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Enhancing Convolutional Neural Network Performance through Binary Particle Swarm Optimization for Feature Selection

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***Abstract*—Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in a variety of pattern recognition and image classification tasks. However, their efficiency and accuracy can be influenced by the selection of relevant features from the extracted representations. Manual feature selection can be tedious, prone to human bias, and computationally inefficient. This paper presents a hybrid framework that integrates Binary Particle Swarm Optimization (BPSO) with CNNs to perform automatic feature selection. The proposed BPSO-CNN approach reduces feature dimensionality, improves classification accuracy, and accelerates training. Experiments conducted on a benchmark image dataset show that the BPSO-based feature subset outperforms the baseline CNN in both accuracy and computational efficiency. The results indicate that metaheuristic optimization, specifically BPSO, can significantly enhance the practical deployment of CNN-based models in real-world applications.**

Keywords—BPSO, CNN, Classification.

I. Introduction

In the last decade, deep learning techniques, particularly Convolutional Neural Networks (CNNs), have become the de facto standard for computer vision tasks, including image recognition, object detection, and medical image analysis [1, 2]. CNNs can automatically learn hierarchical feature representations from raw input data, eliminating the need for manual feature engineering. This capability has enabled breakthroughs in domains ranging from autonomous driving [3] to disease diagnosis in medical imaging [4].
Despite these advantages, CNNs often generate a high-dimensional set of features in the later layers, many of which may be redundant or irrelevant to the classification task. The presence of redundant features not only increases computational costs but can also lead to overfitting, particularly when training data is limited [5, 6]. Therefore, feature selection remains a crucial step in building efficient and accurate CNN models. While traditional statistical or filter-based feature selection methods can be applied, they may not capture complex interdependencies between features. Recent studies have shown that integrating optimization-based selection can yield more discriminative feature subsets [7].

Binary Particle Swarm Optimization (BPSO) is a metaheuristic algorithm inspired by the social behavior of bird flocks and fish schools [8]. Unlike standard PSO, which operates in a continuous search space, BPSO works in a binary search space, making it suitable for problems where decisions are binary in nature, such as whether to select or discard a feature [9]. Modern variants of BPSO have incorporated adaptive inertia weights, hybrid crossover strategies, and opposition-based learning to improve convergence speed and avoid local optima [10, 11].

Integrating BPSO into the CNN pipeline enables the automated selection of the most relevant features from high-dimensional feature maps, reducing computational overhead while improving classification accuracy. Recent applications of CNN-BPSO hybrids have demonstrated promising results in hyperspectral image classification [12], facial expression recognition [13], and medical imaging diagnostics [14]. This research aims to explore the effectiveness of combining CNNs [15, 1] with BPSO for feature selection. The proposed BPSO-CNN framework is evaluated on a benchmark dataset to assess its performance in terms of classification accuracy, feature reduction rate, and training time.

II. Related Work

CNNs have been widely adopted for tasks such as handwritten digit recognition, object classification, and medical diagnostics [15, 1]. While CNNs can learn effective representations, several studies have shown that not all extracted features contribute equally to final classification performance [5].
Feature selection methods can be broadly categorized into three types: filter methods, wrapper methods, and embedded methods [5]. Wrapper methods, which evaluate feature subsets using a predictive model, often achieve higher accuracy but at the cost of increased computation. Metaheuristic algorithms, such as Genetic Algorithms (GA), Ant Colony Optimization (ACO), and Particle Swarm Optimization (PSO), have been successfully applied for wrapper-based feature selection.
BPSO, first introduced by Kennedy and Eberhart [8], extends PSO into binary search spaces, making it ideal for problems with yes/no feature selection decisions. Studies in various domains have reported promising results with BPSO:

- **Medical Imaging**: Optimal feature selection for diabetic retinopathy detection from CNN-extracted features [9].
- **Biometric Verification:** Selection of discriminative CNN features for signature and fingerprint verification [5].
- **Text Classification:** Improvement in sentiment classification by removing irrelevant word embeddings [5].
- However, limited work has been done in systematically integrating BPSO into the CNN training pipeline for general image classification tasks. This paper addresses this gap.

III. METHODOLOGY

3.1 Overview

The proposed framework consists of two main phases:
- Feature Extraction: A CNN model is trained on the dataset to extract deep features from an intermediate layer.
- Feature Selection via BPSO: BPSO searches for the optimal subset of features that maximizes classification accuracy.

3.2 Convolutional Neural Network (CNN)

The CNN architecture used in this study includes:
- Convolutional Layers: Extract local patterns from the input image using multiple filters.
- Pooling Layers: Reduce spatial dimensions while retaining important information.
- Fully Connected Layers: Combine features for classification.

The output of the penultimate fully connected layer is treated as the feature vector for BPSO optimization.

3.3 Binary Particle Swarm Optimization (BPSO)

In standard PSO, each particle represents a candidate solution as a position vector in a continuous search space. In BPSO, the position vector is binary (0 or 1), where each bit corresponds to the inclusion (1) or exclusion (0) of a particular feature.

Velocity Update Equation:
$v_{i}^{t+1} = w * v_{i}^{t} + c1*r1*(p_{ibest} - x_{i}^{t}) + c2*r2*(g_{best} - x_{i}^{t})$

Position Update Equation (Sigmoid Transfer Function):
$S(v_{i}^{t+1}) = 1 / (1 + e^{-v_{i}^{t+1}})$

If $S(v_{i}^{t+1}) > rand()$, then $x_{i}^{t+1} = 1$, else $x_{i}^{t+1} = 0$.

3.4 Fitness Function

Fitness = $\alpha \times$ Accuracy $-$ $\beta \times$ (Selected Features / Total Features)
where α and β control the trade-off between accuracy and feature reduction.

IV. EXPERIMENTAL SETUP

4.1 Dataset

A standard image classification dataset with 10 categories was used. The dataset was split into 70% training, 15% validation, and 15% testing. Images were resized to 32×32 pixels.

4.2 Baseline Model

A baseline CNN was trained without feature selection to establish a reference accuracy and training time.

4.3 BPSO-CNN Model

The CNN was first trained to extract features. These features were fed into the BPSO algorithm to select an optimal subset. The selected features were then used to retrain a final CNN classifier.

4.4 Parameters

- Population Size: 30 particles
- Max Iterations: 50
- Inertia Weight (w): 0.7
- Acceleration Coefficients: c1 = c2 = 1.5
- Evaluation Metric: Classification accuracy on the validation set.

V. RESULT AND DISCUSSION

5.1 Performance Comparison

Model	Accuracy (%)	Features Selected (%)	Training Time (s)
Baseline CNN	91.2	100	210
BPSO-CNN	94.5	65	145

The BPSO-CNN model achieved a 3.3% improvement in accuracy while reducing the feature set by 35%. Training time decreased by 30% due to the smaller input dimensionality.

5.2 Analysis

The feature subset selected by BPSO removed noisy and redundant features, enabling the CNN to focus on the most discriminative aspects of the input. This not only improved accuracy but also reduced the risk of overfitting.

5.3 Limitations

The BPSO search process adds an extra optimization step, which can increase total computational time in the initial phase. Parameter tuning for BPSO is also crucial to achieve optimal results.

VI. Conclusion and future work

This paper presented a hybrid BPSO-CNN framework for automatic feature selection in deep learning. By integrating BPSO into the CNN pipeline, we achieved higher accuracy, reduced feature dimensionality, and decreased training time compared to a baseline CNN.

Future work :

Multi-objective BPSO to balance accuracy, speed, and memory usage.

- Applying the framework to larger, more complex datasets.
- Using advanced PSO variants such as Quantum-behaved PSO or Opposition-based PSO.

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