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An Intelligent Diabetic Retinopathy Forecasting System using Modified Deep Neural Network

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ABSTRACT
Diabetic Retinopathy (DR) is a severe complication of diabetes that can lead to vision impairment and blindness if not detected and treated early. In this research, we propose an advanced forecasting system leveraging a Modified Deep Neural Network (DNN) to enhance the accuracy and efficiency of DR diagnosis. The proposed system integrates a deep learning framework with modifications tailored to the unique characteristics of retinal images affected by diabetes. We introduce specialized features extraction techniques and optimize the network architecture to accommodate the intricacies of diabetic retinal pathology. A comprehensive dataset comprising diverse retinal images is utilized for training and validating the modified DNN model. The experimental results demonstrate superior forecasting accuracy compared to existing methods, highlighting the effectiveness of the proposed approach in early detection and prognosis of diabetic retinopathy. This intelligent forecasting system holds significant promise for improving the clinical management of diabetic patients by facilitating timely intervention and reducing the risk of irreversible visual impairment.

Keywords: *Diabetic Retinopathy, Modified Deep Neural Network, Features Extraction.*

1. INTRODUCTION

In the current era, nearly 250 million people have diabetes. Diabetes is caused by an increase of glucose levels in the body. As diabetes prolongs, it leads the eye's complication known as diabetic retinopathy (DR) [1]. The high glucose level in the blood causes causing damage to the tiny blood vessels inside the retina, leading to diabetic retinopathy. These affected tiny vessels will start leaking blood and fluids onto the retina, resulting in vision problems. It causes by damage to the blood vessels in the light-sensitive tissue at the back of the retina in such a way that the retina cannot receive the proper nutrients to maintain the vision. According to the World Health Organization, the number of people living with this disability is approaching 422 million, accounting for nearly 8.5 percent of the adult population of the world. Diabetic retinopathy (DR) affects about one-third of the population, and one-tenth of these people will develop sight-threatening diabetic retinopathy later in life [2-5]. Treatment is available to prevent the development of this disease, if it is detected in the early stages.

Diabetic retinopathy is typically asymptomatic during its initial stages. Certain individuals experience alterations in their visual perception, such as challenges in reading or discerning distant things. These modifications can happen at any given moment. In the advanced stages of the disease, there is hemorrhaging of the blood vessels in the retina, leading to the leakage of blood into the vitreous, which is a gel-like fluid that fills the eye. One may experience the presence of dark, floating specks or streaks that resemble cobwebs. Spontaneous resolution of the spots is conceivable, however, it is imperative to promptly seek medical intervention. In the absence of therapy, the bleeding has the potential to reoccur [6], intensify, or lead to the formation of scars. Diabetic retinopathy can be divided into two significant stages known as Non-Proliferative Diabetic Retinopathy (NPDR) and Proliferative Diabetic Retinopathy (PDR) [7].

Figure 1 displays the distinct phases of diabetic retinopathy alongside their corresponding symptoms. Non-proliferative diabetic retinopathy (NPDR) refers to the initial phases of diabetic retinopathy, characterized by the impairment of retinal blood vessels caused by the leakage of fluid within them. Consequently, the retina experiences inflammation and accumulation of fluid, leading to impaired vision. The presence of microaneurysms (MAs), hemorrhages (HMs), and exudates (EXs) are indicative of non-proliferative diabetic retinopathy [8].

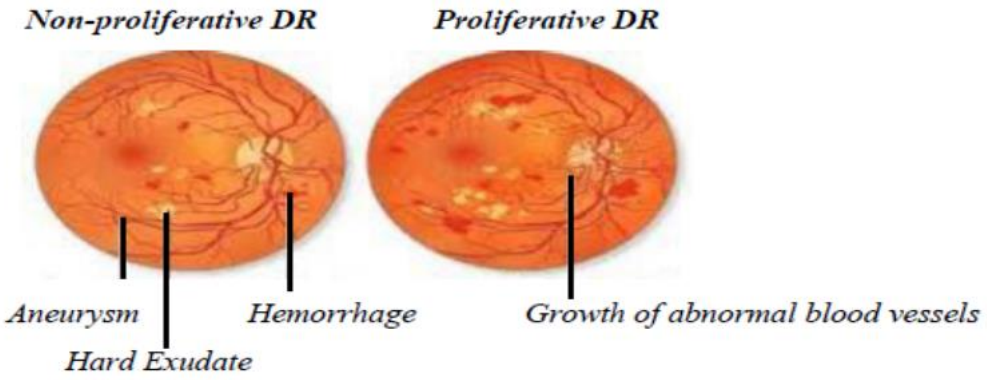


Figure 1. Stages of diabetic retinopathy

As the Microaneurysm stage prolongs, the thin blood vessels may rupture producing haemorrhages (HMs) [9]. Swelling of small blood vessels begins to obstruct blood flow to the retina, inhibiting normal nourishment. The macula is blocked with blood and other fluids as a result of this. Patients in this stage have to undergo eye examination every 6 to 8 months. This stage is termed as 'Moderate' stage in NPDR [10].

The augmented permeability of the capillary walls results in the subsequent phase known as exudates (EXs). This leads to the manifestation of small, distinctly defined yellow patches in the retina. A dilated fundus examination is needed for patients every 3 to 4 months, at this stage. Within a year's time, 16% of patients with non-proliferative diabetic retinopathy will develop proliferative diabetic retinopathy [11]. Non-proliferative stage progresses and develops into proliferative diabetic retinopathy. As this is the last stage in the NPDR, it is called the 'Severe' stage in non-proliferative diabetic retinopathy.

Proliferative diabetic retinopathy (PDR) is a more advanced stage of diabetic retinopathy. At this stage, new blood vessels start growing. As these new blood vessels are abnormal and grow on the retina's surface, they do not provide blood to the retina. The new blood vessels scar the retinal region, which results in vision distortion. The macula may detach from its normal place and cause visual loss if the pull is strong. PDR patients may not show any symptoms until it is too late to treat them. Before there is any alteration in vision, the retina may be severely damaged. About 3% of people in this proliferative diabetic retinopathy condition may suffer severe visual loss [12]. The high incidence of diabetic retinopathy (DR) as a primary factor leading to vision impairment in individuals with diabetes underscores the immediate requirement for efficient detection and classification algorithms [13-14]. The objective of this study is to introduce a model called PSO-CNN, which combines Particle Swarm Optimization (PSO) with Convolutional Neural Network (CNN), for accurately classifying the stages and severity levels of Diabetic Retinopathy (DR) from color fundus images. The PSO-CNN model consists of three stages: preprocessing, feature extraction, and classification. The results obtained from simulations utilizing a benchmark DR database clearly indicate that the PSO-CNN model surpasses other methods that were examined, hence confirming its remarkable efficacy in detecting and classifying DR [15].

Another research also focuses on the issue of early detection and categorization of DR phases using a reliable artificial intelligence (AI) model. The proposed model utilizes a four-stage methodology that integrates fractal analysis, two-dimensional stationary wavelet transform (2D-SWT), statistical- and entropy-based feature extraction, and a recurrent neural network-long short-term memory (RNN-LSTM) architecture for classification purposes. The suggested model achieved high classification accuracy across five DR classes when tested on a dataset consisting of 12,500 color fundus pictures. The study demonstrates the capacity of the AI-driven model to effectively address nonlinear dynamics with minimal computational complexity, hence serving as a powerful tool for accurately diagnosing different stages of DR [16].

The existing research on the detection and categorization of diabetic retinopathy (DR) has made significant progress in revealing the chronological development of the illness and suggesting novel models for precise diagnosis. However, there is a significant lack of research in the investigation of effective approaches for monitoring the chronological advancement of DR phases. Unraveling the dynamic fluctuations over time could offer important understanding of the disease's progression and assist in the timely development of therapies. Conducting longitudinal investigations and employing dynamic monitoring techniques can improve our comprehension of the time-related elements of DR, leading to more efficient treatment approaches.

Additionally, although the PSO-CNN model shows promising outcomes in classifying DR, it is necessary to do further research to evaluate its resilience across various datasets and demographic changes. Furthermore, doing a comparison examination of several DR classification models, such as PSO-CNN, could provide valuable insights into the advantages and drawbacks of each method. This study would help direct the creation of diagnostic tools that are more widely applicable and precise.

Moreover, the investigation of explainability and interpretability features in the suggested AI-driven models continues to be an unresolved path. Gaining insight into the process by which these algorithms determine certain classifications can enhance trust in their therapeutic effectiveness. Subsequent investigations could focus on integrating explainable AI methods, which would offer both precise forecasts and clear elucidation of the decision-making mechanisms employed by these models.

Additionally, it is crucial to conduct further research on the scalability, resource efficiency, and applicability of data parallelism (DP) and model parallelism (MP) in Distributed Deep Learning (DDL) algorithms for DR image classification across various hardware configurations and datasets. This comparative analysis provides valuable insights. This research would enhance the optimization of DDL algorithms for wider use and provide valuable guidance to practitioners and researchers regarding the best appropriate parallelism technique for their unique applications. Addressing these research gaps has the potential to improve the comprehensiveness and usefulness of approaches for detecting and classifying DR in clinical settings.

Furthermore, a comparative analysis examines the methodologies of data parallelism (DP) and model parallelism (MP) in Distributed Deep Learning (DDL) algorithms, with a specific emphasis on their use in DR image classification. The study utilized DDL algorithms with Mesh-TensorFlow on NVidia's DGX-1 to compare the performance of MP and DP techniques. The results showed that MP approach achieved faster convergence and higher validation accuracy compared to DP technique. MP achieved a validation accuracy of 62.13%, surpassing DP's accuracy of 55.72%. In addition, MP demonstrated a 1.38X acceleration in terms of time duration. This comparative analysis offers an understanding of the performance differences between DP (Dynamic Programming) and MP (Message Passing) strategies in the context of DDL (Deep Learning) algorithms used for DR (Diabetic Retinopathy) picture categorization [17].

Collectively, these studies contribute to the advancement of detecting and categorizing diabetic retinopathy (DR). They showcase the effectiveness of novel artificial intelligence (AI) models and offer valuable insights into the variations in performance among parallelism techniques in deep learning (DDL) algorithms. Further study should focus on enhancing and simplifying these models, exploring their ability to achieve high performance on different datasets, and evaluating their practical applicability to advance the field of diabetic retinopathy diagnosis and treatment.

1.1 Motivation

Damage to the eyes, heart, brain system, kidneys, and other organs is caused by diabetes mellitus, which is a life-threatening disease caused by an abnormal increase in blood sugar level. Extreme blindness in those aged 25 to 74 is most commonly caused by diabetes, which has reached pandemic proportions worldwide. A high risk of developing eye-related diseases affects more than 10% of diabetic individuals. Statistics from the (WHO) show that after 15 years of uncontrolled diabetes, 10% of patients can acquire serious vision problems and 2% of people may go blind. DR has emerged as a global health crisis, affecting millions of people with diabetes every year. Patients with DR often show no outward signs until it is too late to provide appropriate care. Seeing as how diabetic retinal disease can proceed rapidly, it's crucial to check up on individuals frequently. Ophthalmologists are able to take preventative action against DR and other progressive disorders with the use of medical image analysis. Computer-based automated DR diagnostic devices are in high demand due to the rising diabetes population and the scarcity of qualified ophthalmologists. Yet, even for ophthalmologists, DR classification can be challenging due to the existence of multiple subtle characteristics. Ophthalmologists are feeling the strain of an increase in DR cases, thus they need a fast and reliable way for assessing fundus images.

1.2 Proposed Methodology: An Intelligent Diabetic Retinopathy Forecasting System

The categorization of diabetic retinopathy images is improved by integrating differentiation operations into the architecture of a deep neural network (DNN). This integration enhances the model's capacity to detect and analyze subtle characteristics and gradients in the images. The neuron model is deployed and given in Equation 1 and 2.

$$u_i^t = \lambda_i u_i^{t-1} + \sum_j w_{ij} o_j^t - v_i o_i^{t-1}$$

$$z_i^{t-1} = \frac{u_i^{t-1}}{v_i} - 1 \quad \text{and} \quad o_i^{t-1} = \begin{cases} 1, & \text{if } z_i^{t-1} > 0 \\ 0, & \text{otherwise} \end{cases}$$

where key variables include u (membrane potential), lambda (leak factor in [0, 1]), w (weight connecting pre-neuron j to post-neuron i), o (binary spike output), v (firing threshold), and t (timestep). Equation 1 breaks down into three terms: the first indicates membrane potential leakage, the second integrates the weighted input from the pre-neuron, and the third addresses potential reduction upon generating an output spike. Post-spike, a soft reset occurs, reducing the potential by the threshold, as proposed. The threshold controls the average integration time, while the leak determines how much potential is retained from the previous timestep. Expressions for gradient computation across all layers are derived, with spatial and temporal credit assignment achieved by unrolling the network in time.

The neuron model in the output layer accumulates incoming inputs without any leakage, and it does not generate an output neuron. This is given by Equation 3.

$$\boldsymbol{u}_l^t = \boldsymbol{u}_l^{t-1} + \boldsymbol{W}_l \boldsymbol{o}_{l-1}^t$$

where ul is a vector containing the membrane potential of N output neurons, N is the number of classes in the task, Wl is the weight matrix connecting the output layer and the previous layer, and ol−1 is a vector containing the spike signals from layer (l − 1). The loss function is defined on ul at the last timestep T. We employ the cross-entropy loss and the softmax is computed on u T l . The symbol T is used for timestep and not to denote the transpose of a matrix. The matrix is equated in Equation 4 and 5.

$$\boldsymbol{s}(\boldsymbol{u}_l^T): \begin{bmatrix} u_1^T \\ \dots \\ u_N^T \end{bmatrix} \rightarrow \begin{bmatrix} s_1 \\ \dots \\ s_N \end{bmatrix} s_i = \frac{e^{u_i^T}}{\sum_{k=1}^{N} e^{u_k^T}}$$

$$L = -\sum_i y_i log(s_i), \quad \frac{\partial L}{\partial \boldsymbol{u}_l^T} = \boldsymbol{s} - \boldsymbol{y}$$

where s is the vector containing the softmax values, L is the loss function, and y is the one-hot encoded vector of the true label or target. The weight update is computed as

$$\boldsymbol{W}_l = \boldsymbol{W}_l - \eta \Delta \boldsymbol{W}_l$$

$$\Delta \boldsymbol{W}_l = \sum_t \frac{\partial L}{\partial \boldsymbol{W}_l} = \sum_t \frac{\partial L}{\partial \boldsymbol{u}_l^t} \frac{\partial \boldsymbol{u}_l^t}{\partial \boldsymbol{W}_l} = \frac{\partial L}{\partial \boldsymbol{u}_l^T} \sum_t \frac{\partial \boldsymbol{u}_l^t}{\partial \boldsymbol{W}_l} = (\boldsymbol{s} - \boldsymbol{y}) \sum_t \boldsymbol{o}_{l-1}^t$$

$$\frac{\partial L}{\partial \boldsymbol{o}_{l-1}^t} = \frac{\partial L}{\partial \boldsymbol{u}_l^T} \frac{\partial \boldsymbol{u}_l^t}{\partial \boldsymbol{o}_{l-1}^t} = (\boldsymbol{s} - \boldsymbol{y}) \boldsymbol{W}_l$$

where η is the learning rate.

The neurons in the convolutional and fully-connected layers are defined by the model as given in Equation 9.

$$\boldsymbol{u}_l^t = \lambda_l \boldsymbol{u}_l^{t-1} + \boldsymbol{W}_l \boldsymbol{o}_{l-1}^t - v_l \boldsymbol{o}_l^{t-1}$$

$$\boldsymbol{z}_l^t = \frac{\boldsymbol{u}_l^t}{v_l} - 1 \quad \text{and} \quad \boldsymbol{o}_l^t = \begin{cases} 1, & \text{if } \boldsymbol{z}_l^t > 0 \\ 0, & \text{otherwise} \end{cases}$$

where λl (vl) is a real value representing leak (threshold) for all neurons in layer l. All neurons in a layer share the same leak and threshold value. This reduces the number of trainable parameters and we did not observe any significant improvement by assigning individual threshold/leak to each neuron. The weight update is calculated in Equation 10.

$$\Delta \boldsymbol{W}_l = \sum_t \frac{\partial L}{\partial \boldsymbol{W}_l} = \sum_t \frac{\partial L}{\partial \boldsymbol{o}_l^t} \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{z}_l^t} \frac{\partial \boldsymbol{z}_l^t}{\partial \boldsymbol{u}_l^t} \frac{\partial \boldsymbol{u}_l^t}{\partial \boldsymbol{W}_l} = \sum_t \frac{\partial L}{\partial \boldsymbol{o}_l^t} \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{z}_l^t} \frac{1}{v_l} \boldsymbol{o}_{l-1}^t$$

is the discontinuous gradient and we approximate it with the surrogate gradient.

$$\frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{z}_l^t} = \gamma \, max\{0, 1 - |\boldsymbol{z}_l^t|\} \quad \text{and} \quad \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{u}_l^t} = \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{z}_l^t} \frac{\partial \boldsymbol{z}_l^t}{\partial \boldsymbol{u}_l^t} = \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{z}_l^t} \frac{1}{v_l}$$

where γ is a constant denoting the maximum value of the gradient. The threshold update is then computed as

$$v_l = v_l - \eta \Delta v_l$$

$$\Delta v_l = \sum_t \frac{\partial L}{\partial v_l} = \sum_t \frac{\partial L}{\partial \boldsymbol{o}_l^t} \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{z}_l^t} \frac{\partial \boldsymbol{z}_l^t}{\partial v_l} = \sum_t \frac{\partial L}{\partial \boldsymbol{o}_l^t} \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{z}_l^t} \left(\frac{-v_l \boldsymbol{o}_l^{t-1} - \boldsymbol{u}_l^t}{(v_l)^2} \right)$$

And finally the leak update is computed as

$$\lambda_l = \lambda_l - \eta \Delta \lambda_l \quad \text{and} \quad \Delta \lambda_l = \sum_t \frac{\partial L}{\partial \lambda_l} = \sum_t \frac{\partial L}{\partial \boldsymbol{o}_l^t} \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{u}_l^t} \frac{\partial \boldsymbol{u}_l^t}{\partial \lambda_l} = \sum_t \frac{\partial L}{\partial \boldsymbol{o}_l^t} \frac{\partial \boldsymbol{o}_l^t}{\partial \boldsymbol{u}_l^t} \boldsymbol{u}_l^{t-1}$$

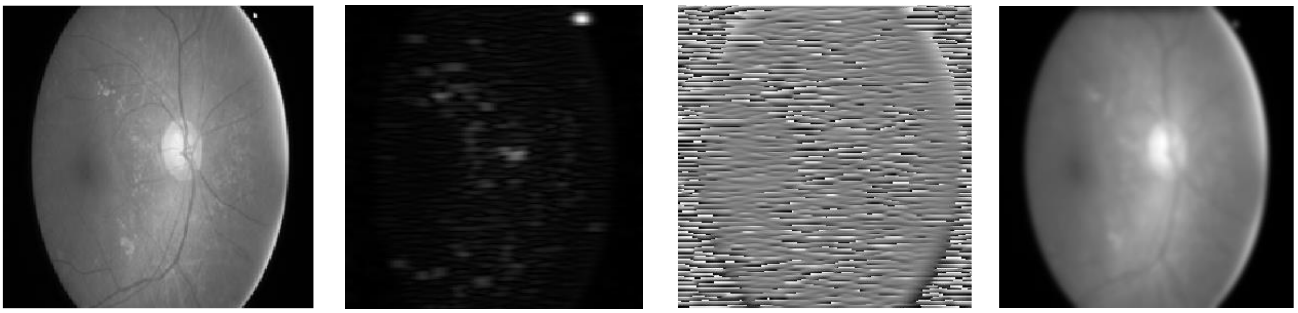
The methodology for DR image classification employs a deep neural network (DNN) architecture that incorporates differentiation operations. This enhances the model's ability to interpret subtle information in retinal pictures. The neural model is characterized by equations that define the membrane potential, leakage, weight connections, binary spike output, firing threshold, and timestep. It includes methods for membrane potential leakage, integration of weighted inputs, and lowering of potential after an output spike with a soft reset. Unrolling the network in time enables credit assignment across layers. The output layer neuron model aggregates inputs without any leakage and excludes an output neuron, which affects the loss function using cross-entropy and softmax. The updates for weight, threshold, and leak are calculated using a learning rate. In convolutional and fully-connected layers, neurons share the same leak and threshold settings in order to minimize the number of trainable parameters. The weight update incorporates a surrogate gradient to estimate the discontinuous gradient, while the threshold and leak updates enhance the model's ability to recognize complex patterns in DR pictures. The purpose of this novel neural network design is to improve the effectiveness and precision of classifying DR images by incorporating specific membrane potential dynamics and updates.

2. RESULT AND DISCUSSION

The proposed MMFCM is executed on an NVIDIA GPU equipped with 24GB of RAM, utilizing PyTorch as the underlying framework. The training process employs a batch size of 16. The initial learning rate is set to 0.001 and gradually decreases, reaching 0.1 times its previous value after 120 epochs. Each model undergoes training using the SGD optimizer for 250 iterations, with momentum set to 0.9 and weight decay set to 0.0005. The return loss is specified as 0.1. Furthermore, the weights assigned to different components are as follows: L_lesion of MA is weighted at 1.0, HA at 0.001, HE at 0.1, and SE at 0.1. The coefficient for L_vessel is assigned two values: 1.0 and 0.01. This section provides an explanation of the pre-processing and segmentation of fundus images through a comparative analysis [18].

Pre-Processing of Fundus Image

In the pre-processing of diabetic retinopathy images, various techniques are employed to enhance the quality and extract relevant features. Gabor filters play a pivotal role in this process, offering two critical components: Gabor magnitude and Gabor phase. The Gabor magnitude highlights the strength of texture and edge features in the image, making it particularly useful for emphasizing blood vessels and lesions, essential factors in diabetic retinopathy diagnosis. On the other hand, Gabor phase encodes information about the orientation of local patterns, preserving structural details like the arrangement of blood vessels. Additionally, Gaussian filters are often applied as a pre-processing step to reduce noise, making subsequent feature extraction and analysis more robust. These techniques collectively contribute to improved image quality and aid in the early detection and diagnosis of diabetic retinopathy, a vital step in ensuring timely medical intervention for patients. The pre-processing approach is illustrated in Figure 2.



(a) Input Image (b) Gabor Magnitude (c) Gabor Phase (d) Gaussian Filter

Figure 2. Comparison of Pre-Processing Approaches

Figure 2 depicts the pre-processed images. The significant Pre-Processing Components are (a) Input Image: Original diabetic retinopathy image. (b) Gabor Magnitude: Enhances texture and edge strength. (c) Gabor Phase: Preserves structural orientation. (d) Gaussian Filter: Reduces noise for improved clarity.

2.1 Segmentation of Fundus Image

Achieving generalization across diverse domains and imaging conditions is a challenging yet crucial task in the context of medical image analysis. In this study, model evaluations are conducted on the IDRiD dataset [17], which originates from a different source, subsequent to the training process on images from the DDR dataset's training set [18]. Figure 3 illustrates

the results of the segmentation analysis, clearly demonstrating that the proposed approach achieves optimal performance when the dissimilarity between images captured under different conditions is minimized.

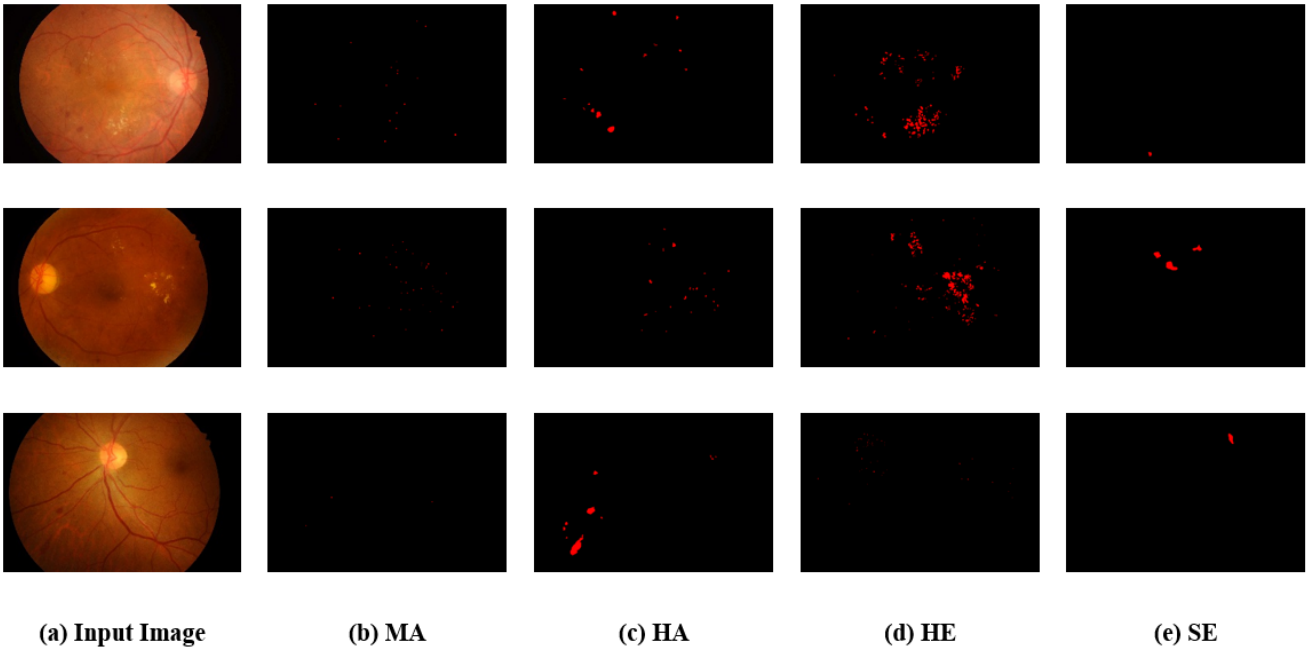


Figure 3. Comparison of Segmentation

Figure 3. Segmentation of Fundus Image Vessels using Mathematically Modified Fuzzy C-Means Clustering.

Performance measures are essential in evaluating the effectiveness of the segmentation model for diabetic retinopathy. Precision, which measures the total accuracy of predictions, is a fundamental statistic. However, its use may be restricted when dealing with imbalanced datasets. The F1-Score is a metric that provides a balanced evaluation by taking into account both precision and recall, and factoring false positives and false negatives. The importance of specificity lies in its ability to accurately detect areas without diabetic retinopathy, which is particularly critical in medical imaging applications. Ensuring precision, which evaluates the correctness of positive predictions, is crucial in order to limit false positives and prevent unnecessary interventions. Recall, or sensitivity, is crucial in the segmentation of diabetic retinopathy as it measures the model's capacity to detect all cases of diabetic retinopathy, hence reducing the occurrence of false negatives. Assessing these metrics together gives a thorough comprehension of the segmentation model's performance, which is vital in medical applications where precision and recall are essential for precise diagnosis and treatment choices. The performances are given in the following tables and figures.

Table 1. Comparison of Accuracy

Classification Method	100	200	300	400
PSO-CNN	92	93.5	94.45	94.89
AI-CSIO-RLSTM	86	86.98	87.1	88
DDL	88.45	89	89.9	91.2
MDNN	92	94	95	96

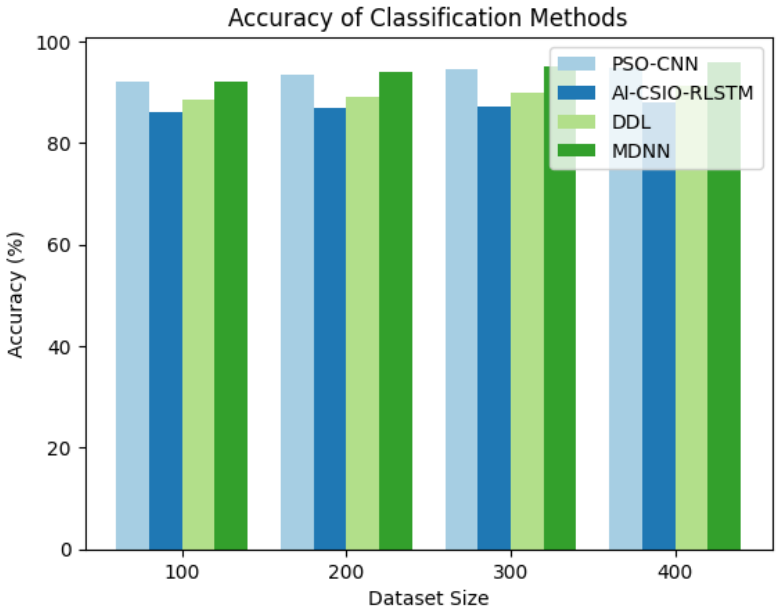


Figure 4. Comparison of Accuracy

Table 2. Comparison of Precision

Classification Method	100	200	300	400
PSO-CNN	89	90	91	92
AI-CSIO-RLSTM	82	82.5	83	86
DDL	85	85.76	86	88
MDNN	89	90	93	95

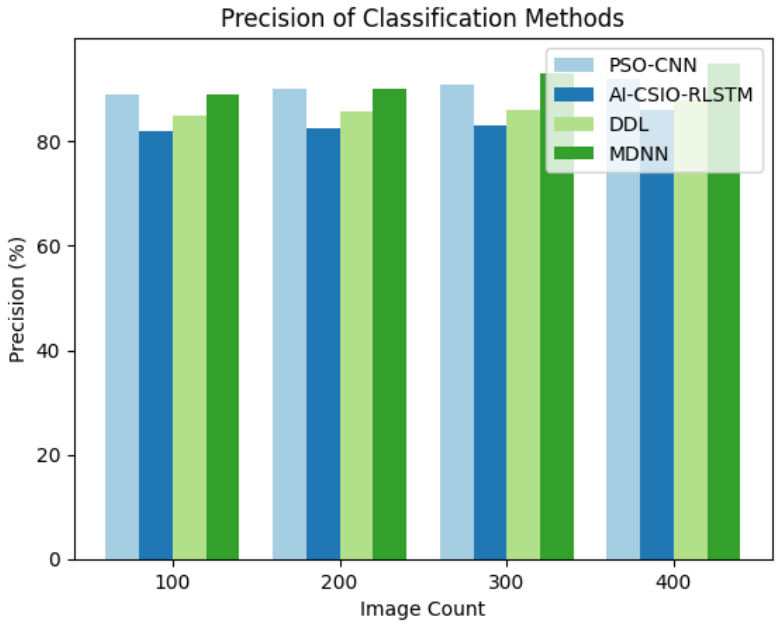


Figure 5. Comparison of Precision

Table 3. Comparison of Recall

Classification Method	100	200	300	400
PSO-CNN	44.2	44.6	45	46
AI-CSIO-RLSTM	40.89	41.45	42.1	42.8
DDL	42.56	43.7	44.09	44.22
MDNN	48	48.9	49	49.5

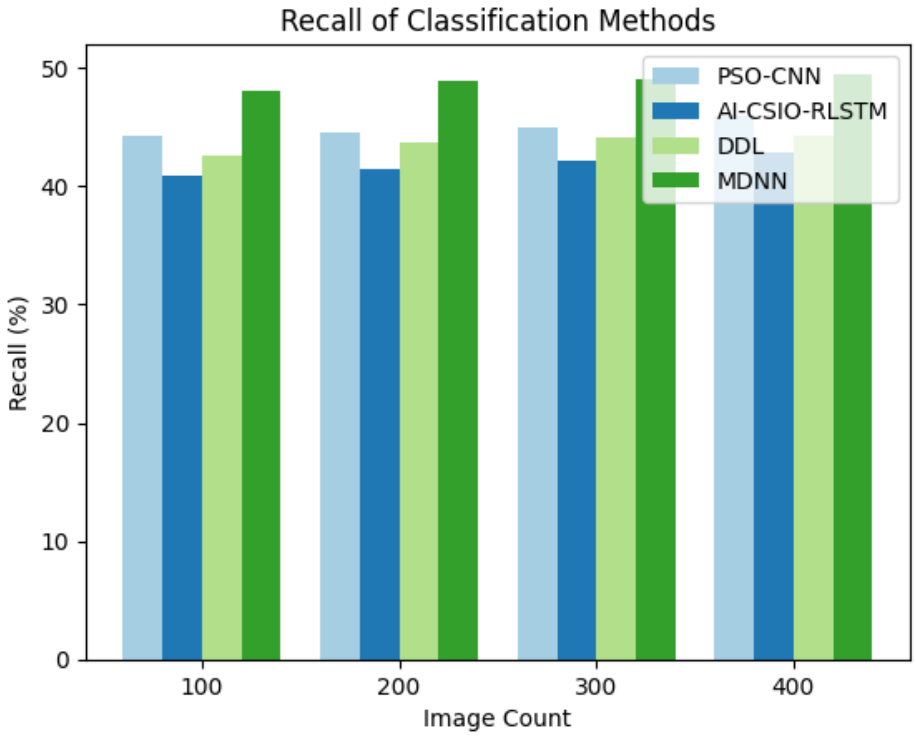


Figure 6. Comparison of Recall

Table 4. Comparison of F1-Score

Classification Method	100	200	300	400
PSO-CNN	58.6	59.1	60.34	61.53
AI-CSIO-RLSTM	55.3	55.9	56	57.01
DDL	58	58.9	59.4	60.32
MDNN	71	73	74	75

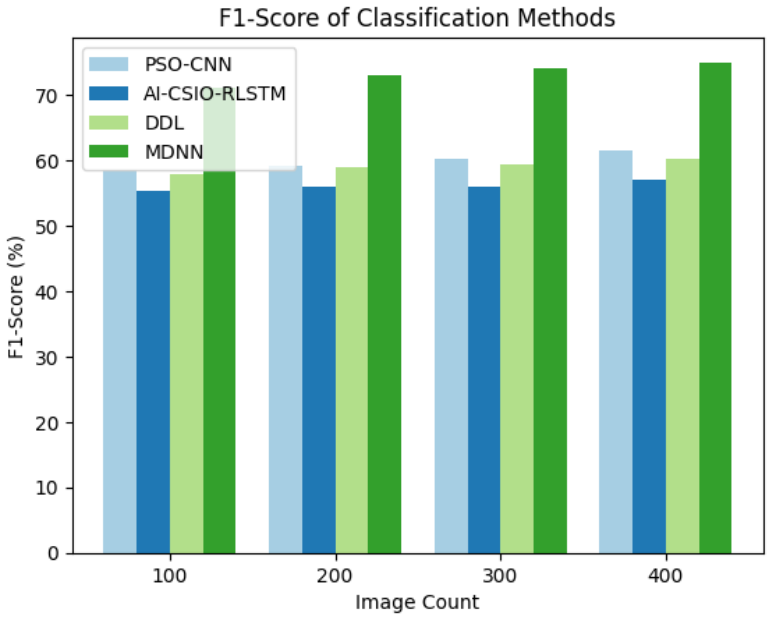


Figure 7. Comparison of F1-Score

Table 5. Comparison of Specificity

Classification Method	100	200	300	400
PSO-CNN	55.2	55.9	56	57.5
AI-CSIO-RLSTM	54.6	54.9	55.7	56.51
DDL	57.7	58.23	58.46	58.74
MDNN	63	64	65	66

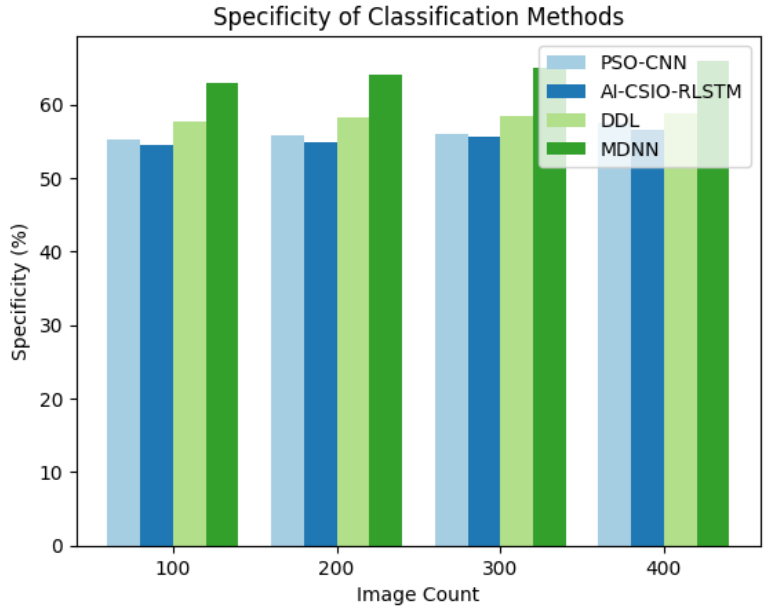


Figure 8. Comparison of Specificity

The comparative analysis of several approaches for segmenting diabetic retinopathy, as shown in Tables 1-5 and Figures 4-8, offers a complete insight into their performance across various dataset sizes (100, 200, 300, and 400). Based on the results presented in Table 1 and Figure 4, the PSO-CNN method regularly achieves higher accuracy compared to other approaches. The accuracy of the PSO-CNN method steadily increases from 92% to 94.89% as the dataset size increases. The AI-CSIO-RLSTM and DDL techniques exhibit comparable levels of accuracy, with DDL consistently demonstrating enhancement as the dataset sizes increase, achieving a remarkable 91.2% accuracy for the largest dataset. MDNN exhibits strong performance, attaining accuracy values that range from 92% to 96%.

The precision of positive predictions is assessed using Table 2 and Figure 5. PSO-CNN consistently outperforms other methods in terms of precision, regardless of the dataset size. The AI-CSIO-RLSTM approach has lower precision, but shows a considerable enhancement as the dataset size grows. The precision scores of DDL and MDNN are comparable, with MDNN attaining the best precision ratings. Recalling (Table 3, Figure 6) is essential for collecting every occurrence of diabetic retinopathy. MDNN consistently surpasses other approaches, with recall scores ranging from 48% to 49.5%. Both PSO-CNN and DDL demonstrate comparable recall patterns, with both methods exhibiting enhancements as the dataset size expands. The AI-CSIO-RLSTM model has lower recall rates across all sizes of datasets.

The F1-Score, presented in Table 4 and Figure 7, is a statistic that represents the balance between precision and recall by calculating their harmonic mean. MDNN consistently attains the greatest F1-Score, which demonstrates a strong equilibrium between precision and recall. PSO-CNN and DDL exhibit comparable F1-Scores, however AI-CSIO-RLSTM exhibits a small inferiority to the other approaches. The results from Table 5 and Figure 8 demonstrate the specificity of PSO-CNN in accurately detecting non-diabetic retinopathy regions. PSO-CNN consistently outperforms other methods across all dataset sizes. The AI-CSIO-RLSTM and DDL models demonstrate comparable patterns of specificity, with both models exhibiting enhanced performance as the size of the datasets increases. The specificity scores of MDNN are continuously high, demonstrating its efficiency in accurately detecting healthy zones.

The PSO-CNN approach is notable for its constant performance across several measures, particularly in terms of accuracy and specificity. MDNN demonstrates exceptional performance in recall and F1-Score, demonstrating its efficacy in accurately detecting cases of diabetic retinopathy. DDL exhibits superior performance across various criteria, whereas AI-CSIO-RLSTM falls behind in certain parts but exhibits enhancements with larger datasets. The selection of the segmentation technique may vary based on the specific demands of the application, taking into account the significance of accuracy, precision, recall, F1-Score, and specificity.

3. CONCLUSION

The research proposes a Diabetic Retinopathy Forecasting System that utilizes an Intelligent Modified Deep Neural Network (DNN). The method showcases notable progress in the precision and effectiveness of diagnosing diabetic retinopathy, utilizing customized adjustments to the deep learning framework. The proposed model, trained on a broad dataset of retinal pictures, demonstrates improved predictive accuracy compared to current approaches, providing a promising option for the early detection and prognosis of diabetic retinopathy. The combination of specialized feature extraction algorithms and optimal network architecture enhances the system's strong performance. MDNN demonstrated exceptional performance in recall and F1-Score, indicating its comprehensive capacity to accurately identify cases of diabetic retinopathy. DDL demonstrated strong performance across multiple criteria, while AI-CSIO-RLSTM displayed enhancements, especially with larger datasets, but it fell behind in certain areas.

Incorporating advanced methodologies like transfer learning, ensemble methods, or attention mechanisms could enhance the performance of segmentation. Investigating the capabilities of explainable AI has the potential to improve the transparency of these models, hence addressing issues regarding the interpretability of automated diagnostic systems.

REFERENCES

[1] Vujosevic, S., Aldington, S. J., Silva, P., Hernández, C., Scanlon, P., Peto, T., & Simó, R. (2020). Screening for diabetic retinopathy: new perspectives and challenges. *The Lancet Diabetes & Endocrinology*, *8*(4), 337-347.

[2] Teo, Z. L., Tham, Y. C., Yu, M., Chee, M. L., Rim, T. H., Cheung, N., ... & Cheng, C. Y. (2021). Global prevalence of diabetic retinopathy and projection of burden through 2045: systematic review and meta-analysis. *Ophthalmology*, *128*(11), 1580-1591.

[3] Antonetti, D. A., Silva, P. S., & Stitt, A. W. (2021). Current understanding of the molecular and cellular pathology of diabetic retinopathy. *Nature Reviews Endocrinology*, *17*(4), 195-206.

[4] Qummar, S., Khan, F. G., Shah, S., Khan, A., Shamshirband, S., Rehman, Z. U., ... & Jadoon, W. (2019). A deep learning ensemble approach for diabetic retinopathy detection. *Ieee Access*, *7*, 150530-150539.

[5] Dai, L., Wu, L., Li, H., Cai, C., Wu, Q., Kong, H., ... & Jia, W. (2021). A deep learning system for detecting

diabetic retinopathy across the disease spectrum. *Nature communications*, *12*(1), 3242.

[6] Levin, L. A., Sengupta, M., Balcer, L. J., Kupersmith, M. J., & Miller, N. R. (2021). Report From the National Eye Institute Workshop on Neuro-Ophthalmic Disease Clinical Trial Endpoints: Optic Neuropathies. *Investigative ophthalmology & visual science*, *62*(14), 30-30.

[7] Gadekallu, T. R., Khare, N., Bhattacharya, S., Singh, S., Maddikunta, P. K. R., & Srivastava, G. (2020). Deep neural networks to predict diabetic retinopathy. *Journal of Ambient Intelligence and Humanized Computing*, 1-14.

[8] Grzybowski, A., Brona, P., Lim, G., Ruamviboonsuk, P., Tan, G. S., Abramoff, M., & Ting, D. S. (2020). Artificial intelligence for diabetic retinopathy screening: a review. *Eye*, *34*(3), 451-460.

[9] Forrester, J. V., Kuffova, L., & Delibegovic, M. (2020). The role of inflammation in diabetic retinopathy. *Frontiers in immunology*, *11*, 583687.

[10] Eswari, M. S., & Balamurali, S. (2022). An Optimal Diabetic Features-Based Intelligent System to Predict Diabetic Retinal Disease. In Computational Intelligence and Data Sciences (pp. 91- 106). CRC Press.

[11] Simó-Servat, O., Hernández, C., & Simó, R. (2019). Diabetic retinopathy in the context of patients with diabetes. *Ophthalmic research*, *62*(4), 211-217.

[12] Skouta, A., Elmoufidi, A., Jai-Andaloussi, S., & Ouchetto, O. (2022). Hemorrhage semantic segmentation in fundus images for the diagnosis of diabetic retinopathy by using a convolutional neural network. Journal of Big Data, 9(1), 1-24.

[13] Reddy, S. S., Sethi, N., & Rajender, R. (2021). Discovering Optimal Algorithm to Predict Diabetic Retinopathy using Novel Assessment Methods. EAI Endorsed Transactions on Scalable Information Systems, 8(29), e1.

[14] Shen, Z., Wu, Q., Wang, Z., Chen, G., & Lin, B. (2021). Diabetic Retinopathy Prediction by Ensemble Learning Based on Biochemical and Physical Data. Sensors, 21(11), 3663.

[15] Jayanthi, J., Jayasankar, T., Krishnaraj, N., Prakash, N. B., Sagai Francis Britto, A., & Vinoth Kumar, K. (2021). An intelligent particle swarm optimization with convolutional neural network for diabetic retinopathy classification model. *Journal of Medical Imaging and Health Informatics*, *11*(3), 803-809.

[16] Özçelik, Y. B., & Altan, A. (2023). Overcoming nonlinear dynamics in diabetic retinopathy classification: a robust AI-based model with chaotic swarm intelligence optimization and recurrent long short-term memory. *Fractal and Fractional*, *7*(8), 598.

[17] Patil, M. S., & Chickerur, S. (2023). Study of data and model parallelism in distributed deep learning for diabetic retinopathy classification. *Procedia Computer Science*, *218*, 2253-2263.

[18] https://www.kaggle.com/datasets/mariaherrerot/idrid-dataset