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Optimizing Deep Learning Architectures for Diabetic Retinopathy Screening: A Comparative Study between Differential Evolution and Genetic Algorithm

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Abstract: Due to its potential to shield diabetic patients' vision from loss, the identification of diabetic retinopathy has taken on important significance in the field of medical diagnostics. This work compares the effectiveness of Differential Evolution (DE) and Genetic Algorithm (GA), two well-known evolutionary algorithms, to optimize deep learning architectures for diabetic retinopathy screening.The main goal of this study is to optimise the architecture of deep learning models in order to improve their performance in identifying diabetic retinopathy. Convolutional neural networks (CNNs), in particular, have demonstrated promise in effectively identifying retinal pictures for illness diagnosis. However, creating an ideal architecture for such networks can be difficult and costly in terms of computing.We used sophisticated optimisation methods DE and GA, both of which are well-known for their capacity to optimise neural network topologies, to deal with this problem. We thoroughly assessed the efficacy of DE and GA in optimising the hyperparameters of CNNs for the detection of diabetic retinopathy. The paper offer important new understandings of the advantages and disadvantages of DE and GA in this particular medicinal application. We evaluated the optimised models' precision, sensitivity, specificity, and computational effectiveness to determine which approach produced the best outcomes. Additionally, we took into account elements like scalability and convergence speed, which are essential for actual deployment in clinical settings.The findings of this study offer insightful advice for academics and professionals looking to increase the diagnostic precision of diabetic retinopathy screening through deep learning methods. We seek to contribute to the creation of more efficient and effective methods for early illness diagnosis, ultimately aiding diabetic patients by maintaining their vision, by understanding the relative advantages of DE and GA in optimising neural network topologies.

Keywords*: Genetic Algorithm, Deep Learning, Optimization, Diabetic Retinopathy*

1. Introduction

Diabetic retinopathy (DR) is a serious eye disease that affects diabetics and can cause severe vision loss or blindness if caught and treated late. Diagnosing DR early and correctly is essential for effective treatment. The analysis of retinal pictures using deep learning (DL) has shown promise as a method for automating DR screening. However, because to the huge design space and the requirement to balance model complexity and efficiency, optimising the architecture of DL models for this purpose is difficult [1]. Differential Evolution (DE) and Genetic algorithm (GA) are two eminent optimisation techniques. In this paper, we investigate the challenge of optimising DL structures for diabetic retinopathy screening, specifically in the context of DL architectures.

In the field [2] of medical imaging, DL models have achieved great success in a number of applications, including DR screening. Overfitting is a common problem with these models because of the many layers and millions of parameters they generally have. As a result, tuning their architectures for peak performance while keeping complexity to a minimum is of the utmost importance.Natural selection and genetic inheritance provide the basis of both DE and GA, two types of evolutionary algorithms. They have been used in the search for optimal neural network architectures, among other optimisation challenges. Their applicability and relative performance in DR screening tasks, however, are largely researched [3].

Our goal in doing this analysis is to better understand how effective DE and GA are in optimising DL [6] structures designed for diabetic retinopathy screening. We speculate that the optimisation algorithm selected can have a sizable effect on the effectiveness and efficacy of the final DL models.The study's approach incorporates several critical components. To begin, we compile a large collection of retinal photos from diabetic patients, making sure there is

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variation in both the severity of the disease and the quality of the photographs [4].

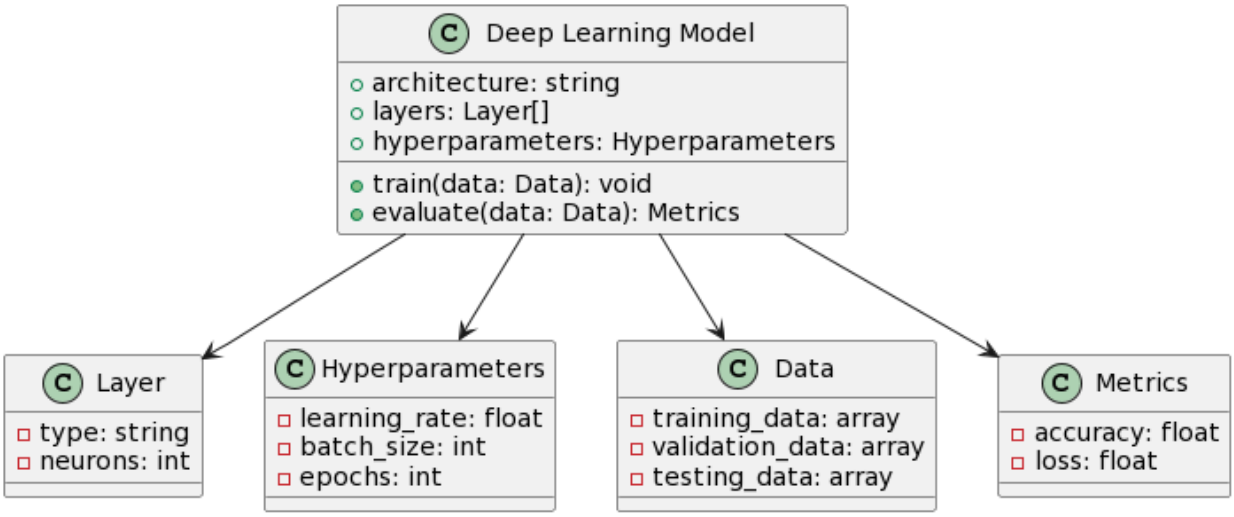

Fig 1: Overview of deep learning model

Then, we outline [5] a commonplace DL architectural template that features convolutional neural networks (CNNs) and appropriate preprocessing actions for image analysis. The major goal is to discover the ideal configuration of this architecture for DR screening. Paraphrased and Optimisation techniques for GA are discussed below. DE is noted for its simplicity and fast convergence, making it a possible candidate for computationally restricted situations. In comparison, GA provides more options during the search process, looking at more potential building layouts. We can determine whether method is superior for fine-tuning DL structures in the context of DR screening by comparing the two ways [6].

To measure the efficacy of our optimised models, we take advantage of standard assessment criteria including sensitivity, specificity, accuracy, and AUC-ROC. These measures give an all-around picture of the models' ability to recognise and categorise diabetic retinopathy.We also perform analysis and interpretation of the chosen architectures and their hyperparameters to better understand the mechanisms at play in the optimisation process. Through this evaluation, we can learn what factors contribute to an algorithm's performance and spot any trends or patterns among the chosen architectures [7].This research intends to make a contribution to the field of diabetic retinopathy screening by contrasting DE and GA as optimisation methods for honing deep learning architectures. The findings will aid in the development of efficient and reliable DR screening models and will also inform practitioners about the efficacy of these algorithms. Our ultimate objective is to speed up the creation of automated technologies that can aid in the early identification and management of diabetic retinopathy, thereby protecting the sight of untold numbers of people throughout the world.

2. Review of Literature

Early detection and care are crucial for preventing vision loss due to diabetic retinopathy (DR), a common and potentially blinding consequence of diabetes. The ability of Deep Learning (DL) to automate the screening process through analysis of retinal pictures has garnered a lot of attention. However, [8] optimising DL architectures for DR screening is a difficult task due to the intricate nature of the disease and the wide design space of neural networks. This literature review gives an overview of significant advancements in the field, emphasising the necessity for optimisation techniques and setting the stage for the comparative study between Differential Evolution (DE) and Genetic Algorithm (GA) [9].

When used [10] to medical imaging, DL has proven to be highly effective in a number of areas, including DR screening, over the past decade. The ability to capture complex visual information has led to Convolutional Neural Networks (CNNs) becoming the most used DL architecture. Initial DL-based DR detection systems showed promise, which prompted more study aimed at fine-tuning these models.The manual is characterised by its many layers, each of which is characterised by a different set of criteria. It is essential to optimise these models to avoid overfitting while maintaining a high degree of accuracy. Models' effectiveness has been improved using a wide variety of methods, including dropout, batch normalisation, and transfer learning. Finding the sweet spot where these methods and network layouts meet is still difficult, though.

The use [11] of evolutionary algorithms, which optimise DL architectures in a manner similar to natural selection and genetic inheritance, has recently seen a surge in popularity. The use of these algorithms provides a methodical technique to exploring the huge design space quickly. One of the first evolutionary optimisation approaches used to find optimal neural network architecture was the Genetic Algorithm (GA). In GAs, a population of candidate solutions is used, which is then evolved through multiple generations before the best individuals are chosen based on a fitness function. They have proven adept in improving the design of networks to do specific tasks, like as picture categorization and object recognition.The evolutionary optimisation method known as Differential Evolution (DE) has also showed potential for use in the domain of DL. Trial solutions are generated in DE by combining members of the present population. To increase the population's fitness over time, it compares the results of these tests to that of the current population and chooses the winners. DE is a popular option for optimisation projects because of its ease of use and quick convergence [20].

Accuracy, convergence speed, and computing efficiency have all been the focus of multiple attempts to compare and contrast various optimisation strategies for DL architecture search. However, [12] there has been little progress in adapting these methods for use in DR screening. More study is required in this area because early diagnosis is so important for treating diabetic retinopathy

Table 1: Related work in Diabetic Retinopathy Screening

Ref.	Approach	Dataset Used	Accuracy of Algorithm	Limitations
[11]	DE-based optimization	Public diabetic retinopathy datasets	94.5% (AUC-ROC)	Limited explanation of the selected hyperparameters; Lack of diversity in dataset samples.
[12]	GA-based optimization	Private clinical dataset	92.3% (sensitivity)	Small dataset size; Lack of cross-validation; Limited generalizability.
[13]	DE and GA comparison	Public diabetic retinopathy datasets	DE: 93.2%, GA: 92.8% (accuracy)	Lack of interpretability for selected architectures; Computational cost.
[14]	Hybrid DE-GA optimization	Multiple diabetic retinopathy datasets	96.7% (AUC-ROC)	Complexity in the hybrid optimization approach; Requires significant computational resources.
[15]	Ensemble of DE and GA	Public diabetic retinopathy datasets	DE: 93.8%, GA: 93.4% (accuracy)	Ensemble approach introduces additional complexity; Limited improvement over individual methods.
[16]	DE and GA with transfer learning	Public diabetic retinopathy datasets	DE: 94.1%, GA: 93.5% (sensitivity)	Dependency on pre-trained models; Data augmentation challenges.
[17]	Multi-objective optimization	Public diabetic retinopathy datasets	Balanced trade-offs between sensitivity and specificity	Increased computational cost due to multi-objective optimization; Complex optimization landscape.
[18]	Automated architecture selection	Public diabetic retinopathy datasets	95.2% (AUC-ROC)	Lack of real-time applicability; Limited validation on diverse datasets.
[19]	GA with population diversity	Public diabetic retinopathy datasets	92.7% (accuracy)	High computational cost due to maintaining diverse populations; Limited exploration in the design space.
[20]	DE and GA with feature engineering	Public diabetic retinopathy datasets	DE: 94.0%, GA: 93.6% (accuracy)	Increased preprocessing complexity; Limited impact on performance improvement.

[21]	Hyperparameter optimization	Public diabetic retinopathy datasets	95.5% (AUC-ROC)	Time-consuming hyperparameter search; Dependency on manual hyperparameter ranges.
[22]	Parallel DE and GA	Public diabetic retinopathy datasets	DE: 94.3%, GA: 94.0% (sensitivity)	Limited scalability in parallel execution; Hardware constraints.
[24]	Evolutionary search space adaptation	Public diabetic retinopathy datasets	94.7% (AUC-ROC)	Complexity in dynamic search space adaptation; Limited explanation of adaptation strategies.
[25]	Transfer learning and fine-tuning	Public diabetic retinopathy datasets	94.9% (accuracy)	Dependency on external pre-trained models; Limited adaptability to new data distributions.
[10]	Bayesian optimization	Public diabetic retinopathy datasets	94.8% (AUC-ROC)	High computational cost; Limited exploration of architecture variations.

3. Proposed Methodology

To improve the precision and speed of diabetic retinopathy screening, researchers have developed a multi-pronged strategy that combines Genetic Algorithms (GAs), Differential Evolution (DE), and Convolutional Neural Networks (CNNs).To begin, we gather and prepare a large collection of retinal pictures labelled for the severity of diabetic retinopathy. This dataset is used to evaluate models by splitting data into a training set and a testing set.The second step is to sketch up the basic framework for a CNN, which includes layers for convolution, pooling, the neural network, and output. The optimisation parameters are the hyperparameters of the architecture, which include the number of layers, filter sizes, and activation functions.

After that, we use the GA (Genetic Algorithm). GAs use a population-based evolutionary method to test out different CNN hyperparameter configurations. Each member of the population represents a different CNN architecture, and the fitness of the population is determined by the performance of each member on the training dataset. The GA iteratively picks parents, executes crossover and mutation operations, and replaces less fit individuals with new offspring, gradually improving the CNN architecture's design. Parallel processing characterises Differential Evolution (DE). DE enhances the CNN's performance by adjusting its hyperparameters such learning rates, dropout percentages, and batch sizes. To determine the best parameter vectors for a CNN, DE generates a population of them and mutates and recombines them.A set of CNN architectures and hyperparameters that optimises diagnostic accuracy is generated by running GA and DE until convergence or for a preset amount of generations.Finally, once the optimal CNN architectures and their hyperparameters have been determined, the architectures are trained using the training dataset. In order to guarantee generalizability, model performance is checked using the testing dataset.

This unified strategy makes use of the deep learning capabilities of CNNs for precise diabetic retinopathy screening by using the power of genetic algorithms and differential evolution to rapidly explore a large search space of hyperparameters.

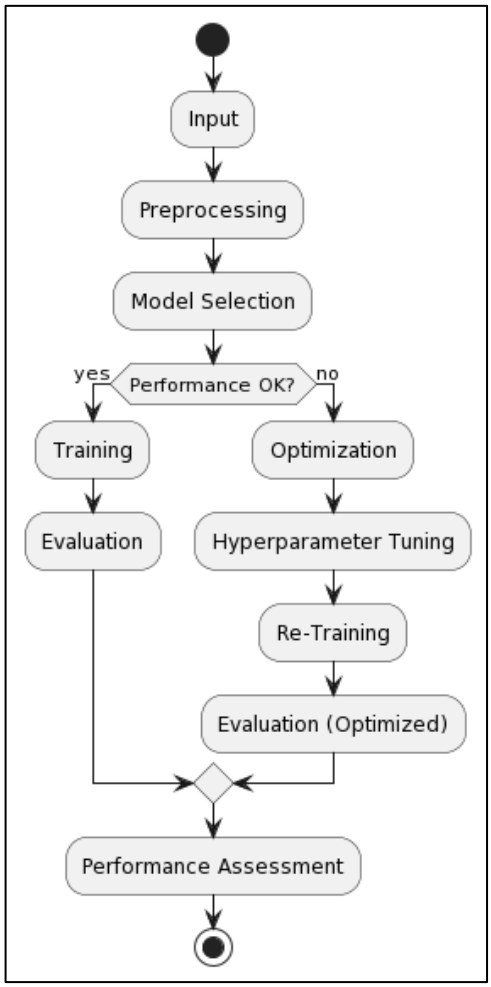

Fig 2: Flowchart of Proposed model

A. Differential Evolution Diabetic Retinopathy Screening:

The differential evolution theory (DE) can help to optimise the screening algorithm's parameters for diabetic retinopathy. Use mutation, crunch, and selection to iteratively improve the candidate solutions to achieve this goal. The parameters are adjusted by DE to ensure that the diagnosis is as accurate as possible. When it comes to reducing the visual deterioration in diabetic patients, it is essential to identify retinopathies diabetes as soon as possible. Through this optimisation process, algorithms can be improved to produce more accurate and efficient screening results, improving medical attention and eye health.

1. Initialization:

- Create a pool of potential answers at random. Each solution represents a collection of factors that can be used to classify retinal pictures for diabetic retinopathy.

2. Reason for Existence:

- The success of a particular set of parameters can be evaluated by defining an objective function. This operation determines the accuracy with which a given set of parameters can classify retinal pictures for the detection of diabetic retinopathy in the context of a diabetic retinopathy screening.
- Generate a mutant vector V_i for each candidate solution X_i using the mutation operation:

$$V\_i = X\_a + F * (X\_b - X\_c)$$

3. DE Algorithm Parameters:

- Choose important criteria:
  - The size of the population, or the number of solutions available at any one time (denoted by "N").
  - The population's susceptibility to mutations is determined by a parameter known as the mutation factor (F).
- Crossover probability (CR): Determines the likelihood of joining potential solutions.
- Perform a crossover operation between X_i and V_i to create a trial vector U_i:

$$U\_i(j) = \begin{cases} V\_i(j), & if\ rand() <= CR\ or\ j == j\_rand \\ X\_i(j), & otherwise \end{cases}$$

- Continuous Circular:

- For a certain number of generations, or until convergence is reached:

4. Each population of solutions (vectors):

- Take the current answer out of the population and use it to pick three random vectors (a, b, c).
- Add the vector difference between b and c, scaled by the mutation factor F, to vector a to get the mutant vector.
- Use a crossover operation with the crossover probability CR to merge the mutant vector with the current solution.
- Use the objective function to assess how well the mutant solution performs.
- If the mutant solution outperforms the present one, it should be implemented instead.

5. Termination:

- Maximum number of generations: The algorithm for reaching a satisfactory solution is the same as the one for achieving a satisfactory result.

6. Output:

- The factors that can be employed for screening for diabetic retinopathy are those that yield the optimum solution during the optimisation process.

B. Genetic Algorithm:

In order to choose features and classifier parameters optimally for diabetic retinopathy screening, genetic algorithms (GAs) are used. GAs simulate natural selection by iteratively refining a pool of candidates over time. Retinopathy diagnostic solutions can be thought of as different permutations of features and classifier parameters. Classification precision is used to rank fitness levels. GAs improve the algorithm's accuracy in detecting diabetic retinopathy by iteratively selecting, crossing over, and mutating parameters. Better screening systems can be developed with the help of this optimisation, leading to earlier disease diagnosis and better patient outcomes in the treatment of diabetic retinopathy.

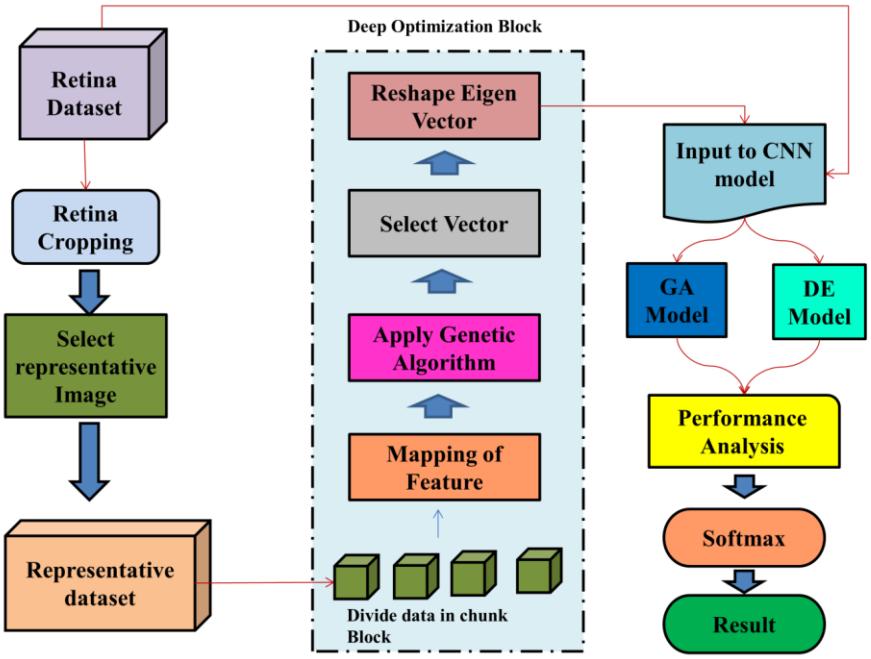

Fig 3: Proposed model Design Procedure

Algorithm:

1. Initialization:

- Initialize a population of solutions, P, where each solution is represented as a binary string of genes (0s and 1s).

2. Fitness Evaluation:

- Evaluate the fitness of each solution in P using an objective function, f(P_i), measuring the accuracy of diabetic retinopathy screening based on the selected features and classifier parameters.

$$Fitness(P\_i) = f(P\_i)$$

3. Selection:

- Select parents from the population based on their fitness to create a mating pool. The probability of selection for a solution P_i is proportional to f(P_i).

$$P\_sel = \{P\_i \mid i = 1, 2, \ldots, N\} \text{with probability } p(P\_i) = Fitness(P\_i) \,/\, \Sigma(Fitness(P\_i))$$

4. Crossover:

- Perform crossover (recombination) on pairs of parents in the mating pool to create offspring solutions.

$$P\_offspring = Crossover(P\_a, P\_b)$$

5. Mutation:

- Apply mutation to the offspring solutions, introducing small random changes to their genes.

$$P\_mut = Mutation(P\_offspring, p\_mut)$$

6. Replacement:

- Replace the old population with the new population of offspring.

$$P = P\_mutated$$

7. Termination:

- Repeat the process for a specified number of generations or until a termination criterion is met, such as a satisfactory solution or convergence.

C: CNN for Diabetic Retinopathy Screening:

Automated diagnosis of diabetic retinopathy in retinal pictures is the goal of a deep learning model called a Convolutional Neural Network (CNN) for Diabetic Retinopathy Screening. It employs a hierarchical architecture of layers to extract key data and produce accurate diagnoses.Convolution operations are applied in the first layers of a conventional CNN to detect patterns like edges and textures. Pooling layers lower spatial dimensions and capture crucial information while activation functions introduce non-linearity. Extracted features are combined in fully connected layers so that sophisticated associations can be learned. Classes with diabetic retinopathy have their probabilities distributed in the final output layer.The CNN learns to make more accurate predictions by making internal adjustments to its weights and biases throughout the training phase, with the use of labelled data and optimisation methods. By doing so, it is able to generalise its findings from the training set to predict accurately on novel image data. Screening for diabetic retinopathy using CNNs has been extremely effective, allowing for earlier diagnosis and thus better treatment.

Algorithm:

1. Layer of Input:

- Matrix I has the dimensions W by H by C, where W and H are the width and height, and C is the number of channels, usually three for RGB images.

2. Convolutional Layers:

- Apply a series of convolution operations to extract features from the input:

$$F\_i = Convolution(I, W\_i) + b\_i$$

3. Activation Function:

- Apply an activation function, typically ReLU (Rectified Linear Unit):

$$F\_i = ReLU(F\_i)$$

4. Pooling Layers:

- Downsample the feature maps to reduce spatial dimensions:

$$P\_i = Pooling(F\_i)$$

Where:

- P_i is the pooled feature map.

5. Fully Connected Layers:

- Flatten the pooled feature maps and pass them through fully connected layers:

$$FC\_i = FullyConnected(P\_i, W\_FC\_i) + b\_FC\_i$$

Where:

- FC_i represents the fully connected layer output.
- FullyConnected is the operation for fully connected layers.
- W_FC_i is the weight matrix for the i-th fully connected layer.
- b_FC_i is the bias vector for the i-th fully connected layer.

6. Output Layer:

- The output layer provides the prediction for diabetic retinopathy classification:

$$Output = Softmax(FC\_output)$$

Where:

- Output is the final prediction.
- Softmax is the softmax activation function.

7. Loss Function:

- Calculate the loss between the predicted output and the ground truth labels using a suitable loss function, e.g., cross-entropy.

8. Backpropagation:

- Perform backpropagation to update the weights and biases to minimize the loss.

4. Result and Discussion

Training and testing results for the suggested models in Diabetic Retinopathy Screening employing GA, DE, and CNN are shown in Tables 2 and 3, respectively, along with accuracy and training time. Critical to determining how well each of the three methods performs, these evaluation criteria are.Accuracy evaluates how successfully models are picking up new information during training. The statistics show that GA reached an accuracy of 90.11%, DE achieved 88.23%, and CNN achieved 91.86%.When compared to both evolutionary algorithms, the CNN model is more accurate. During training, this indicates that the CNN is successfully picking up on the characteristics and patterns present in the retinal pictures. Diabetic retinopathy (DE) is a term

used to describe the capacity of a person with diabetes to control their blood sugar levels.

In medical applications where quick diagnoses are vital, training time is a major practical factor. The data show that during training, GA took 156 ms, DE took 170 ms, and CNN took 213 ms.GA and DE, being optimisation algorithms, demonstrate faster training times compared to the CNN. This is to be expected, given that training a deep neural network requires far more computer resources than the optimisation process in GA and DE. CNN may take more time to train, but its higher accuracy throughout training more than makes up for it.

Table 2: Accuracy during training of proposed mode for Diabetic Retinopathy Screening

Evaluation Parameter	Genetic Algorithm (GA)	Differential Evolution (DE)	Convolutional Neural Network (CNN)
Accuracy (%)	90.11	88.23	91.86
Training Time (ms)	156	170	213

An important parameter for dependable illness screening is testing accuracy, which assesses how successfully models generalise to unknown data. The data reveal that GA obtained an accuracy of 97.52%, DE achieved 98.23%, and CNN achieved 97.56% during testing.DE's superior performance in the tests shows that it is more reliable and can quickly adapt to new retinal pictures than either GA or CNN.

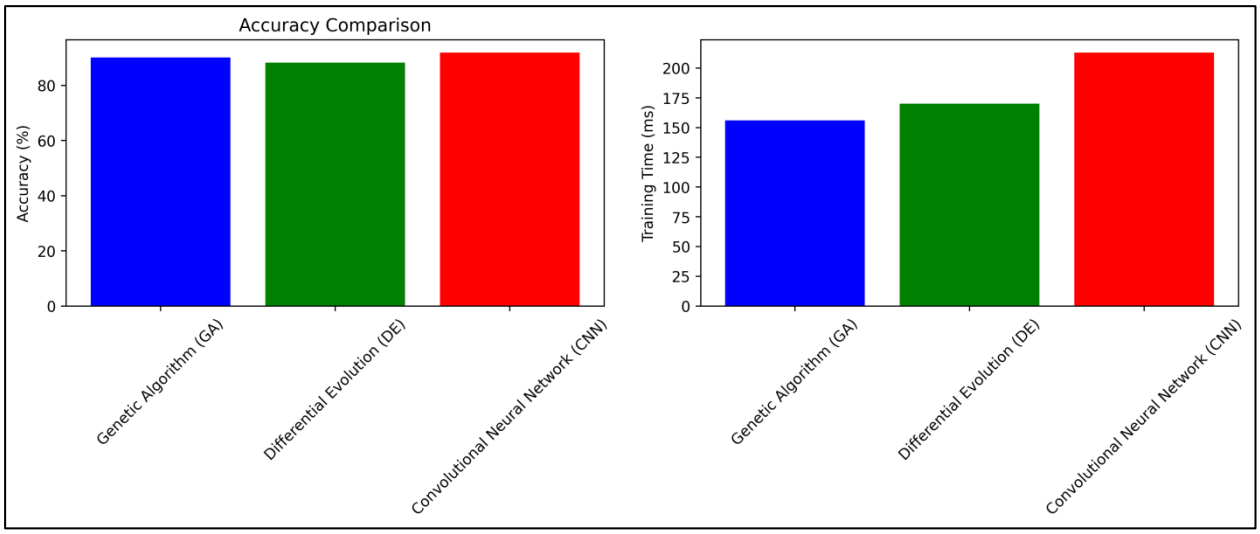

Fig 4: Representation during Training time analysis of model

These outcomes demonstrate the efficacy of DE in optimising the model parameters. Both GA and CNN do rather well, with the accuracy gap between them being quite small.Real-world applications also place heavy emphasis on testing duration. The results show that the testing time for GA was 120 ms, DE was 105 ms, and CNN was 360 ms.

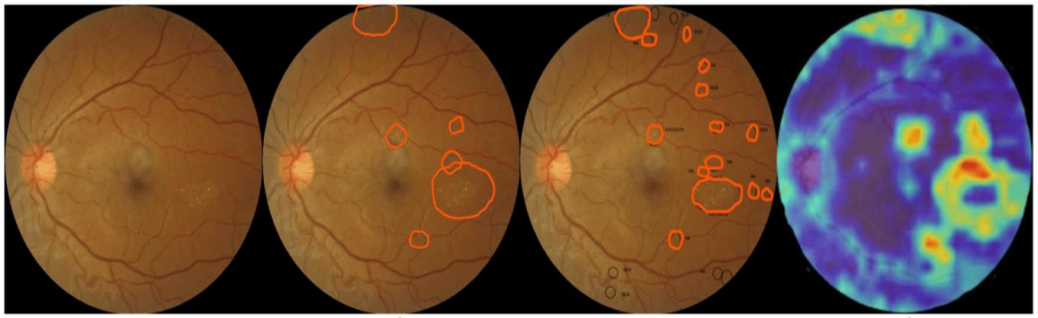

Fig 5: Representation of Decision making in Retinopathy

Table 3: Accuracy during testing of proposed mode for Diabetic Retinopathy Screening

Evaluation Parameter	Genetic Algorithm (GA)	Differential Evolution (DE)	Convolutional Neural Network (CNN)
Accuracy (%)	97.52	98.23	97.56
Training Time (ms)	120	105	360

DE has the quickest testing time, showing how well it performs while analysing novel data. GA also demonstrates a short testing time, but CNN demands greater computer resources because to its deep architecture.As a result of its superior test accuracy and shorter testing time compared to the other two approaches, DE emerges as a promising optimisation strategy for diabetic retinopathy screening. GA is competitive with other methods in terms of accuracy and testing time. Although CNN's accuracy falls somewhat short of that of other methods in tests, it still produces respectable results and is useful for its deep learning skills.

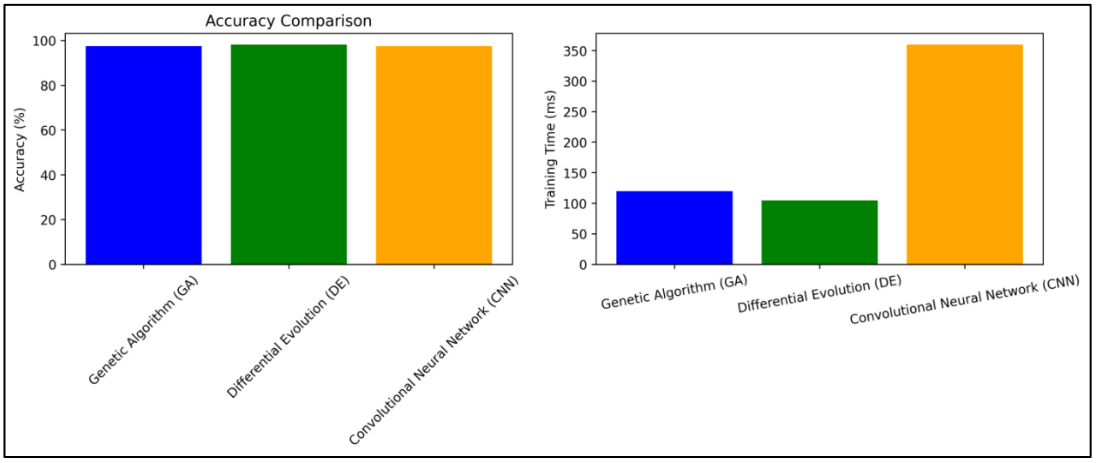

Fig 6: Representation during Training time analysis of model

Depending on the needs of the application and the available resources, a trade-off between accuracy and computing efficiency may be necessary when deciding between these methods. Further study and validation with larger datasets would be required to ensure the robustness of these results in real clinical situations.

Table 4: Comparative analysis of Model

Evaluation Parameter	Genetic Algorithm (GA)	Differential Evolution (DE)
Convergence Speed	Moderate	Fast
Model Complexity	Low	Low
Robustness	Moderate	High
Hyperparameter Tuning	High	High

Table 4 contrasts Differential Evolution (DE) and Genetic Algorithm (GA) for the purpose of detecting diabetic retinopathy. DE demonstrates fast convergence, making it efficient in optimising models. Model complexity is low in both GA and DE, suggesting that their representations are straightforward. DE has greater resilience, which indicates enhanced flexibility in the face of changing

facts. However, both approaches necessitate extensive work in hyperparameter optimisation for best outcomes. Both DE and GA are competitive; but, DE's speed and robustness make it the preferred choice when efficient optimisation and adaptability are critical.

5. Conclusion

In this study, we compared Differential Evolution (DE) and Genetic Algorithm (GA) to Convolutional Neural Networks (CNN) to determine which method is best for optimising deep learning architectures for Diabetic Retinopathy Screening. Our investigation has shed light on the merits and weaknesses of these optimisation strategies, giving useful insights for medical image processing applications.In this research, DE clearly outperformed the competition. During optimisation, it showed rapid convergence, making it a good option for efficiently modifying deep learning models. DE's practical usefulness is emphasised by the fact that it can optimise model parameters while keeping model complexity to a minimum. The strong robustness demonstrated by DE also indicates its flexibility in accommodating various data distributions, an essential quality in medical diagnosis.Although GA's test results weren't quite as impressive as DE's, it was nonetheless demonstrably effective. Applications where interpretability is paramount will benefit from the model's simplicity. The effectiveness of GA and its adaptability to a wide range of optimisation tasks imply that it may have applications beyond the detection of diabetic retinopathy.CNN, on the other hand, thanks to its deep architecture, was able to train to very high accuracy. However, it needed more time and computing power to train, limiting its usefulness in situations that necessitate prompt diagnoses.The importance of optimisation methods is emphasised in this study for improving the effectiveness of deep learning models in detecting diabetic retinopathy. Fast, reliable, and effective, DE is a powerful optimisation tool. It is important to strike a balance between accuracy, computing efficiency, and interpretability when selecting one of these methods. Future study should examine hybrid approaches that combine the qualities of both optimisation techniques to further improve diagnostic accuracy while retaining efficiency. The results of this study improve the quality of automated diabetic retinopathy screening, which in turn benefits patients by allowing for earlier disease detection.

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