Training Feed-Forward Neural Networks for Medical Image Registration Using Sine-Cosine and Teaching-Learning-Based Fusion

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Abstract

This study presents a novel hybrid metaheuristic algorithm, Sine-Cosine Adaptive Teaching-Learning-Based Optimization (SCATLBO),designed to train Feed-Forward Neural Networks (FNNs) for mono and multi-modal medical image registration. SCATLBO combines the strengths of the Sine-Cosine Algorithm (SCA) for exploration with Teaching-Learning-Based Optimization (TLBO) for exploitation, achieving a balance that enhances the algorithm's capability to avoid local minima and improve convergence rates. Medical image registration, essential for accurate medical analysis, benefits from this hybrid approach as it aligns complex multi-modal images effectively. In this work, SCATLBO was applied to train FNNs on breast MRI images from the Cancer Genome Atlas Breast Invasive Carcinoma (TCGA-BRCA) dataset. The performance of SCATLBO is benchmarked against several well-known metaheuristic algorithms, including TLBO, Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), and Evolution Strategy (ES), with evaluations based on Mean Squared Error (MSE) for mono-modal and Mutual Information (MI) for multi-modal registration. Experimental results demonstrate that SCATLBO outperforms other techniques in terms of accuracy, convergence speed, and robustness, establishing it as a promising tool for neural network-based image registration tasks. This work contributes to the advancement of metaheuristic training approaches for FNNs, with potential applications in diverse medical imaging fields.

Keywords

Medical Image Registration,, Metaheuristic Optimization, Sine-Cosine Algorithm (SCA), Teaching-Learning-Based Optimization (TLBO), Feed-Forward Neural Network (FNN), Multimodal Image Alignment

1. Introduction

Image registration, which is very useful in medical applications, entails aligning various image files inside a similar coordinate system to match imaging content. Comparing images captured from different angles, at different times, or with different sensors or modalities [1, 2].The fundamental components of the human brain, biological neurons, serve as the inspiration for the machine learning modality known as an Artificial Neural Network (ANN) [3].Just as the vast complexity of the human brain, artificial neural systems form a maze of computational pathways that are primed for acquiring knowledge. From computer eyes deciphering visual scenes to clever algorithms mastering games of strategy, and from medical machines diagnosing disorders to programs facilitating cross-language communication, neural nets have demonstrated adaptable intelligence in many diverse fields. Whether discerning patterns in social webs or recognizing speech, neural networks continue to surprise with their knack for teasing out the intricate structures underlying immense troves of unrefined data, enabling novel insight and innovative progress across a growing roster of promising applications. The most basic artificial neural network capable of resolving non-linear issues is a Feed-forward Neural Network (FNN). Neuronal connections in a FNN do not form cycle. Input, hidden, and output layers are the three layers in

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which neurons are placed. Every neuron in the deepest layer connects to all neurons above it. Feed-forward neural networks can effectively categorize and forecast continuous values. Firstly, FNNs learn patterns, classes, or clusters within information to perform categorization and prediction.Supervised, unsupervised, and reinforcement learning represent the three principle categories of machine instruction. Whereas datasets for unsupervised learning only comprise attribute values alone, training and testing materials for supervised learning have both goal and attribute values paired. Across many iterations or epochs, the interactions between two neurons in an FNN are assigned weights for optimal functioning based on the issue at hand and therefore enable knowing. Some linkages may have great impact whilst others contribute less. The most fruitful connections are reinforced through ongoing alteration as the network is exposed to more information.

Methods of training strategy can be classified into two stochastic and exact methods. Exact methods are classical mathematical methods based on the gradient. The training algorithm most commonly used is back-propagation, which relies on gradient descent techniques [4].Back-propagation algorithm primarily uses gradient descent method to determine the optimal weights. Not only the gradient descent algorithm itself, many other methods based on gradient data such as Newton method, Quasi-Newtonmethod and conjugate-gradient method etc are also applicable. Although these algorithms are quicker than other approaches, they suffer from local minima entrapment. Such techniques typically provide a local optimum (or perhaps a close local optimum) of the basin in which the original solution is found. Consequently, initialization plays a crucial role in the solution at the end. Stochastic techniques are often employed to facilitate the training of FNNs through mitigating the proclivity toward becoming ensnared by local optima. Non-determinism is leveraged by metaheuristics, general-purpose stochastic optimization algorithms, to escape the captivity of local optima. The malleability and derivative-free nature of metaheuristics, permitting handling of non-continuous and non-differentiable activation functions, represents an additional benefit. These advantages have rendered metaheuristics a fascinating domain of inquiry for FNN training. In this paper, we presented a workflow using hybrid SCATLBO algorithm for training feed forward Neural Networks (FFNs) to learn the mapping functions corresponding to mono and multimodal image registration, and compared our results with some of the state-of-the-art algorithms that are conventionally used for training such FFN systems, namely Teaching-Learning Based Optimization (TLBO)[5, 6], Particle Swarm Optimization (PSO)[7, 8, 9], Ant Colony optimization(ACO)[10, 11, 12], Grey Wolf optimizer (GWO)[13], Evolution Strategy (ES)[14]. The Hybrid SCATLBO algorithm trained the Feed forward Neural Networks (FNNs) more effectively than other metaheuristic algorithms. Most of them are metaheuristics in the sense that they are natural inspired algorithms based on physical laws, biological evolution, neurobiological system, swarm behaviour. Metaheuristics can be roughly divided into two broad categories: single-solution-based or population-based. Single-solution metaheuristics: One candidate solution at a time explores the search space, while population-based methods have multiple solutions searching the space simultaneously. This incorporation of SCA and TLBO exploit both the exploration and exploitation abilities can increase the training performance as well as offers a robust FNN for image registration problems.

In this study, we explore a novel approach for training Feed-Forward Neural Networks (FNNs) using a hybridized metaheuristic algorithm, combining Sine-Cosine Algorithm (SCA) [15]and Teaching-Learning-Based Optimization (TLBO), referred to as SCATLBO.This approach optimizes FNNs for medical image registration, specifically aligning multi-modal medical images for enhanced analysis. Below, we outline each section and the specific methodologies and concepts they address.

We begin with the **Methodology** section(2), where we detail the phases of the SCATLBO algorithm, including the Teaching Phase (Exploitation) (2.1), where the model learns from the best solutions, and the Learning Phase (Exploration) (2.2), enhancing the algorithm's robustness by promoting diverse learning strategies. We also introduce the Sine-Cosine Modification (SCA) technique (2.3) to improve exploration capabilities and avoid local minima.

The **Feed-Forward Neural Network (FNN)** framework (2.4) is explained, including the calculation of Mean Squared Error (MSE) (2.4.1) as a primary loss function for monomodal image registration and Mutual Information (MI) (2.5) for multimodal scenarios. This section also discusses the dataset used in this study (2.6) and how we configured parameters for the algorithm (2.7).

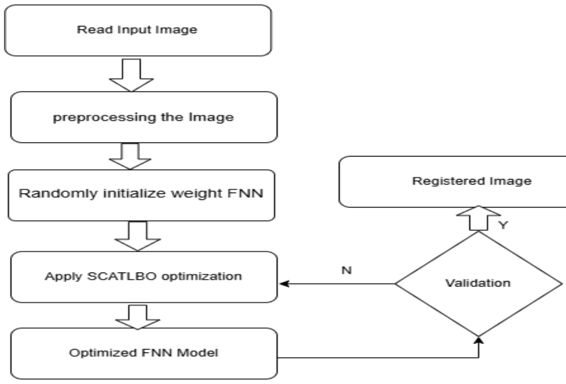

Figure 1: Workflow of the proposed method

In the **Result and Discussion** section (3), we analyze the algorithm's performance. We assess the statistical significance of our results using the Wilcoxon Signed-Rank Test (3.1) and make decisions based on multiple criteria through the TOPSIS method (3.2).

Finally, the **Conclusion** (4) highlights our main findings and suggests future research directions for optimizing FNN structures and tuning parameters in advanced applications.

2. Methodology

The proposed methodology leverages the SCATLBO (Sine-Cosine Algorithm combined with Teaching-Learning-Based Optimization) for training a FNN to enhance image registration accuracy. The workflow of proposed method is outlined in Figure 1. This process can be summarized as follows:

1. **Read Input Image**: The workflow starts by reading the input image, such as a DCE-MRI scan, that requires registration.
2. **Preprocessing the Image**: The input image undergoes preprocessing, which involves normalization, resizing, or other necessary transformations. This step ensures that the image data is consistent and free of noise, preparing it for effective processing by the neural network.
3. **Randomly Initialize Weight FNN**: The FNN model is initialized with random weights, creating a baseline model that can be iteratively refined. This initialization is essential for ensuring that the model starts from an unbiased point.
4. **Apply SCATLBO Optimization**: The core of the proposed methodology involves applying SCATLBO optimization to fine-tune the weights of the FNN. The SCATLBO algorithm enhances the optimization process by combining the exploration and exploitation capability. This hybrid approach allows the model to search the weight space more effectively, finding optimal weights that improve the accuracy and robustness of the registration.
5. **Validation**: After optimization, the model is evaluated through a validation process. The registered image produced by the model is assessed to determine if it meets specific accuracy criteria.
    - If the validation is successful, the process moves to finalize the optimized FNN model.
    - If the validation fails, the process loops back to the SCATLBO optimization step, allowing further refinement of the model weights. This iterative process continues until the registered image meets the desired quality standards.
6. **Optimized FNN Model**: Once the model passes validation, the final output is an optimized FNN model capable of performing high-quality image registration. This optimized model is now ready for deployment in tasks requiring accurate and reliable for image registration.

This methodology outlines a systematic approach for developing an optimized FNN model through SCATLBO, which iteratively adjusts the model's parameters to achieve improved accuracy in image registration. By combining adaptive mechanisms and hybrid optimization strategies, the SCATLBO-FNN model provides an effective solution for tasks requiring precise alignment of medical images, improving both performance and reliability in medical image analysis applications.

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4. **Apply SCATLBO Optimization**: The core of the proposed methodology involves applying SCATLBO optimization to fine-tune the weights of the FNN. The SCATLBO algorithm enhances the optimization process by combining the exploration capability of the sine-cosine mechanism with the exploitation capability of TLBO. This hybrid approach allows the model to search the weight space more effectively, finding optimal weights that improve the accuracy and robustness of the registration.
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2.1. Teaching phase (Exploitation)

In the TLBO algorithm, the Teacher phase adjusts the network parameters (such as weights and biases) based on the best-performing solution in the population. This phase can be seen as an exploitation phase, where the best solution tries to bring other solutions closer to its performance. The parameter update equation for the teacher phase is given by:

$$W_{\text{new}} = W_{\text{old}} + r \times (W_{\text{best}} - T \times W_{\text{mean}}) \tag{1}$$

Where:

1. W_{new} and W_{old} are the updated and current weights.
2. W_{best} is the weight of the best-performing solution (teacher).
3. W_{mean} is the mean weight of the population.
4. r is a random number between 0 and 1.
5. T is a teaching factor, usually chosen as 1 or 2.

2.2. Learning phase (Exploration)

In the Learning phase, individuals learn from each other by updating their weights based on the difference between two randomly chosen individuals:

$$W_{\text{new}} = W_{\text{old}} + r \times (W_j - W_k) \tag{2}$$

W_j and W_k be the weights of two randomly selected solutions from the population, and r be a random number.

2.3. Sine-Cosine Modification (SCA)

The sine-cosine modification introduces a non-linear exploration mechanism that enhances global search capability. The SCA operator is incorporated as follows:

$$W_{\text{new}} = \begin{cases} W_{\text{old}} + r \times \sin(\theta) \times |W_{\text{best}} - W_{\text{old}}| \\ W_{\text{old}} + r \times \cos(\theta) \times |W_{\text{best}} - W_{\text{old}}| \end{cases} \tag{3}$$

Where θ is an angle that modulates exploration using sine or cosine waves, and r is a random number that controls the intensity of exploration. The SCA phase helps balance exploration and exploitation by using these sine and cosine functions, making the search space more diverse and preventing the network from being trapped in local minima. The Feedforward Neural Network (FNN) is trained to minimize a registration loss, such as Mean Squared Error (MSE)[16] between intensities of corresponding pixels in the two images, or Mutual Information (MI) to capture the statistical dependency of the images in multimodal registration. The intensity features are mapped to the ideal transformation parameters using the FNN. Consider the following:

$$\theta = [\theta_1, \theta_2, \ldots, \theta_d]$$

Rotation, translation, scaling, and other transformation parameters are represented by the vector $\theta = [\theta_1, \theta_2, \ldots, \theta_d]$.

Using the formula

$$\theta = \mathcal{F}(x; W, b) \tag{4}$$

the FNN, represented as $\mathcal{F}$, maps input intensity pairs x_i to transformation parameters. W and b represent the network's weights and biases.

A transformation T_θ is applied to the output θ in order to align I_m with I_f.

2.4. Feed-forward Neural Network (FNN)

A feed-forward neural network (FNN) is the most fundamental type of artificial neural network, characterized by a layer-structured architecture where connections between neurons do not form cycles. In FNNs, neurons are organized into three layers: the input layer, the hidden layer, and the output layer. Data flows unidirectionally from one layer to the next, with each neuron in a layer connected to every neuron in the subsequent layer, ensuring there are no backward connections, loops, or cycles.

The output signals generated by artificial neurons are determined by applying an activation function, frequently called a transfer function, to the weighted linear combination $(wx) + b$ of inputs. By introducing non-linearity through these activation functions, feedforward neural networks gain the ability to learn intricate, non-trivial patterns in vast amounts of data. Figure 2 depicts a basic schematic of a simple feed-forward network, demonstrating how information flows through it in one direction from input to output. Additionally, Figure 3 displays common activation functions along with their corresponding graphs, which are integral to comprehending how these mathematical operators mold a network's behavior during the learning process. The interplay between weights, inputs, and activation functions unlocks neural networks potential to model complex patterns beyond the capabilities of shallow architectures like logistic regression.

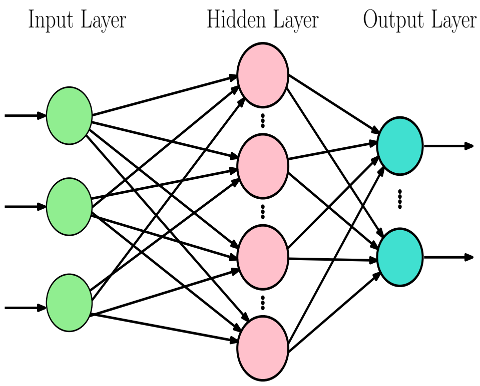

Figure 2: Schematic representation of a simple FNN

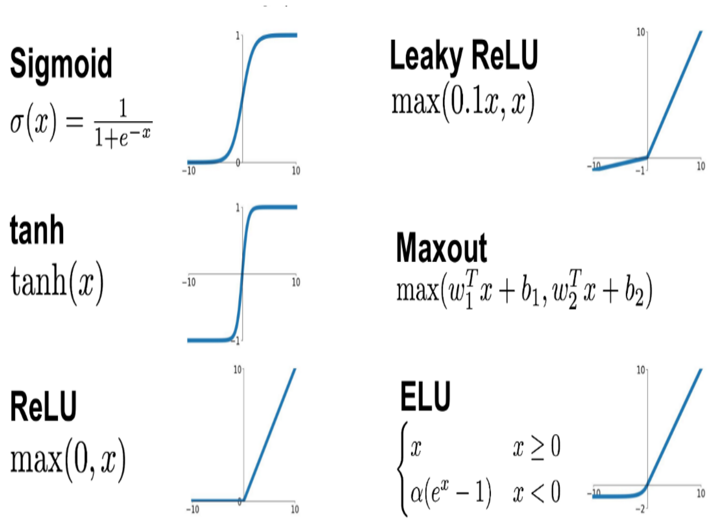

Figure 3: List of Activation Functions with graphs

2.4.1. Mean Squared Error (MSE)

The loss function L measures the difference in intensity between I_f and the transformed $I_{m'}$:

$$L_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^{N} (I_f(p_i) - I_{m'}(q_i))^2 \tag{5}$$

For monomodal registration, we used Mean Squared Error (MSE), where $I_f(p_i)$ and $I_{m'}(q_i)$ are the intensities at corresponding points in the fixed and moving images.

The goal of training is to minimize this loss function:

$$\min_{W,b} L(\mathcal{F}(x; W, b)) \tag{6}$$

where $\mathcal{F}(x; W, b)$ represents the FNN model with weights W and biases b.

2.5. Mutual Information (MI)

MI measures the shared information between the two images:

$$L_{\text{MI}} = -\sum_{i=1}^{N}\sum_{j=1}^{M} P(I_f(p_i), I_{m'}(q_j)) \log \frac{P(I_f(p_i), I_{m'}(q_j))}{P(I_f(p_i)) \cdot P(I_{m'}(q_j))} \tag{7}$$

Where

- $P(I_f(p_i))$ is the marginal probability of the intensity $I_f(p_i)$ in the fixed image I_f,
- $P(I_{m'}(q_j))$ is the marginal probability of the intensity $I_{m'}(q_j)$ in the transformed moving image $I_{m'}$,
- $P(I_f(p_i), I_{m'}(q_j))$ is the joint probability of the intensities $I_f(p_i)$ and $I_{m'}(q_j)$ occurring together.

For multi-modal registration, we used Mutual Information (MI).

2.6. Dataset

The Cancer Genome Atlas Breast Invasive Carcinoma (TCGA-BRCA) dataset, which is accessible via the Cancer Imaging Archive (TCIA), provided 40 pairs of 2D T2-weighted DCE-MRI slices in total [17]. Every MR image that had a resolution higher than 256 x 256 pixels was reduced to that size. An experienced radiologist manually segmented the images to provide ground truth images, which were the gold standard for assessment. In this work, we register breast MRI images Ten separate runs of 40 pairs of breast MR images are used to test this technique, with 10 images examined for each patient. Four distinct impacted individuals' mean and standard deviation for these registrations were determined using data from 10 separate runs

2.7. Configuring appropriate parameters for the algorithm

In the experiment, we used SCATLBO, TLBO, GWO, PSO, ACO, and ES algorithms to test their performance. In the TLBO algorithm, the population size is set to 25 potential solutions in each iteration. WEPMax (Weighted Exploitation Probability Maximum) controls the maximum exploitation probability, with a value of 1 indicating the highest level of exploitation. WEPMin (Weighted Exploitation Probability Minimum) is set to the minimum level of exploitation.

In PSO, the population size of 25 particles remains constant across iterations, much like TLBO. The velocity of each particle is influenced by its previous velocity through the inertia weight W. Additionally, particles are cognitively drawn towards their personal best location via the cognitive coefficient C_1.

In GWO, the number of search agents is set to 40, and the maximum number of iterations is 50.

In ES, the population size (λ) is set to 40, and the number of neurons (σ) is set to 1.

In ACO, the initial pheromone level (τ) is set to a very small value of 1×10^{-6}. The pheromone update constant (Q) is 20 while the evaporation constant (q) is 1. Pheromone decays globally at 0.9 and locally at 0.5 per iteration. Solutions are found based on pheromone strength (α) of 1 and visibility (β) of 5. Additionally, particles are socially attracted towards the global best location through C_2.

3. Result and Discussion

The results demonstrate that the SCATLBO algorithm exhibits strong exploration capabilities, which significantly contributes to its effectiveness in training FNNs. SCATLBO's opposition-based learning mechanism enhances its exploration by generating diverse solutions, allowing the algorithm to identify promising new areas in the search space while avoiding local minima. This balance of exploration and exploitation is essential for successful stochastic optimization, as it enables SCATLBO to navigate the search space effectively and converge on optimal solutions without being trapped in suboptimal regions.

Algorithm 1 SCATLBO (Sine-Cosine Adaptive Teaching-Learning-Based Optimization)

Input: Objective function $f(W)$, population size N, dimension d, max iterations $T_{\max}$
Initialize: Population $W = \{W_1, W_2, \ldots, W_N\}$ randomly.
Evaluate fitness $f(W_i)$ for all individuals in the population.
for $t = 1$ to $T_{\max}$ **do**
  Teacher Phase (Exploitation):
  Identify the teacher W_{best} as the solution with the best fitness.
  Compute the mean of the population W_{mean}.
  for each W_i **do**
    Generate a random number $r \in [0, 1]$.
    Compute the teaching factor $T = 1$ or $T = 2$ (randomly chosen).
    Update W_i:

$$W_i^{\text{new}} = W_i^{\text{old}} + r \times (W_{\text{best}} - T \times W_{\text{mean}})$$

    Apply SCA modification:

$$W_i^{\text{new}} = W_i^{\text{new}} + r \times \sin(\theta) \times |W_{\text{best}} - W_i^{\text{new}}|$$

or

$$W_i^{\text{new}} = W_i^{\text{new}} + r \times \cos(\theta) \times |W_{\text{best}} - W_i^{\text{new}}|$$

where $\theta \in [0, 2\pi]$ is a random angle.
  end for
  Learning Phase (Exploration):
  for each W_i **do**
    Select two random individuals W_j and W_k ($j \neq k$).
    Generate a random number $r \in [0, 1]$.
    Update W_i:

$$W_i^{\text{new}} = W_i^{\text{old}} + r \times (W_j - W_k)$$

    Apply SCA modification:

$$W_i^{\text{new}} = W_i^{\text{new}} + r \times \sin(\theta) \times |W_j - W_k|$$

or

$$W_i^{\text{new}} = W_i^{\text{new}} + r \times \cos(\theta) \times |W_j - W_k|$$

  end for
  Evaluate fitness $f(W_i)$ for all updated solutions.
  Replace W_i with W_i^{new} if $f(W_i^{\text{new}}) < f(W_i)$.
  Check stopping criteria (e.g., maximum iterations or desired accuracy).
end for
Output: Best solution W_{best} and its fitness $f(W_{\text{best}})$.

Tables 1 and 2 compare SCATLBO-FNN with other well-known metaheuristic algorithms Teaching-Learning-Based Optimization (TLBO), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Grey Wolf Optimizer (GWO), and Evolution Strategy (ES)-using two key performance metrics: Mean Squared Error (MSE) for mono-modal image registration and Mutual Information (MI) for multi-modal registration. These metrics are critical for assessing the accuracy and stability of the registration process, with lower MSE indicating better alignment for mono-modal images and higher MI signifying greater statistical dependency in multi-modal cases.

From the tables, it is evident that SCATLBO-FNN achieves the lowest average error (AVG) and highest accuracy in both mono-modal (Table 1) and multi-modal (Table 2) registrations, indicating superior

Table 1
Comparison of Algorithm Performance Metrics Using MSE for Mono-Modal Imaging

Algorithm	AVG	STD	Accuracy	Ex. Time (s)
SCATLBO-FNN	0.003026	0.043015	98.00%	492.05
TLBO-FNN	0.056356	0.073298	90.00%	649.75
PSO-FNN	0.010569	0.032736	89.33%	339.25
ACO-FNN	0.054556	0.073498	91.00%	647.75
GWO-FNN	0.004356	0.043298	92.00%	641.75
ES-FNN	0.056356	0.073298	90.00%	569.75

Table 2
Comparison of Algorithm Performance Metrics Using MI for Multi-Modal Imaging

Algorithm	AVG	STD	Accuracy	Ex. Time (s)
SCATLBO-FNN	0.083045	0.034023	95.00%	552.05
TLBO-FNN	0.062356	0.073278	90.00%	649.75
PSO-FNN	0.010572	0.032737	89.00%	439.25
ACO-FNN	0.056363	0.073294	90.00%	649.75
GWO-FNN	0.056356	0.073298	90.00%	649.75
ES-FNN	0.056358	0.073289	89.00%	649.75

alignment performance and consistent accuracy. Additionally, SCATLBO demonstrates a competitive execution time compared to other algorithms, balancing performance efficiency with computational cost. The low standard deviation (STD) values for SCATLBO also reflect its stability, showing less variation across different trials, which is crucial in achieving reliable results in medical image registration.

Figure 5 illustrates the convergence behavior of SCATLBO-FNN in both mono-modal and multi-modal scenarios. The convergence graph shows that SCATLBO quickly minimizes the error, highlighting its strong initial exploration phase. As the iterations proceed, the algorithm stabilizes, indicating effective exploitation of promising solutions. This stability in convergence confirms that SCATLBO is less likely to be trapped in local optima, allowing it to achieve optimal or near-optimal solutions across different registration tasks.

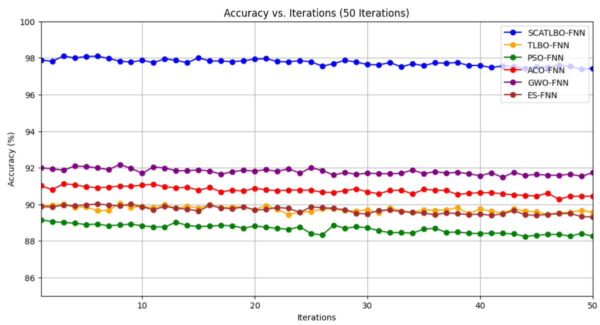

Figure 4: Convergence graph of mono modality

Overall, these comparative metrics underscore the robustness of SCATLBO-FNN. The hybrid approach, which combines SCA's exploration with TLBO's exploitation, makes SCATLBO a powerful and efficient tool for training FNNs in complex medical imaging tasks. This combination enables SCATLBO to outperform other metaheuristic algorithms in terms of accuracy, stability, and convergence speed, establishing it as a highly effective optimization technique for neural network-based image registration.

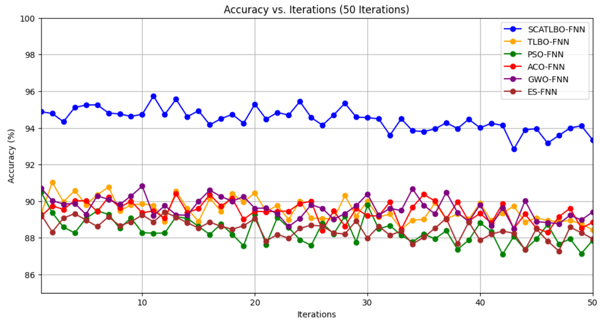

Figure 5: Convergence graph of multi modality

3.1. Statistical significance

The Wilcoxon Signed-Rank Test [18], a non-parametric statistical method, was implemented in order to assess significance as appropriate for paired data. Here, we did this analysis on the average and standard deviation of MI and MSE from our results. In particular, we estimated p-values for the comparison between SCATLBO-FNN and all other techniques. A p-value below 0.05 is considered statistically significant.

Our results, shown in both mono-modality (Table 3) and multi-modality (Table 4) evaluations, yielded a p-value of 0.002, which is well below the 0.05 threshold. This confirms that SCATLBO-FNN outperforms other methods with statistical significance, validating its effectiveness in FNN optimization for image registration tasks.

Table 3
Wilcoxon Signed-Rank Test for Statistical Analysis of MSE in Mono-Modality Imaging

Sl. No.	Comparison	p (2–tailed)
1	SCATLBO-FNN vs. TLBO-FNN	0.00002
2	SCATLBO-FNN vs. PSO-FNN	0.00002
3	SCATLBO-FNN vs. ACO-FNN	0.00002
4	SCATLBO-FNN vs. GWO-FNN	0.00002
5	SCATLBO-FNN vs. ES-FNN	0.00002

Table 4
Wilcoxon Signed-Rank Test for Statistical Analysis of MI in Multi-Modality Imaging

Sl. No.	Comparison	p (2–tailed)
1	SCATLBO-FNN vs. TLBO-FNN	0.00003
2	SCATLBO-FNN vs. PSO-FNN	0.00003
3	SCATLBO-FNN vs. ACO-FNN	0.00003
4	SCATLBO-FNN vs. GWO-FNN	0.00003
5	SCATLBO-FNN vs. ES-FNN	0.00003

Furthermore, Table 5 provides a comparative performance ranking of the algorithms based on their overall efficiency and accuracy in training Feed-Forward Neural Networks (FNNs). SCATLBO-FNN achieved the highest rank, indicating its superior performance across both mono-modal and multi-modal registration tasks. This advantage is attributed to SCATLBO's balanced exploitation and exploration phases, achieved by combining the strengths of SCA for exploration and TLBO for exploitation.

In contrast, other algorithms such as TLBO, PSO, ACO, GWO, and ES ranked lower due to slower convergence or a tendency to become trapped in local minima. The rankings underscore the benefits of SCATLBO's hybrid approach, where the integration of SCA and TLBO enables faster and more accurate

Table 5
Comparison of methods by rank

Methods	Rank	Methods	Rank
SCATLBO-FNN	1	ACO-FNN	4
TLBO-FNN	2	GWO-FNN	5
PSO-FNN	3	ES-FNN	6

convergence compared to standalone metaheuristics. This comparative ranking, together with the Wilcoxon test results, supports SCATLBO as a robust and effective choice for FNN optimization in medical image registration, offering greater accuracy and consistency than other established methods.

3.2. Decision-Making Based on Multiple Criteria

The Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) is a widely used multi-criteria decision-making (MCDM) method that facilitates the ranking and selection of optimal solutions based on multiple evaluation standards [19, 20]. Developed in the 1980s, TOPSIS ranks options by calculating their Euclidean distance from an ideal solution (the best possible outcome) and a negative-ideal solution (the worst possible outcome). The option closest to the ideal and farthest from the negative-ideal solution is assigned the highest ranking, making it the preferred choice.

In this study, TOPSIS was employed to evaluate and rank SCATLBO against other metaheuristic algorithms based on key performance metrics such as accuracy, convergence speed, and error minimization. By taking both ideal and worst-case scenarios into account, TOPSIS provides an objective framework to compare SCATLBO?s effectiveness in optimizing Feed-Forward Neural Networks (FNNs) for medical image registration tasks. This robust decision-making approach ensures that SCATLBOs performance is assessed comprehensively, validating it as a highly effective algorithm for complex, multi-modal registration problems.

4. Conclusion and future work

In this work, we introduced SCATLBO, a hybrid metaheuristic combining the Sine-Cosine Algorithm (SCA) and Teaching-Learning-Based Optimization (TLBO), to train Feed-Forward Neural Networks (FNNs) for medical image registration. SCATLBO was evaluated on the TCGA-BRCA dataset and compared with five established algorithms, demonstrating superior accuracy, faster convergence, and robustness against local minima. Its balanced exploration-exploitation strategy and opposition-based learning contribute to its high performance in both mono-modal and multi-modal registration tasks.

Future Work: SCATLBO could be extended to other neural architectures, such as CNNs, to handle more complex imaging tasks. Additionally, future studies could explore adaptive mechanisms for parameter tuning, as well as applications across diverse medical datasets to assess generalizability and robustness in various medical imaging contexts.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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