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Deep Learning Flower Pollination Optimization Using Evolutionary Algorithms: A Review

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A B S T R A C T

Deep learning (DL) has emerged as a powerful tool for solving complex problems across various domains, ranging from image and speech recognition to natural language processing and medical diagnosis. However, the success of DL models heavily relies on the optimization of their parameters, which often involves dealing with high-dimensional and non-convex optimization landscapes. Optimization techniques play a crucial role in enhancing the efficiency and effectiveness of deep learning models. Evolutionary algorithms (EAs) offer promising solutions to address these challenges by leveraging principles from natural evolution. This review paper provides a comprehensive overview of the use of evolutionary algorithms for optimizing deep learning models. The methodology involves defining research questions, conducting literature searches, selecting relevant papers, and analyzing their contributions. The related work section examines selected papers, discusses their strengths and limitations, and identifies emerging trends. The discussion section highlights similarities and differences among the reviewed papers, presenting insights and future research directions. Overall, this review aims to inform researchers and practitioners about the potential of EAs for improving deep learning optimization.

Keywords: Deep learning, Optimization, Evolutionary algorithms, Meta-heuristic algorithms, Flower Pollination Algorithm (FPA)

1. Introduction

Deep learning is a powerful technique in various domains, including computer vision, natural language processing, and healthcare. However, training deep neural networks often requires extensive computational resources and is prone to issues, such as slow convergence and overfitting (Wakili et al., 2022). While convolutional neural networks (CNNs), such as DenseNet, offer remarkable parameter efficiency and feature reuse capabilities (Ma et al., 2019). However, they suffer from excessive connections that can impede computational and parameter efficiency, leading to overfitting (Wakili et al., 2022). Transfer learning presents a promising approach to mitigate these challenges by leveraging knowledge from related domains to enhance the efficiency and performance of models (Wakili et al., 2022). By transferring learned features from a source domain to a target domain, transfer learning can improve the classification ability of models while conserving computational resources (Wakili et al., 2022). Despite the strides made in breast cancer diagnosis using transfer learning, there remains a need to address the limitations of existing performance metrics, algorithmic assumptions, and computational complexities to refine classification algorithms (Rehman et al., 2023). In light of these challenges, there is a compelling need for innovative optimization strategies that can facilitate the seamless application of DenseNet-based breast cancer image classification in real-life clinical scenarios (Wakili et al., 2022).

To address the challenges mentioned above, researchers have turned to optimization techniques, with evolutionary algorithms (EAs) gaining significant attention (Li et al., 2022). This paper aims to provide an overview of the use of evolutionary algorithms for optimizing deep learning models. By combining the principles of evolution with deep learning, EAs offer promising solutions to improve training efficiency, convergence speed, and generalization ability of deep neural networks (Li et al., 2022).

The problem statement revolves around the need for efficient optimization methods to tackle the complexities of training deep learning models. Despite the remarkable success of deep learning, optimizing large-scale neural networks remains a daunting task, especially with limited computational resources (Zhan et al., 2022). Evolutionary algorithms present a novel approach to address the challenges by mimicking the process of natural selection to improve models' performance iteratively. The main contribution of this paper lies in synthesizing and analysing existing literature on the application of evolutionary algorithms in deep learning optimization. By examining the strengths and limitations of different approaches, this review aims to provide insights into the state-of-the-art techniques and identify potential areas for future research. The remainder of the paper is organized as follows; section 2 presents a literature review, and section 3 discusses the findings.

2. Research Methodology

The methodology used in this review paper aims to systematically investigate the role of evolutionary algorithms (EAs) in optimizing deep learning models. The approach encompasses defining research questions and objectives, conducting thorough literature searches, selecting important papers, and critically analysing their contributions.

2.1 Research Questions

i. What is available research works in the literature on deep learning flower pollination algorithms?

ii. How effective are flower pollination optimization techniques based on evolutionary Algorithms?

The research questions mentioned above are centered on assessing the effectiveness of evolutionary algorithms in optimizing deep learning models. Our objective is to compare various EA techniques, elucidate their strengths and limitations, and identify the best practices for their integration into deep learning frameworks.

3. Related Work

The concept of nature serves as a significant muse for researchers, offering a plethora of inspiration. Presently, a predominant trend in algorithmic development involves drawing insights from the natural world. While the focus remains on the source of inspiration, various levels of classification are feasible, depending on the desired level of detail and the extent of sub-sources utilized. For the sake of simplicity, broader categories such as biology, physics, or chemistry are commonly employed (Fister Jr et al., 2013). Fundamentally nature stands as the primary wellspring of inspiration. The majority of contemporary algorithms can be categorized as nature-inspired. Among these, a substantial portion draws upon successful attributes observed in biological systems. Consequently, the predominant fraction of nature-inspired algorithms falls under the domain of biology-inspired, often abbreviated as bio-inspired. We can divide all existing algorithms into four major categories: swarm intelligence (SI) based, bio-inspired (but not SI-based), physics/chemistry-based, and others.

While Swarm Intelligence (SI) algorithms fall within the broader category of bio-inspired algorithms, it's important to recognize that not all bio-inspired algorithms rely on swarm behavior. From a set theory perspective, SI-based algorithms constitute a subset of bio-inspired algorithms, which in turn are a subset of nature-inspired algorithms. In other words, SI-based ⊂ bio-inspired ⊂ nature-inspired (Fister Jr et al., 2013).

However, not all nature-inspired algorithms are strictly bio-inspired; some are rooted in principles of physics and chemistry. Many bio-inspired algorithms diverge from traditional swarming behavior. Hence, it's more accurate to refer to them as bio-inspired but not SI-based. For instance, genetic algorithms draw inspiration from biological processes but do not involve swarming behavior. Similarly, the classification of certain algorithms like differential evolution (DE) can be challenging. Although DE lacks a direct biological link, its conceptual similarity to genetic algorithms and the term 'evolution' prompts its categorization as bio-inspired.

3.1 Application in Optimization Problems

Abdel-Basset and Shawky (2019)explored the Flower Pollination Algorithm (FPA), a metaheuristic inspired by the proliferation mechanism observed in flowers within plants. The study conducted a thorough examination of various aspects concerning FPA, including its biological inspiration, underlying principles, previous research, comparative analyses, implementation strategies, variants, hybrids, and practical applications. They conducted a comparative assessment between FPA and six other metaheuristic algorithms, such as genetic algorithms, cuckoo search, and grasshopper optimization algorithm, in addressing a constrained engineering optimization problem. Through statistical analysis utilizing non-parametric Friedman test, the experimental findings revealed that FPA exhibits superior performance compared to its counterparts in effectively addressing the specified optimization problem.

In the field of optimization for Neural Network (NN) training, (Chiroma et al., 2016) introduced a novel Flower Pollination Algorithm (FPA) as an alternative to conventional methods. This innovative algorithm exhibits a commendable equilibrium between consistency and exploration. The study aimed to harness the FPA to construct a predictive model for forecasting petroleum consumption by the Organization of the Petroleum Exporting Countries (OPEC), presenting a distinctive approach compared to established meta-heuristic algorithms.

The primary objective of (Chiroma et al., 2016) work was to propose a more effective algorithm for NN training, acknowledging the significance of achieving a balance between exploration and consistency. The methodology employed involved the development and implementation of the Flower Pollination Algorithm, specifically tailored for the task of forecasting OPEC petroleum consumption. In their pursuit of enhancing predictive accuracy and convergence speed, the proposed approach was rigorously compared against conventional meta-heuristic algorithms.

In the study conducted by Ma et al. (2019), a distinctive approach is taken towards the computer-aided diagnosis of thyroid diseases utilizing Single-Photon Emission Computed Tomography (SPECT) images. This research focuses on the optimization of a Convolutional Neural Network (CNN) tailored for diagnostic purposes, specifically targeting three categories of thyroid diseases: Graves' disease, Hashimoto disease, and subacute thyroiditis. The employed model utilizes a modified DenseNet architecture within the CNN framework, with a notable enhancement in the training methodology.

The key modification in the DenseNet architecture involves the incorporation of trainable weight parameters to each skip connection, thereby augmenting the network's capacity to capture intricate features. Simultaneously, the training methodology is refined by integrating the Flower Pollination Algorithm (FPA) for optimizing the learning rate during network training. This dual refinement aims to elevate the overall efficacy of the CNN model in diagnosing thyroid diseases based on SPECT images.

Yazid et al. (2019) advocated for the utilization of artificial neural networks as decision support tools for heart disease detection, a concept previously explored. However, challenges were identified in the conventional application of the back propagation algorithm for error minimization, which tended to encounter difficulties, particularly becoming trapped in local minima. To address this issue, the paper proposed an innovative approach by introducing the flower pollination algorithm as an alternative to the conventional back propagation algorithm for error minimization.

In their research endeavor, Dutta and Kumar (2019) introduced a comprehensive model for liquid flow processes, employing an artificial neural network (NN) as the fundamental framework. To enhance the model's performance and circumvent issues related to local minima, they ingeniously incorporated a flower pollination algorithm (FPA) for optimization, thereby aiming to improve both accuracy and convergence speed. The initial phase involved training the NN model with a dataset derived from experiments conducted under varying conditions, encompassing different sensor output voltages, pipe diameters, and liquid conductivities. The model's responses were cross-verified against experimental results, demonstrating satisfactory alignment.

They leveraged the flower pollination algorithm to identify optimal conditions for sensor output voltages, pipe diameter, and liquid conductivity, leading to the attainment of the minimum flow rate in the liquid flow process. The proposed model underwent thorough cross-validation and testing on subdatasets, yielding impressive accuracy rates of approximately 94.17% and 99.25%, respectively.

A. Das et al. (2022) noted that performance of FPA hinges significantly on achieving a harmonious equilibrium between exploration and exploitation phases. Inherent FPA operators may occasionally lead to false positives in identifying optimal solutions within complex, multimodal surfaces. This study proposed modifications to the original FPA structure aimed at enhancing its capability to accurately pinpoint optima across multimodal landscapes. To bolster FPA performance, two well-established mutation techniques from differential evolution (DE) and a fitness-based dynamic inertia weight mechanism were integrated. This augmentation aimed to foster a more balanced progression across evolutionary stages and enable FPA to navigate multimodal surfaces with greater efficiency. The resulting modified FPA (PMFPA) is then applied within the domain of image enhancement to assess its efficacy. Their experimental findings validated the superiority of PMFPA over conventional swarm intelligence algorithms, the original FPA, and select variants.PMFPA demonstrated heightened robustness, scalability, and precision, thereby affirming its potential as a potent optimization tool for diverse applications.

Alweshah and Abdullah (2015) explained that classification is a crucial task in data mining, and the probabilistic neural network (PNN) is recognized for its efficiency in this domain. They aimed to enhance the PNN approach by developing a more effective method for solving classification problems, targeting both high classification accuracy and rapid convergence speed. To achieve this goal, they proposed a hybrid method that combines the firefly algorithm with simulated annealing (referred to as SFA), where simulated annealing was used to control the randomness within the firefly algorithm while optimizing the weights of the standard PNN model.They explored the effectiveness of incorporating Lévy flight into the firefly algorithm (referred to as LFA) to improve the exploration of the search space. Furthermore, they integrated SFA with Lévy flight (referred to as LSFA) to enhance the PNN's performance further. These algorithms were evaluated using 11 standard benchmark datasets. The experimental results demonstrated that LSFA outperforms both SFA and LFA. Moreover, when compared to other algorithms in the literature, LSFA achieved superior classification accuracy.

Suganuma et al. (2017) explored the automatic construction of CNN architectures for image classification using Cartesian genetic programming (CGP). Their approach leveraged highly functional modules, such as convolutional blocks and tensor concatenation, as node functions within the CGP framework. The CNN's structure and connectivity, as encoded by the CGP method, were optimized to maximize validation accuracy. To assess the efficacy of their proposed method, they applied it to create a CNN architecture for the CIFAR-10 image classification task. The experimental results demonstrated that their method can automatically discover CNN architectures that are competitive with state-of-the-art models.

Sun et al. (2019) introduced an automatic architecture design method for CNNs using genetic algorithms, capable of identifying effective CNN architectures for image classification tasks. Their proposed algorithm operates fully automatically, requiring no pre-processing or post-processing of the discovered CNNs. They validated the algorithm using widely recognized benchmark datasets, comparing it against state-of-the-art peer competitors, including eight manually designed CNNs, four semi-automatically designed CNNs, and four additional automatically designed CNNs. The experimental results demonstrated that their algorithm consistently achieved the highest classification accuracy among both manually and automatically designed CNNs. It offers competitive classification accuracy compared to semi-automatic methods while using ten times fewer parameters. On average, the proposed algorithm utilizes only one percent of the computational resources required by other architecture discovery algorithms.

Sahoo et al. (2023) explained that abundance of features in datasets often leads to erroneous predictions, necessitating feature selection methods. Their research, employed correlation-based feature selection (CFS) and the flower pollination algorithm (FPA) to enhance the quality of the Wisconsin Prognostic Breast Cancer (WPBC) and University Medical Centre, Institute of Oncology (UMCIO) breast cancer relapse datasets, respectively. Pre-processing stages involved data imputation, scaling, and raw data preprocessing. CFS was applied to identify discriminative features based on crucial feature correlations. The FPA was then utilized to identify the optimal attribute combination for maximal precision. Their proposed approach was evaluated using 10-fold cross-validation stratification, yielding promising results. The trials demonstrated accuracies of 84.85% and 83.92% on the WPBC and UMCIO breast cancer relapse datasets, respectively. Their hybrid method excelled in feature selection, thereby augmenting the accuracy of breast cancer relapse classification.

3.2 Applications in Medical Image Analysis

Dhal et al. (2020) to enhance the FPA's effectiveness, their study introduced three global search and two local search strategies aimed at fostering a better equilibrium among its evolutionary stages. The methodology incorporated parameter adaptation techniques to further refine its performance. The modified FPA was then applied to the problem of histopathological image segmentation. Their experimental and computational analyses demonstrated the enhanced efficiency and robustness of the modified FPA compared to existing swarm intelligence algorithms and machine learning methods. These findings emphasize the potential of the proposed methodology in addressing optimization challenges across various domains.

Salim and Sarath (2024) study, the challenge of automatic segmentation of breast tumors persists due to the inherent difficulties posed by poor contrast and unclear structures of tumor cells in histopathological images was explored. To overcome these obstacles, an innovative approach for breast cancer (BC) detection and classification was proposed, leveraging a DenseNet-based Chronological Circle Inspired Optimization Algorithm (CCIOA). Their proposed methodology integrates Deep Learning (DL) techniques to achieve precise segmentation and identification of BC lesions. Specifically, ResuNet++ was used for image segmentation, while an efficient optimization method known as Invasive Water Ebola Optimization (IWEO) was utilized to fine-tune the parameters of the DL network. DenseNet was used for BC detection, with CCIOA serving as the optimization algorithm for training the DenseNet model. The performance of the CCIOA-DenseNet model was evaluated using key metrics such as accuracy, True Positive Rate (TPR), and True Negative Rate (TNR). Experimental results demonstrate the superior performance of the CCIOA-DenseNet model, achieving an accuracy of 97.1%, TPR of 96.6%, and TNR of 95.4%.

Atban et al. (2023) their focus revolved around the selection of optimal features essential for the classification of breast cancer pathological images while mitigating the challenges posed by the curse of dimensionality. To address this, the study leveraged optimized deep features as a solution.The approach entailed employing the ResNet18 architecture to extract deep features crucial for the classification task. Subsequently, meta-heuristic algorithms such as Particle Swarm Optimization (PSO), Atom Search Optimization (ASO), and Equilibrium Optimizer (EO) are harnessed to further refine and enhance the representativeness of these features in breast cancer pathological images. The significance of optimized deep features in classification is comprehensively investigated by employing traditional machine learning (ML) algorithms. The experimental evaluation of the proposed approach was conducted using the publicly available benchmark dataset BreakHis. The experimental outcomes underscore the efficacy of the proposed methodology, particularly highlighting the notable performance achieved when utilizing features derived from ResNet18-EO. Specifically, the proposed approach attains an impressive F-score of 97.75% when employing the Support Vector Machine (SVM) with gaussian and radial-based functions (RBF) on these optimized features.

Das et al. (2022) stated that contemporary approaches predominantly leverage deep learning models for predictive tasks. These methods may encounter challenges related to high-dimensional features and the inclusion of irrelevant or redundant information. To address this limitation, their study adopted the widely used particle swarm optimization (PSO) algorithm to attain an optimal feature set. Initial preprocessing involved obtaining stain-normalized images, followed by feature extraction using a pre-trained MobileNet model. Evaluation was conducted on a recent dataset provided by the ICIAR BACH 2018 grand challenge. Experimental findings demonstrated a notable 6.25% enhancement in recognition accuracy while reducing features by approximately 54%. Furthermore, a comparison with two state-of-the-art CNN models, InceptionResNet and DenseNet, revealed the superiority of MobileNet. The performance of their model was found to be on par with certain state-of-the-art methods applied to the BACH dataset.

Karthikeyan and Rajaguru (2023) have developed algorithms aimed at identifying lung cancer in histopathological images. This study proposed a computer-aided detection method that utilized Flower Pollination Optimization for feature extraction from histopathological images. Standard histopathological images from the Kaggle database were employed in this investigation. Five classifiers, including the Gaussian Mixture Model (GMM), Non-Linear Regression (NLR), Naïve Bayes Classifier (NBC), Logistic Regression (LR), and Fisher Discriminant Classifier (FDC), were employed to evaluate and classify the Benign and Adenocarcinoma classes. The results demonstrated that the Naïve Bayes Classifier, in conjunction with Flower Pollination, achieves the highest accuracy at 87.86%, based on established benchmark metrics.

Sha et al. (2020) presented a comprehensive approach for identifying cancerous regions within mammogram images. The method integrated techniques such as image noise reduction, optimal image segmentation using convolutional neural networks (CNNs), and feature extraction and selection facilitated by the grasshopper optimization algorithm (GOA). Through this combined approach, the study aimed to enhance precision while reducing computational costs. Their proposed method was tested using the Mammographic Image Analysis Society Digital Mammogram Database and Digital Database for Screening Mammography breast cancer databases. Simulation results were then compared with 10 state-of-the-art methods to evaluate the system's efficiency. The findings indicated that the proposed method achieved notable performance metrics, including 96% sensitivity, 93% specificity, 85% positive predictive value (PPV), 97% negative predictive value (NPV), and 92% accuracy. Moreover, it demonstrated superior efficiency compared to traditional methods across various evaluation criteria. Despite the time-consuming nature of learning for the GOA-based CNN, this stage was conducted only once, minimizing its impact on overall efficiency.

Rehman et al. (2023) have devised a novel framework for breast cancer diagnosis utilizing entropy-controlled deep learning alongside flower pollination optimization applied to mammogram images. The framework incorporated a filter fusion-based approach for contrast enhancement, enhancing the effectiveness of subsequent processing stages. The pre-trained ResNet-50 model undergoes refinement and training via transfer learning on both the original and enhanced datasets. Deep features were then extracted and consolidated into a unified vector using a serial mid-value feature technique. The extracted features were classified using neural networks and machine learning classifiers. To facilitate this process, they have introduced a flower pollination optimization technique with entropy control. The framework's efficacy was evaluated using three publicly available datasets: CBIS-DDSM, INbreast, and MIAS, achieving accuracies of 93.8%, 99.5%, and 99.8%, respectively. Their study demonstrated significant improvements in accuracy and computational efficiency compared to existing methods.

Chakravarthy and Rajaguru (2021) introduced a methodology aimed at enhancing early detection of breast cancer. Their methodology employed ensemble-based classifiers, specifically the histogram-based Gradient Boosting Machine (hbGBM), Gradient Boosting with Light GBM (lGBM), and Gradient Boosting with CatBoost (GBCB) algorithms. The research utilized the Mammogram Image Analysis Society (MIAS) database to evaluate the efficacy of these algorithms. Feature extraction was carried out using the Haar wavelet transform, while the Flower-Pollination Algorithm (FPA) was employed for optimal feature selection.They used a flower-pollination-based Haar wavelet feature approach, combined with three ensemble-based classifiers, for automatic mammogram classification. Performance evaluation was conducted using benchmark metrics including specificity, sensitivity, precision, accuracy, F1 score, and Matthews Correlation Coefficient (MCC) analysis. Their results indicated that the ensemble GBCB-based FPA algorithm achieved the highest classification accuracy at 91%, outperforming existing models. However, a key challenge lies in selecting the optimal combination of classifiers with the appropriate feature extractor and selector algorithm.

Alshehri (2023) presented a novel approach to breast cancer (BC) detection by integrating deep learning models with advanced image processing techniques to mitigate existing limitations. The BC dataset underwent preprocessing steps such as histogram equalization and adaptive filtering, followed by data augmentation using cycle-consistent Generative Adversarial Networks (CycleGANs). Handcrafted features including Haralick features, Gabor filters, contour-based features, and morphological features were extracted alongside features obtained from the VGG16 deep learning architecture. A hybrid optimization model, named Hybrid Red Deer with Sparrow Optimization (HRDSO), which combines the Sparrow Search Algorithm (SSA) and Red Deer Algorithm (RDA), was employed to select the most informative subset of features. For BC detection, a novel DenseXtNet architecture was proposed by integrating DenseNet with optimized ResNeXt, optimized using the HRDSO hybrid optimization model. The performance of the proposed model was evaluated using various metrics and compared with existing methods, demonstrating an accuracy of 97.58% in BC detection. MATLAB was utilized for both implementation and evaluation tasks.

Reshma et al. (2022)aimed to enhance various phases of computer-aided diagnosis (CAD) systems, thereby reducing variability among observers. An automated segmentation method, followed by self-guided post-processing activities, was developed to integrate Fourier Transform-based Segmentation into the CAD system, enhancing its performance. The proposed segmentation approach offered several advantages over existing methods: it incorporated spatial information, eliminated the need for pre-defined parameters, remains independent of magnification levels, automatically determines inputs for morphological operations to enhance segmented images, and operates efficiently. Extensive testing was conducted to evaluate the effectiveness of different feature extraction techniques and to assess the impact of textural, morphological, and graph characteristics on classification accuracy. A classification strategy for breast cancer detection was devised, employing weighted feature selection and an enhanced version of the Genetic Algorithm in tandem with a Convolutional Neural Network Classifier. The application of these improved segmentation and classification algorithms within the CAD framework has the potential to reduce diagnostic errors and enhance classification accuracy. They could serve as valuable adjunct tools for pathologists, aiding in early disease detection. **Error! Reference source not found.** presents a comparative analyses of different EA techniques, performance metrics, and experimental limitations. Furthermore, the discussion addresses emerging trends, open research questions, and potential future directions in the field of deep learning optimization using evolutionary algorithms.

Table 1 : Comparative analyses of different EA techniques based on performance metrics, and experimental limitations

S/N	Source	Problem	Technique	Methodology	Contribution	Limitation
1	(Chiroma et al., 2016)	Forecasting petroleum consumption	Enhancing OPEC petroleum consumption forecast	Flower Pollination Algorithm for NN training	Improved OPEC petroleum consumption forecast accuracy and convergence speed compared to established meta-heuristic algorithms	Limited exploration of NN training with FPA, Need for diverse applications
2	Ma et al. (2019)	Diagnostic challenges in thyroid diseases	CNN-based diagnosis of thyroid diseases	Modified DenseNet architecture with trainable parameters, optimized learning rate using FPA	Superior diagnostic performance in thyroid diseases using SPECT images, outperforming other CNN methods	Limited exploration of thyroid diseases, Need for enhanced training strategies
3	(Yazid et al., 2019)	Heart disease detection with ANN	Enhancing heart disease detection accuracy	Integration of Flower Pollination Algorithm for error minimization	Improved classification accuracy achieved with the proposed Flower Pollination Neural Network compared to conventional back propagation neural network algorithm	Challenges in conventional back propagation algorithm, Local minima issues

4	(Dutta & Kumar, 2019)	Liquid flow process modeling	Enhancing model accuracy for liquid flow processes	Integration of NN and FPA for optimization	Achieved nearly 94.17% and 99.25% accuracy in cross-validation and testing subdatasets,respectively	Addressing local minima issues, Improving convergence speed
5	(Atban et al., 2023)	Efficient feature selection for breast cancer classification	Optimized deep features extraction	Utilization of ResNet18 architecture and meta-heuristic algorithms	Improved feature representation.The proposed approach attains an impressive F-score of 97.75%	Limited evaluation beyond SVM classifier and BreakHis dataset
6	(Karthikeyan & Rajaguru, 2023)	Identification of lung cancer in histopathological images	Computer-aided detection method using Flower Pollination Optimization	Utilization of standard histopathological images from the Kaggle database	Achievement of highest accuracy (87.86%) with Naïve Bayes Classifier combined with Flower Pollination	Th research will explore Convolutional Neural Network (CNN) to enhance classifier performance in this area.
7	(Sha et al., 2020)	Locating cancerous regions in mammogram images	Image noise reduction, optimal segmentation using (CNN), Grasshopper Optimization Algorithm (GOA), optimized feature extraction and selection using GOA	Comprehensive method integrating image processing, CNN segmentation, GOA optimization for feature extraction and selection	Improved precision, decreased computational cost	Time-consuming learning phase for GOA-based CNN, but performed only once for overall efficiency
8	(Rehman et al., 2023)	Breast cancer diagnosis framework development	Deep learning optimization based on pre-trained ResNet-50 model with flower pollination	A novel framework integrating entropy-controlled deep learning and flower pollination optimization for breast cancer diagnosis using mammogram images.	Achievement of high accuracies (93.8%, 99.5%, and 99.8%) on three publicly available datasets, showcasing improved accuracy and reduced computational time compared to existing methods.	Complexity of implementing and fine-tuning the proposed framework based on time complexity and with the algorithm executing on all initialized iterations.
9	(Chakravarthy & Rajaguru, 2021)	Early breast cancer detection using Mammogram images	Ensemble-based classifiers using haar wavelet features extracted from mammogram images	Feature extraction via Haar wavelet transform and optimal feature selection using the Flower-Pollination Algorithm (FPA).	Introduction of a flower-pollination-based Haar wavelet feature approach combined with ensemble-based classifiers for automatic mammogram classification, achieving high accuracy (91%) compared to existing models.	Challenge in selecting the optimal combination of classifiers with suitable feature extractor and selector algorithms.
10	(Alshehri, 2023)	Breast Cancer Detection and Classification	Deep Learning Models, Image Processing Techniques and	Application of hybrid optimization model HRDSO for feature selection and DenseXtNet	Improved accuracy in BC detection compared to existing methods based on DenseXtNet architecture and optimization.	Generalizability of results to broader clinical settings and datasets may be

			Optimization Algorithms	architecture for BC detection.		limited and challenging.
11	(Reshma et al., 2022)	Breast cancer diagnosis among observers through improved strategies in computer-aided diagnosis (CAD) systems.	Automated segmentation combined with self-driven post-processing activities, integrating Fourier Transform-based Segmentation into the CAD system.	Development of a classification strategy utilizing weighted feature selection and an enhanced Genetic Algorithm with a Convolutional Neural Network Classifier.	Enhancement of CAD system performance by integrating advanced segmentation and classification algorithms, potentially reducing diagnostic errors and improving classification accuracy.	The effectiveness of the proposed segmentation and classification algorithms may be influenced by specific dataset characteristics and may require further validation across diverse datasets and clinical settings.
12	(Alweshah & Abdullah, 2015)	Classification	Probabilistic Neural Network (PNN)	Hybridization of Firefly Algorithm with Simulated Annealing (SFA)	Development of a hybrid method (LSFA) for classification problems, for optimizing PNN weights, demonstrating superior performance in terms of classification	Performance may vary depending on the dataset used and specific problem requirements
13	(Suganuma et al., 2017)	Image Classification	Convolutional Neural Network (CNN)	Cartesian Genetic Programming	Automatic construction of CNN architectures using Cartesian Genetic Programming (CGP)	Performance may vary depending on the datasets and problem domain
14	(Sun et al., 2019)	Image Classification	Convolutional Neural Network (CNN) and Genetic Algorithm	Automatic architecture design method for CNNs by using genetic algorithms	No pre-processing or post-processing required, Validated on benhcmark datasets. Reduced parameters and computational resources	Perfomance dependant onm datasets and problem requirements
15	(Salim & Sarath, 2023)	Poor contrast and unclear tumor cell structures pose challenges for automatic segmentation of breast tumors	DenseNet-based Chronological Circle Inspired Optimization Algorithm (CCIOA)	Integration of Deep Learning (DL) approaches for precise segmentation and identification of breast cancer lesions using ResuNet++ for segmentation and IWEO for parameter fine-tuning. DenseNet is utilized for breast cancer detection with CCIOA serving as the optimization algorithm for model training.	Improved accuracy, TPR, and TNR in breast cancer detection and classification. Achieved an accuracy of 97.1%.	Evaluation limited to metrics of accuracy, TPR, and TNR

4. Discussion

In this work, we analysed research on the application evolutionary algorithms for deep learning optimization. We have focused on the use's cases of EAs in optimizing deep learning, like medical in classifying breast cancer images. In addition, we realized that EAs have a very important role to play in deep feature selection and parameter tuning of deep learning algorithms. They are well suited for feature selection phase, because of their general ability in search and optimality. Metaheuristic optimization algorithms are known for its efficacy in addressing complex optimization problems. The integration of the Flower Pollination Algorithm (FPA) into the classification model serves as a distinctive facet of lots of research, drawing inspiration from the natural foraging behavior of flowers. This nature-inspired optimization algorithm introduces a novel dimension to the project, aiming to enhance the model's adaptability and efficiency in navigating complex parameter spaces, thereby contributing to improved overall performance (Yang, 2012)

4.1 Emerging Trends

One of the notable emerging trends in this field is the increasing integration of hybrid models that combine multiple evolutionary algorithms with deep learning techniques. These hybrid models leverage the strengths of various optimization methods to enhance the performance and efficiency of deep learning models. For instance, the combination of genetic algorithms with particle swarm optimization or differential evolution has shown promising results in optimizing complex neural network architectures (Zhan et al., 2022). Another trend is the use of multi-objective optimization to balance various conflicting objectives, such as accuracy, computational efficiency, and model complexity. This approach helps in creating more robust and generalized models that perform well across different tasks and datasets.

4.2 Open Research Questions

Despite the advancements, several open research questions remain in the field. One major question is how to effectively scale evolutionary algorithms to handle the growing complexity and size of deep learning models. As models become deeper and more intricate, the computational cost of optimizing them using EAs increases significantly, posing a challenge for researchers (Zhan et al., 2022). Unfair comparisons of different Evolutionary Deep Learning (EDL) methods often arise due to several factors. Firstly, uniform benchmarks are crucial. In feature engineering, the lack of a standardized benchmark for fair comparison of different algorithms is problematic because of the varying downstream prediction models and feature sets used (Li et al., 2022).

Another important question is the interpretability and explainability of the EA models. While evolutionary algorithms can discover highly effective neural architectures, understanding the underlying mechanisms and reasons for their effectiveness remains a challenge. EDLs are often regarded as black-box optimization methods, and there is a lack of theoretical analysis to explain their superiority. For instance, it is difficult to explain why EA-based methods tend to select features that enhance the performance of classification models in feature engineering. Consequently, the development of EDL in sensitive domains such as finance and medicine has been slow. Future research could focus on developing methods to interpret the results of evolutionary optimization, thereby making the models more transparent and trustworthy. Therefore, improving the interpretability of EDL presents an interesting and promising research direction.

4.3 Potential Future Directions

There is significant potential for enhancing the performance of Evolutionary Deep Learning (EDL) on both benchmark datasets and real-world applications. Although EDL methods surpass manually designed models on various image benchmarks like CIFAR-10 and ImageNet, the current state-of-the-art EDL techniques fall short in Natural Language Processing (NLP) compared to human-designed models, such as GPT-2 and Transformer-XL. Real-world tasks present additional challenges, including the presence of noise (e.g., mislabeling and imbalanced data) and small-scale datasets that can lead to overfitting. To address these challenges, incorporating techniques such as unsupervised and self-supervised learning into EDL could be beneficial (Li et al., 2022)

Another direction is the development of more efficient EA-based optimization frameworks that leverage advancements in hardware, such as GPUs and TPUs, to accelerate the optimization process. This could make it feasible to apply EAs to larger and more complex models. The integration of reinforcement learning with evolutionary algorithms. This hybrid approach can exploit the strengths of both techniques, where reinforcement learning can guide the search process of the EA, leading to more efficient exploration and exploitation of the search space.

There is also a potential in exploring the use of EAs for optimizing specific components of deep learning models, such as activation functions, loss functions, and regularization techniques. This fine-grained optimization could lead to significant improvements in model performance and generalization. Advancing the theoretical understanding of why and how evolutionary algorithms work effectively for deep learning optimization can provide valuable insights and guide the development of more sophisticated and powerful optimization technique (Zhan et al., 2022).

5. Conclusion

In conclusion, this paper presents a comprehensive review of the state-of-the-art research works in deep learning optimization using evolutionary algorithms. By synthesizing the existing literature and analyzing the strengths and limitations of different approaches, this study reveals to researchers and practitioners the potential of EAs for enhancing the efficiency and effectiveness of deep learning models. While evolutionary algorithms have shown great promise in optimizing deep learning models, there is still much to explore and develop in this field. Addressing the open research questions and exploring the potential future directions can lead to significant advancements, making deep learning models more efficient, robust, and applicable to a wider range of tasks. Future work in this area may focus on developing hybrid optimization techniques, addressing scalability issues, and exploring novel applications of evolutionary algorithms in deep learning.

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