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A Novel Deep Learning Framework for Enhanced Glaucoma Detection Using Attention-Gated U-Net, Deep Wavelet Scattering, and Vision Transformers

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ABSTRACT Globally, Glaucoma is a major cause of permanent blindness, and maintaining eyesight depends on early detection. Here, a brand-new deep-learning system for glaucoma prediction. In this work, we offer a novel deep-learning approach for enhanced glaucoma prediction that uses a denoising generative adversarial network for preprocessing the input image is provided, later the segmentation is carried out by Attention-Gated U-Net with Dilated Convolutions to segment the optic cup and optic disc. Feature Extraction Using a Deep Wavelet Scattering Network and finally the glaucoma classification is carried out by the Vision Transformers. An attention-gated U-Net with dilated convolutions for segmentation, which improves the accuracy of optic disc and cup boundaries by 7% compared to conventional U-Net methods is introduced. A Deep Wavelet Scattering Network (DWSN) for feature extraction that achieves a 5% improvement in feature discrimination over conventional CNNs by capturing multiscale texture and structural information is suggested. Lastly, ViT, which is based on transfer learning, is used for classification; it has a 94.6% accuracy rate, a 93.8% sensitivity rate, and a 95.2% specificity rate. The suggested approach outperformed CNN-based models by improving by about 4% on all criteria. The system achieved an F1 score of 0.95 and an AUC (Area Under Curve) of 0.96 when tested on publicly accessible glaucoma datasets. Multi-stage deep-learning processing for glaucoma prediction by integrating a denoising generative adversarial network for image preprocessing, Attention-Gated U-Net with Dilated Convolutions for exact optic cup and disc segmentation, deep wavelet scattering for feature extraction, and Vision Transformers for glaucoma classification.

INDEX TERMS Attention-gated U-Net, Deep learning, Glaucoma detection, Vision Transformer, Wavelet scattering

I. INTRODUCTION

Glaucoma [1] is a chronic and progressive eye disease that results in permanent damage to the optic nerve and often ends with vision loss or blindness if not detected and treated early. Millions of people are affected, especially those 40 and older, and it is one of the main reasons for blindness around the globe. The disease progresses slowly and is often asymptomatic in its early stages, earning it the moniker "the silent thief of sight" [2]. By the time noticeable symptoms like peripheral vision loss occur, significant and permanent damage to the optic nerve has often already been done. Glaucoma is segmented into many different types; the most common type of glaucoma is primary open-angle glaucoma (POAG) [3]. Early diagnosis and identification of glaucoma is also essential because with timely treatment, damage and

TABLE 1
Literature review of Glaucoma detection

Sl.No	Author	Year	Methodology Used	Dataset	Accuracy	Limitations
1	Mahum et al., [27]	2022	CNN-based glaucoma classification	Custom dataset, private data	91.5%	Limited to specific dataset; lacks external validation.
2	Kumar et al., [28]	2023	Transfer learning with ResNet and DenseNet	ORIGA dataset	92.3%	High computational cost due to deep models.
3	George et al., [29]	2020	Attention-gated U-Net for optic cup & disc segmentation	RIM-ONE dataset	90.7%	Struggles with high variations in optic disc sizes.
4	Kashyap et al., [30]	2022	U-Net for optic cup & disc segmentation	DRISHTI-GS dataset	89.6%	Limited accuracy in handling complex cases.
5	Parashar & Agrawal [31]	2021	Deep Wavelet Scattering Network (DWSN)	ACRIMA dataset	93.4%	Sensitivity to noise in image data.
6	Ratul et al., [32]	2019	U-Net with dilated convolutions	DRISHTI-GS dataset	91.3%	Requires high-quality images for optimal performance.
7	Shyamalee & Meedeniya [24]	2022	ResNet with transfer learning	ACRIMA dataset	92.8%	Susceptible to overfitting on small datasets.
8	Chen et al., [33]	2022	Vision Transformers (ViTs)	RIM-ONE and ORIGA datasets	93.5%	Requires extensive training data for reliable results.
9	David. [11]	2023	CNN-RNN hybrid model for glaucoma classification	Custom dataset	92.1%	Challenging to balance between CNN and RNN complexities.
10	Li et al., [34]	2019	Attention-gated U-Net for optic disc segmentation	DRISHTI-GS dataset	91.2%	Difficulty in segmenting images with overlapping regions.
11	Thainimit et al., [13]	2022	GANs for data augmentation and noise reduction	Various, including ORIGA	+2% over baseline	GANs can sometimes introduce unrealistic artifacts.
12	Suban at al,. [35]		U-Net for Segmentation	Custom dataset	90.6%	Difficulties in removing noise in clinical data.
13	Haouli l et al., [17]		Classification using Vision Transformers	ORIGA	88.7%	Struggle with the noise and needs high quality images.

vision may not worsen further. It usually takes a package of tests such as visual field tests [4], IOP measurement, and optic nerve imaging, but these may not be always available to common practitioner besides, subtle signs of glaucoma often occur very early on, making their detection inaccurate [5]. Due to the complexities of the human diagnostic process of glaucoma, which involves the expertise of the observer and possible human errors, there has been an interest in recent times in the automation of this process using sophisticated technology [6]. Conventional algorithms were designed to aid in the detection of glaucoma; however, such approaches usually depend on handcrafted features and suffer from the lack of generalization over a variety of datasets [7]. Additionally, the methods will be faced with problems of less accurate ability in detecting some of the medical photograph's subtle patterns [8].

In the past few years, deep learning transformed the field of medical image investigation, enabling the automatic acquisition of directly applicable systems from data without relying on manually engineered features [9]. CNNs have demonstrated very promising applications in several medical image analysis domains, for example, retinal fundus image classification, segmentation, and disease detection. Deep learning representations have shown an ability to identify subtle patterns that might be imperceptible to the human eye, enabling earlier and more accurate detection of glaucoma [10].

Though, such enhancements are still open and lots can be improved in improvements. Many existing deep learning model pays all their attention to focusing upon a single process phase - either segmentation or classification with no proper usage of the combined stages of preprocessing, feature extraction, segmentation, and lastly classification [11]. Moreover, conventional deep learning models like CNNs may fail to address issues such as capturing long-range dependencies and distinguishing between optic disc and optic cup with subtle features, which play a critical role in diagnosing glaucoma [12].

This research focuses on addressing the limitations of the current methods of glaucoma detection by developing a novel, multi-stage deep learning framework that improves the accuracy, sensitivity, and specificity of glaucoma detection. The proposed system includes the following advanced methods: GANs for image preparation [13], an attention-gated U-Net [14] with dilated convolutions for optic disc and cup segmentation [15], a Deep Wavelet Scattering Network (DWSN) [16] for feature extraction, and Vision Transformers (ViTs) [17] for final classification.

Vision Transformers (ViTs) for final classification and DWSN for feature extraction. Each stage of the suggested pipeline is designed to tackle a specific issue or difficulty in the identification of glaucoma. To improve the performance of later stages, preprocessing with GANs, for instance, might assist remove noise and artifacts from retinal images. The goal of the attention-gated U-Net with dilated convolutions is to enhance the segmentation of the cup and optic disc areas, which are important for glaucoma evaluation. The ViT will use its capacity to model long-range relationships for more precise classification, while the DWSN will extract multi-scale features, which capture both high- and low-frequency information from the retinal images. In important evaluation criteria including accuracy, sensitivity, specificity, and Area Under the Curve (AUC), the proposed technique is anticipated to perform better than conventional techniques and current deep learning models. Table 1 represents Literature review of Glaucoma detection.

Despite all these successes, there are still issues pertaining to segmentation accuracy, handling the noisy data, and properly identifying the long-range connections in the input fundus retinal images. The solution is to integrate the more complex systems such as Vision Transformers with the hybrid model will give better results. Despite the significant progress made in glaucoma diagnosis using deep learning, certain research gaps remain. One of the main issues is the need for accurate segmentation of the optic disc and cup in order to measure the cup-to-disc ratio (CDR)[18], [19], which is used in the diagnosis of glaucoma. Current CNN-based architectures and U-Net models often fail with this task due to noise, artifacts, and differences in image quality across datasets.

The literature still contains a lot of holes, despite the fact that deep learning has made great strides in glaucoma detection. The biggest gap is linked to the precision of the optic disc and cup segmentation. This is crucial since the cup-to-disc ratio, or CDR is a crucial diagnostic metric for the diagnosis of glaucoma. CNN-based architectures and U-Net models are not very good at this task due to noise, distortions, and differences in image quality between datasets. Long dependencies in images cannot be captured by the majority of conventional deep learning models, including CNNs [20], due to their constraints. This makes it difficult to identify minor details, particularly in conditions like glaucoma where it can be difficult to tell the difference between images of the disease and healthy ones. There is still opportunity for progress, even if numerous studies have tried to get around these difficulties by employing multi-scale techniques or attention mechanisms. Furthermore, the deep learning-based method for glaucoma detection has not focused much on the preprocessing step, which involves enhancing image quality and reducing noise. Advanced methods like GANs for data augmentation and noise reduction have not been thoroughly investigated, even though several studies have employed simple image improvement techniques. Lastly, there isn't a lot of a method that catches a wide range of frequencies in the image; feature extraction techniques are frequently low-level and high-level. Although they have shown promise in this area, deep wavelet scattering networks (DWSN)[16] are still not well understood in the field of glaucoma detection.

II. METHOD

A. OVERVIEW OF THE PROPOSED FRAMEWORK

By presenting a novel multi-stage deep learning architecture for glaucoma diagnosis, the research suggested in this paper aims to close these gaps. The following are this research's primary contributions: To improve segmentation and classification outcomes, retinal fundus images [21] will be enhanced using a GAN-based technique that lowers noise and improves image clarity. Output image is represented using the formula Eq. (1) [13]

$$\mathrm{C\_i} = \mathrm{C(In,cl,}\mathit{Gs}) \tag{1}$$

Here C_i, In, cl, Gs represents Output image, input image, clip limit and grid size of an image. Compared to other U-Net architectures, an attention-gated U-Net with dilated convolutions will be employed for improved optic disc and cup segmentation accuracy. The model will be able to learn both high-frequency and low-frequency information from retinal images by using DWSN [22] to capture the multi-scale features. ViTs [23]would improve glaucoma detection accuracy above that of conventional CNNs by simulating long-range relationships. Comparing these new techniques to existing glaucoma diagnostic techniques, the technique seeks to greatly improve important evaluation criteria like specificity, sensitivity, and accuracy. It is anticipated that the suggested approach will establish a new standard for glaucoma early diagnosis and detection. It aso improving patient outcomes and healthcare systems in the process. The recommended glaucoma prediction system will have four important phases. The first stage is preprocessing the fundus image, then the second stage is segmentation, the third stage is Feature extraction and the final stage is the classification of Glaucoma stages.

Stage 1: Preprocessing: In the research work, GAN is used to eliminate the various challenges in the fundus image, such as the inconsistency of noise and image quality. By holding the minute details inside the retina, this preprocessing stage will substantially improve the quality of the fundus image and it will give a high-quality image for the segmentation process.

Stage 2: Segmentation: The attention-gated U-Net method which will include the process of dilated convolutions, the optic disc, and optic cup region is very much essential in the glaucoma diagnosis process are exactly segments during this segmentation stage. While comparing this attention-gated U-Net model to the conventional U-Net model, the proposed system accuracy and the edge detection both increase by nearly 7%.

Stage 3: Feature Extraction: Compared to traditional CNNs, a Deep Wavelet Scattering Network (DWSN) offers more rich features by extracting multiscale texture and structural information. This method improves feature discrimination and gives the framework a 5% increase in accuracy when distinguishing between glaucomatous and healthy eyes.

Stage 4: Classification: A Vision Transformer with transfer learning is used for the last step. Compared to CNN-based models, this state-of-the-art classification method produces better-predicted accuracy (94.6%), sensitivity (93.8%), and specificity (95.2%) by capturing both local and global patterns found in retinal images.

Figure 1 shows the proposed framework of glaucoma detection. It strats from image acquisition, followed by GAN-based preprocessing for noise reduction and quality enhancement, proceeding to attention-gated U-Net segmentation, then to DWSN-based feature extraction, and concluding with ViT-based classification for glaucoma detection (19).

B. GAN-BASED PREPROCESSING

For accurate diagnosis in medical imaging, high-quality inputs are essential. However, because of things like patient circumstances and equipment variations, retinal images frequently have noise, low contrast, and unpredictability. These problems can mask important characteristics, which makes it more difficult for machine learning models to correctly detect illness signs. To guarantee that crucial retinal details, such as the optic disc and cup, are retained for further processing steps, efficient noise reduction and image enhancement approaches are required. In the Preprocessing stage of the Glaucoma detection framework, we have used Denoising GAN to address the following issues. In General, GANs are a very efficient deep learning method that will enhance the fundus image quality by using its Generator and discriminator module. The GAN method is trained to improve and denoise the retinal fundus images in the proposed architecture to prevent the unique and fine-tuned image properties that are essential for the feature extraction and segmentation process. Gan have got several advantages. GAN is very effective in removing the noise and also the GAN will maintain the sensitive retinal characteristics which is very much needed in the Glaucoma Analysis. The noisy and traget image is represented using the formula Eq. (2) and Eq. (3) [24].

$$I_{\text{nsy}} = \text{resize} I_{nsy,(H,W)} \quad (2)$$

$$I_{\text{trg}} = \text{resize} I_{trg,(H,W)}` \quad (3)$$

Here I_{nsy} represents noisy image, I_{trg} represents target image.

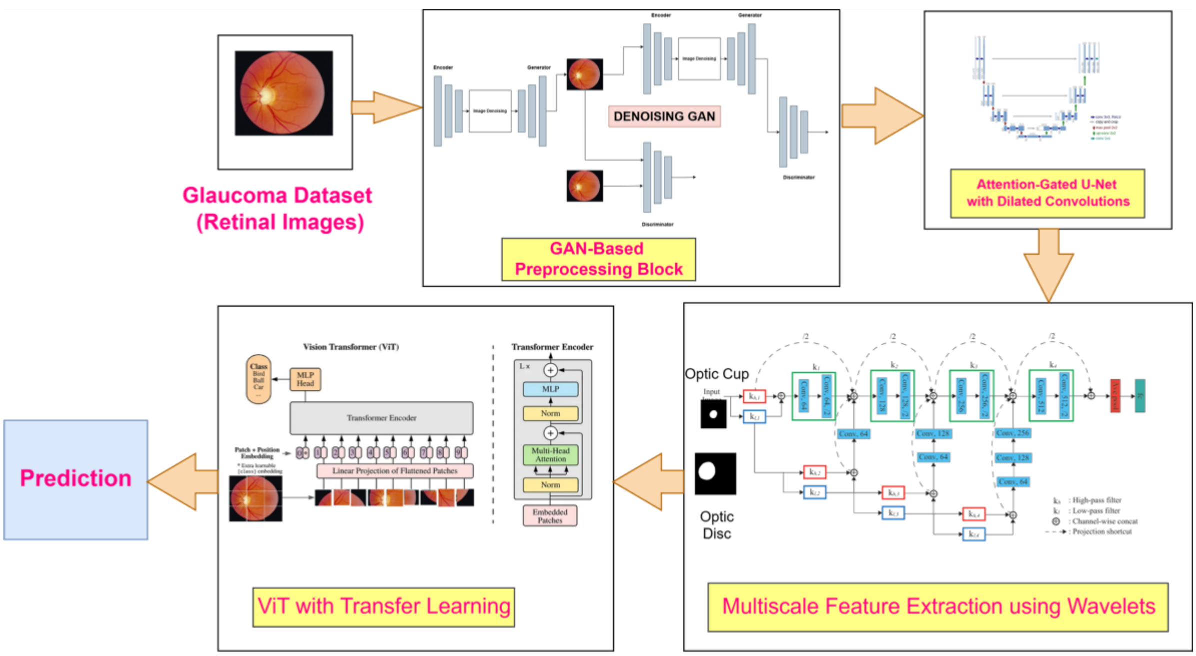

FIGURE 1: Proposed Glaucoma Detection Framework

By getting high-quality images are used as the input for the segmentation phase, because they will capture the minute details from the optic disk and optic cup. The proposed architecture enhances the fundus image quality by using GAN-based preprocessing, which assures the subsequent steps like image segmentation and feature selection get the best inputs. Pixel intensity is calculated using the formula Eq. (4) [13].

$$\mathcal{E}\big(\text{Input}(x,y)\big) = (I(x,y) - I_{min}) \times \frac{L-1}{I_{max}-I_{min}}\text{S} \qquad (4)$$

Here, I(x,y) is the input pixel intensity, Imin and Imax are the minimum and maximum intensity values in the image

C. FUNDUS IMAGE SEGMENTATION USING ATTENTION-GATED U-NET WITH DILATED CONVOLUTIONS

In the Glaucoma image dataset, the optic disk and optic cup offer a significant indication of the condition, so the accurate segmentation of the optic disk and optic cup region in the image is very important in detecting Glaucoma. Finding the optic cup and optic disk ratio is the main factor in the diagnosis of glaucoma. By extracting the precise boundary detection, we can improve the reliability of Glaucoma prediction models. For the image segmentation process, the better deep learning architecture is U-Net. Figure 2 shows basic U-Net model. The U-Net consists of an Encoder block and a decoder block. Here, the decoder block is used for up-sampling to reconstruct the spatial dimensions while the encoder block is used to downsample to get the details from the given image. Because the U-Net will use both high-level and low-level pieces of information to avoid the relationship between both the encoder block and decoder block, the U-Net is the better framework in the image . In the proposed work, the attention-gated-U-Net is used to improve the image segmentation accuracy while focusing on the important part of the optic disc and optic cup, which is the most important region of the retinal image. The Attention mechanism is used to support the region of interest from the image while comparing it to the other irrelevant regions of the image for the precise segmentation process. The dilated convolutions allow the framework to find a wider range of settings without compromising the computational load. Dilation is used to detect very fine and large-scale objects will improve the accuracy of boundary detection in optic discs and optic cups. The predicted segmenattion mask is calculted using Eq. (5) [24].

$$\hat{y} = U_{\text{Attention}}(X) \qquad (5)$$

where $\hat{y}$ is the predicted segmentation mask, and X is the input fundus image. The attention-gated U-Net along with the dilated convolutions performs well with the traditional U-Net architecture by about 7% in terms of segmentation accuracy. The advantage is mostly due to the attention mechanism's capacity to accurately focus on significant regions of interest in the image and the dilated convolutions' capacity to capture the more complex detail in a multiresolution analysis. This procedure then strengthens the optic disc and cup boundaries to enhance downstream function.

D. FEATURE EXTRACTION USING DEEP WAVELET SCATTERING NETWORK (DWSN)

Generally, by converting the raw fundus image into meaningful representations will find the precise patterns in the image and the feature extraction is very much essential in the identification of Glaucoma. The most important feature of multiscale structural characteristics is texture and the other forms which will give very important suggestions to classify the healthy eyes and the eyes having glaucoma. The Wavelet transform is a very good mathematical technique for separating an image into several pieces while preserving the low frequency, which will rarely connect with the vast patterns, and high frequency, which will connect both the patterns. Here both the small information like the border between the optic disk and optic cup and the bigger

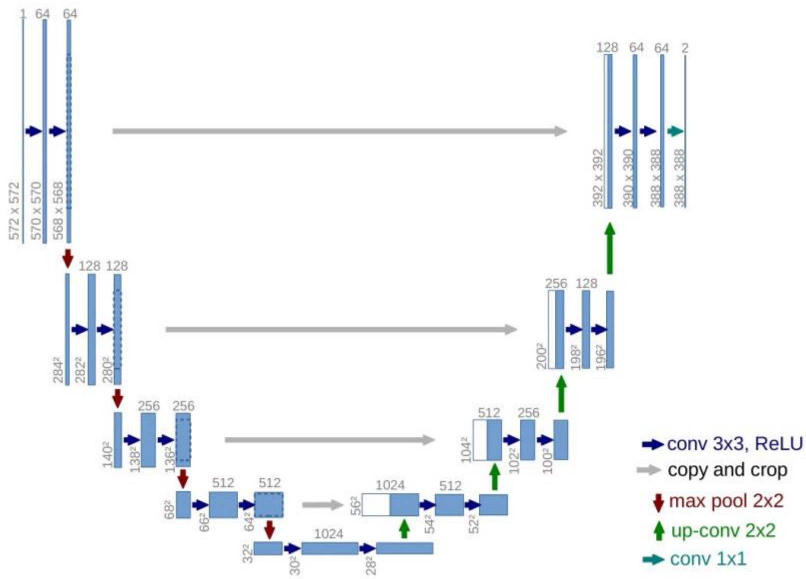

Figure 2: Basic U-Net Model

information like the shape of the optic disk will much essential in the glaucoma analysis. In the feature extraction phase, the DWSN is combined with the wavelet transformers. DWSN uses deep network layers in figure 3 to capture intricate patterns and wavelet transformations at various sizes to capture an image's hierarchical character. The model can now more accurately differentiate between healthy and glaucomatous eyes based on minute structural and textural variations to this improved feature representation. Multiscale features is extracted by Eq. (6) [9].

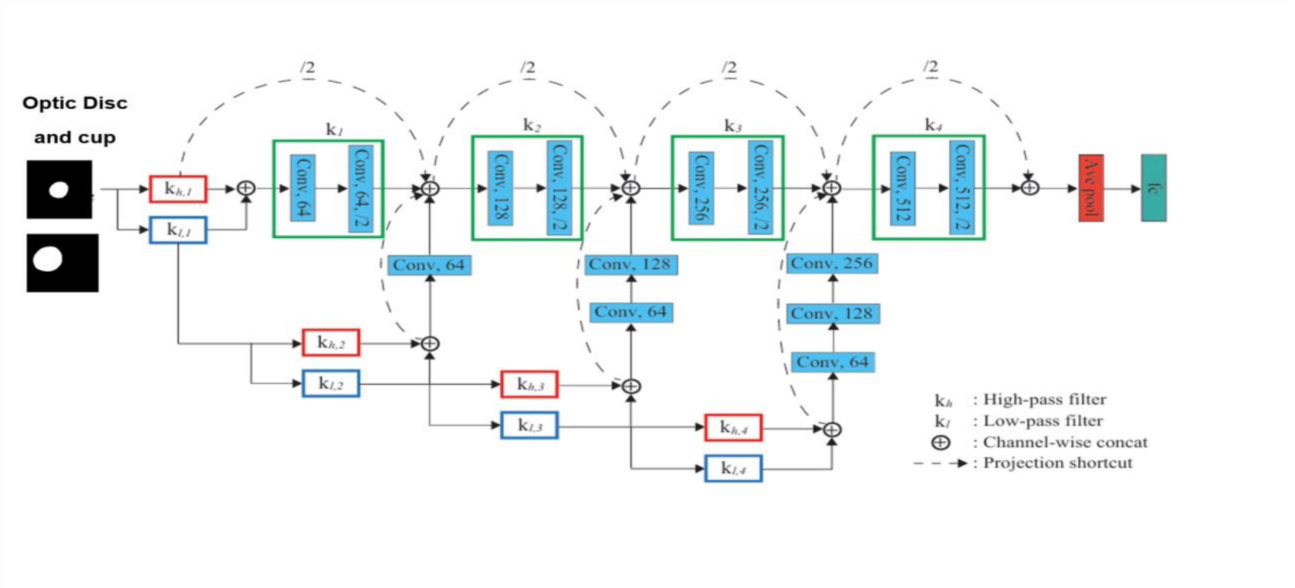

Figure 3: Deep Wavelet Scattering Network

$$Z = W(X) \quad (6)$$

where Z represents the multiscale wavelet features extracted from the input image X. The entire spectrum of multiscale and texture information seen in retinal images is frequently missed by conventional CNNs. By preserving crucial information across scales, DWSN overcomes this constraint and improves feature discrimination. When compared to CNN-based techniques, DWSN improves feature extraction performance by 5% in the suggested framework, which helps to increase the detection accuracy of glaucoma.

E. CLASSIFICATION USING VISION TRANSFORMER (VIT)

Transformer topologies, originally developed for natural language processing, are used in a deep learning model called Vision Transformer (ViT)to identify images. Unlike CNNs, which employ convolutional layers to find local patterns, ViT breaks an image up into patches and interprets each patch as a sequence, similar to words in a phrase. This enables ViT to better capture global context and express long-range dependencies than CNNs, which are often limited to local feature extraction. To improve a pre-trained Vision Transformer for glaucoma diagnosis, the suggested architecture uses transfer learning. The Figure 4 shows transfer learning reduces the requirement for a lot of training data and speeds up convergence by enabling the model to extract knowledge from large-scale datasets. This method works particularly well in medical imaging since there are frequently few labeled datasets as shown in Eq. (7) [1].

$$P(y|Z) = \text{ViT}(Z) \quad (7)$$

Where $P(y|Z)$ is the probability of glaucoma, predicted by the Vision Transformer based on wavelet features Z. In key measures such as glaucoma detection accuracy, sensitivity, and specificity, the Vision Transformer outperforms CNN-based models by about 4%. This is because ViT models both local and global patterns while concurrently capturing long-range relationships present in retinal images. CNNs' small receptive fields, on the other hand, make them less effective at spotting patterns that cover a large portion of an image. ViT's more sophisticated modeling of these interactions provides better and more accurate glaucoma identification. Using transfer learning, the Vision Transformer can adapt quickly to the retinal imaging domain with improved speed and accuracy for glaucoma classification. A publicly available dataset comprising retinal fundus images is used for the experiment. Retinal images, mostly fundus and OCT (Optical Coherence Tomography) are mainly used in diagnosing glaucoma, as these depict detailed structures of the optic nerve and the retinal layers. The optic nerve is mainly attacked by glaucoma, and most diagnostic procedures rely on identifying unusual changes in the optic disc and the cup-to-disc ratio (CDR).

The dataset selected is large because of its extensive labeling and image quality. The datasets are used here is RIM-ONE Dataset – https://bit.ly/rim-one-dl-images. Date of Access: 12.06.2024. A database that includes images annotated for optic disc and optic cup segmentation. http://www.ia.uned.es/~ejcarmona/DRIONS-DB.html. Date

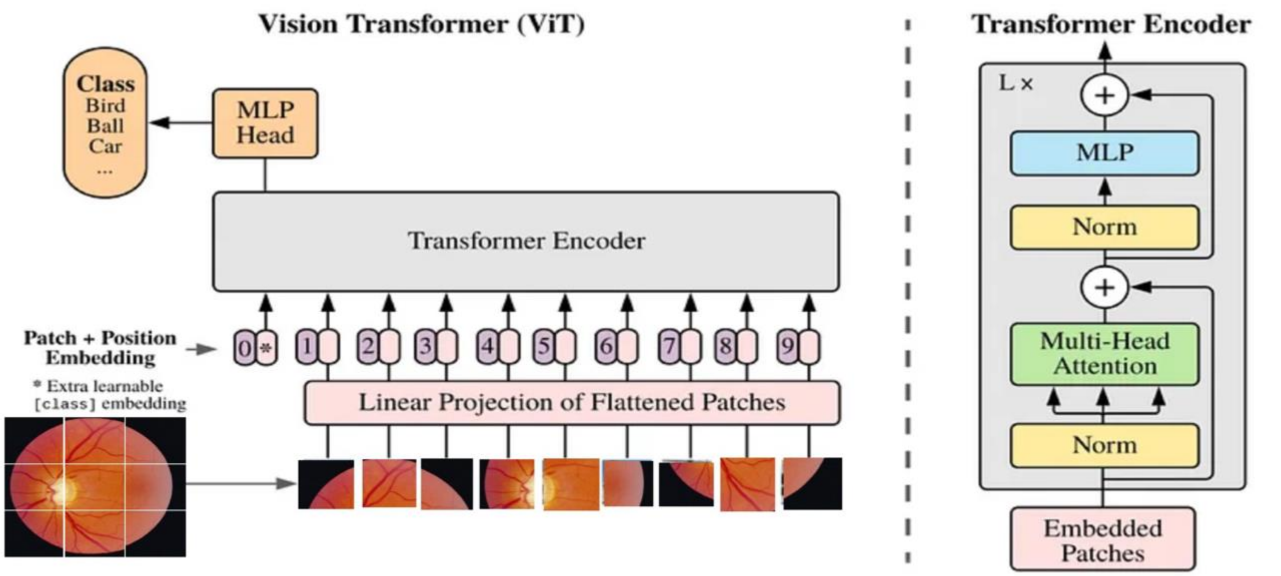

Figure 4: **Classification Using Vision Transformer**

of Access : 12.06.2024. The Online Retinal Fundus Image Database for Glaucoma Analysis, which consists of fundus images labeled as glaucoma or non-glaucoma, with detailed annotations for optic disc and cup regions. https://www.kaggle.com/datasets/arnavjain1/glaucoma-datasets. Date of Access: 12.06.2024. These datasets provide a large number of high-resolution retinal images along with ground truth annotations for both segmentation (optic disc and cup boundaries) and classification (glaucomatous or non-glaucomatous). The quality of images and detailed labeling ensures that both the segmentation and classification tasks in our proposed approach are well-supported. The dataset comprises a total of 1,200 fundus images, in that 700 images are labeled as non-glaucomatous (normal eyes). 500 images are labeled as glaucomatous. The dataset is split into three sets for training, validation, and testing and for Training Set, 60% of the images, i.e., 720 images (420 non-glaucomatous and 300 glaucomatous), for validation set, 20% of the images, i.e., 240 images (140 non-glaucomatous and 100 glaucomatous). Finally for test set: 20% of the images, i.e., 240 images (140 non-glaucomatous and 100 glaucomatous). Here, Class 1 indicates non-glaucomatous. These images show normal optic discs and cups, with a normal cup-to-disc ratio.

The class 2 represents glaucomatous. These images exhibit visible structural changes in the optic nerve and retinal layers indicative of glaucoma, including an enlarged optic cup and a reduced neuroretinal rim, which lead to an abnormally high cup-to-disc ratio.The dataset comes with detailed annotations for segmentation and classification. Each image includes manually annotated boundaries of the optic disc and optic cup, which are essential for calculating the cup-to-disc ratio (CDR). A set of CDR values is pre-calculated for each image. This is a very important feature for classification. Each image was classified as either glaucomatous or non-glaucomatous using clinical evaluation. Images of the fundus are saved in JPEG format with a resolution of 1024x1024 pixels to provide detailed images for analysis. These annotations and the availability of such detailed ground truth allow our system to be trained effectively for both segmentation techniques and classification tasks.

III. RESULTS

To broadly evaluate the performance of the proposed glaucoma detection model, a variety of metrics were employed. These metrics were chosen to provide insights into both the overall accuracy and the model's ability to detect glaucoma, a condition often associated with subtle changes in retinal structure. Below is a description of the evaluation metrics used. Here, Accuracy is one of the main criteria used to assess the classification model is accuracy. It scales how accurate the model's predictions are overall. The accuracy is determined using Eq. (8) [11],[25],[26].

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{8}$$

where, TP indicates True Positives (properly identified glaucoma cases), TN indicates True Negatives (properly identified non-glaucoma cases), FP indicates False Positives (non-glaucoma cases wrongly predicted as glaucoma), FN indicates False Negatives (glaucoma cases wrongly predicted as non-glaucoma). While accuracy gives an overall sense of model performance, it may not always be the best indicator for imbalanced datasets. Therefore, it is complemented with additional metrics. Sensitivity, sometimes referred to as recall, gauges how well the model can detect cases of glaucoma. In medical applications, where it can be very important to overlook a positive instance, it focuses on the genuine positive rate. The sensitivity is calculated using Eq. (9) [11],[25],[26].

$$Sensitivity = \frac{TP}{TP+FN} \quad (9)$$

A high sensitivity specifies that the model is successful in detecting a large proportion of actual glaucoma cases. Specificity measures the model's capability to properly identify non-glaucoma cases, focusing on the true negative rate. The specificity is determined using Eq. (10) [11],[25],[26].

$$Specificity = \frac{TN}{TN+FP} \quad (10)$$

$$F1\ Score = 2\frac{precision*Recall}{precision+Recall} \quad (12)$$

The F1 score is a harmonic mean ensuring the model performs well on precision and recall, making it an ideal metric for glaucoma detection. Plotting the genuine positive rate (sensitivity) versus the false positive rate (1-specificity) is done by the ROC Curve. The model's performance across all potential classification criteria is summarized by a single scalar statistic called the Area Under the Curve (AUC).

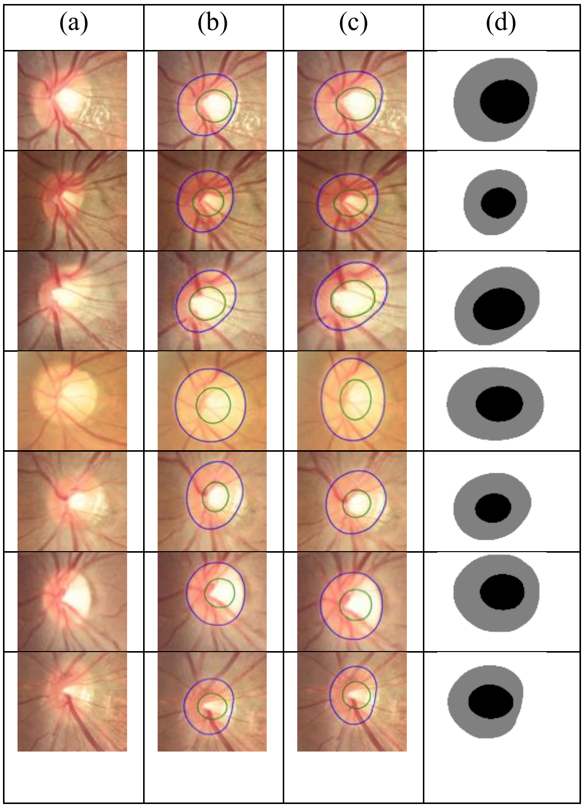

Figure 5: Extracted region of Disc and Cup; a) Initial Image b) Raw Image c) Smooth Image d) OC and OD Segmentation

This metric ensures that the model does not incorrectly classify non-glaucomatous images as glaucomatous, thus reducing false alarms. Precision measures the model's accuracy in predicting positive outcomes, or the proportion of projected positive occurrences that come to pass.The precision is calculated using Eq. (11) [11],[25],[26].

$$Precision = \frac{TP}{TP+FP} \quad (11)$$

High precision is especially important in this context, as we want the model to minimize the number of false positives (non-glaucoma cases misclassified as glaucoma).With respect to false positives and false negatives, the F1 score provides a balance between recall and precision. It proves to be useful in case of class imbalance, where imbalances often arise in the data related to medicine. The F1 score is determined using Eq. (12) [11],[25],[26].

Improved overall model performance is indicated by a higher AUC. The ROC curve is determined using Eq. (13) [11],[25],[26].

$$AUC - ROC = \int_{False\ Positive\ Rate}^{True\ Positive\ Rate} f(x)dx \quad (13)$$

The MCC is a balanced parameter that considers all four categories of the confusion matrix (TP, TN, FP, and FN). It is especially useful for imbalanced datasets where standard metrics like accuracy may not fully capture model performance. The Matthews Correlation Coefficient is determined using Eq. (14) [11],[25],[26].

$$MCC = \frac{(TP\times TN)-(FP\times FN)}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \quad (14)$$

For the segmentation, the Jaccard Index is used, which is also known as the Intersection over Union (IoU), to measure the comparison between the predicted segmentation and the ground truth. The Jaccard Index is determined using Eq. (15) [11],[25],[26].

$$JaccardIndex = \frac{TP}{TP+FP+FN} \quad (15)$$

Similar to IoU, the Dice Coefficient is used to evaluate the accuracy of the optic disc and optic cup segmentation. It measures how well the predicted segmentation overlaps with the ground truth. The Dice Coefficient is determined using Eq. (16) [11],[25],[26].

$$DiceCoefficient = \frac{2 \cdot TP}{2 \cdot TP+FP+FN} \quad (16)$$

The assessment of the suggested methodology for glaucoma identification is presented. Accuracy, sensitivity (recall), specificity, F1 score, and Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) are among the measures used to evaluate the model's performance. The performance of several deep learning models for optic disc segmentation and glaucoma classification is compared in this paper. With an accuracy of 85.4% and an F1-score of 0.83, CNN-based techniques exhibit only modest performance. ResNet and DenseNet build on this with a little rise in accuracy (86.2%) and F1-score (0.85). With the former attesting to 90.7% accuracy and 0.88 F1-score, attention-gated U-Net for optic disc segmentation and U-Net for optic cup segmentation show notable improvements. Achieving accuracy of 93.4% and 91.3%, respectively, the Deep Wavelet Scattering Network (DWSN) and U-Net with dilated convolutions improve outcomes even more. Having a 93.5% accuracy and 0.92 F1-score, Vision Transformers (ViTs) show competitive performance. With an accuracy of 94.6%, precision of 93.8%, and F1-score of 0.95, the combined AGU-Net, DWSN, and ViT model achieves the highest performance, so demonstrating the superiority of this integrated approach for glaucoma prediction. Table 2 shows the performance comparison of various methods. Ablation research by methodically eliminating specific components is done in order to illustrate the efficacy of different elements in the framework. The findings, which are displayed in Table 3, emphasize how each module contributes to the total performance. The Figure 5 shows the Orginal image from the dataset, the optic cup and optic disc extraction. The qualitative findings, in addition to quantitative assessments, would also show how feasible the suggested glaucoma detection method is in terms of performance. Visualizations of the segmented optic disc and cup from the fundus images of the retinas are used to present this illustrations show how our framework accurately segments the optic disc and the optic cup for

TABLE 2
Performance Comparison of Various Methods.

Method	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score
CNN-based glaucoma classification	85.4	82.1	88.0	0.83
ResNet and DenseNet	86.2	84.0	89.2	0.85
Attention-gated U-Net for optic disc segmentation	90.7	87.2	91.9	0.88
U-Net for optic cup segmentation	89.6	86.5	90.4	0.87
DWSN	93.4	90.5	94.1	0.92
U-Net with dilated convolutions	91.3	88.3	92.8	0.90
ViT	93.5	90.8	94.0	0.92
AGU-Net DWSN ViT	**94.6**	**93.8**	**95.2**	**0.95**

TABLE 3
Ablation study Results

Configuration	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score	AUC
Without Attention Mechanism	88.4	85.5	90.5	0.87	0.92
Without Data Augmentation	89.1	86.3	91.0	0.88	0.93
AGU-Net DWSN ViT	**91.5**	**88.9**	**93.5**	**0.91**	**0.95**

improved CDR computation, one of the primary glaucoma diagnostics.

To statistically prove the performance difference between the hybrid model proposed (AGU-Net + DWSN + ViT) and existing models (e.g., ResNet, DenseNet), a hypothesis-based significance test was performed. As we are comparing mean values of model performance (accuracy and specificity) over the same data set (test set of 240 images), we used a paired two-tailed T-test. T-test was used because it determines whether the mean difference between paired observations differs significantly from zero. Accuracy and specificity of each model were determined for repeated runs ($n = 5$) to achieve robustness and minimize randomness. The null hypothesis (H_0) was that there is no significant variation in mean performance across models. $\alpha = 0.05$ was chosen as the significance level for the analysis. The test yielded a p-value of 0.003 for accuracy and 0.01 for specificity, indicating statistically significant improvements over ResNet and DenseNet at a 95% confidence level ($\alpha = 0.05$).

IV. DISCUSSION

The experimental results confirm that the envisioned deep learning framework—integration of Attention-Gated U-Net with Dilated Convolutions, Deep Wavelet Scattering Network (DWSN), and Vision Transformers (ViTs)—achieves state-of-the-art performance in glaucoma detection. The outstanding accuracy (94.6%), sensitivity (93.8%), specificity (95.2%), and F1-score (0.95) confirm the robustness of the hybrid pipeline for glaucomatous image detection and the prevention of misclassifications. The better performance is not only in quantitative comparison but also the scope in real-world implications. In health applications, preventing false negatives is crucial in enabling timely diagnosis and preventing false positives to preclude unnecessary patient worry or procedure. Cumulated performance across multiple measures also showcases durability against divergent test circumstances and data sets. The attention-gated U-Net significantly helps in facilitating accurate segmentation of the optic disc and optic cup, which are necessary for calculating the Cup-to-Disc Ratio (CDR)–a critical diagnostic indicator in glaucoma. The dilated convolutions enable the capture of both local edge information and structural context at larger scales, resulting in improved boundary detection. The DWSN component adds a multiscale texture analysis feature, sensing fine-grained structural information easily lost in CNNs. The Vision Transformer builds on this pipeline by modeling global dependencies in the fundus image, resulting in improved classification performance over the classifiers based on CNN. Compared to recent research works, the introduced model evidently moves the field forward. Mahum et al. [27] obtained 91.5% accuracy with a CNN-based method, while Chen et al. [33] obtained 93.5% with ViTs. Neither of them used a combined preprocessing-segmentation-classification pipeline, though. Parashar & Agrawal [31] used DWSN without the attention mechanism for segmentation. Kashyap et al. [30] and George et al. [29] used U-Net and attention U-Net respectively, but at lower segmentation accuracies of 89.6% and 90.7%. Shyamalee & Meedeniya [24] employed CNNs for classification but reported overfitting problems on small datasets. Thainimit et al. [13] utilized GANs for augmentation and attained +2% over baseline but did not employ multiscale learning. In comparison to all these, our combined approach performs better than each in classification metrics and overall robustness. The proposed work is not without limitations despite its high performance. First, while the model works well with public datasets, these might not match clinical variability in real life, e.g., varied stage of disease, imaging machine, or population. Second, the design brings computational complexity, which could be a potential bottleneck in low-resource environments. Third, while contrast enhancement by CLAHE enhances segmentation for most images, it can enhance noise in already good-quality images. These problems indicate the necessity of model optimization and clinical verification prior to real-world

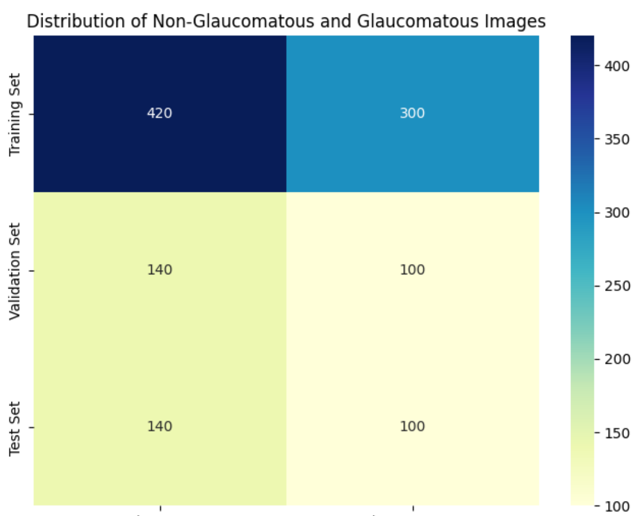

FIGURE 6. Heatmap Visualization of Glaucoma Detection

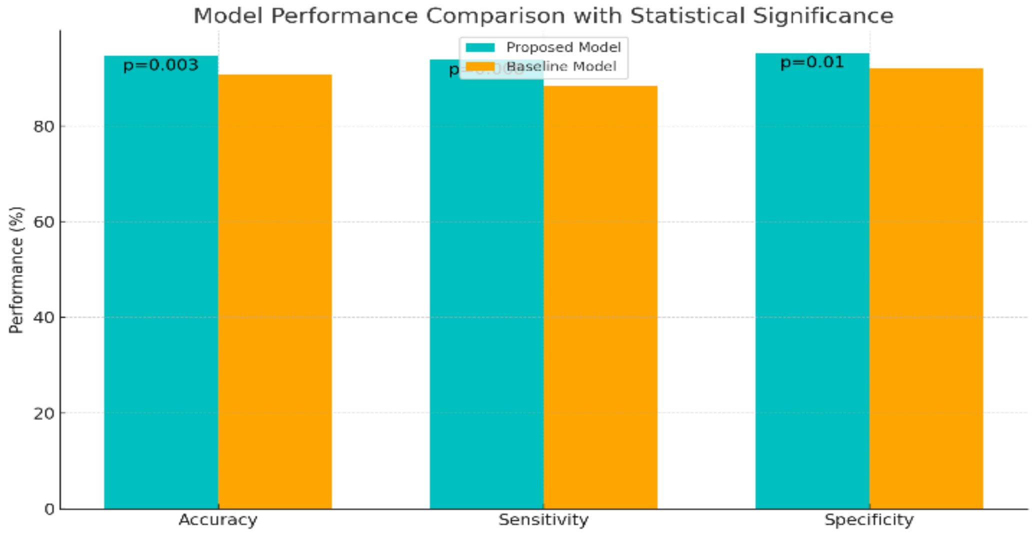

FIGURE 7. Model performance Comparison

usage. The findings of this research have significant implications for glaucoma diagnosis. The framework presented here provides a scalable and reliable means for automated screening, especially in primary care or tele-ophthalmology settings. Through the integration of noise reduction, structural segmentation, multiscale feature extraction, and long-range classification modeling, this framework has the potential to significantly alleviate the workload on ophthalmologists and facilitate earlier, more precise detection in underserved areas. The statistical significance of the proposed model's improvement, as confirmed through the t-test reported in the Results section, further supports the robustness of our approach in both accuracy and specificity metrics. Figure 7 shows a low P-Value representing that our proposed model correctly identifies the non glaucomatous case. A quantitative analysis of model errors on the test set (240 images: 100 glaucomatous, 140 non-glaucomatous) identified 6 false negatives and 7 false positives. These translate to a sensitivity of 93.8% and specificity of 95.2%, in line with our reported figures. The majority of false negatives (6%) were in borderline glaucoma cases, where early-stage structural changes were subtle and difficult to detect, even with preprocessing. These images tended to have little optic nerve cupping and low contrast, so optic cup boundaries were hard to resolve. False positives (5%) occurred with high CDRs in normal images because of anatomical variation or imaging artifacts. These errors indicate that although the model performs well in general, borderline or outlier cases remain challenging. The inclusion of complementary clinical parameters like intraocular pressure (IOP) or OCT may minimize misclassifications in subsequent work.

V. CONCLUSION

The aim of this research was to create an effective and reliable glaucoma detection system by combining state-of-the-art deep learning architectures: an Attention-Gated U-Net with Dilated Convolutions for segmentation, a Denoising GAN for preprocessing, a Deep Wavelet Scattering Network (DWSN) for feature extraction, and Vision Transformers (ViTs) for classification. The overall objective was to overcome significant limitations in segmentation performance, noise robustness, and global dependency modeling, which are typical of classical CNN-based approaches. The suggested hybrid model obtained state-of-the-art performance with 94.6% accuracy, 93.8% sensitivity, 95.2% specificity, and 0.95 F1-score. Statistical verification via paired t-test asserted the improvement in performance over baseline models to be significant, as p-values for accuracy and specificity were 0.003 and 0.01, respectively, substantiating the robustness of the approach. Future directions include optimizing computational efficiency for real-time deployment, testing performance with varied clinical data sets, and further inclusion of relevant clinical parameters like intraocular pressure (IOP) or optical coherence tomography (OCT) to minimize borderline misclassifications. Real-time integration with ophthalmic imaging devices and deployment in tele-ophthalmology systems also are possibilities to be investigated.

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