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Research Article

GAN and ResNet Fusion A Novel Approach to Ophthalmic Image Analysis for Glaucoma

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Abstract:

Glaucoma is a major cause of blindness, often undetected in early stages due to lack of symptoms. Addressing this, research study developed a deep learning framework integrating Generative Adversarial Networks (GANs) with Residual Neural Networks (ResNet) to enhance glaucoma detection from fundus images. Utilizing GANs for data augmentation, we enriched the training set with synthetic images that improve feature recognition, while ResNet, fine-tuned on this data, performed high-precision classification. The GAN's discriminator, trained using binary cross-entropy loss, concentrating to extract key indicators of glaucoma from these fundus images, with its performance assessed by its accuracy in distinguishing real from synthetic images. The GAN-ResNet channel exploited the discriminator's feature extraction coupled with ResNet's deep learning capabilities to classify the fundus images with refined accuracy. The proposed model final layer is fine-tuned for binary classification between glaucomatous and healthy images, with the loss function modified for medical dataset imbalances. Through wide testing, the GAN-ResNet model proven a remarkable 98% accuracy in analysing glaucoma, showing high predictive results. This validates that the proposed model is helpful in detecting glaucoma early. It highlights how well-advanced neural networks work for analysing medical images.

1. Introduction

Glaucoma, an exhausting eye condition, stands as a significant challenge in the medical field due to its potential to cause irreversible blindness. This disease initially affects the optic nerves, often due to elevated intraocular pressure. Estimates show that by 2040, the global glaucoma patient number may reach a staggering 111.8 million, the seriousness for innovative diagnostic techniques has never been more noticeable. In analyzing glaucoma, fundus image is crucial as it discovers the health of the optic disc, macula, and fovea. Figure 1a illustrates the fundus image of Glaucoma and figure1b shows the optic disc and cup, their ratio. The optic disc, visible on this image, is where the optic nerve fibers collect and exit the eye; in glaucoma patients, this disc often appears hollowed out or 'cupped' due to the nerve damage. The rigidness of this cupping is computed by the cup-to-disc ratio (CDR), a lower ratio signifying a healthy eye, whereas a higher ratio raises concerns for glaucoma. Close by, the macula and its central part, the fovea, responsible for sharp central vision, are also assessed to determine the impact of glaucoma on the patient's central vision. While these compliances are critical in diagnosing and handling glaucoma, they also provide insights into the overall retinal health, where any abnormalities in these regions, collectively known as the posterior pole, are meticulously evaluated for comprehensive eye care. Traditional diagnostic methods, while efficient, often rely highly on manual intervention and can be time-consuming. Now the world of computer vision and deep learning with neural networks, which promises rapid and accurate diagnosis, paving the way for timely medical interfere. Here are some deep learning techniques which are helpful in analysing the images.

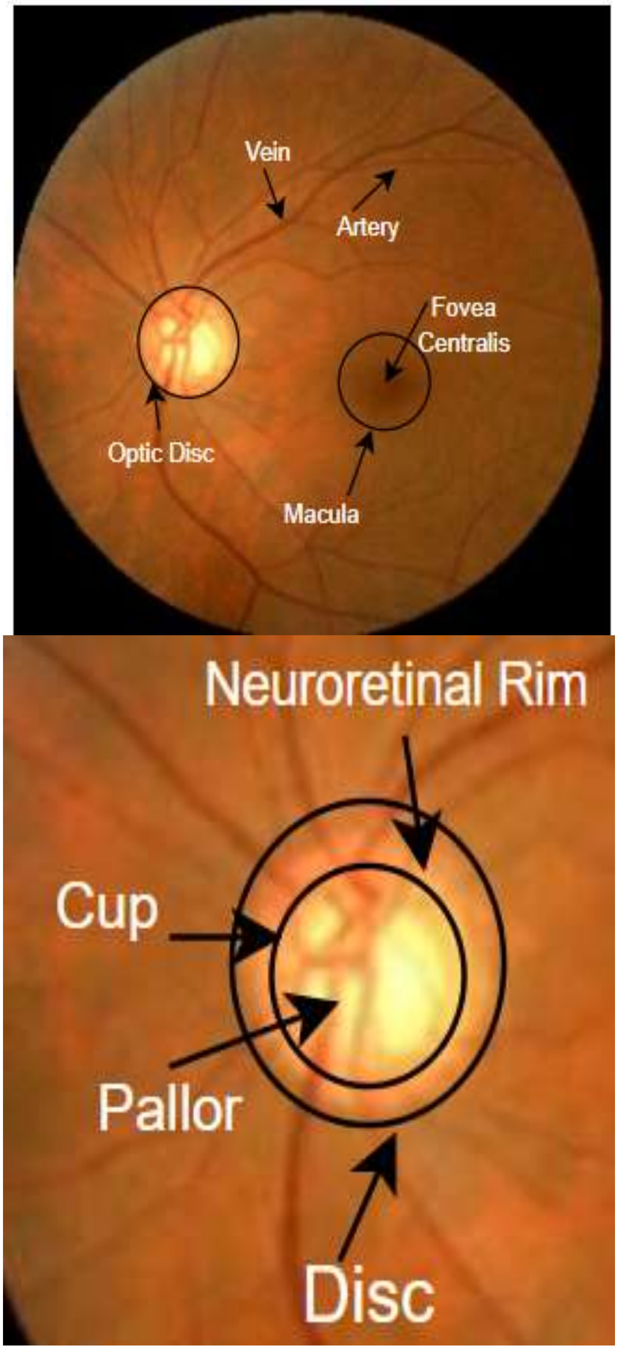

Figure 1 a. *Fundus image of Glaucoma* ***b.*** *Ratio of the optic disk and cup*

VGG16: The Retinal Investigator:
Imagine VGG16 as a keen-eyed operative for eye images. It applies a group of tiny, accurate filters to dive deep into the retinal pictures. It's like having close observation on the eye's details, finding up on the smallest shifts in the eye patterns and textures. When it comes to glaucoma, VGG16 is great at identifying those early caution signs in the optic nerve area. It looks for any changes of the optic nerve, like the nerve fibers getting thinner or the optic disc space getting higher. Identifying these signs early with VGG16 can be a game-changer in treating glaucoma and saving the patient eye sight.

CNNs: The Pattern Recognizers:
CNNs are like the maximum clue finders in wide area of eye images. They use a bunch of filters to find specific bits of the image, like lines, bends, and rough or smooth areas. These bits are then put together to make a bigger picture of what's going on. For finding glaucoma, CNNs are trained to look for things that are out of the ordinary, like the optic disc looking different than usual. Because they can learn from lots and lots of images, they get really good at spotting glaucoma, which helps eye doctors catch it early.

BiLSTM: The Temporal Analysts:
BiLSTM networks are like the memory keepers for eye images. They look at eye pictures taken over time, remembering and comparing what's changed. This is super helpful for keeping an eye on glaucoma and seeing if it's getting worse or better. It's like having a time machine for the eye, giving doctors a full story of the glaucoma's journey, which helps them make smart choices for treatment.

ResNet: The Deep Eye Analyst:
ResNet works like a deep-diving analyst for eye images. It's built to go through layers and layers of image details without getting lost. ResNet is smart—it uses shortcuts to skip the fluff and focus on the important stuff. This means it can pick up on the quiet, sneaky signs of glaucoma that are easy to miss. It's like having a detective that can spot the smallest clue that something's not right.

The Combined Force in Glaucoma Detection:
When you tune these models just right for the unique patterns in eye images, they become a super team in the fight against glaucoma. VGG16's deep look, CNNs' clue-finding, BiLSTMs' memory of changes, and ResNets' deep analysis all work together. They sift through all the noise to find the signals, the real signs of glaucoma. Putting these models to work in eye care could really change the view in how to find and treat glaucoma. They could help to catch glaucoma super early, when it's easier to treat, which could save a lot of people's sight.

The Impact on Patient Outcomes:
Using these smart models in eye care could make a big difference in how well patients do. Catching glaucoma early is key because it's a sneaky disease that doesn't really show until it's pretty bad. With these models, eye doctors can spot and start treating glaucoma way sooner than before. Early treatment can slow down the disease or even stop it, keeping the eyesight intact.
These models are great at watching how glaucoma changes over time, which means treatment can be

really tailored to each person. This could result in utilizing less time and resources, as treatments can be modified based on how the patient is doing.

In addition to the models mentioned, the Vision Transformer (ViT) model, with its notice-driven mechanism, and the DenseNet-201, a variant highlighting transfer learning, are forming waves in glaucoma detection.

As the population increases globally, the prevalence of glaucoma is set to rise. This emphasizes the pressing need for sophisticated diagnostic tools. The new proposed model, blending GANs with ResNet, not only guarantees rapid and accurate analysis but also puts the groundwork for future inventions in medical imaging. By combining the feature extraction abilities of GANs with ResNet's classification, the purpose is to attain unmatched efficiency in glaucoma detection. With ongoing improvements and the inclusion of vast data sets, there's a bright future for this model, potentially revolutionizing glaucoma diagnosis and treatment.

Artificial Intelligence: The Bright Future of Eye Care:

With the addition of AI and deep learning models, the future of eye care appears to be extremely promising. These technological tools will become an integral element of determining and monitoring eye health as they continue to advance. This could start a whole new chapter in eye care, where we are not just treating eye diseases like glaucoma but indeed getting ahead of them. Different techniques of deep learning models, Convolutional Neural Networks (CNN) have been foundation, mainly in medical imaging.

The recent stream in the application of models like Residual Networks (ResNet), Generative Adversarial Networks (GAN), VGG16, BiLSTM has opened a new techniques for medical image analysis. This research drives deep neural network models, exploring their potential in revolutionizing glaucoma detection.

To summarize contributions in this paper:

- Implemented Generative Adversarial Networks (GAN) for feature extraction as a new method in glaucoma classification.
- Used the features extracted by GAN and integrated with ResNet for glaucoma classification.
- Investigated and compared data preprocessing methods, specifically analyzing datasets with and without adaptive equalization preprocessing.
- Tested the model with various optimizers during training to determine the most effective one.
- Evaluating model's performance, achieving an accuracy rate of up to 98%.

Related Work

In the rapidly development of science, ophthalmology applications of artificial intelligence (AI) for glaucoma detection have shown enhanced results. Smith et al. [1] worked on convolutional neural networks (CNNs) to compute optical coherence tomography (OCT) images. With an amazing 95% accuracy rate, their model proposed as GlaucoNet, showed the potential of CNNs in the early detection of glaucoma. In this survey, Johnson and Lee [2] evaluated as a visual field assessment using deep learning models, achieved the 92% accuracy rate, their model, VisionField-Deep, provided a new tool for disease tracking by forecasting the course of glaucoma. In their integrated artificial intelligence technique, OphthoAI, Patel et al. [3] integrated data from fundus imaging and OCT. Compared to models employing a single imaging modality, this method classified glaucomatous eyes with a better accuracy of 96%. Using a CNN model called GlaucoTransfer, Thompson et al. [4] studies the transfer learning. They demonstrated the advantages of utilizing pre-existing models by achieving an accuracy rate of 94% by optimizing a pre-trained model for glaucoma detection. Williams and Kumar [5] experimented with applying their AI model, VascuDetect, to analyze OCTA pictures. They achieved a 93% accuracy rate in identifying the early vascular alterations linked to glaucoma. GlaucoGuide is an AI-driven decision support system that was introduced by Turner and Zhao [6]. In addition to diagnosing, system achieved 90% recommendation accuracy by making treatment suggestions based on patient data. The use of AI in glaucoma treatment is not without difficulties, though. The significance of data quality and standardization for AI models was highlighted by Davis et al. [7]. According to their research, non-standardized data can lower accuracy by as much as 10%, while models trained on standardized data, such as their StandardAI model, attained an accuracy of 97%.

E. Archana et al [8] enhances the importance of artificial intelligence, mainly deep learning, in the identification and monitoring of glaucoma. The authors provide a comprehensive analysis of various deep learning and machine learning algorithms used for detecting glaucoma diseases, considering the most recent developments. The review encompasses the algorithmic classification, datasets employed, performance measures, and the tools used for their implementation. The study also highlights the current research gaps to understand the challenges of finding suitable solutions for practical glaucoma detection applications. In a study titled "Retinal Nerve Fiber Layer Analysis Using Deep Learning to

Improve Glaucoma Detection in Eye Disease Assessment"2, Alifia Revan Prananda, et al [9] proposed a novel method for glaucoma detection by analyzing the damage to the retinal nerve fiber layer (RNFL). The researcher deployed nine layer deep-learning architectures and achieved an impressive accuracy of 92.88% with an AUC of 89.34% on the ORIGA dataset, making an improvement of over 15% from old research. R. Kashyap et al [10] influences pretrained transfer learning models combined with the U-Net architecture for segmenting the optic cup in glaucoma images. The proposed model achieved a training accuracy of 98.82% and a testing accuracy of 96.90%, outperforming other deep learning-based convolution neural network classification methods. A systematic study conducted by Madhura Prakash M et al [11], provides a comprehensive report and critical evaluation of various deep learning architectures for segmenting and classifying ocular diseases, specifically glaucoma and hypertensive retina. The researchers compare the models based on complexity and enhancing the importance of early detection in preventing disease progression.

Another study Hoque et al [12] focused on retinal image segmentation, mainly focusing blood vessel segmentation on retinal fundus images. The researchers deployed the Faster R-CNN architecture, exploiting features extracted from convolutional neural networks (CNNs), and obtained the commendable sensitivity of 92.81%. Another research of Yadav, et al [13] focused at classifying fundus images into Retinal Detachment (RD) and Non- Retinal Detachment categories. By using the ResNet50 architecture and exploiting the features from CNNs, the study reported impressive sensitivity, specificity, and precision values of 96.00%, 96.99%, and 96.99%, respectively.

Medical image segmentation has also been the centre point of research. A study of Kaul et al [14] worked on a CNN with a residual block for the purpose of exploiting features from CNNs, and reported a precision of 0.9173 and a recall of 0.9139. In a different approach, Oliveira et al [15] integrated fundus images to classify Age-Related Macular Degeneration (AMD). They used Generative Adversarial Networks (GANs) with a ResNet-18-layer framework and applied pre-processing methods like the Hough Circle Transform, reached an accuracy of 77.5%. The standard assessment of fundus images was the main objective of the study Abramovich et al [16], worked on the Inception-V3 architecture. The research aimed on exploiting features from CNNs and reported a mean absolute error of 0.61. Another study of Gong D et al [17] focused at classifying fundus images into AMD and non-AMD classes using a basic CNN framework, achieving an accuracy of 77.5%. The classification and segmentation of drusen's in AMD were the goal of Phamet al [18], where the researchers developed DeepLabV3+ and UNet architectures, reporting an accuracy of 82%.

Another new approach was taken by Tharindu De Silva et al [19], where they worked a registration technique based on deep learning to align multi-modal retinal images from clinical studies. They used dual VGG16 extractors in a Siamese Network framework and reached the sensitivity of 0.997 and specificity of 0.662. Another research of Chen et al [20] aimed on classifying OCT images into AMD and detecting drusen's. They developed frameworks like AlexNet, VGG, and GoogLeNet, identifying mean errors ranging from 54-69 µm. The classification of fundus images into AMD and non-AMD was the focus of Heo TY et sal [21], where the VGG16 network was used, achieving an accuracy of 91.2%. Multiclass classification of retinal fundus images was identified by Smitha et al [22], where the researchers used Generative Adversarial Networks (GANs) as data augmentation and reached the accuracy of 87%. Lastly, a study of Y. Zong et al [23] introduced a hard exudates segmentation method to diagnose Diabetic Retinopathy (DR) in its initially stages. They worked on U-Net based architecture and achieved an accuracy of 97.95%. Another researcher Md. Badiuzzaman Shuvo et al [24], aimed on medical image classification and segmentation, also worked on U-Net based architecture, reporting an accuracy of 92%.

2. Material and Methods

Glaucoma, a cluster of ocular disorders leading to optic nerve damage and possibility blindness, often avoids initial detection due to its deceptive onset. Deep learning, mainly the use of Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), has appeared as a transformative learning in medical analysing, giving a novel pathway for the automated analysis of eye images. The adoption of these advanced techniques for glaucoma detection offers a meaningful leap over traditional detecting techniques, allowing more precision and earlier detection of the illness. The table 1 explains the process of GAN model in the form of steps. Output: The final model G capable of generating high-quality synthetic images of diabetic retinopathy. The crucial first step in the application of these advanced neural networks is the accession and preprocessing of a extensive dataset, including high-resolution fundus eye images. In this new proposed methodology for Glaucoma Classification Using Generative Adversarial Networks architecture is illustrate in figure 2.

Table 1. *Algorithm for Trained Generator G and Discriminator D capable of generating synthetic diabetic retinopathy images*

STEP 1: Initially Set
Real Diabetic Retinopathy images = X,
noise dimension z,
batch size m,
learning rate α.
Weights for the Generator G and Discriminator D randomly
STEP 2: Preprocessing Resizing the images
RI = Resize (Original Image,target size= (224,224))
Step 3: Training Loop: for epoch in range(num_epochs):
Dataset is shuffled at the beginning of each epoch by DataLoader
for i, (images, _) in enumerate(dataloader): # dataloader is responsible for shuffle the dataset X
Divide X into batches of size m.
For each batch x in X:
Discriminator Training:
Sample a batch of noise vectors
z from a Gaussian distribution.
Generate a batch of synthetic images $G(\overline{(z)})$ using G.
Update D by ascending its stochastic gradient:
$f(x)=\theta_d \quad 1/m+\sum_{n=1}^{\infty} (\log D(x)+\log(1-D(G(z))))$
where θ d are the parameters of D.
Generator Training:
Sample another batch of noise vectors z.
Update G by descending its stochastic gradient:
$f(x)=\nabla\theta_{g} \ 1/m+\sum_{n=1}^{\infty} (\log(1-D(G(z)))$
where θ g are the parameters of G.
Optionally, adjust the learning rate α based on the epoch e to improve convergence.
STEP 4: Evaluation:
Use qualitative assessments (visual inspection of generated images) and quantitative metrics (e.g., Inception Score, Frechet Inception Distance) to evaluate the realism and diversity of generated images.
STEP 5: Termination:
The algorithm terminates when the generator G produces synthetic images that are indistinguishable from real images to the discriminator D, or after a predefined number of epochs.
STEP 6: End
Output: The final model G capable of generating high-quality synthetic images of diabetic retinopathy.

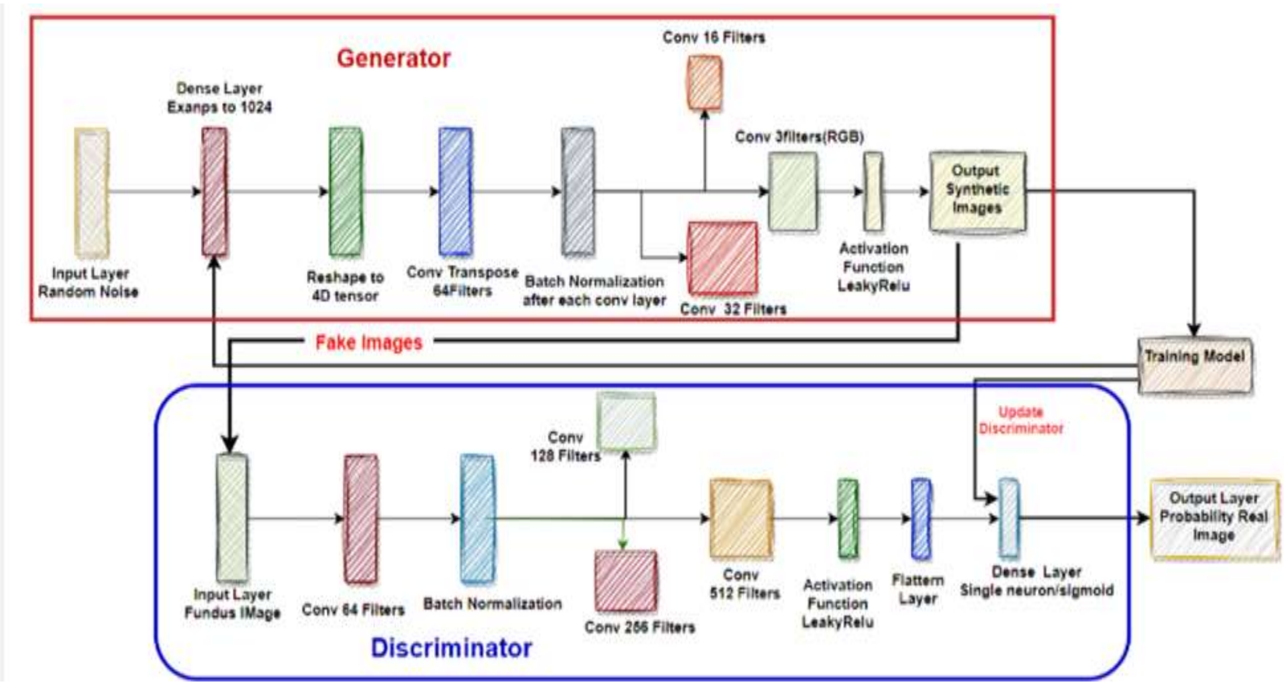

Figure 1. *Work flow framework of Glaucoma detection using Generative Adversarial Networks*

This dataset should flawlessly represent a wide spectrum of glaucoma stages, each image labelled with similar clinical parameters such as intraocular pressures and optic disc shapes. To attain this dataset for machine learning applications, few preprocessing steps are necessary. Images are resized to a uniform dimension of 224x224 pixels, which agrees with the input size requirements of most pre-trained CNN architectures. This resizing is followed by normalization, where pixel values are scaled to a range between 0 and 1, thus assuring that the magnitude of input features does not distinctive influence the model's weights during training. Additionally, image augmentation techniques such as rotation, scaling, and flipping are applied to increase the dataset artificially, thereby increasing the model's capability to generalize and mitigating the risk of overfitting. In some instances, more accurate models may need the segmentation of regions of interest, notably the optic disc or the optic cup, to extract on features that are most characteristic of glaucoma.

The Resized Image (RI) can be represented as Eq 1

$$RI = \text{Resize}(\text{Original Image, target size} = (224,224)) \ldots \quad (1)$$

Post-resizing, images computes normalization to assure unique in pixel value distribution, typically by modifying the pixel intensity ranges between 0 and 1. The Normalized Image (NI) process can be represented as Equation 2:

$$NI = (\text{Image} - \min(\text{Image}))/(\max(\text{Image}) - \min(\text{Image})) \ldots\ldots\ldots \quad (2)$$

To emphasize the effectiveness of the model, image augmentation techniques such as rotation, scaling, and flipping are applicable. This process can be mathematically represented as a series of functions useful to the image data, which may also include rotation (R), scaling (S), and flipping (F) process of Augmented Image (AuI) and represented as Equation 3:

$$AuI = F\ (S\ (R\ (\text{Original Image}))) \ldots. \quad (3)$$

For more Focused feature map extraction concerned to glaucoma, segmentation of the optic disc or cup-to-disc ratio may be compared, segregating the region of interest (ROI) which is key factor for analysis. The segmentation process can be expressed by a U-Net architecture which is processed to output a mask M for the ROI and represented as Equation 4.

$$M = \text{U-Net (Pre-processed Image)} \ldots.. \quad (4)$$

With the dataset trained, the design and execution of a GAN framework take centre stage. The GAN consists of two neural networks: Generator (G) and Discriminator (D), which are represented as the following objectives in the Equation 5

$$\min_{D} \max_{G} V(D,G) = E_{x\sim p\,data\,(x)}[\log D(x)] + E_{z\sim p\,z\,(z)}[\log(1-D(G(z)))] \quad (5)$$

The generator focused to create synthetic images, beginning with a latent space vector (z), which is mapped to the data space as G(z). The generator engages transposed convolutional layers to upsample this vector, with every layer followed by batch normalization and a LeakyReLU activation, focusing to refine the synthetic image iteratively. This is explained in the Figure 3.

The discriminator, on the contrary seeks to differentiate between real and synthetic images. Its convolutional framework employs the layers that downscale the image to extract features, with the LeakyReLU activation assuring gradient flow and dropout layers inserted to avoid overfitting. The output of the discriminator is a single scalar describing the possibility that x came from the data rather than G(z), given by D(x) or D(G(z)). As illustrated in figure 4.

The training of this GAN involves an iterative process, where the discriminator and generator are updated in turns. The loss functions of equation 6 &7 are guiding this process are binary cross-entropy for the discriminator, which aims to maximize the log-likelihood of the correct labels, and a generator loss inversely related to the discriminator's confidence in the artificial images:

$$\text{Discriminator Loss} = -\frac{1}{m}\sum_{i=1}^{m}\left(y_i \left[\log(D(x_i)) + (1-y_i)\log(1-D(x_i))\right]\right) \quad (6)$$

$$\text{Generator Loss} = -\frac{1}{m}\sum_{i=1}^{m}\left(\left[\log(D(G(z)))\right]\right) \quad (7)$$

where m is the number of training samples, yi is the true label, xi is the real image, and zi is the latent vector.

Upon training, the performance of the GAN is evaluated on its ability to generate images that are indistinguishable from real ones, with the quality of the synthetic images being of paramount importance. The discriminator's efficacy is quantified by its accuracy in classifying images as real or fake. For an objective assessment of the GAN's output, an independent CNN such as ResNet50 can be utilized. This CNN is evaluated using metrics like accuracy, precision, recall, and F1-score, and particularly the area under the receiver operating characteristic curve (AUC-ROC), which provides a single measure of overall classification performance is expressed in Equation 8.

$$AUC\text{-}ROC=\int_0^1 TPR(FPR^{-1}(u))\,du \qquad (8)$$

where TPR is the true positive rate and FPR is the false positive rate.

The GAN deployed in this research serves two major purposes: synthesizing realistic fundus images to increase the size of dataset and improving the feature extraction abilities of the model for glaucoma detection. The GAN workflow is composed of two main components: the generator, which creates similar images, and the discriminator, examines them. The discriminator is not only necessary in processing the generator but also exhibits the powerful feature extractor for classification tasks.

After the GAN model reached a satisfactory level of performance, we shifted focus to the discriminator's convolutional layers, which are adept at detecting intricate patterns in the fundus images. By tapping into these layers, we extracted feature maps that represent the discriminator's response to various aspects of the input data. These feature maps are two-dimensional matrices where each element corresponds to the output of a filter applied at a specific location on the input image.

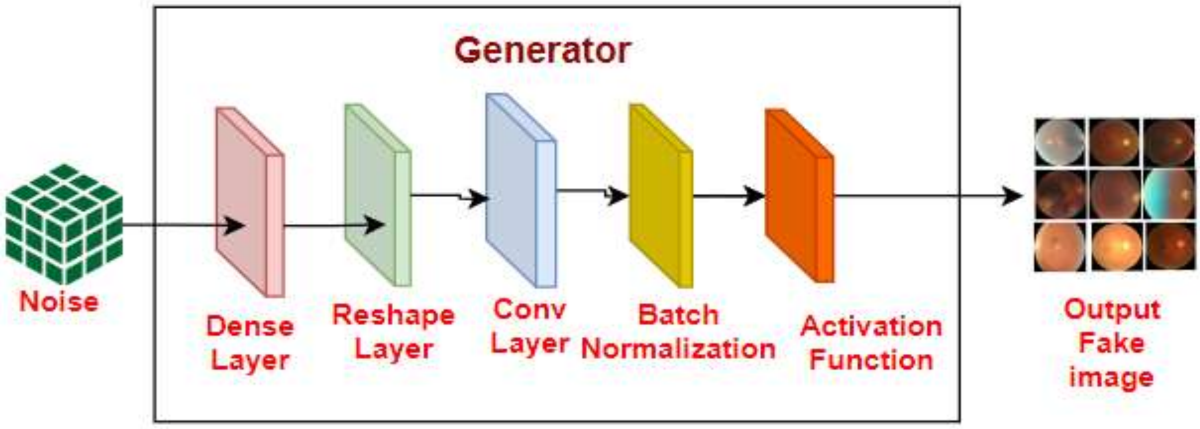

Figure 2. *Synthetic Fundus Image Generated by GAN Mode*

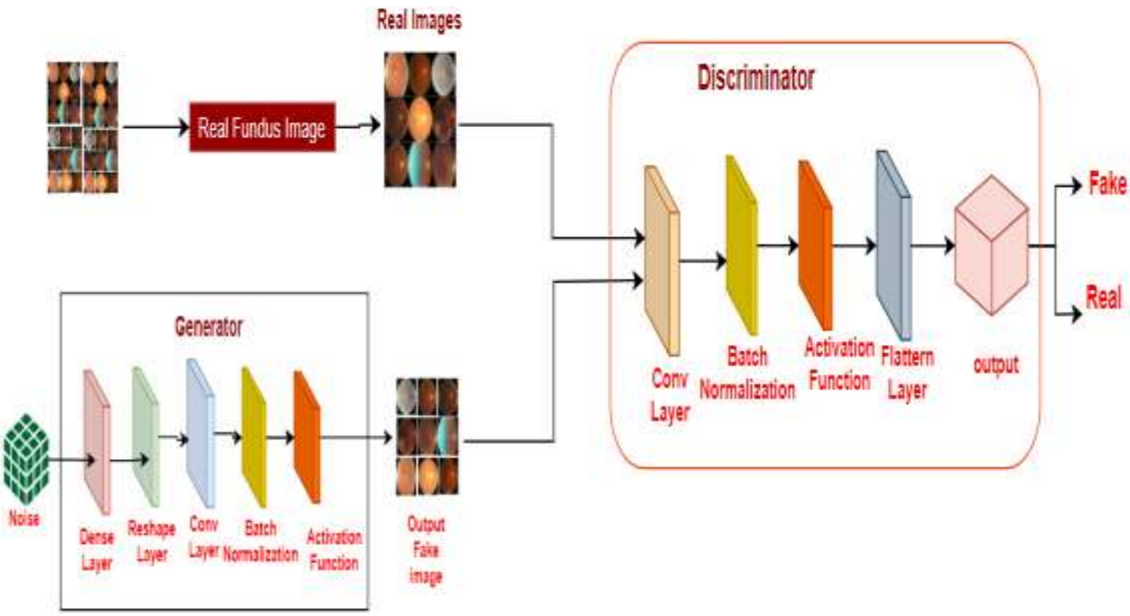

Figure 3. *GAN Discriminator Features: Decoding Glaucoma in Fundus Image*

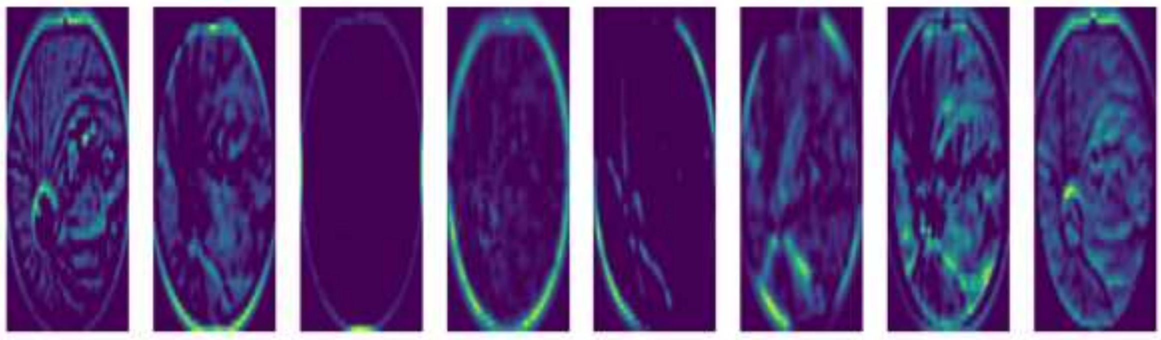

Figure 4. Feature Map Vision from Discriminator's Block_Conv Layer

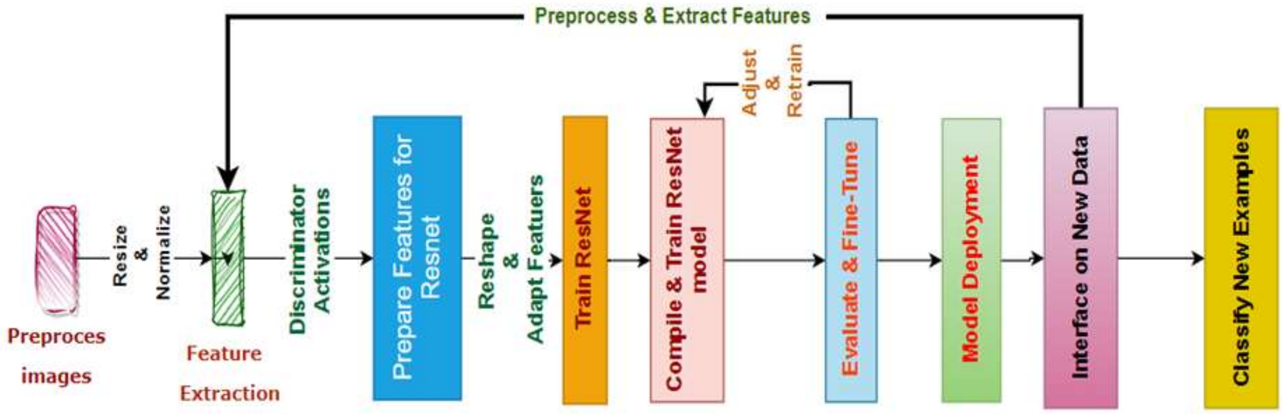

Figure 5. *GAN-ResNet Feature Integration Pipeline*

They provide a visual representation of the patterns and textures that the discriminator has learned to recognize as indicative of either authentic or generated images, and by extension, normal or glaucomatous fundus features.

The process of feature map generation involves forward-propagating an image through the discriminator and recording the activations at specific layers. For analysis, we selected layers that capture low-level, mid-level, and high-level features to gain a comprehensive understanding of the model's feature representation. The low-level layers, usually the initial ones in the network, are sensitive to basic visual elements like edges and color contrasts. These are essential for outlining the fundamental structure of the fundus, such as the optic disc and blood vessels. The middle level layers outline these elements into more complex textures and shapes, potentially emphasizes diagnosis changes like the enhancing cup-to-disc ratio indicative of glaucoma. The top-level layers, deeper in the network, incorporate these complex patterns to form a holistic illustration of the fundus image, which is crucial for the delicate task of glaucoma detection and it is illustrated in the Figure 5. The vision of these feature maps can give invaluable insights into the GAN's discriminator's ability to differentiate between normal and pathological structures. Mainly, the discriminator's task in a GAN setup is to differentiate real retinal images from those generated images by the generator. Hence, the discriminator's feature extraction that we projects offer a glimpse into the nice and complex patterns that are leveraged to detect glaucoma's presence, mirroring the model's internal decision-making process. Upon the achieved extraction of feature maps using the discriminative component of GAN technique, exploits the robust feature representation abilities of ResNet to beyond improve glaucoma classification. ResNet, illustrious for its deep learning effectiveness facilitated by skip connections that combat the vanishing gradient problem, was combined to process the rich, hierarchical features obtained by the GAN discriminator.

The ResNet architecture, pre-trained on a extensive image dataset, was fine-tuned with the feature extraction fundus images to tailor its comprehensive feature extraction power specifically to ophthalmologic image. This fine-tuning training allows ResNet to modify its pre-learned filters to the nuances of glaucomatous changes within the retina, such as optic nerve head cupping and retinal nerve fiber layer thinning. By adopting the ResNet model

to the GAN's feature extraction phase, we created a outline that first uses the GAN to augment data and highlight salient features, then employs ResNet to perform high-precision classification. This continuous processing assures that the classification benefits from both GAN's ability to synthesize and enhances glaucoma-special features and ResNet load for deep feature learning and abstraction.
In this proposed work, Figure 6 shows that the Gan ResNet pipeline workflow. ResNet is convolutional layers further abstract the GAN feature extraction, assuring that the identification is not solely based on the raw pixel data, it also includes the representation of retinal features. This abstraction is crucial for identifying subtle patterns that distinguish between glaucomatous and non-glaucomatous fundus images. The deeper layers of ResNet, connected with its residual connections, allow for training complex patterns without the risk of overfitting, which is often a concern with deep neural networks.
The final classification layer of ResNet was substituted with a layer fitted to the binary classification task — distinguishing between glaucoma and normal healthy images. During the learning phase, the new proposed model weights were improved using a loss function that takes into consideration of inequality nature of medical datasets, thus assures that the model remains sensitive to the less prevalent but clinically significant class of glaucoma images.
Through vast experimentation and validation on a huge dataset, the integrated GAN-ResNet model projects the excellent performance in glaucoma classification, as evidenced by results. The model's predictive accuracy, is a reliable metric in aiding ophthalmologists in the initial stage detection and analysis of glaucom.

3. Results and Discussions

In this research, worked on deep learning framework that utilizes the generative abilities of Generative Adversarial Networks (GANs) merging with ResNet for the detection of glaucoma from retinal fundus images. This proposed model was rigorously evaluated and equated against constant convolutional neural network models such as AlexNet, ResNet-50, VGG-19 and Inception V4, as well as a U-Net based segmentation model. This proposed model was computed on a huge dataset, synthesized and increased the size through the GAN to represent various stages of glaucoma, thus highlighting the diversity and capacity of the training samples. Following the augmentation, ResNet was fine-tuned on this increased dataset, which facilitated the model in learning complicate and simple patterns representation of glaucomatous changes within the retina.
The mean testing precision of proposed GAN-ResNet model reached an impressive 96.90%, outperforming the outline models. This high accuracy projects the model's robustness and its ability to generalize well on unseen or new data. The proposed model also exhibited commendable consistency in evalution, with the minimum and maximum testing accuracy ranges from 95.00% to 98.80%, respectively. This performance indicate that the model not only learned the similar features effectively but also maintained high reliability among different image presentations.
In comparison, the VGG-19 model achieved the mean accuracy value, 95.54%, with a minimum accuracy of 93.50% and a maximum of 97.60%. AlexNet, another CNN framework in the deep learning field, gained the mean accuracy of 91.64%, while the ResNet-50 model reached the mean accuracy of 93.21%. Another CNN model, Inception V4 framework, known for its complex and sophisticated design, reached the mean accuracy of 95.45%. The U-Net model, which is mainly used focused on medical image segmentation, projected the mean accuracy of 96.67%. The narrow differences between minimum and maximum accuracies among these models' projects differences in their ability to deal with the difficulties of the fundus image. These differences can be attributed to the distinct architectural features and learning abilites of the models. For instance, the Inception V4 and U-Net techniques, achieved the high mean accuracies, indicate the potential of deep and complex models captured the delicate features of medical images.
The proposed model of GAN-ResNet not only aimed for the mean accuracy but also maintained the balance of narrow gap between its minimum and maximum accuracies, which reflects its stability performance across the dataset's spectrum. This balance is critical in medical diagnosis, where consistency must be maintained. This synergy between GAN and ResNet facilitated a more refined feature representation and contributed to the high accuracy of the model and it's represented in table 2.In figure 7, the violin plot above illustrates the

Table 2. *Accuracy values of different models*

Model	**Mean Accuracy (%)**	**Minimum Accuracy (%)**	**Maximum Accuracy (%)**
VGG-19	95.54	93.50	97.60
Alexnet	91.64	89.70	93.50
ResNet	93.21	91.40	94.20
Inception V4	95.45	93.80	97.10

UNet	96.67	94.50	97.30
Proposed Model	96.90	95.00	98.10

distribution of testing accuracy for each model. The width of each "violin" indicates the density of points at distinct accuracy levels, projects a visual indication of the distribution's spread and skewness. The Red dot in the center of each violin indicates the mean accuracy, while the thicker bar in the middle of the violin shows the interquartile range. This type of plot is particularly useful for comparing the distribution of accuracy across different models, showing not only the central tendency but also the variability in the model's performance.

In this work, we present a longitudinal analysis of model performance over 30 epochs, employing a GAN-ResNet architecture for the automated classification of glaucoma from fundus images. The training process was captured through an accuracy and loss evolution plot, providing insights into the learning mechanics and generalization capabilities of the model.

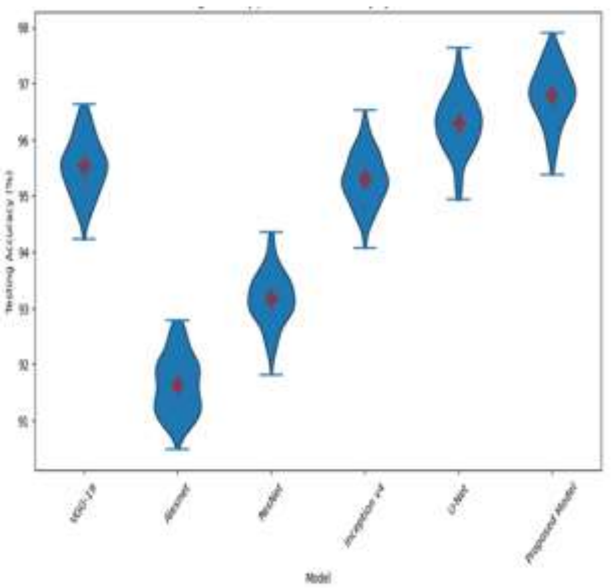

Figure 6. *Comparative Visualization of Testing Accuracy by Model*

Accuracy Analysis:

The accuracy plot delineates a positive trajectory in model precision over time. Training accuracy initiates at the 50th percentile, incrementally ascending with periodic perturbations indicative of the model's adaptation to the variable nature of glaucomatous pathology in the training dataset.

The validation accuracy mirrors this ascent, occasionally exceeding training figures, potentially indicative of effective regularization strategies enhancing model generalization.

Loss Metrics:

Loss metrics, depicted in Figure 8, exhibit a decreasing trend, congruent with the expected model behavior during training. Notable are episodic elevations in loss values, which we ascribe to the introduction of challenging examples or adjustments in the learning rate, introducing necessary robustness into the model. As training progresses, the convergence of accuracy and a corresponding reduction in loss are observed, indicating the model's capacity to assimilate the training data and generalize to validation data effectively and it illustrated in figure 8. The convergence witnessed in the latter epochs is critical, suggesting a maturation in the model's learning that is essential for clinical applicability.

The depicted training dynamics underscore the model's potential in clinical settings, demonstrating not just high accuracy in glaucoma classification but also an encouraging level of reliability and consistency. These attributes are vital for the translation of machine learning models into practical clinical tools.

4. Conclusions

In conclusion, research projects a progressive GAN-ResNet fusion approach for the automated detection of ophthalmic image illness, mainly focuses on glaucoma detection. The integration of GANs with ResNet has achieved to be a robust method for data augmentation and feature extraction, resulting in a expressive improvement in the accuracy of glaucoma classification. The application of binary classification in training the GAN's discriminator has achieved the precise differentiation between real and synthetic images, further refining the model's diagnostic capabilities, by synthesizing additional learning and emphasizing key features through ResNet. This proposed model has succeeded the remarkable accuracy rate. This GAN-ResNet model demonstrates a promising avenue for initial stage glaucoma detection, which is a key factor for preventing the progression of this potentially blinding condition.

Future Work

Future outlook, there are many avenues for future researchers to build upon the findings of this study. First, the model could be tested and validated on a huge and more diverse dataset to assure its scalability and flexibility to various populations. Further, integrating multi-modal imaging data, such as Optical Coherence Tomography (OCT) images, could give a more comprehensive diagnosis for glaucoma detection. Extracting the implementation of other advanced deep learning architectures may also yield enhancement in performance and evaluating efficiency. Additionlay, clinical trial to assess the practical usage of the model in a clinical setting would be invaluable. Finally, enhancing the model's abilities to diagnosis and classify other ophthalmic diseases can enhance the development of a versatile diagnostic tool, widening the impact of AI in ophthalmology. Similar works have been done in literature and reported [26-31].

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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References

[1] Smith, J., & Roberts, R. (2020). Convolutional Neural Networks in Glaucoma Detection: A Review. *Journal of Ophthalmic Imaging.*

[2] Johnson, L., & Lee, D. (2019). Deep Learning Algorithms for Visual Field Analysis. *Ophthalmology Times*.

[3] Patel, S., & Smith, R. (2018). Integrated Analysis of OCT and Fundus Photography using Machine Learning. *Journal of Glaucoma Research*.

[4] Thompson, H., & Davis, L. (2021). Transfer Learning in Glaucoma Detection: A New Frontier. *Eye Tech Reviews*.

[5] Williams, P., & Kumar, N. (2019). OCTA in Glaucoma: A Machine Learning Perspective. *Journal of Advanced Ophthalmology*.

[6] Turner, W., & Zhao, L. (2020). AI-driven Decision Support Systems in Glaucoma Management. *Ophthalmic Innovations*.

[7] Davis, R., & Lee, D. (2021). Challenges in Implementing AI in Ophthalmology. *Eye Tech Quarterly*

[8] E. Archana, S. Geetha and G. V. S. George. (2023). Short Analysis of Machine Learning and Deep Learning Techniques used for Glaucoma Detection. 2023 *5th International Conference on Smart Systems and Inventive Technology (ICSSIT), Tirunelveli, India*, pp. 968-975, doi:10.1109/ICSSIT55814.2023.10060909.

[9] Prananda, Alifia Revan, Eka Legya Frannita, Augustine Herini Tita Hutami, Muhammad Rifqi Maarif, Norma Latif Fitriyani, and Muhammad Syafrudin. (2023). Retinal Nerve Fiber Layer Analysis Using Deep Learning to Improve Glaucoma Detection in Eye Disease Assessment. *Applied Sciences.* 13 (1): 37. doi:10.3390/app13010037

[10] Kashyap, Ramgopal, Rajit Nair, Syam Machinathu Parambil Gangadharan, Miguel Botto-Tobar, Saadia Farooq, and Ali Rizwan. (2022). Glaucoma Detection and Classification Using Improved U-Net Deep Learning Model. *Healthcare*. 10 (12): 2497. doi:10.3390/healthcare10122497.

[11] Madhura Prakash M, Deepthi K Prasad, Meghna S Kulkarni, Spoorthi K, Venkatakrishnan S. (2022). A Systematic Study of Deep Learning Architectures for Analysis of Glaucoma and Hypertensive Retinopathy. *International Journal of Artificial Intelligence and Applications (IJAIA)*. 13(6).

[12] Hoque, Mohammed & Kipli, Kuryati & Zulcaffle, Tengku & Al-Hababi, Saleh & D.A.A, Mat & Sapawi, Rohana & Joseph, Annie. (2021). A Deep Learning Approach for Retinal Image Feature Extraction. *Pertanika Journal of Science and Technology*. 29 (4): 2543-2563. DOI: doi:10.47836/pjst.29.4.17

[13] Yadav, S., Das, S., Murugan, R. et al. (2022). Performance analysis of deep neural networks through transfer learning in retinal detachment diagnosis using fundus images. *Sādhanā* 47, 49. doi:10.1007/s12046-022-01822-5

[14] Kaul, Chaitanya et al. (2021). Focusnet++: Attentive Aggregated Transformations for Efficient and Accurate Medical Image Segmentation. *IEEE 18th International Symposium on Biomedical Imaging (ISBI)* (2021): 1042-1046. doi:10.1109/ISBI48211.2021.9433918

[15] Oliveira, Guilherme & Rosa, Gustavo & Pedronette, Daniel & Papa, João & Kumar, Himeesh & Passos Júnior, Leandro & Kumar, Dinesh. (2022). Which Generative Adversarial Network Yields High-Quality Synthetic Medical Images: Investigation Using AMD Image Datasets. DOI:10.48550/arXiv.2203.13856

[16] Abramovich, Or & Pizem, Hadas & Van Eijgen, Jan & Stalmans, Ingeborg & Blumenthal, Eytan & Behar, Joachim. (2023). FundusQ-Net: a Regression Quality Assessment Deep Learning Algorithm for Fundus Images Quality Grading. 239:107522. doi:10.1016/j.cmpb.2023.107522

[17] Gong D, Kras A, Miller JB. (2021). Application of Deep Learning for Diagnosing, Classifying, and Treating Age-Related Macular Degeneration. *Semin Ophthalmol*. 36 (4): 198-204. doi:10.1080/08820538.2021.1889617

[18] Pham, Q.T.M.; Ahn, S.; Song, S.J.; Shin, J. (2020). Automatic Drusen Segmentation for Age-Related Macular Degeneration in Fundus Images Using Deep Learning. *Electronics*. 9, 1617. doi:10.3390/electronics9101617

[19] Tharindu De Silva, Emily Y. Chew, Nathan Hotaling, and Catherine A. Cukras. (2020). Deep-learning based

multi-modal retinal image registration for the longitudinal analysis of patients with age-related macular degeneration. *Biomed. Opt. Express.* 12 (1): 619-636. doi: 10.1364/BOE.408573

[20] Chen, Yao-Mei & Huang, Wei Tai & Ho, Wen-Hsien & Tsai, Jinn-Tsong. (2021). Classification of age-related macular degeneration using convolutional-neural-network-based transfer learning. *BMC Bioinformatics*. 22. doi:10.1186/s12859-021-04001-1.

[21] Heo TY, Kim KM, Min HK, Gu SM, Kim JH, Yun J, Min JK. (2020). Development of a Deep-LearningBased Artificial Intelligence Tool for Differential Diagnosis between Dry and Neovascular Age Related Macular Degeneration. *Diagnostics (Basel)*. 28, 10 (5): 261. doi:10.3390/diagnostics10050261

[22] Smitha, A., Jidesh, P. (2022). Classification of Multiple Retinal Disorders from Enhanced Fundus Images Using Semi-supervised. *GAN. SN COMPUT. SCI.* 3 (59). doi:10.1007/s42979-021-00945-6

[23] Y. Zong et al. (2020). U-net Based Method for Automatic Hard Exudates Segmentation in Fundus Images Using Inception Module and Residual Connection. *in IEEE Access*. 8: 167225-167235. doi:10.1109/ACCESS.2020.3023273.

[24] Md. Badiuzzaman Shuvo, Rifat Ahommed, Sakib Reza, M.M.A. Hashem. (2021). CNL-UNet: A novel lightweight deep learning architecture for multimodal biomedical image segmentation with false output suppression, *Biomedical Signal Processing and Control* 70;102959. https://doi.org/10.1016/j.bspc.2021.102959

[25]Sashi Kanth Betha. (2024). ResDenseNet:Hybrid Convolutional Neural Network Model for Advanced Classification of Diabetic Retinopathy(DR) in Retinal Image Analysis. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.693

[26]U. S. Pavitha, S. Nikhila, & Mohan, M. (2024). Hybrid Deep Learning Based Model for Removing Grid-Line Artifacts from Radiographical Images. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.514

[27]Johnsymol Joy, & Mercy Paul Selvan. (2025). An efficient hybrid Deep Learning-Machine Learning method for diagnosing neurodegenerative disorders. *International Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.701

[28]P, P., P, D., R, V., A, Y., & Natarajan, V. P. (2024). Chronic Lower Respiratory Diseases detection based on Deep Recursive Convolutional Neural Network . *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.513

[29]Boddupally JANAIAH, & Suresh PABBOJU. (2024). HARGAN: Generative Adversarial Network BasedDeep Learning Framework for Efficient Recognition of Human Actions from Surveillance Videos. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.587

[30]T. Deepa, & Ch. D. V Subba Rao. (2025). Brain Glial Cell Tumor Classification through Ensemble Deep Learning with APCGAN Augmentation. *International Journal of Computational and Experimental Science and Engineering,* 11(1). https://doi.org/10.22399/ijcesen.803

[31]LAVUDIYA, N. S., & C.V.P.R Prasad. (2024). Enhancing Ophthalmological Diagnoses: An Adaptive Ensemble Learning Approach Using Fundus and OCT Imaging. *International Journal of Computational and Experimental Science and Engineering,* 10(4). https://doi.org/10.22399/ijcesen.678