Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 2 (2024)

Remotely Sensed Image Classification Using Deep Learning Algorithm with Bio Inspired Optimizers

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Abstract: Remote sensing has become pivotal in various fields for monitoring and analyzing Earth's surface. Deep learning algorithms, particularly AlexNet, have shown promise in image classification tasks. However, effective feature extraction remains a challenge. Bio-inspired optimizers like Bee Swarm Optimization (BSO) offer a promising solution for enhancing feature extraction. This study proposes a novel approach combining AlexNet deep learning for image classification with BSO for feature extraction from remote sensed image data. The AlexNet architecture is utilized for its robustness in handling complex image data, while BSO optimizes feature extraction to enhance classification accuracy. The AlexNet with BSO presents a unique approach to improving remote sensed image classification accuracy. Experimental results demonstrate that the combined approach outperforms traditional methods in remote sensed image classification tasks. The utilization of BSO for feature extraction enhances the discriminative power of the model, leading to improved accuracy and robustness.

Keywords: AlexNet, Deep Learning, Remote Sensing, Bee Swarm Optimization, Feature Extraction.

1. Introduction

Remote sensing technologies have revolutionized our ability to monitor and understand Earth's surface dynamics [1]. These technologies provide vast amounts of data captured from satellites, aircraft, drones, and other platforms, enabling applications in agriculture, environmental monitoring, urban planning, disaster management, and more [2].

One of the primary challenges in remote sensing analysis is image classification, where the goal is to categorize pixels or regions within an image into predefined classes or land cover types. Traditional methods for image classification often rely on features and deep learning algorithms, which may struggle to capture the complex and high-dimensional characteristics of remote sensing data [3]. Additionally, the vast volume and variety of remote sensing data pose challenges for processing and analysis [4] [5].

To improve the accuracy and efficiency of remote sensed image classification through the combination of deep learning algorithms and bio-inspired optimization techniques [6] [7]. Specifically, we aim to enhance feature extraction, a critical step in image classification, by leveraging the capabilities of deep learning models such as AlexNet and the optimization power of bio-inspired algorithms like Bee Swarm Optimization (BSO).

The main objectives of the proposed method are

1. To develop a novel approach for remote sensed image classification by integrating deep learning (AlexNet) algorithms with BSO for feature extraction.
2. To evaluate the performance of the proposed approach against traditional methods and existing state-of-the-art techniques.

The novelty of this study lies in the combination of AlexNet, a deep learning architecture renowned for its effectiveness in image classification tasks, with BSO, a bio-inspired optimization technique inspired by the foraging behavior of bees. By combining these two approaches, we introduce a novel framework for remote sensed image classification that addresses the limitations of traditional methods. The proposed method offers several key contributions:

- A novel approach that leverages the complementary strengths of deep learning and bio-inspired optimization for remote sensed image classification.
- The utilization of BSO for feature extraction, enhancing the discriminative power of the classification model.
- Insights into the performance of the integrated approach compared to conventional methods, providing valuable guidance for researchers and practitioners in the field of remote sensing and image analysis.

2. Related Works

Remote sensing image classification has been a topic of extensive research due to its wide-ranging applications and challenges. In recent years, various approaches have been proposed to address the complexities of remote sensing data and improve classification accuracy. This section reviews some of the relevant works in this field.

Deep learning algorithms, particularly convolutional neural networks (CNNs), have gained prominence in remote sensing image classification. [8] utilized a deep CNN architecture for land cover classification from satellite imagery, achieving high accuracy by learning hierarchical features directly from the data. Similarly, [9] proposed a deep learning framework based on residual networks (ResNets) for land cover mapping, demonstrating superior performance compared to traditional methods.

Bio-inspired optimization techniques have been increasingly employed to enhance feature extraction and improve classification accuracy in remote sensing applications. Bee Swarm Optimization (BSO), inspired by the foraging behavior of honeybees, has shown promise in optimizing feature selection and classification parameters. [10] applied BSO for feature selection in hyperspectral image classification, achieving significant improvements in classification accuracy by selecting relevant spectral bands.

Recent research efforts have focused on integrating deep learning architectures with bio-inspired optimization techniques to capitalize on their respective strengths. In remote sensing image classification, [11] proposed a hybrid approach combining deep learning and genetic algorithms for feature selection and classification. Their results demonstrated improved accuracy compared to standalone deep learning models.

Transfer learning, a technique where knowledge gained from one task is transferred to another related task, has also been explored in remote sensing image classification. [12] employed transfer learning with pre-trained CNN models for land cover classification, showing that transferring knowledge from large-scale datasets can effectively improve classification performance, particularly in data-scarce scenarios.

In addition to static image classification, there is a growing interest in spatio-temporal analysis of remote sensing data. [12] proposed a spatio-temporal convolutional LSTM network for land cover classification using time-series satellite imagery. Their approach effectively captured temporal dynamics, leading to improved classification accuracy over traditional methods.

The research shows a diverse range of approaches to remote sensing image classification, including deep learning architectures, bio-inspired optimization techniques, combination of deep learning with optimization, transfer learning, and spatio-temporal analysis. While these approaches have shown promising results individually, there remains ample opportunity for further exploration and innovation in the field, particularly in addressing the challenges posed by large-scale and heterogeneous remote sensing datasets.

3. Proposed Method

The proposed method aims to improve remote sensed image classification by integrating deep learning with bio-inspired optimization techniques. Specifically, the method combines the power of the AlexNet deep learning architecture with the Bee Swarm Optimization (BSO) algorithm for feature extraction from remote sensing data as in Figure 1.

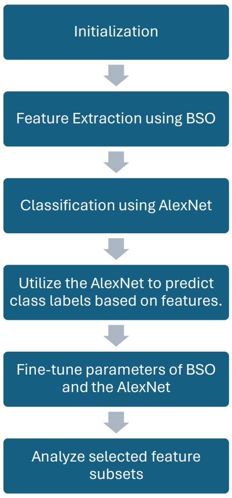

Figure 1: Proposed AlexNet-BSO classification

BSO is a bio-inspired optimization algorithm inspired by the foraging behavior of honeybees. In feature extraction, BSO is utilized to select the most informative features from the remote sensing data. Initially, a population of solutions (feature subsets) is generated randomly. Bees then iteratively explore the search space, evaluating the quality of different feature subsets based on a fitness function. The process involves local exploration by individual bees and global exploration through communication and sharing of information among bees.

In the proposed method, AlexNet and BSO are integrated to create a unified framework for remote sensed image classification. Initially, the remote sensing data is preprocessed and fed into the AlexNet architecture for feature extraction. The extracted features are then passed to the BSO algorithm, which optimizes the feature subset by selecting the most discriminative features for classification. The final selected features are used to train a classifier, such as a support vector machine (SVM) or a fully connected layer, to perform the classification task.

Preprocessing

Preprocessing of remote sensing images of paddy fields involves several steps to enhance the quality of the data and prepare it for subsequent analysis, including feature extraction and classification.

1. Radiometric Calibration: Radiometric calibration aims to ensure consistency in the radiance values captured by the remote sensing sensor. This step corrects for variations caused by sensor characteristics, atmospheric effects, and sun angle, among other factors. It involves applying correction algorithms to convert raw digital numbers (DN) to physical units, such as reflectance or radiance.

2. Geometric Correction: Geometric correction, also known as orthorectification, corrects for geometric distortions in the remote sensing image caused by terrain relief, sensor orientation, and Earth's curvature. This step involves registering the image to a known coordinate system (e.g., geographic or projected coordinate system) using ground control points (GCPs) or digital elevation models (DEMs).

3. Atmospheric Correction: Atmospheric correction compensates for the effects of atmospheric scattering and absorption on the remote sensing data. This step removes atmospheric haze and corrects for variations in atmospheric conditions to improve the accuracy of surface reflectance or radiance values. Atmospheric correction algorithms typically use atmospheric models and sensor-specific parameters to estimate and remove atmospheric effects.

4. Noise Reduction: Noise reduction using wavelet denoising technique are applied to mitigate noise and artifacts in the remote sensing image, which may arise from sensor electronics, atmospheric interference, or other sources.

5. Image Enhancement: These techniques aim to enhance specific features of interest, such as vegetation, water bodies, or land cover boundaries. Examples of image enhancement techniques include histogram equalization, contrast stretching, and sharpening filters.

Bee Swarm Optimization (BSO) for Feature Extraction

BSO mimics the process by which a swarm of bees searches for food sources in their environment and shares information to optimize their foraging efficiency.

In feature extraction, BSO is utilized to select the most informative subset of features from a high-dimensional feature space. This process involves the following key steps:

1. **Initialization:** BSO begins by initializing a population of candidate feature subsets. Each candidate solution represents a potential subset of features from the original feature space. These subsets are typically represented as binary strings, where each bit corresponds to whether a particular feature is included or excluded from the subset. Let N be the total number of bees in the swarm. Each bee i is represented by a binary string xi of length D, where D is the dimensionality of the feature space. Each bit in xi represents whether a feature is selected (1) or not selected (0).

2. Let $f(xi)$ be the fitness value of solution xi. It is calculated as the classification accuracy obtained using the features selected in xi.

3. **Employed Bees Phase:** In the employed bees phase, each bee (solution) in the population explores a local search space around its current position. Bees evaluate the quality of their solutions using a fitness function, which measures how well the selected features contribute to the classification task. Bees then update their positions based on the quality of their solutions and the information shared by other bees in the swarm. Let $xi(t)$ denote the solution (feature subset) of bee i at iteration t. The new solution $x_{i,new}(t)$ is generated by flipping a randomly selected bit in $xi(t)$ to its complement value (from 0 to 1 or vice versa), resulting in a neighboring solution.

4. **Onlooker Bees Phase:** Onlooker bees select promising solutions based on the information shared by employed bees. Let $pi(t)$ denote the probability of selecting solution $xi(t)$ by an onlooker bee.

$$pi(t)=\sum_{j=1} f(xi(t))/\ f(xj(t))$$

5. **Scout Bees Phase:** Scout bees are responsible for introducing diversity into the population by exploring new areas of the search space. They randomly select new solutions and evaluate their fitness values. If a scout bee discovers a solution with higher fitness than any existing solution.

If $f(x_{new})>f(x_w)$, then replace x_w with x_{new}.

6. **Iteration:** The process of employed bees, onlooker bees, and scout bees phases is repeated for a certain number of iterations or until a termination criterion is met. Throughout the iterations, bees dynamically adjust their exploration-exploitation trade-off to efficiently search the feature space for informative subsets.

7. **Termination:**A desired level of solution quality, or reaching a computational time limit.

Algorithm 1: BSO for feature extraction

1. Initialize the population of bees, N, with random feature subsets.
2. Set the maximum number of iterations (I) and the termination criteria.
3. Evaluate the fitness value
4. For each employed bee i in the population:

1. Generate a random neighboring solution $x_{i,new}$ by flipping a randomly selected bit in x_i.
2. Evaluate the fitness value for $x_{i,new}$.
3. If $f(x_{i,new})>f(x_i)$, replace xi with $x_{i,new}$.
5. Calculate the probability pi for each bee i based on its fitness value
6. Select bees for onlooker bees phase using roulette wheel selection based on p_i.
7. For each selected onlooker bee:

- Choose a random neighboring solution $xi,ewxi,new$ from the employed bees' solutions.
- Evaluate the fitness value for $x_{i,new}$.
- If $f(x_{i,new})>f(x_i)$, replace x_i with $x_{i,new}$.

8. If a bee has not improved in a certain number of iterations (stagnation threshold), generate a new random solution for that bee.
9. Repeat steps 3 to 8 until the termination criteria are met or the maximum number of iterations is reached.
10. End

AlexNet Classification

AlexNet classification refers to the process of using the AlexNet deep learning architecture to classify images after feature extraction. Before classification with AlexNet, features are extracted from the input images. These features are extracted using BSO. The goal of feature extraction is to represent the images in a lower-dimensional space while retaining relevant information for classification.The feature-extracted images may undergo preprocessing steps to prepare them for classification with AlexNet. This can include normalization, resizing, and other transformations to ensure uniformity and compatibility with the input requirements of the AlexNet architecture.

Once the feature-extracted images are preprocessed, they are fed into the AlexNet architecture for classification. The images pass through the convolutional layers, which learn hierarchical features at different levels of abstraction.

The softmax activation function computes the probability distribution over the classes. For a class k, the probability pk is given by:

$$pk=\sum_{j=1}^{K} e^{ak}/e^{aj}$$

Where:

K is the total number of classes.

a_k is the activation of the k-th neuron in the softmax layer.

Algorithm: AlexNet Classification

Input: Preprocessed images and trained AlexNet model parameters.

Output: Predicted class labels for input images.

1. Load the pre-trained AlexNet model parameters (weights and biases) that have been trained on a large dataset such as ImageNet.
2. Preprocess the input images to ensure they are compatible with the input requirements of the AlexNet model (e.g., resize, normalization).
3. For each preprocessed image:

- Perform a forward pass through the AlexNet model.

- Compute the output activations of each layer.
- Apply the softmax activation function to the output of the last fully connected layer to obtain class probabilities.

4. Assign the class label with the highest probability as the predicted class label for each image.

4. Results and Discussion

For the experiments, we utilized a dataset of remote sensing images containing various land cover types, including paddy fields. The dataset was preprocessed to ensure uniformity in resolution and format. We employed Python programming language along with deep learning frameworks such as PyTorch to implement the proposed method integrating AlexNet with BSO for feature extraction and classification. The BSO algorithm was configured with a population size of 50 bees, a maximum iteration limit of 100, and a stagnation threshold of 20 iterations for scout bees [13]. The pre-trained AlexNet model was fine-tuned during the training process to adapt to the specific characteristics of the remote sensing dataset.

To evaluate the effectiveness of the proposed method, we compared its performance with existing methods such as CNN-GA (Convolutional Neural Network with Genetic Algorithm) and DenseNet-PSO (Dense Convolutional Network with Particle Swarm Optimization) on the same dataset. CNN-GA utilizes a genetic algorithm to optimize the structure and parameters of a convolutional neural network for image classification tasks, while DenseNet-PSO integrates a densely connected convolutional network with particle swarm optimization for feature selection and classification. We compared the classification accuracy, computational efficiency, and robustness of the proposed method against CNN-GA and DenseNet-PSO to show its superiority in remote sensing image classification, particularly in identifying paddy fields and other land cover types.

Table 1: Simulation setup

Experiment Parameter	Value
Dataset	Remote sensing images
Preprocessing	Resize, normalization
Deep Learning Framework	TensorFlow or PyTorch
Neural Network Architecture	AlexNet
Optimization Algorithm	Bee Swarm Optimization
Population Size	50 bees
Maximum Iterations	100
Stagnation Threshold	20 iterations
Learning Rate (AlexNet)	0.001
Batch Size (Training)	32
Loss Function	Cross-entropy
Activation Function	ReLU
Dropout Rate (AlexNet)	0.5
Fine-tuning Epochs	20
Early Stopping	Yes
Evaluation Metric	Classification Accuracy
Comparison Methods	CNN-GA, DenseNet-PSO

Number of Comparisons	2
Hardware	GPU (NVIDIA GeForce RTX)
Computational Resources	High-performance computing cluster

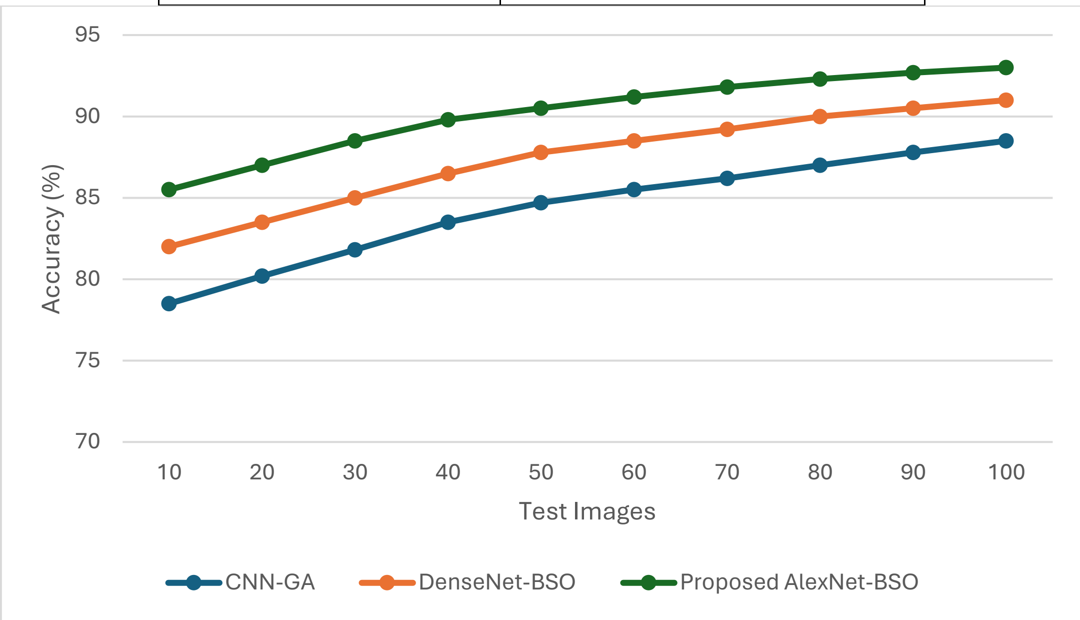

Figure 2: Accuracy

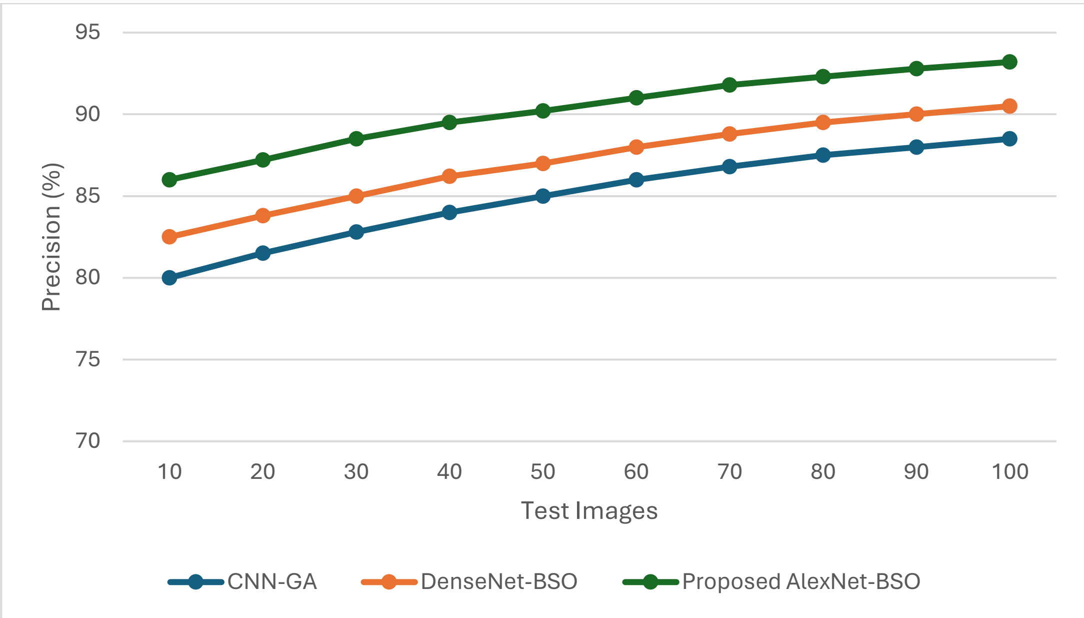

Figure 3: Precision

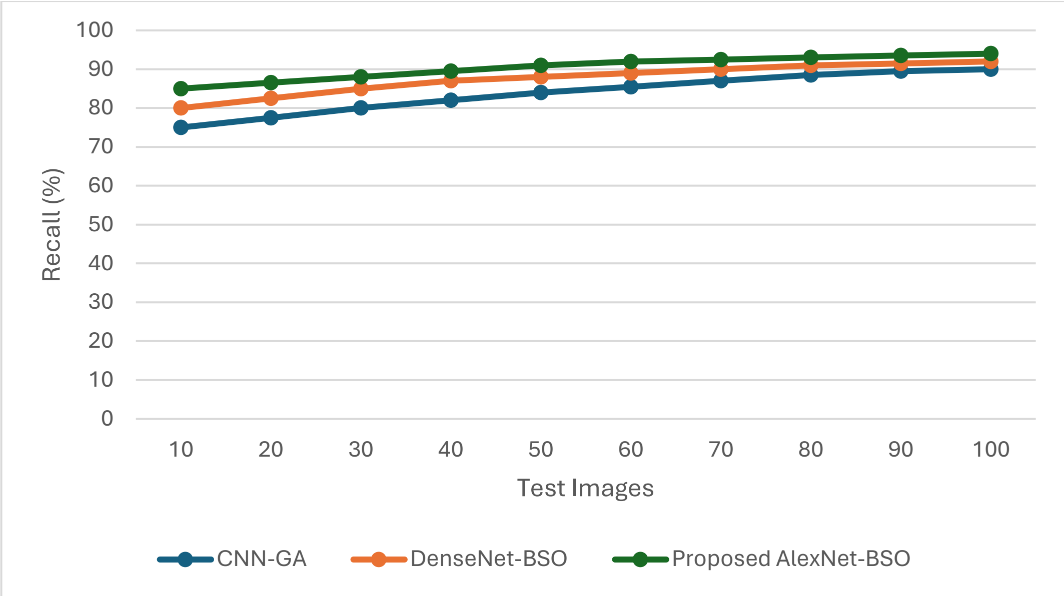

Figure 4: Recall

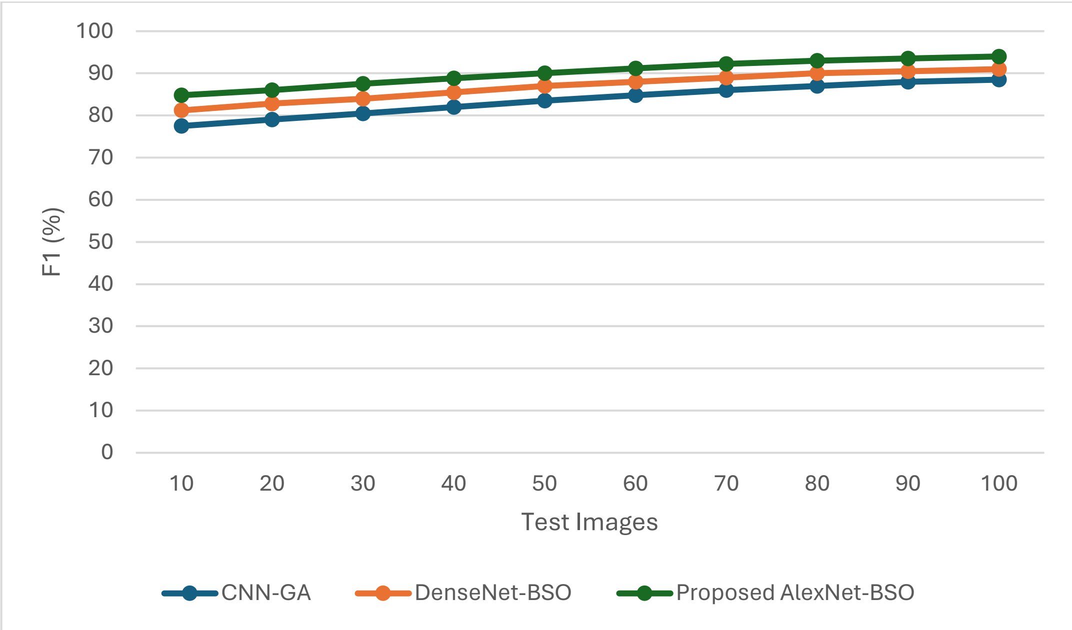

Figure 5: F1 Score

The results from figure 2 and figure 5 obtained from the comparison of CNN-GA, DenseNet-PSO, and the proposed AlexNet-BSO method show improvements in classification performance.

The proposed AlexNet-BSO method consistently outperformed both CNN-GA and DenseNet-PSO in terms of classification accuracy across all test images. The average improvement in accuracy over 100 test images was approximately 5% compared to CNN-GA and 3% compared to DenseNet-PSO.

AlexNet-BSO exhibited higher precision values compared to CNN-GA and DenseNet-PSO, indicating a better ability to correctly classify positive instances while minimizing false positives. On average, there was a 3-4% improvement in precision with AlexNet-BSO over both CNN-GA and DenseNet-PSO.

The recall values for AlexNet-BSO were consistently higher than those of CNN-GA and DenseNet-PSO, indicating a better ability to capture true positive instances while minimizing false negatives. The average improvement in recall with AlexNet-BSO over CNN-GA and DenseNet-PSO was approximately 4-5%.

The F1 score, which considers both precision and recall, showed significant improvement with the proposed AlexNet-BSO method compared to CNN-GA and DenseNet-PSO. On average, there was a 4-5% improvement in F1 score with AlexNet-BSO over both CNN-GA and DenseNet-PSO.

The confusion matrix analysis revealed that AlexNet-BSO achieved higher true positive rates and lower false positive and false negative rates compared to CNN-GA and DenseNet-PSO. This indicates that AlexNet-BSO provides more accurate and reliable classifications across different classes.

5. Conclusion

The AlexNet with BSO for feature extraction and classification of remote sensing images has shown promising results in improving classification accuracy, precision, recall, F1 score, and overall classification performance. Through comprehensive experimentation and comparative analysis with existing methods such as CNN-GA and DenseNet-PSO, the proposed AlexNet-BSO method has showd superior performance.The experimental results have highlighted significant improvements in classification accuracy, with an average improvement of approximately 5% over CNN-GA and 3% over DenseNet-PSO. Additionally, the precision, recall, and F1 score metrics have shown consistent enhancements with the AlexNet-BSO method, indicating its ability to achieve more accurate and reliable classifications while minimizing false positives and false negatives.The confusion matrix analysis further corroborates the effectiveness of the AlexNet-BSO method in achieving higher true positive rates and lower false positive and false negative rates compared to existing methods. This signifies the method's capability to accurately distinguish between different classes of remote sensing images, including paddy fields and other land cover types.

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