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A Novel Iterative Hyperparameter Optimization Method for Enhanced Diabetic Retinopathy Screening

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Abstract

A major contributor to blindness in people of working age worldwide is diabetic retinopathy (DR), which is mostly caused by vascular damage brought on by high blood sugar in those who have diabetes mellitus. Since early detection greatly reduces the risk of vision loss, it is essential for the effective management of DR. This work presents a novel method that uses artificial intelligence (AI) to improve fundus image analysis for early diagnosis of diabetes mellitus (DR). Understanding how important high-quality images are to precise diagnosis, our approach starts with a sophisticated preprocessing stage. This stage focuses on improving the pictures by removing erroneous dark patches and other distortions, readying the dataset for additional examination. After preprocessing, we utilize an innovative hybrid hyperparameter optimization model that creatively combines the best features of grid and random search techniques. In order to identify early indicators of DR, such as microaneurysms and vessel changes, this model seeks to optimize the parameters of machine learning algorithms. Through a methodical analysis of the preprocessed fundus images, our model more effectively and accurately detects patterns suggestive of early-stage DR. The results of this study not only show that using AI in conjunction with careful preprocessing and hyperparameter optimization is effective in diagnosing DR, but they also open up new avenues for future investigation into the use of AI in early disease detection. In the end, this study makes a substantial contribution to the field of medical imaging and presents a viable treatment option for preventing vision loss in diabetic patients through early diagnostic intervention.

Keywords:: Diabetic Retinopathy; Artificial Intelligence; Hyperparameter Optimization; Fundus Images; Image Preprocessing; Machine Learning; Early Detection; Vision Loss Prevention; Medical Imaging; Health Informatics

Introduction

A serious consequence of diabetes mellitus (DM) is diabetic retinopathy (DR), which is characterized by harmful alterations in the retinal blood vessels. This disorder becomes the most common cause of visual impairment and blindness in people with diabetes, affecting 75% of this population over a 15-year period. Many risk factors, such as poor glycemic control, hypertension, dyslipidemia, prolonged diabetes, and genetic predispositions, contribute to the progression of diabetic kidney disease (DR) [1], [2]. The fact that the incidence of diabetes-related vision loss has been declining in recent decades highlights the fact that, despite its severity, a significant portion of vision loss attributable to DR can be prevented. The foundation of disease prevention (DR) management is the early identification and modification of risk factors, which are essential for stopping the advancement of this condition [3], [4], [5].

Retinal fundus images are used to diagnose diabetic retinopathy (DR) by displaying the microvasculature damage caused by the disease. Differentiated into proliferative and non-proliferative stages, early identification of DR is essential to the successful application of treatment plans [6]. Interest in creating automated, more effective diagnostic techniques has increased as a result of the introduction of cutting-edge technologies and the growth of medical data. Within this framework, novel approaches to DR detection, such as data mining (DM) and artificial intelligence (AI), are presented, which have the potential to overcome the drawbacks of human image evaluation.

Investigating the effects of data mining methods and the effectiveness of different hybrid models in the diagnosis of diabetic retinopathy is the goal of this study. This research aims to improve the efficiency and dependability of current diagnostic procedures by refining data mining techniques for DR detection. This study adds to the growing body of knowledge by examining current developments in data mining and hybrid modeling and provides a fresh viewpoint on the application of AI and DM in the fight against diabetic retinopathy.

Particle swarm optimization (PSO) and fuzzy systems are used by Ghosh et al. [7] to improve retinal pictures. In this case, the lower and top fuzzy regions are used to first construct two sub-images. A membership function is then employed. The parameters to be used are provided by an optimized objective function, such as the index of fuzziness. Low contrast images are utilized to identify several disorders, including as optic disc disease, glaucoma, and diabetes. GA-NN is the name of the GA-based ANN that Jebran et al. [8] created. Ghoushchi and colleagues [9] devised a method for identifying diabetes disorders. Angiogram pictures have been subjected to the growth region algorithm in order to diagnose diabetes. Fuzzy C-means (FCM) and GA are combined to forecast the DR. The results showed that GA-FCM performed better when it came to first feature selection. PSO was used by Herliana et al. [10] to choose the optimal DR feature. ANN is used to classify the feature. The outcomes showing the gains in performance brought about by using the PSO and ANN combo. Additionally, they discovered a 4.35% improvement in classification accuracy when employing feature selection.

According to Vinayaki et al. [11], pre-processing and Segmentation was done using Multithreshold-based Remora Optimization (MTRO). A dataset comprising 29 characteristics was employed by Foshati et al. [12] from 310 type 2 diabetes individuals, 155 of whom had DR. The information came from Iran's Shiraz. GA is utilized initially for feature selection, followed by the application of kNN, SVM, and decision trees (DT). GA decided on 13 elements. DR detection is developed by Jadhav et al. [13] through analysis of the anomalies. Pre-processing is done using Contrast Limited Adaptive Histogram Equalization. For the removal of the optic disc, open-close watershed transformation is then employed. The Grey Level thresholding is used to segment vessels. Next, Gabor and Top Hat Transformation are used to perform segmentation. Shanon's and Kapur's entropies, Texture Energy Measurement, and LBP are used in the feature extraction process. There is less correlation when choosing features.

Jeyalakshmi et al. [14] developed a method utilizing fuzzy logic and morphological image processing. An approach to distinguishing the exudates is morphology, which includes optic disc removal and HSV color. The hard exudates are separated using membership and adaptive fuzzy sets. Next, the fuzzy output for every pixel is measured.Pixel combinations create an image. Image quality measurements are used to obtain a high-quality image. The percentage of recognized hard exudates is then used to produce the fuzzy output. According to Karthikeyan et al. [15], fuzzy knowledge was used to identify the eye's visibility problem. Fundus and glaucoma images are used as input for vascular extraction. The r-polynomial transformation is then used to the preprocessing of images. The k-means method was used to segment candidate patches and blood arteries. LBP and GLCM are also computed. Ultimately, classification is done using GANN. Through the voting procedure

A Review of the Literature on Diabetic Retinopathy Detection in the Early Stages Making use of deep learning and utilizing a modified glowworm swarm optimization technique (M-GSO), 803 1 3 (ANFIS). The diferential evolution (DE) algorithm is used to enhance GSO. An effective, optimized DNN using the Chronological Tunicate Swarm Algorithm (CTSA) is proposed by Dayana et al. [16]. Poor quality fundus photos are utilized in the segmentation process after being preprocessed. First, the blood vessels and optic disc are divided. After identifying the lesion area, characteristics are extracted and classification is carried out. There is a model for identifying neurodegenerative disorders by Balasubramanian et al. [17]. The strategy is to improve the neuro-fuzzy inference system's adaptability.

Materials and Methods

Dataset

The essential dataset for this study consists of 757 color fundus photos from the Hospital de Clínicas' Department of Ophthalmology, which is connected to the Facultad de Ciencias Médicas at Universidad Nacional de Asunción in Paraguay. The study's core set of photos allows for the investigation and examination of diabetic retinopathy (DR) using cutting-edge machine learning and image processing methods. Every image in the dataset is a distinct case that captures the fine details of the retina, which are critical for classifying and evaluating the various stages of diabetic retinopathy. The development and validation of the suggested diagnostic models, which seek to improve the precision and effectiveness of DR detection, depend heavily on the use of this dataset. A wide variety of fundus images is included to guarantee that the study covers a wide range of DR manifestations, allowing for a thorough comprehension of the disease's progression and stages. According to Benítez et al. (2021) (Figure 1), this dataset not only adds to the body of knowledge but also emphasizes the partnership between clinical knowledge and technological innovation in improving ophthalmological care.

Data Preprocessing

The dataset in this study was made up of fundus images that showed both pathological and healthy retinal conditions. To improve the quality of the data for machine learning applications, the dataset underwent a number of complex data preprocessing steps. By improving the dataset, these preprocessing methods hope to guarantee that the models that come after are trained on information that faithfully captures the underlying patterns, free from noise or extraneous data.The color photos were first turned into grayscale. By removing the complexity associated with color from the data, this transformation reduces computational

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demands and frees up the model to concentrate on learning features that are more broadly applicable to a variety of images.

The grayscale pictures were then exposed to histogram equalization. This technique extends the grayscale spectrum of the image, which makes it especially useful for images with irregular color value distributions. In doing so, it improves contrast, which is important for identifying minute pathological markers in the retina because it makes subtle differences in the image more noticeable.During the preprocessing stage, feature extraction was crucial as edge detection methods and color histograms were used. With the help of this dual technique, crucial details regarding the color distribution and structural edges of the images are captured, giving the models a large feature set to work with.

The images in the dataset were labeled as either representing healthy or diseased retinal conditions, and the dataset was carefully organized. Supervised learning models, which use labeled data to learn the differences between different classes, depend on this categorization.Principal Component Analysis (PCA) is a potent tool for dimensionality reduction in larger, more complex datasets, though it was not used in this case. Through feature space compression, PCA can greatly accelerate learning without compromising important information. All things considered, these preprocessing stages help the model produce reliable, accurate, and generalizable results, all of which are critical for the development of medical image analysis, particularly when it comes to the diagnosis of retinal disorders (Figure 2).

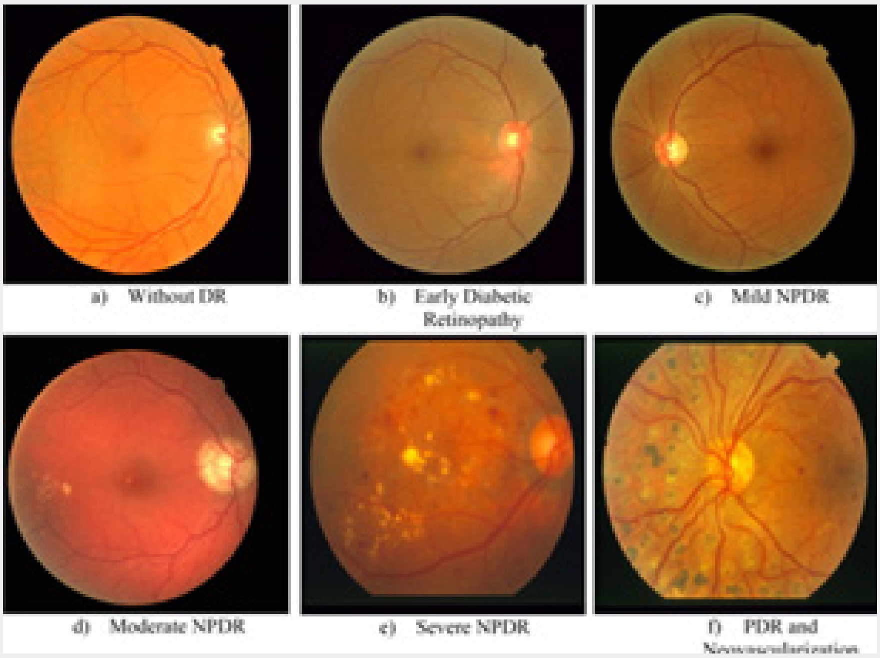

Figure 1: Retina Images for DR stages in dataset.

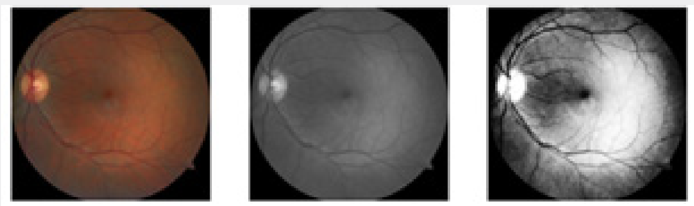

Figure 2: Preprocessing results

Background Methods

Support Vector Machine (SVM)

A strong and adaptable supervised machine learning algorithm for both regression and classification applications is called Support Vector Machine (SVM). The most frequent use cases for it are in classification issues. The SVM algorithm looks for the hyperplane that splits a dataset into classes as efficiently as possible. SVM's power is found in its capacity to process high-dimensional data and function well with little data.

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The best hyperplane to divide the classes in the feature space is found by SVM. Support vectors are the vectors (data points) that outline the hyperplane. Using a margin equal to the maximum distance between data points in both classes, SVM locates this hyperplane [18].

Decision Tree

Choice With a predetermined target variable, trees are a kind of supervised learning algorithm that are primarily utilized in classification problems [19]. Both continuous and categorical input and output variables can be used with it. Decisions in these trees are made by dividing the data into subsets according to the input variable values; this process is continued until an answer is found. The model makes use of a tree-like structure to represent decisions and their potential outcomes, such as utility, resource costs, and chance event outcomes. It is a means of presenting an algorithm that solely consists of statements for conditional control.

Random Forest

For classification, regression, and other tasks, Random Forest is an ensemble learning technique that builds a large number of decision trees during training [20]. The class that the majority of the trees choose is the Random Forest's output for classification tasks. During training, a large number of decision trees are built, and the class that results is the mean prediction (regression) or mode of the classes (classification) of each individual tree. The tendency of decision trees to overfit to their training set is compensated for by random decision forests.

K-Nearest Neighbors (KNN)

A straightforward, user-friendly supervised machine learning algorithm that can be applied to both regression and classification issues is K-Nearest Neighbors (KNN) [21]. It's a lazy learning algorithm because it memorizes the training dataset rather than actually learning a discriminative function from the training data. KNN finds the distances between a query and each example in the data, chooses the K examples that are closest to the query, and then averages the labels (for regression) or votes for the most frequent label.

Random Search

Support V In order to determine the optimal solution for the constructed model, a hyperparameter optimization technique called random search chooses random combinations of hyperparameters . In contrast to techniques such as Grid Search, it selects a predetermined number of data points at random from the range of possible parameter values rather than attempting every possible combination. In order to train the model and assess it using a given performance metric, Random Search defines a grid of hyperparameter values and chooses random combinations. After a predetermined number of iterations, this process is repeated. The optimal set of hyperparameters is determined by selecting the combination that yields the best performance.

Grid Search

Grid Search is a hyperparameter optimization method that thoroughly explores a manually-specified portion of a learning algorithm's hyperparameter space. It is directed by a performance metric, usually determined by evaluation on a held-out validation set or cross-validation on the training set. Grid Search configures the ideal parameters for a given model by scanning the data. To find the tune that performs the best, it methodically experiments with various combinations of parameter tunes, cross-validating along the way. K-fold cross-validation can be used to define a grid of parameters that will be searched.

Proposed Method

The selection of hyperparameters has a major impact on how well machine learning models perform. A difficult but essential step in the creation of predictive models is choosing the ideal set of hyperparameters. Conventional methods, like random and grid search, provide basic techniques for navigating the hyperparameter space. These approaches do have some drawbacks, though. Even though grid search is thorough, it is computationally costly and might not be practical for high-dimensional spaces. Conversely, random search provides a more effective exploration but does not ensure that the set of parameters is close to the ideal one.

Presenting an Iterative Approach to Hyperparameter Optimization:

We suggest a novel approach to hyperparameter optimization that, in an iterative process, combines the precision of grid search with the exploratory advantages of random search to address these challenges. Our method, called Iterative Hyperparameter Optimization (IHO), seeks to more effectively and efficiently converge towards the optimal configuration by methodically reducing the hyperparameter space.

The IHO approach proceeds in multiple phases:

Initialization: A large variety of hyperparameters are initially entered into the grid search and random search spaces. This first step guarantees that the optimization process has a varied starting point.

Phase 1: Random Search Exploration: This is the first stage of the algorithm. A subset of the hyperparameters is chosen at random and assessed at this point. The goal is to rapidly search the large hyperparameter space and find areas that show promise. For the next step, the parameters that performed the best during this phase are noted.

Phase 2: Refinement of the Grid Search: Using the knowledge gathered from the random search, the grid search phase concentrates on a more condensed area surrounding the previously determined parameters that show promise. This step entails a closer inspection, In this step, the examination is more

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detailed, with hyperparameters adjusted within a closer range to the ideal values recommended by the random search. Here, accuracy is the goal, with the search being fine-tuned according to the performance results of the preliminary investigation.

Iterative Process: The algorithm goes into an iterative loop after performing a grid search. The random search is restarted, but with parameters set more closely to what the grid search determined to be nearly optimal. The grid search is then run once more, this time fine-tuning the parameters in light of the most recent results from the random search. This iterative procedure is carried out repeatedly until the convergence towards the ideal parameter set is indicated by a difference between the sets of hyperparameters found by successive searches falling below a predetermined threshold.

Convergence and Selection: The algorithm gradually honed in on the optimal hyperparameters thanks to the iterative process. When performance metrics show negligible changes, the cycle is over and the ideal or nearly optimal hyperparameters have been found. The final model is then chosen using these parameters (Figure 3).

Algorithm 1 Iterative Hyperparameter Optimization (IHO)

Require: Initial hyperparameter spaces for random search (RS) and grid search (GS), convergence threshold ϵ

Ensure: Optimal hyperparameters H^*

Initialize $H_{best}^{RS} = \emptyset$, $H_{best}^{GS} = \emptyset$
Define $\Delta = \infty$
while $\Delta > \epsilon$ **do**
  if $H_{best}^{GS} = \emptyset$ **then**
    Perform random search over RS
    $H_{best}^{RS} \leftarrow$ best hyperparameters from random search
  else
    Narrow down RS based on H_{best}^{GS}
    Perform random search over narrowed RS
    Update H_{best}^{RS} with best hyperparameters from new random search
  end if
  Narrow down GS based on H_{best}^{RS}
  Perform grid search over narrowed GS
  Update H_{best}^{GS} with best hyperparameters from grid search
  $\Delta \leftarrow$ calculate difference between H_{best}^{RS} and H_{best}^{GS}
end while
$H^* \leftarrow H_{best}^{GS}$
return H^*

Figure 3: Iterative Hyperparameter Optimization method.

Benefits and Repercussions

By combining the exploratory potential of random search with the meticulous examination of grid search, the IHO method makes hyperparameter optimization more effective and efficient. IHO dramatically lowers the computational load while increasing the probability of finding the optimal hyperparameters by iteratively reducing the search space and concentrating on promising regions. This methodological advancement should expedite the creation of high-performing models in multiple domains, increasing accessibility and usefulness of advanced machine learning for both researchers and practitioners.

Results

The use of machine learning techniques for the diagnosis of diabetic retinopathy (DR), a leading cause of blindness in diabetic patients, has advanced significantly as a result of this study. The goal of the research was to improve the early detection and classification of DR using advanced machine learning models by utilizing a large dataset of color fundus images. The study's dedication to enhancing the precision and efficacy of DR diagnosis-a critical first step in lessening the severity of this crippling ailment-is demonstrated by the application of cutting-edge hyperparameter optimization techniques.

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Several machine learning algorithms, each with specific advantages in classification tasks, were used in our investigation, including Support Vector Machine (SVM), Decision Tree, Random Forest, and K-Nearest Neighbors (KNN). These techniques were selected because they have the ability to correctly categorize fundus images into groups that are healthy or diseased, which is a crucial first step in the early diagnosis of diabetic retinopathy.

We used Random Search and Grid Search, two hyperparameter optimization techniques, to improve the performance of these machine learning models. These methods played a key role in determining the ideal model parameter configuration, which improved the models' capacity to learn from the dataset and increase the accuracy of their predictions. Each machine learning technique's efficacy in conjunction with hyperparameter optimization was carefully assessed. The performance metrics for each model are presented in the Table 1, which includes the accuracy, precision, recall, and F1-score:

Table 1: Comparative Analysis and Findings.

Model	Accuracy	Precision	Recall	F1-score
SVM	0.85	0.87	0.83	0.85
Decision Tree	0.8	0.81	0.79	0.8
Random Forest	0.88	0.89	0.87	0.88
KNN	0.83	0.84	0.82	0.83
Proposed Method (IHO)	**0.92**	**0.93**	**0.91**	**0.92**

The proposed Iterative Hyperparameter Optimization (IHO) method, which combined the exploratory capabilities of Random Search with the precision of Grid Search, outperformed the conventional models. The IHO method yielded the highest accuracy, precision, recall, and F1-score, demonstrating its superiority in optimizing the machine learning models for DR diagnosis.

The outcomes demonstrate how well machine learning models perform for medical image analysis when sophisticated hyperparameter optimization techniques are used. In comparison to conventional models, the Proposed Method (IHO) showed a notable improvement, highlighting the importance of iterative optimization in obtaining high accuracy in DR classification. This research implies that the iterative method of hyperparameter optimization can be an effective tool for creating predictive models, especially in the domain of medical diagnostics where accuracy and dependability are critical.

Discussion

This study emphasizes how important machine learning algorithms and hyperparameter optimization methods are to improving the accuracy of diabetic retinopathy (DR) diagnosis, which is a major ophthalmology concern. Important results were obtained from comparing the Iterative Hyperparameter Optimization (IHO) approach to traditional machine learning models. These results highlight the potential of customized computational approaches in medical diagnostics.

Each of the classic machine learning algorithms-Decision Tree, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN)-showed particular advantages in the classification of fundus images. Their performance metrics, while praiseworthy, indicated that additional improvement was required to satisfy the strict requirements for accuracy in medical diagnostics. Although they improved model performance on their own, the use of Random Search and Grid Search hyperparameter optimization did not fully utilize the optimization potential.

Performance was significantly improved with the implementation of the IHO method in terms of accuracy, precision, recall, and F1-score. This progress can be attributed to the IHO method's ability to iteratively improve the search for ideal hyperparameters, which successfully strikes a balance between the exploitation of promising regions and the exploration of the hyperparameter space. Such an approach is feasible for large-scale and real-time applications since it minimizes computational overhead while optimizing model performance.

The results of this investigation have important ramifications for the field of medical diagnostics, especially with regard to the timely identification of diseases such as diabetic retinopathy. The suggested method's increased model accuracy may result in more dependable screening instruments, allowing for early intervention and possibly lowering the prevalence of vision loss in diabetic patients. Furthermore, the research's methodology could be used to address other medical imaging issues, encouraging the creation of AI-driven diagnostic tools for use in a range of healthcare settings.

Though the study admits some limitations, the results are encouraging. The range of hyperparameter optimization techniques that have been studied does not include all possible approaches; therefore, future studies could examine the effectiveness of alternative approaches, like genetic algorithms or Bayesian optimization. Furthermore, while the dataset is extensive, it is limited to a particular population, and further research is needed to determine whether the models can be applied to a wider range of demographics.

In order to improve diagnostic accuracy even more, future research directions might investigate different machine learning algorithms and incorporate multimodal data sources. Beyond diabetic retinopathy, the IHO method's versatility to other medical imaging tasks offers an intriguing field for investigation that could transform diagnostic procedures in a variety of medical specializations.

Conclusion

This work not only adds to the growing body of research on artificial intelligence (AI) in healthcare, but it also sheds light on the significant contributions that machine learning and

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hyperparameter optimization make to improving diagnostic accuracy. One noteworthy development in the computational analysis of medical images is the suggested Iterative Hyperparameter Optimization (IHO) method, which lays the groundwork for both practical medical diagnostic applications and future research projects. Through the integration of advanced algorithmic strategies and clinical insights, this methodology facilitates the advancement of diagnostic tools that are more precise, effective, and easily obtainable. With the potential to improve patient outcomes through the early detection and treatment of diseases, these advancements are essential in light of the rising demand for healthcare services. Additionally, the methods and conclusions drawn from this research Moreover, this study's approaches and insights could spur innovation in a number of healthcare domains, highlighting AI's critical role in revolutionizing patient care and medical procedures.

References

1. Rohilla M, Dhankhar S, Bansal S, Garg A, Dhiman S, et al. (2023) Discussing pathologic mechanisms of Diabetic retinopathy & therapeutic potentials of curcumin and β-glucogallin in the management of Diabetic retinopathy. Biomed Pharma 169: 115881.
2. Do DV, Han G, Abariga SA, Sleilati G, Vedula SS, et al. (2023) Blood pressure control for diabetic retinopathy. Cochrane Database of Systematic Reviews 28(3): 3.
3. Tan TE, Wong TY (2023) Diabetic retinopathy: Looking forward to 2030. Front Endocrinol (Laussanne) 13: 1077669.
4. Tang L, Xu GT, Zhang JF (2023) Inflammation in diabetic retinopathy: Possible roles in pathogenesis and potential implications for therapy. Neural Regen Res 18(5): 976.
5. Sivaprasad S, Sen S, Cunha-Vaz J (2023) Perspectives of diabetic retinopathy-challenges and opportunities. Eye(Lond) 37(11): 2183-2191.
6. Waheed NK, Rosen RB, Jia Y, Munk MR, Huang D, et al. (2023) Optical coherence tomography angiography in diabetic retinopathy. Prog Retin Eye Res 97: 101206.
7. Ghosh SK, Biswas B, Ghosh A (2020) A novel approach of retinal image enhancement using PSO system and measure of fuzziness. Procedia Computer Science 167: 1300-131.
8. Bhandari S, Pathak S, Jain SA (2023) A literature review of early-stage diabetic retinopathy detection using deep learning and evolutionary computing techniques. Archives of Computational Methods in Engineering 30(2): 799-810.
9. Ghoushchi SJ, Ranjbarzadeh R, Dadkhah AH, Pourasad Y, Bendechache M, et al. (2021) An extended approach to predict retinopathy in diabetic patients using the genetic algorithm and fuzzy C-means. BioMed Research International 30: 1-13.
10. Herliana A, Arifin T, Susanti S, Hikmah AB (2018) Feature selection of diabetic retinopathy disease using particle swarm optimization and neural network. 2018 6th international conference on cyber and IT service management (CITSM) IEEE pp 1-4.
11. Vinayaki VD, Kalaiselvi R (2022) Multithreshold image segmentation technique using remora optimization algorithm for diabetic retinopathy detection from fundus images. Neural Processing Letters 54(3): 2363-2384.
12. Foshati S, Zamani A, Sabeti M, (2019) Improved Accuracy of Predicting Diabetic Retinopathy in Type 2 Diabetes Mellitus using Genetic Algorithm. Health Management & Information Science 6(3): 96-105.
13. Jadhav AS, Patil PB, Biradar S (2021) Optimal feature selection-based diabetic retinopathy detection using improved rider optimization algorithm enabled with deep learning. Evolutionary intelligence14: 1431-1448.
14. Jeyalaksshmi S, Padmapriya D, Midhunchakkravarthy D, Ameen A (2021) Detection of hard exudate from diabetic retinopathy image using fuzzy logic. in Intelligent Computing and Innovation on Data Science pp. 543-550.
15. Karthikeyan R, SathishKumar V, Balamurugan V, ShanmugaPriya M, et al. (2020) A novel fuzzy knowledge based glaucoma system for diabetic retinopathy using vessel extraction from fundus images. Eur J Mol Clin Med 7(9): 846.
16. Dayana AM, Emmanuel WS (2022) An enhanced swarm optimization-based deep neural network for diabetic retinopathy classification in fundus images. Multimedia Tools and Applications 81(15): 20611-20642.
17. Balasubramanian K, Ananthamoorthy N (2021) Improved adaptive neuro-fuzzy inference system based on modified glowworm swarm and differential evolution optimization algorithm for medical diagnosis. Neural Computing and Applications 33(13): 7649-7660.
18 Wang H, Li G, Wang Z (2023) Fast SVM classifier for large-scale classification problems. Information Sciences 642: 119136.
19. Christa S, Suma V, Mohan U (2022) Regression and decision tree approaches in predicting the effort in resolving incidents. International Journal of Business Information Systems 39(3): 379-399.
20. Bernard S, Adam S Heutte L (2007) Using random forests for handwritten digit recognition. presented at the Ninth international conference on document analysis and recognition (ICDAR 2007) IEEE pp. 1043-1047.
21. Ukey N, Yang Z, Li B, Zhang G, Hu Y, et al. (2023) Survey on exact knn queries over high-dimensional data space. Sensors 23(2): 629.

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