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Accurate Segmentation and Classification of Glaucoma Disease Utilising Grey Wolf Based U-Net++ with Capsule Network

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Abstract: Glaucoma, an eye condition marked by elevated eye pressure, is one of the leading causes of complete blindness for those affected. Early intervention through treatment and screening programs for glaucoma may reduce its detrimental consequences and help keep people seeing clearly. Glaucoma testing can be complex, and finding qualified healthcare providers to conduct assessments may prove challenging. Delays in diagnosis and treatment lead to an increasing global population suffering blindness or vision impairment. An automated screening system must be created quickly to address the limitations of existing manual screening methods, enabling early detection and treatment of abnormalities within either the Optic Cup (OC), Optic Disc or both eye regions. Accurate classification has become even more challenging as abnormalities overlap visually with the natural colour of eye tissue. This research paper introduces an automated framework designed to detect glaucoma. Our approach involves two stages - segmentation and classification - both crucial for an accurate diagnosis. At UNet++ we have developed a novel initial segmentation architecture combining the Grey Wolf optimization algorithm and UNet++ architecture specifically tailored for extracting optic disk from retinal fundus images. This approach uses an automatic evolutionary model which intelligently determines optimal and precise network configuration parameters through the Grey Wolf Optimization Algorithm (GWOA). Once the segmentation is complete, for the accurate classification of glaucoma, we utilize CapsNet (an advanced deep learning architecture known for its effectiveness in image recognition tasks) for this task. Our proposed method achieves an outstanding accuracy rate of 98.23% - surpassing other approaches and highlighting its power to enhance the accuracy and efficiency in diagnosing glaucoma. This remarkable feat highlights our automated system's potential to improve accuracy and efficiency when diagnosing this condition.

Keywords: *Capsule Network (CapsNet), Contrast Limited Adaptive Histogram Equalization (CLAHE), Histogram Equalization (HE), U-Shape Network technique (UNet++).*

1. Introduction

Glaucoma is an incapacitating and excruciating optic neuropathy condition caused by retinal ganglion cell loss. Left untreated, it may lead to significant visual impairment. Clinical manifestations of glaucoma include visible anatomical changes that appear within the head of optic nerve (ONH) such as lamina cribrosa sheet thinning along with posterior bowing in its head - these characteristics should help doctors make educated clinical judgments of this neuropathy condition. To make informed clinical judgements regarding glaucomatous optic neuropathies it's essential that an in-depth investigation of symptoms will take place before making clinical judgements about any specific cases glaucomatous optic neuropathies is conducted [1, 2].

At present, diagnosing Glaucoma involves extensive tests as well as gathering a great deal of information derived from eye exams, with interpretation of this data often becoming a daunting challenge. Separating early-stage glaucoma features from those seen in healthy individuals is also difficult; further efforts have been undertaken to create additional diagnostic tools, including artificial intelligence systems that can distinguish true disease-related changes from normal variations, while tracking progression of the disease between tests [3]. Unfortunately, glaucoma cannot be treated, but early diagnosis and prompt intervention can drastically diminish its symptoms. Therefore, it is crucial that automated techniques for early glaucoma detection be developed [4]. Fundus images of the retina provide invaluable information that allows for assessment of different eye components such as macula, vitreous retina, and blood vessels for nerves. Optometrists typically use fundus cameras to take images of retinas for diagnostic use in cases such as glaucoma. Glaucoma is one of the primary causes of blindness, thus necessitating more effective techniques for diagnosis. Optic nerves play an essential role in transmitting images between retinas and brains [5].

One of the key visual indicators used to diagnose Glaucoma is Cup-to-Disc Ratio (CDR) [33]. Most symptoms of glaucoma manifest at its Optic Disc (OD). Automated methods that rely on segmenting an OD are highly dependent upon its accuracy; even slight discrepancies can dramatically alter diagnosis [6]. Localization techniques

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provide important contextual data regarding both its exact location in an image as well as surrounding elements - therefore making such techniques less prone to mistakes than their counterparts [7]. Finding subtle and complex retinal fundus images that reveal disease is an enormous challenge for automated classification. While natural scenes with their vivid colors, shapes, and textures are easily discernible, medical images tend to conceal important indicators of disease that require expert knowledge for interpretation. Recently though, advances in Deep Learning have shown its capability of recognising accurate representations that allow detection of subtle differences [8]. This makes these representations extremely concise and informative.

Implementation of Computer-Assisted Diagnosis (CAD) devices into medical screening programs could bring substantial improvements in efficiency and quality, with less human error, faster health care delivery in underserved regions, stress relief among medical staff and removal of bias or discrimination being among their potential benefits. One of the primary visual indicators used to detect Glaucoma is Cup-to-Disc Ratio (CDR). Its symptoms typically manifest themselves on Optic Disc (OD). Automated methods that rely on segmenting OD are very dependent on its accuracy - any slight error can significantly compromise diagnostic accuracy. Localization techniques offer invaluable insight not only regarding exact OD location but also in context with other images within an image, providing invaluable contextual clues that make their detection methods less susceptible to mistakes [9]. Automated classification can be an enormously complex challenge when dealing with retinal fundus images in Fig.1. While natural scenes offer color, shape and texture cues for identification of disease indicators more easily, medical images often hide key indicators and require years of expert knowledge for accurate interpretation. Recent advances in Deep Learning have proven their ability to recognize accurate representations of data which allow for the detection of subtle variations; this allows these representations to be extremely concise and informative. Computer-Assisted Diagnosis (CAD) devices could bring significant improvements in efficiency and quality for medical screening programs. Potential benefits may include decreased human error, faster healthcare delivery in underserved regions and the removal of stress and bias among medical professionals [10].

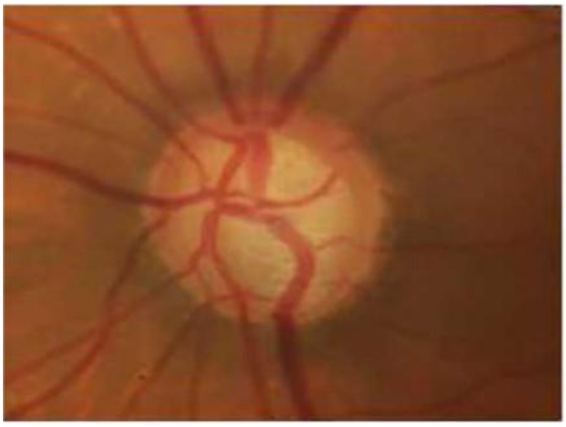


Fig.1 Retinal Fundus Image

Recently there has been an increasing trend toward using deep learning techniques to increase disc and optic cup segmentation while simultaneously decreasing computation time. This innovative approach utilizes Convolutional Neural Networks (CNNs) with impressive results when segmenting both cups and discs using RIM-ONE dataset. For instance, RIM-ONE dataset proved an especially effective venue where this model achieved exceptional disc segmentation accuracy with unprecedented ease.

At the core of this unique method lies its application of an ensemble-learning-based convolutional neural network to segment fundus images for detecting glaucoma. The multi-step procedure comprises two key steps. First is finding Region-of-Interest (ROI) within retina images, followed by splitting retinal optic disc images. One key feature of this method of detection is using M-Net for implementation. M-Net methodology was recently enhanced with an additional step, called Polar Transformation, designed to increase its overall effectiveness [11]. Before initiating testing and learning phases of M- Net, its vicinity will be exposed for transformation by way of Polar Transformation. Traditional deep learning techniques have typically focused on extracting data through optical discs. But with recent advances, there may be the possibility to expand this approach by including optic cup and disc segmentation as a strategy to provide greater accuracy when diagnosing early stages of glaucoma. Therefore, an innovative deep learning-based method has been created that uses this strategy with segmentation of optic cup and disc segments, such as described in reference [12]. This new method could not only advance this field further but could also make significant strides forward toward improving accuracy and efficacy when diagnosing early glaucoma early.

The major contributions made by advanced deep-learning techniques in glaucoma detection. Deep learning-based technology is being employed to identify and monitor progression of glaucoma with retinal fundus pictures, thus helping patients preserve their vision by intervening at an early stage in the disease's course.

- An effective segmentation method was designed, specifically to identify optical cups in retinal fundus images. It uses UNet++ to precisely delineate cup and disc features in retinal fundus images as well as provide detailed information on them. UNet++ generates segmentation results which have proven insufficient, leading to poor diagnostic quality and ultimately decreasing efficiency of diagnosis of glaucoma. To improve this situation, an adaptive optimization algorithm known as Grey Wolf Optimization Algorithm (GWOA) is being designed. This algorithm optimizes UNet++ parameters so as to produce superior segmentation results, ultimately leading to superior glaucoma diagnosis results.
- Another significant development is the introduction of CapsNet deep-learning architecture which allows for detection of glaucoma diseases. This cutting-edge method serves as an advanced diagnostic and detection method. To determine the effectiveness and reliability of the new Glaucoma detection model, a thorough comparison with recently developed detection methods was carried out. Performance metrics were used to test its efficacy and reliability.

These achievements represent significant advances on the path towards screening for glaucoma and have the potential to revolutionise early diagnosis and treatment processes that will protect vision from degenerative disease in vulnerable individuals at risk of contracting it.

2. Literature Survey

Computer-aided systems for intelligent Glaucoma diagnosis have gained increasing prominence over recent years, as evidenced by [13]. They rely heavily on both image processing and machine learning methods; specifically using retinal photos as examples, machine learning algorithms categorize images into normal or glaucomatous categories while unsupervised learning algorithms assist with segmenting optic disc and cup images from enhanced retina images [14]. Recently, research scientists have developed new methods for diagnosing glaucoma by employing various classifiers, such as Multi-layer Perceptron Random Forest classifiers and Radial Basis Function classifiers [15]. Deep learning and heuristics are two primary diagnostic approaches used for the detection of glaucoma. Heuristic approaches utilize feature extraction through image processing techniques and screening methods that assess how thick is the retinal nerve fiber layer (RNFL). Also [16], focused on improving glaucoma diagnosis through extracting higher-order spectral and texture features; [17] studied the impact of wavelets on energy. Support Vector Machines (SVMs) and non-naive Bayesian classification algorithms were utilized by both authors [18, 19] for classifying extract features. However, both techniques have their limitations since they only consider a portion of fundus pictures features found therein; as a result, their classification accuracy was relatively low.

Deep learning-based techniques offer another approach for glaucoma detection. Research efforts have focused on this form of detection with deep-learning models capable of automatically segmenting disc and optic cup surfaces [20, 21], however these studies often solely focus on optic discs as possible indicators of glaucoma without offering an exhaustive solution. The idea of multistream convolutional neural system (CNN), with final segmentation results and complete optical images included as output from this method [23], however, introduced an extensive CNN-based method for the detection of glaucoma. Subsequently [24] refined this CNN structure to classify glaucoma based on both local and global aspects [25] and utilized pre-processing techniques on initial fundus images by eliminating redundant regions to achieve more consistent images, but prior attempts encountered difficulty reaching high sensitivity and accuracy due to limited training data and ineffective neural networks. Retinal fundus images allow us to segment optical cups efficiently using U-Net segmentation method. This segmentation method has shown great promise in helping to detect glaucoma efficiently by distinguishing between optic cups and discs more quickly and separating their respective nerve fiber bundles more efficiently [26]. Optic disc images serve as the basis of our approach when defining regions of interest for trimming and segmentation using U-Net algorithm [27].

An Attention-Based Convolutional Neural Network (AG-CNN) model developed to enhance detection of Glaucoma; they rigorously tested it against an extensive Database of Glaucoma Patients using Attention (LAG) [28]. Notable amongst the features of AG-CNN is its attention to potential issues that might arise when large quantities of redundant data are removed from fundus images. To address this problem, the AG-CNN model combines subnetworks for attention prediction as well as pathological localization and classification. This combination produced an impressive model with 96.2 percent sensitivities and an AUC (Area under the Curve) score of 0.983 to provide accurate diagnosis of glaucoma; however, sometimes only partial images could be detected, making it hard to determine exactly where problems existed [29].

Another model departs from traditional methods that utilize raw images as an input, by instead using features extracted from images and feeding into a CNN model which then classifies images as normal or abnormal [30]. Islam etl al. also developed an innovative hybrid graph convolutional neural network (HGCN) for retinal image classification [31]. This method integrates features from convolutional neural networks into an underlying framework for graph learning based on modularity to form a highly efficient graph convolutional system that successfully classifies retinal images according to their specific characteristics. An ensemble-learning-based model is invented to classify retinal images during their research. In another effort by Bilal et al., they presented a deep learning strategy for retinal image recognition using both U-Net and Inception V3 network architectures. Furthermore, an eye glaucoma detection model is developed which combined U-Net with Efficient Net technology [32].

Now, manual separation of indistinct optical features has been rendered obsolete thanks to convolutional neural network (CNNs)' ability to recognize patterns and categorize objects based on multiple unique attributes. Notably, many U-Net types have been developed to segment medical images using CNNs, such as U-Net [33], 3D-U-Net [34], Attention U-Net [35], Ce-Net [36], U-Net++ and Trans U-Net [36]. Unfortunately, all these methods often lack adequate training data which frequently leads to overfitting or overfitting due to undersaturation or overfitting by CNNs. However, an issue common to them all is an insufficient training data which leads to overfitting due to undersaturation by overfitting algorithms which prevent overfitting by overfitting occurring during overfitting or overfitting, often due to inadequate training data which frequently leads to overfitting occurring due to overfitting caused by overfitting. Transfer learning can be an efficient solution when faced with limited data. Research in this area centres around classification of natural images as well as more precise detection of glaucoma on fundus images. Fundus images present unique challenges when trying to detect glaucoma due to having many similar areas such as white backgrounds and peripheral parts of an eyeball that might distort CNN-driven processes from their focus by including irrelevant information in them [37].

To address all the aforementioned problem, this study proposes an innovative solution involving a U-Net++ segmentation method and the parameters are optimized utilised grey wolf optimization approach and automated identification model of glaucoma using CaspNet.

3. Methodology

In this research, we present a hybrid approach which encompasses of Grey Wolf Optimization Algorithm (GWOA) based UNet++ model and Capsule Network (CapsNet). Here Grey Wolf Optimization Algorithm (GWOA) is specifically works to optimise the parameter of UNet++ which leads to precisely delineate optic cup and disc features in retinal fundus images. Then the segmented features are taken as input for classification process. Here, we have used Capsule Network (CapsNet) for effective detection of glaucoma.

3.1. Grey Wolf Optimization Algorithm (GWOA) Based UNet++

This algorithm, proposed by [45], draws its inspiration from grey wolf hunting patterns observed. Within any pack of wolves, alpha wolves tend to take the highest positions and be responsible for making important decisions. This algorithm replicates key aspects of wolf behaviour including social hierarchy as well as hunting techniques used by alphas (\alpha); predator attacks; prey capture techniques and pursuit hunting as well as attacks by prey against each other and attacks against prey during hunting expeditions mentioned in the Fig 2.

Alphas, which represent dominant wolves within this pack, play an essential part in this algorithm. When solving optimally, alphas take precedence as being identified first followed by beta (β), then delta (δ). After that comes omegas (ω) with solutions which correspond with their methods employed by beta, alpha, and delta wolves.

To address all the aforementioned problem, this study proposes an innovative solution involving a U-Net++ segmentation method and the parameters are optimized utilised grey wolf optimization approach and automated identification model of glaucoma using CaspNet.

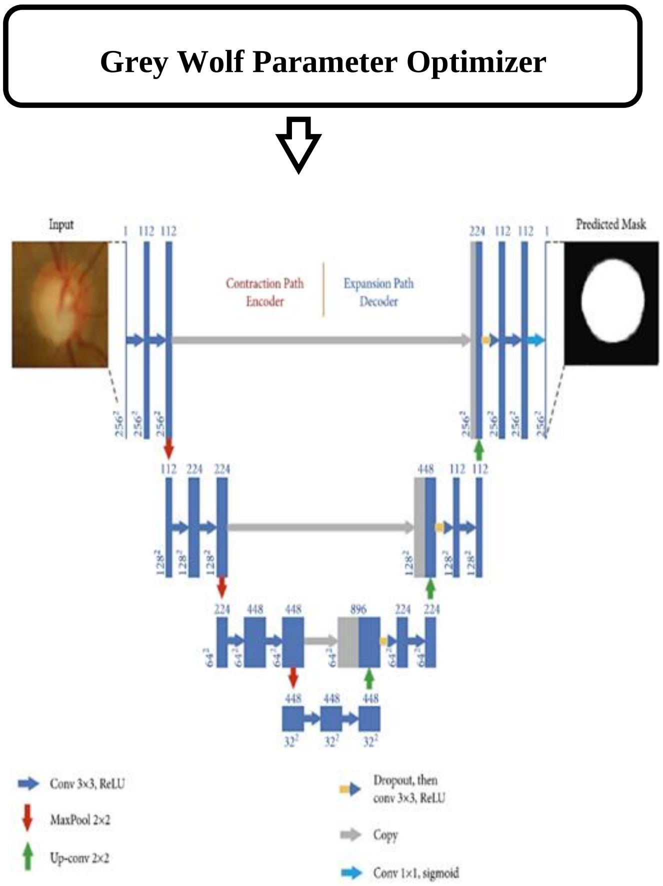


Fig.2 Proposed GWOA based UNet++

Gray wolves in nature exhibit the characteristic behaviour of circling when hunting, which can be mathematically expressed via formulae in (1) and (2).

$$\vec{X} = \left|\vec{Y}.\overrightarrow{Z_p(t)} - \overrightarrow{Z(t)}\right| \quad (1)$$

$$\overrightarrow{Z(t+1)} = \overrightarrow{Z_p(t)} - \vec{D}.\vec{X} \quad (2)$$

From above Equ. (1) & Equ. (2), the current position of the prey is given as $\overrightarrow{z_p}$ and current position of the grey wolf is given as $\vec{Z}$. The coefficient vector is given is as $\vec{Y}$ and $\vec{D}$ with respect to each iteration 't'.

$$\vec{D} = 2\vec{y} - \vec{r}_1 - \vec{y} \quad (3)$$

$$\vec{Y} = 2.\vec{r}_2 \quad (4)$$

The vector represented by "y" contains components which decrease in intensity from 2 to zero over each iteration, as well as random vectors with values between 0 and 1. Additionally, we have two random vectors $\vec{r}_1$ and $\vec{r}_2$, both consisting of values between 0 and 1, that we call random.

$$\overrightarrow{X_\alpha} = \left|\overrightarrow{Y_1}.\overrightarrow{Z_\alpha} - \vec{Z}\right|$$

$$\overrightarrow{X_\beta} = \left|\overrightarrow{Y_2}.\overrightarrow{Z_\beta} - \vec{Z}\right|$$

$$\overrightarrow{X_\delta} = \left|\overrightarrow{Y_3}.\overrightarrow{Z_\delta} - \vec{Z}\right| \quad (5)$$

$$\overrightarrow{Z_1} = \overrightarrow{Z_\alpha} - \overrightarrow{D_1}.\overrightarrow{B_\alpha}$$

$$\overrightarrow{Z_1} = \overrightarrow{Z_\alpha} - \overrightarrow{D_1}.\overrightarrow{B_\alpha}$$

$$\overrightarrow{Z_2} = \overrightarrow{Z_\beta} - \overrightarrow{D_2}.\overrightarrow{B_\beta}$$

$$\overrightarrow{Z_3} = \overrightarrow{Z_\delta} - \overrightarrow{D_3}.\overrightarrow{X_\delta}$$

$$\overrightarrow{Z(t+1)} = \frac{\overrightarrow{Z_1} + \overrightarrow{Z_2} + \overrightarrow{Z_3}}{3}$$

Exploitation refers to the process of tracking down prey, also known as hunting. Over time, vector $\vec{y}$ decreases from 2 to 0, while vector $\vec{D}$ encompasses random values within this range $(-D, D)$. Therefore, any searcher may end up anywhere between their current position and that of its prey. Exploitation follows Exploration as exploration is the next phase. Divergence and successful exploration depend on various components. $\vec{D}$ facilitates divergence by encouraging solutions to diverge further, leading to an extended search process, while vector $\vec{Y}$ assumes values within (0, 2, 0) which gives predators weighted randomly for increased exploration without falling into traps associated with local optimal.

Grey Optimization Program (GWO) seeks to enhance the efficiency and performance of U-Net++ systems, the most popular architectural framework used in computer vision tasks like segmenting images or classifying them, U-Net++ are well known for detecting intricate patterns or features found within images - this makes them indispensable tools in medical imaging analysis, object recognition and many other fields that use images for various reasons in the above Fig 2.

The process of optimizing different settings and parameters carefully for their efficiency in fine-tuning the U-Net++ to achieve greater performance. Scientific analyses have confirmed them as being key factors that help achieve this aim, with specific factors having significant ramifications on system efficiency - thus fulfilling grey wolf optimizer's goals in an essential fashion.

To make this process simpler and to ensure an unbiased selection process of parameters, a mathematical equation was employed. This equation calculates the total dimensions (DM) for each agent involved in optimization; dimensions play an essential part of search space refinement by grey-wolf optimization tool and thus affect search space itself. Furthermore, using such formula allows for targeted and effective strategy to optimize U-Net++ performance more quickly.

$$DM = 2 + (5 * \mathrm{B}) + \left(\mathrm{B} * (\mathrm{h} + \mathrm{g} + \mathrm{xg})\right) \quad (6)$$

The total number of blocks that can be utilised by grey wolf optimizer is given as 'B'. The convolutional layers, batch normalization and activation function are given as h, g, xg.

U-NET network++ has been optimized, traditional decoding and encoding pathways become active. Batch Normalization becomes essential at this stage after up-sampling has taken place.

Batch Normalization involves subtracting an average batch value and then dividing by its standard deviation to create normalized inputs for neural network layers, to ensure their alignment at zero and have similar sizes. By eliminating problems caused by diminishing gradients and speeding up convergence training processes, Batch Normalization speeds up neural network training significantly resulting in quicker and more effective training processes overall in the below Fig 3.

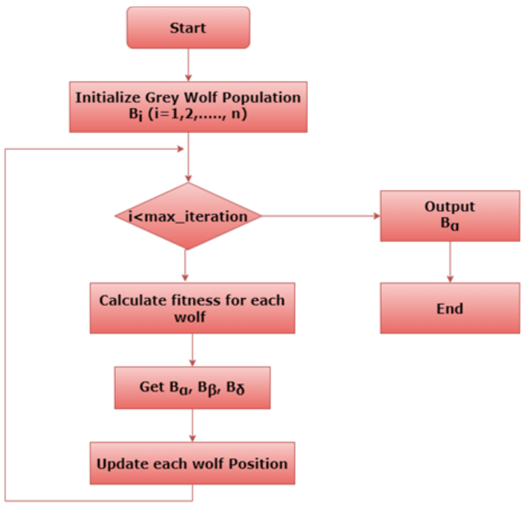


Fig.3 Workflow of Grey Wolf Optimization Algorithm

3.2. Capsule Network (CapsNet)

Capsule Networks (CapsNets) consist of several layers, with each layer housing several capsules that represent instances from an image that occur at specific locations and each neuron representing their likelihood that such instances exist; their length corresponds with their probability.

Similar to conventional Convolutional Neural Networks (CNN), each Capsule "j", defined by its instantiation parameter, attempts to predict what its outputs will be in subsequent layers using an easily trainable weight matrix. Due to this link between each Capsule 'j" and subsequent layers derived from it, data and predictions can easily disperse across the network refer to the Fig 4.

$$\hat{w}_{a|b} = Z_{ba} w_a \tag{7}$$

Based on (7), the Capsule Network, or CapsNet, illustrates predictions made by one capsule (a) concerning another (b), quantified by their prediction coefficient denoted as $\hat{v}_{i|j}$. To produce output (sb) from Capsule ‘b’ is determined via routing by Agreement which leverages coefficient weighting by taking into account weighted sum of predictions across several Capsules in addition to taking weighting factors into consideration in its algorithm; ultimately this procedure determines final output (sb).

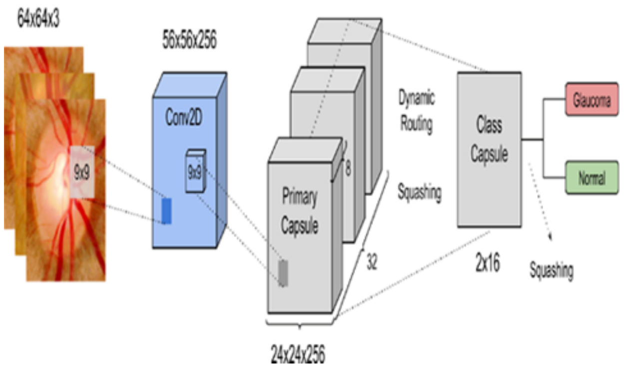


Fig.4 Capsule Network (CapsNet) for accurate classification of Glaucomatous or Normal

Capsule Network (CapsNet) stands apart from conventional Convolutional Neural Networks (CNNs) through the innovative application of "Routing by Agreement." This ground-breaking technique enables CapsNet to recognize spatial relationships within input datasets by assigning predictions that align with actual outputs with an agreement score denoted as "x_{ab}" while individual predictions receive contributions scores known as “D_{ab}” quantifying their contributions towards final outputs. By employing "Routing by Agreement," CapsNet distinguishes itself by being able to detect spatial relationships among various elements present within input data sets.

In Equation (8) CapsNet loss_functions can be determined by evaluating functions associated with capsule 'c, as is described below.

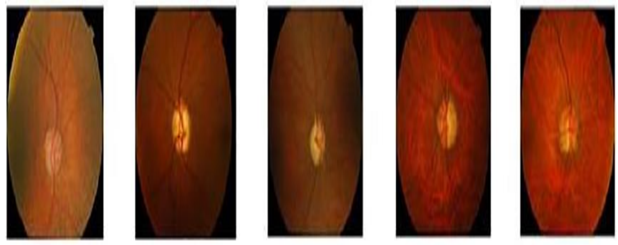
$$\text{loss\_function} = T_d max(0, m^+ - \|\boldsymbol{p}_d\|)^2 + \lambda(1 - T_c)\, max(0, \|p_d\| - m^-)^2 \tag{8}$$

From loss_function, $T_d$is defined to take on the value one when class 'd' is present and zero otherwise. Hyperparameters m+, m^-, and l also play an essential part in controlling model behavior; this brief summary offers an introduction into CapsuleNets by outlining key components and their significance within it.

4. Experimentation and Result Discussions

We conducted extensive experiments to test our approach's efficacy at detecting and classifying glaucoma cases. Here, we report on these tests using the publicly accessible ORIGA database and applying our approach via Matlab so as to maintain dimensional stability. The ORIGA database comprises 650 samples, with 168 illustrating regions affected by glaucoma in human eyes and 482 representing healthy eye conditions. Unfortunately, its classification task can be particularly challenging due to various artifacts present within its dataset - these artifacts include discrepancies in terms of size, color, position, texture of optic discs (OD) and optic cups (OC), noise blurring distortions affecting color or intensity changes among others - as evidenced in Fig 5. These distortions can also be observed through image enhancement techniques allowing for accurate representation in terms of eye conditions, in terms of both classification tasks in Fig 5.

Glaucomatous Fundus Images



Normal Fundus Images

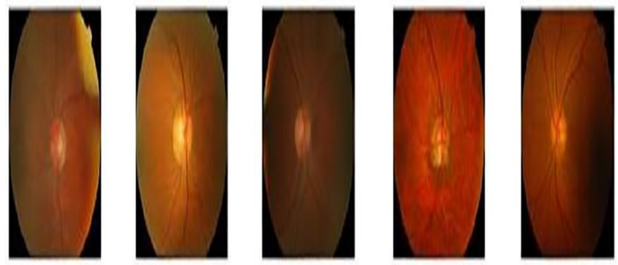


Fig.5 Sample Image from the ORIGA Dataset [31**]**

To facilitate both training and testing, our dataset was divided in an 80:20 ratio; this ensures 80% of samples would go toward training the model while 20% could be set aside to assess its performance.

Evaluation metrics such as accuracy, precision, recall, sensitivity, specificity and F1-score are used to gauge the success of proposed approaches in research studies such as this one. Using (9) to (11) illustrate these evaluation metrics used for this evaluation purpose.

$$\text{Accuracy} = \frac{\sum \text{True Positive,True Negative}}{\sum \text{True Positive,True Negative,False negative,Fale Positive}} \quad (9)$$

$$\text{Precision} = \frac{\text{True Positive}}{\sum \text{True Positive,False Positive}} \quad (10)$$

$$\text{Recall} = \frac{\text{True Positive}}{\sum \text{True Positive,False Negative}} \quad (11)$$

Precise identification of lesions on optical disc heads is critical in developing computerized systems to detect and classify regions affected by glaucoma. In order to evaluate our Grey Wolf-based U-Net++ model's localization abilities, we conducted an experiment utilizing the ORIGA dataset as our evaluation basis.

In Fig 6 provides the results of our experiments conducted using this approach. Our proposed Grey Wolf-based U-Net++ model displays exceptional accuracy when diagnosing lesions within both optic disc (OD) and cup (OC), regardless of size or position. Furthermore, its robustness in handling common sample distortions such as blurring, color variations and differences in brightness makes this model effective at detecting and classifying glaucoma; its segmented output from U-Net++ model can be seen in Fig 6.

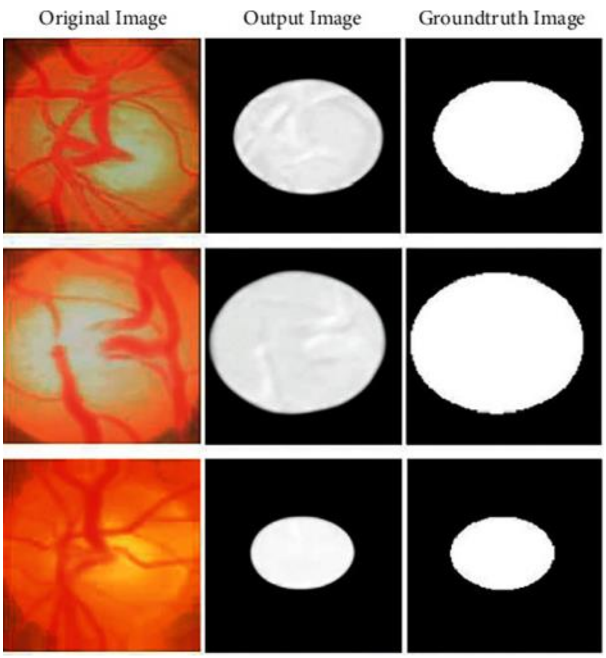


Fig.6 Segmented Output

After segmentation of optical cup and optic disc, Capsule Network (CapsNet) is used for effective classification of glaucoma. Accuracy and loss model are given in Fig 6 and Fig 7 respectively. The segmented output is given as input to the Capsule Network (CapsNet) for effective classification of glaucoma. The respective performance of classification is given in Fig 7 and Fig 8.

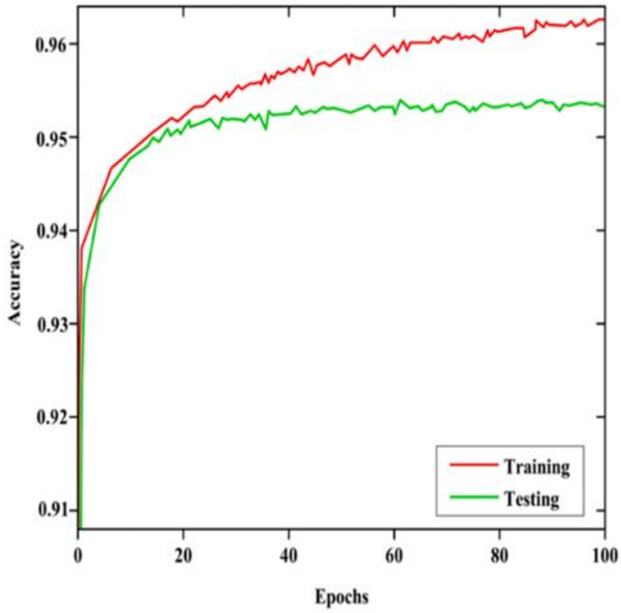


Fig.7 Training and Testing Accuracy of the Proposed Approach

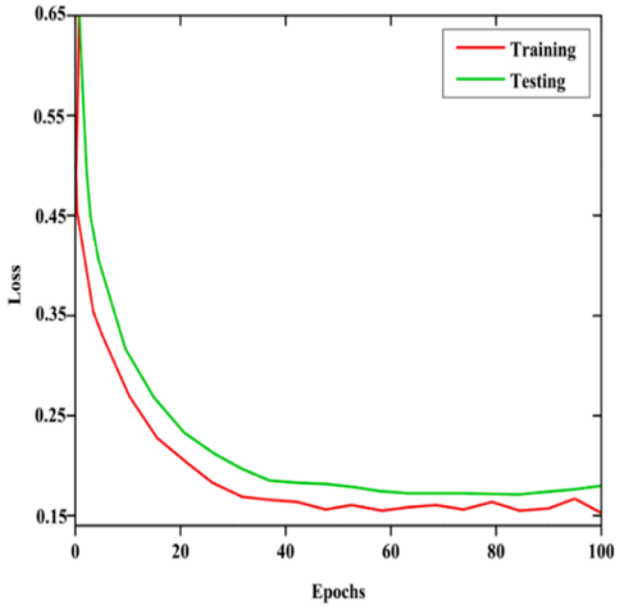


Fig.8 Training and Testing Loss of the Proposed Approach

As part of our assessment to prove the efficacy of our glaucoma classification method, we conducted an in-depth comparative evaluation using state-of-the-art techniques applied to the same dataset. To ensure objectivity during our evaluation process we routinely compared results obtained using our approach with those reported in references [22, 31, 32, 33-35].

Table 1, demonstrates the Performance comparison of proposed Model along with (U-Net++) + CapsNet. (U-

Net++) + CapsNet is developed model in previous work.

When compared that, our proposed grey wolf based (U-Net++) + CapsNet produces more reliable outcomes in terms of all the evaluation metrices used. Specifically, it attains the accuracy of 98.01% accuracy which was far better than previously developed work. Also, the respective comparison was given in Fig 9.

Table 1. Performance Comparison of Proposed against (U-Net++) + CapsNet

Methods	***Accuracy (%)***
(U-Net++) + CapsNet	97.06
Grey wolf based (U-Net++) + CapsNet [Proposed]	98.01

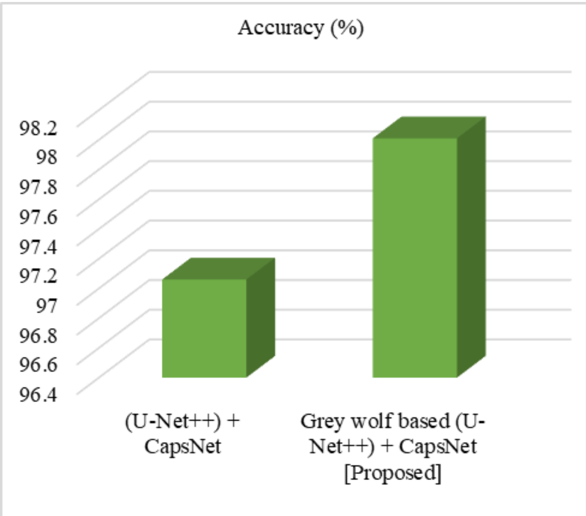


Fig.9 Testing accuracy of Proposed Vs (U-Net++) + CapsNet

Table 2. includes quantitative metrics to help gauge effectiveness and superiority over other available approaches while Fig. 10 to Fig. 13 showcase the comparative graphical displays to facilitate more in-depth examination of results allowing more rigorous assessment than other existing approaches.

Table 2. Resultant Comparison of Proposed Approach against Existing Technique

Methods	***Accuracy (%)***	***Precision (%)***	***Recall (%)***	***Specificity (%)***	***Sensitivity (%)***
Deep CNN [37]	92.5	92.3	91.3	90.4	90.3
Graph CNN [27]	92.9	92.9	91.2	91.3	90.8
Ensembling [28]	93.1	93.2	92.3	92.3	91.1
U-Net + Inception V3 [29]	93.6	94.9	93.7	93.3	94.2
ODGNet [36]	95.2	95.1	94.6	94.5	95.3
U-Net + EfficientNet [22]	96.5	95.3	95.7	95.1	96.3
(U-Net++) + CapsNet	97.6	96.9	96.2	97.1	96.8
Proposed	98.01	97.12	97.31	97.34	97.56

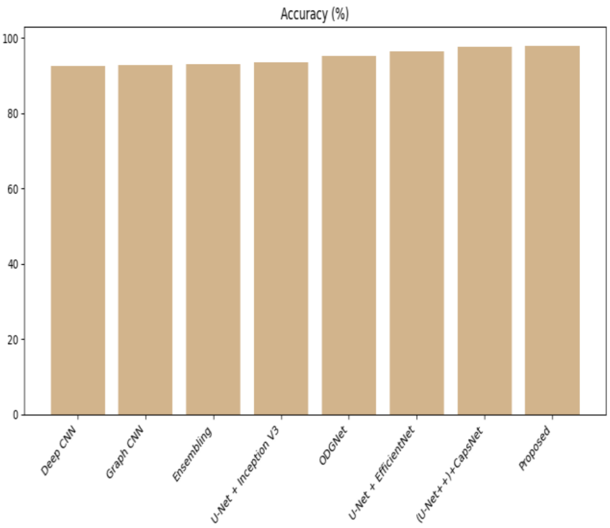


Fig. 10 Accuracy

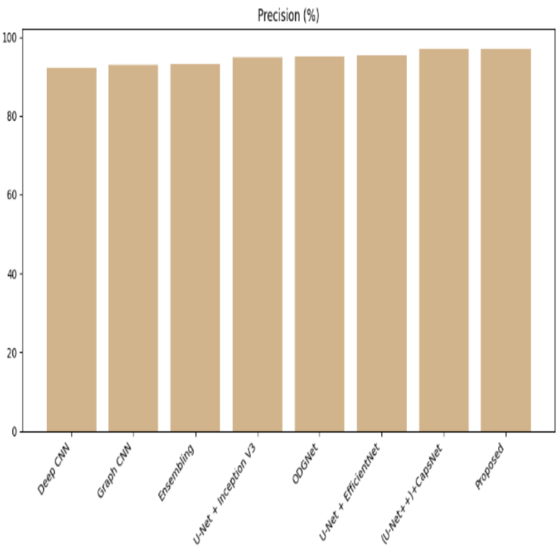


Fig. 11 Precision

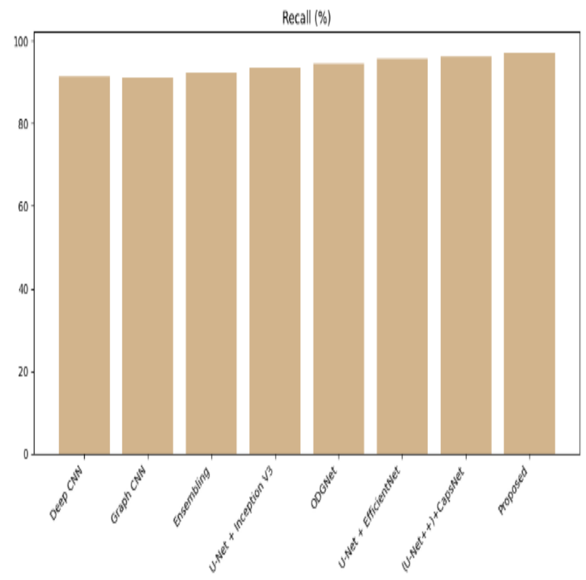


Fig. 12 Recall

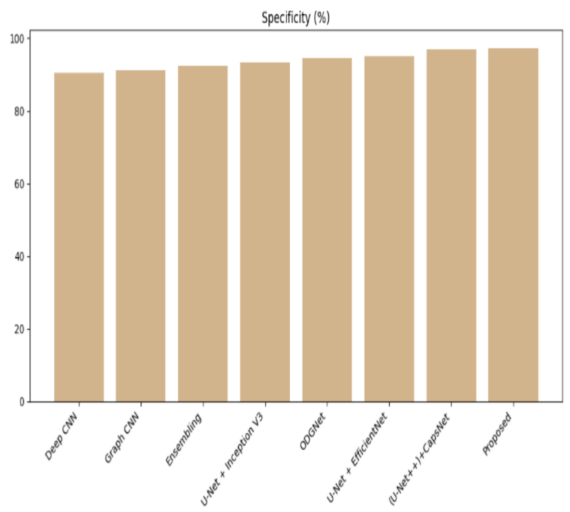


Fig.13 Specificity

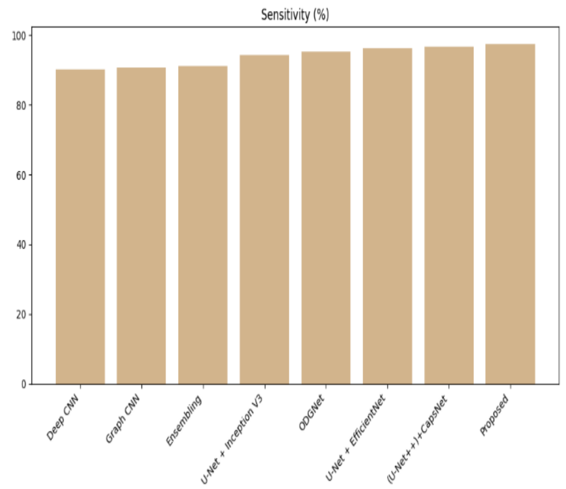


Fig.14 Sensitivity

5. Conclusion

Glaucoma detection in fundus samples often requires trained professionals capable of distinguishing subtle visual differences and categorizing images according to clinical criteria. Due to the intricacies of glaucomatous regions and difficulties accessing specialists with domain expertise, there is an urgent need for a fully automated system. This paper proposes a Novel Hybrid Approach designed to improve segmentation of Glaucoma disease effectively. Our proposed method developed Grey Wolf based UNet++ for segmenting optic disc and cup within fundus images and CapsNet for accurate classification, leading to highly reliable outcomes and an impressive 98.01% accuracy rate - surpassing traditional approaches. In future work, planning to develop GAN deep learning architecture over Glaucoma detection in fundus samples which offers solution to dataset scarcity issue.

Author contributions

Govindharaj I and Karthick G: Conceptualization, Methodology, Software, Field study **Govindharaj I and Michael G:** Data curation, Writing-Original draft preparation, Software, Validation., Field study **Govindharaj I and Karthick G:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

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