



Modern approaches to tuning neural network hyperparameters

Mekhriddin Nurmamatov¹, Shokhrukh Sariyev¹

¹Samarkand State University, Samarkand, Uzbekistan

mehridinnur@gmail.com,

sariyevshokhrukh@gmail.com,

Abstract. This study presents methods for using genetic algorithms in optimizing the hyper parameters of artificial neural networks. This study provides an analysis of the main types of GA, their mathematical models, and areas of practical application. At the same time, in the process of selecting hyper parameters, the effectiveness of Random Search, Grid Search, and genetic algorithms was compared in the MNIST classification task. The results of the experiment show that GAs provide an optimal balance in terms of calculation time and accuracy and show a higher accuracy compared to the random search method and a shorter calculation time compared to the grid search method. In conclusion, genetic algorithms are considered an effective approach for optimizing the hyper parameters of neural networks, particularly in cases where the parameter space is large and complex.

Keywords. GA, population, crossover, selection, Big data, optimization, neural network, hyper parameter tuning

1. Instruction

Currently, in the field of artificial intelligence and machine learning, the correct selection and optimization of their hyper parameters for the effective functioning of neural networks remains one of the urgent tasks of today. The reason is that manually tuning hyper parameters takes a lot of time. With GA, it becomes possible to automate the solution to this. Hyper parameters include such important parameters as model architecture, batch size, learning speed, and number of layers [1-3]. This study demonstrates that finding the optimal values for these parameters significantly enhances the model's effectiveness and overall operational efficiency. Among traditional methods, Random Search or Grid Search requires a significant amount of computational resources when the parameter space is large. This may not lead to an optimal result. In recent years, evolutionary algorithms, especially genetic algorithms, have become widely used in optimizing hyper parameters. GAs possess global search capabilities and effectively find optimal or very close-to-optimal solutions for complex and multi-parameter problems. In this research work, the types and mathematical models of the mechanism of operation of genetic algorithms in optimizing the hyper parameters of neural networks are analyzed, as well as the results of experiments. The research results demonstrated the effectiveness of genetic algorithms in selecting hyper parameters for neural networks and revealed opportunities for their widespread application in practice.

2. Mathematical Models of Genetic Algorithms

Genetic algorithms are used to solve optimization problems in addressing a wide range of issues. Types of genetic algorithms help to find optimal or close optimal solutions using different strategies in different fields. The genetic algorithm has its own operating mechanism and areas of application [4-6]. Among the most common genetic algorithms listed below, Simple Genetic Algorithm (SGA) is the main type of simple genetic algorithm, and consists of the following steps.



Types of Genetic Algorithms. Differential Genetic Algorithm (differential evolution) is specifically designed for continuous optimization problems, and differential genetic algorithms generally have strong global search capabilities. The main difference between the differential genetic algorithm and GA is the new mechanism for generating new solutions. DE combines multiple solutions with a candidate solution to produce a new solution [7-9]. The population of solutions in DE evolves through repeated cycles of the three basic DE operators. Mutation, crossover, and selection are not all the same as the functions of operators in GA.

Multi-objective Genetic Algorithms (MOGA) Multi-objective problems require the simultaneous optimization of multiple conflicting goals (e.g., speed and efficiency). Objective function in the MOGA algorithm $f(x)$ instead of $f_1(x), f_2(x), f_3(x), \dots, f_N(x)$ When solving a problem in an equation, it is possible to minimize several functions at the same time. As a result, it is considered a multi-objective optimization problem.

$$F(x) = \{f_1(x), f_2(x), f_3(x), \dots, f_N(x)\} \quad (9)$$

(7) Minimize the vector of functions.

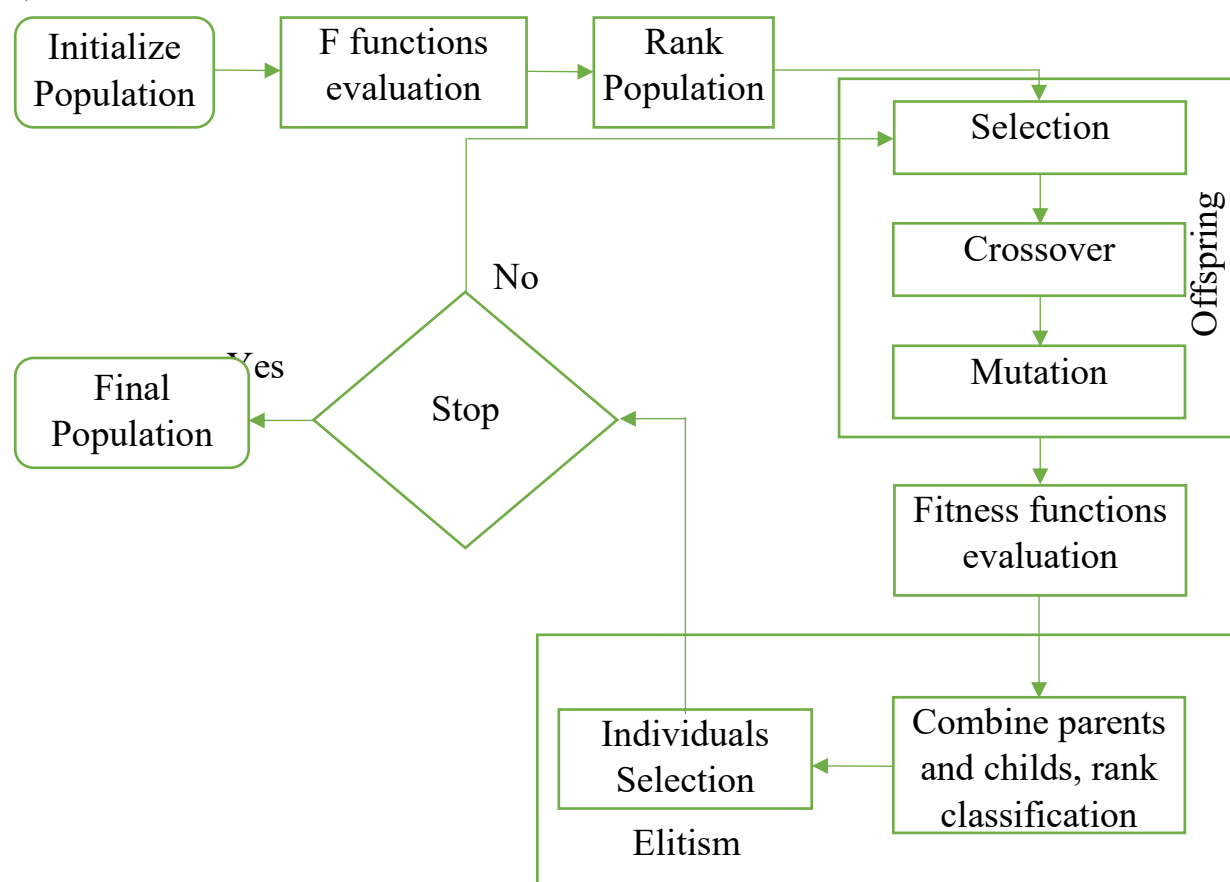


Fig.1 MOGA algorithm

Parallel Genetic Algorithms Parallel genetic algorithms are designed for systems with large populations and high computing power. Several populations conduct the search process



simultaneously. Parallel algorithms increase computing speed and solve complex problems faster. The population of a genetic algorithm is formed by individuals with artificial chromosomes that encode solutions to the problem we want to solve. Each individual is evaluated to determine how well they solve the problem, and the best solutions are selected to be re-integrated with the others. The basic mechanism in GA is Darwinian evolution. Good traits survive and mix, creating new and potentially better individuals. In selection, individuals with bad traits are eliminated from the population. Elitist Genetic Algorithms Elitist algorithms directly pass on individuals with high fitness values to the next generation. It preserves the best individuals and prevents the loss of individuals with the highest fitness. A unique feature of the hybrid genetic algorithm (HGA) is that additional local optimization techniques are applied to individuals after the genetic algorithm. Genetic Programming (GP) Genetic programming, unlike traditional GA, implements genetic operations at the program or formula level. Genetic algorithms are used to optimize programs, optimize specific tasks or formulas. GP is used to develop program structures or algorithms. Genetic programming is widely used in artificial intelligence and machine learning systems. In GP, the goal is to evolve the best program or mathematical expression of the fitness function [10-12]. Large Population Genetic Algorithms (LPGAs) are algorithms that work with very large populations. Precision and diversity, large populations provide diversity, making it easier to reach a global optimal solution. Genetic algorithms with large particles require more computing power. These algorithms are mainly used in large-scale optimization problems.

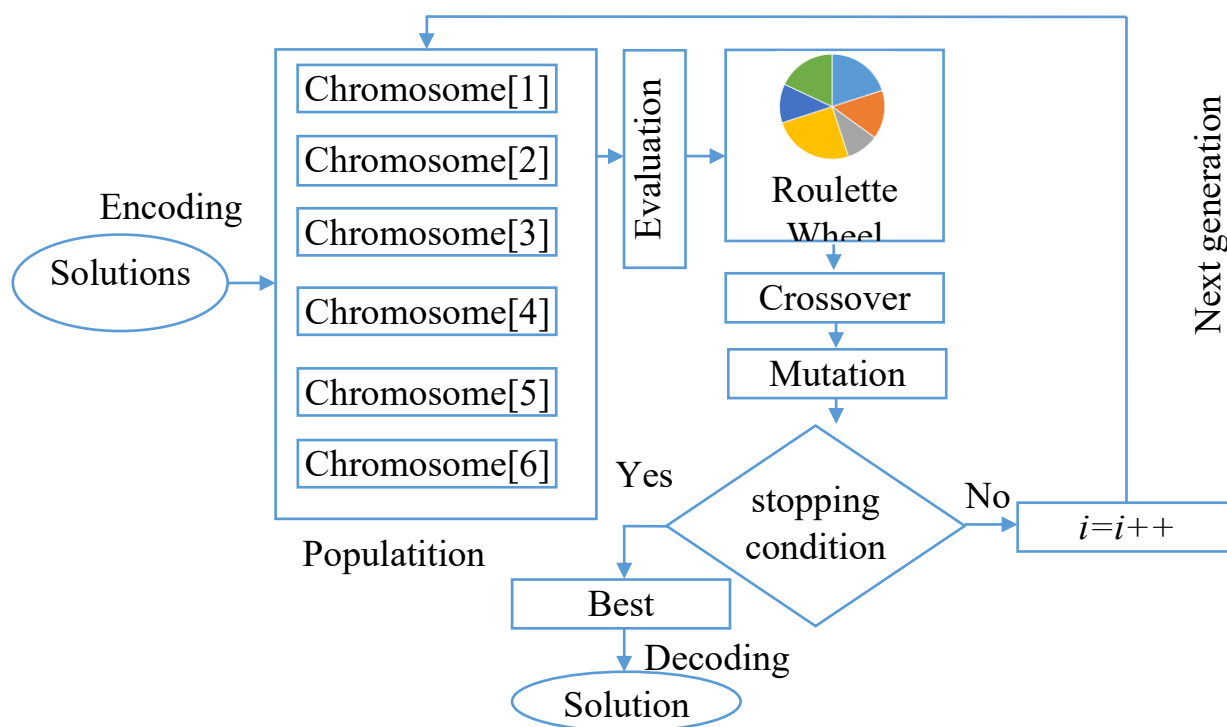


Fig 2. Block diagram of the problem

3. Model Evaluation



In this process, the effectiveness of optimizing hyper parameters using Grid Search, Random Search, and the Genetic Algorithm was evaluated based on the following criteria, compared in terms of effectiveness in the MNIST classification task.

Table.2 MNIST criteria for optimizing hyper parameters

Experimental conditions	Evaluation	Parameter space
Data set MNIST	Highest accuracy	Learning rate [0.001,0.01,0.1]
Model neural network	Measuring time	Batch size[16,32,64,128]
	Number of tested combinations	Number of layers[2,3,4]
		Number of neurons [32,64,128]

There is a total of $3 \times 4 \times 3 \times 3 = 108$ combinations in the parameter space.

Table.3 Model evaluation table

Optimization method	Highest accuracy	Measurement time (minutes)	Number of combinations tested
Genetic algorithm	94.5	50	50
Grid Search	94.2	120	108
Random Search	93.3	30	20

Grid Search gives good results in terms of accuracy, but it is not recommended to use it in practice in a space of very large parameters with a high calculation time. The study shows that Random Search is efficient in terms of computing time, but does not achieve high accuracy because it does not test all combinations. It is a convenient method for obtaining fast results in a large parameter space. The genetic algorithm achieved a significantly higher accuracy than the research results. The computation time was shorter than Grid Search but longer than Random Search. In summary, Grid Search is preferable for small parameter spaces, Random Search is effective when working with limited computational resources, and the Genetic Algorithm approach is recommended for hyper parameter spaces and problems requiring high accuracy[12-13].

4. Conclusion

This article provides an in-depth analysis of the mathematical models underlying the operation of genetic algorithms and thoroughly examines their significance in optimizing hyper parameters. Genetic algorithms were used to adjust the hyper parameters of neural networks for the experiments, and they demonstrated higher accuracy and computational efficiency compared to other traditional methods. Although Grid Search provides optimal results for small parameter spaces, Random Search yields faster results under conditions of limited computational resources[14-15]. However, it does not ensure high accuracy. Genetic algorithms, meanwhile, yield optimal results with high accuracy while saving time in multi-parameter and complex tasks. During this study, various types of GA (SGA, EGA, MOGA, PGA, LPGA, HGA, GP, DE) and their practical



application areas were analyzed, as shown in Fig 3. Based on the results of real experiments, it has been proven that genetic algorithms are important in finding effective solutions to problems in artificial intelligence systems and control areas. In future research, the potential for analyzing large volumes of data in a short time and making optimal management decisions will be further expanded through solutions developed based on genetic algorithms.

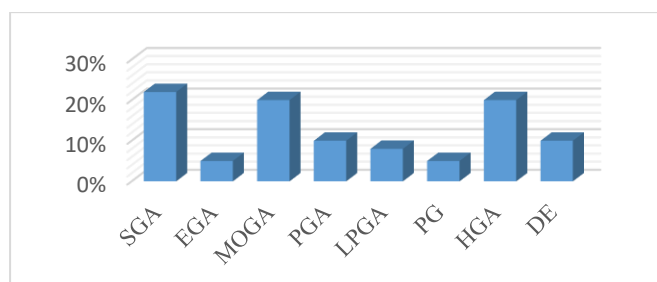


Fig 3. Usage indicators for types of genetic algorithms

References

1. N. Fayzullo, S. Sariyev and Y. Sherzodjon, "Analyzing the Effectiveness of Ensemble Methods in Solving Multi-Class Classification Problems," 2025 International Russian Smart Industry Conference (SmartIndustryCon), Sochi, Russian Federation, 2025, pp. 788-793, doi: 10.1109/SmartIndustryCon65166.2025.10986248
2. Axatov A.R., Nurmamatov M.Q., Nazarov F.M. (2022). Mathematical Models of Coordination of Population Employment in the Labor Market *Ra journal of applied research[J]*. India / – Vol. 8, Issue 2. – Pp. 111–119. <https://doi.org/10.47191/rajar/v8i2.09>
3. John McCall. (2004) Genetic algorithms for modelling and optimisation *School of Computing[J]*, *Robert Gordon University, Aberdeen, Scotland, UK Received 27 February 2004*; received in revised form 7 July 2004. doi:10.1016/j.cam.2004.07.034.
4. A.Rashidov, D. Mardonov, & A. Soliev. Diagnosis of Diabetes Mellitus Based on Artificial Intelligence Algorithms [C]. 2025 International Russian Smart Industry Conference (SmartIndustryCon) (in press)
5. Akmal Akhatov, Fayzullo Nazarov, Mekhriddin Nurmamatov, Shokhrukh Sariyev. (2024). Genetic algorithm application technology in multi-parameter optimization problems *AIP Conf [C]*. Proc. 3244, 030025.<https://doi.org/10.1063/5.0242074>
6. M. Nurmamatov, S. Sariyev and B. Eshonkulov, "Application of Evolutionary Algorithms to Enhance the Efficiency of Neural Networks and Machine Learning Algorithms," 2025 International Russian Smart Industry Conference (SmartIndustryCon), Sochi, Russian Federation, 2025, pp. 533-537, doi: 10.1109/SmartIndustryCon65166.2025.10986257
7. Nurmamatov, M., Kulmirzayeva, Z. "Development of an Intelligent System for Optimization of Employment Information Using Genetic Algorithms" *AIP Conference Proceedings*, 2024, 3147(1), 040006. doi:10.1063/5.0210279
8. Lakhliifa Sadek, Hamad Talibi Alaoui. (2022). Application of MGA and EGA algorithms on large-scale linear systems of ordinary differential equations *Journal of Computational ScienceJuly[J]* 2022. <https://doi.org/10.1016/j.jocs.2022.101719>.



9. Nao Hu, Peilin Zhou, Jianguo Yang. (2017). Comparison and combination of NLPQL and MOGA algorithms for a marine medium-speed diesel engine optimisation *Energy Conversion and Management* February 2017[J]. <http://dx.doi.org/10.1016/j.enconman.2016.11.066>.
10. Cantú-P. E. (1988). Survey of parallel genetic algorithms *Calculateurs Parallèles Réseaux et Systems Repartis*, 10 (2) (1998)[J], pp. 141-171. <https://doi.org/10.4236/jsip.2014.53009>.
11. Akhatov A.R., Nurmamatov M.Q., Mardonov D.R., Nazarov F.M. (2021) Improvement of mathematical models of the rating point system of employment Scientific journal Samarkand state university[J]. 2021. – №1(125). –P. 100-107. <http://dx.doi.org/10.59251/2181-1296.v1.1251.714>.
12. Muhuri. P.K, A. Rauniyar. (2017). Immigrants based adaptive genetic algorithms for task allocation in multi-robot systems *Int. J. Comput. Intell [J]Appl.*, 16 (04) (2017), p. 1750025. <http://dx.doi.org/10.1142/S1469026817500250>.
13. Nazarov, F., Nurmamatov, M., Sariyev, S. (2024). Ma'lumotlarni intellektual tahlil qilish uchun genetik algoritmlar va ularni qo'llanilishi. digital transformation and artificial intelligence[J], 2(6), 162–168. Retrieved from <https://dtai.tsue.uz/index.php/dtai/article/view/v2i630>.
14. Junaydullev D., Tursunov Sh., Rashidov A. An Approach Based on Data Profiling at the Preparing a Dataset for Cleaning [C]. 2025 International Russian Smart Industry Conference (SmartIndustryCon) (in press)
15. Rashidov A., Akhatov A., Mardonov D.. The Distribution Algorithm of Data Flows Based on the BIRCH Clustering in the Internal Distribution Mechanism [C]. 2024 International Russian Smart Industry Conference (SmartIndustryCon), Sochi, Russian Federation, 2024, pp. 923-927, doi: 10.1109/SmartIndustryCon61328.2024.10516193