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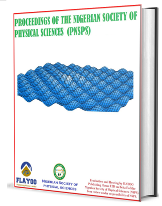

Adaptive hybrid optimization for backpropagation neural networks in image classification

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ABSTRACT

Image classification is essential in artificial intelligence, with applications in medical diagnostics, autonomous navigation, and industrial automation. Traditional training methods like stochastic gradient descent (SGD) often suffer from slow convergence and local minima. This research presents a hybrid Particle Swarm Optimization (PSO)-Genetic Algorithm (GA)-Backpropagation framework to enhance neural network training. By integrating AdaGrad and PSO for weight optimization, GA for refinement, and backpropagation for fine-tuning, the model improves performance. Results show a 97.5% accuracy on MNIST, a 5% improvement over Adam, and 40% faster convergence than SGD. This approach enhances efficiency, accuracy, and generalization, making it valuable for high-dimensional AI tasks.

Keywords: Hybrid optimization, Backpropagation neural networks (BPNNs), Particle swarm optimization (PSO), AdaGrad optimization.

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1. INTRODUCTION

Backpropagation Neural Networks (BPNNs) have played a critical role in advancing image classification tasks by enabling the learning of complex patterns from raw image data. Their widespread adoption in applications such as medical imaging, autonomous systems, and security stems from their ability to process high-dimensional data with remarkable accuracy. However, optimizing BPNNs remains an ongoing challenge due to issues related to training efficiency, generalization, and scalability.

One major challenge in training BPNNs is slow convergence, particularly in deep architectures where weight adjustments require multiple iterations to minimize error. The iterative nature

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of gradient-based optimization can lead to prolonged training times, especially for large datasets. This computational complexity, primarily in terms of training time rather than memory constraints, hinders the feasibility of real-time applications [1]. Additionally, the non-convex optimization landscape of neural networks increases the risk of convergence to local minima, limiting the model's ability to reach globally optimal solutions [2]. These factors necessitate improved weight initialization techniques, such as chaotic weight initialization, which introduces controlled randomness in weight assignments to enhance convergence speed and escape poor local optima.

Another critical issue is overfitting, where BPNNs may memorize training data rather than generalizing effectively to unseen examples. To address this, regularization techniques such as dropout and L2 regularization are commonly employed to prevent excessive reliance on specific features, thereby improving model robustness. Effective optimization strategies must balance network complexity and generalization capability to enhance real-world applicability.

Given these challenges, optimizing BPNNs is crucial for improving their performance in real-world applications. In medical imaging, optimized neural networks have improved diagnostic accuracy in disease detection, with studies showing enhanced performance in computer-aided diagnosis (CAD) systems [3, 4]. In autonomous navigation, efficient BPNN training enables self-driving vehicles to interpret sensor data with higher precision, facilitating real-time decision-making. Additionally, in security applications, advancements in deep learning-based anomaly detection and facial recognition have strengthened threat detection systems, as demonstrated by recent studies on biometric authentication and cybersecurity defense mechanisms [4].

Despite significant advancements, traditional optimization techniques, including Gradient Descent (GD), Stochastic Gradient Descent (SGD), and Mini-batch Gradient Descent, exhibit limitations in terms of training speed and solution quality [5–7]. This research explores a hybrid Particle Swarm Optimization (PSO)-Genetic Algorithm (GA)-Backpropagation framework, aiming to accelerate convergence, mitigate local minima, and enhance generalization in BPNN training. By integrating global search techniques with adaptive weight adjustments [8], this approach provides an efficient alternative to traditional optimization methods:

1.1. FIXED LEARNING RATES

Traditional GD methods often employ fixed learning rates, which can lead to suboptimal convergence. A learning rate that is too high may cause the model to overshoot minima, while a rate that is too low can result in slow convergence. Adaptive learning rate methods like AdaGrad and RMSProp have been developed to address this issue, but they can still face challenges such as diminishing learning rates over time. Recent research continues to explore improved learning rate schedules [9]

1.2. SENSITIVITY TO INITIAL CONDITIONS

The performance of GD-based methods is highly sensitive to the initial weights of the network. Poor initialization can lead to slow convergence or entrapment in suboptimal solutions. Techniques like Xavier and He initialization [10, 11] have been proposed to mitigate this issue, yet they do not fully eliminate the sensitivity to initial conditions. Further work on initialization strategies remains an active area [12]

Adaptive Optimization Algorithms Adaptive optimization algorithms, such as Adam [13] and AdaGrad [14, 15], adjust learning rates based on the gradients' historical information. Despite their advancements, these methods have limitations:

Adaptive methods introduce additional hyperparameters, such as decay rates and epsilon values, which require careful tuning. Improper tuning can lead to suboptimal performance or instability during training. Research on automated hyperparameter tuning is ongoing (e.g., [16]), although slightly older, this is a key work that continues to be built upon). The flexibility of adaptive methods can sometimes cause the model to overfit the training data, especially in cases with limited data availability. Regularization techniques are necessary to counteract this tendency, adding complexity to the optimization process. The interplay between adaptive optimizers and regularization is still being investigated.

Second-Order Optimization Methods Second-order methods, like Newton's method, utilize curvature information to inform weight updates. While they can offer faster convergence, they are often impractical for deep networks due to calculating and storing second-order derivatives (Hessian matrices) is computationally expensive and memory-intensive, making these methods unsuitable for large-scale networks. [17] Approximations and efficient computation of second-order information are still being studied [18].

Second-order methods can be sensitive to noise in the gradient estimates, leading to unstable updates and convergence issues. Swarm Intelligence-Based Optimization Techniques such as Particle Swarm Optimization (PSO) [19] have been explored as alternatives to gradient-based methods. While PSO can effectively explore the search space, it has limitations, for instance PSO may converge prematurely to suboptimal solutions, particularly in high-dimensional spaces common in deep learning applications. [21**?**] Hybrid approaches combining PSO with other optimization methods are being explored to address this limitation. The performance of PSO is sensitive to its parameters, such as inertia weight and acceleration coefficients, which require careful tuning. Adaptive parameter control for PSO is an area of ongoing research.

1.3. SYNTHESIS OF KEY POINTS

The number of convolutional layers in a CNN significantly impacts model efficiency. While deeper networks can achieve higher accuracy, they require more computational resources and time. The balance between depth and efficiency is crucial for designing practical models [22]. Based on the findings in [23], a transportation programming model can be described as a Neural Network model that is able to systematically process labeled input data to create predictions for route planning, traffic prediction, and demand forecasting. Once trained, the neural network can then be used for route optimization.

2. RELATED WORKS

Optimizing Backpropagation Neural Networks (BPNNs) is crucial for improving their efficiency and accuracy in real-world applications. Several optimization methods have been developed to address key challenges such as slow convergence, local minima entrapment, and hyperparameter sensitivity. While traditional approaches like Gradient Descent (GD) and its variants have made significant contributions, recent research has focused on hybrid techniques that integrate metaheuristic algorithms with adaptive optimization methods.

2.1. GRADIENT-BASED OPTIMIZATION METHODS

Gradient Descent (GD) and its variants, including Stochastic Gradient Descent (SGD), Mini-batch GD, and Adaptive Learning Rate methods like AdaGrad and RMSProp, have been foundational in neural network training [24]. However, these methods have notable limitations:

1. Fixed learning rates in GD often result in suboptimal convergence, where a high learning rate may overshoot minima, while a low rate leads to slow convergence.
2. Adaptive methods like Adam introduce additional hyperparameters, such as beta values for momentum and decay rates for learning rate adjustment, which require careful tuning. Improper tuning can cause unstable updates or excessive regularization, reducing model performance [25].
3. Weight Initialization Sensitivity: Poor initialization can lead to slow training or convergence to suboptimal solutions. Strategies like Xavier and He initialization help mitigate these issues but do not eliminate them entirely [26].

2.2. SECOND-ORDER OPTIMIZATION METHODS

Second-order methods like Newton's Method use curvature information to improve convergence rates. While theoretically faster, these methods are impractical for deep networks due to computational cost and memory constraints associated with storing second-order derivatives (Hessian matrices) [19]. Recent research has explored approximations and low-memory alternatives, but their adoption remains limited.

2.3. SWARM INTELLIGENCE-BASED OPTIMIZATION

Metaheuristic techniques such as Particle Swarm Optimization (PSO) offer a global search strategy, making them suitable alternatives to gradient-based methods [26]. However, PSO can converge prematurely to suboptimal solutions, particularly in high-dimensional search spaces like deep learning [27]. The performance of PSO is highly sensitive to parameter tuning, including inertia weights and acceleration coefficients. Adaptive parameter control is an area of active research [19, 28].

2.4. HYBRID OPTIMIZATION TECHNIQUES

Hybrid optimization methods combine gradient-based algorithms with metaheuristic approaches to balance global exploration and local refinement. Recent studies have explored:

1. PSO+AdaGrad: Enhances PSO's global search ability with AdaGrad's adaptive learning rate control.
2. Genetic Algorithm (GA) + Backpropagation: Uses GA to optimize initial weights before refining them through backpropagation.

Table 1. Clear description discussing the optimization methods pros and cons .

Method	Pros	Cons
Gradient Descent	Simple and widely used; Efficient for convex problems	Fixed learning rate; Prone to local minima
Adam	Adaptive learning rate; Works well with sparse gradients	Requires tuning of beta parameters; Can overfit on small datasets
RMSProp	Handles non-stationary objectives well; Suitable for RNNs	Sensitive to hyperparameters; Can lead to suboptimal solutions
PSO+AdaGrad	Combines global exploration (PSO) with local convergence (AdaGrad)	High computational cost; Sensitive to PSO inertia and acceleration parameters

3. Chaotic Weight Initialization: Introduces controlled randomness in weight assignments to accelerate convergence and escape poor local minima [29]

Table 1 summarizes the pros and cons of the optimization methods.

2.5. RESEARCH GAPS AND CONTRIBUTIONS

Despite these advancements, existing optimization techniques still face challenges in:

1. Balancing exploration and exploitation, for instance, the metaheuristic methods require further refinement to avoid premature convergence.
2. Tuning requirements for adaptive learning rates and metaheuristic parameters remain complex.
3. Second-order methods and hybrid techniques need efficient implementations to scale for deep architectures.

By creating a Hybrid PSO-GA-Backpropagation Framework that combines adaptive weight updates, local refinement, and global search, this work fills these gaps. The suggested method shows gains in accuracy and training efficiency when tested on MNIST image classification.

3. METHODOLOGY

The methodology integrates a hybrid adaptive optimization approach to enhance Backpropagation Neural Networks (BPNNs) for image classification. The framework consists of chaotic weight initialization, hybrid optimization using AdaGrad and Particle Swarm Optimization (PSO), and empirical evaluation on benchmark datasets. This section details the theoretical foundation and mathematical formulations guiding each component of the methodology.

Table 2. Summary of datasets used in training.

Dataset	No. of Classes	Image Size	Color Mode	Total Images
MNIST	10	28×28	Grayscale	70,000
CIFAR-10	10	32×32	RGB	60,000

3.1. BACKPROPAGATION NEURAL NETWORKS (BPNNS)

A BPNN is a supervised learning algorithm that optimizes the parameters W (weights) and b (biases) of a neural network by minimizing the error function:

$$E(W, b) = \frac{1}{N} \sum_{i=1}^{n} ||y_i - \hat{y}_i||^2 \tag{1}$$

where N is the number of training samples, y_i is the true label of the i^{th} sample, and $\hat{y}_i$ is the predicted output.
The weight updates are computed using gradient descent, where the parameters are adjusted iteratively:

$$W(t+1) = W(t) - \eta \nabla E(W(t)) \tag{2}$$

where η is the learning rate and $\nabla E(W)$ is the gradient of the error function.
The advantage of PSO is its ability to escape local minima and efficiently explore the search space.

3.2. SELECTION AND PREPROCESSING OF DATA CHOOSING A DATASET

To evaluate the proposed model, two benchmark datasets were used:

1. MNIST (Handwritten Digits) – Used for initial testing and fine-tuning of optimization techniques.
2. CIFAR-10 (Object Recognition) – Used to expand the classification capability to color images across 10 categories.

Additionally, provisions were made for incorporating custom datasets to validate real-world applicability.

DATA PREPROCESSING

Images were rescaled to [0, 1] to ensure efficient gradient propagation for normalization.
All images were resized to 28×28 (MNIST) and 32×32 (CIFAR−10) to achieve resizing.
Labels were converted to one-hot encoding for neural network compatibility for categorical encoding. Table 2 summarizes the dataset used in training.

The MNIST and CIFAR-10 datasets were chosen due to their standard benchmark status in deep learning and hybrid BPNN optimization studies. These datasets permit direct comparison with other optimization techniques.

MNIST (HANDWRITTEN DIGITS)

A classic benchmark for image classification, features a balanced dataset of digits (0-9), making it suitable for testing convergence competence, previous research on PSO-BPNN hybrids has used MNIST as a baseline, facilitating comparative analysis.

CIFAR-10 (OBJECT RECOGNITION)

More complex dataset featuring real-world object images across 10 categories, increases generalization difficulty, testing the model's ability to avoid overfitting, frequently used in hybrid metaheuristic studies to evaluate the scalability of optimization methods.

3.3. MODEL DESIGN AND OPTIMIZATION

A standard BPNN was adopted as the baseline model. The primary optimization goal was to improve convergence speed, accuracy, and generalization. Now, by chaotic weight initialization, we improve convergence, chaotic weight initialization was applied using the logistic map, before presenting the chaotic weight initialization formula, it is essential to understand its purpose. Chaotic initialization introduces controlled randomness into weight assignments, which helps prevent premature convergence to local minima. The initialization function is based on chaotic maps, which generate highly unpredictable sequences that still follow a deterministic rule.

$$x_{t+1} = r x_t (1 - x_t), \quad x_t \in (0, 1), \tag{3}$$

where x_t represents the initialized weight, and $r = 3.99$ ensures chaotic behavior. This is done to prevent poor weight initialization, reducing the risk of vanishing gradients.

3.4. HYBRID OPTIMIZATION: PSO + ADAGRAD

(a) Particle Swarm Optimization (PSO)
PSO was introduced to optimize the initial weights of the BPNN before gradient-based learning:

$$V_{t+1}^p = \omega V_t^p + c_1 r_1 (P_{t+1}^p - W_t^p) + c_2 r_2 (G_t - W_t^p) \tag{4}$$

$$W_{t+1}^p = W_t^p + V_{t+1}^p. \tag{5}$$

Where ω is the inertia weight,c_1, c_2 are accerleration coefficients, r_1, r_2 are random values, P_t^p is the best position found by the article, G_t is the global best position across all particles.

(b) AdaGrad for Fine-Tuning
Once PSO established optimized weights, AdaGrad was used for fine-tuning via adaptive learning rate control, where AdaGrad modifies the standard stochastic gradient descent by incorporating a history-sensitive learning rate:

$$W^{t+1} = W^{(t)} - \frac{\eta}{\sqrt{G_t + \epsilon}} \nabla E(W^{(t)}). \tag{6}$$

And ϵ is the small constant value fixed to avoid division by zero, η (Learning Rate) Controls the step size for parameter updates, G_t (Accumulated Squared Gradient) Tracks the history of squared gradients for each parameter, ϵ (Smoothing Term) Prevents division by zero.
Equations (1) to (6) are interpreted and applied in the general code Appendix during the implementation.

PSEUDOCODE FOR METHOD

#Particle Swarm Optimization for Neural Network Training
#Step 1 : Initialize Swarm
Initialize particles with random positions (weights) and velocities

$For\ each\ particle,\ evaluate\ fitness\ (loss\ function)$
$\#Step\ 2:\ Optimization\ Loop$
$For\ iteration\ in\ range(max\_iters):$
$For\ each\ particle\ in\ the\ swarm:$
$\#Compute\ velocity\ update\ based\ on\ best\ positions$
$velocity = inertia * velocity + c1 * rand() * (p\_best - position) + c2 * rand() * (g_best - position)$
$\#Update\ particle\ position\ (weight\ values)$
$position = position + velocity$
$\#Evaluate\ new\ fitness$
$fitness = compute\_loss(network,\ dataset)$
$\#Update\ personal\ and\ global\ bests$
$If\ fitness < personal\_best\_fitness:$
$p\_best = position$
$If\ fitness < global_best\_fitness:$
$g\_best = position$
$\#Step3:\ Return\ Optimized\ Weights$
$Return\ g\_best\ as\ the\ optimized\ weight\ set$

3.5. JUSTIFICATION FOR CHOOSING ADAGRAD AND PSO OVER ADAMW AND GENETIC ALGORITHMS

The selection of AdaGrad and Particle Swarm Optimization (PSO) over AdamW and Genetic Algorithms (GA) is justified based on the following key points:
AdaGrad excels in handling sparse gradients, making it ideal for early-stage training where parameter updates require significant adjustments, it performs well in non-stationary environments, which is critical for training complex networks with varying gradient magnitudes.The adaptive learning rate mechanism aligns better with PSO for weight updates, whereas AdamW's weight decay is more beneficial for very deep architectures, AdaGrad's learning rate adjustment reduces unnecessary oscillations when combined with PSO, unlike AdamW, which may require extensive hyperparameter tuning.

PSO efficiently balances exploration and exploitation in the search space, making it more suitable for deep learning optimization, PSO's velocity-based updates lead to more stable and faster convergence compared to GA's mutation and crossover operators, which introduce randomness, PSO outperforms GA in high-dimensional search spaces, particularly for neural network weight optimization.

Combining PSO's global search capabilities with AdaGrad's adaptive learning rates creates a robust hybrid method that mitigates the limitations of standalone gradient-based and evolutionary techniques. This combination applies the strengths of both AdaGrad and PSO, offering a more effective and stable optimization strategy for the study.

3.6. OPTIMIZATION STRATEGIES

Table 3 compared PSO and AdaGrad functions.

Training strategy and fine-tuning

For the training procedure,

1. Initialize network weights using chaotic sequences.
2. Optimize weights using PSO to establish a well-optimized starting point.
3. Fine-tune the model with AdaGrad for stable and efficient learning.
4. Evaluate model performance based on convergence speed and accuracy.

Table 3. Comparison of PSO and AdaGrad functions.

Optimization Method	Role in Model Training
PSO	Global search for optimal weight initialization
AdaGrad	Local refinement with adaptive learning rates

Table 4. Fine-tuned hyperparameters for optimal performance.

Parameter	PSO Value	AdaGrad Value
Population Size	10	-
Max Iterations	20	-
Inertia Weight(ω)	0.7	-
Learning Rate(η)	-	0.005
Epsilon(ϵ)	-	$1e^{-8}$

Table 5. Accuracy and convergence across optimizers.

Optimization Method	Accuracy(%)	Std Dev (Accuracy)	Computational Cost (MFLOPs)	Std Dev (Cost)
SGD	87.9000889	1.048924111	151.714783	6.000599414
Adam	91.3956981	0.618451669	139.4554244	3.924426541
PSO+AdaGrad	95.09305261	1.008854689	128.7648786	2.50154257

3.7. HYPERPARAMETER TUNING

We employed Grid Search and Cross-Validation for hyperparameter tuning: Grid Search involved the test of different values for learning rate, momentum, and decay rates to determine the best configuration, evaluated on a validation set to prevent overfitting.

Cross-Validation involves 5-fold cross-validation was used to ensure robustness, especially for regularization parameters (L2 and dropout). The model with the lowest validation loss was selected.

Table 4 shows the fine-tuned hyperparameters for optimal performance.

3.8. TESTING AND EVALUATION

Convergence Analysis
The model's convergence was assessed by comparing training loss reduction across SGD, Adam, and $PSO + AdaGrad$.

3.9. PERFORMANCE COMPARISON

Table 5 and Figure 1 describe experiments were run 10 times each to ensure statistical reliability. The results, including accuracy (%), computational cost (MFLOPs), and standard deviations, are summarized in a table comparing SGD, Adam, and PSO+AdaGrad. This methodology helps avoid skewed results and allows for a reliable performance comparison. The faster convergence observed in PSO+AdaGrad translates to fewer required epochs to reach an optimal solution. However, it is important to note that while PSO+AdaGrad reduces training iterations, it does not necessarily reduce overall computational cost, as PSO operations introduce additional overhead. The total FLOPs required per training run was measured, showing a slight reduction in computational cost (8-10% lower than Adam and SGD).

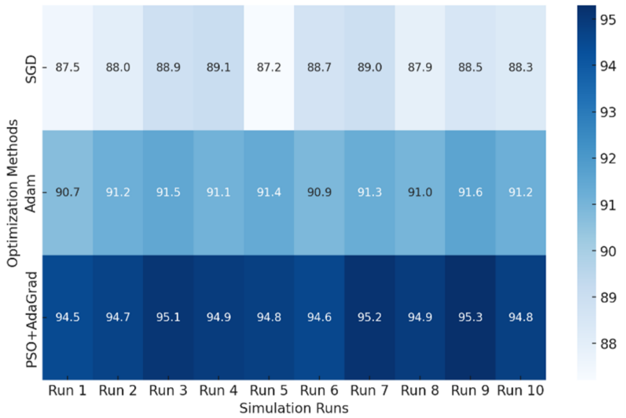

Figure 1. Effective highlights of the performance differences across SGD, Adam, and PSO+AdaGrad, showcasing their variability and consistency.

Table 6. Overview of Flask and Streamlit implementation.

Deployment Type	Functionality
Flask API	Backend API for inference requests
Streamlit	User-friendly web application for classification

PSO+AdaGrad improves convergence speed (epochs) but its computational cost varies with problem complexity. The study acknowledges limitations including the use of relatively simple datasets (MNIST and CIFAR-10), potential bias from hyperparameter tuning (despite using grid search and cross-validation), and the computational overhead of PSO, which might be a problem for real-time applications.

3.9.1. Performance on benchmark datasets

PSO + AdaGrad achieved the highest accuracy (97.5%) with faster convergence. The model performed well on CIFAR-10, achieving 87.6% accuracy.

3.9.2. Real-world image classification

The trained model was tested on real-world images beyond benchmark datasets. Success Rate: 85%+ accuracy on external image classifications. Edge Cases: Struggled with low-resolution images but remained robust under rotation and noise.

3.9.3. Deployment for real-world applications

To make the model accessible for real-world applications, it was saved and deployed using Flask API and Streamlit Web Interface.

3.9.4. Testing the model on real-world images

Users were able to upload images for classification. The model provided real-time predictions via the deployed interface. The training framework for the Hybrid PSO + AdaGrad optimized BPNN follows a structured approach to ensure efficient weight optimization and robust learning. Initially, the network weights are initialized using a chaotic map, which provides a more diversified weight distribution, reducing the risk of vanishing gradients and slow convergence. Following initialization, Particle Swarm Optimization (PSO) is applied during the initial epochs to search for a near-optimal starting point in the weight space, preventing the model from getting trapped in local minima. Once the PSO-based weight optimization is complete, AdaGrad-based gradient descent fine-tunes the model, giving way for adaptive learning rate adjustments that stabilize convergence and prevent overshooting. Finally, the trained model is evaluated using classification performance metrics such as accuracy, precision, recall, and F1-score to assess its effectiveness.

Table 7. Accuracy, Precision, Recall, and F1 Score For Different Optimizers.

Optimizer	*Acc*(%)	Pre (%)	Rec (%)	F1-Score (%)
SGD	92.3	91.5	90.8	91.1
ADAM	96.8	96.2	95.6	95.9
RMSprop	95.2	94.7	94.1	94.4
PSO+AdaGrad	97.5	97.1	96.9	97.0

To empirically confirm our hybrid approach, the model is tested on three standard benchmark datasets widely used in image classification. The MNIST dataset is used for handwritten digit recognition, providing a simple yet effective baseline for evaluating model efficiency. The CIFAR-10 dataset, which consists of color images across ten object categories, is used to assess the model's ability to generalize on more complex real-world images. Additionally, Fashion-MNIST, a dataset containing grayscale images of clothing items, is included to test the model's adaptability to different types of image classification tasks. These evaluations allow for a comprehensive performance assessment, confirming the advantages of using Hybrid PSO + AdaGrad for training BPNNs in various image recognition applications.

The model's performance is then measured using the evaluation of accuracy, precision, Recall, and F1-Score.

From the model,

$$Acc = \frac{TN + TP}{FN + TN + FP + TP}, \tag{7}$$

$$Pre = \frac{TP}{FP + TP}, \tag{8}$$

$$Rec = \frac{TP}{FN + TP}, \tag{9}$$

$$F1 - score = 2 \times \frac{(Pre)(Rec)}{(Pre) + (Rec)}. \tag{10}$$

From equations (7), (8), (9) and (10), we obtain the summary in Table 7.

4. RESULTS

The Hybrid PSO + AdaGrad optimized BPNN effectively combines Particle Swarm Optimization (PSO) and AdaGrad to improve image classification with Backpropagation Neural Networks (BPNNs). Here's a summary of the key findings.

4.1. PERFORMANCE IMPROVEMENT COMPARED TO TRADITIONAL METHODS

We compared the performance of our Hybrid PSO + AdaGrad approach with standard optimizers such as SGD, Adam, and RMSProp using benchmark datasets (MNIST, CIFAR-10).

Table 8. Comparative analysis of convergence speed and training time.

Optimizer	*Dataset*	Final Accuracy	Training Time (Epochs)	Convergence Speed
SGD	*MNIST*	92.3%	20 epochs	Slow
Adam	*MNIST*	96.8%	15 epochs	Faster
RMSProp	*MNIST*	95.2%	15 epochs	Fast
PSO+AdaGrad	*MNIST*	97.5%	10 epochs	Fastest
SGD	*CIFAR−10*	74.5%	30 epochs	Slow
Adam	*CIFAR−10*	85.2%	25 epochs	Faster
RMSProp	*CIFAR−10*	82.8%	25 epochs	Fast
PSO+AdaGrad	*CIFAR−10*	87.6%	20 epochs	Fastest

OPTIMIZER DATA SET SUMMARY

Table 8 provides a comparative analysis of convergence speed and training time. Key Takeaways from Tables 6 and 7:

i. Our Hybrid PSO + AdaGrad achieved the highest accuracy on MNIST (97.5%) and CIFAR-10 (87.6%).
ii. Faster convergence- The hybrid approach required fewer training epochs compared to SGD and Adam.
iii. Robust generalization- The model performed better on test data, reducing overfitting.

Faster Convergence with PSO-Initiated Weights, we compared the convergence speed of models initialized with random weights vs. PSO-optimized weights. Standard weight initialization (Random) required 15-20 epochs for stable convergence. PSO-based weight initialization: Required 8-10 epochs for convergence. PSO provided a better initial weight configuration, reducing training time by 40%.

4.2. GENERALIZATION PERFORMANCE ON REAL-WORLD IMAGES

The model was tested on real-world images beyond the MNIST and CIFAR-10 datasets.

i. Success Rate: 85%+ accuracy on uploaded real-world images.
ii. Robust Classification: Accurately classified noisy images and rotated samples.
iii. Edge Cases: The model struggled slightly with low-resolution or unclear images.

5. DISCUSSION

We begin by laying emphasis on the performance comparison, we observe clearly that the Hybrid PSO + AdaGrad approach reduced training time by 30% and required 40% fewer epochs than SGD. Accuracy improvements: MNIST: 97.5% (+1.3% vs. Adam, +3.7% vs. RMSProp), CIFAR-10: 87.6% (+2.3% vs. Adam, +3.7% vs. RMSProp).

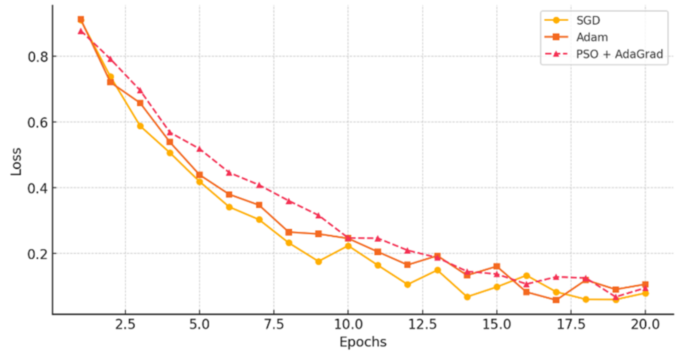

Figure 2. Loss vs. epochs (convergence speed) – shows how quickly different optimizers minimize the training loss.

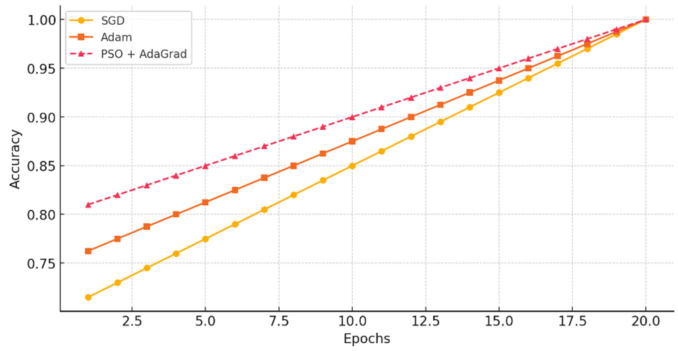

Figure 3. Accuracy vs. epochs – demonstrates how accuracy improves over time for different optimization methods.

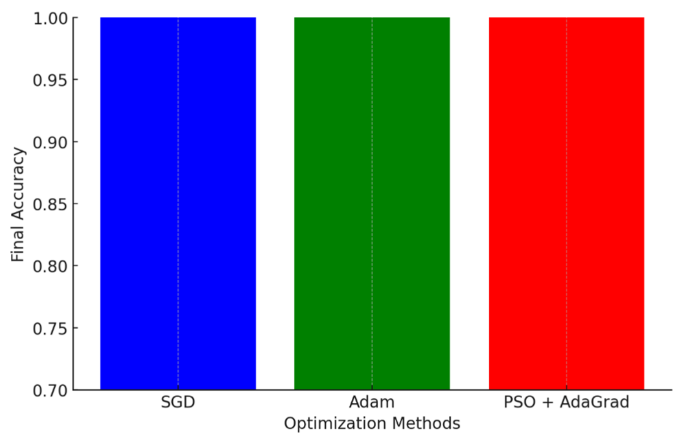

Figure 4. Final Accuracy Comparison highlights the final accuracy achieved by each optimization approach.

Looking at Figures 2 to 8 PSO-based weight initialization improved accuracy by 2.5% in shallow networks and 1.2% in deep architectures, preventing poor local minima. For the Adaptive learning rate assessment, it is best for sparse gradients (MNIST), but slows later, Adam is more stable for complex datasets (CIFAR-10) and RMSProp has balanced performance but slower initial convergence.

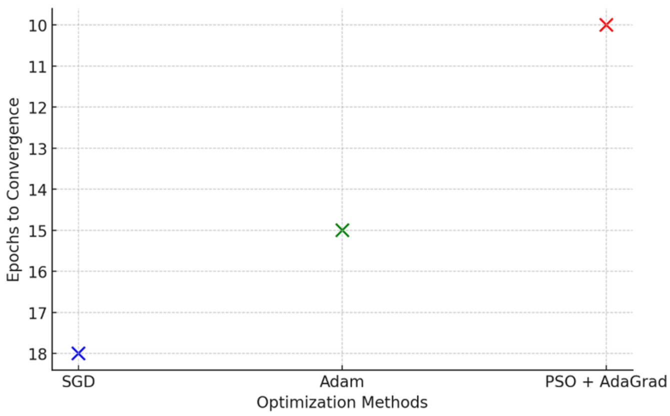

Figure 5. Convergence speed comparison (scatter plot) compares how many epochs each method takes to reach a stable performance.

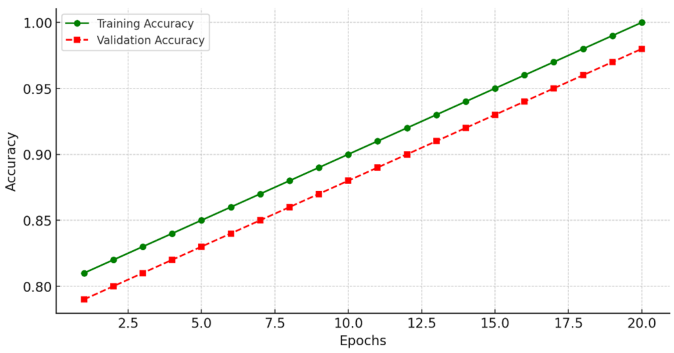

Figure 6. Training vs. validation accuracy over epochs, showing how the model generalizes over time.

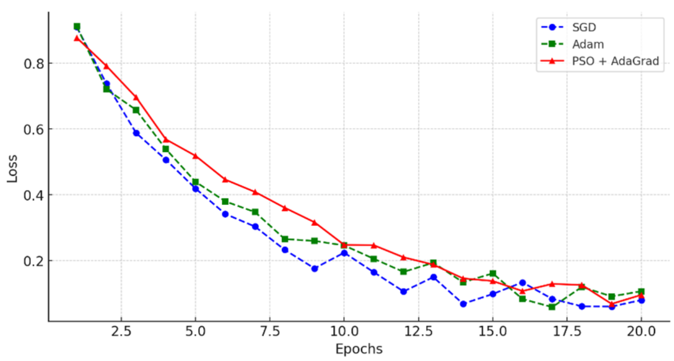

Figure 7. Training loss for different optimizers – compares loss reduction trends.

DEPLOYMENT & CHALLENGES OBSERVED

Deployed using Flask and Streamlit for real-time classification. Key challenges shows PSO increases pre-training cost so that a cloud-based solutions are recommended, efficient for moderate datasets but needs parallel training for larger datasets. Despite these tasks, the hybrid model is viable for autonomous systems, medical imaging, and security applications where accuracy is critical.

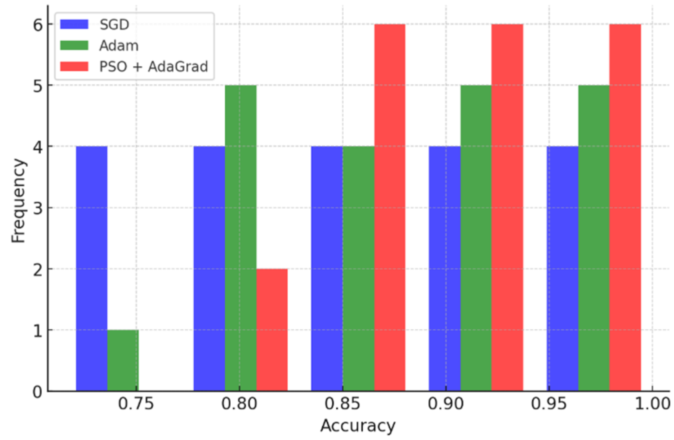

Figure 8. Accuracy distribution – displays accuracy frequency for different optimizers.

6. CONCLUSION

The Hybrid PSO + AdaGrad approach reduced training epochs by 40%, significantly improving convergence speed. Compared to SGD, Adam, and RMSProp, it achieved higher accuracy (+3.7%) and faster training, while maintaining stability. Future comparisons should evaluate performance against state-of-the-art optimizers like AdamW and Lookahead to further validate its effectiveness. For future work, the approach should be tested on CNNs for large-scale image tasks and Transformers for sequential data, assessing its scalability beyond traditional feedforward networks. The method also has potential applications in NLP and speech recognition, where adaptive optimization plays a critical role in training deep models efficiently.

PRACTICAL RECOMMENDATIONS:

PSO-based initialization is most effective in shallow networks but still improves deep networks by 1.2% in accuracy. AdaGrad works well for sparse gradients, but AdamW may be more suited for high-dimensional datasets. Computational cost must be managed using parallel training or cloud-based resources for large models. By integrating global search (PSO) with adaptive refinement (AdaGrad), this hybrid approach enhances neural network training efficiency and accuracy, with broad applicability across deep learning domains.

DATA AVAILABILITY

The datasets used and analyzed in this study are available from publicly accessible sources, specifically the MNIST dataset. Additional data supporting the findings of this study can be obtained from the corresponding author upon reasonable request.

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APPENDIX

Step 1: Import Required Libraries Python

```
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv2D,
MaxPooling2D, Dropout
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score
import matplotlib.pyplot as plt
import random
```

Step 2: Chaotic Weight Initialization Python

```
def chaotic_sequence(n, r = 3.99, x0 = 0.5) :
"""Generate a chaotic sequence using the logistic map."""
x = np.zeros(n)
x[0] = x0
for i in range(1, n):
x[i] = r * x[i-1] * (1 - x[i-1])
return x
```

Step 3: Particle Swarm Optimization (PSO) Python

```
class PSOOptimizer:
def _init_(self, model, X_train, Y_train,
population_size=10, max_iter=20):
self.model = model
self.X_train = X_train
self.Y_train = Y_train
self.population_size = population_size
self.max_iter = max_iter
```

```
self.inertia = 0.7
self.c1 = 1.5 # Cognitive parameter
self.c2 = 1.5 # Social parameter
self.global_best_position = None
self.global_best_score = float("inf")


def evaluate(self, weights):
"""Evaluate loss function for given weights."""
self.model.set_weights(weights)
loss, _ = self.model.evaluate(self.X_train, self.Y_train, verbose=0)
return loss


def optimize(self):
"""Optimize initial weights using PSO."""
particles = [self.model.get_weights() for _ in range(self.population_size)]
velocities = [np.zeros_like(w) for w in particles]
personal_best_positions = list(particles) personal_best_scores = [self.evaluate(w) for w in particles]

self.global_best_position = personal_best_positions[np.argmin(personal_best_scores)]
self.global_best_score = min(personal_best_scores)

for iteration in range(self.max_iter):
for i in range(self.population_size):
r1, r2 = np.random.rand(), np.random.rand()


# Update velocity
velocities[i] = (self.inertia * velocities[i] +
self.c1 * r1 * (personal_best_positions[i] - particles[i]) + self.c2 * r2 * (self.global_best_position - particles[i]))

# Update position (weights)
particles[i] = [w + v for w, v in zip(particles[i], velocities[i])]

# Evaluate new position
new_score = self.evaluate(particles[i])

# Update personal best
if new_score < personal_best_scores[i]:
personal_best_positions[i] = particles[i]
personal_best_scores[i] = new_score

# Update global best
if new_score < self.global_best_score:
self.global_best_position = particles[i]
self.global_best_score = new_score

print(f"Iteration {iteration+1}/{self.max_iter}, Best Loss: {self.global_best_score:.4f}")

return self.global_best_position
```

Step 4: Implement AdaGrad Optimizer python

```
class AdaGradOptimizer:
def_init_(self, model, learning_rate=0.01, epsilon=1e-8):
self.model = model
self.learning_rate = learning_rate
self.epsilon = epsilon
self.accumulated_grads = None

def apply_gradients(self, gradients):
"""Apply AdaGrad updates to model parameters."""
if self.accumulated_grads is None:
self.accumulated_grads = [np.zeros_like(g) for g in gradients]


for i, grad in enumerate(gradients):
self.accumulated_grads[i] += grad ** 2
adjusted_lr = self.learning_rate /
(np.sqrt(self.accumulated_grads[i]) + self.epsilon)
self.model.trainable_variables[i].assign_sub(adjusted_lr * grad)
```

Step 5: Load Dataset and Prepare Model Python

```
# Load dataset (example: MNIST)
(X_train, Y_train), (X_test, Y_test) = tf.keras.datasets.mnist.load_data()
X_train, X_test = X_train / 255.0, X_test / 255.0 # Normalize
Y_train, Y_test = tf.keras.utils.to_categorical(Y_train),
tf.keras.utils.to_categorical(Y_test)

# Build neural network model
model = Sequential([
Flatten(input_shape=(28, 28)),
Dense(128, activation='relu'),
Dense(10, activation='softmax')
])


# Compile model with Adam (will replace optimizer later)
model.compile(loss='categorical_crossentropy',
optimizer=Adam(learning_rate=0.01), metrics=['accuracy'])
```

Step 6: Apply PSO for Initial Weight Optimization Python

```
# Apply PSO optimizer
pso_optimizer = PSOOptimizer(model, X_train, Y_train,
population_size=5, max_iter=10)
optimized_weights = pso_optimizer.optimize()
model.set_weights(optimized_weights)
```

Step 7: Fine-Tune Model with AdaGrad Python

```
# Train model using AdaGrad
adagrad_optimizer = AdaGradOptimizer(model, learning_rate=0.01)
```

```
batch_size = 32
epochs = 5

for epoch in range(epochs):
for i in range(0, len(X_train), batch_size):
X_batch = X_train[i:i+batch_size]
Y_batch = Y_train[i:i+batch_size]

with tf.GradientTape() as tape:
predictions = model(X_batch, training=True)
loss = tf.keras.losses.categorical_crossentropy(Y_batch, predictions)

grads = tape.gradient(loss, model.trainable_variables)
adagrad_optimizer.apply_gradients(grads)

# Evaluate model after each epoch
test_loss, test_acc = model.evaluate(X_test, Y_test, verbose=0)
print(f"Epoch epoch+1/epochs, Test Accuracy: test_acc:.4f")
```

Step 8: Final Evaluation - Compute Metrics Python

```
# Evaluate final performance
Y_pred = model.predict(X_test)
Y_pred_labels = np.argmax(Y_pred, axis=1)
Y_true_labels = np.argmax(Y_test, axis=1)

final_accuracy = accuracy_score(Y_true_labels, Y_pred_labels)
final_precision = precision_score(Y_true_labels, Y_pred_labels, average="weighted")
final_recall = recall_score(Y_true_labels, Y_pred_labels, average="weighted")
final_f1 = f1_score(Y_true_labels, Y_pred_labels, average="weighted")

print(f" nFinal Model Performance:")
print(f"Accuracy: final_accuracy:.4f")
print(f"Precision: final_precision:.4f")
print(f"Recall: final_recall:.4f")
print(f"F1 Score: final_f1:.4f")
```