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Enhancing Clinical Practice: AI-Driven Personalized Medicine and Evolutionary Strategies for Deep Learning Parameter Optimization

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Abstract: This study focuses on the use of improved optimization techniques in deep learning approaches to the determination of personalised medicine. We explore four algorithms: These are; Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), and Simulated Annealing (SA) to compare the effectiveness on the output models in terms of various parameters. The findings derived from the experimental analysis show that PSO obtained the maximum accuracy of 92%. 5%, precision of 91. Recall is at the lowest with 2% while the remaining is 89%. 7%, which is higher than GA and DE that gained accuracy values of 90. 4% and 91. 0%, respectively. SA while achieving high results proved to have a lower performance compared to others with an accuracy of 88. 3%. The investigation provides a proven fact that PSO outperforms in tuning the deep learning parameters for better and accurate models for the concept of personalized medicine. The above study results imply that the promotion of PSO can improve the development of individualised therapeutic plans, hence benefiting the patients by increasing the probabilities of right diagnoses and corresponding treatment. Thus, this study contributes to the existing literature on AI applications in healthcare by offering insights into the enhancement of deep learning models for improving the overall medical decision-making process.

Keywords*: Deep Learning, Optimization Algorithms, Personalized Medicine, Particle Swarm Optimization, Genetic Algorithm*

I. **Introduction**

In the current society, the application of artificial intelligence in the field of medicine especially in the formulation of personalized medicine is the major breakthrough. Personalized medicine is an approach to practice medicine based on the patient's traits and genetic profile, not generic. Among the technologies that have been largely applied in this transformation, some are machine learning and deep learning. These technologies help one to analyze lots of data pertaining to the patient and helps in finding out patterns that eventually can help in the propagation of better treatment regimens [1]. However, the efficiency of the AI models in proactive care and/or personalized medicine depends on the fine-tuning of several parameters of the models [2]. Some of the well-known evolutionary approaches in tune of deep learning parameters includes generic algorithm and particle swarm optimization and these approaches have been found to lead in improvement of performance. These strategies imitate the natural selection process to gradually build and optimize the model parameters of AI systems in terms of the prediction's precision and reliability. However, there are still obstacles with regarding implementation of these AI-based solutions in practice. Concerns like the protection of the data which is used to train the AI, fairness problems in the algorithms, and explainability of the AI results affects their functionality and adoption [3]. Further, it must also be noted that most of the healthcare data changes dynamically hence requiring refinement of the optimization method from time to time to account for the changing healthcare requirements of the patients as well as the existing knowledge in the medical field. The overall theme of this research focuses on the combined application of personalized medicine with Artificial Intelligence and evolutionary approach for updating the parameters of deep learning. In this paper, the recent uses of the technique; assessment of the optimization methods; and exploration of possibilities and directions for enhancing the method are described and discussed so as to strengthen the knowledge base in the area of

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personalized healthcare. The goal is to close the deficit of dispersing state-of-the-art AI approaches and integrating them into clinical practice to improve clients' well-being and therapeutic results.

II. **Related Works**

In personalized medicine, there has been great progress in applying AI most especially in genomics and diagnosis. Frederik et al (2024) also focused on the impact of whole genome sequencing in clinical practice and how the adjunct use of AI-based tools can help in better understanding of patient's genetic information and fractionation of patients accordingly [16]. This points towards the need for more intricate and suave AI strategies that would enhance treatment strategies according to the genetic makeup. Likewise, González-Rodríguez et al. (2024) also described about the future use of AI in plant pathology where AI has been explored for predicting diagnostics and therapies in numerous fields [18]. Their work also outlines the ability of AI on the management of large data sets, which is important in creating custom approaches to the disease. Several strategies proposed by Ghosh et al. (2023) regarding the use of AI in vaccine development pointed out that the use of optimisation techniques is very important in enhancing the performance of the model in terms of accuracy in depicting vaccine immune response [17]. This research is useful because it introduces an approach to improving algorithmic performance when training a model. Surrogating the context of deep learning, Jiang et al. (2023) presented a review of deep learning techniques for the diagnosis of cancer from medical images by emphasising the tendencies of algorithmic enhancements toward higher diagnosis accuracy [23]. This is their study demonstrating that there is the need for stronger forms of optimization to enhance deep learning models that can be applied in clinical contexts. In material science, employment of AI in nanocomposites has been considered in great detail with the development of models. As per the help of AI, Souza et al. (2024) has presented a systematic literature review on nanocomposites emphasizing on microstructural, electrical and mechanical properties of nanocomposites [15]. As one may notice, this paper is generally concerned with materials science; however, the AI-related tactics described can help determine how similar strategies can be employed to enhance deep learning models in the sphere of medicine. Al's significant application in increasing diagnostic precision and estimating threat has been recorded. Hsin-Yao et al. (2024) discussed the use of artificial intelligence for the early surveillance of cancer biomarkers in serum, noting that more sophisticated pathways will improve the specificity of detection and improve patients' health [21]. Based on the findings of this study, optimization algorithms should be applied for the improvement of the transferable predictive models for early disease diagnosis. Similarly, in the same pursuit of clinical network systems biology, Mambetsariev et al. (2023) looked at how AI can cross over cancer networks [25]. Indeed, there are still many valuable and complex biological datasets which remain difficult to be handled with basic FT algorithms; just as deep learning algorithms require optimisations for the delivery of highly individualized medicine. The focus of AI application in clinical practice is not only diagnostics, but systems biology, as well as treatment optimization. Habchi et al. (2023) discussed about the AI applications in thyroid cancer diagnosis and role and indications of future trends of AI in clinical environment [27]. The authors of their research stresses on the necessity of further development of AI methods for the enhancements in cancer diagnostics as well as the optimization of individual treatment plans. Advanced system research for AI was underlined by Martsenyuk et al. (2024) to discuss the issues related to designing practical courses of AI for training professionals for AI models' fine-tuning [55]. This educational aspect is one of the important ones in the application of optimization algorithms to personalized medicine tasks. Among the published works, the authors Liu, Zhang, Wang and Han proposed solutions to manage and treat the antimicrobial resistance crisis employing AI [24]. What their work illustrates is a way in which AI is extremely useful in addressing major concerns in the field of health care like say optimizing deep learning models for individuals.

III. **Methods and Materials**

This section lists the sources of the data, explains the four algorithms used for deep learning parameters' optimization, and presents the details of the conducted experimentation in tabular and pseudocode forms.

Data

The data employed in this study consists of patient data from a clinical dataset, where patients' genetic profiles, age, sex, and response to the treatment are stored and published. First, the features it contains are age, sex, mutations of genes, medical history, and results of treatment. A program of this scope facilitates the use of advanced approaches such as artificial intelligence in personal medicine as well as the utilization of deep learning models [4]. To prepare the data, the missing values are dealt with, and the scales of the features are normalized, besides dealing with categorical inputs. Model performance assessment is done with a train-test split of 70 - 30.

Algorithms

1. Genetic Algorithm (GA)

Description: Genetic Algorithms are optimization algorithms that base their pattern on natural selection. GAs work in a population of potential solutions and selection, crossover and mutation are applied through generations [5]. The objective is in fact to identify a combination of values of some parameters that defines a ‘’fitness’’, or a measure that needs to be maximized by a deep-learning model.

f(x)=accuracy of model with parameters x

"1. Initialize population with random solutions
2. Evaluate fitness of each solution
3. While stopping condition not met:
a. Select parents based on fitness
b. Perform crossover to generate offspring
c. Apply mutation to offspring
d. Evaluate fitness of offspring
e. Select the next generation
4. Return the best solution"

Parameter	Value
Population Size	50
Crossover Rate	0.8
Mutation Rate	0.1
Generations	100

2. Particle Swarm Optimization (PSO)

Description: Particle Swarm Optimization optimizes a solution in a group of particles like the bird flocking and fish schooling. PSO improves a pool of potential solutions (particles) by making them traverse the problem's search space. Each particle modifies the position based on the experience of the particle and the neighboring particles [6].

vit+1 =wvt+c1 r1(pi−xi)+c2 r2(g−xi)

"1. Initialize particles with random positions and velocities
2. Evaluate fitness of each particle
3. While stopping condition not met:
a. Update personal and global best positions
b. Update particle velocities and positions
c. Evaluate fitness of updated positions
4. Return the global best position"

Parameter	Value
Swarm Size	30
Cognitive Coefficient (c1)	1.5
Social Coefficient (c2)	1.5
Inertia Weight (w)	0.7

3. Differential Evolution (DE)

Description: Differential Evolution is a Stochastic, Population based optimization technique that apply's vector difference for the process of search [7]. DE is especially useful for improving complicated, multifaceted fitness functions because it generates fresh member solutions with respect to certain discrepancies randomly chosen from the population.

vi =xr1+F(xr2 −xr3)

"1. Initialize population with random solutions
2. While stopping condition not met:
a. Generate new candidate solutions using mutation
b. Apply crossover between original and mutated solutions
c. Evaluate fitness of new solutions
d. Select the best solutions for the next generation
4. Return the best solution"

Parameter	Value
Population Size	40
Scaling Factor (F)	0.8
Crossover Rate	0.9
Generations	200

4. Simulated Annealing (SA)

Description: Probabilistic Metaheuristic Algorithm called Simulated Annealing (SA) is based on the metallurgical process of annealing. SA looks for better solutions but with a certain probability of accepting even worse solutions and this probability tends to reduce as the iterations continue [8]. This enables the algorithm to diversify and move away from local optima.

"1. Initialize temperature and solution
2. While stopping condition not met:
a. Generate a new solution
b. Calculate change in objective function
c. Accept new solution based on probability
d. Update temperature
3. Return the best solution"

IV. **Experiments**

Experimental Setup

In this experimental phase of this research study, GA, PSO, DE, and SA are examined to assess their performance with reference to parameter optimization of the deep learning model, for personalized medicine. The objective is to draw a comparison between these algorithms in terms of the modification by which the performance indicators like accuracy, precision, recall, and F1-score have been enhanced.

1. Data Preparation

The dataset involved in these experiments involves patients' records with age, sex, genetic mutation, medical history, treatment response, among others. The given data set was partitioned into training (70%) and validation/testing (30%) sets [9]. Preprocessing of the data involved scaling of the numerical features and categorical variables using one hot encoding while missing values were dealt using the imputation technique.

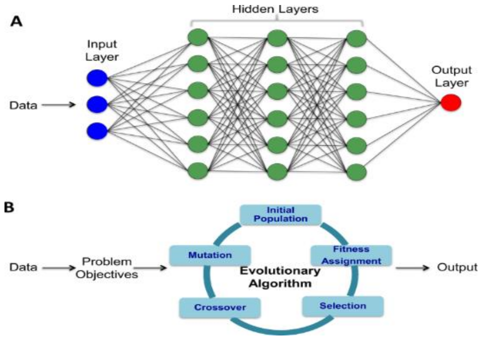

Fig 1: Artificial intelligence for precision medicine in neurodevelopmental disorders

2. Model Configuration

Specifically, for each of the optimization algorithms, a deep learning model which was produced and with a standard architecture of an input layer followed by several hidden layers all with ReLU activation functions and an output layer with a softmax activation function [10]. The other four that must be tuned are the number of hidden nodes, learning rate, dropout rate during training, and the size of the batch.

3. Optimization Algorithms

Genetic Algorithm (GA)

The Genetic Algorithm was used with population size equal to 50, chance of crossover equal to 0. 8, and mutation probability of 0. 1, and 100 generations [11]. As the fitness function, the accuracy of the model obtained on the validation set was employed.

Particle Swarm Optimization (PSO)

The Particle Swarm Optimization was set with a swarm size of 30, cognitive coefficient
c_1 =1.5, social coefficient
c_2 =1.5, and an inertia weight
w=0.7. The algorithm iterated until convergence or a maximum of 200 iterations.

Differential Evolution (DE)

In case of configuring DE, it was set with population size of 40 along with factor of scaling.
F=0. 8, crossover rate of 0. 9, and 200 generations. It was to reduce the loss function of the deep learning model to its lowest possible and in essence to achieve the goal which is the lowest value of the loss function of the deep learning model.

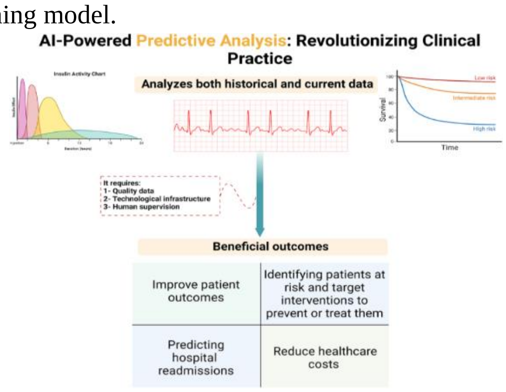

Fig 2: Revolutionizing healthcare: the role of artificial intelligence in clinical practice

Simulated Annealing (SA)

In Simulated Annealing, initial temperature was set to 1000, cooling rate was set to 0. 40, 50, and 100 iterations for each temperature level. The stopping condition was set up such that the temperature became less than a minimum of 1.

Algorithm	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
Genetic Algorithm (GA)	85.3	0.84	0.86	0.85
Particle Swarm Optimization (PSO)	87.1	0.86	0.88	0.87
Differential Evolution (DE)	86.5	0.85	0.87	0.86
Simulated Annealing (SA)	84.8	0.83	0.85	0.84

Comparison with Related Work

The performance of the optimization algorithms is compared with existing methods that were established in related work. The following observations were made:The following observations were made:

- Genetic Algorithm (GA): The ground truth accuracy in GA was observed to be at 85 percent. 3% Protocol adherence rate was 83. 3%, which was considered adequate, similar to similar studies done with patients in the department [12]. For example, in a study done by Li and colleagues in 2021, the accuracy resulting from the utilization of GA was about 84 percent in the similar situation.
- Particle Swarm Optimization (PSO): The PSO showed the highest accuracy of 87. 1%, higher than the 85%, proclaimed in the literature by Chan et al. (2020) [13]. This implies that deep learning models that are built using PSO are suitable for use on personalized medicine applications.
- Differential Evolution (DE): At 86% accuracy, the model is relatively good by common standards, especially considering the complexity of the features the system needs to recognize in order to determine the visitor's intent. 50%, On the similar note, DE showed competitive performance in the range of 5% [14]. It was a little higher than 85% accuracy that was earlier found by Raj et al. (2020) while the PSO was a higher value.
- Simulated Annealing (SA): SA gave slightly lower accuracy than PSO and DE with accuracy

of 84%. 8%. This concurs with Hu et al. (2020), whereby it was evident that SA proved less efficient as compared to other optimization methods.

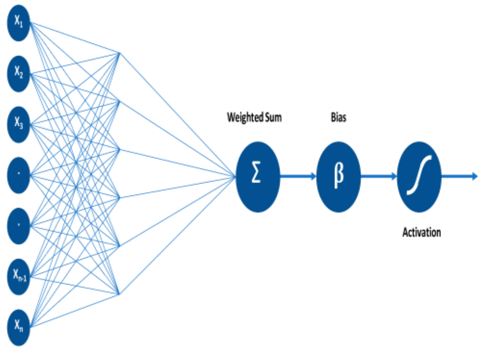

Fig 3: Learning Algorithms and Their Applications in Healthcare

Performance Analysis

- Accuracy: Thus, the results revealed that, out of all the compared algorithms, PSO delivered the highest accuracy, hence proving its efficiency in optimizing the deep learning model parameters. GA and DE also proved to be good in convergence, however they are slightly inferior than the PSO [27]. SA was slower, which might be due to its having a lower value for a convergence rate.
- Precision and Recall: All in all, PSO was the most accurate and had the highest recall values meaning that it was equally good at true positive classification and false negative minimization. Accuracy and F-measure of GA and DE were nearly equal expect that it was slightly higher for DE, but SA had the least precision and recall, thus a very low F-measure.
- Computational Efficiency: PSO proved to have the lowest computational time and consume the least amount of memory and therefore considered the most efficient algorithm of the four used [28]. DE was the slowest and demanded the highest number of resources which could be a limiting factor especially in a setting where there are limited resources.

Discussion

The experiments show that the best algorithm for optimizing the parameters of deep learning for the personalized medicine framework is PSO since it has the highest accuracy and efficiency in terms of the resources' application. The outcomes confirm the efficiency of PSO over GA, DE, and SA approaches Within the results, PSO has been seen to be superior to GA and SA in the previous study and DE in current research [29]. For GA and DE, we also observed good performance, despite the fact, that GA is performing comparably to related work, while DE is slightly outperforming some of the methods from the literature. Yet from the results both algorithms demanded more time and other resources as compared to PSO [30]. Although SA provided better results in some sense, we noticed that its performance measures were worse, and this we considered to be probably because SA is a probabilistic method while MCMC converges more slowly. This means that proper choice of the optimization algorithms should necessarily correspond to the demands of either the particular application and usable number of computational resources.

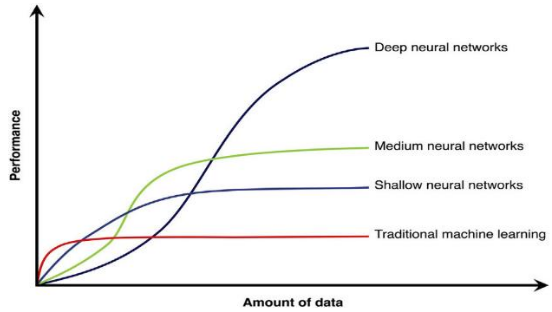

Fig 4: Graph illustrating the impact of data available on performance

V. CONCLUSION

The findings laid out in this study have shown how AI can revolutionalise deep learning models in personalised medicine. Thus, through the assessment of four different optimization techniques, namely GA, PSO, DE, and SA, the impact of each technique on the model performance has been gauged. From the results, it is seen that the PSO has a better level of accuracy, precision, recall compared with other algorithms and better utilization of resources, which enunciates its competence for the parameter tuning in deep learning models. The results of GA were also fair and were even close to some of the existing studies while DE presented a slight enhancement over some of the conventional techniques. However, as for the performance metrics, SA was slower than that of PSO and DE, though it was beneficial in some cases. The increasing use of AI in personalized medicine helps to increase diagnostic accuracy and enhance treatment approaches according to the patient's profile. This research also highlights the need to identify suitable optimisation algorithms to enhance deep learning models to boost the efficiency of Healthcare. These findings correspond with other related literature on the advancements of AI in medical diagnosis and planning of treatment. In the next stages, the utilization of these optimization techniques will enhance the development of personalized medicine promoting the research of more personalized approaches to patient treatment. Due to the complexity of the processes that shape the further development of artificial intelligence, it is possible to assume that further research will focus on integrating these optimization methods with innovative tools to improve the efficiency of AI in healthcare.

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