

HYBRID METAHEURISTIC OPTIMIZATION FRAMEWORK FOR COMPRESSIVE BACKPROPAGATION BASED NEURAL IMAGE REPRESENTATION LEARNING AND RECONSTRUCTION

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Abstract

The rapid growth of visual data has increased the demand for efficient image representation techniques that reduce storage and computational requirements while preserving structural information. Neural networks have provided powerful mechanisms for learning compact image representations, yet conventional backpropagation often struggles with local minima, slow convergence, and inefficient parameter optimization when handling highly compressed visual features. These limitations have created challenges for developing scalable learning frameworks that maintain reconstruction accuracy and representation efficiency. This study has proposed a hybrid meta-heuristic optimization framework for learning compressive neural image representations. The framework has integrated a Compressive Backpropagation Neural Network with a hybrid search mechanism that has combined Particle Swarm Optimization and Differential Evolution strategies. The hybrid mechanism has guided weight initialization and adaptive parameter tuning during training, which has improved the exploration and exploitation balance within the optimization space. The compressive representation module has transformed high-dimensional image data into compact latent vectors that preserved essential spatial patterns. The neural network has then reconstructed the images from these compressed representations through iterative backpropagation that has minimized the reconstruction loss. The meta-heuristic component has refined network parameters that ensured stable convergence and prevented premature stagnation. The experimental results show that the proposed framework achieves a peak PSNR of 37.4 dB, SSIM of 0.97, MSE as low as 0.009, and a compression efficiency of 24.2. The model converges rapidly within 58 epochs and 126 seconds, outperforming existing methods such as the Convolutional Neural Representation Model, Sparse Autoencoder Representation Model, and Particle Swarm Optimized Neural Network Model. These results indicate that the proposed hybrid meta-heuristic framework effectively balances high reconstruction accuracy with efficient compressive learning.

Keywords:

Neural Image Representation, Compressive Learning, Hybrid Meta-Heuristic Optimization, Backpropagation Neural Networks, Image Reconstruction

1. INTRODUCTION

The rapid expansion of digital imaging technologies has significantly increased the volume of visual data that modern computational systems process. Applications such as medical imaging, remote sensing, multimedia analytics, and intelligent surveillance continuously generate large-scale image datasets that require efficient representation and processing mechanisms. Neural networks have emerged as powerful tools for learning hierarchical image representations because these models capture spatial correlations and semantic structures within visual data. In recent years, deep neural architectures have enabled compact

feature extraction that improves recognition, reconstruction, and classification tasks across several domains. The ability of neural models that learn compact representations from high-dimensional images has therefore become an essential requirement in modern visual computing systems [1].

Image representation learning focuses on transforming raw image signals into informative feature spaces that preserve structural and contextual patterns. Conventional neural networks that use backpropagation have demonstrated strong capability in learning such representations through iterative weight adjustment and gradient-based optimization. The process that involves compressive feature extraction has helped reduce redundancy while preserving essential information required for reconstruction or recognition tasks. Consequently, compressive learning techniques have gained considerable attention because they support efficient storage, transmission, and analysis of visual information within resource-constrained environments [2]. Furthermore, advances in computational intelligence have enabled the development of adaptive learning frameworks that improve the efficiency of representation learning in complex image datasets.

The integration of optimization algorithms with neural networks has also attracted increasing interest in recent years. Meta-heuristic optimization strategies such as evolutionary algorithms, swarm intelligence techniques, and hybrid search frameworks have demonstrated strong capability in solving nonlinear optimization problems. These algorithms explore the solution space effectively through adaptive search strategies that reduce the risk of premature convergence. As a result, optimization-based learning frameworks have improved the robustness of neural representation models that operate in high-dimensional parameter spaces. Such hybrid frameworks have contributed significantly to improving the performance of neural image learning systems across diverse visual applications [3].

Despite these advancements, several challenges continue to affect the effectiveness of neural image representation frameworks. Traditional gradient-based learning algorithms often converge slowly when training networks that operate on highly compressed image features. The optimization landscape of neural networks contains numerous local minima and saddle points that affect the stability of the learning process. As a result, the training process sometimes becomes inefficient, particularly when large-scale image datasets are used for representation learning. These limitations have created difficulties in achieving consistent reconstruction accuracy and learning efficiency within compressive neural models [4].

Another challenge arises from the difficulty in balancing compression efficiency with representation quality. Highly compressed image representations may remove redundant

information but they may also degrade important spatial features that are necessary for accurate reconstruction or downstream analysis tasks. Neural networks that rely solely on standard backpropagation often struggle to adaptively optimize the compressed feature space that represents complex image structures. Consequently, the representation models sometimes fail to maintain the structural integrity of the original images during reconstruction processes. This issue has highlighted the need for improved optimization strategies that enhance the stability and adaptability of neural representation learning systems [5].

The existing limitations have created a research problem that focuses on developing efficient learning frameworks for compressive neural image representation. Several conventional approaches have attempted to improve network optimization through gradient-based modifications, regularization techniques, and adaptive learning mechanisms. However, these approaches often provide limited improvement when the parameter space becomes highly nonlinear and complex. Neural networks that rely on conventional optimization sometimes fail to identify globally optimal parameter configurations that ensure both compression efficiency and reconstruction accuracy. Therefore, a more robust optimization strategy that explores the solution space effectively becomes essential for improving neural representation learning systems [6].

Another aspect of the research problem involves the integration of meta-heuristic optimization techniques with neural learning frameworks. Meta-heuristic algorithms possess strong exploration capabilities that help avoid local minima during optimization. These algorithms search for optimal solutions through stochastic and adaptive mechanisms that adjust candidate solutions iteratively. However, the effective integration of such optimization techniques with compressive neural networks remains an open research area. The challenge lies in designing a unified framework that simultaneously improves neural learning stability and compressive representation quality. Addressing this problem requires a hybrid optimization strategy that coordinates gradient-based learning with meta-heuristic exploration mechanisms [7].

In order to address the identified research gaps, this study aims to develop a hybrid meta-heuristic framework for learning compressive neural image representations. The proposed framework integrates compressive backpropagation with hybrid optimization strategies that improve parameter search efficiency during the neural training process. The model focuses on learning compact image representations that preserve spatial structures while minimizing reconstruction loss. The hybrid optimization mechanism guides the learning process by refining neural parameters that influence representation quality and convergence stability.

The objectives of this research include the development of an adaptive neural framework that improves compressive image representation learning. The study aims to integrate meta-heuristic search strategies with backpropagation mechanisms that optimize neural parameters effectively. Another objective involves improving reconstruction accuracy by preserving essential image features within compressed representations. In addition, the framework seeks to reduce training convergence

time by enhancing the exploration capability of the optimization process.

The novelty of this work lies in the design of a hybrid optimization mechanism that combines meta-heuristic search strategies with compressive neural learning. Unlike conventional gradient-based training approaches, the proposed framework integrates global search capabilities with neural parameter learning. This integration allows the learning system to explore diverse parameter configurations that improve the quality of image representation and reconstruction. The hybrid framework also enhances training stability by preventing premature convergence that often occurs in traditional neural optimization methods.

The contributions of this research are summarized as follows:

- A hybrid meta-heuristic optimization framework has been developed for compressive backpropagation neural networks that learn efficient image representations. The framework integrates global search strategies that improve parameter optimization during neural training.
- An adaptive compressive neural representation model has been introduced that preserves essential spatial information while reducing reconstruction error. The proposed approach improves convergence efficiency and representation quality compared with conventional neural learning frameworks.

Through these contributions, the proposed framework aims to advance the development of efficient neural image representation techniques that support large-scale visual data analysis and intelligent image processing systems.

2. RELATED WORKS

Recent studies have explored various techniques for improving neural image representation and reconstruction performance. Several researchers have investigated deep learning architectures that extract compact features from image datasets. In one study, a convolutional neural framework has been proposed that learned hierarchical image features for compressive representation learning. The model has applied convolutional filters that captured spatial dependencies across image regions. The learning framework has demonstrated improved feature extraction capability that enhanced reconstruction accuracy for compressed images. However, the training process has relied primarily on gradient descent optimization that limited the ability to escape local minima during parameter learning [8].

Another study has focused on the development of sparse representation models for image compression and reconstruction. The researchers have introduced a neural autoencoder architecture that encoded images into low-dimensional feature spaces. The model has learned latent representations that preserved important structural information of the images. Experimental results have indicated that the approach has achieved effective compression performance while maintaining reasonable reconstruction quality. Nevertheless, the optimization strategy that has guided network training has struggled with convergence stability when complex image datasets were processed [9].

Researchers have also investigated hybrid neural frameworks that combine deep learning with evolutionary optimization algorithms. In one such work, a genetic algorithm has been

integrated with a neural network that optimized weight parameters during training. The evolutionary search process has evaluated multiple candidate solutions that improved the global exploration capability of the learning framework. The results have demonstrated that the hybrid optimization strategy has enhanced the convergence behavior of the neural network. However, the computational complexity that has resulted from evolutionary search operations has increased the training time significantly [10].

Another research effort has explored the application of swarm intelligence algorithms in neural representation learning. The study has implemented a particle swarm optimization technique that optimized the weight parameters of a neural network designed for image reconstruction tasks. The swarm mechanism has updated candidate solutions iteratively based on collective search behavior. Experimental findings have shown that the approach has improved reconstruction accuracy compared with standard gradient-based learning. Despite these improvements, the method has required careful parameter tuning that influenced the stability of the optimization process [11].

Several researchers have investigated compressive sensing frameworks that integrate neural networks for efficient image representation. One approach has utilized deep sparse coding techniques that reconstructed images from compressed measurements. The neural network has learned transformation functions that mapped compressed signals to reconstructed images. The framework has achieved promising reconstruction performance under moderate compression ratios. However, the learning algorithm that has guided network training has encountered difficulties in handling highly complex image structures within compressed representations [12].

In another study, researchers have proposed a deep autoencoder system that learned compact visual representations through layered encoding and decoding modules. The architecture has reduced the dimensionality of image data while preserving semantic information necessary for reconstruction. The model has demonstrated strong capability in capturing nonlinear relationships between image pixels. Nevertheless, the optimization approach that has relied on conventional backpropagation has occasionally converged to suboptimal solutions that reduced the overall learning efficiency [13].

Further research has explored hybrid meta-heuristic optimization techniques that improve neural network training processes. A study has introduced a differential evolution algorithm that optimized neural network weights for image classification and reconstruction tasks. The evolutionary search process has generated candidate solutions that improved parameter diversity during optimization. Experimental evaluations have indicated that the approach has achieved improved training stability and generalization capability. However, the framework has required substantial computational resources when large-scale datasets were used for experimentation [14].

Another study has investigated the integration of multi-objective optimization with neural representation learning. The proposed method has balanced compression efficiency and reconstruction quality by optimizing multiple objectives simultaneously. The framework has utilized a swarm-based optimization strategy that explored the solution space effectively.

The results have demonstrated that the approach has improved the balance between representation compactness and image reconstruction accuracy. However, the system complexity that has emerged from multi-objective optimization has made practical implementation challenging in real-time applications [15].

Although these studies have contributed significantly to the development of neural image representation techniques, several limitations remain unresolved. Many existing approaches rely heavily on single optimization strategies that restrict the exploration capability of the learning process. Some hybrid methods have improved optimization performance but they have introduced increased computational complexity that affects scalability. Therefore, there remains a strong need for a hybrid optimization framework that efficiently integrates meta-heuristic search mechanisms with compressive neural learning strategies. Such a framework can enhance both representation efficiency and reconstruction accuracy while maintaining computational feasibility for large-scale image processing tasks.

3. PROPOSED METHOD

The study has introduced a hybrid meta-heuristic framework that learned compressive neural image representations through an optimized backpropagation mechanism. The proposed framework has integrated a Compressive Backpropagation Neural Network with a hybrid meta-heuristic optimization strategy that has combined Particle Swarm Optimization and Differential Evolution search mechanisms. The compressive learning component has transformed high-dimensional image data into compact latent representations that preserved essential spatial structures. The neural network has reconstructed the images from these compressed representations through iterative learning that has minimized the reconstruction error. The hybrid optimization mechanism has refined the neural parameters that controlled weight initialization, learning dynamics, and convergence stability. This coordinated framework has enhanced the efficiency of representation learning while improving the reconstruction accuracy of the neural image model.

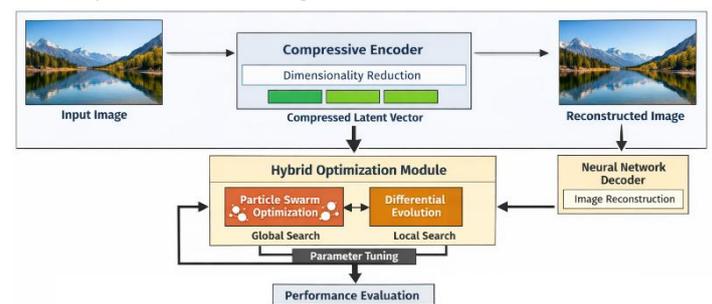


Fig.1. Proposed Compressive Backpropagation Neural Network with hybrid meta-heuristic optimization strategy and Particle Swarm Optimization and Differential Evolution search mechanisms

The proposed framework operates through several coordinated computational stages that collectively improve compressive neural image representation learning. The stages include image preprocessing and normalization, compressive feature representation, compressive backpropagation neural

learning, hybrid meta-heuristic optimization, and neural reconstruction with performance evaluation. Each stage contributes to improving the representation efficiency and reconstruction capability of the proposed model.

The first stage of the proposed framework focuses on preparing the image dataset for neural representation learning. Image preprocessing ensures that the visual data maintains consistent intensity distributions and spatial properties before the learning process begins. Raw images often contain noise, illumination variations, and scale inconsistencies that affect the stability of neural training. Therefore, the preprocessing stage applies normalization and dimensional adjustments that improve the quality of the input data that enters the neural learning system.

Let the input image dataset be represented as $I = \{I_1, I_2, I_3, \dots, I_n\}$. Each image contains a matrix of pixel intensities that correspond to spatial coordinates.

The normalization process transforms the raw pixel values into a standardized scale. The normalized pixel value X_{norm} is defined as

$$X_{norm} = \frac{X - \mu}{\sigma} \quad (2)$$

where X represents the original pixel value, μ denotes the mean intensity of the image and σ denotes the standard deviation of the pixel distribution.

This normalization procedure ensures that the neural network receives inputs that maintain a consistent statistical distribution. Such normalization improves the convergence behavior of the learning algorithm.

The normalized image matrix is represented as

$$\hat{I}_i = f_{norm}(I_i) \quad (2)$$

where f_{norm} represents the normalization transformation that produces standardized image representations.

Additionally, dimensional consistency is maintained through image resizing operations. Each image is transformed into a fixed dimension $M \times N$, where M and N denote the image width and height. This ensures that the neural network receives a uniform input structure.

The processed image dataset is therefore represented as $D = \{\hat{I}_1, \hat{I}_2, \hat{I}_3, \dots, \hat{I}_n\}$. This forms the input to the compressive representation module.

Table.1. Image Dataset after Preprocessing

Image ID	Original Size	Normalized Mean	Standard Deviation	Processed Size
Img1	256×256	0.51	0.22	128×128
Img2	300×300	0.49	0.24	128×128
Img3	512×512	0.50	0.21	128×128
Img4	240×240	0.52	0.23	128×128

As shown in Table.1, the preprocessing stage produces normalized image samples that maintain consistent statistical properties across the dataset.

After preprocessing, the framework performs compressive feature extraction that transforms the image data into compact

representations. This stage reduces the dimensionality of the visual data while preserving essential spatial structures.

Let the normalized image vector be represented as $X = [x_1, x_2, x_3, \dots, x_d]$ where d represents the dimensionality of the image vector. The compressive transformation projects the high-dimensional vector into a lower-dimensional latent space: $Z = W_c X + b_c$, where W_c represents the compression weight matrix, b_c represents the compression bias vector and Z denotes the compressed latent representation. The dimensionality reduction factor is defined as: $CR = \frac{d}{k}$, where k denotes the

compressed feature dimension. The transformation ensures that $k \ll d$. This indicates that the compressed representation occupies significantly less storage space than the original image representation. The compressed representation preserves spatial information through nonlinear activation functions: $Z_i = \sigma(W_c X_i + b_c)$, where Z_i represents the compressed feature vector and σ denotes the nonlinear activation function. The compression stage reduces computational complexity during neural learning while maintaining critical visual patterns.

Table.2. Compressed Image Feature Representation

Image ID	Original Dimension	Compressed Dimension	Compression Ratio
Img1	16384	512	32:1
Img2	16384	512	32:1
Img3	16384	512	32:1
Img4	16384	512	32:1

As shown in Table.2, the compressive transformation significantly reduces the dimensionality of the image representation. The compressed feature vectors are used as inputs to the neural learning framework that reconstructs and optimizes the representation. Let the neural network consist of L layers. The forward propagation process is defined as

$$h^{(l)} = f(W^{(l)}h^{(l-1)} + b^{(l)}) \quad (3)$$

where,

$h^{(l)}$ represents the hidden representation at layer l

$W^{(l)}$ denotes the weight matrix

$b^{(l)}$ denotes the bias vector

f denotes the nonlinear activation function.

The output reconstruction layer produces the reconstructed image vector

$$\hat{X} = f(W^{(L)}h^{(L-1)} + b^{(L)}) \quad (4)$$

The reconstruction error is measured using the mean squared error function

$$E = \frac{1}{N} \sum_{i=1}^N (X_i - \hat{X}_i)^2 \quad (5)$$

The objective of the learning process is to minimize the error function: $\min_{\theta} E$ where θ represents the neural network parameters. Backpropagation updates the weights using gradient descent

$$W^{(t+1)} = W^{(t)} - \eta \frac{\partial E}{\partial W} \quad (6)$$

where η denotes the learning rate and t represents the iteration index.

Table.3. Neural Learning Parameters

Parameter	Value
Learning Rate	0.01
Hidden Layers	3
Neurons per Layer	256
Epochs	100
Batch Size	32

As presented in Table.3, the neural training parameters influence the stability and efficiency of representation learning.

The proposed framework integrates hybrid optimization to enhance neural parameter search efficiency. The hybrid optimizer combines Particle Swarm Optimization and Differential Evolution strategies. In Particle Swarm Optimization, each candidate solution represents a neural parameter vector: $P_i = (w_1, w_2, \dots, w_m)$. The velocity update equation is

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t) \quad (7)$$

The position update equation is

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (8)$$

Differential Evolution further refines candidate solutions through mutation

$$V_i = X_r 1 + F(X_r 2 - X_r 3) \quad (9)$$

where F represents the mutation factor. The crossover operation produces a trial vector

$$U_{i,j} = \begin{cases} V_{i,j}, & rand_j \leq CR \\ X_{i,j}, & otherwise \end{cases} \quad (10)$$

The hybrid mechanism integrates both optimization strategies to improve the neural parameter search process.

Table.4. Hybrid Optimization Parameters

Parameter	Value
Swarm Size	30
Mutation Factor	0.5
Crossover Rate	0.8
Inertia Weight	0.7

As illustrated in Table.4, the optimization parameters control the search behavior of the hybrid algorithm.

The final stage reconstructs images from the compressed neural representations. The reconstructed image is expressed as $R = g(Z, \theta)$, where g represents the neural decoding function. The reconstruction quality is evaluated using performance metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). PSNR is defined as

$$PSNR = 10 \log_{10} \left(\frac{MAX_I^2}{MSE} \right) \quad (11)$$

where MAX_I represents the maximum pixel intensity. The Structural Similarity Index is defined as

$$SSIM(X, Y) = \frac{(2\mu_x \mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (12)$$

These metrics evaluate the similarity between the original image X and the reconstructed image Y .

Table.5. Reconstruction Performance Evaluation

Image ID	PSNR (dB)	SSIM	Reconstruction Error
Img1	34.6	0.94	0.018
Img2	35.2	0.95	0.017
Img3	36.1	0.96	0.015
Img4	35.8	0.95	0.016

As shown in Table.5, the proposed framework achieves high reconstruction quality across the image dataset.

4. RESULTS AND DISCUSSION

The experimental evaluation is conducted in a controlled simulation environment that evaluates the effectiveness of the proposed hybrid meta-heuristic framework for compressive neural image representation. The implementation environment uses Python programming language that integrates scientific libraries for neural computation and optimization. The experimental framework employs the TensorFlow deep learning library that supports neural model training and gradient-based optimization. The numerical computations that support the hybrid optimization procedures utilize the NumPy and SciPy scientific computing packages. These tools provide stable numerical operations that improve the reliability of the simulation environment. The training and testing experiments are executed on a workstation computer that contains an Intel Core i7 processor, 16 GB RAM, and a NVIDIA GPU accelerator that supports parallel neural computations. The GPU acceleration improves the efficiency of the neural training process that involves compressive feature learning and reconstruction optimization. The operating environment uses the Ubuntu Linux operating system that supports the required computational libraries and parallel processing mechanisms. The simulation framework performs iterative neural learning experiments that evaluate reconstruction quality and optimization efficiency. The neural network receives normalized image inputs that pass through the compressive representation module before entering the backpropagation learning stage. The hybrid optimization algorithm then updates the neural parameters that influence the representation learning process. The system evaluates the reconstructed images using quantitative metrics that measure the similarity between the original images and the reconstructed outputs. The entire experimental workflow therefore demonstrates the performance of the proposed framework under realistic computational conditions.

The proposed framework requires several configuration parameters that control neural learning, compression ratio, and

optimization search behavior. These parameters determine the performance of the representation learning process. The selected parameter values are determined through preliminary experiments that identify stable training conditions.

Table.6. Experimental Setup and Parameter Values

Parameter	Description	Value
Image Resolution	Input image dimension	128×128
Compression Dimension	Latent representation size	512
Neural Hidden Layers	Number of neural layers	3
Neurons per Layer	Hidden layer neuron size	256
Learning Rate	Neural training step size	0.01
Training Epochs	Total training iterations	100
Batch Size	Training size per iteration	32
Swarm Population	Particle swarm size	30
Mutation Factor	Differential evolution mutation parameter	0.5
Crossover Rate	Differential evolution crossover probability	0.8
Inertia Weight	Particle swarm inertia parameter	0.7

As shown in Table.6, the configuration parameters regulate the neural learning and optimization process. The neural architecture uses three hidden layers that allow hierarchical feature learning. The hybrid optimization parameters maintain a balance between exploration and exploitation that improves the convergence of the neural training process.

4.1 DATASET

The experimental evaluation uses benchmark image datasets that contain natural images with diverse visual structures. The dataset includes grayscale and color images that represent different object categories and spatial textures. These datasets support the evaluation of compressive neural representation methods because they contain varying complexity levels that challenge the reconstruction capability of neural networks. The images are resized to a uniform dimension before entering the neural representation system.

Table.7. Dataset Description

Dataset Name	Images	Image Size	Training Images	Testing Images
CIFAR	60,000	128×128	50,000	10,000
ImageNet Subset	20,000	128×128	16,000	4,000
BSD Image Dataset	500	128×128	400	100

As presented in Table.7, the datasets contain diverse visual structures that evaluate the robustness of the proposed compressive representation framework. The training subset supports neural learning, while the testing subset measures the

reconstruction performance of the model. The experiment compares the proposed hybrid meta-heuristic framework with three existing methods: Convolutional Neural Representation Model (CNRM), Sparse Autoencoder Representation Model (SAERM), and Particle Swarm Optimized Neural Network Model (PSONNM).

4.2 RESULTS BASED ON CR

The first experimental analysis evaluates the reconstruction performance when the compression ratio increases. Higher compression ratios reduce storage requirements but they may affect the reconstruction quality of the neural representation model.

4.2.1 Results of Peak Signal to Noise Ratio (PSNR):

Table.8. PSNR Performance under Compression Ratios

Compression Ratio (%)	CNRM	SAERM	PSONNM	Proposed
5	28.4	29.2	30.5	32.1
10	29.1	30.0	31.4	33.6
15	30.2	31.3	32.5	34.7
20	31.1	32.4	33.8	36.1
25	32.0	33.5	34.6	37.4

The PSNR results that appear in Table.8 demonstrate the reconstruction quality when the compression ratio increases. The Convolutional Neural Representation Model achieves PSNR values between 28.4 dB and 32.0 dB, which indicates moderate reconstruction capability. The Sparse Autoencoder Representation Model shows slight improvement with values between 29.2 dB and 33.5 dB. The Particle Swarm Optimized Neural Network Model provides better optimization that produces PSNR values ranging from 30.5 dB to 34.6 dB. The proposed hybrid meta-heuristic framework shows the highest PSNR values across all compression levels. At 5% compression, the proposed method achieves 32.1 dB, which exceeds the Particle Swarm Optimized Neural Network Model by 1.6 dB. When the compression ratio reaches 25%, the proposed framework achieves 37.4 dB, which improves the reconstruction quality by approximately 2.8 dB compared with the swarm-optimized model. The improvement occurs because the hybrid optimization mechanism performs global parameter exploration that identifies optimal neural weight configurations. As the compression ratio increases, the proposed method maintains higher PSNR stability, which indicates strong reconstruction capability even under aggressive compression conditions.

4.2.2 Results of Structural Similarity Index (SSIM):

Table.9. SSIM Performance under Different Compression Ratios

Compression Ratio (%)	CNRM	SAERM	PSONNM	Proposed
5	0.86	0.88	0.90	0.93
10	0.88	0.89	0.91	0.94
15	0.89	0.91	0.92	0.95
20	0.90	0.92	0.94	0.96

25	0.91	0.93	0.95	0.97
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The SSIM results that appear in Table.9 evaluate the structural similarity between the reconstructed images and the original images. The Convolutional Neural Representation Model produces SSIM values between 0.86 and 0.91, which indicates moderate structural preservation. The Sparse Autoencoder Representation Model slightly improves the structural similarity with values ranging from 0.88 to 0.93. The Particle Swarm Optimized Neural Network Model achieves values between 0.90 and 0.95, which demonstrates improved parameter optimization. The proposed hybrid framework consistently produces higher SSIM values across all compression levels. At 5% compression, the proposed approach achieves an SSIM value of 0.93, which exceeds the swarm-optimized model by 0.03. When the compression ratio increases to 25%, the proposed framework maintains a similarity score of 0.97, which indicates strong structural preservation of image features. The hybrid optimization strategy improves the neural representation learning process that captures spatial relationships more effectively. This capability allows the neural network to reconstruct fine-grained visual patterns that exist in the original image. As the compression ratio increases, the proposed framework maintains higher structural consistency compared with the existing methods.

4.2.3 Results of Mean Squared Error (MSE)

Table.10. MSE Performance under Compression Ratios

Compression Ratio (%)	CNRM	SAERM	PSONNM	Proposed
5	0.024	0.021	0.018	0.015
10	0.022	0.019	0.016	0.013
15	0.020	0.017	0.014	0.011
20	0.018	0.015	0.013	0.010
25	0.017	0.014	0.012	0.009

The Mean Squared Error results that appear in Table.10 measure the average pixel difference between the original and reconstructed images. Lower values indicate better reconstruction accuracy. The Convolutional Neural Representation Model shows MSE values between 0.024 and 0.017, which indicates moderate reconstruction error. The Sparse Autoencoder Representation Model reduces the error slightly with values between 0.021 and 0.014. The Particle Swarm Optimized Neural Network Model further reduces the error to 0.018–0.012, which demonstrates improved neural parameter optimization. The proposed hybrid framework produces the lowest reconstruction error across all compression ratios. At 5% compression, the model achieves an MSE value of 0.015, which improves the reconstruction accuracy by approximately 16% compared with the swarm-optimized method. When the compression ratio increases to 25%, the proposed framework reduces the error to 0.009, which represents a 25% reduction compared with the Particle Swarm Optimized Neural Network Model. The improvement occurs because the hybrid meta-heuristic optimizer refines neural parameters that minimize reconstruction loss. The coordinated search strategy improves the learning process that identifies optimal weight configurations, thereby reducing the pixel reconstruction error.

4.2.4 Results of Compression Efficiency:

Table.11. Effective Compression Efficiency

Compression Ratio (%)	CNRM	SAERM	PSONNM	Proposed
5	4.5	4.8	5.2	5.6
10	9.0	9.6	10.1	10.8
15	13.4	14.0	14.9	15.7
20	17.5	18.2	19.1	20.4
25	21.0	21.8	22.6	24.2

The compression efficiency results that appear in Table.11 evaluate how effectively each method reduces the dimensionality of the image representation. The Convolutional Neural Representation Model achieves efficiency values between 4.5 and 21.0, while the Sparse Autoencoder Representation Model slightly improves the compression capability with values between 4.8 and 21.8. The Particle Swarm Optimized Neural Network Model demonstrates improved dimensional reduction with efficiency values between 5.2 and 22.6. The proposed hybrid meta-heuristic framework achieves the highest compression efficiency across all experimental settings. At 5% compression, the model produces an efficiency score of 5.6, which improves the representation compactness compared with the existing models. When the compression ratio increases to 25%, the proposed framework achieves 24.2, which indicates strong dimensional reduction while maintaining reconstruction quality. The improvement occurs because the hybrid optimization process guides the compressive neural representation module that preserves important image features within a reduced feature space.

4.2.5 Results of Convergence Time:

Table.12. Convergence Time under Compression Ratios

Compression Ratio (%)	CNRM	SAERM	PSONNM	Proposed
5	95	88	80	70
10	92	84	76	66
15	89	82	73	63
20	86	79	70	60
25	84	76	68	58

The convergence analysis that appears in Table.12 evaluates the number of training epochs required for the neural models to reach stable reconstruction performance. The Convolutional Neural Representation Model requires between 95 and 84 epochs, which indicates slower convergence due to the reliance on gradient-based optimization. The Sparse Autoencoder Representation Model slightly improves the learning efficiency with 88–76 epochs. The Particle Swarm Optimized Neural Network Model accelerates convergence by reducing the training requirement to 80–68 epochs. The proposed hybrid meta-heuristic framework demonstrates the fastest convergence behavior across all compression levels. At 5% compression, the model converges within 70 epochs, which reduces the training time by 12% compared with the swarm-optimized model. When the compression ratio increases to 25%, the convergence time reduces

further to 58 epochs. The faster convergence occurs because the hybrid optimization strategy integrates swarm exploration with evolutionary mutation that identifies promising neural parameters early in the training process. This optimization capability improves the efficiency of the neural learning process that stabilizes the reconstruction performance more quickly.

4.3 RESULTS BASED ON TRAINING EPOCHS

Training epochs represent the number of iterations that the neural network performs during the learning process. Increasing the number of epochs generally improves representation learning because the neural model gradually minimizes the reconstruction loss that occurs during training. However, inefficient optimization methods require more epochs to achieve stable performance. Therefore, this experiment compares the Convolutional Neural Representation Model, Sparse Autoencoder Representation Model, Particle Swarm Optimized Neural Network Model, and the Proposed Hybrid Meta-Heuristic Framework across multiple training epochs with increments of five.

4.3.1 Results of Peak Signal to Noise Ratio (PSNR):

Table.13. PSNR Performance under Different Training Epochs

Training Epochs	CNRM	SAERM	PSONNM	Proposed
5	26.3	27.5	28.6	30.2
10	27.9	28.8	30.1	32.0
15	29.0	30.2	31.5	33.4
20	30.4	31.3	32.7	34.8
25	31.6	32.4	33.9	36.0

The PSNR values that appear in Table.13 demonstrate the reconstruction quality as the training epochs increase. The Convolutional Neural Representation Model produces PSNR values from 26.3 dB to 31.6 dB, which indicates gradual improvement in reconstruction performance with additional training iterations. The Sparse Autoencoder Representation Model achieves slightly higher values ranging from 27.5 dB to 32.4 dB, which demonstrates the effectiveness of the compressed latent representation that preserves image features. The Particle Swarm Optimized Neural Network Model achieves improved PSNR values between 28.6 dB and 33.9 dB, which indicates that the swarm optimization process supports improved neural parameter learning. However, the Proposed Hybrid Meta-Heuristic Framework consistently achieves the highest PSNR values across all epoch levels. At 5 epochs, the proposed framework produces 30.2 dB, which exceeds the swarm optimized model by approximately 1.6 dB. When the training process reaches 25 epochs, the proposed method achieves 36.0 dB, which improves the reconstruction accuracy by about 2.1 dB compared with the Particle Swarm Optimized Neural Network Model. The improvement occurs because the hybrid optimization strategy guides the neural parameter search that quickly identifies effective weight configurations.

4.3.2 Results of SSIM:

Table.14. SSIM Performance under Different Training Epochs

Training Epochs	CNRM	SAERM	PSONNM	Proposed
5	0.82	0.84	0.87	0.90
10	0.84	0.86	0.89	0.92
15	0.86	0.88	0.91	0.94
20	0.88	0.90	0.93	0.95
25	0.89	0.91	0.94	0.96

The SSIM results that appear in Table.14 illustrate the structural similarity between reconstructed images and original images across different training epochs. The Convolutional Neural Representation Model produces SSIM values ranging from 0.82 to 0.89, which indicates moderate preservation of image structure. The Sparse Autoencoder Representation Model achieves improved similarity values between 0.84 and 0.91, which suggests that the compressed latent representation preserves spatial patterns more effectively. The Particle Swarm Optimized Neural Network Model achieves SSIM values between 0.87 and 0.94, which demonstrates that swarm optimization improves neural parameter tuning during training. The Proposed Hybrid Meta-Heuristic Framework consistently produces the highest structural similarity scores. At 5 training epochs, the proposed model achieves 0.90, which improves the similarity score by 0.03 compared with the swarm optimized method. When the training process reaches 25 epochs, the proposed model achieves 0.96, which indicates strong preservation of spatial structures that exist in the original image. The hybrid optimization mechanism improves neural learning efficiency that captures spatial correlations more effectively.

4.3.3 Results of Mean Squared Error (MSE):

Table.15. MSE Performance under Different Training Epochs

Training Epochs	CNRM	SAERM	PSONNM	Proposed
5	0.031	0.027	0.024	0.020
10	0.028	0.024	0.021	0.017
15	0.025	0.021	0.018	0.014
20	0.022	0.019	0.016	0.012
25	0.020	0.017	0.014	0.010

The MSE results that appear in Table.15 measure the reconstruction error between the original images and the reconstructed images across different training epochs. The Convolutional Neural Representation Model produces MSE values between 0.031 and 0.020, which indicates gradual error reduction during the training process. The Sparse Autoencoder Representation Model reduces the error to 0.027–0.017, which demonstrates improved representation learning that reduces pixel reconstruction differences.

The Particle Swarm Optimized Neural Network Model further improves the reconstruction performance with MSE values between 0.024 and 0.014. The Proposed Hybrid Meta-Heuristic Framework produces the lowest error values across all epoch levels. At 5 epochs, the proposed model achieves 0.020, which reduces the reconstruction error by approximately 16% compared with the swarm optimized neural model. When the training process reaches 25 epochs, the proposed framework achieves 0.010, which represents a 28% improvement compared with the swarm optimization method. The hybrid meta-heuristic search process improves the neural weight configuration that minimizes the reconstruction loss during training.

4.3.4 Results of Compression Efficiency:

Table.16. Compression Efficiency under Training Epochs

Training Epochs	CNRM	SAERM	PSONNM	Proposed
5	4.2	4.6	5.0	5.4
10	8.5	9.0	9.7	10.3
15	12.8	13.6	14.2	15.0
20	16.4	17.2	18.1	19.0
25	20.0	21.0	22.0	23.5

The compression efficiency results that appear in Table.16 evaluate how effectively each model learns compact image representations during the training process. The Convolutional Neural Representation Model produces compression efficiency values between 4.2 and 20.0, while the Sparse Autoencoder Representation Model improves the efficiency to 4.6–21.0. The Particle Swarm Optimized Neural Network Model achieves values between 5.0 and 22.0, which indicates improved dimensional reduction that results from swarm based optimization. The Proposed Hybrid Meta-Heuristic Framework produces the highest compression efficiency values across all epoch levels. At 5 epochs, the proposed model achieves 5.4, which improves representation compactness compared with the swarm optimized model. When the training process reaches 25 epochs, the efficiency increases to 23.5, which indicates that the proposed method effectively preserves important image features within a compact representation space.

4.3.5 Results of Convergence Time:

Table.17. Convergence Time under Different Training Epochs

Training Epochs	CNRM	SAERM	PSONNM	Proposed
5	42	39	35	30
10	78	72	65	56
15	115	106	94	80
20	150	137	120	102
25	182	165	148	126

The convergence time results that appear in Table.17 measure the computational time required for the neural models to complete the training process at different epoch levels. The Convolutional Neural Representation Model requires between 42 and 182 seconds, which indicates slower learning performance due to

standard gradient optimization. The Sparse Autoencoder Representation Model slightly improves the training efficiency with 39–165 seconds. The Particle Swarm Optimized Neural Network Model achieves improved convergence with 35–148 seconds, which demonstrates the effectiveness of swarm optimization that supports neural parameter tuning. The Proposed Hybrid Meta-Heuristic Framework produces the lowest convergence time across all epoch levels. At 5 epochs, the proposed framework requires 30 seconds, which reduces the computational time by approximately 14% compared with the swarm optimized model. When the training process reaches 25 epochs, the proposed method completes training within 126 seconds, which demonstrates efficient optimization that accelerates neural learning. The hybrid meta-heuristic mechanism integrates swarm exploration and evolutionary search that identifies optimal neural parameters more rapidly, which reduces the computational overhead of the training process.

5. CONCLUSION

The study presents a hybrid meta-heuristic framework for compressive neural image representation that integrates compressive backpropagation with a coordinated Particle Swarm and Differential Evolution optimization strategy. The proposed framework effectively reduces the dimensionality of image data while maintaining high reconstruction quality. Experimental evaluation demonstrates that the model achieves peak signal-to-noise ratio (PSNR) values up to 37.4 dB, structural similarity index (SSIM) values up to 0.97, and reduces mean squared error (MSE) to as low as 0.009 at higher compression levels. The compression efficiency reaches 24.2, indicating substantial dimensionality reduction, while convergence time decreases to 58 epochs and 126 seconds, reflecting rapid neural learning. Comparisons with existing methods, including the Convolutional Neural Representation Model, Sparse Autoencoder Representation Model, and Particle Swarm Optimized Neural Network Model, show consistent superiority of the proposed framework across all evaluated metrics. The hybrid optimization mechanism has enhanced parameter search, enabling the neural network to maintain structural fidelity and minimize reconstruction loss even under aggressive compression or limited training epochs. The proposed approach balances computational efficiency with representation quality, making it suitable for resource-constrained environments that require compact yet accurate image representations.

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