, \\ S_1(a,b) & if\ S_1(a,b) > 0\ and\ S_2(a,b) = 0, \\ S_2(a,b) & if\ S_1(a,b) = 0\ and\ S_2(a,b) > 0, \\ 0 & otherwise. \end{cases} \quad (1)$$

Where $S_1(a,b)$ and $S_2(a,b)$ represent the two orthogonal Gaussian filters applied at point (a,b) in the frequency domain, the filter outputs the maximum of the two Gaussian filters value if both filters are greater than zero at (a,b), indicating the presence of significant data in both directions.

$S_1(a,b) = \sum_n e^{-D_1(a,b)^2/N}$, $S_2(a,b) = \sum_n e^{-D_2(a,b)^2/N}$, and $M_1(a,b)$ and $M_2(a,b)$ are the distances from the center of the noise peaks:

$M_1(a,b) = \sqrt{(a - a_{1n})^2 + (b - b_{1n})^2}$, $M_2(a,b) = \sqrt{(a - a_{2n})^2 + (b - b_{2n})^2}$,

Finally, the Gaussian Star Filter (GaSF) is defined as:

$$GaSF(a,b) = 1 - GaSLF(a,b) \quad (2)$$

Where $GaSF(a,b)$ is the output of the Gaussian Star filter at the frequency at the frequency coordinates (a,b), $GaSF(a,b)$ is the Low-Pass Filter, which is designed to detect and suppress noise, $1 - GaSLF(a,b)$ensure that the filter removes noise where the $GaSLF(a,b)$ detects high noise presence while noise is reduced. This approach helps in reducing noise while preserving image information in areas where both filters are active.

3.3. Disease detection using EfficientNetb0

EfficientNet-B0 is used to foundational network for deriving the profound characteristics from the uncertain samples. The EfficientNet approach consistently employs a predefined set of scaling coefficients, as opposed to conventional approaches that scale width, depth, and resolution randomly, to adjust each network parameter. In addition to reducing calculation time, the EfficientNet-B0's ability to calculate a more representative set of visual characteristics with fewer parameters enhances detection accuracy. The EfficientNet-B0 framework's organizational structure is shown in Figure 2. The EfficientNet framework may more effectively address the issue of missing ROI location information since it can appropriately describe the complex transformation. Moreover, the EfficientNet framework's ability to reuse computed features makes it better suited for identifying glaucoma diseases and expedites the training process.

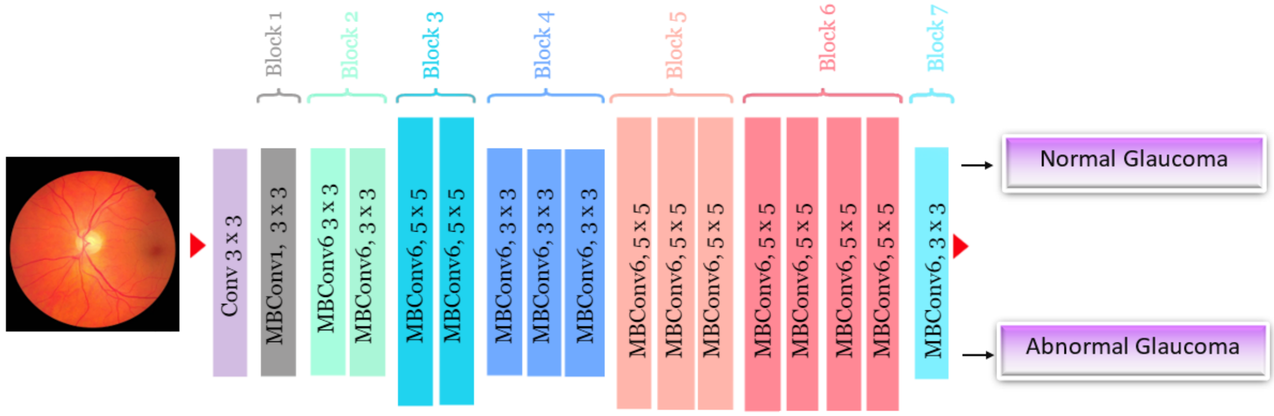

Figure 2. The Architecture of EfficientNet-B0

EfficientNet-B0's scalability and reusability of extracted features make it highly effective for glaucoma detection by reducing computational costs and improving accuracy. This adaptability makes it ideal for medical image analysis tasks that require precision and efficiency.

3.4. Segmentation using UNet

U-Net Segmentation is used for segmenting affected regions on Glaucoma images to identify and diagnose disease at an early stage. Convolutional neural networks like U-Net, which are intended for image segmentation, have a contracting route that records context by reducing spatial dimensions and an expanding path that recovers localization through upsampling and skip connections. To apply U-Net, a dataset of Normal and abnormal Glaucoma images must be collected and annotated with segmentation masks indicating diseased areas. The model is trained to differentiate between Normal and abnormal pixels using loss functions like binary cross-entropy or dice loss, with optimizers such as Adam or SGD. After training, post-processing techniques like thresholding and noise reduction help refine the segmented regions. The architecture of proposed Unet is shown in Figure 3.

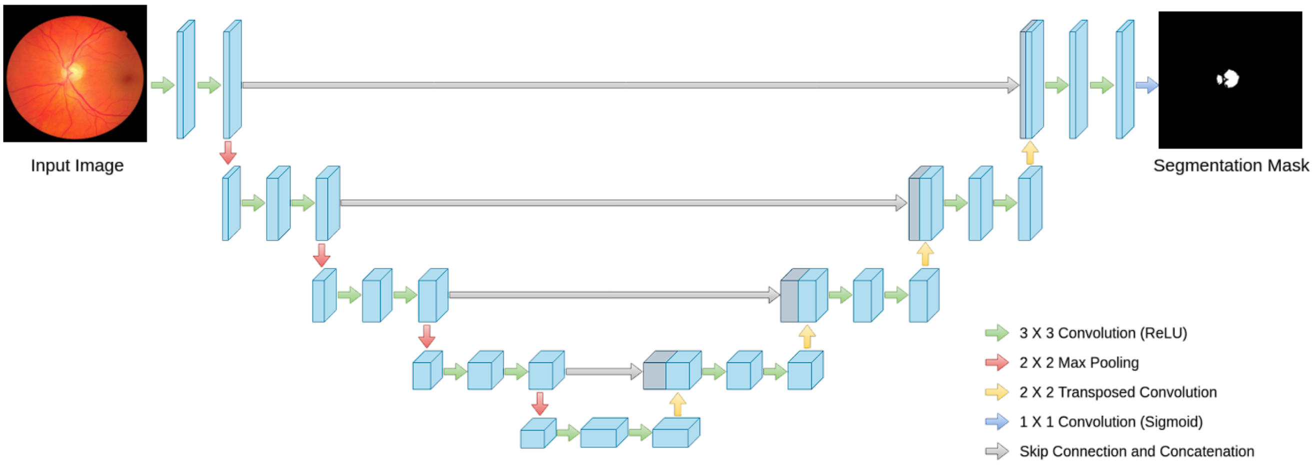

Figure 3. The Architecture of Proposed UNet

Utilizing metrics, the model's performance is measured, like IoU and Dice Coefficient. Despite challenges related to data quality and generalization, U-Net provides an effective method for precise segmentation of Glaucoma disease, facilitating accurate diagnosis and timely intervention.

4. RESULT AND DISCUSSION

The proposed GD^2-EffiNet technique was evaluated in this section utilizing several measures like memory, accuracy, precision, specificity, F1 score, and correctness depending on the images are gathered from the ACRIMA datasets.

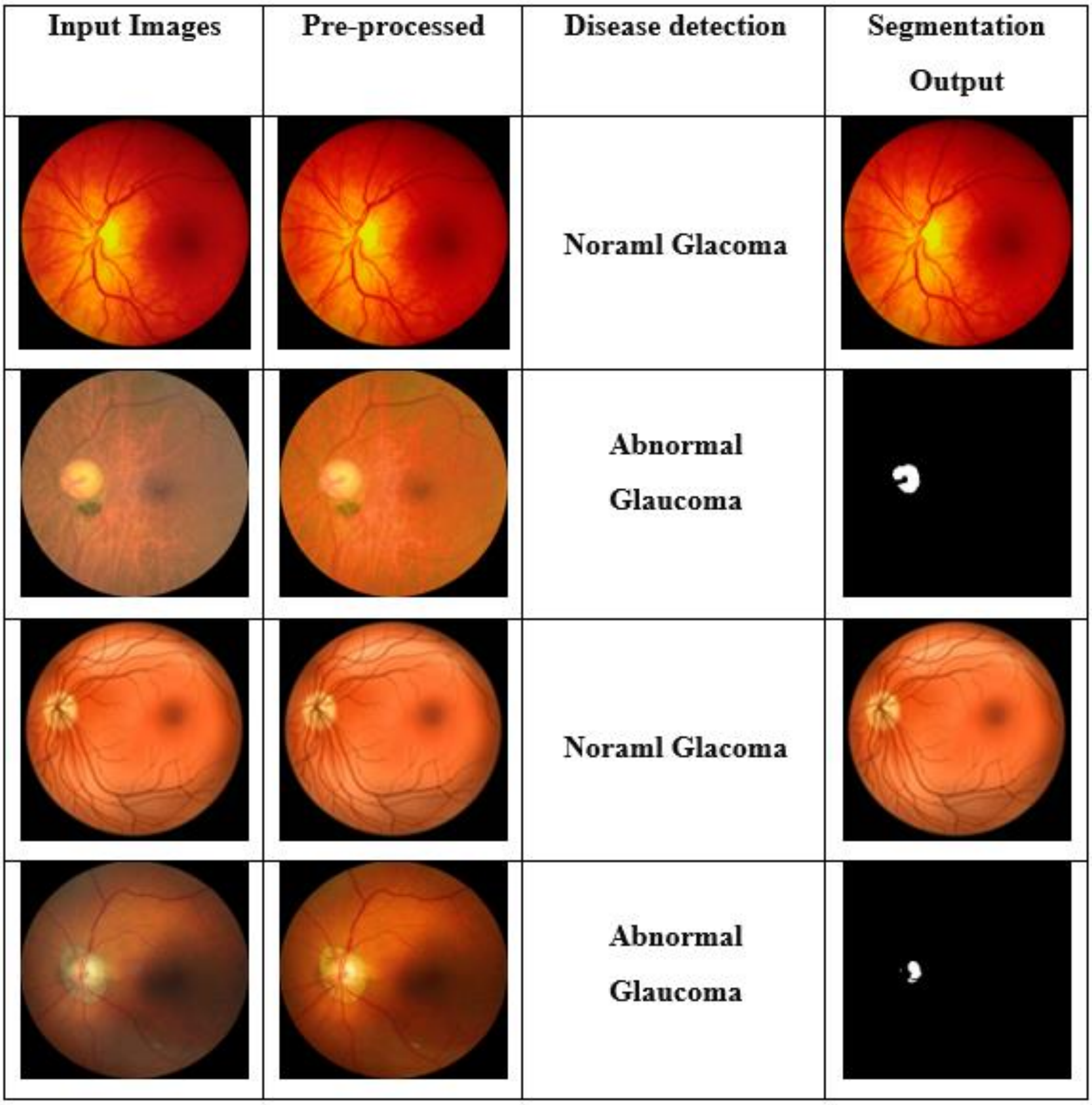

Figure 4. The Experimental result of Proposed GD^2-EffiNet model

The outcomes of the suggested experiment approach GD^2-EffiNet are shown in Figure 4. In column 1, the input Glaucoma images are gathered from the ACRIMA dataset. GaSF is used to improve the clarity of the image and remove the noises from Glaucoma images in column 2. In Glaucoma disease detection using a EfficientNetb0 is used in order to obtain the deep characteristics from the possible sample to classify Normal Glaucoma and Abnormal Glaucoma in column 3. Finally, UNet Segmentation is used to segmenting the abnormal Glaucoma images.

4.1. Performance Analysis

The Common metrics used to evaluate the performance of a classification method include accuracy, precision, recall, specificity, and the F1 score.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Specificity = \frac{TN}{TN+FP} \quad (4)$$

$$Precision = \frac{TP}{TP+FP} \quad (5)$$

$$recall = \frac{TP}{TP+FN} \quad (6)$$

$$f_1 = 2\left(\frac{precision*recall}{precision+recall}\right) \quad (7)$$

where T_{pos} and T_{neg} indicates the actual benefits and drawbacks of the provided images, F_{pos} and F_{neg} shows the sample images false positives and negatives.

Table 1. Performance analysis of GD^2-EffiNet model

Classes	Accuracy	Specificity	precision	Recall	F1score
Normal Glaucoma	99.84%	97.21%	99.52%	97.55%	97.62%
Abnormal Glaucoma	98.98%	98.89%	98.44%	94.79%	96.27%

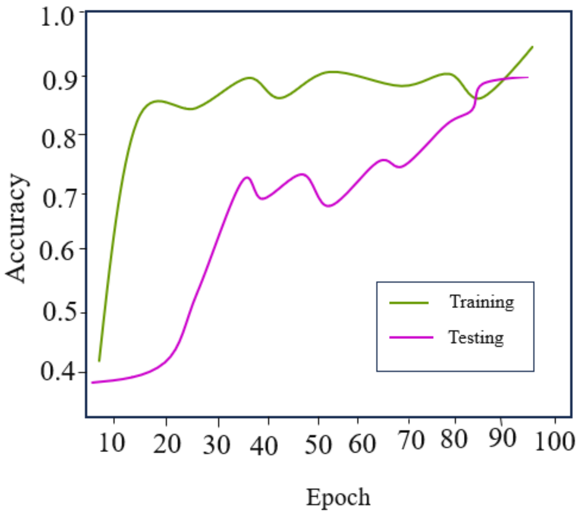

Figure 5. Training and Testing accuracy of the GD^2-EffiNet model.

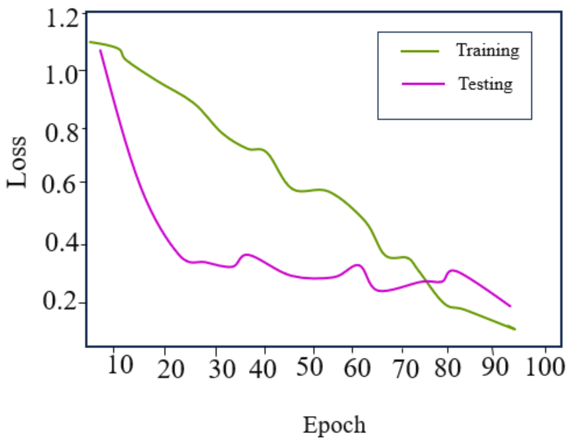

Figure 6. Training and Testing loss of the GD^2-EffiNet model.

Table 1 displays precision, recall, F1 score, accuracy, and specificity proposed technique for various classes. The efficiency metrics of the proposed approch are show in Table 1 for the following classes: Normal Glaucoma and Abnormal Glaucoma. The accuracy of the proposed method is 99.84% for Normal Glaucoma and 98.98% for Abnormal Glaucoma.

The proposed GD^2-EffiNet seen in Figures 5 and 6 demonstrates the excellent accuracy that the model has attained during training and testing. Based on the obtained data, the accuracy of classification for the proposed GD^2-EffiNet model is 99.41%.

4.2. Comparative Analysis

In a comparison between the proposed model and was assessed in comparison to existing approaches to demonstrate its accuracy and efficiency. When the performance of this methodology is compared with traditional methods, it performs better than those methods. Performance is assessed using F1 score, recall, accuracy, precision, specificity, and specificity. The suggested model is benchmarked against three current deep learning methodologies in this comparative analysis.

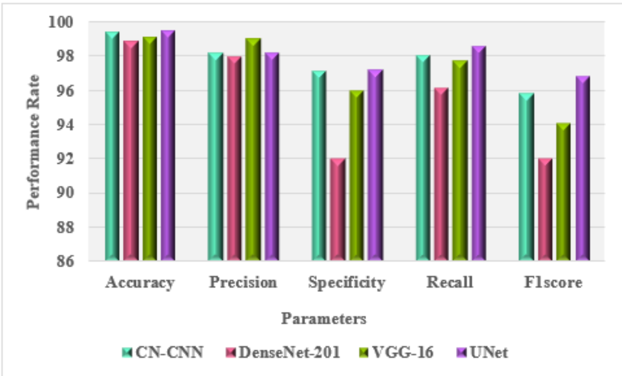

Figure 7. Comparison between existing and proposed method

Table 2. Comparison between traditional deep neural networks

Networks	Accuracy%	Precision%	Specificity%	Recall%	F1score%
CN-CNN [4]	99.39	98.12	97.11	97.98	95.78
DenseNet-201 [10]	98.82	97.92	92.02	96.08	91.95
VGG-16 [14]	99.06	99.02	95.94	97.66	94.06
UNet	**99.46**	**98.12**	**97.13**	**98.55**	**96.78**

Table 2, the accuracy level of the proposed Network results was very high. Table 2 and Figure 7 illustrate that traditional network such as CN-CNN, DenseNet-201, and VGG-16 approach produced more accurate findings, although at a lower level of precision. The proposed method maintains excellent curacy accuracy ranges.99.46%. The proposed method achieves a higher accuracy rate compared to the existing models. Therefore, the proposed GD^2-EffiNet method shows performs better than other techniques.

Table 3. Comparison of the existing and proposed model

Authors	Methods	Accuracy
Geetha, A. and Prakash (2022) [11]	CG-EffiNet	99.38%
Latif, J., et al., (2022) [12]	ODGNet	97.85%
Sudhan, M.B., et al., (2022) [15]	SEG-UNet	98.82%
Proposed	GD^2-EffiNet	**99.41%**

Table 3 shows a comparison of deep learning networks such CN-CNN, DenseNet-201, and VGG-16 are not as precise as the proposed GD^2-EffiNet model. The proposed technique maintains excellent accuracy levels of 99.41%. The proposed GD^2-EffiNet model enhances the total accuracy by 0.03%, 1.56%, and 0.59% better than CG-EffiNet, ODGNet, SEG-UNet respectively. The comparison above indicates that in terms of precision, the proposed GD^2-EffiNet model performs better than the existing models.

5. CONCLUSION

In this research, a novel GD2-EffiNet model has been proposed for detecting namely Normal Glaucoma, and Abnormal Glaucoma. Initially, images are pre-processed using the Gaussian Star Filter (GaSF) to enhance image quality and remove noise. EfficientNet-B0 is employed to extract deep features, enabling categorizing images of glaucoma as normal or abnormal. Finally, UNet is used to segment the abnormal regions, facilitating early diagnosis. The effectiveness of the proposed GD2-EffiNet method using metrics like F1 score, sensitivity, accuracy, and specificity. The classification accuracy of the proposed GD2-EffiNet model was 99.41%. The proposed model enhanced the total accuracy 0.03%, 1.56%, and 0.59% better than CG-EffiNet, ODGNet, SEG-UNet respectively. Future work in glaucoma disease detection could focus on developing more advanced AI algorithms to improve early diagnosis through retinal imaging analysis and integrating multimodal data.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

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AUTHORS

Shobana R received her master degree from Anna University, Coimbatore, India. Now she is working towards the PhD degree in Anna University, Chennai in India. From 2011 she was working as Assistant Professor and took a break of 7 years. Now she is working as Assistant Professor in S.A. Engineering College from 2022. Her primary research interests are deep learning, cyber security, cloud computing and quantum computing.

Abitha VK Lija completed her B.E in CSE from CSI Institute of Technology, Thovalai affilated to Anna University. She completed her M.E in CSE from Jerusalem College of Engineering affiliated to Anna University. She is currently working as Assistant Professor in the Department of CSE in Meenakshi College of Engineering, Chennai, India. She is currently pursuing Ph.D. in the Department of Computer Science and Engineering in S.A. Engineering College under Anna University, Chennai, India. Her area of interest includes IoT, Cyber security, Big data, Deep learning and Machine Learning

Shikky Marice. S, Research Scholar with more than 4 years of teaching experience. I obtained my M.E in Communication Systems Engineering from Cape Institute of Technology (affiliated to Anna University) in the year 2013. My research interests lie in the domain of Computer Vision, Pattern Recognition, Anomaly Detection & Clustering.

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