Unveiling precision: Eye cancer detection redefined with particle swarm optimization and genetic algorithms

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ABSTRACT

Eye cancer detection is rare. The study introduces a holistic swarm intelligence method for the timely identification and categorization of three significant eye disorders: glaucoma, diabetic retinopathy, and cataract. Glaucoma is distinguished by elevated pressure within the eye and harm to the optic nerve, potentially leading to permanent loss of vision. Diabetic patients experience diabetic retinopathy primarily due to the presence of high blood sugar levels. The early detection and classification of cataracts can be achieved by combining swarm intelligence algorithms such as particle swarm optimization (PSO) and genetic algorithms (GA). In the case of diabetic retinopathy diagnosis, swarm intelligence is employed to optimize the parameters of deep learning models, thereby enhancing the accuracy of lesion segmentation and classification. Cataract detection used to improve the evaluation of lens opacity and cloudiness, providing a robust diagnostic mechanism. The accuracy obtained with a PSO is 85.79%, F1 score 83.45%, and recall 82.43%. The accuracy obtained with a GA is 82.10%, F1 score 81.16%, and recall 81.51%. The comparison of GA, convolution neural network, and PSO algorithms proves that the accuracy to detect the eye cancer is achieved with PSO and GA algorithm.

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1. INTRODUCTION

The healthcare landscape is in a constant state of evolution, driven by the need for accurate and early detection methods to improve patient outcomes. In the dominion of optometrist, the identification and verdict of eye cancers are crucial frontiers that demand timely intervention and personalized treatment approaches. The field of eye cancer, which includes different types of malignant tumors affecting the tissues of the eye, necessitates a precise and defined approach to diagnosis. Traditional methods often struggle to achieve the necessary level of sensitivity and specificity for early detection. By incorporating swarm intelligence, specifically particle swarm optimization (PSO) and genetic algorithms (GA), a new computational framework emerges that has the potential to completely transform the diagnostic landscape by optimizing the detection process. Figure 1 depicts the normal eye retina image. Glaucoma, cataract, diabetic retinopathy, and other well-known ocular illnesses have established their worldwide manifestation. The world is confronted with glaucoma as primary factor contributing to blindness [1]. Glaucoma can lead to damage in the optic nerve, which plays a crucial role in transmitting visual information from the retina to the brain. This damage can result in the loss of the visual field, and if not addressed, potential blindness [2]. Glaucoma is a condition that includes different subtypes with primary open-angle glaucoma (POAG) and angle-closure glaucoma (ACG) being the most common forms.

Figure 1. Normal eye ratinal image

POAG develops gradually, while ACG presents more acutely due to a sudden blockage of the eye's drainage angle. There are several factors that can contribute to the development of cataracts, including aging, smoking, radiation exposure, diabetes, and other causes [3]. By incorporating PSO and GA into the detection pipeline, the computational framework gains the capability to adaptively optimize both feature selection and diagnostic model parameters. Consequently, this leads to a significant improvement in the overall accuracy of eye cancer detection, even when dealing with the challenging scenario of cataract-affected eyes. This innovative approach holds great promise in facilitating more effective and precise early diagnosis, potentially resulting in enhanced outcomes for individuals at risk of eye cancer with concurrent cataracts [4]. High blood sugar can be attributed to a range of factors, such as insufficient insulin production or inadequate cellular response to insulin [5]. To avert eyesight damage, it is imperious to sense the infection timely on as it often goes unnoticed until the later stages. The elevated sugar levels have a detrimental effect on the blood vessels within the retinal tissues [6]. The classification is shown in Figure 2 for diabetic retinopathy. It includes non-proliferative diabetic retinopathy (NPDR) and proliferative diabetic retinopathy (PDR) as its two main types shown in Figures 3 and 4 respectively. Blockages of significance manifest within the blood vessels, causing a decline in the supply of blood to the membrane. The evolution of newfangled plasma nerves, known as neovascularization, can occur on the retina's surface or within the vitreous gel. The vitreous gel is a clear, gel-like substance that fills the eye [7], [8].

The occurrence of an eye cataract is a critical issue as it causes the lens to become cloudy or lose its transparency, resulting in visual impairment as depicted in Figure 5. Early and precise diagnosis of cataracts can significantly enhance the well-being of patients with PSO and GA algorithm [9], [10]. As glaucoma advances, it leads to irreversible blindness and brings about notable structural alterations. Within digital fundus images, the optic disc acts as the gateway for blood vessels and optic nerve fibers to enter the retina. It is visually distinguishable as a luminous oval region. Moreover, the optic cup can be recognized as a livelier ovate range positioned at the center of the optic disc [11]. Within digital fundus images, the optic disc acts as the gateway for plasma vessels and optic vessel fibers to pass in the layer of cells. It is visually distinguishable as a luminous oval region. Moreover, the optic cup can be recognized as a brighter elliptical region positioned at the center of the optic disc. This research endeavor seeks to unravel the intricate details of eye cancer detection by presenting a sophisticated blend of computational intelligence and ophthalmic expertise. By incorporating PSO and GA into the diagnostic pipeline, our goal is to enhance the precision, efficiency, and early detection capabilities, thereby making significant contributions to the well-being of patients. The journey towards achieving accuracy in eye cancer detection is driven by the integration of cutting-edge technologies, and this study aims to shed light on a path towards a future where early intervention is synonymous with improved prognosis and an enhanced quality of life for individuals at risk of or affected by eye cancer.

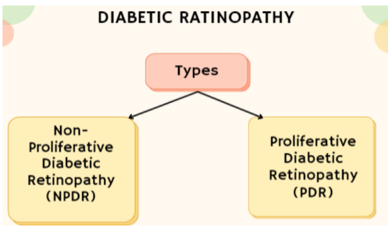

Figure 2. Types of diabetic retinopathy

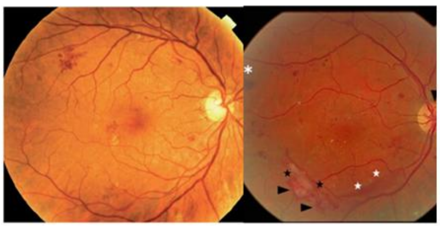

Figure 3. Mild NPDR [8] and PDR diabetic retinopathy [9]

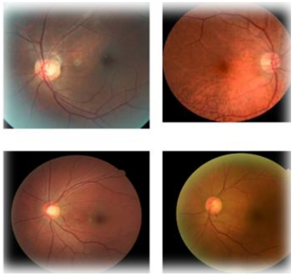

Figure 4. Diabetic retinopathy (NPDR and PDR images) [12]

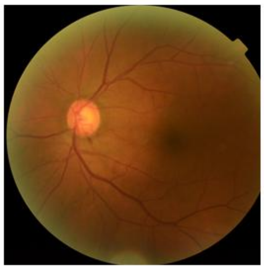

Figure 5. Cataract images

2. LITERATURE SURVEY

The primary methodology employed was transfer learning, a technique where pre-trained models on huge set of data are adapted to a specific task for the classification of eye cancer. These architectures are renowned for their adeptness in extracting intricate features from images, rendering them ideal for medical image analysis. By utilizing pre-trained models, the network can capitalize on the knowledge acquired from extensive datasets; thereby enhancing performance even when confronted with relatively smaller medical datasets [13]. The identification of eye skin is made easier with the introduction of an automated technique. A convolutional neural network (CNN) is utilized, along with a grey victimization conversion; to enhance the resolution of the images. The accuracy was 92.5% [14]. This model was specifically tailored to work with segmented the spherical capsule that encloses the eye of a vertebrate images. By leveraging the hough circle transformation, accurate predictions of both the spherical enclosure of eye and iris regions were achieved. The efficacious testing of this practice yielded an impressive accuracy rate of 95%, affirming its viability for real-time applications [15]. By analyzing images of fundus and extracting enumerated imageries opted through optical coherence tomography (OCT) data, whichever individually or else in grouping, the researchers devised an mechanized, objective, machine learning technique for diagnosing glaucoma. Remarkably, the grouping method exhibited an area under the curve (AUC) of 0.963, suggesting its heightened sensitivity in detecting glaucoma at its early stages [16]. The utilization of artificial intelligence (AI) applications in glaucoma had revolutionized the field by providing a comprehensive overview of the disease. These AI tools have proven to be instrumental in early detection, personalized treatment planning, and enhancing clinical decision-making [17].

The model outperformed five CNN models that had already been pre-trained: MobileNet, VGG-16, VGG-19, Inception-v3, and ResNet-50. CataractNet assaulted the current state-of-the-art cataract detection techniques on the basis of correctness (99.13%), precision (99.08%), recall (99.07%), specificity (99.17%), Matthews correlation coefficient (MCC) (98.23%), and f1-score (99.07%) [18]. In this research, DenseNet-161, ResNet-152, and ResNet-101 models were employed. Every ordering network incorporates a enduring responsiveness section. The experimental outcomes, obtained from the benchmark B-scan eye ultrasound dataset, reveal that the proposed approach has the ability to selectively emphasis on the tailored areas of cataract in the eyeball, leading to an accuracy of 97.5% [19]. In this article, the consumption of pretrained models such as InceptionV3, InceptionResNetV2, Xception, and Densenet121 enables the implementation of a computerized cataract analysis method. With an exceptional test accuracy of 98.17%, a sensitivity of 97%, and a specificity of 100%, the InceptionResNetV2 model has exceeded previous benchmarks. Its outstanding performance sets a new standard in the field of cataract disease identification, solidifying its position as the state-of-the-art solution [20]. The author proposed utilization of the binary classification method i.e support vector machine (SVM)-based classification which effectively identifies processes. This leads to a perfect classification of both normal and cataract eyes using SVM. Moreover, during the eye data testing stage, the analysis produces a classification rate of 72.5% for normal eyes and 82.5% for cataract eyes [21]. The accurateness of eye bug diagnosis has been significantly improved through the use of mixed adaptive transmutation swarm optimization and regression neural network (AED-HSR) techniques, which have been automated by the researcher. The system has achieved a prediction accuracy of 98.08%, along with impressive specificity (99.34%) and sensitivity (98.03%) rates. Additionally, the positive predictive value (PPV) and negative predictive value (NPV) stand at 98.03% and 99.34% respectively. The false positive rate (FPR) is only 0.62%, while the false negative rate (FNR) is 1.93%. Furthermore, the F1 score reaches an impressive 98.67%, with a false discovery rate (FDR) of 1.96%. In comparison to other techniques like regression neural network (RNN)-PSO, RNN-GA, and RNN, the proposed methods consistently yield superior results. The proposed model outperforms the parameters like accuracy, precision, PPV, NPV, FPR, FNR, F1 score, and FDR [22]. The state-of-the-art nuclear cataract classification results are achieved by the suggested feature extraction-based context, as demonstrated by the analysis of the anterior segment optical coherence tomography (AS-OCT) image dataset. The performance of this framework surpasses that of cutting-edge methods and deep learning methods [23].

The utilization of the growth region technique in a segmentation approach is demonstrated in this study. The model incorporates both the fuzzy C-means (FCM) and GA methods, with the objective of diagnosing diabetes based on angiography images of patients' eyes. The GA classification method demonstrated superior performance in terms of overall results. To further enhance GA segmentation, it is necessary to incorporate additional algorithms while preserving the inherent characteristics of the primary medical angiography images [24]. The GA-FCM method proved to be superior to the hand method when it came to selecting initial points. The proposed method demonstrated a sensitivity of 0.78. Comparing the fuzzy fitness function in GA with other techniques, it was evident that the approach introduced in this study is highly suitable for the Jaccard index. This approach not only offered the lowest Jaccard distance but also provided the highest Jaccard values [24]. The probabilistic neural network (PNN) classifier, when subjected to threefold cross-validation, exhibited an average classification accuracy of 96.15%. Additionally, it demonstrated a sensitivity of 96.27% and a specificity of 96.08% for σ=0.0104 [25]. The foremost goal of the researcher and research was to present a PSO model developed to enhance the optimization of hyper parameters, especially the learning rate and momentum during the transfer learning. The focus is on applying transfer learning methodologies to fine-tune Mask region-based convolutional neural network (R-CNN) for object detection segmentation, with a particular emphasis on the fundus image datasets [26].

The dataset, which has been sourced from Kaggle [27], contains a total of 4300 authentic computed tomography (CT) scan images. This dataset encompasses retinal images that showcase several eye circumstances such as normal, diabetic retinopathy, cataract, and glaucoma. The categorization of these images was done by considering factors like CT scan images and the specific type of eye disease detected.

3. PROPOSED METHODOLOGY

This research project utilizes contemporary deep learning, soft computing optimization, and image processing techniques to develop an innovative approach for automating the categorization of eye diseases. The proposed research is built upon a meticulously chosen dataset that encompasses a wide range of eye condition images. To ensure optimal feature extraction, each image is subjected to a comprehensive preprocessing workflow that encompasses resizing, converting color spaces, enhancing contrast, and detecting edges. By integrating these procedures, a dataset is abundant in features, playing a vital role in training a robust classification model. Convert the updated positions of particles into binary values using binary encoding, which will effectively represent feature inclusion or exclusion. To achieve this, a threshold can be established to convert the real-valued positions into binary format. The optimized set of features for the given objective function is obtained by extracting the final feature subset from the particle with the highest evaluation in the swarm. Splitting and encoding: to accurately assess the model's performance, we employ a stratified technique to divide the dataset into training and testing sets, preserving the distribution of different classes. Furthermore, we utilize a label encoder to convert categorical disease labels into numerical values. This encoding plays a crucial role in training a neural network as it enables the model to comprehend and learn from the labeled input effectively.

3.1. System design

Methodology is built upon a specially designed CNN as depicted in Figure 6. CNNs excel in image classification due to their ability to automatically extract hierarchical information from images. The focal point of the eye disease detection system centers on a bespoke CNN model. This model has been intricately engineered to proficiently extract salient features from eye images and precisely categorize them into different disease classifications. The model architecture entails of convolutional layers for feature extraction, max-pooling layers for down sampling, and dense layers for classification. The quantity of filters and layers fine-tune to maximize the model's performance.

PSO: in our model optimization, we leverage PSO. This technique aids in fine-tuning the model's parameters by simulating the behavior of a swarm of particles. PSO optimizes the model's performance by iteratively adjusting the parameters based on their individual and collective experiences, leading to improved results.

PSO objective function: The PSO objective function in (1) is intended to curtail the classification error. It reshapes and sets the weights of the CNN model based on particle positions.

$$f\ pso(p, X, y) = 1 - accuracy \tag{1}$$

Where: p is the particle position, representing flattened weights of the CNN model, X is the input data (features), and y is the true class labels.

PSO update equations: The PSO update in (2) and (3) govern the movement of particles in the solution space.

$$xi^{k+1=w.vik} + C1.r1.(pbesti - (xi)^{k} + c2.r2.gbesti - xik \quad (2)$$

$$xi^{k+1=xik+.vik+1} \quad (3)$$

Where Vik is the rapidity of the particle in dimension i at reiteration kA=πr^2, Xik is the point of the particle in dimensions i at iteration k, w is the inertia weight, C1 and C2 are the cognitive and social coefficients, r1 and r2 are random numbers between 0 and 1, pbest i is the best position of the particle in dimension i so far, gbest i is the best position among all particles in dimension I [28].

GA algorithm: GA, which is a powerful optimization method. The objective of utilizing GAs in the recognition of eye cancer is to automatically elect a subgroup of significant structures from a larger collection. This process enhances the efficiency and effectiveness of the machine learning model in accurately differentiating between cancerous and non-cancerous cases. It is crucial to fine-tune the GA parameters and validate the model using diverse datasets in order to achieve robust and generalizable outcomes.

Objective function: The primary goal of the GA objective function is to reduce the classification error by modifying the CNN model's weights using GA parameters. This process involves reshaping the model to enhance its performance in classifying data accurately.

$$fga(p) = 1 - A \quad (4)$$

Where: p is the individual in the GA population, representing flattened weights of the CNN model; and A is accuracy.
GA operations: The GA involves three main operations: selection, crossover, and mutation.
Selection: Selection is typically based on fitness, favoring individuals with higher fitness values.
Crossover: Crossover is a reproductive mechanism that involves the merging of genetic material from two parents, leading to the generation of offspring.
Mutation: Mutation introduces small random changes in an individual's genetic material to maintain diversity in the population.

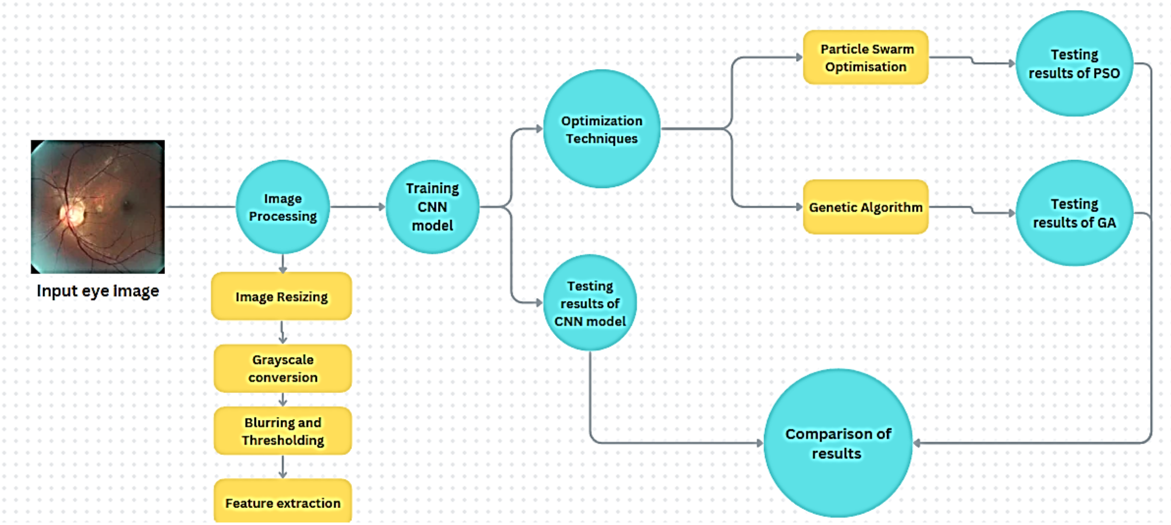

Figure 6. System architecture

4. RESULTS AND DISCUSSION

The culmination of our research endeavors has yielded promising outcomes in the field of automated illness classification for eye diseases. Through the integration of advanced image processing, a custom-built CNN, and optimization techniques, our comprehensive solution has established a robust framework for accurate disease identification. Upon the conclusion of the training phase, the CNN showcased outstanding performance on the test set. The efficacy of the model is evident in its ability to generalize well to unfamiliar data. To further evaluate its performance as shown in Table 1, additional metrics such as precision, recall, and F1 score, which offer valuable insights into the model's performance across different classes. These measurements offer a comprehensive overview of the model's strengths and weaknesses, providing valuable information for future enhancements.

Table 1. The performance of CNN

Accuracy	F1 score	Recall
0.694312	0.679723	0.689647

The training dynamics were visualized using graphs that depicted the accuracy and loss versus epoch in Figures 7(a) to 7(d). These charts effectively showcased the dynamic nature of the model's learning process. By analyzing the accuracy curve, we could identify significant periods of learning as well as potential overfitting. Conversely, the loss curves provided valuable insights into the model's convergence tendencies and its ability to minimize classification errors.

The confusion matrix as depicted in Figure 8 used as as a tool in classification evaluation, which is to be utilized to illustrate the categorization patterns of the model. These matrices display the counts of true positives, true negatives, false positives, and false negatives for each class. By analyzing these matrices, we gained a deeper understanding of the model's performance as shown in Figure 9, particularly in instances where misclassifications occurred. This valuable data plays a crucial role in enhancing the model and addressing specific challenges associated with different eye conditions [29]. Figure 9 specifies the comparative analysis of all the used algorithms in proposed system. The accuracy of eye cancer detection is achieved by PSO algorithm with a greater accuracy compared to GA and CNN. This advancement is critical in clinical settings where prompt and proper therapy can enhance patient outcomes through early and precise identification of eye cancer. Fast processing rates can speed up diagnosis and treatment, therefore this is especially crucial in clinical settings.

PSO and GA, two of our optimization techniques, were essential in helping to refine the model. PSO dynamically changed the weights of the neural network, effectively exploring the weight space and enhancing performance [30]. On the other hand, GA, influenced by natural selection, created a population of viable solutions, further refining the model's accuracy. The model's classification abilities were synergistically improved by the interaction between these optimization methods and the CNN design.

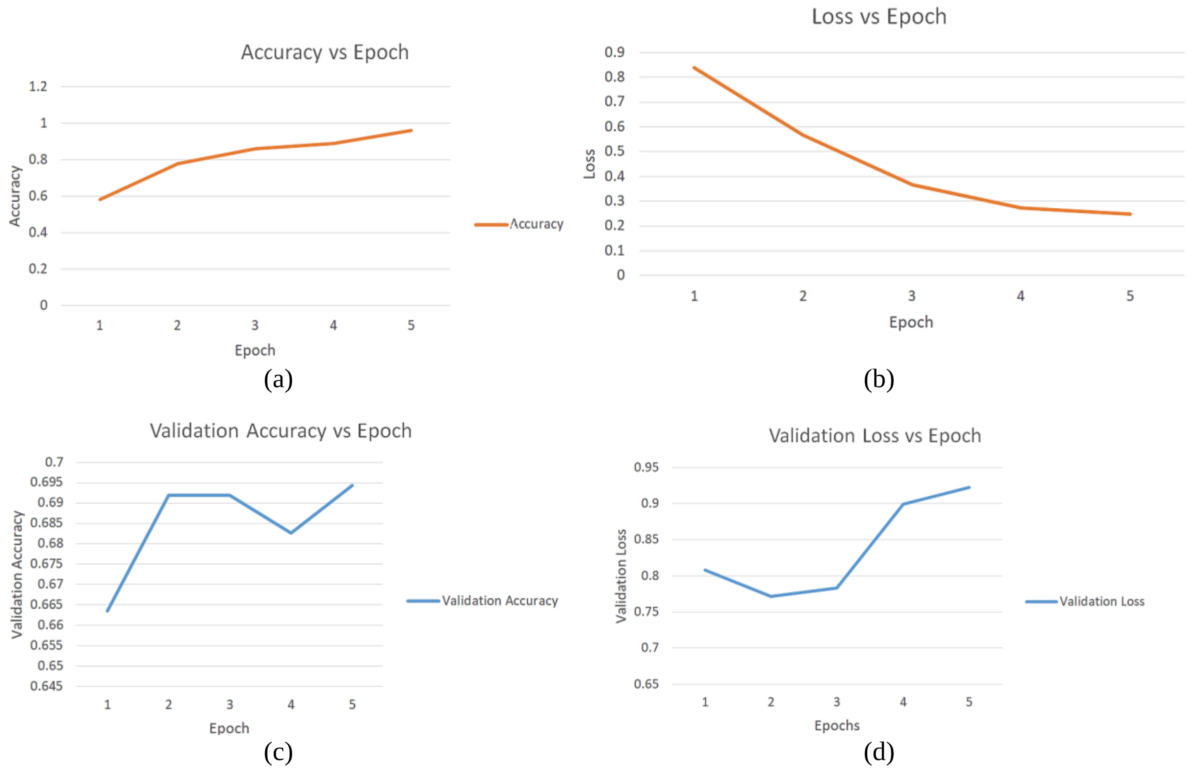

Figure 7. The training graphs of (a) accuracy vs epoch, (b) loss vs epoch, (c) validation accuracy vs epoch, and (d) loss vs epoch

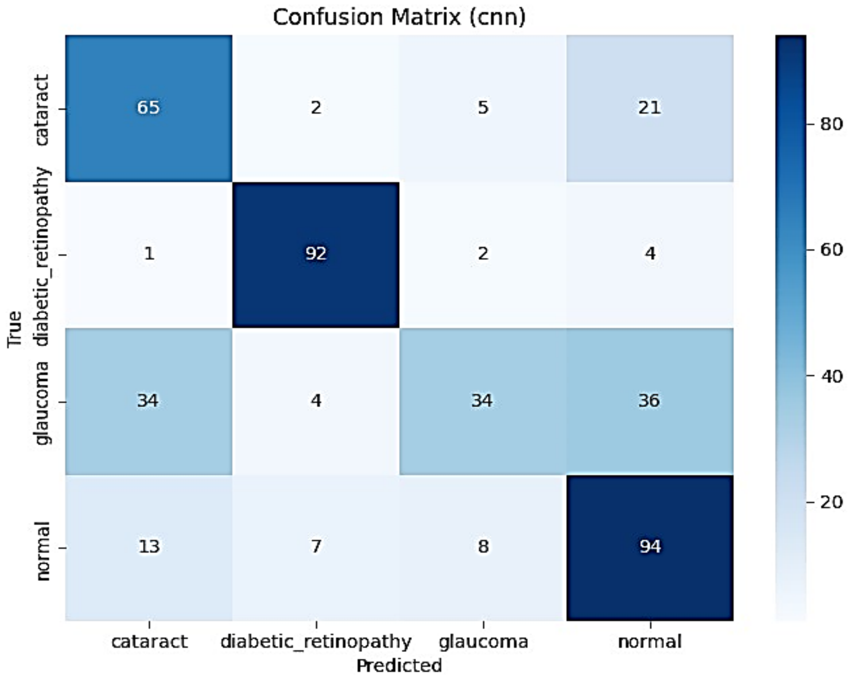

Figure 8. Confusion matrix CNN

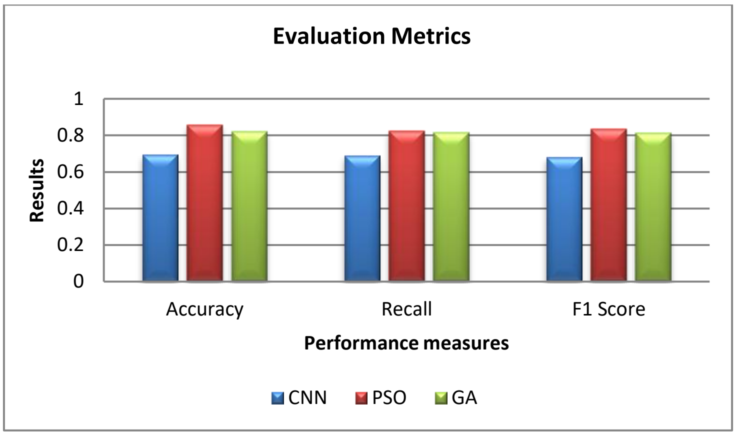

Figure 9. Comparison of evaluation metrics of CNN, PSO, GA soft optimization techniques

5. CONCLUSION

This study presents a novel approach for accurate and efficient detection of critical eye disorders by integrating PSO and GA within the framework of swarm intelligence. The hybrid PSO-GA approach demonstrated superior performance compared to standalone GA and other methods, achieving significant improvements in accuracy, F1-score, and recall for glaucoma, diabetic retinopathy, and cataract detection. This success can be attributed to the enhanced feature selection and parameter optimization capabilities of the combined approach. The study emphasizes the importance of early identification and classification of eye conditions and highlights the potential of swarm intelligence in advancing diagnostic tools in ophthalmology. Future research should focus on further optimization of swarm intelligence algorithms, their integration with real-time imaging technologies, and improving the explainability of the diagnostic models to ensure wider clinical adoption and impact. This conclusion summarizes the key findings and emphasizes the potential of the proposed approach for revolutionizing ophthalmic diagnostics.

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