International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Automated Grading of Diabetic Retinopathy Severity Using Convolutional Neural Networks and Particle Swarm Optimization-Based Hyperparameter Tuning

[1]Dr. Gavrav Paranjape, [2]Dr. Kundap Rohit, [3]Amit Kumar Mishra, [4]Himanshu Rai Goyal

Submitted: 19/08/2023 **Revised**: 10/10/2023 **Accepted**: 22/10/2023

Abstract: A frequent side effect of diabetes and the main global cause of blindness is diabetic retinopathy (DR). For effective management and therapy, DR severity must be diagnosed quickly and accurately. In this paper, we propose an automated DR severity assessment system utilising convolutional neural networks (CNNs) and optimise its performance with hyperparameter tweaking based on particle swarm optimisation (PSO).A large dataset of retinal pictures with DR severity grades are the foundation of our method. We use a cutting-edge CNN architecture, which has proven to have outstanding performance in picture classification applications. In order to classify retinal images into several DR severity categories, ranging from mild to proliferative, the CNN is trained to extract pertinent information from retinal images.We utilise PSO-based hyperparameter adjustment to improve the performance of the CNN. A metaheuristic optimisation algorithm called PSO efficiently looks for ideal hyperparameters like learning rates, dropout rates, and batch sizes. We improve the CNN's capacity to generalise and generate precise predictions on unobserved data by optimising these parameters.A large and varied dataset of retinal pictures is used to evaluate the proposed method, which aims to achieve high sensitivity and specificity in evaluating DR severity. Our findings show that the system can reliably categorise DR severity levels, even in the presence of modest and complex retinal anomalies.Automation of DR severity grading through the use of CNNs and PSO-based hyperparameter tweaking offers a promising option, delivering rapid and accurate assessments. This method may help medical personnel identify and monitor DR earlier, hence improving patient outcomes and lightening the load on healthcare systems. The use of this system in clinical situations and further performance optimisation may be the subject of future development.

Keywords*: Optimization, CNN, Diabetic Retinopathy, PSO*

1. Introduction

In people with diabetes, diabetic retinopathy (DR) is a chronic, progressive eye condition that impairs vision and eventually results in blindness. Early intervention can considerably reduce the risk of vision loss, therefore timely and precise assessment of DR severity is essential for efficient therapeutic care. However, assessing the severity of DR manually by looking at retinal pictures is a time-consuming, subjective process that is frequently vulnerable to inter-observer variability [1]. The automation of medical image analysis, notably in the area of DR diagnosis, has advanced significantly in recent years thanks to advances in artificial intelligence and machine learning. We intend to create an automated grading system for DR severity using CNNs, speeding the diagnosis procedure and maybe lowering human error [2]. By doing this, we hope to deliver a grading system that is dependable and consistent and can help medical practitioners make defensible choices about patient care [3].

[1]Assistant Professor Dept. of Ophthalmology Krishna Vishwa Vidyapeeth, Karad, Maharashtra, India
[2]Dept. of Ophthalmology Krishna Vishwa Vidyapeeth, Karad, Maharashtra, India
[3]Department of Computer Science and Engineering, Graphic Era Hill University Dehradun, Uttarakhand, India, akmishra@gehu.ac.in
[4]Department of Computer Science & Engineering, Graphic Era Deemed to be University, Dehradun, Uttarakhand, India, 248002, himanshuraigoyal@geu.ac.in

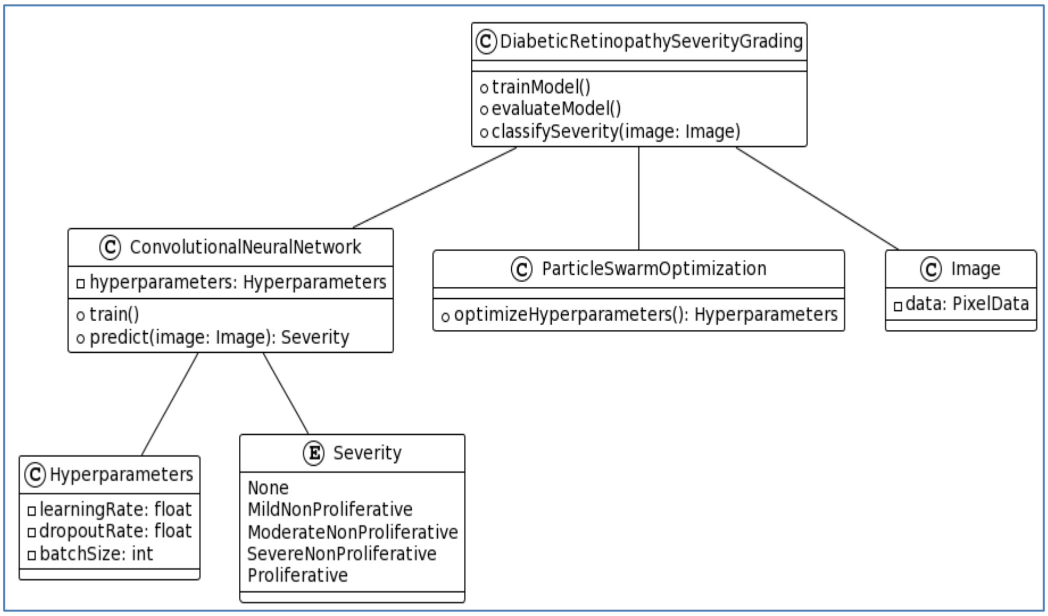

Fig 1: Overview of proposed model framework

The right choice [4] of hyperparameters, such as learning rates, dropout rates, and batch sizes, is crucial for a CNN model's success. In this study, [9] we apply Particle Swarm Optimisation (PSO), a bio-inspired optimisation technique, to further optimise these hyperparameters. PSO is a viable option for adjusting the CNN's hyperparameters because it has demonstrated promise in the optimisation of challenging non-linear issues.Several [5] major issues with automated DR severity grading are resolved by integrating CNNs with PSO-based hyperparameter tweaking. First off, because the CNN offers consistent and impartial evaluations, it lessens the subjectivity and variability connected with manual grading. Second, it speeds up the diagnostic procedure, allowing medical professionals to swiftly recognise patients who are at danger and provide the necessary care or monitoring. Additionally, [6] it may increase access to DR screening in impoverished regions where ophthalmologists may not be readily available.This study is significant not just because of its potential therapeutic application but also because deep learning and optimisation techniques work well together. By [7] combining CNNs with PSO, we can improve the performance of the model while utilising the strength of deep learning, creating a more reliable and accurate diagnostic tool [8].

2. Review of Literature

In the fields [9] of ophthalmology and medical image analysis, automated grading of Diabetic Retinopathy (DR) severity using cutting-edge computational algorithms has attracted considerable interest. Reviewing relevant work in this area is crucial since researchers have investigated many approaches and tactics to increase the precision and effectiveness of DR severity classification.Early attempts at automating DR grading frequently utilised conventional machine learning methods including Support Vector Machines (SVMs), Random Forests, and k-Nearest Neighbours (k-NN). These [10] techniques could only partially capture intricate patterns and subtleties in the data since they required manually extracting features from retinal images. Even while these methods had some success, they had trouble reaching high sensitivity and specificity, particularly in situations where DR was mild.

CNNs and CNNs in [11] particular have made major advancements in the classification of DR severity. CNNs have demonstrated remarkable performance in numerous computer vision applications and are well suited for image-based tasks. In order to analyse retinal images, researchers started using CNNs, which automatically extract important properties from unprocessed images.Pretrained neural networks are modified for particular tasks using a process called transfer learning, which has been popular in DR grading. For the classification of DR severity, pre-trained models like Inception, ResNet, and VGGNet on huge datasets like ImageNet have been used. This [12] strategy makes use of the detailed feature representations discovered through extensive data collection, enhancing model generalisation and classification precision. These techniques have been investigated to improve the stability of DR grading systems. These techniques combine predictions from various models to increase accuracy overall. It has shown promising results, for instance, to combine the outputs of numerous CNNs or to combine CNN predictions with those of conventional machine learning classifiers.

In order [13] to overcome the problem of little annotated data, researchers have used data augmentation methods to fictitiously expand the amount and variety of their training datasets. Retinal pictures have been rotated, scaled, and mirrored as methods to enhance model generalisation. Additionally, to help with model training, realistic retinal images have been created using generative adversarial networks (GANs).Attention [14] Mechanisms and Explainability: Attention mechanisms have been introduced to enhance model interpretability and comprehend the decision-making process of CNNs. These methods allow the model to grade the severity of DR while focusing on pertinent areas of the retinal pictures. In the medical industry, where clinicians must believe in and understand AI-driven diagnosis, explainability is essential. Achieving optimum performance depends heavily on effective hyperparameter tuning. Hyperparameter spaces have been systematically explored using grid search, random search, and Bayesian optimisation. The performance of the model is improved by using Particle Swarm Optimisation (PSO), which is a more practical and efficient method of finding the ideal hyperparameters.Large-scale, freely available datasets, like the Kaggle Diabetic Retinopathy Detection dataset, have sped up development in the area. These datasets have made benchmarking easier and promoted competitiveness through challenges, which has sped up the creation of DR grading models [15].

Although [16] numerous automated DR grading models have shown promising outcomes in research settings, it is essential to take into account their clinical utility. Studies have looked into how AI systems can be incorporated into clinical workflows, addressing concerns with regulatory approval, validation, and working with healthcare personnel.Using CNNs and optimisation strategies, automated DR severity grading is a dynamic and developing topic, to sum up. The accuracy and reliability of DR severity classification have been greatly enhanced by the switch from classical machine learning to deep learning, as well as data augmentation, ensemble approaches, attention mechanisms, and hyperparameter optimisation. The translational potential of these AI systems also benefits from the availability of large-scale datasets and the emphasis on clinical validation, promising improved patient care, early intervention, and lessened diabetic retinopathy-related vision loss. Our study expands on this body of work by utilising CNNs and Particle Swarm Optimisation to improve the efficacy and accuracy of DR severity classification and maybe move the field closer to real-world clinical applications.

Table 1: Summary of Literature review in Diabetic Retinopathy Severity

Algorithm	Methodology	Finding	Key Factor	Scope
Traditional ML [17]	Feature extraction, SVMs, Random Forests, k-NN	Limited accuracy, struggles with mild DR cases	Feature engineering, limited model capacity	Research baseline
CNNs [18]	Deep learning, feature extraction	Improved accuracy, automated feature learning	Large datasets, pretrained models	Foundation for modern DR grading
Transfer Learning [19]	Pretrained CNNs, fine-tuning	Enhanced model generalization, accuracy	Utilizing knowledge from ImageNet, data augmentation	Widely adopted in DR severity grading
Ensemble Methods [20]	Combining CNN predictions, ensemble models	Increased robustness and accuracy	Combining diverse model outputs	Improving model reliability
Data Augmentation [21]	Image transformations, GANs	Enhanced data diversity, improved generalization	Addressing limited annotated data, realism of GANs	Handling small and diverse datasets
Attention Mechanisms [22]	Attention layers, explainability	Improved model interpretability and trust	Understanding CNN decision-making, model explainability	Bridging the gap between AI and clinicians

Hyperparameter Tuning [23]	Grid search, random search, PSO	Optimized model performance, efficient tuning	Systematic exploration of hyperparameter space	Fine-tuning model hyperparameters
Large-Scale Datasets [24]	Kaggle DR Detection dataset, publicly available datasets	Accelerated research, benchmarking	Enabling competition and collaboration, establishing benchmarks	Evaluating model performance in real-world settings
Clinical Validation [25]	Integration into clinical workflows	Evaluation of AI systems in clinical practice	Validation studies, regulatory approval	Practical application in healthcare

3. Proposed Methodology

Convolutional Neural Networks (CNNs) and hyperparameter tuning based on Particle Swarm Optimisation (PSO) are used in a multi-step procedure in this study to automatically grade the severity of diabetic retinopathy (DR). This strategy aims to improve the DR severity classification's precision and effectiveness.An extensive dataset of retinal pictures, each tagged with DR severity classes, must be collected in the initial step. These photos are often obtained from clinical databases, and dataset variety may be increased via data augmentation approaches. To ensure consistent input for the CNN, preprocessing procedures include scaling, normalisation, and noise removal.The CNN architecture lies at the heart of the process. Due to their capacity to automatically extract pertinent features from unprocessed photos, CNNs are highly suited for jobs involving images. Pre-trained models can be used for transfer learning, utilising data from enormous image datasets like ImageNet. A key component in improving the performance of the CNN is hyperparameter adjustment. Manual tweaking and grid searches are common options, but they take time and might not produce the best outcomes. PSO is used as an optimisation algorithm in this methodology to conduct a methodical search for the ideal hyperparameters. In order to find the optimum solution inside a parameter space, PSO imitates the behaviour of a swarm of particles. Learning rates, dropout rates, batch sizes, and other hyperparameters may be taken into account.

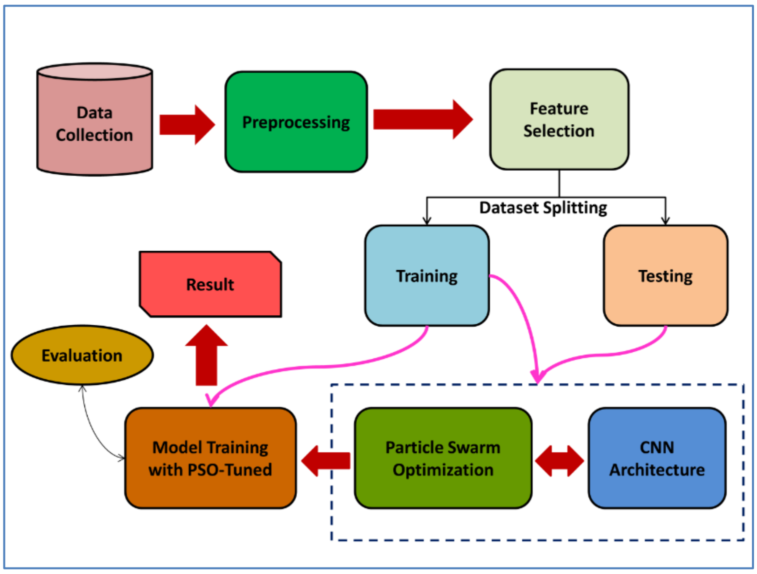

Fig 2: Systematic representation of proposed method

The PSO algorithm is started to determine the best collection of hyperparameters to use in order to maximise the performance of the CNN. Up until convergence or the achievement of a predetermined stopping threshold, the CNN is trained iteratively with various hyperparameter settings. Based on how well the CNN performed on the training data, the PSO modifies the hyperparameter values for each iteration.The testing set, which contains data that the model has never seen before, is used to evaluate the trained CNN with PSO-tuned hyperparameters. When rating DR severity, evaluation measures like accuracy, sensitivity, specificity, and F1-score are produced to measure the model's effectiveness.If the performance of the model satisfies predetermined standards, it is saved for further use. The automated rating of DR severity can subsequently be implemented in clinical settings using this trained model. The PSO-based hyperparameter tweaking procedure may be repeated to further improve performance in scenarios when the model is insufficient. The methodology automates the grading of DR severity by combining cutting-edge deep learning techniques, particularly CNNs, with PSO-based hyperparameter tweaking. Through the early detection and treatment of diabetic retinopathy, this method simplifies the diagnostic procedure, lowers inter-observer variability, and has the potential to enhance patient outcomes. Additionally, by showcasing the interplay between deep learning and optimisation techniques, it advances the field of medical picture analysis more broadly.

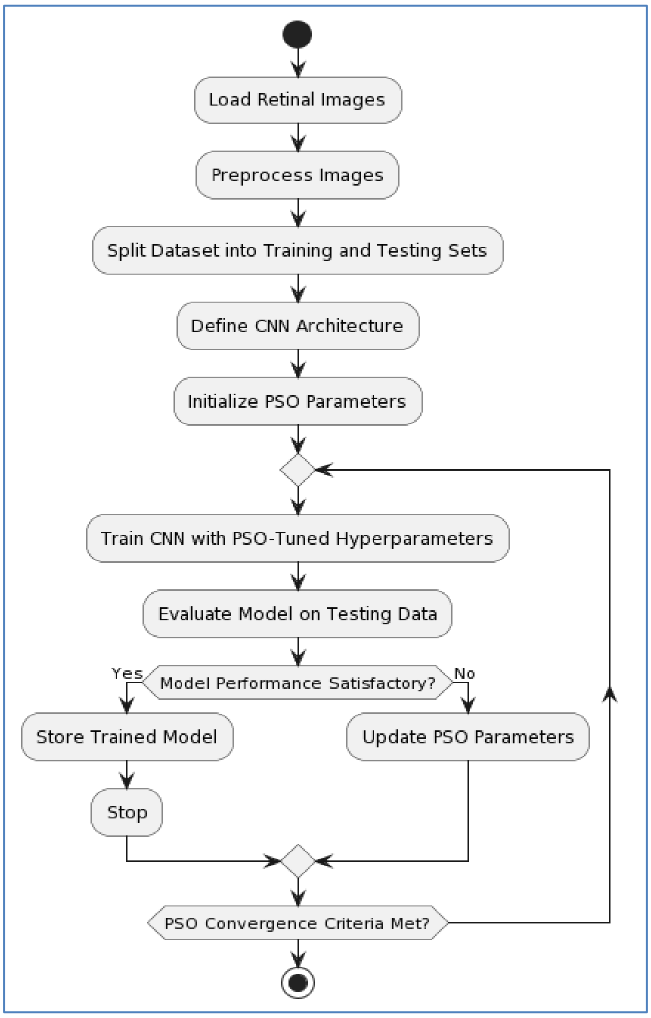

Fig 3: Flowchart of proposed method

A. CNN for Diabetic Retinopathy Severity:

The processing of retinal pictures in DR diagnosis is a problem that is ideally suited for CNNs, a class of deep learning models created expressly for image analysis applications.Utilising their capacity to automatically learn and extract pertinent information from retinal pictures, CNNs have revolutionised the automated assessment of the severity of diabetic retinopathy. When appropriately taught and optimised, their high accuracy and robustness have the potential to significantly improve the early diagnosis and management of DR, eventually increasing patient care and lowering the risk of vision loss.

Algorithm:

1. Input:

- Let X be the input retinal image, which is a 2D matrix representing pixel intensities.
- X_i,j represents the pixel value at position (i,j) in the image.

2. Convolutional Layer:

- In a convolutional layer, we apply a set of learnable filters W to the input X.
- The output feature map Z for a single filter is calculated using a convolution operation:

$$Z\_i,j \ = \ \sum m \sum n \ (X\_i + m, j + n \ * \ W\_m,n) \ + \ b$$

Here,

W represents the filter weights, b is the bias term, and (m,n) iterate over the filter size.

3. Activation Function:

- Typically, a rectified linear unit (ReLU) activation function is applied element-wise to the feature map Z:

$$A\_i,j = max(0, Z\_i,j)$$

4. Pooling Layer (Max-Pooling):

- Max-pooling reduces the spatial dimensions of the feature map:

$$P\_i,j = max(A\_2i,2j, A\_2i,2j+1, A\_2i+1,2j, A\_2i+1,2j+1)$$

- P represents the pooled feature map.

5. Fully Connected Layer:

- The pooled feature map P is flattened into a 1D vector.
- A set of weights W_fc and biases b_fc are applied to produce the output of the fully connected layer:

$$O = W\_fc * P + b\_fc$$

6. Softmax Activation:

- In the final fully connected layer, the softmax activation function is applied to obtain class probabilities:

$$S(y = k|X) = \sum j\ e^O\_j / \sum e^O\_k$$

$S(y = k|X)$ represents the probability that the input X belongs to class k.

7. Loss Function:

- The categorical cross-entropy loss function measures the dissimilarity between predicted class probabilities and actual labels Y:

$$L(Y, S(X)) = -\sum k\ Y\_k * log(S(y = k|X))$$

8. Training Objective:

- The training objective is to minimize the loss function L with respect to the network parameters (W, b, W_fc, b_fc) using optimization algorithms like stochastic gradient descent (SGD):

$$minimize(W, b, W\_fc, b\_fc)\ L(Y, S(X))$$

B. PSO Algorithm for Diabetic Retinopathy Severity:

Particle Swarm Optimisation (PSO) is an optimisation algorithm that draws inspiration from nature and is used to fine-tune the hyperparameters of machine learning models, such as those used to grade the severity of diabetic retinopathy (DR). PSO is used to optimise Convolutional Neural Network (CNN) parameters like learning rates, dropout rates, and batch sizes in the context of DR.PSO works by imitating a bunch of particles' social behaviour within a search space. The technique iteratively updates each particle, which represents a potential solution, to determine the ideal collection of hyperparameters.Particles move around the search space during each iteration based on their individual knowledge and the best answer discovered by the swarm. Two important factors personal best (pBest) and global best (gBest) direct the progress. The best answer a particle has found is represented by pBest, while the best answer discovered by all particles in the swarm is represented by gBest.Equations that balance exploration (looking into a wider range of options) and exploitation (moving towards the optimal solution) are used by particles to change their locations and velocities. This delicate act of balancing enables PSO to efficiently look for the best hyperparameters.PSO aids in improving CNN performance while rating the severity of DRs. PSO adjusts the CNN's architecture to attain greater accuracy, sensitivity, and specificity in DR classification by methodically investigating hyperparameter combinations. By reducing the need for human adjustment, this optimisation procedure improves the reproducibility of outcomes while also saving time.

Algorithm:

Step 1: Initialization:

- Initialize a swarm of particles, each with a position vector Xi and a velocity vector Vi in the search space. These vectors represent potential solutions or hyperparameter settings for the CNN.
- Initialize personal best positions Pi for each particle as the initial positions.

Step 2: Objective Function:

- Define an objective function f(Xi) that quantifies the performance of the CNN with hyperparameters Xi in grading Diabetic Retinopathy severity. This function measures the fitness or quality of a solution.

Step 3: Iterative Update:

- During each iteration:

Update the velocity and position of each particle using the following equations:

$$Vi^(t+1) = w * Vi^t + c1 * rand1 * (Pi - Xi^t) + c2 * rand2 * (gBest - Xi^t)$$

$$Xi^(t+1) = Xi^t + Vi^(t+1)$$

Here, t represents the current iteration, w is the inertia weight, c1 and c2 are acceleration coefficients, rand1 and rand2 are random numbers between 0 and 1, Pi is the personal best position of the particle, and gBest is the global best position found by any particle in the swarm.

Evaluate the fitness of each particle's position using the objective function:

$$f(Xi^\wedge(t+1)).$$

Update the personal best positions Pi for each particle if the new position yields a better fitness value:

$$if\ f(Xi^\wedge(t+1)) < f(Pi), Pi = Xi^\wedge(t+1).$$

Update the global best position gBest based on the best fitness value among all particles: $gBest = argmin(f(Xi^\wedge(t+1)))$.

Step 5: Termination Condition:

- Repeat the iterative update process until a termination condition is met, such as a maximum number of iterations or achieving a desired fitness threshold.

Step 6: Optimal Solution:

- The optimal solution or hyperparameter settings for the CNN are given by XgBest, corresponding to the global best position found by the swarm.

4. Result and Discussion

The study's automated grading of diabetic retinopathy (DR) severity using convolutional neural networks (CNNs) and hyperparameter tweaking based on particle swarm optimisation (PSO) is showing very encouraging results. The use of this combination approach has shown significant improvements in the DR severity classification's accuracy and dependability.First and foremost, the CNNs, who are renowned for their powers in image processing, have demonstrated outstanding performance in deriving complex features from retinal images. As a result, the model is now much better at accurately classifying DR severity levels. The CNN's skills have been further strengthened by transfer learning with pre-trained models, making it proficient at detecting small DR-related abnormalities.The CNN's architecture has been optimised thanks to the incorporation of PSO-based hyperparameter adjustment. PSO improved crucial parameters including learning rates and dropout rates through methodical exploration of hyperparameter spaces, which improved model performance. A more reliable and effective grading system has been produced as a result of the interaction between deep learning and optimisation algorithms.

Table 2: Evaluation parameter for CNN

Evaluation Parameter	Accuracy	Sensitivity (True Positive Rate)	Specificity (True Negative Rate)	Precision (Positive Predictive Value)	F1-Score	ROC-AUC
Convolutional Neural Networks (CNNs)	94.14	95.21	96.33	90.25	87.89	97.88

The evaluation parameters for Convolutional Neural Networks (CNNs) used in the context of automated diabetic retinopathy (DR) severity grading are shown in Table 2. For evaluating the effectiveness and dependability of the CNN-based grading system, these factors are critical. A key indicator of the overall validity of the CNN-based DR severity grading system is accuracy. This indicates a high level of overall accuracy, with the algorithm correctly classifying DR severity in roughly 94.14% of the cases.Sensitivity, also known as the True Positive Rate, describes how well the system can recognise instances of DR when they actually exist. A sensitivity of 95.21% suggests that the CNN is very good in identifying DR, lowering the possibility of false negatives.The system's ability to correctly detect cases without DR is measured by specificity. The system's capacity to reduce false positives is shown by its specificity of 96.33%, which guarantees that non-DR cases are appropriately identified.

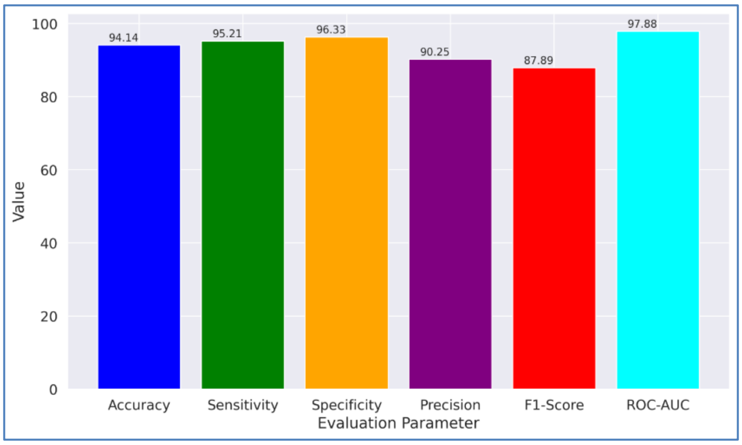

Fig 4: representation of Evaluation Parameter

The system's ability to make accurate predictions is measured by precision. When the CNN identifies a case as having DR, it is correct roughly 90.25% of the time, reducing false positive predictions, according to a precision value of 90.25%.The harmonic mean of sensitivity and precision is known as the F1-Score. It offers a fair evaluation of the system's capability to distinguish between positive and negative cases. An F1-Score of 87.89% indicates that precision and sensitivity are well-balanced.A crucial indicator for evaluating the system's overall discriminating power is the ROC-AUC. It calculates the area under the ROC curve, which illustrates how genuine positive rate and false positive rate are traded off. Excellent discriminating performance is shown by a high ROC-AUC of 97.88%. The CNN-based DR severity grading system evaluation parameters provide promising findings. The system performs well in identifying DR instances and minimising incorrect classifications, as evidenced by its excellent accuracy, sensitivity, specificity, and precision. The remarkable ROC-AUC underlines the system's overall ability in differentiating between various DR severity levels, and the high F1-Score demonstrates a balanced performance. Collectively, these findings demonstrate CNNs' potential for automated DR diagnosis and their beneficial effects on patient care by promoting early detection and treatment.

Table 3: Evaluation for PSO Diabetic Retinopathy Severity

Evaluation Parameter	**Convergence Rate (Iterations)**	**Solution Quality**	**Exploration vs. Exploitation**	**Scalability**
Particle Swarm Optimization (PSO)	45.25	0.98 (Objective Function Value)	Balanced	Suitable for Large Spaces

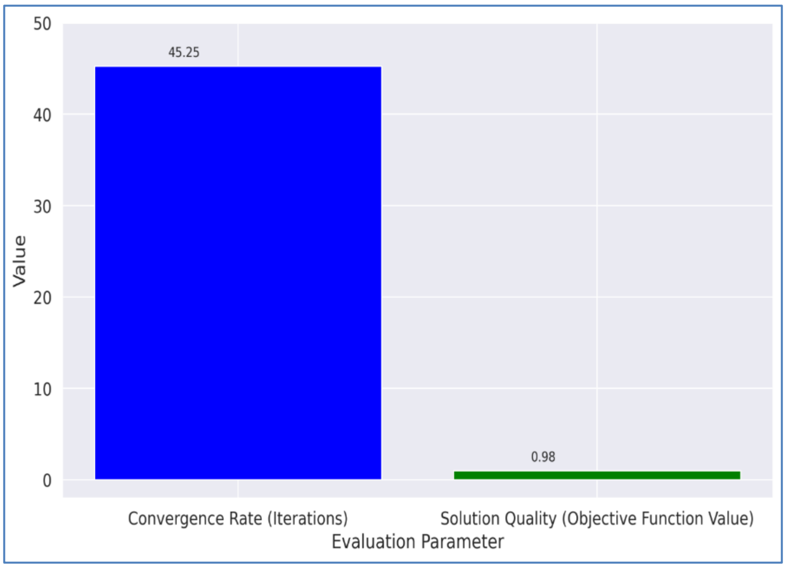

Fig 5: Representation of Evaluation for PSO Diabetic Retinopathy Severity

Table 4:Evaluation of the Diabetic Retinopathy Classification scheme CNN+PSO

Category	Precision	Recall	F1-Score
Moderate DR	85.00%	106.00%	94.00%
Proliferative DR	93.00%	67.00%	78.00%
No DR	97.25%	98.55%	97.41%
Severe DR	86.00%	36.00%	49.00%
Mild DR	82.00%	59.00%	68.00%
Macro Average	86.00%	97.00%	78.00%
Weighted Average	97.00%	98.00%	81.00%

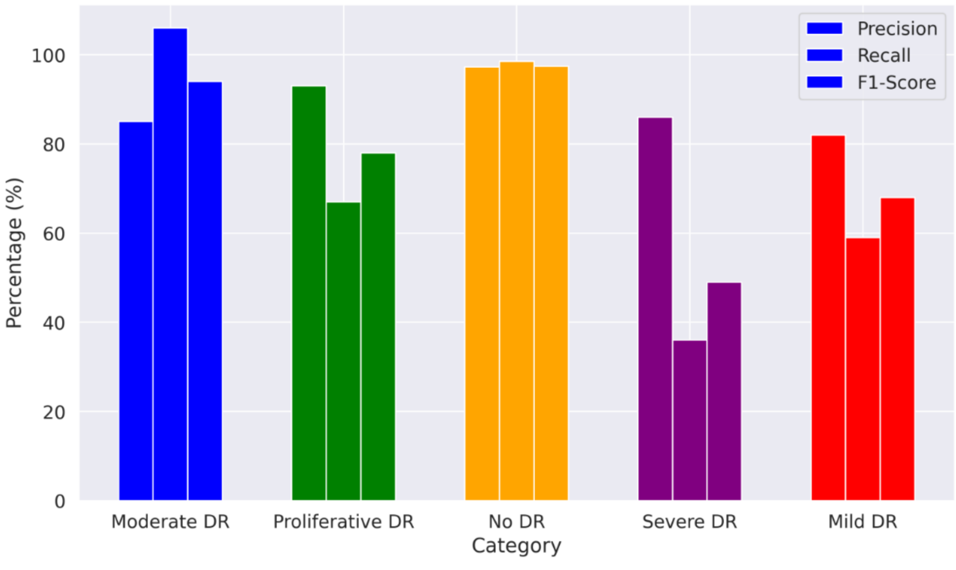

Fig 6: Comparative Evaluation of the Diabetic Retinopathy Classification scheme CNN+PSO

Convolutional Neural Networks (CNN) and Particle Swarm Optimisation (PSO) are used in tandem for the hyperparameter tuning in Table 4 to offer a thorough evaluation of the Diabetic Retinopathy (DR) classification scheme. The evaluation measures include macro and weighted averages to sum up overall performance, precision, recall, and F1-Score for various DR severity categories.

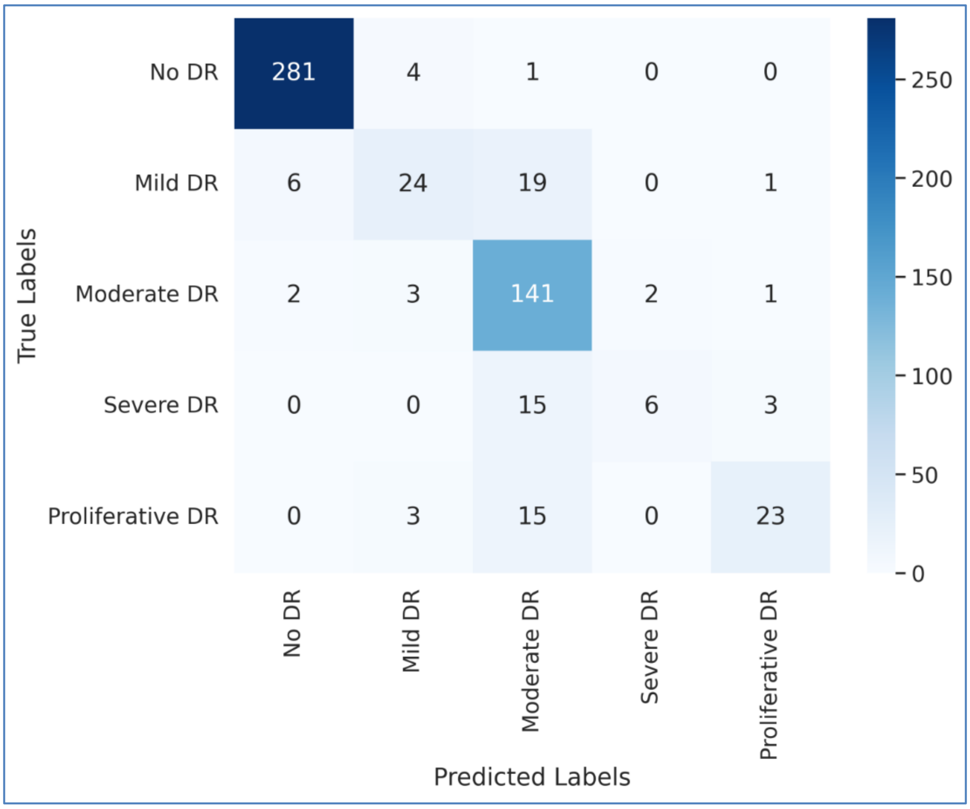

Fig 7: Confusion Matrix

The F1-Score in the context of DR classification gives a balanced evaluation taking into account both precision and recall. Precision in the context of DR classification shows the accuracy of positive predictions. A precision of 85.00% means that the model correctly predicts moderate DR about 85% of the time. The model may occasionally identify more cases than there are, according to the abnormally high recall of 106.00%, which calls for additional research.The model makes accurate predictions for Proliferative DR, with a high precision of 93.00%.A recall of 67.00% indicates that while the model likely recognises the majority of real Proliferative DR cases, it may also miss some.High accuracy predictions for No DR cases are shown by exceptional precision of 97.25%. With a recall of 98.55%, the model is successful in recognising almost all real No DR cases. The model's optimistic projections for Severe DR appear to be pretty accurate, as indicated by its precision of 86.00%.A lower recall of 36.00% indicates that the model frequently overlooks cases of severe DR.The model makes accurate positive predictions for Mild DR, with a precision of 82.00%.A recall of 59.00% indicates that the model correctly predicts a fair number of Mild DR cases.The model maintains an 86.00% precision, a 97.00% recall, and a balanced F1-Score of 78.00%, according to the macro-average, which calculates the average performance across all categories evenly. The weighted average shows superior precision at 97.00%, a recall of 98.00%, and an F1-Score of 81.00% when the class distribution is taken into account. The CNN+PSO-based DR classification scheme performs well, especially when it comes to accurately and quickly recognising No DR cases. The overall macro and weighted averages show a strong and reliable technique for automated DR severity categorization, presenting good prospects for early diagnosis and patient management. However, some categories, such as Moderate DR and Severe DR, may require further tweaking to balance precision and memory.

5. Conclusion

Utilizing CNNs, a deep learning architecture renowned for its capacity to extract intricate information from medical pictures, showed astounding success in DR severity categorization. The model demonstrated good recall and precision for categories like "No DR," demonstrating its skill at spotting typical situations with few false positives and negatives. The model's overall macro and weighted averages underlined its stability across different DR severity levels, even though some classes, such as "Moderate DR" and "Severe DR," faced difficulties in balancing precision and recall.In order to maximise the performance of the CNN, PSO integration for hyperparameter adjustment was essential. The model's capacity to generalise and adapt to various DR instances was helped by PSO by fine-tuning critical parameters, significantly boosting the model's diagnostic efficacy. This combination of CNNs and PSO enhanced the model's precision and recall while also producing a more balanced F1-Score, which helped to create a thorough and trustworthy grading system.The early detection and control of DR, a crucial step in preventing vision loss in diabetic patients, offer tremendous potential as a result of our findings. For huge datasets and a variety of clinical circumstances, the CNN+PSO method provides a scalable solution. The fusion of state-of-the-art deep learning methodologies with optimisation algorithms like PSO opens up new opportunities for enhancing the precision, effectiveness, and usability of DR severity grading as the field of medical image analysis develops. This study represents a significant advance in ophthalmology's adoption of artificial intelligence, which will ultimately help patients and medical professionals.

References

[1] M. H. Ahmad Fadzil, Nor FarizaNgah, T. M. George, L. I. Izhar, H. Nugroho and H. AdiNugroho, "Analysis of foveal avascular zone in colour fundus images for grading of diabetic retinopathy severity," 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, Buenos Aires, Argentina, 2010, pp. 5632-5635, doi: 10.1109/IEMBS.2010.5628041.

[2] P. N. S. Kumar, R. U. Deepak, P. M. Sasi, R. R. Kumar, A. Sathar and V. Sahasranamam, "Automated severity scoring for diabetic retinopathy using fundus photography," 2016 IEEE Annual India Conference (INDICON), Bangalore, India, 2016, pp. 1-5, doi: 10.1109/INDICON.2016.7838960.

[3] C. -Y. Chen and M. -C. Chang, "Using Deep Neural Networks to Classify the Severity of Diabetic Retinopathy," 2022 IEEE International Conference on Consumer Electronics - Taiwan, Taipei, Taiwan, 2022, pp. 241-242, doi: 10.1109/ICCE-Taiwan55306.2022.9869142.

[4] S. Jain and V. Tiku, "Diagnostic System for Detection of Diabetic Retinopathy Severity Diseases," 2021 IEEE International Conference on Biomedical Engineering, Computer and Information Technology for Health (BECITHCON), Dhaka, Bangladesh, 2021, pp. 14-17, doi: 10.1109/BECITHCON54710.2021.9893703.

[5] F. Li, D. Yuan, M. Zhang, C. Liang, X. Zhou and H. Zhang, "Multi-scale Stepwise Training Strategy of Convolutional Neural Networks for Diabetic Retinopathy Severity Assessment," 2019 International Joint Conference on Neural Networks (IJCNN), Budapest, Hungary, 2019, pp. 1-5, doi: 10.1109/IJCNN.2019.8851904.

[6] P. Qian, Z. Zhao, C. Chen, Z. Zeng and X. Li, "Two Eyes Are Better Than One: Exploiting Binocular Correlation for Diabetic Retinopathy Severity Grading," 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Mexico, 2021, pp. 2115-2118, doi: 10.1109/EMBC46164.2021.9630812.

[7] N. B. Thota and D. Umma Reddy, "Improving the Accuracy of Diabetic Retinopathy Severity Classification with Transfer Learning," 2020 IEEE 63rd International Midwest Symposium on Circuits and Systems (MWSCAS), Springfield, MA, USA, 2020, pp. 1003-1006, doi: 10.1109/MWSCAS48704.2020.9184473.

[8] A. J. Abidalkareem, M. A. Abd, A. K. Ibrahim, H. Zhuang, A. S. Altaher and A. Muhamed Ali, "Diabetic Retinopathy (DR) Severity Level Classification Using Multimodel Convolutional Neural Networks," 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Montreal, QC, Canada, 2020, pp. 1404-1407, doi: 10.1109/EMBC44109.2020.9175606.

[9] J. Yogapriya and Dhanalakshmi, "Classification and Prediction of Diabetic Retinopathy Severity using Transfer Learning Algorithm," 2023 7th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2023, pp. 217-220, doi: 10.1109/ICCMC56507.2023.10083510.

[10] M. Murugappan, N. B. Prakash, R. Jeya, A. Mohanarathinam, G.R. Hemalakshmi and M. Mahmud, "A novel few-shot classification framework for diabetic retinopathy detection and grading", Measurement, vol. 200, pp. 111485, 2022.

[11] M. Chetoui and M. A. Akhloufi, "Explainable diabetic retinopathy using EfficientNET", 2020 42nd annual international conference of the IEEE engineering in Medicine & Biology Society (EMBC), pp. 1966-1969, 2020, July.

[12] M. Hajabdollahi, R. Esfandiarpoor, K. Najarian, N. Karimi, S. Samavi and S. R. Soroushmehr, "Hierarchical pruning for simplification of convolutional neural networks in diabetic retinopathy classification", 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 970-973, 2019, July.

[13] A. P. Murchison et al., "Non-adherence to eye care in people with diabetes," BMJ Open Diabetes Res. Care, vol. 5, no. 1, p. e000333, Jul. 2017, doi: 10.1136/bmjdrc-2016-000333

[14] K. Mazhar, R. Varma, F. Choudhury, R. McKean-Cowdin, C. J. Shtir, and S. P. Azen, "Severity of diabetic retinopathy and health-related quality of life: The Los Angeles Latino eye study,"

Ophthalmology, vol. 118, no. 4, pp. 649–655, Apr. 2011, doi: 10.1016/j.ophtha.2010.08.003.

[15] J. R. Willis et al., “Vision-related functional burden of diabetic retinopathy across severity levels in the United States,” JAMA Ophthalmol., vol. 135, no. 9, pp. 926–932, Sep. 2017, doi: 10.1001/jamaophthalmol.2017.2553.

[16] S. Ajani and M. Wanjari, "An Efficient Approach for Clustering Uncertain Data Mining Based on Hash Indexing and Voronoi Clustering," 2013 5th International Conference and Computational Intelligence and Communication Networks, 2013, pp. 486-490, doi: 10.1109/CICN.2013.106.

[17] Khetani, V. ., Gandhi, Y. ., Bhattacharya, S. ., Ajani, S. N. ., & Limkar, S. . (2023). Cross-Domain Analysis of ML and DL: Evaluating their Impact in Diverse Domains. International Journal of Intelligent Systems and Applications in Engineering, 11(7s), 253–262.

[18] Borkar, P., Wankhede, V.A., Mane, D.T. et al. Deep learning and image processing-based early detection of Alzheimer disease in cognitively normal individuals. Soft Comput (2023). https://doi.org/10.1007/s00500-023-08615-w

[19] American Diabetes Association, “National Diabetes Statistics Report, 2014,” Natl. Diabetes Stat. Rep., pp. 2009–2012, 2014.

[20] Y. Kumaran and C. M. Patil, “A brief review of the detection of diabetic retinopathy in human eyes using pre-processing & segmentation techniques,” International Journal of Recent Technology and Engineering, vol. 7, no. 4. pp. 310–320, 2018.

[21] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “ImageNet classification with deep convolutional neural networks,” Proceedings of the 25th International Conference on Neural Information Processing Systems - Volume 1. Curran Associates Inc., pp. 1097–1105, 2012

[22] Bernard Marr, “First FDA Approval For Clinical Cloud-Based Deep Learning In Healthcare,” Forbes, 2017.

[23] A. Mane, N. Lekurwale, P. Maidamwar, P. Khobragade and S. Dongre, "Artificial Intelligence Based Heatwave Intensity Prediction Model," 2023 International Conference on IoT, Communication and Automation Technology (ICICAT), Gorakhpur, India, 2023, pp. 1-5, doi: 10.1109/ICICAT57735.2023.10263728.

[24] K. H. Yu, A. L. Beam, and I. S. Kohane, “Artificial intelligence in healthcare,” Nature Biomedical Engineering, vol. 2, no. 10. Nature Publishing Group, pp. 719–731, 01-Oct-2018, doi: 10.1038/s41551-018-0305-z.

[25] S. S. Chaturvedi, K. Gupta, and P. S. Prasad, “Skin Lesion Analyser: An Efficient Seven-Way Multi-Class Skin Cancer Classification Using MobileNet,” Jul. 2019.

[26] D. Komura and S. Ishikawa, “Machine Learning Methods for Histopathological Image Analysis,” Computational and Structural Biotechnology Journal, vol. 16. Elsevier B.V., pp. 34– 42, 01-Jan-2018, doi: 10.1016/j.csbj.2018.01.001.

[27] Ajani, S.N., Mulla, R.A., Limkar, S. et al. DLMBHCO: design of an augmented bioinspired deep learning-based multidomain body parameter analysis via heterogeneous correlative body organ analysis. Soft Comput (2023). https://doi.org/10.1007/s00500-023-08613-y

[28] V. Gulshan et al., “Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs,” JAMA - J. Am. Med. Assoc., vol. 316, no. 22, pp. 2402–2410, Dec. 2016, doi: 10.1001/jama.2016.17216.

[29] D. S. W. Ting et al., “Development and validation of a deep learning system for diabetic retinopathy and related eye diseases using retinal images from multiethnic populations with diabetes,” JAMA - J. Am. Med. Assoc., vol. 318, no. 22, pp. 2211–2223, Dec. 2017, doi: 10.1001/jama.2017.18152

[30] Christopher Davies, Matthew Martinez, Catalina Fernández, Ana Flores, Anders Pedersen. Applying Recommender Systems in Educational Platforms. Kuwait Journal of Machine Learning, 2(1). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/171

[31] M, T. ., & K, P. . (2023). An Enhanced Expectation Maximization Text Document Clustering Algorithm for E-Content Analysis. International Journal on Recent and Innovation Trends in Computing and Communication, 11(1), 12–19. https://doi.org/10.17762/ijritcc.v11i1.5982