Grasshopper Optimization Technique with Deep Learning Driven Retinal Fundus Image Grading and Retrieval

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Abstract: ***In the domain of ophthalmology and medical image analysis, the accurate estimation of retinal fundus images is important for analyzing and treating different eye diseases, comprising Diabetic Retinopathy (DR). This study introduced an innovative architecture that integrates the capability of deep learning with content-based image retrieval (CBIR) to transform the evaluation of retinal fundus images. Consequently, this study establishes a Grasshopper Optimization Algorithm with Deep Learning Driven Retinal Fundus Image Grading and Retrieval (GOADL-RFIGR) method. The introduced GOADL-RFIGR technique is a comprehensive system for retinal fundus image retrieval, incorporating advanced technologies for hyper parameter optimization, pre-processing, similarity measurement, and feature extraction. We apply Bilateral Filtering (BF) as a pre-processing stage for improving the quality of retinal fundus images. We introduce a Lightweight Convolutional Neural Network (CNN) developed for effectively removing distinctive features from retinal fundus images. For more improvement of the retrieval performance, we employ the ability of the Least Square Support Vector Machine (LS-SVM) for classification. Moreover, we leverage the Grasshopper Optimization Algorithm for optimizing hyperparameters over the CBIR technique. This nature-inspired optimization method supports in fine-tuning diverse modules of the system and lastly, maximizing retrieval efficiency and accuracy. The simulated validation of the GOADL-RFIGR model on benchmark dataset represents a better performance over other systems.***

Keywords: Deep learning; Retinal fundus images; Image classification; Parameter tuning; Image retrieval

1. Introduction

In the current scenario, Data retrieval plays a vital role in the evolution of technology with numerous databases [1]. Among others, Content-Based Image Retrieval (CBIR) is one of the most common image retrieval techniques which has effective features in many domains such as historical research, incorporating military applications, medical image analysis, etc [2]. Feature extraction and effective data representation are the primary elements for effective medical imaging tasks. Generally, the researchers grab medical field knowledge & skills and ask for explanations from the medical specialists. All important areas of internal eye organize the 'fundus' part and it can be recognized just opposite the eye lens [3]. The fundus encloses the fovea, optic disc, posterior pole, macula, and retina as well and blood vessels are also presented in the eye part. The ophthalmoscope is mainly developed to analyse the fundus area of the eye. Once the process is over, the eye can be dilated. With the aid of the 'Fundus camera' (FC), the analysis of the fundus area is executed [4]. The FC operates on the same principle which is parallel to the ophthalmoscope and covers a high-resolution camera. Exudates, constrictions, haemorrhages, cotton wool spots and abnormalities in the blood vessels, etc. are considered as medical conditions of the eye [5]. All these can be examined by utilizing images which are developed from FC.

The deep Learning (DL) technique has been appeared and executed in numerous domains over the years including Medical Image Analysis (MIA) [6]. The DL method identifies features accurately from the input data to classify or segment and generally performs conventional image analysis techniques. This method need not develop the handcrafted features but it requires extensive data for training [7]. And also Machine Learning (ML) techniques require the removal of hand-crafted features. But, it does not need wide information for the training purpose. In Diabetic Retinopathy (DR) discovery, the ML technique must develop the vessel primarily which is followed by the 'DR lesions' extraction feature for detection purposes. DL features covers segmentation, registration, detection, retrieval, and classification of images. Convolutional Neural Network (CNN) is one the types of DL method which is generally employed for image analysis because it is an effective and very potential technique [8]. For automation of DR image detection, there was a significant amount of effort to help eye experts in identifying the disease in the initial stage. Most of the endeavours will concentrate only on determining DR instead of finding numerous DR stages [9]. Moreover, there were only restricted efforts to localize as well as classify each & every DR lesion type. It was highly effective in practice time so that ophthalmologists could evaluate the importance of DR and perceive its improvement associated with the presence of such lesions [10].

This study develops a Grasshopper Optimization Algorithm with Deep Learning Driven Retinal Fundus Image Grading and Retrieval (GOADL-RFIGR) technique. To enhance the quality of retinal fundus images, we employ Bilateral Filtering (BF) as a preprocessing step. We introduce a Lightweight Convolutional Neural Network (CNN) designed to extract discriminative features from retinal fundus images efficiently. To further enhance the retrieval performance, we utilize the power of Least Square Support Vector Machine (LS-SVM) for classification. Additionally, we leverage the Grasshopper Optimization Algorithm to optimize hyperparameters across the CBIR system. The experimental validation of the GOADL-RFIGR model on benchmark dataset portrays a better performance over other models.

2. Related Works

Gupta et al. [11] proposed an Optimal-Deep CNN for Retinal Fundus Image Classification (ODCNN-RFIC) method. It consists of the pre-processing unit in two phases such as Guided Filter (GF) and Adaptive Median Filter (AMF). The U-Net technique was specially used for image segmentation and aid to permit the infected part that identified correctly. Moreover, the EfficientNet extracting feature has been utilized to build a feature vector. The mayfly optimization with KELM (MFO-KELM) method was implemented as a classification method. Gupta et al. [12] developed a new AI with an optimum DCNN (AI-ODCNN) method for RFIC. At first, the designed technique employs the Gaussian Blur based on noise removal and contrast enhancement system (CLAHE) based on the contrast enhancement method to process the RFI. In addition to that, the DCNN method is used in RFIC with the help of RMSProp Optimizer.

In [13], an effective 2-step Optic Disk localization and Glaucoma Diagnosis Network (ODGNet) was developed. At the initial time, a visual saliency map combined with shallow CNN was used for OD localization in the fundus image. In the next step, the Transfer Learning (TL)-based pre-training techniques were used to analyse glaucoma. Numerous techniques are integrated with saliency maps namely AlexNet, ResNet and VGGNet. Pal et al. [14] proposed a novel DL multi-model network known as G-EyeNet for glaucoma detection in RFIs. G-EyeNet has a convolutional auto-encoder (AE) and a classic CNN method which shares the encoded structure. The multi-model network is combined with optimization to decrease classifier error or image reconstruction error which depends upon the multi-task learning method.

Bajwa et al. [15] study a 2-phase structure that initially detects and also limits optic disc (OD) and later classifies it as glaucomatous. The primary stage was dependent only upon the Regions with CNN (RCNN) and had a high responsibility to extract and localize OD in RFI. However, the secondary stage employs DCNN to identify the extracted disc as glaucomatous. Therefore, the authors have designed a rule-based semi-automatic ground truth generation method because it provides effective clarifications to train RCNN-based techniques to program disc localized. Acharya and Puhan [16] developed an essential process that depends upon LSTM to exploit the classification need of 1D feature signal extracting in MAs and help in its classification algorithm from colour fundus images. This method was mainly trained to make use of 1D intensity-based signals created in numerous areas of pre-processing fundus images.

3. The Proposed Model

In this study, a new GOADL-RFIGR method was formulated for the retrieval and classification of retinal fundus images. The presented GOADL-RFIGR technique mainly aims to retrieve and classify the retinal fundus images. It follows different subprocesses namely BF-based preprocessing, feature extraction, similarity measurement, LS-SVM classification, and GOA hyperparameter tuning.

3.1 Image Pre-processing

In the first stage, the presented GOADL-RFIGR technique employed the BF approach to preprocessing the retinal images. BF is a classical pre-processing algorithm in denoising and image enhancement [17]. It successfully lessens noise while retaining the fine details and sharpness of edge. Different fromclassical smoothing filter, BF consider the intensity similarity and spatial proximity between pixels, which ensures that adjacent pixels with similar intensity contribute more to the filtering process. This technique makes BF especially useful in scenarios where noise reduction is vital while retaining the simplicity of significant features namely image post-processing, medical imaging, and CV.

3.2 Image Retrieval Process

For image retrieval process, the GOADL-RFIGR technique uses Lightweight CNN based on scratch learning with Euclidean distance based similarity measurement. Lightweight CNN belongs to DL architecture finely developed for resource-constraint environments and applications where computation efficacy is vital [18]. This network aims to strike a balance between predictive accuracy and model size. The hallmark of lightweight CNN is their capability to accomplish outstanding performance while minimalizing computation requirements, which makes them suitable for deployment on mobile applications, embedded systems, and edge devices.

The classical approach used in lightweight CNN is the decline of complexity model through depth wise separable convolution that decomposes typical convolution into depth-wise and point-wise convolutions. Fig. 1 depicts the architecture of CNN. This technique considerably decreases the number of computations and parameters, which makes the model highly effective without compromising prediction ability. Furthermore, lightweight CNN might apply algorithms like model distillation, channel pruning, and quantization to further enhance the resource application. Consequently, this model excels in real-time object detection, image classification, and other computer vision tasks in resource-constraint scenarios, making them essential for AI at the edge. Lightweight CNN comes under various architectures and sizes, with widespread examples involving ShuffleNet, MobileNet, and SqueezeNet. This network has illustrated proficiency in fields like IoT applications, mobile app development, and autonomous robotics, allowing AI to effectively and efficiently operate in a multitude of edge computation contexts.

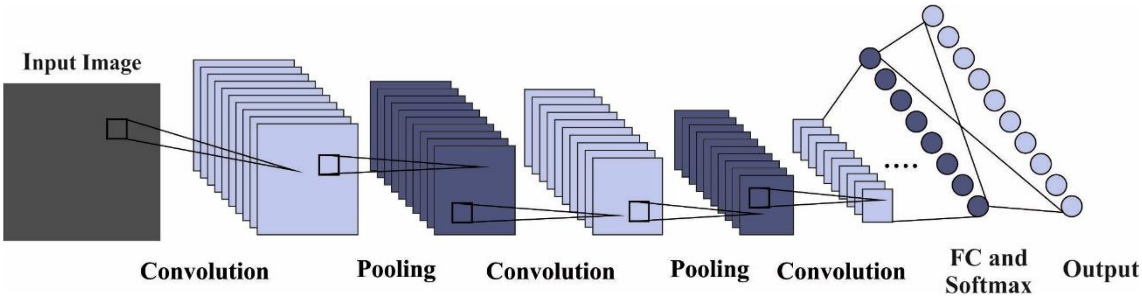

Figure 1: CNN structure

3.3 Image Classification Process

At last, the GOADL-RFIGR technique makes use of GOA with the LS-SVM model for image classification. LSSVM is a ML method developed in the classical SVM method [19]. The SVM is mainly designed for classifier problems and nonlinear function evaluation. However, some researcher workers formulated the SVM reliant on regression systems namely support vector regression (SVR), for solving specific modelling such as prediction drive. Generally, the SVR system was defined as follows:

$$f(x) = \langle \omega, \varphi(x) \rangle + b \tag{1}$$

In Eq. (1),χ signifies input database and $\rangle$ epitomizes the dot product. ω, b, and $\varphi(x)$ indicate the weight vectors, bias, and nonlinear operation that maps input to high-dimension feature space.

The augmented problem was defined to generate$N$amount of data instances from the SVM, as:

$$\min \frac{1}{2}\left\|\omega\right\|^2 + C\sum_{k=1}^{N}\left(\xi_k + \xi_k^*\right) S.T.\begin{cases} y_k - \langle \omega, \varphi(x_k)\rangle - b \le \varepsilon + \xi, e \\ \langle \omega, \varphi(x_k)\rangle + b - y_k \le \varepsilon + \xi_e^* \\ \xi\ \xi_e^* \ge 0 \end{cases} \tag{2}$$

In Eq. (2),ξ and ε-insensitive correspondingly represent slack variable and insensitive loss function. Note that the SVM could model problems with high-dimension input space. Thus, the SVM is efficiently used for modelling hydrological procedures. Now, it utilizes the original term SVM for the predictive or classifier approaches. Though, as SVM's major constrained optimized programming, it undergoes high computation costs in modelling complicated phenomena. LSSVM method was established to address these problems. Sum squared error (SSE) and equality constraints are exploited for the training model:

$$\min \frac{1}{2}\|\omega\|^2 + \frac{1}{2}\gamma\sum_{e=1}^{N} e_k^2\ S.T.\begin{cases} \langle \omega, \varphi(x_k)\rangle + b + e_k \\ \gamma \ge 0 \\ k = 1, \dots, N \le \varepsilon + \xi_{1e} \end{cases} \tag{3}$$

In Eq. (3), $e_k$denotes error parameter and γshowsthe normalization constant. The LSSVM reduces the modelling system of SVM such that the solution was described by the Karush- KuhnTucker (KKT) linear algorithm. The proposed KKT linear method is simply determined by the iterative technique involving gradient-based optimization method.

The output (predicted value) of the LSSVM is estimated using Eq. (4):

$$y(k) = \sum_{k=1}^{\Sigma} \alpha_k\, K(x, x_k) + b \tag{4}$$

$K(.,.)$denotes the kernel function. Considera RBF for the kernel function:

$$K(x, x_k) = \exp\left(-\frac{(x - x_k)^T(x - x_k)}{2\sigma^2}\right) \tag{5}$$

σ shows the width of kernel function. The parameters related to the LS-SVM model are optimally chosen by the use of GOA.GOA is an optimization technique which mimics the behaviors of grasshopper swarm [20]. Firstly, the parameter of GOAs including, population size, maximum iteration $cmax$, and $cmin$shows the defined, and the fitness of all thegrasshoppersareevaluated. At all the iterations, c coefficient is updated by the following expression:

$$c = cmax - l\frac{cmax\ - cmin}{L} \tag{6}$$

In Eq. (6), l refers to the existing iteration, and Ldenotes the maximal iteration. $cmax$ and $cmin$shows the maximum and minimum values for c, correspondingly. For each grasshopper, after implementing these formulae, the distances between grasshoppers are normalized into [1,4], and the new position is evaluated by the following equations:

$$x_{i,d}^{t+1} = c\left(\sum_{j\neq i}^{N} c\frac{ub_d - lb_d}{2}\left(fe^{\frac{-|x_{i,d}^t - x_{i,d}^t|}{l}} - e^{-|x_{i,d}^t - x_{i,d}^t|}\right)\frac{x_j^t - x_i^t}{|x_j^t - x_i^t|}\right) + \widehat{T_d} \tag{7}$$

Now N refers to the overall amount of grasshoppers, $f$shows the intensity of attraction, l denotes the attractive length scale. ub_d and lb_drepresents the upper and lower boundaries of the d^{th}dimensions of the searching area. $\widehat{T_d}$ indicates the better location until the iteration continues or the maximum iteration is obtained, and lastly, the fittest location is returned as a GHA solution.

4. Results and Discussion

The performance validation of the GOADL-RFIGR method is investigated on DR Kaggle dataset [21] with 35126 samples and five class labels. Fig. 2 visualizes the sample retrieval results of the GOADL-RFIGR model.

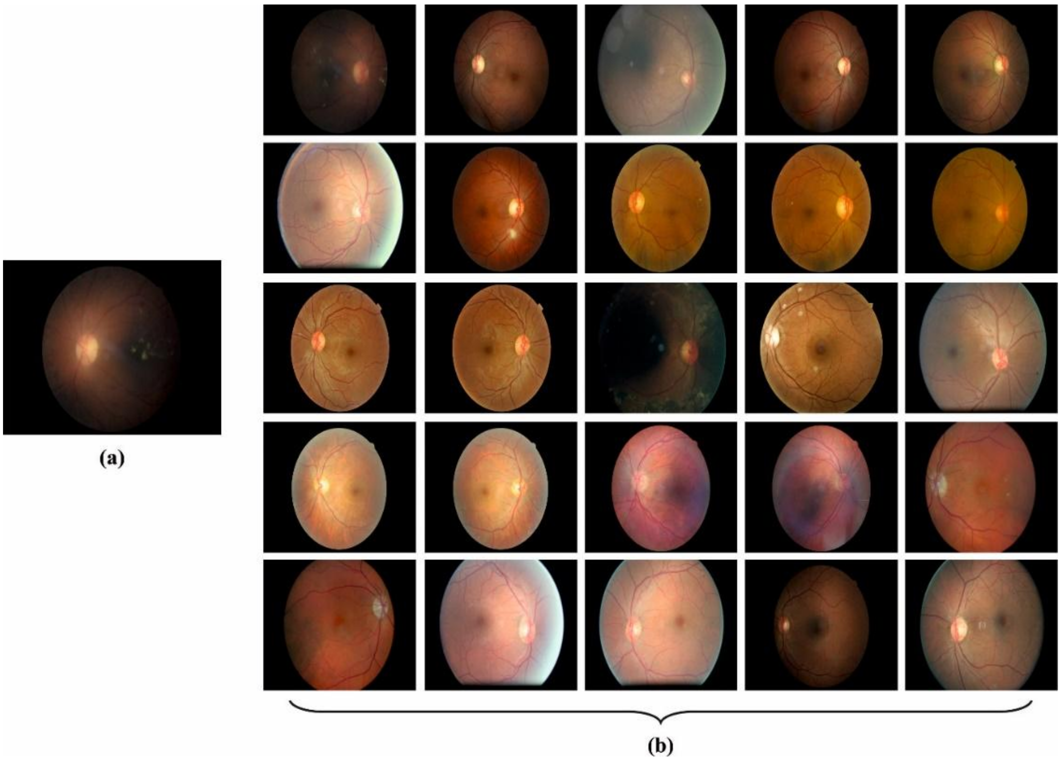

Figure 2: a) Query Image b) Retrieved Images

Table 1 and Fig. 3show an overall DR classification analysis of the GOADL-RFIGR system on80% of TR phase and 20% of TS phase. Based on80% of TR data, the GOADL-RFIGR technique has provided average values$accu_y$, $prec_n$, $reca_l$, F_{score}, and AUC_{score} of 99.77%, 97.87%, 98.96%, 98.41%, and AUC_{score} of 99.39%. At the same time, with 20% of TS database, the GOADL-RFIGR model has reduced average $accu_y$, $prec_n$, $reca_l$, F_{score}, and AUC_{score} of 99.84%, 98.99%, 99.47%, 99.23%, and AUC_{score} of 99.67% correspondingly.

Table 1: DR classifier analysis of GOADL-RFIGRsystem under 80:20 of TR/TS data

Class	Accuracy	Precision	Recall	F-Score	AUC Score
Training Phase (80%)					
No DR	99.52	99.83	99.51	99.67	99.52
Mild DR	99.83	98.30	99.34	98.82	99.61
Moderate DR	99.77	99.06	99.44	99.25	99.63
Severe DR	99.86	96.14	98.10	97.11	99.00
Proliferative DR	99.89	96.02	98.40	97.20	99.16
Average	**99.77**	**97.87**	**98.96**	**98.41**	**99.39**
Testing Phase (20%)					
No DR	99.66	99.88	99.65	99.77	99.66
Mild DR	99.81	98.07	99.13	98.60	99.50
Moderate DR	99.80	99.04	99.61	99.33	99.72
Severe DR	99.97	100.00	98.94	99.47	99.47
Proliferative DR	99.96	97.96	100.00	98.97	99.98
Average	**99.84**	**98.99**	**99.47**	**99.23**	**99.67**

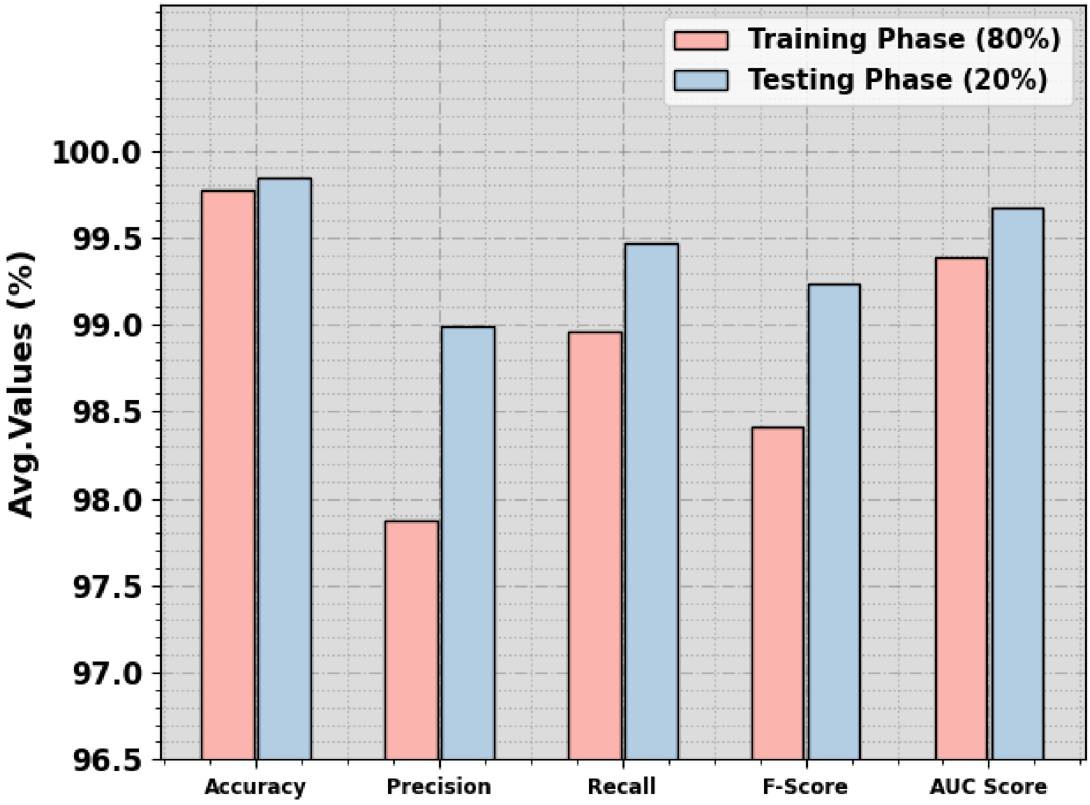

Figure 3: Average of GOADL-RFIGR system under 80:20 of TR/TS data

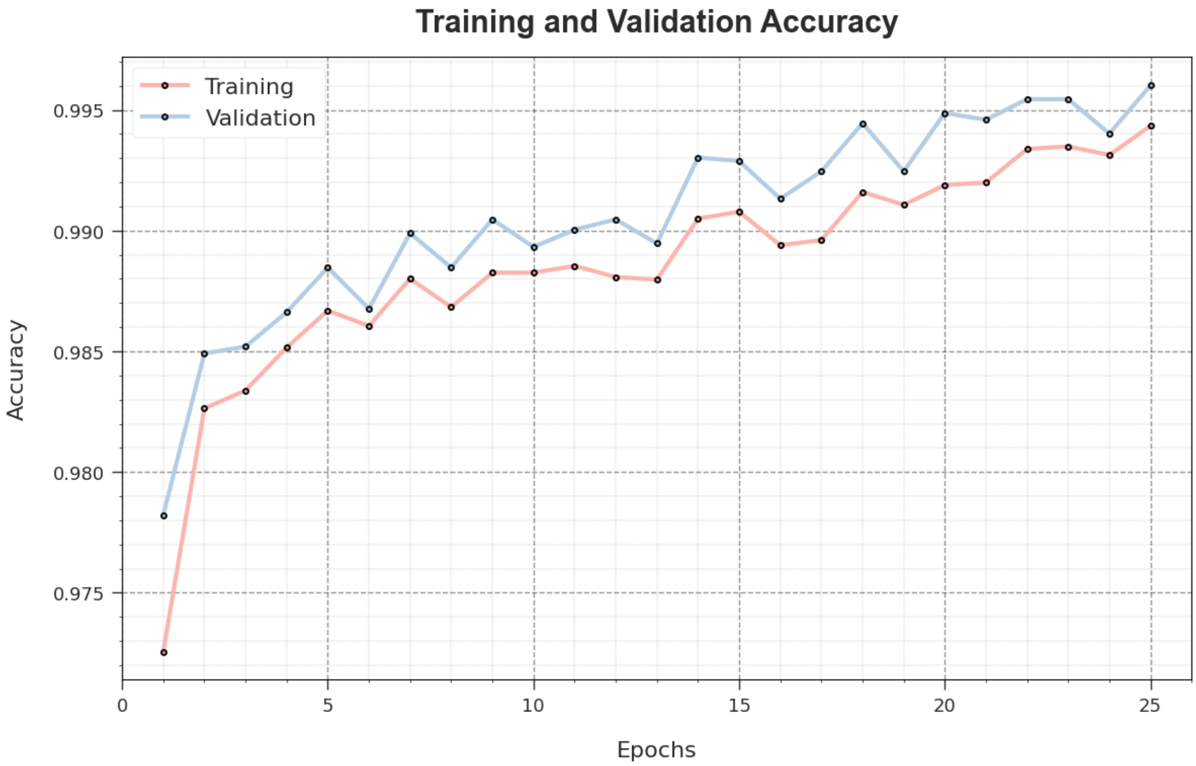

Figure 4: $Accu_y$ curve of the GOADL-RFIGR system

To determine the performance of the GOADL-RFIGR method, TR and TS $accu_y$ curves are defined, as illustrated in Fig. 4. The TR and TS $accu_y$ curves exhibit the performance of the GOADL-RFIGR system over numerous epochs. The figure offers meaningful details about the learning tasks and generalisation capabilities of the GOADL-RFIGR algorithm. With arise in epoch count, it is observed that the TR and TS $accu_y$ curves acquire enhanced. It is evidenced that the GOADL- RFIGR approach achieves enriched testing accuracy that has the potential to recognize the patterns in the TR and TS data.

Fig. 5 demonstrates the overall TR and TS loss values of the GOADL- RFIGR system over epochs. The TR loss represents the model loss acquired a reduced over epochs. Mainly, the loss values obtained diminished as the model adapted the weight for decreasing the predicted error on the TR and TS data. The loss curves show the extent to which the model is fitting the training data. It is clear that the TR and TS loss is progressively minimized and described that the GOADL-RFIGR methodology successfully learns the patterns revealed in the TR and TS data. It is also remarked that the GOADL-RFIGR technique changes the parameters for lessening the difference between the predicted and actual training label.

Figure 5: Loss curve of the GOADL-RFIGRsystem

Fig. 6 demonstrates the comparative outcome of GOADL-RFIGR system with existing approaches. The simulation value inferred that the GOADL-RFIGR approach has attained increased performances under distinct aspects. The AlexNet technique has gained least outcome while MobileNet and Xception approaches have accomplished slightly improved performances. In addition, the ResNet-50, WFDLN, and MRFODL-FIRC methods have offer reasonable performances compared to other approaches. However, the GOADL-RFIGR algorithm has achieved better performances of $accu_y$, $prec_n$, $reca_l$, and F_{score} of 99.84%, 98.99%, 99.47%, and 99.23% respectively.

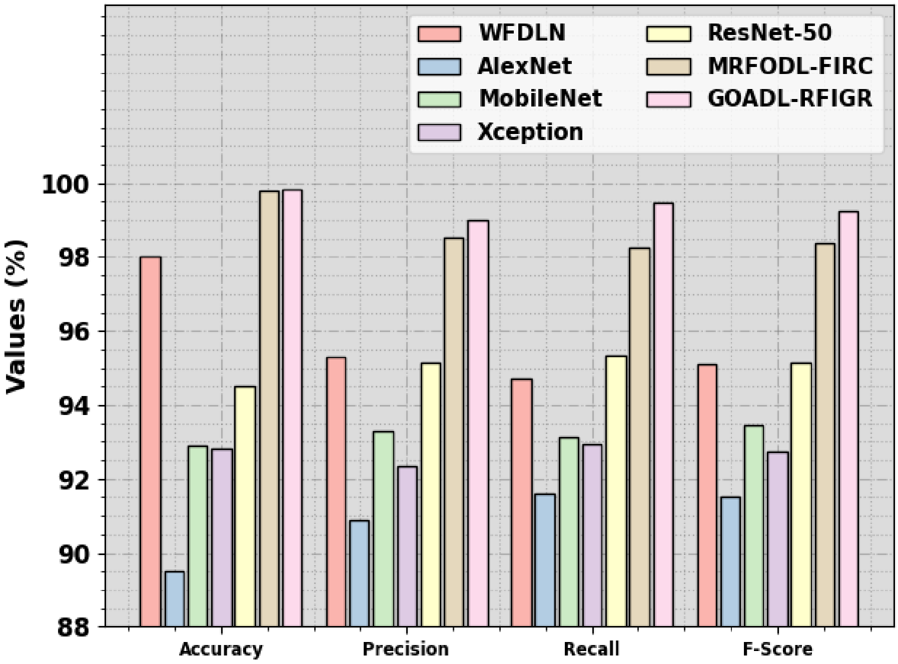

Figure 6: Comparative outcome of GOADL-RFIGR approach with other methods

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5. Conclusion

In this study, a new GOADL-RFIGR method was formulated for the retrieval and classification of retinal fundus images. The presented GOADL-RFIGR approach a comprehensive framework for retinal fundus image retrieval, integrating advanced techniques for preprocessing, feature extraction, similarity measurement, and hyperparameter optimization. To enhance the quality of retinal fundus images, we employ BF as a preprocessing step. We introduce a Lightweight CNN designed to extract discriminative features from retinal fundus images efficiently. To further enhance the retrieval performance, we utilize the power of LS-SVM for classification. Additionally, we leverage the GOA to optimize hyperparameters across the CBIR system. The experimental validation of the GOADL-RFIGR model on benchmark dataset portrays a better performance over other models.

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