Abstract: The performance of deep learning (DL) models is highly dependent on hyperparameter selection, including learning rate, network depth, dropout, and optimizer choice. Traditional methods such as manual tuning and grid search are computationally expensive and ineffective in high-dimensional, non-convex search spaces. This paper reviews Evolutionary Strategies (ES) as a population-based meta-heuristic approach for automated hyperparameter optimization (HPO) in DL. Inspired by biological evolution, ES iteratively refines candidate solutions through selection, crossover, and mutation to explore optimal regions of the search space. The study synthesizes ES methodologies alongside related optimization approaches such as Bayesian optimization, and presents key variants including Genetic Algorithms and Covariance Matrix Adaptation Evolution Strategy (CMA-ES). Comparative insights highlight the advantages of ES over traditional HPO techniques like random search and gradient-based methods, particularly in complex and multimodal landscapes. Empirical evidence across applications—such as CNN-based image analysis, LSTM-based time-series prediction, and radiomics—demonstrates strong performance and robust exploration capabilities. However, challenges remain, including high computational cost, the need for parallelization, and efficient fitness design. Future directions include neuroevolution, multi-objective optimization, and applications in emerging domains such as finance, IoT, and multimodal AI.

Keywords: Evolutionary Strategies, Hyperparameter Optimization, Deep Learning, Genetic Algorithms, Meta-Heuristics, Neural Architecture Search, Automated Machine Learning (AutoML), Model Tuning.