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IMPROVED SEGMENTATION AND CLASSIFICATION OF GLAUCOMA USING U-NET WITH DEEP LEARNING MODEL

[1]T. SWAPNA, [2]Y. SAI RAJA VARSHTIHA, [3]K.L.SUDEEPTHI, [4]B.MANAVIKA, [5]T.SAISHREE

ABSTRACT

Glaucoma, a common eye illness that affects the optic nerve, is a major global health concern,with a prevalence rate of 3.54 percent among those aged 40 to 80. Early identification is criticalin preventing irreversible vision loss caused by optic nerve damage. The conventional techniques for early analysis rely on analysing the optic cup and disc boundaries in fundus pictures, but they face obstacles such as class imbalance, which reduces recognition quality. To address these challenges, a new solution combines the U-Net architecture for fundus retinal image segmentation with Convolutional Neural Networks (CNNs) for classification. This studyuses the U-Net architecture to segment glaucoma images, taking use of its capacity to successfully collect detailed details and spatial information, improving the precision of detecting optic cup and disc borders. Furthermore, the use of Convolutional Neural Networks (CNNs) for classification allows for the differentiation of non-glaucoma and glaucoma patterns, resulting in more accurate diagnostic conclusions. By combining both approaches, the study takes advantage of the complimentary qualities of U-Net for segmentation and CNN for classification, yielding a comprehensive and robust approach to glaucoma analysis. This integrated system attained an impressive 90.8% accuracy rate, demonstrating its efficiency in enhancing the accuracy and reliability of glaucoma diagnosis.

1. INTRODUCTION

Glaucoma represents a significant global health concern, ranking as the second-leading cause of blindness worldwide following cataracts. Its impact is profound, affecting approximately 3% of the world's population aged 40 to 80, with over 76 million individuals already grappling with the disease. Disturbingly, this number is projected to surge to 111.8 million by 2040 due to aging demographics and increased life expectancy. In 2019 alone, glaucoma contributed to
3.9 million incidents of blindness, a figure expected to soar by 50% to 5.9 million by 2040. Compounding this challenge is the fact that an estimated half of those afflicted with glaucomaare unaware of their condition, underscoring the critical importance of early detection and intervention.

1 Asst.Prof.,G Narayanamma Institute of technology and Science,Hyderabad 2,3,4,5 student, G Narayanamma Institute of technology and Science,Hyderabad

Glaucoma, a progressive eye condition, leads to gradual vision loss due to damage to the opticnerve. Its onset is often subtle, with symptoms emerging only in advanced stages. Elevated intraocular pressure (IOP) is a primary factor, exerting pressure on the optic nerve andimpairing its ability to transmit visual signals to the brain. The optic nerve, responsible for conveying visual information from the retina to the brain, suffers damage from increased pressure, resulting in the deterioration of its delicate fibers. This damage manifests as visual field defects, initially minor but worsening over time. If left untreated, glaucoma can cause significant vision impairment and even blindness. Early detection and treatment are essential for preserving vision, with interventions aimed at minimizing further optic nerve damage. One diagnostic approach for glaucoma involves assessing the optic cup-to-disc ratio (CDR) derived from optic and fundus images. The optic disc, where the optic nerve enters the eye, and the optic cup, a central depression within the optic nerve head, are crucial anatomical landmarks. The CDR, calculated as the ratio of optic cup to optic disc size, serves as a key indicator of optic nerve damage and potential glaucoma. A CDR exceeding 0.6 is often considered abnormal, signalling the presence of glaucoma.

This paper focuses on employing various preprocessing methods to enhance image quality andapplying an integrated system containing segmenting glaucoma images into optic cup and optic disc using U-NET architecture and CNNs for classification of glaucoma images.

2. LITERATURE SURVEY

Several recent studies have used convolutional neural networks to classify glaucoma among them,the models ResNet-50 and GoogLe Net deep convolutional neural network algorithms are applied on fundus images and images are trained and fine-tuned using transfer learning for classification [1]. An adaptive histogram equalizer is used to minimize image noise in fundus images. The ML- DCNN architecture is utilized for separating and categorizing features into two stages, one for theidentification of glaucoma referred to as detection-net and the second for classification of influenced the retinal glaucoma images to three distinct groups: Advanced, Moderate, and Early [2].
The convolutional neural network (CNN) unsupervised architecture was utilized to obtain characteristics of raw pixel intensities via multilayer. This suggested approach, known as Glaucoma-Deep, was tested on 1200 retinal pictures gathered from publicly and privately available datasets. The statistical parameters sensitivity, specificity, accuracy, and precision (PRC) were used to assess the functioning of the Glaucoma-Deep system [3].

Multi-task Convolutional Neural Network (CNN) that jointly segments the Optic Disc (OD), Optic Cup (OC) and predicts the presence of glaucoma in color fundus images is also implemented. The CNN utilizes a combination of image appearance features and structural features obtained from theOD-OC segmentation to obtain a robust prediction [4]. A study that combines segmentation and classification with CNN architecture to detect glaucoma is performed. At the segmentation stage, U-Net CNN

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architecture is applied. U-Net has encoder and decoder sections to get output in the form of images containing

Xcep-Dense is a CNN architecture that combines Exception and Dense. TheXcep-Dense seeks the advantages possessed by Xception and Dense architecture and overcomes the weaknesses of each architecture [5].

The deep encoders with aggressive downsampling layers used in current CNN-based segmentation systems are generally limited in their ability to simulate explicit long-range dependency. In order to do this, this study provides a novel segmentation pipeline called UTNet, which combines the benefits of transformer and U-Net in its encoding layer with an attention-gated bilinear fusion technique. In addition, we apply Multi-Head Contextual Attention to supplement the usual self-

attention used in standard vision transformers. As a result, low-level characteristics and global dependencies are captured in a shallow manner. Additionally, we extract context information at several encoding layers to help the model develop deep hierarchical representations and to facilitate better exploration of receptive fields. Finally, an improved mixing loss is proposed to closely monitor the overall learning process. The suggested approach has been applied to three publicly accessible datasets (DRISHTI-GS, RIM-ONE R3, and REFUGE) for joint OD and OC segmentation [6].

Previously many U-Net-based optic disc segmentation methods have been proposed. However, the channel dependence of different levels of features is ignored. In this study, novel aggregation channel attention network to fully utilize the impact of context on semantic segmentation is presented. In contrast to the current attention method, it takes advantage of channel dependencies and includes data from several scales into the system. The network's performance in small area

only the features needed. At the classification stage, the study proposes the Xcep-Dense Net.

segmentation was improved concurrently by us improving the fundamental classification framework based on cross entropy, combining the dice coefficient and cross entropy, and balancing the contribution of dice coefficients and cross entropy loss to the segmentation task. The network further enhances the segmentation performance of medical pictures by retaining more image features and accurately restoring the important elements. We use it for the task of fundus optic disc segmentation. We assess the suggested architecture and show the model's segmentation performance on the RIM-ONE and Messidor datasets [7].

Another study involves deep learning system which has been presented to analyze glaucoma images using the glaucoma dataset. Pre-trained transfer learning models are incorporated with the U-Net architecture to acquire the necessary results when applying deep learning principles to the task of segmenting the optic cup. The DenseNet-201 deep convolution neural network (DCNN) is utilised for feature extraction. The diagnosis of glaucoma is made using the DCNN method. The main objective of this field of study is to identify glaucoma in retinal fundus images in order to help determine if a patient actually has the illness [8].

The basic CNN and the CNN ensemble were used to classify diabetic retinopathy and were compared to accuracy to determine the optimum performance. The results show that the ensembleapproach is more accurate than a basic CNN due to the selection of hyper-parameters, with an accuracy of 75% [9]. The proposed model synthesizes highly realistic controllable fundus images to obtain precision in detecting glaucoma through a deep learning model. Generative adversarial network (GAN) is a strategy used to improve datasets and yield the collected images to be indistinguishable from the real-world data. The enhanced dataset which is obtained from data augmentation as well as the original ACRIMA dataset of fundus images are separately given to CNN classification model for detection of glaucoma disease [10].

In order to segment fundus images, the following study suggests using attention U Net models with three different Convolutional Neural Networks (CNNs) architectures: Inceptionv3, Visual Geometry Group 19 (VGG19), and Residual Neural Network 50 (ResNet50). A number of data augmentation methods like rotation, zooming, shearing, height shift, width shift, horizontal flip, brightness contrast were applied in order to attain high accuracy and prevent overfitting. This method is employed on two publicly available datasets, namely RIM-ONE and ACRIMA datasets[11].

A study is performed by effectively making advantage of the Grey Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP), two significant texture properties. These textural features are taken both from the optically dense image created from the fundus image and the fundus image itself. The Green channel of the fundus image is used to get the region of interest prior to feature extraction since it has a greater contrast than the other two-color elements. The Support Vector Machine (SVM) classifier is used to classify fundus images as either normal or

abnormal based on the retrieved features [12]. The transfer learning model is used to classify Glaucoma images by using Local Interpretable Model-Agnostic Explanations (LIME) method which introduces understandability to the system [13].

A different study suggested the use of a Cup Disc Encoder Decoder Network (CDEDNet) to segment optic discs (OD) and optic cups (OC) together. To lower the system's overall computing cost, the elimination of the pre- and post-processing stages are done. The segmentation of (OD) and OC is represented as a semantic labelling problem at the pixel level. The RIM-ONE, REFUGE, and DRISHTI-GS datasets were used to train the model [14].

Various Image segmentation techniques are performed to detect important features: the actual sizesof the optic cup and optic disc in vertical and horizontal directions. Automatic screening techniqueto diagnose glaucoma using a support vector machine (SVM). SVMs with a linear kernel function are used to generate the classifier model, and the results show that using threshold-based classification is inadequate to screen glaucoma [15].

3. METHODOLOGY

3.1 Datasets Description

This work leverages two datasets for glaucoma research: DRISHTI, primarily utilized for extractingoptic cup and optic disc from fundus images, and a private dataset from L.V. Prasad Eye Hospital featuring two classes: glaucoma and no-glaucoma. DRISHTI offers annotated clinical data, facilitating comprehensive analysis and model training for glaucoma detection and optic nerve evaluation. Additionally, different traditional data augmentation techniques such as rotation, flipping, scaling, and cropping are employed to generate more images, enhancing the diversity andsize of the training dataset for improved model performance and generalization. This combination of datasets provides a robust foundation for the development and validation of algorithms aimed atimproving glaucoma diagnosis and management.

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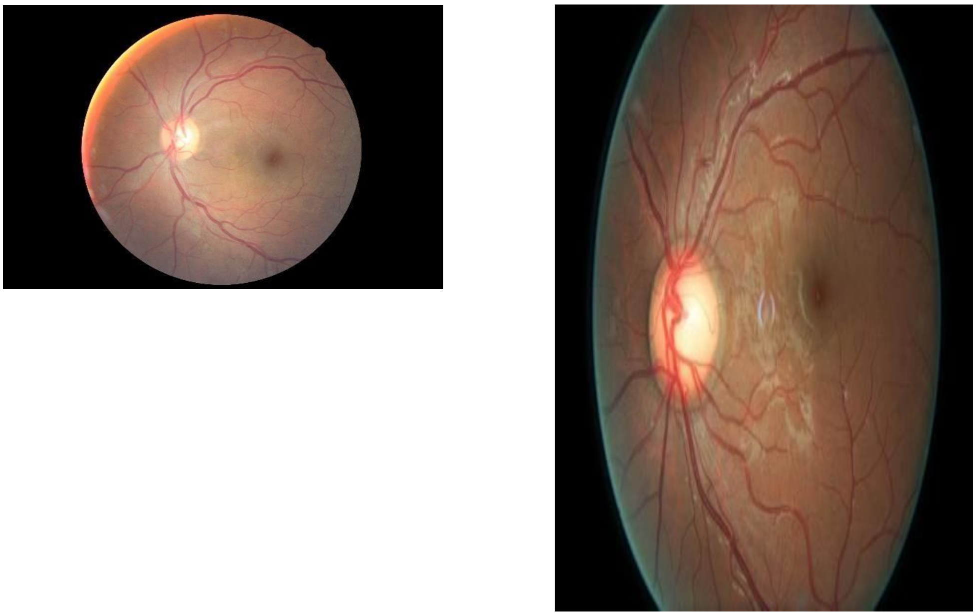

(a) (b)

Fig 3.1: (a) and (b) represents sample retinal images of the No-glaucoma and Glaucoma class respectively

3.2 Model Description

U-NET

U-Net is a convolutional neural network architecture designed for image segmentation tasks. It consists of a contracting path for feature extraction, utilizing convolutional layers and max-pooling operations to capture contextual information. The contracting path is followed by an expanding path, employing transposed convolutions for up-sampling and skip connections to integrate low and high-level features. This architecture enables precise localization and segmentation of objects within images, making it particularly effective in medical imaging. Accurate segmentation is essential for quantifying structural changes in these regions, providing clinicians with valuable insights into the progression of glaucoma. By precisely locating and outlining the boundaries of the optic cup and optic disc, segmentation enables the measurement of parameters such as cup-to-disc ratio, which is a key diagnostic indicator in glaucoma assessment. Advanced techniques, particularly deep learning models like U-Net, are commonly employed for segmentation tasks in glaucoma imaging. These models leverage their ability to learn intricate patterns and features from large datasets to accurately identify and delineate the optic cup and optic disc boundaries.

CNN

Convolutional Neural Networks (CNNs) represent a class of deep learning algorithms specifically designed for image analysis tasks. CNNs are structured to automatically and adaptively learn hierarchical representations of image data, progressively extracting features at increasing levels ofabstraction. The architecture of a CNN typically consists of several layers, including convolutional layers, pooling layers, and fully connected layers. In the convolutional layers, filters are applied to the input image to detect various features such as edges, textures, and patterns. Pooling layers then down sample the feature maps produced by the convolutional layers, reducing their spatial dimensions while retaining important information. Finally, fully connected layers aggregate these features to make predictions or classifications based on learned patterns.

In the context of glaucoma diagnosis, CNNs have demonstrated remarkable efficacy. To classify images into glaucoma and non-glaucoma categories, a CNN is trained on a dataset of labeled eye images, where each image is associated with a binary label

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indicating the presence or absence of glaucoma. During training, the CNN learns to automatically extract relevant features from the images and map them to the corresponding class labels. This process involves iteratively adjustingthe network's parameters to minimize the difference between predicted and actual labels, a technique known as backpropagation. Once trained, the CNN can effectively classify new, unseenimages into glaucoma or non-glaucoma categories based on the learned patterns.

4. PERFORMANCE EVALUATION

4.1 Pre-Processing Results

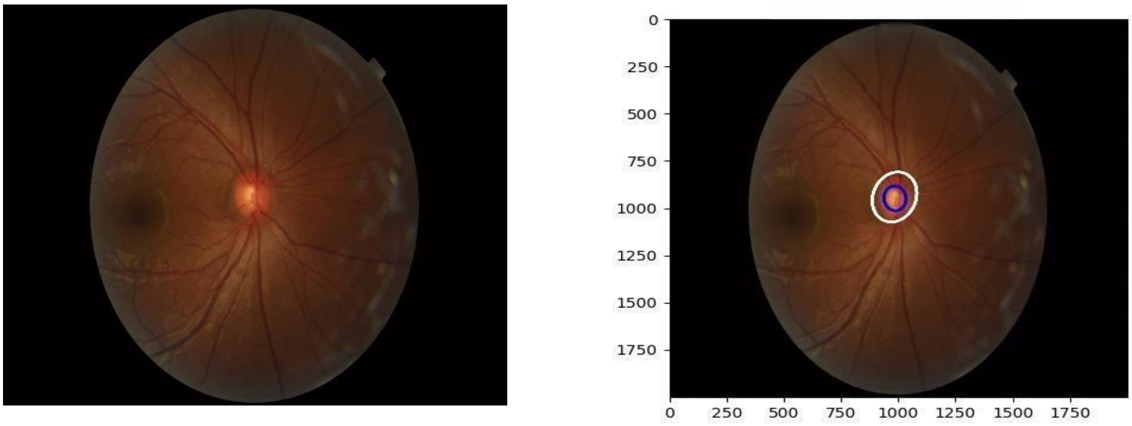
The research draws on diverse image datasets from sources like Drishti and LV Prasad Eye Hospital. It assesses image quality using the Peak Signal-to-Noise Ratio (PSNR) metric. Through a combination of Green Channel extraction and noise removal methods, the study achieves the highest PSNR value of 48.8. This approach enhances both the quality and reliability of the images, which is essential for further modelling endeavors. PSNR serves as a measure of image fidelity, with higher values indicating a closer match to the original image.

S.No	Technique Used	PSNR Value
1.	CLAHE	27.7
2.	CLAHE followed by Green Channel Extraction	29.3
3.	Green Channel Extraction	32
4.	Green Channel followed by removing noise and equalization	31
5.	Green Channel followed bu Noise Removal	48.8

Table 1. Peak to signal noise ratio (PSNR) for various preprocessing techniques used

4.2 Segmentation Results

Our research began with training the U-Net model on a substantial portion of the Drishti dataset. This phase required iterative optimization of the model's parameters to accurately identify and delineate the OD and OC regions in retinal images. Following model training, we proceeded to the next phase, which involved testing the U-Net model using a separate set of real-world retinal images. These test images enabled us to assess the model's performance in conditions closely resembling those encountered in clinical settings.



(a) (b)

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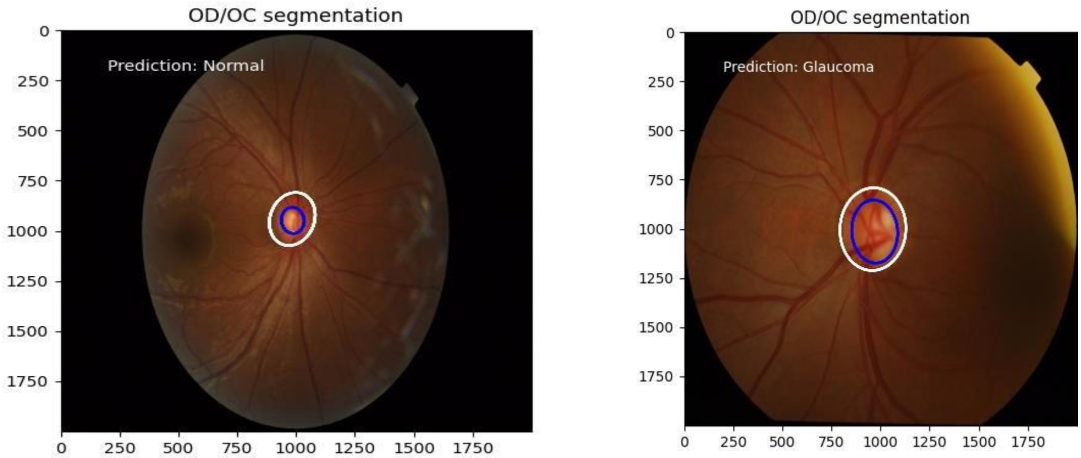
Fig 4.1: (a) and (b) represents the original image and the predicted image respectively

The image illustrates the segmentation outcome on a test image. The white border indicates the model's prediction for normal optical disc segmentation, while the blue border represents the model's prediction for normal optical cup segmentation, with an associated 90% confidence interval.This segmentation analysis provides a visual representation of the model's performance in accurately delineating both the optical disc and cup regions in retinal images, offering valuable insights into its precision and reliability.

4.3 Classification Results

The classification is based on the optic cup to optic disc ratios determined during segmentation, allowing the model to use complex anatomical information for accurate categorization. This approach leverages intricate details of the retinal structure, enhancing the model's ability to discernbetween glaucoma and non-glaucoma cases with precision. The classification of the images depictedin the below image is based on discerning whether it represent cases of glaucoma or non-glaucoma.



(a) (b)

Figure 4.2 Classification of the image into Normal and Glaucoma

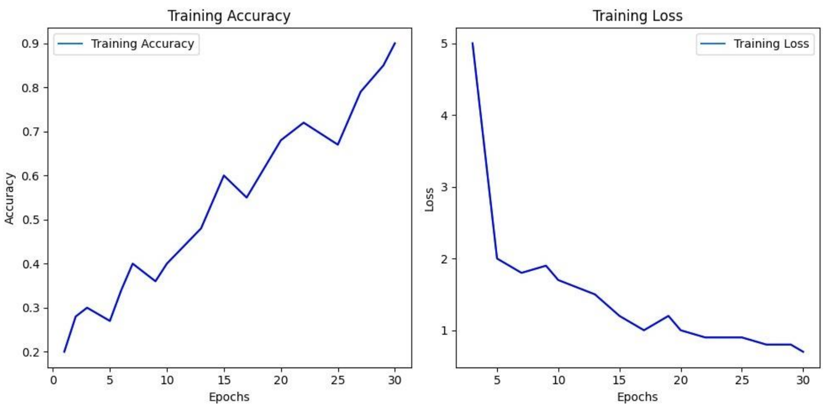


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Figure 4.3 Representation of training accuracy and loss using CNN for classification

The above image displays the training accuracy and loss trends of a CNN model employed for classifying glaucoma images. The accuracy steadily rises, reaching 90.8%, while the loss consistently diminishes, reducing to 7% across the epochs. This indicates the model's effective learning process, steadily improving its ability to classify glaucoma images with each iteration.

The classification process utilizes three distinct techniques: Support Vector Machine (SVM), VGG, and Convolutional Neural Network (CNN). Among these methods, CNN emerges as the most effective, achieving a remarkable accuracy of 90.8%. Following closely behind, VGG demonstrates a respectable accuracy rate of 88%, while SVM exhibits a slightly lower accuracy of 86%.

METHODS	ACCURACY
Support Vector Machine (SVM)	86%
Visual Geometry Group (VGG-16)	88%
PROPOSED MODEL (CNN)	90.8%

Table 2: Accuracies of the various algorithms implemented

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The Convolutional Neural Network (CNN) likely achieved the highest accuracy due to its inherent ability to automatically learn relevant features directly from the data. CNNs excel at capturing intricate patterns and relationships within images, making them well-suited for tasks like retinal image classification. Additionally, CNNs can adaptively adjust their parameters during training, optimizing their performance specifically for the task at hand, which may contribute to their superior accuracy in glaucoma classification.

5. CONCLUSION

This Research has addressed significant challenges in analyzing glaucoma images, covering preprocessing, segmentation, and addressing class imbalances. It focused on enhancing image quality during preprocessing to ensure accurate segmentation. By employing techniques like rotation, flipping, scaling, and cropping for data augmentation, balanced class distributions, enriching the dataset with diverse synthetic images are generated. U-Net-inspired segmentation model adeptly delineates optic cup and disc boundaries, offering valuable insights for glaucoma diagnosis and progression tracking. Integration of CNN for automated glaucoma classification enhances diagnostic efficiency by identifying pathological features within fundus images. This holistic approach empowers healthcare professionals with advanced tools for enhanced patient care, aligning with the broader aim of leveraging deep learning to improve glaucoma diagnosis. Future enhancements may involve diversifying datasets, employing more advanced deep learning models, and integrating real-time monitoring for continuous refinement. Such improvements hold promise for early glaucoma detection and management, ultimately leading to improved patient outcomes andbetter disease management.

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