**1. Krishnamoorthy V., 2. Logeswari S., 3. Sivanantham S., 4. Akshaya V., 5. Ganagavalli K., 6. Mohanraj V.**

ORCID: 1.0009-0007-4840-5671; 2. 0000-0002-9503-5104; 3.0000-0001-5215-8211; 4. 0009-0003-9822-0035; 5. 0000-0002-2103-7369; 6. 0000-0002-5254-9279

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# Glaucoma detection with the segmentation of optic disc and cup region using improved u-net and classification algorithm

*Wykrywanie jaskry poprzez segmentację tarczy nerwu wzrokowego i obszaru kielicha przy użyciu ulepszonego algorytmu u-net i klasyfikacji*

***Abstract**. A major contributor to irreversible blindness worldwide, glaucoma affects millions of people each year. To stop vision loss, early detection through precise diagnosis is crucial. In this work, we offer a hybrid deep learning approach for glaucoma prediction that combines ensemble learning approaches with convolutional neural networks (CNNs). The method combines the use of MobileNet V2 and ResNet-18 for classification with an enhanced U-Net model that incorporates residual connections and attention mechanisms for image segmentation. To increase prediction accuracy, our hybrid system makes use of the advantages of both optic cup-disc segmentation and CNN-based classifiers. To maintain computational efficiency and compliance with data privacy requirements, the model is optimized through the use of sophisticated techniques like as AdamW, cyclic learning rate schedulers, and stochastic weight averaging. In the present paper, we have analyzed the various performance metrics like accuracy, sensitivity, specificity, dice coefficient, Jaccard index, F1 score for the conventional methods, and Res-U-Net Architecture (Improved U-Net). Here, Res-U-Net Architecture (Improved U-Net) achieves an accuracy of 0.93 by 80% of the training data. Hybrid deep learning approach for glaucoma prediction that combines ensemble learning approaches with convolutional neural networks (CNNs).*

***Streszczenie.** Jaskra, która jest głównym czynnikiem przyczyniającym się do nieodwracalnej ślepoty na całym świecie, dotyka milionów ludzi każdego roku. Aby zapobiec utracie wzroku, kluczowe znaczenie ma wczesne wykrycie poprzez precyzyjną diagnozę. W tej pracy oferujemy hybrydowe podejście do głębokiego uczenia się do przewidywania jaskry, które łączy podejścia do uczenia zespołowego z konwolucyjnymi sieciami neuronowymi (CNN). Metoda łączy w sobie wykorzystanie MobileNet V2 i ResNet-18 do klasyfikacji z ulepszonym modelem U-Net, który obejmuje szczątkowe połączenia i mechanizmy uwagi do segmentacji obrazu. Aby zwiększyć dokładność predykcji, nasz system hybrydowy wykorzystuje zalety zarówno segmentacji tarczy optycznej, jak i klasyfikatorów opartych na CNN. Aby utrzymać wydajność obliczeniową i zgodność z wymogami prywatności danych, model jest optymalizowany dzięki zastosowaniu zaawansowanych technik, takich jak AdamW, cykliczne harmonogramy szybkości uczenia się i stochastyczne uśrednianie wag. Tutaj przeanalizowaliśmy różne wskaźniki wydajności, takie jak dokładność, czułość, swoistość, współczynnik kostki, indeks Jaccarda, wynik F1 dla metod konwencjonalnych i architektura Res-U-Net (Improved U-Net). W tym przypadku architektura Res-U-Net (Improved U-Net) osiąga dokładność 0,93 przy 80% danych treningowych. Hybrydowe podejście do głębokiego uczenia się do przewidywania jaskry, które łączy podejścia do uczenia zespołowego z konwolucyjnymi sieciami neuronowymi (CNN).*

**Keywords:** Glaucoma Prediction, Convolutional Neural Networks (CNNs), Image Segmentation, U-Net Model, Ensemble Learning Techniques
**Słowa kluczowe:** Przewidywanie jaskry, konwolucyjne sieci neuronowe (CNN), segmentacja obrazu, model U-Net, techniki uczenia zespołowego

## Introduction

Glaucoma is the second most common cause of blindness globally, affecting more than 76 million people in 2020 and expected to affect 112 million persons by 2040. The progressive destruction to the optic nerve that characterizes this chronic eye disease is frequently linked to increased intraocular pressure. Due to glaucoma's sneaky nature, individuals frequently incur irreparable visual loss [1] before exhibiting any symptoms, making early detection and intervention crucial. The foundation of glaucoma screening has been traditional diagnostic techniques like tonometry and visual field testing. The methods have a lot of drawbacks which include possible human error, so it needs specific tools and qualified medical personnel clarification.

The recent advancement in the Deep Learning (DL) field of the medical image gives the potential solution for automated glaucoma detection [2-3] using the medical image of optical coherence tomography (OCT) [4] and fundus images. Here the convolutional neural networks (CNNs) [5], the deep learning algorithm have shown effectiveness in classifying the various medical images by learning the frequent pattern and its pattern for the disease. Even though it has been identified correctly or incorrectly, there are still problems, including as interpretability of the model, computational effectiveness, and sensitivity when working with noisy or incomplete information.

To improve the Glaucoma detection accuracy, we develop a hybrid approach that will integrate with segmentation methods and a CNN-based classifier. The main aim of this hybrid strategy is to combine the advantages of deep learning classification with image segmentation. In the first step of the proposed method, the input fundus images are pre-processed using Contrast Limited Adaptive Histogram Equalisation (CLAHE). This will largely improve image contrast and clarity, which is the need for accurate feature extraction.

After the preprocessing stage, we develop an improved U-Net architecture (Res-U-Net), which combines multi-scale feature extraction capabilities with an attention mechanism. The accurate segmentation of the optic cup and disc in fundus images is very important in the diagnosis of glaucoma. With the segmented images, we will calculate the Cup-to-Disc Ratio (CDR) [6] to identify the glaucoma diagnosis.

Next step, the segmented images are processed using modified versions of MobileNet V2[7][8] and ResNet-18[9] in the next classification step. Here the models were chosen because they can accurately classify the fundus images as either healthy or glaucomatous. Our method improves a wider variety of features by employing two different CNN architectures.

In the final step, we integrate the results from the segmentation step and classification subsystems step using an ensemble voting technique. Because it will largely reduce the false negatives, which is a very a fundamental component in medical diagnostics. This stage is a very crucial step in the final diagnosis. By combining the strengths of multiple models, the ensemble method improves diagnostic accuracy for the system. Our proposed hybrid solution tries to find an early and precise glaucoma detection [10-11] by eliminating the drawbacks of conventional approaches and using deep learning and cutting-edge image processing techniques. This proposed method largely aims to improve clinical outcomes while simultaneously democratizing access to glaucoma screening. The incorporation of automation in the identification of glaucoma is a noteworthy advancement in enhancing patient care and averting visual loss [12] worldwide.

**Existing works**

Over the past ten years, deep learning has made major strides in medical imaging, especially in the diagnosis of ophthalmological conditions like glaucoma. Civit-Masot et al. [7] presented a dual CNN technique that achieved good accuracy by combining transfer learning for fundus image classification with U-Net for optic disc segmentation. But the computational complexity of the model prevents it from being used in real-time situations.

To make sure their model could be reliably implemented in a variety of clinical contexts, Thakoor et al. [8] concentrated on interpretability utilising Testing with Concept Activation Vectors (TCAV) in convolutional neural networks. Although the results showed promise, their application to fresh datasets resulted in a decline in performance, indicating the need for improved generalization techniques.

In their investigation of CNN-based automatic glaucoma detection using fundus images, Diaz-Pinto et al. [9] reported great sensitivity but poor specificity, which resulted in higher false-positive rates. The cup-to-disc ratio (CDR) was an important component in Nayak et al.'s morphology-based approach [10], which demonstrated good performance on smaller datasets but remained challenging to scale.

Although it required OCT data, which is more difficult to get in resource-constrained environments, Hood et al. [11] used a CNN ensemble that incorporated transfer learning on OCT data to produce reliable and generalizable predictions.

Al-Bander et al. [12] segmented optic discs with high specificity in 2021 by using a dense fully convolutional network. But because of its heavy processing load, this method is not as appropriate for real-time clinical applications. For the study of fundus images, Zilly et al. [13] used a multi-stage CNN that produced good segmentation accuracy but had a propensity for overfitting when evaluated on smaller datasets. Sevastopolsky et al. [14] used the methodology of U-Net for segmenting cups and discs that is lightweight and it produced precise segmentation in data that is noisy but it has Restricted extraction of features.

Fuzzy c-means clustering was applied by Khalid et al. [15] for optic cup segmentation in noisy data, demonstrating its accuracy but also exposing its complexity as a real-time processing difficulty.

While recent studies by Diaz et al. [16] and George et al. [17] in 2023–2024 explored ensemble techniques and 3D-CNN frameworks, respectively, demonstrated improved performance in spatial feature extraction and robustness, these models remain computationally expensive, making deployment difficult in standard clinical settings. Despite the advancements in glaucoma detection, methods that strike a balance between computational efficiency and diagnostic accuracy are still needed. Research indicates that combining segmentation techniques with classification models can yield a more reliable solution, which is the driving force behind the hybrid approach proposed in this study

**Proposed Work**

This section introduces a hybrid approach that uses optimized deep-learning models [19] and sophisticated segmentation techniques to predict glaucoma. The proposed system will be divided into two parts. First is the segmentation sub-system, which extracts the optic cup and optic disc from the input image dataset, and second is the prediction system, which predicts glaucoma [20] by using the features to identify direct fundus image classification. Here we are using the ensemble voting mechanism to make the prediction.

**Stage 1: Input image**

In the first stage, we are getting input fundus images [21] from the dataset. When diagnosing glaucoma, fundus image is a critical diagnostic technique is used for visualization of the back of the eye, especially the optic disc and optic cup. The glaucoma databases from which these images were taken from publicly available datasets. The dataset ensures both image quality and patient diversity in demographics. The Quality of the segmentation and classification procedures is directly impacted by the accuracy of these images. To maintain consistency across the dataset, the input fundus images are usually resized to fit the 254*254 dimensions of the deep learning models used in subsequent phases of glaucoma detection.

**Stage 2: Preprocessing the data**

Data preprocessing is an important stage in which to prepare the image dataset for further analysis. Our approach uses Contrast Limited Adaptive Histogram Equalisation (CLAHE), which improves the contrast of the fundus image and increases the ability to differentiate between the optic disc and optic cup. In medical imaging, where minute contrast variations may be essential for diagnosis, CLAHE works especially very well to prevent over-amplification of noise. The input fundus images are also scaled and normalized to fit the segmentation's input size. To ensure uniformity, the input fundus images are also scaled and normalized to fit the input size of the segmentation and classification networks. To increase the accuracy of feature extraction and segmentation in later stages, this preprocessing stage is essential.

**Stage 3: Segmentation**

In the segmentation stage, the important task is to calculate the Cup-to-Disc Ratio (CDR). The CDR is a very important aspect in terms of diagnosis of glaucoma, the optic cup and disc must be segmented. While input fundus image segmentation has seen success with traditional U-Net architectures, we propose an improved U-NET architecture to make several enhancements to improve accuracy and efficiency.

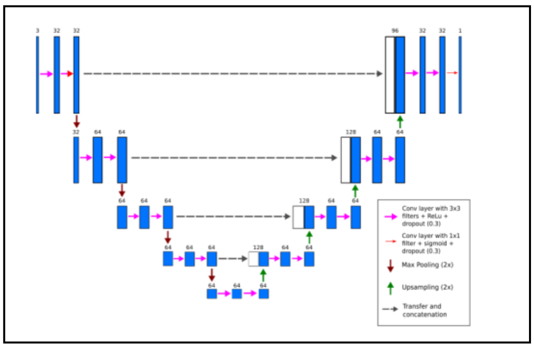


Fig. 1. U-Net Architecture

**Modified U-Net Architecture with Residual Blocks:**

We use a Res-U-Net variation that adds residual connections to the U-Net architecture in order to improve segmentation accuracy as depicted in Fig. 2. During training, residual connections improve convergence by assisting the network in learning deeper characteristics without running into the vanishing gradient issue. Additionally, by using this method, boundary precision is improved by being able to record finer features of the optic disc and cup. The encoder-decoder blocks that make up the architecture are equipped with skip connections, which allow features to be passed straight to the appropriate decoder layer while maintaining spatial information as shown in Fig 1.

**Attention U-Net:**

We incorporate an attention mechanism into the U-Net[25] to enhance focus on the regions of the optic disc and cup while disregarding unimportant portions. Here the attention module allows our hybrid system to evaluate the importance of the different spatial sections dynamically. This helps in cases where the image quality is poor or obstructed by noise.

**Multi-Scale Feature Fusion:**

To ensure that the model can adjust to differences in optic disc and cup sizes across various patients, a multi-scale feature extraction approach will be used to capture both global and local information. To collect characteristics at many scales and enable the model to manage differences in size, shape, and texture in the fundus images, Atrous Spatial Pyramid Pooling (ASPP) will be incorporated.

**Segmentation Loss Function:**

To address class imbalance, a hybrid loss function that combines Dice Loss and Focal Loss (to concentrate more on hard-to-segment areas) will be employed. This guarantees that the model correctly segments the optic disc and cup regions in addition to predicting the dominant class (background).

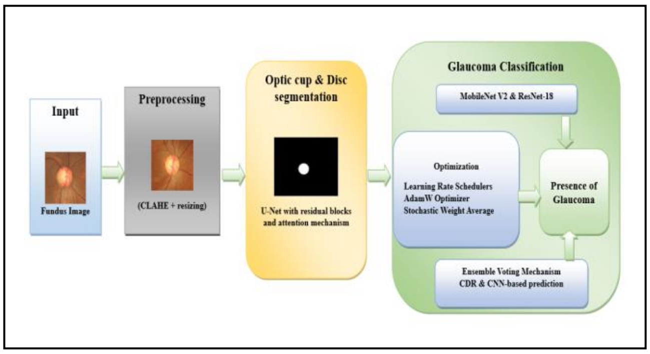



Figure 2. Proposed Model of Glaucoma Detection

**Res-U-Net Architecture (Improved U-Net)**

With the addition of multi-scale feature extraction, residual connections, and attention mechanisms, this design is a variation on the traditional U-Net architecture. Particularly for the optic cup and disc segmentation in fundus images, each component improves the segmentation performance.

**Res-U-Net Algorithm:**

Step 1: input - pre-processed image (fundus image enhanced by CLAHE).

Step 2: Contracting path (downsampling): Apply multiple residual-block convolutional layers.

The structure of each residual block is as follows:

$$y = x + f(x, \{Wi\}) \text{ ------(2)}$$

where x is the input, y is the block's output, and F stands for convolution, batch normalization, and ReLU activation. To decrease the spatial dimensions while keeping important properties, max pooling is employed.

Step 3: Bottleneck (Bridge): By joining the expanding and contracting routes, the bottleneck layer preserves spatial information while capturing high-level properties. To detect features of varying sizes, such as the optic disc and cup, multi-scale features are retrieved using convolution filters of different sizes.

Step 4: Expanding the Path via Up sampling:

To up-sample the feature maps, apply transposed convolutions, commonly known as deconvolutions. Concatenation of the features from the corresponding contracting path layers (via skip connections) aids in the accurate localization of features. Additionally, the up-sampling approach takes advantage of residual blocks.

Step 5: Attention Mechanism:

Both the down-sampling and up-sampling pathways use attention gates calculated as per Equation 1. These gates are trained to suppress unnecessary regions and concentrate on relevant areas like the optic disc and cup.

Attention gate formula:

$$g_{output} = \sigma(W1.x + W2.g).x \text{ ------(1)}$$

where x is the input feature map, g is the gating signal, and σ is the sigmoid function.

Step 6: Final Layer: A softmax or sigmoid activation function is used in the last layer to produce a binary segmentation map that differentiates the optic cup and disc.

Step 7: Output: Segmented optic cup and optic disc.

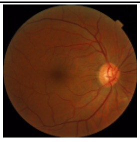
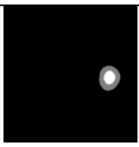
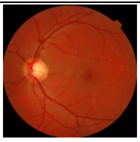
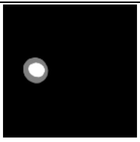
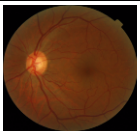
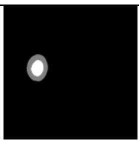
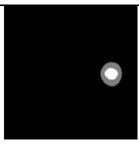
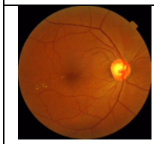
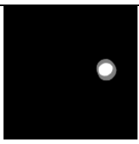
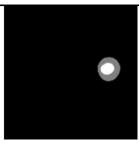
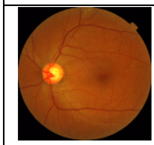
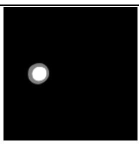
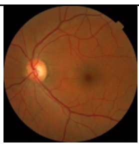
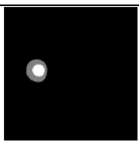
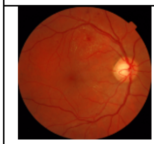
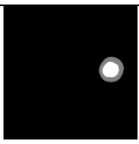
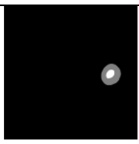
The final image of the extracted optic cup and sic segmented image will be extracted.

Classification Parameters for Res-U-Net (Improved U-Net) used in this model:

- Input Layer: Shape: (H, W, 3) (Resized input image dimensions)
- Convolution Layer 1: Filters: 64, Strides: (1, 1), Padding: 'same', Activation: 'ReLU'
- Convolution Layer 2: Filters: 128, Strides: (1, 1), Padding: 'same', Activation: 'ReLU'
- Dropout Layer: Dropout rate: 0.5
- Max Pooling Layer: Pool Size: (2, 2)
- Convolution Layer 3 (Bottleneck): Filters: 256, Strides: (1, 1), Padding: 'same', Activation: 'ReLU'
- Up-sampling Layer: Pool Size: (2, 2), Activation: 'ReLU'
- Attention Mechanism: Applied in down-sampling and up-sampling paths to enhance focus on key regions (optic disc and cup).

- **Stage 4: Classification Subsystem**
- We use MobileNet V2 and ResNet-18, two lightweight and very accurate CNNs, for categorization. These networks are suited for real-time deployment because of their high computational efficiency. Using the glaucoma dataset, these models are refined by the application of transfer learning [22].
- **MobileNet V2:** A lightweight CNN tailored for mobile and embedded vision applications. Depth-wise separable convolutions are used to minimize computing expenses without sacrificing precision. We refine the last layers on fundus images for glaucoma identification, having previously trained on ImageNet.
- **ResNet-18:** ResNet-18 can efficiently train deeper models since it makes use of skip connections. We alter the upper layers of ResNet-18, substituting a dense layer and a softmax classifier that has been fine-tuned to identify glaucoma determined via fundus images.
- **Stage 5: Optimization Techniques**
- To ensure optimum performance, the subsequent optimization techniques are applied:

Table 1. Extraction of Optic disc and optic cup segmentation using Res-U-Net Architecture

| Input image | Segmented Optic cup and Disk | Input image | Segmented Optic cup and Disk |
|---|---|---|---|
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |
|  |  |  |  |

**Learning Rate Schedulers:**
We'll employ a dynamic learning rate schedule, like the Cyclic Learning Rate or One-Cycle Policy. During training, these methods modify the learning rate by beginning at a lower number, raising it to a maximum, and then lowering it as the training progresses. By preventing the model from becoming locked in local minima, this aids in improved generalisation and convergence.
**AdamW Optimiser:**
We employ AdamW, which decouples the weight decay from the learning rate and improves regularisation, in place of the conventional Adam optimiser. In particular, when fine-tuning on medical datasets with smaller sample numbers, this helps avoid overfitting.
**Stochastic Weight Averaging (SWA):**
SWA produces a smoother and flatter solution terrain during training by averaging the weights of many models, which improves generalization. When it comes to medical image classification problems, such as glaucoma detection, where sparse data sometimes lead to overfitting, this approach is very helpful.
**Early Stopping with Model Checkpoints:**
We combine model checkpointing with early termination depending on validation loss. This guarantees that the optimal version of the model—one with the lowest validation loss—is maintained and that the model does not overtrain.
Ensemble Voting Mechanism
The outputs from the segmentation (CDR-based) and classification (CNN-based) models will be combined by an ensemble voting system once the segmentation and classification models have been trained:

**CDR-based prediction:** A threshold-based determination is made (e.g., CDR > 0.6 implies glaucoma) utilizing the CDR computed from the segmented optic cup and disc regions.
CNN-based prediction: The likelihood that a patient has glaucoma is indicated by the probabilistic output produced by the CNN models, ResNet and MobileNet.
**Final Prediction:** A majority vote system between the CNN and CDR models is used to make the ultimate choice. By using a hybrid method, false positives and false negatives are less common.

**Results and Discussion**

For the segmentation or classification, the suggested approaches' accuracy is essential. Several evaluation metrics are used to evaluate these approaches' dependability and performance as shown in from equation 3 to 8. These metrics offer a numerical assessment of the model's performance relative to the ground truth.
**Accuracy:** Calculates the percentage of all forecasts that are accurate (true positives and true negatives combined). Though it might be less trustworthy in unbalanced datasets, it offers a broad indicator of model performance. Here TP refers to True Positive, TN refers to True Negative, FP refers to False Positive and FN refers to False Negative [23].

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

**Sensitivity (Recall):** Assesses the model's accuracy in identifying positive cases, or images of glaucoma. In order to prevent the missed diagnosis of glaucoma, high sensitivity is essential in medical diagnostics.

$$Sensitivity = \frac{(TP)}{(TP+FN)} \text{ ------(4)}$$

**Specificity:** Evaluates the model's capacity to accurately detect negative cases, or images that are healthy. It minimises false positives by making sure that healthy instances are not mistakenly reported as glaucoma [24].

$$Specificity = \frac{(TN)}{(TN+FP)} \text{ ------(5)}$$

**Dice Coefficient:** The degree of overlap between the ground truth and the projected segmentation is measured by the dice coefficient. In particular, when optic disc and cup segmentation is needed, it is essential for assessing segmentation models.

$$Dice\ Coefficient = \frac{(2TP)}{(2TP+FP+FN)} \text{ ------(6)}$$

**Jaccard Index:** Like the Dice Coefficient but with a heavier penalty for improper segmentations is the Jaccard Index. Because erroneous positives and false negatives are taken into account, it provides a reliable indicator of segmentation quality.

$$Jaccard\ Index = \frac{(TP)}{(TP+FP+FN)} \text{ -----(7)}$$

**F1 Score:** A harmonic mean of recall and precision that strikes a balance between the two. For unbalanced datasets when recall and precision are crucial, it is highly helpful.

$$F1\ Score = \frac{2.Precision\,.Recall)}{(Precision\,.Recall)} \text{ ------(8)}$$

It is clear from Table 2 and 3, its clear that the suggested hybrid system is a strong contender for glaucoma prediction because it outperforms other cutting-edge methods by a small margin, particularly in terms of sensitivity, Dice Coefficient.

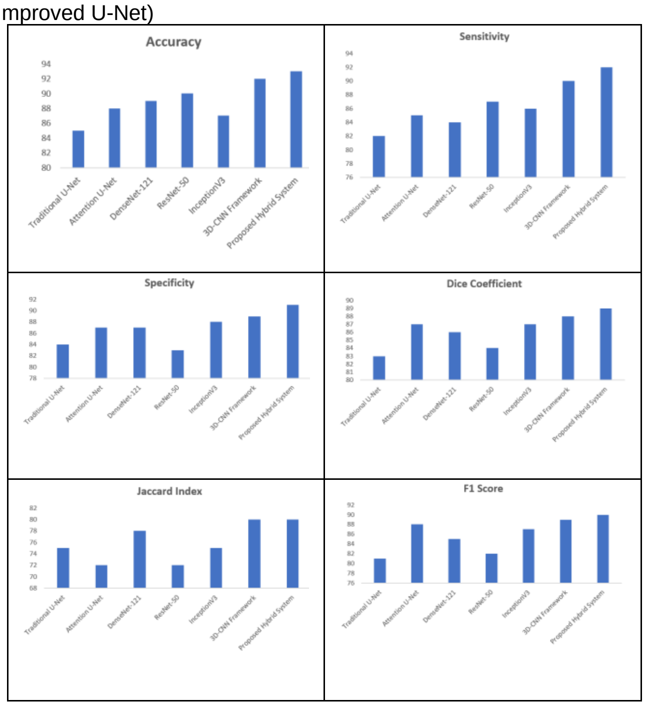
Table 2. Results Comparison with Traditional Algorithm vs Res-U-Net (Improved U-Net)

| Methodology | Accuracy (%) | Sensitivity (%) | Specificity (%) | Dice Coefficient | Jaccard Index | F1 Score |
|---|---|---|---|---|---|---|
| Traditional U-Net | 85 | 82 | 84 | 83 | 75 | 81 |
| Attention U-Net | 88 | 85 | 87 | 87 | 78 | 84 |
| DenseNet-121 | 89 | 86 | 87 | 86 | 78 | 85 |
| ResNet-50 | 90 | 87 | 88 | 86 | 77 | 86 |
| InceptionV3 | 91 | 89 | 88 | 87 | 79 | 87 |
| 3D-CNN Framework | 92 | 90 | 89 | 88 | 80 | 89 |
| Res-U-Net (Improved U-Net) | 93 | 92 | 91 | 89 | 80 | 90 |

## Conclusion

Our hybrid deep learning model, which combines segmentation and classification methods, performs better at predicting glaucoma. The model's enhanced segmentation subsystem improves Cup-to-Disc Ratio extraction accuracy when combined with residual blocks and attention methods. This Hybrid approach gives better accuracy than previous models which leads to the prediction of glaucoma in a better way. This gives a reliable and computationally effective system when paired with CNN-based classification and optimized utilising cutting-edge methods like AdamW and cyclic learning rates.

Table 3. Comparison charts for traditional algorithms vs Res-U-Net (Improved U-Net)




***Authors***: *Krishnamoorthy V., Assistant Professor, Computer Science & Engineering, Sri Venkateswara College of Engineering, Chennai, Tamil Nadu, India; Logeswari S., Professor, Information Technology, Karpagam College of Engineering, Coimbatore, Tamil Nadu, India; Sivanantham S., Professor, Computer Science & Engineering, Saveetha School of Engineering, SIMATS, Chennai, Tamil Nadu, India; Akshaya V., Assistant Professor, Artificial Intelligence & Machine Learning, Rajalakshmi Engineering College, Chennai, Tamil Nadu, India; Ganagavalli K., Assistant Professor, Computer Science & Engineering, Bannari Amman Institute of Technology, Sathyamangalam, Tamil Nadu, India; Mohanraj V., Professor, Information Technology, Sona College of Technology, Salem, Tamil Nadu, India*

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