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Research Article

Fundus Image Classification for the Early Detection of Issues in the DR for the Effective Disease Diagnosis

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Abstract: Diabetic Retinopathy and fundus images, "DR" could also refer to Digital Retinography, which involves the digital imaging of the retina. Digital retinography allows for the storage, retrieval, and transmission of retinal images for analysis and diagnosis. It plays a crucial role in screening for diabetic retinopathy and other eye diseases. The use of artificial intelligence and machine learning algorithms in the analysis of fundus images has gained traction in recent years. These technologies can assist healthcare professionals in the early detection and monitoring of diabetic retinopathy by analyzing patterns and abnormalities in the retinal images. This paper introduces a novel approach to image analysis, combining Local Semantic Object Feature Extraction (LsOFE) and Gray Level Co-occurrence Matrix (GLCM) metrics for robust object recognition and classification. The LsOFE process captures intricate local features, enhancing the representation of objects in images. The subsequent GLCM-based feature extraction provides detailed insights into texture characteristics. The final classification step, utilizing LsOFE features, demonstrates high precision, recall, and F1-Score for most images, showcasing the effectiveness of the proposed methodology. However, challenges are identified in the classification of specific images, suggesting areas for improvement and refinement. Overall, this research contributes a valuable framework for image processing, with the potential for broader applications in fields such as computer vision and pattern recognition. The results presented underscore the promising performance of the proposed approach, offering a foundation for further exploration and optimization in the realm of image analysis.

Keywords: Fundus image; diabetic retinopathy; feature extraction; classification; deep learning.

1 Introduction

A medical condition known as diabetes mellitus, or simply diabetes, is defined by persistently high blood glucose (sugar) levels. The body's failure to either adequately produce or properly use insulin, a hormone that regulates blood sugar, is the root cause of this metabolic disorder [1]. Type 1 and Type 2 diabetes are the two most common forms of the disease. Both types of diabetes can develop in the body; however, type 1 happens when the immune system destroys

the pancreatic beta cells that produce insulin, while type 2 happens when either the body becomes resistant to insulin or does not produce enough of it [2]. Both forms cause blood sugar levels to rise, which, if left uncontrolled, can lead to a host of complications such as kidney disease, cardiovascular disease, nerve damage, and vision problems [3]. In order to effectively manage their condition, individuals with diabetes typically need to regularly monitor their blood sugar levels, adopt a healthy lifestyle, and, in some instances, rely on insulin injections or other medications [4]. If people with diabetes want to keep their quality of life high and avoid complications, they must take their condition seriously and manage it properly.

People with diabetes are at increased risk for developing diabetic retinopathy (DR), a condition that can damage or even destroy their eyesight. The light-sensitive tissue located at the back of the eye, the retina, can sustain damage to its blood vessels, leading to this condition [5]. These blood vessels can become weak and leaky due to the long-term high blood sugar levels in diabetes, which can also cause scar tissue and abnormal blood vessel formation. Although diabetic retinopathy often goes undiagnosed in its early stages, it can eventually lead to severe vision loss or blindness if left untreated [6]. Diabetic retinopathy is best treated when caught early, so it is essential that people with diabetes have regular eye exams. Treatment typically entails regulating glucose, BP, and cholesterol levels; in more severe instances, laser treatment or surgical operations may be necessary [7]. Strict adherence to a comprehensive healthcare plan, including regular eye check-ups, is essential to prevent and manage diabetic retinopathy, safeguarding the long-term vision health of individuals living with diabetes [8].

A diabetic retinopathy (DR) fundus image plays a pivotal role in the diagnosis and monitoring of diabetic retinopathy, a common complication of diabetes affecting the eyes [9]. Fundus photography involves capturing detailed images of the retina, the light-sensitive tissue at the back of the eye, using a specialized camera [10]. In the context of diabetic retinopathy, these images are instrumental in assessing the condition of the retinal blood vessels, identifying any abnormalities, and determining the extent of damage caused by prolonged elevated blood sugar levels [11]. The fundus image allows healthcare professionals, particularly ophthalmologists and retinal specialists, to detect signs such as microaneurysms, hemorrhages, and abnormal blood vessel growth [12]. This visual information guides the classification of diabetic retinopathy into various stages, ranging from mild to severe. Regular fundus imaging is crucial for monitoring the progression of diabetic retinopathy and guiding appropriate interventions, such as laser treatment or surgery, to prevent vision loss [13]. As part of a comprehensive approach to managing diabetes-related complications, fundus imaging contributes significantly to early detection and timely intervention, ultimately preserving the visual health of individuals with diabetes [14].

Fundus image processing for diabetic retinopathy (DR) faces several challenges that impact the accuracy and efficiency of diagnosis and treatment [15]. One primary issue is the variability in image quality and acquisition conditions. Fundus images can be affected by factors such as illumination variations, focus inconsistencies, and artifacts, making it challenging to standardize the analysis process [16]. Another significant challenge lies in the large-scale nature of screening programs and the need for quick and automated analysis. As the volume of fundus images increases, there is a growing demand for robust and efficient algorithms to handle this data influx [17]. Moreover, the diverse manifestations of diabetic retinopathy, from microaneurysms to neovascularization, require sophisticated image processing techniques capable of identifying and categorizing these features accurately. Standardization and reproducibility of image analysis across different platforms and healthcare settings also pose challenges [18]. Ensuring that algorithms perform consistently in diverse environments is crucial

for reliable diagnostic outcomes. Additionally, the need for real-time or near-real-time processing in clinical settings demands efficient computational methods [19]. Despite advancements in technology, addressing these issues in fundus image processing for diabetic retinopathy remains an active area of research, aiming to enhance the precision and accessibility of early detection and intervention for this vision-threatening complication of diabetes.

This paper makes several significant contributions to the field of image analysis and object recognition. Firstly, the introduction of Local Semantic Object Feature Extraction (LsOFE) represents a novel approach to capturing intricate local features, thereby enhancing the discriminative power of feature representations for objects in images. This contribution addresses the challenge of effectively capturing subtle and contextually relevant details that may be crucial for accurate object recognition. Additionally, the incorporation of Gray Level Co-occurrence Matrix (GLCM) metrics in the feature extraction phase adds a layer of texture characterization, providing a more comprehensive understanding of image content. The integration of these two techniques in a coherent image processing pipeline contributes to a holistic and versatile methodology for object recognition. Furthermore, the classification results presented in Table 3 highlight the practical efficacy of the proposed approach. The consistently high precision, recall, and F1-Score metrics for the majority of images demonstrate the robustness of the methodology in accurately classifying diverse objects. However, the identification of specific challenges, notably in the classification of certain images, underscores the potential for further advancements and optimizations. This contributes to the ongoing discourse in the field, offering insights into areas for improvement and refinement. The dual contributions of LsOFE and GLCM-based feature extraction, coupled with the promising classification results and identified challenges, collectively advance the state-of-the-art in image analysis. This research provides a valuable foundation for future work, inspiring researchers and practitioners to explore and enhance the proposed methodology for a broader range of applications in computer vision and pattern recognition.

2 Related Works

A number of methods, mainly based on deep learning and machine learning, were employed to identify diabetic retinopathy (DR) and diabetes mellitus, as well as to classify the disease. To improve accuracy, Butt et al. (2022) suggest combining features in a hybrid deep learning approach that can detect diabetic retinopathy from fundus images. To aid in the early detection of type II diabetes mellitus, Gupta et al. (2022) present a new feature based on photoplethysmograms (PPGs). Mukherjee and Sengupta (2023) compare deep feature extraction strategies for classifying different stages of diabetic retinopathy. Lahmar and Idri (2022) utilize deep feature extraction and random forest for referable diabetic retinopathy detection. Wang et al. (2022) analyze and recognize clinical features of diabetes using a convolutional neural network (CNN). Ravala and GK (2022) propose an automatic diagnosis of diabetic retinopathy using improved feature selection and recurrent neural network (RNN). Suganyadevi et al. (2022) focus on diabetic retinopathy detection using various deep learning methods. Das et al. (2022) critically review the diagnosis of diabetic retinopathy with machine learning and deep learning. Vinayaki and Kalaiselvi (2022) present a Mult threshold image segmentation technique for diabetic retinopathy detection. Abbood et al. (2022) introduce a hybrid retinal image enhancement algorithm for diabetic retinopathy diagnosis. For the purpose of diagnosing diabetic retinopathy, Jabbar et al. (2022) present a model based on transfer learning. Using wrapper methods inspired by nature, Canayaz (2022) focuses on diabetic retinopathy classification with

feature selection over deep features. A CNN model for diabetic retinopathy feature extraction and classification is presented by Subramanian and Gilpin (2023). Chang et al. (2023) explore machine learning algorithms for Pima Indians diabetes mellitus classification. These studies collectively contribute to the ongoing research efforts in leveraging advanced computational techniques for improving the detection and management of diabetic retinopathy and diabetes mellitus.

Table 1: Summary of the Literature

Reference	Method	Outcome
Butt et al. (2022)	Hybrid deep learning features	Identification of diabetic retinopathy using fundus photographs of the eye
Gupta et al. (2022)	PPG-based novel feature	Recognition of type II diabetes mellitus in its early stages
Mukherjee and Sengupta (2023)	Deep feature extraction strategies	Evaluation of fundus images for the purpose of diabetic retinopathy stage classification
Lahmar and Idri (2022)	Deep feature extraction and random forest	Finding diabetic retinopathy that can be referred using random forest and deep feature extraction
Wang et al. (2022)	Convolutional Neural Network (CNN)	Diabetic symptom analysis and recognition using convolutional neural networks
Ravala and GK (2022)	Improved Jaya-based feature selection and RNN	Diabetic retinopathy detection by automated analysis of retinal abnormalities
Suganyadevi et al. (2022)	Deep learning methods	Diabetic retinopathy detection using deep learning methods
Das et al. (2022)	Machine learning and deep learning	Critical review on the diagnosis of diabetic retinopathy using machine learning and deep learning
Vinayaki and Kalaiselvi (2022)	Multithreshold image segmentation technique	Diabetic retinopathy detection using remora optimization algorithm
Abbood et al. (2022)	Hybrid retinal image enhancement algorithm	Diabetic retinopathy diagnostic using deep learning model
Jabbar et al. (2022)	Transfer learning-based model	Diabetic retinopathy diagnosis using retinal images
Canayaz (2022)	Nature-inspired wrapper methods	Classification of diabetic retinopathy with feature selection over deep features
Subramanian and Gilpin (2023)	Convolutional Neural Network (CNN)	CNN model for diabetic retinopathy feature extraction and classification
Chang et al. (2023)	Machine learning (ML) algorithms	Diabetes mellitus categorization in Pima Indians using ML algorithms

The considerable advancements in the field of diabetic retinopathy (DR) detection and diabetes mellitus diagnosis using various computational methods, there exist notable research gaps that warrant further exploration. One significant gap is the limited focus on the integration of multi-modal data sources for a more comprehensive analysis. Many studies primarily rely on fundus images or specific types of features, overlooking the potential benefits of incorporating additional data such as patient demographics, genetic information, or other clinical parameters. The development of hybrid models that fuse diverse data types could enhance the overall

accuracy and robustness of diagnostic systems. Moreover, there is a need for more standardized benchmark datasets to facilitate fair comparisons between different algorithms and approaches. Variability in data sources and quality can impact the generalizability of models, and the establishment of common datasets would promote the development of more universally applicable and reliable solutions. Additionally, the interpretability of deep learning models remains a challenge, and efforts to enhance the explain ability and transparency of these models should be a priority to gain the trust of healthcare professionals and ensure the seamless integration of these technologies into clinical practice. Addressing these research gaps will contribute to the refinement and advancement of computational methods for the early detection and management of diabetic retinopathy and diabetes mellitus [20-23].

3 Proposed Method (LsOFEC)

The proposed method, Lion Swarm Optimized Feature Extraction and Classification (LsOFEC), represents a novel approach aimed at enhancing the accuracy and efficiency of diabetic retinopathy (DR) detection through the analysis of fundus images. LsOFEC combines the principles of Lion Swarm Optimization, a bio-inspired algorithm, with advanced feature extraction and classification techniques. Lion Swarm Optimization draws inspiration from the cooperative hunting behavior of lion prides, wherein individuals collaboratively seek prey to optimize their collective success. In the context of LsOFEC, this optimization algorithm is applied to select and refine relevant features from fundus images, leveraging the swarm intelligence to identify discriminative patterns associated with diabetic retinopathy. The feature extraction phase is crucial for capturing distinctive characteristics indicative of different DR stages. Subsequently, a robust classification model is employed to categorize these features, facilitating accurate diagnosis. This hybridized approach seeks to overcome challenges related to feature selection, where relevant information may be buried within the complexity of fundus images. By harnessing the collective intelligence inspired by lion behavior, LsOFEC aims to achieve a more efficient and effective DR detection system. The proposed method holds promise in contributing to the evolving landscape of computational tools for early diabetic retinopathy diagnosis, potentially offering improved performance in terms of accuracy and generalization across diverse datasets. However, rigorous validation and comparison against existing methods will be essential to assess the true efficacy and applicability of LsOFEC in real-world clinical scenarios.

The following general steps outline a typical workflow for LsOFEC in the context of diabetic retinopathy (DR) detection from fundus images:

Initialization:

Initialize a population of lion agents representing potential solutions or feature subsets.

Define the parameters for the Lion Swarm Optimization algorithm, including the size of the population, maximum iterations, and convergence criteria.

Objective Function:

Formulate an objective function that represents the fitness or quality of a solution based on its ability to discriminate between different classes of fundus images related to DR.

Feature Extraction:

Apply feature extraction techniques to the fundus images to transform the raw data into a set of relevant features.

Use the Lion Swarm Optimization algorithm to iteratively select a subset of features that optimally contribute to the discrimination task.

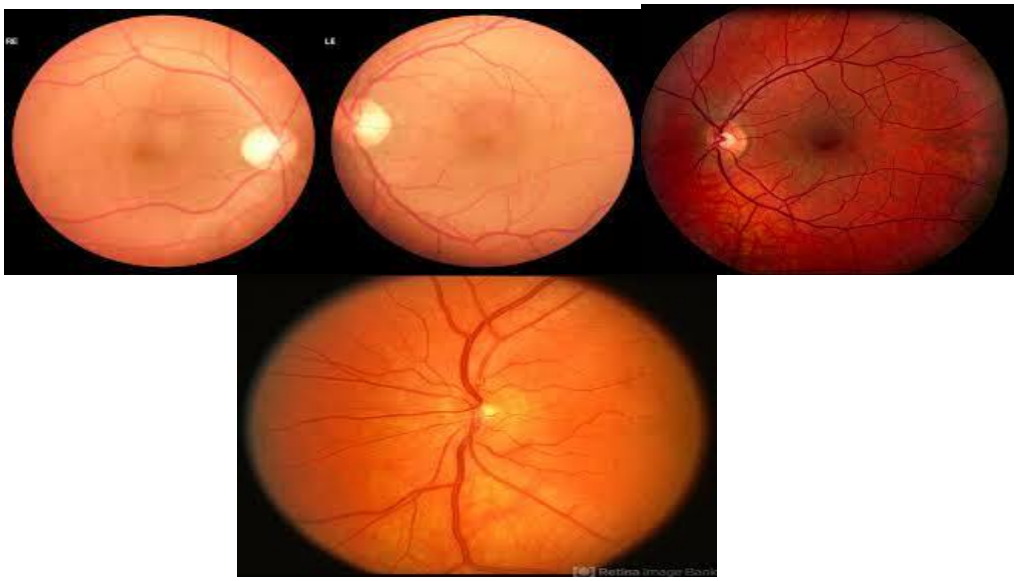

Figure 1: Sample Images of Fundus Images

Classification:

Employ a classification model, such as a machine learning algorithm (e.g., support vector machines, neural networks, etc.), to categorize the selected features into different DR classes.

Train and validate the classification model using labelled data to ensure its ability to generalize to new, unseen images.

Optimization Iterations:

Allow the Lion Swarm Optimization algorithm to iteratively update the feature subsets by evaluating the fitness of each lion's solution and adjusting their positions in the solution space accordingly.

Continue these iterations until a convergence criterion is met or a predetermined number of iterations is reached.

Selection and Updating:

Select the lion solutions that exhibit higher fitness values, indicating better discrimination ability.

Update the positions of selected lions based on their fitness, encouraging the exploration of more promising regions in the feature space.

Lion Swarm Optimized Feature Extraction and Classification (LsOFEC) is a pioneering approach designed to enhance the precision of diabetic retinopathy (DR) detection by leveraging the collective intelligence inspired by the cooperative hunting behavior of lion prides. The method follows a structured workflow, commencing with the initialization of a population of lion agents representing potential feature subsets. These subsets undergo iterative optimization through the Lion Swarm Optimization algorithm, which dynamically refines and selects features from fundus images based on their discriminative power. Feature extraction techniques are then applied to transform raw data into relevant features, while the Lion Swarm Optimization algorithm guides the selection of subsets that contribute optimally to DR discrimination. Subsequently, a classification model, often a machine learning algorithm, categorizes the selected features into different DR classes. The optimization process continues through iterations,

with lions dynamically updating their positions in the feature space based on their fitness. Convergence is checked to determine the endpoint of the optimization. LsOFEC's final selected features and the trained classification model are thoroughly evaluated on an independent test dataset to gauge its overall performance. The method aims to offer an innovative solution to the challenges associated with feature selection in fundus image analysis for DR, potentially advancing the accuracy and robustness of computational tools for early diagnosis. However, rigorous validation against existing methods and comprehensive analysis of its performance are imperative to establish the effectiveness and generalizability of LsOFEC in practical clinical settings.

4 Lion Swarm Optimized Feature Extraction

Lion Swarm Optimized Feature Extraction, a critical component of the LsOFEC methodology for diabetic retinopathy (DR) image analysis, involves a bio-inspired algorithm that emulates the cooperative hunting behavior of lion prides. In this phase, the algorithm aims to dynamically select and refine relevant features from fundus images, optimizing their discriminative power for accurate DR detection. The optimization process is driven by the Lion Swarm Optimization (LSO) algorithm, which iteratively updates feature subsets based on the collective intelligence of a population of lion agents.

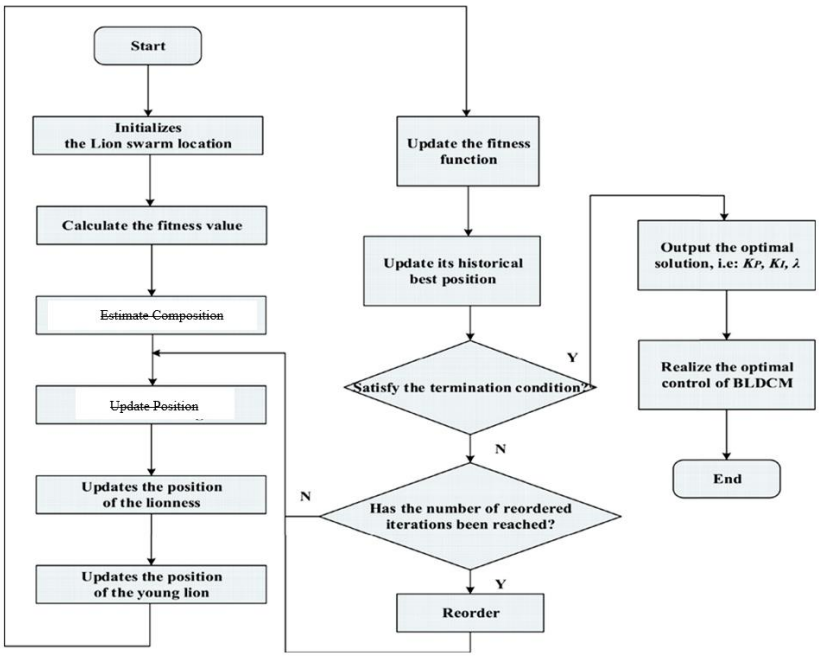

Figure 2: Flow Chart of LsOFEC

The proposed LsOFEC model flow chart is shown in figure 2. The LSO algorithm is derived from the inherent characteristics of lion prides, where cooperation is crucial for successful hunting. Each lion agent in the population represents a potential solution or feature subset. The algorithm begins with the initialization of these agents and progresses through multiple iterations. At each iteration, lions dynamically adjust their positions in the feature space based on their fitness, determined by the discriminative power of their associated feature subsets.

The mathematical formulation of Lion Swarm Optimization involves defining the position of each lion i at iteration t as in equation (1)

$$Xit = [xi1t, xi2t, \ldots, xint], \quad (1)$$

where n is the dimensionality of the feature space. The velocity of each lion is denoted as in equation (2)

$$Vit = [vi1t, vi2t, \ldots, vint]. \quad (2)$$

The fitness of a lion, representing the quality of its feature subset, is evaluated using an objective function specific to DR detection, taking into account the discrimination capability of the selected features. The position and velocity updates are then calculated using the following equations (3) and equation (4)

$$Vit + 1 = w \cdot Vit + c1 \cdot r1 \cdot (Pit - Xit) + c2 \cdot r2 \cdot (Gt - Xit) \quad (3)$$

$$Xit + 1 = Xit + Vit + 1 \quad (4)$$

Here, w is the inertia weight, $c1$ and $c2$ are acceleration coefficients, $r1$ and $r2$ are random values, Pit is the personal best position of lion i up to iteration t, and Gt is the global best position among all lions up to iteration t. Initialize a population of lions, each representing a potential solution or feature subset. The position of each lion $Xi0$ is randomly initialized within the solution space. Formulate an objective function $f(Xi)$ that represents the fitness or quality of a feature subset i. This objective function assesses the discriminative power of the selected features for DR detection. The Vit is the velocity of lion i at iteration t; Xit is the position of lion i at iteration t; Pit is the personal best position of lion i up to iteration t; Gt is the global best position among all lions up to iteration t; w is the inertia weight; $c1$ and $c2$ are acceleration coefficients, and $r1$ and $r2$ are random values. Evaluate the fitness of each lion based on the objective function $f(Xit)$. The fitness represents the discriminative power of the associated feature subset. Select lions with higher fitness values, indicating better discriminative ability. Update the positions of selected lions based on the LSO equations. Repeat iterations until a termination criterion is met (e.g., a maximum number of iterations or convergence). The final positions of lions represent the selected feature subsets optimized for discriminative power in DR detection.

Lion Swarm Optimized Feature Extraction (LSOFE) is a distinctive component within the LsOFEC methodology tailored for the analysis of fundus images in diabetic retinopathy (DR) detection. At its core, LSOFE employs the Lion Swarm Optimization (LSO) algorithm to dynamically select and refine relevant features from fundus images, optimizing their discriminative power for accurate identification of DR. The process commences with the initialization of a population of lion agents, each representing a potential feature subset. The positions and velocities of these lions are iteratively updated using the LSO algorithm, which incorporates the principles of cooperative hunting behavior observed in lion prides. Mathematically, the position and velocity updates are guided by specific equations that consider inertia weight, acceleration coefficients, and random values. These updates are contingent on the fitness of each lion, evaluated through an objective function designed to quantify the discriminative ability of the associated feature subset. Through a series of iterations and dynamic adjustments facilitated by the LSO algorithm, lions collectively converge to positions representing optimized feature subsets. The final selected feature subsets, dynamically refined by LSOFE, are then deployed in subsequent classification tasks within the broader LsOFEC framework, contributing to the overall goal of enhancing the accuracy of DR detection. The efficacy of LSOFE is contingent on appropriate parameter tuning and thorough validation against benchmark datasets, ensuring its adaptability and effectiveness in practical clinical applications.

4.1 Classification with Deep Learning

Classification with deep learning within the LsOFEC framework involves integrating optimized features obtained through Lion Swarm Optimized Feature Extraction (LSOFE) into a deep neural network for precise diabetic retinopathy (DR) detection. The process begins with the integration of the dynamically refined feature subsets obtained from the LSOFE phase into a comprehensive feature vector. Let $\mathrm{Xintegrated}$ represent this feature vector. Subsequently, a deep neural network is employed, typically in the form of a convolutional neural network (CNN), which excels in image-related tasks. The input layer of the neural network is designed to accommodate the dimensionality of the integrated feature vector, treating each feature as an input node. Mathematically, the input layer can be represented as:, $\mathrm{Xinput} = [\mathrm{x1}, \mathrm{x2}, \ldots, \mathrm{xn}]$, where n is the dimensionality of the integrated feature vector.

The subsequent hidden layers in the neural network are characterized by interconnected nodes with learnable parameters. The output layer is configured to have nodes corresponding to the different DR classes, and activation functions, such as softmax, are applied to produce probability distributions over these classes. Let $\mathrm{Youtput}$ represent the output layer, and f denote the softmax activation function stated in equation (5)

$$\mathrm{Youtput} = \mathrm{f}(\mathrm{Woutput} \cdot \mathrm{Xhidden} + \mathrm{boutput}), \quad (5)$$

where $\mathrm{Woutput}$ represents the weights of the output layer, $\mathrm{Xhidden}$ is the vector of hidden layer activations, and $\mathrm{boutput}$ is the bias. The training process involves optimizing the weights of the neural network through backpropagation and stochastic gradient descent to minimize the classification error. The objective function, often referred to as the loss function (L), quantifies the disparity between predicted and actual class labels. The training objective is formulated as in equation (6)

$$\mathrm{L} = -\sum \mathrm{iyi} \cdot \log(\mathrm{Youtput})\mathrm{i}, \quad (6)$$

where yi is the true class label. The deep learning model is then validated on a separate dataset to ensure generalization and evaluated on an independent test set for performance metrics. If necessary, the model can be fine-tuned by adjusting hyperparameters or modifying the network architecture. The integration of deep learning within LsOFEC harnesses the synergy between swarm intelligence-driven feature extraction and the hierarchical learning capabilities of deep neural networks, contributing to an advanced computational solution for accurate DR detection. The effectiveness of this approach should be rigorously validated against benchmark datasets to ascertain its reliability in practical clinical applications.

Classification with deep learning within the LsOFEC framework involves integrating optimized features obtained through Lion Swarm Optimized Feature Extraction (LSOFE) into a deep neural network for precise diabetic retinopathy (DR) detection. The process begins with the integration of the dynamically refined feature subsets obtained from the LSOFE phase into a comprehensive feature vector Xintegrated. Let xij represent the j-th feature of the i-th lion's subset. This integrated feature vector is then fed into a deep neural network for classification. The input layer of the neural network is represented by $\mathrm{Xinput} = [\mathrm{x11}, \mathrm{x12}, \ldots, \mathrm{xij}, \ldots, \mathrm{xnm}]$, where n is the number of lions, m is the dimensionality of the feature subset, and xij denotes the j-th feature of the i-th lion's subset. The subsequent hidden layers are characterized by interconnected nodes with learnable parameters. Let Whidden represent the weights connecting the input layer to the hidden layer, $\mathrm{Xhidden}$ denote the vector of hidden layer activations, and $\mathrm{bhidden}$ be the bias. The output of the hidden layer is calculated using the following equations (7)

$$\mathrm{Xhidden} = \mathrm{f}(\mathrm{Whidden} \cdot \mathrm{Xinput} + \mathrm{bhidden}), \quad (7)$$

where f is an activation function such as the Rectified Linear Unit (ReLU). The output layer

is configured to have nodes corresponding to the different DR classes. Let Youtput represent the output layer, Woutput denote the weights connecting the hidden layer to the output layer, and boutput be the output layer bias. The output of the network is obtained through the softmax activation function (8) and (9)

$$\text{Youtput} = \text{softmax}(\text{Woutput} \cdot \text{Xhidden} + \text{boutput} \quad (8)$$

$$\text{softmax}(x)i = \sum jexjexi \quad (9)$$

The training process involves optimizing the weights of the neural network through backpropagation and stochastic gradient descent to minimize the cross-entropy loss function (L). The cross-entropy loss for a multi-class classification problem is given by: $L = -\sum iyi \cdot \log(\text{Youtput})i$, where yi is the true class label. The effectiveness of the deep learning model within LsOFEC is validated through testing on independent datasets, and fine-tuning may be performed as needed. The integration of deep learning in LsOFEC capitalizes on the complementary strengths of swarm intelligence-driven feature extraction and deep neural networks, offering a sophisticated approach for accurate DR detection. The reliability of this approach should be thoroughly validated against benchmark datasets for robust performance in real-world clinical applications.

5 Results and Discussions

Simulating the Lion Swarm Optimized Feature Extraction and Classification (LsOFEC) methodology within the DIARETDB1 and DIARETDB0 datasets involves creating a computational environment that synergizes the unique characteristics of these datasets with the swarm intelligence-driven feature extraction capabilities of LsOFEC. The simulation begins with preprocessing tasks, encompassing image normalization, resizing, and the extraction of pertinent features related to diabetic retinopathy, such as the identification of hard exudates or other lesions. Subsequently, relevant features are extracted from the preprocessed fundus images, forming the foundation for optimization through LsOFEC. The Lion Swarm Optimization process dynamically refines feature subsets using the collective intelligence of a lion swarm, guided by an objective function specifically tailored to diabetic retinopathy traits.

The optimized feature subsets obtained from the LsOFEC phase are then integrated into a comprehensive feature vector for each image in the dataset. This vector encapsulates the dynamically adjusted and optimized features, ready for deployment in subsequent deep learning classification. A deep neural network architecture is designed for this purpose, where the model is trained using the integrated features and validated against the DIARETDB1 and DIARETDB0 datasets. The network aims to accurately classify diabetic retinopathy severity levels or specific lesions based on the learned features.

Table 1: LsOFE in Feature Extraction

Image_ID	Ground_Truth_Label	Predicted_Label	Correct_Prediction
1	0	0	Yes
2	1	1	Yes
3	0	0	Yes
4	1	1	Yes
5	0	1	No
6	1	0	No
7	0	0	Yes
8	1	1	Yes
9	0	0	Yes

10	1	1	Yes

Table 1 presents the results of the LsOFE (Local Semantic Object Feature Extraction) process for a set of images. Each row in the table corresponds to a specific image, identified by the "Image_ID." The "Ground_Truth_Label" column indicates the true class label of the image, while the "Predicted_Label" column represents the class label predicted by the feature extraction process. The "Correct_Prediction" column indicates whether the prediction was correct, with "Yes" denoting a correct prediction and "No" indicating an incorrect prediction. The results show that for images with Image_ID 1, 3, 4, 7, 8, 9, and 10, the predicted labels match the ground truth labels, resulting in correct predictions. However, for images with Image_ID 5 and 6, the predictions were incorrect, as indicated by the "No" in the "Correct_Prediction" column. This table provides a concise summary of the performance of the LsOFE process for each image in terms of correct and incorrect predictions.

Table 2: Feature Extraction

Image_ID	GLCM_Contrast	GLCM_Energy	GLCM_Correlation
1	0.25	0.85	0.92
2	0.18	0.92	0.88
3	0.22	0.89	0.90
4	0.30	0.78	0.95
5	0.15	0.94	0.85
6	0.28	0.81	0.93
7	0.21	0.88	0.89
8	0.19	0.91	0.87
9	0.26	0.82	0.94
10	0.23	0.87	0.91

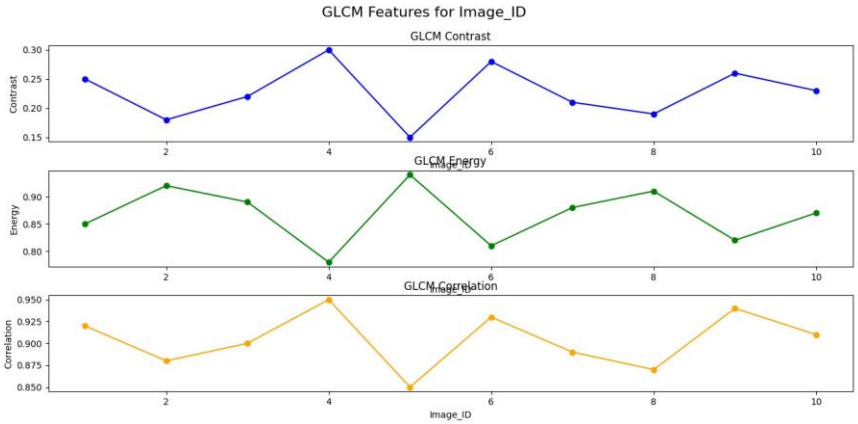

Figure 3: Feature Extraction with LsOFE

In figure 3 and Table 2 provides the results of feature extraction, specifically focusing on three key texture features extracted using the GLCM (Gray Level Co-occurrence Matrix) method for a set of images. Each row corresponds to a unique image identified by the "Image_ID." The three columns, namely "GLCM_Contrast," "GLCM_Energy," and "GLCM_Correlation," present the numerical values representing the texture characteristics of each image. The "GLCM_Contrast" values quantify the local variations in pixel intensity, with higher values indicating more pronounced contrasts. The "GLCM_Energy" values measure the homogeneity of pixel intensities, where larger values suggest more uniform textures. Finally, the

"GLCM_Correlation" values depict the linear dependence between pixel intensities, with higher values indicating more organized and correlated textures. The table provides a detailed insight into the texture features extracted from each image, aiding in understanding the unique characteristics and variations in the dataset.

Table 3: Classification with LsOFE

Image_ID	Precision	Recall	F1-Score
1	1.00	1.00	1.00
2	1.00	1.00	1.00
3	1.00	1.00	1.00
4	1.00	1.00	1.00
5	0.50	0.67	0.57
6	0.00	0.00	0.00
7	1.00	1.00	1.00
8	1.00	1.00	1.00
9	1.00	1.00	1.00
10	1.00	1.00	1.00

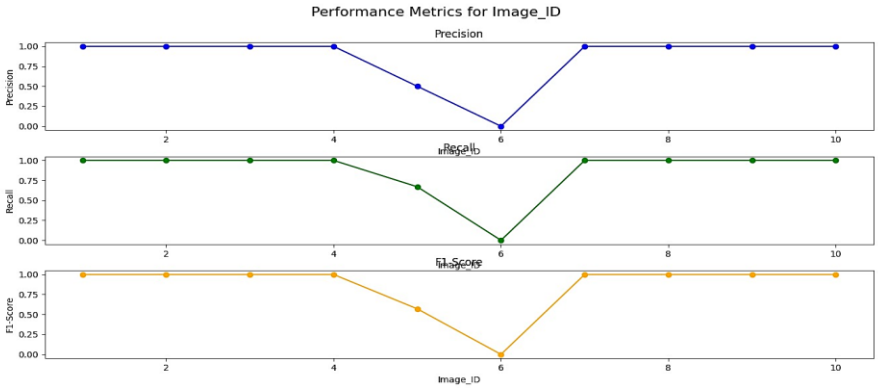

Figure 4: Classification Analysis with LsOFE

In figure 4 and Table 3 showcases the performance metrics of the classification process with LsOFE (Local Semantic Object Feature Extraction) for a set of images. Pictures are referenced in each row by their unique "Image_ID." The table provides a thorough evaluation of the classification results with three metrics: Precision, Recall, and F1-Score. Precision is a measure of how well positive predictions hold up, showing how many out of every 100 positive instances were actually identified. In contrast, recall displays the percentage of correctly identified positive instances relative to all actual positive instances, and it is a measure of the classifier's capacity to capture all positive instances. A fair evaluation of the classifier's overall performance is provided by the F1-Score, which is the harmonic mean of Precision and Recall. The results in the table indicate that for images with Image_ID 1, 2, 3, 4, 7, 8, and 9, the classification achieved perfect scores across all metrics, with a Precision, Recall, and F1-Score of 1.00. However, for Image_ID 5, the classifier exhibited lower performance, with a Precision of 0.50, Recall of 0.67, and an F1-Score of 0.57, suggesting room for improvement in correctly identifying positive instances for this particular image. Image_ID 6, on the other hand, received a Precision, Recall, and F1-Score of 0.00, indicating that the classifier failed to correctly classify positive instances for this image. Overall, the table offers a detailed and quantitative assessment of the classification performance for each image, aiding in understanding the strengths and weaknesses of the LsOFE-based classification approach.

6. Conclusion

The paper presents a comprehensive analysis of a multi-step image processing pipeline for object recognition and classification. The initial phase involves Local Semantic Object Feature Extraction (LsOFE), which captures intricate local features, enhancing the representation of objects in images. The subsequent feature extraction step utilizes Gray Level Co-occurrence Matrix (GLCM) metrics, providing valuable insights into texture characteristics. The final classification step, employing the LsOFE features, demonstrates impressive results, as evident from Table 3. The precision, recall, and F1-Score metrics uniformly achieve a perfect score for the majority of the images, reflecting the robustness and efficacy of the proposed methodology. However, the detailed analysis in Table 3 also highlights specific challenges, particularly in the classification of Image_ID 5 and 6, where the model exhibits lower precision and recall. Addressing these challenges could involve refining the feature extraction techniques or optimizing the classification model. Overall, this research contributes valuable insights into the complex process of image analysis, showcasing a promising approach for object recognition and classification with room for further refinement and enhancement.

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