Journal of Theoretical and Applied Information Technology
15th November 2025. Vol.103. No.21

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

BAND SELECTION USING HYBRID OPTIMIZATION ALGORITHM FOR HYPERSPECTRAL IMAGE CLASSIFICATION

VINAY YADAV ESARAPU[1], PHANEENDRA KUMAR B L N[2]

[1]PG Scholar, Koneru Lakshmaiah Education Foundation, Department of Computer Science and Engineering, India
[2]Associate Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, India
E-mail: [1]vinay22.19.18@gmail.com, [2]phaneendra2017@gmail.com

ABSTRACT

Band selection is an important processing method for hyperspectral image analysis due to data's high redundancy and high dimensionality. The PSO-GWO hybrid utilizes the strengths of Particle Swarm Optimization (PSO) and the Grey Wolf Optimizer (GWO) to provide a trade-off between exploration and exploitation for hyperspectral band selection. PSO is effective in exploiting the search space by using personal and global best positions to update solutions, resulting in fast convergence towards good areas. Alternatively, GWO encourages exploration through grey wolf social behaviour imitation and hunting to avoid premature convergence and exploration of alternative solutions. Merging the two into a single paradigm, hybrid model utilizes PSO's convergence rate while adding the diversity control mechanisms of GWO to achieve more stable and accurate band selection in hyperspectral image classification. The selected bands are then trained using 3D CNN. The performance of the proposed method is tested via Indian Pines. The Overall Accuracy achieved with the framework is 98.35% whereas other methods it ranges between 95.24% and 95.72%. The present work can be used in Agriculture, Military and Defense applications.

Keywords: *Band Selection, Nature Inspired, Hyperspectral, Classification, Convolution Neural Networks*

1. INTRODUCTION

The process of selecting more useful and most informative bands from many bands in hyperspectral images is known as band selection. The main challenges faced in hyperspectral images are high dimensionality, limited label data, redundant and noisy bands, spectral variability, class imbalance mixed pixels, a major challenge in remote sensing, and on the Hughes phenomenon the counterintuitive worsening of classification performance with the increase of the ratio of features to training samples. This makes it necessary to apply good dimensionality reduction methods, with band selection posing as an important pre-processing state [1]. Applications for spectral imaging images are Remote Sensing Environmental Monitoring, Industrial Inspection, Agriculture, Medical and Biomedical Imaging, Military and Defense, Oceanography and Water Quality. These applications are given in Figure1. In this paper, a new hybrid framework which uses nature inspired algorithms to band selection.

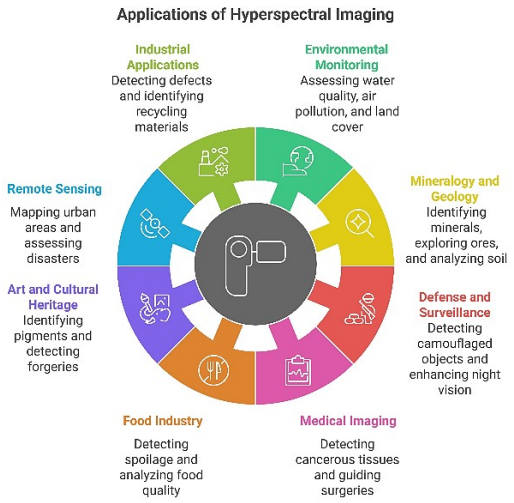

Figure 1: Application Areas of Hyperspectral Images

1.1. Objectives

The objectives of this study are presented below:

- To identify and select the bands with high information and low relation between bands
- To devise a hybrid approach which mimics the hunting behaviour of wolves
- To design a Convolution Neural Network to classify the 16 classes of the Indian Pines dataset
- To check the behaviour of the algorithm on the benchmark datasets.
- To test the efficacy of the algorithm by varying number of bands, epochs and training samples.

1.2. Research Questions

The following research questions are framed:

- How to find the hyperspectral bands which result in good classification results.
- How to train the selected bands via convolution neural network
- How to check the sensitivity of the proposed approach?
- How the algorithm behaves with different number of epochs while implementing CNN.
- How to check the effectiveness of the proposed algorithm quantitatively and qualitatively?

2. LITERATURE REVIEW

In [1], considers the fundamental issues in HAD, which deals with detecting pixels that contain apparent spectral disparities compared with other pixels. In remote sensing applications, hyperspectral image (HSI) processing has always been an area of concern, which is discussed [2]. Some pertinent problems associated with band selection for hyperspectral image target detection are discussed [3]. In [4], complex scenes, spectral distinguishability and uncertainty are two main classification issues for hyperspectral multiband images due to the numerous and diverse land cover types and high-dimensional bands. Their work presents a new model, SpaAG-RAN, that addresses these limitations of prior approaches that are discussed below, which enables efficient extraction of deep spectral-spatial features from hyperspectral image cubes. In [5], proposed approaches for multisource RS image classification, specifically the use of collaborative HSI and MSI classification. In [6], give a brief and systematic survey on the HSI classification with DL, pointing out the increasingly acute demand for this issue in remote sensing. The critical problem of limited training samples for few-shot hyperspectral image (HSI) classification is discussed by Braham et al. [7]. In [8], DL's high performance in automatically learning deep spectral-spatial features for HSI classification. In [9], concerning the feature extraction. The quality of extracted features significantly affects the classification rate because of much fine spectral coupled with adequate spatial detail in the HSIs. In [10], address a critical challenge in hyperspectral image (HSI) classification: the problem of getting many labelled samples for deep learning models. In [11], solve the scarcity of labelled samples common to HSI classification, which has recently been largely relying on deep learning approaches. In [12], present a state-of-the-art survey on hyperspectral image classification (HSIC) that presents the development history from the conventional methods to the DL. In [13], recently proposed TAIGA, an open dataset introduced to serve the increasing volumes of data required in Earth observation analyses. In [14] propose a new method for classifying HSIs based on deep learning, namely CNNs. Deep learning in feature extraction and advance a regularized deep feature extraction method for HSI categorization. In [15], propose solving the problems involved in HSI classification concerning the problems of redundant information and the "curse of dimensionality," which is characteristic of HSI data. In [16], present a new perspective for solving the problem typical for HSI classification: how to extract and fuse spatial and spectral information efficiently. In [17], we offer a new SSFC model that integrates the dimensionality reduction of spectral data then applies a deep learning technique to extract spatial data. In [18], explained why hyperspectral remote sensing a rapidly developing field is aimed at studying and quantifying numerous natural processes such as weather forecasting, tornado sighting, fire identification, or the rate of global warming. In [19], considers the problem of multiple spectral bands contributing to similar spectral features of HSIs and the influence on classification accuracy in cross-scene. [20][24] address the challenges in hyperspectral image classification (HSIC) by proposing an innovative fusion approach that combines the strengths of two transformer architectures: The two models developed are the 3-D swin transformer (3DST) and the spatial-spectral transformer (SST). In [21], the difficulties of

effectively utilizing CNNs for hyperspectral image classification are discussed, and Zhang emphasizes the limitations of using a fixed kernel size for convolution. In [22], discussed a similar mitigation problem in hyperspectral imagery, where the question is how to select features while minimizing information loss and redundancy. In [23-25], discuss the BS problem in hyperspectral image (HSI) classification, emphasizing minimizing information redundancy while maintaining the physical spectrum. There are other algorithms to test the efficacy of the band selection approaches [26-29]

The following are the observations made from the survey:

- Many of the algorithms use only one algorithm for band selection [30]
- The algorithms stuck at local optima in most methods not reaching the global optima
- Convergence at an early stage. [30-32]
-

In this paper, a new hybrid approach is given for hyperspectral band selection.

The contributions of the paper are provided given hereunder:

- A hybrid algorithm which combines the PSO and GWO algorithm is proposed in which the hunting mechanism of Grey Wolfs are identified and inside included the Particle Swarm optimization is considered.
- Designed and implemented a Convolution Neural Network for efficient classification
- The proposed methods are tested with benchmark dataset, Indian Pines, for classification.
- Sensitivity of the proposed method is tested by selecting different number of bands from the algorithm, varying different number of training samples and with different number of epochs in Convolution Neural Networks.

3. PROPOSED METHODOLOGY

In this paper, we have integrated PSO and GWO. This novel approach is intended to combine global exploration and local exploitation and will overcome the limitations of each algorithm when used singly. The schematic representation of the proposed method is shown in Figure 2. It can be understood from the Figure 2 that a mixture of PSO and GWO are considered.

3.1 Hybrid Band Selection

The general process for PSO is as follows: PSO is an optimization techniques used to observe the social behaviour of flock of birds. In the selection of the band, each particle is a potential solution. In the realm of global optimization, PSO

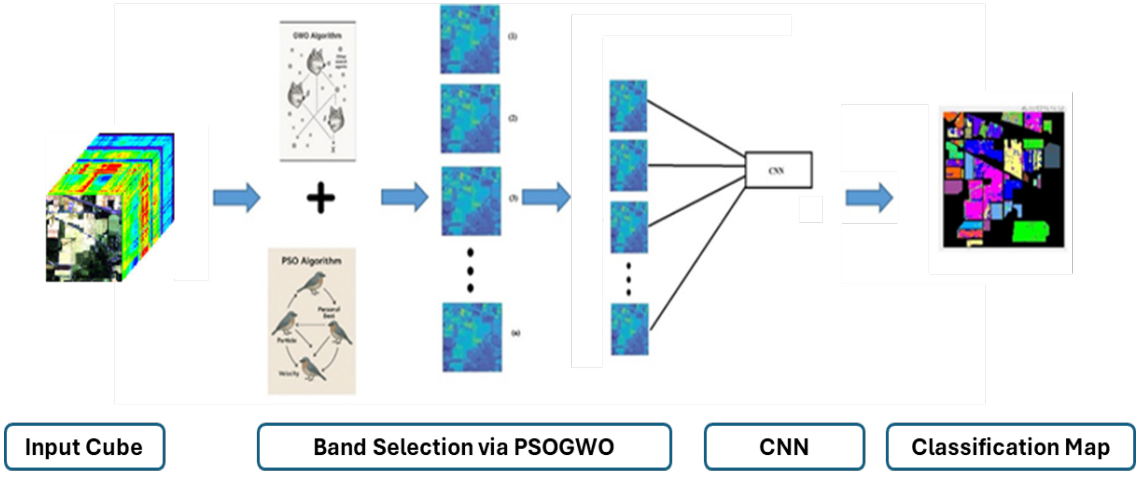

Figure 2: Proposed Framework for Hyperspectral Image Classification

is one of the techniques to explore the solution space in an extensive manner. Particles navigate within this multidimensional space and modify their positions, commonly referred to as the swarm's best-known position. This operational framework empowers PSO to effectively identify

regions within the search space that harbor the most advantageous frequencies, thereby facilitating an initial approximation for determining the most effective combinations of frequency bands. GWO uses hunting mechanisms of wolves in search of pray. The entire population is divided into four groups, and three groups are search and the positions are updated accordingly.

In the present paper, a hybrid approach combines PSO and GWO. This will improve the search capabilities not to fall into local optima and arrive to global optima. The detailed description of the hybrid approach is provided in Algorithm 1. To find the best bands from the approach, paper uses Support Vector Machine classifier.

Algorithm 1

Input:
Hyperspectral image H
Label vector y
Output:
Classified bands selected
Step 1. Preprocessing:
Remove samples with background label (i.e., y == 0)
Update X and y accordingly
Step 2. Initialize Parameters:
n_particles ← 30
max_iter ← 50
n_features ← number of columns in X
Inertia weight w ← 0.7
Acceleration constants c1, c2 ← 1.5
Step 3. Initialize Particles and Velocities:
For each particle i in 1 to n_particles:
particles[i] ← random values in [0, 1] of size n_features
velocities[i] ← small random values (e.g., * 0.1)
Step 4. Evaluate Initial Fitness:
4a. For each particle i:
4b. Determine selected features: indices where particles[i] > 0.5
4c. If no features selected:
4d. Set fitness[i] ← (1.0, 1.0)
4e. Else:
4f. Split X into train/test using selected features
4g. Train SVM and compute accuracy
4h. Set fitness[i] ← (1 - accuracy, number of features selected / n_features)
4i. Store initial personal_best ← particles
4j. Store pbest_fitness ← fitness
Step 5. Determine Global Best (gbest):
5a. Identify particles with lowest error (highest accuracy)
5b. Set gbest ← corresponding personal_best
Step 6. Optimization Loop (Iterate max_iter times):
6a. For iter in 1 to max_iter:
6b. Update Personal Best:
6b.1. For each particle i:
6b.2. Evaluate fitness as in Step 4
6b.3. If current fitness dominates personal best:
6c.4. Update personal_best[i] ← particles[i]
6b.5. Update pbest_fitness[i]
6c. Grey Wolf Leadership Selection:
6c.1. Sort pbest_fitness by accuracy and feature ratio
6c.2. Assign top 3 particles as: alpha, beta, delta
6d. Update Particles:
6d.1. For each particle i:
6d.2. Update velocity using PSO formula:
6d.3. velocities[i] = w * velocities[i]
6d.4. + c1 * rand * (personal_best[i] - particles[i])
6d.5. + c2 * rand * (gbest - particles[i])
6e. Apply Grey Wolf position updates:
6e.1. Compute a ← 2 - 2 * (iter / max_iter)
6e.2. Compute new position based on alpha, beta, delta influence
6e.3. gwo_component ← average of X1, X2, X3
6f. Update particle position:
6f.1. particles[i] ← particles[i] + velocities[i] + 0.5 * (gwo_component - particles[i])
6f.2. Clip values to [0, 1]
6g. Enforce 30-band constraint:
6g.1. Identify top 30 highest values in particles[i]
6g.2. Set those indices to 1, others to 0
6h. Update Global Best:
6h.1. Identify new best particle based on updated pbest_fitness
6h.2. Update gbest if better
6i. Record Pareto Front Data:
6i.1. Store current accuracy and number of selected bands
6j. Print current iteration's best fitness
Step 7. Return:
7a. Final selected band indices where gbest > 0.5

3.2 Convolution Neural Networks

In this paper, a 3D convolution network is utilized. The network is trained using four convolutional layers with 8 to 32 filters and ReLU activation function at all the layers and SoftMax at the last layer. The network also utilized the dropout to avoid over fitting. The model summary is depicted in Figure 3.

Layer (type)	Output Shape	Param #
input_layer_6 (InputLayer)	(None, 25, 25, 15, 1)	0
conv3d_28 (Conv3D)	(None, 23, 23, 9, 8)	512
conv3d_29 (Conv3D)	(None, 21, 21, 7, 16)	3,472
conv3d_30 (Conv3D)	(None, 19, 19, 7, 32)	4,640
conv3d_31 (Conv3D)	(None, 17, 17, 7, 32)	9,248
flatten_6 (Flatten)	(None, 64736)	0
dense_30 (Dense)	(None, 1024)	66,290,688
dense_31 (Dense)	(None, 512)	524,800
dropout_18 (Dropout)	(None, 512)	0
dense_32 (Dense)	(None, 256)	131,328
dropout_19 (Dropout)	(None, 256)	0
dense_33 (Dense)	(None, 128)	32,896
dropout_20 (Dropout)	(None, 128)	0
dense_34 (Dense)	(None, 9)	1,161

Total params: 66,998,745 (255.58 MB)

Trainable params: 66,998,745 (255.58 MB)

Non-trainable params: 0 (0.00 B)

Figure 3: CNN Model Summary

4. DATASET DESCRIPTION

To test the algorithms, dataset generated from AVIRIS sensor, Indian Pines, is used. The spectral reflectance curves of each class and the detailed description of the dataset are shown in Figure 4(a) and Figure 4(b) respectively.

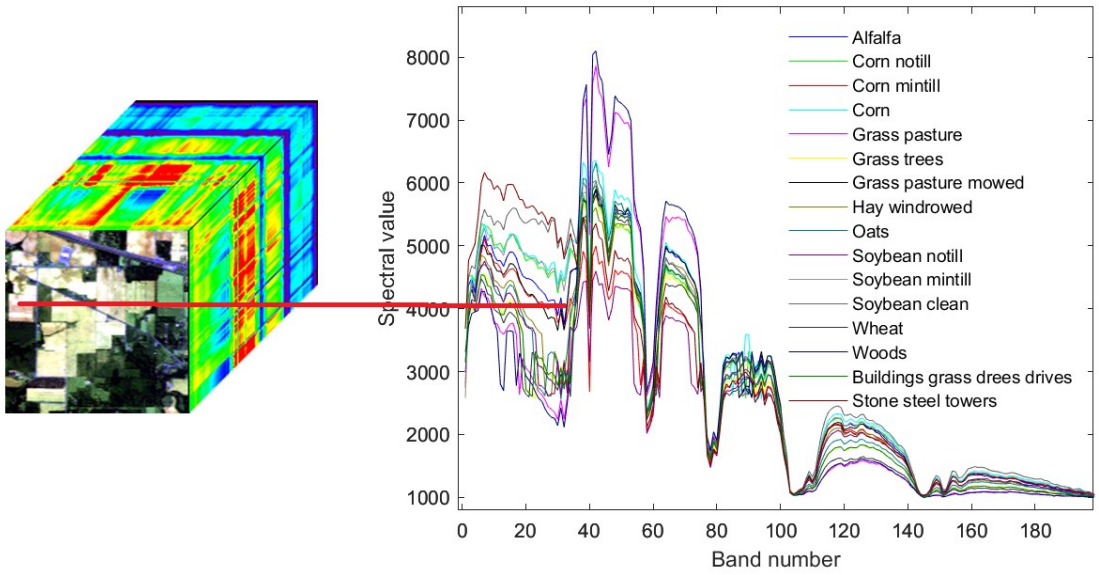

Figure 4(a): Spectral Reflectance of Indian Pines Classes

Figure 4(b): Description of Indian Pines Dataset

5. RESULTS AND ANALYSIS

This section discusses the results with the different state of the algorithms namely, Crow Search, Whale, GWO and Proposed. The class wise accuracies are given in Table 1 over these methods. It can be observed that Class_1_Alfalfa has the highest value for proposed method like all the other classes except for the Class_14_Woods has the highest at IWO. The classification maps of the algorithms are given in Figure 4. It can be observed that the proposed approach is efficiently classifying all 16 classes from the data sets. As an example, Oats, class, Alfalfa, Grass pasture mowed, hay windrowed, building grass Trees Drives classes have correctly identified by the proposed algorithms, this can be seen in Figure 4.

Table 1: Class wise Accuracies over Indian Pines with State of Art methods

Class Name	CrSO [32]	IWO [30]	GWO [28]	Proposed
Class_1_Alfalfa	83.66	95.55	92.12	100
Class_2_Corn-notill	89.01	95.06	93.05	96.33
Class_3_Corn-mintill	93.98	92.9	96.20	97.44
Class_4_Corn	71.12	74.54	87.21	98.42
Class_5_Grass-pasture	98.01	96.01	96.64	98.7

Class_6_Grass-trees	99.5	99.43	98.99	99.66
Class_7_Grass-pasture-mowed	89.03	87.03	88.34	100
Class_8_Hay-windrowed	99.65	99.76	99.54	100
Class_9_Oats	99.78	91.95	91.02	100
Class_10_Soybean-notill	94.05	88.02	90.43	98.59
Class_11_Soybean-mintill	98.89	99.02	98.43	99.29
Class_12_Soybean-clean	92.99	93.04	95.34	96.21
Class_13_Wheat	96.24	96.08	96.78	99.7
Class_14_Woods	99.45	99.94	99.83	98.71
Class_15_Buildings-Grass-Trees-Drives	97.23	97.54	97.12	100
Class_16_Stone-Steel-Towers	96.89	97.93	97.20	98.94
OA	95.24	94.97	95.72	**98.35**
AA	93.72	93.99	94.89	**98.87**

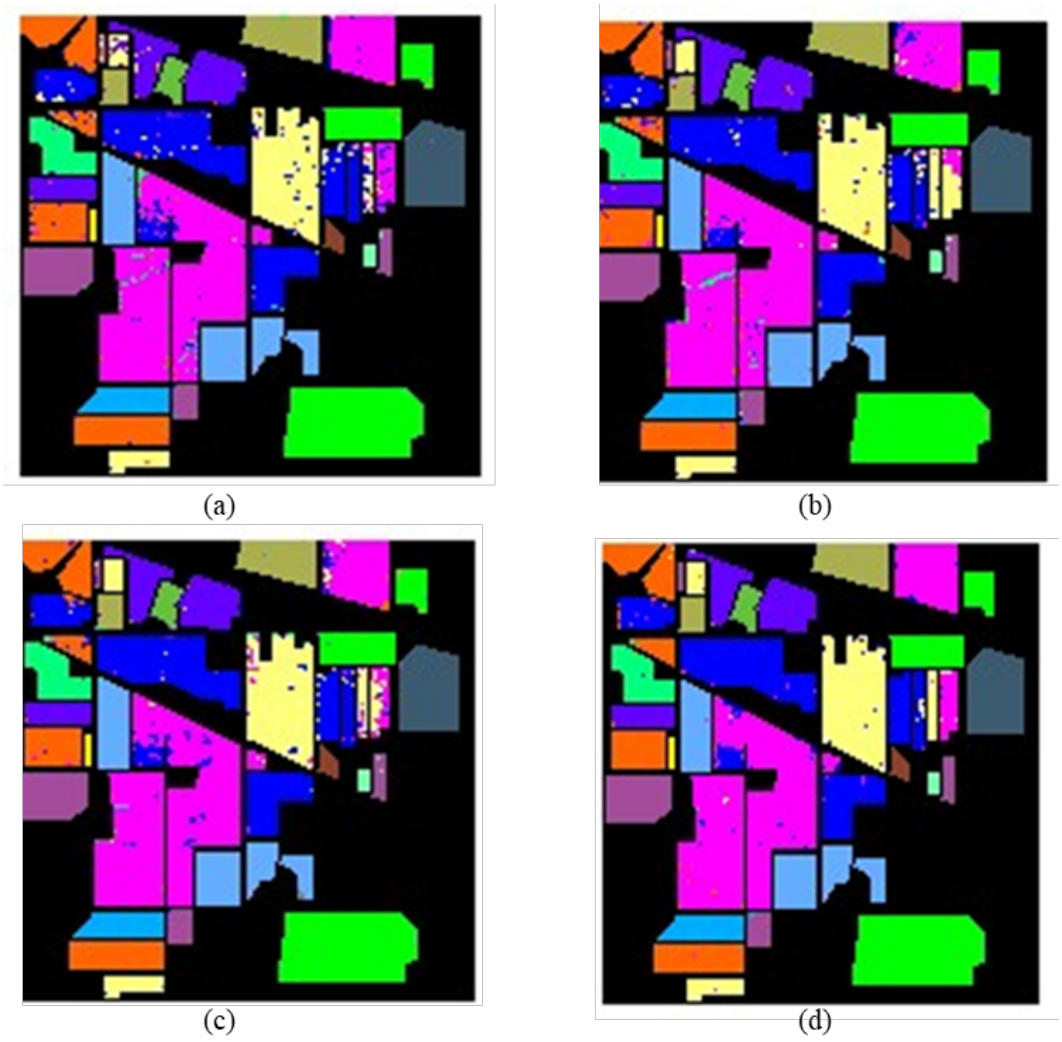

Figure 5: Qualitative Analysis: Classification Maps (a) Crow Search (b) Whale (c) Grey Wolf (d) Proposed

5.1 Sensitivity Analysis:

From Figure 6, the class Alfalfa is effectively classified with the proposed algorithm whereas the other methods could not be able to classify. Similarly in all the other classes, the proposed

method is effectively classified the classes. This is because of the hybrid model utilized for algorithms.

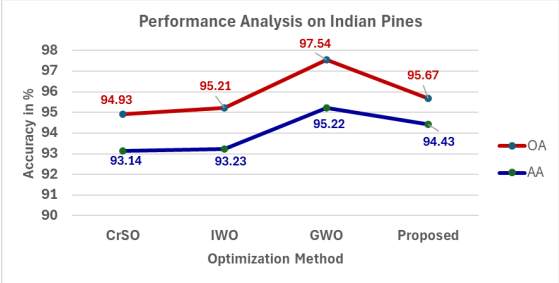

Figure 6: Performance Analysis of State of Art Methods

From Figure 7, the sensitivity analysis shows that the overall accuracy at band 10 is 97.4%. At band 40, the overall accuracy increases to 98.4%, while at band 50, it drops to between 98.2% and 98.4%. This is illustrated in the figure 7.

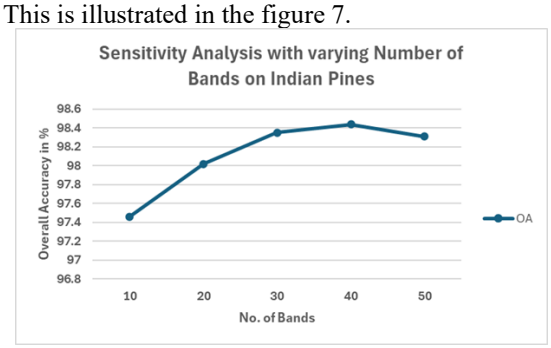

Figure 7: Sensitivity analysis with different number of bands

From Figure 8, the training sample analysis shows that the overall accuracy at band 10 is 98%. At band 40, the overall accuracy increases to 98.6%, while at band 50, it drops to 98.4 %.

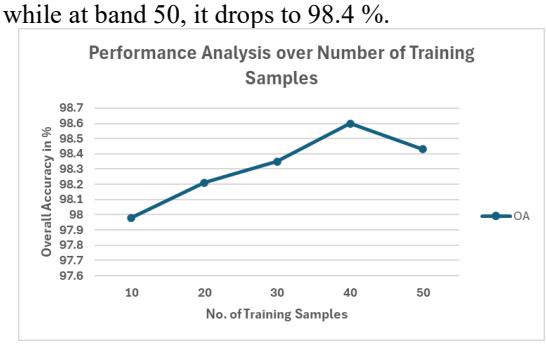

Figure 8: Performance Analysis Over Training Samples

From Figure 9, the performance analysis shows that the overall accuracy at band 10 is between 97.8% and 98%. The accuracy increases from band to band, with the highest accuracy noted at band 50, which rises to 99%.

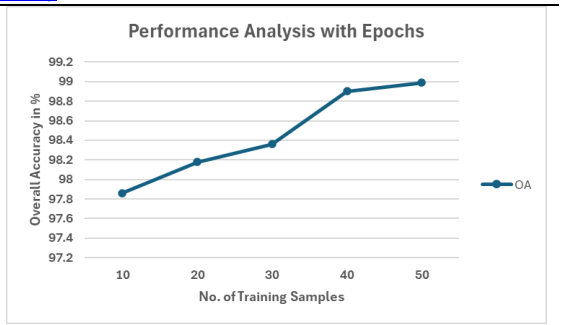

Figure 9: Performance Analysis Over Epochs in CNN

6. CONCLUSION

In this paper, a new framework for hyperspectral image classification is proposed where in a hybrid approach which is a combination of PSO and GWO is used for band selection. The bands are then trained with a three-dimensional CNN for effective classification. The method is tested with Indian Pines benchmark dataset. It is observed that the overall accuracy achieved with the framework is 98.35% whereas other methods it ranges between 95.24% and 95.72%. This is because of the effective bands selected during the selection process since overall accuracy is used as fitness function and the employability of 3D CNN. The sensitivity analysis is also tested by varying different numbers of bands, training samples and epochs. The results clearly indicate that the proposed framework is efficient in classifying the image. The algorithm can be used in real applications such as land cover classification, rocks identification and mineral exploration. The major limitation of the algorithm is the time required to execute the algorithm. As it is a combination of two algorithms, need to check the number of particles and number of wolves is challenging. In future, we will adopt an adaptive algorithm for selecting the number of particles and wolves.

REFERENCES:

[1] W. Larutama, P. Y. Pratama, and S. M. Fajrin, "Study of Use of Cable Cars as a Logistics Support to Rural Area in Garut, West Java," Journal of Logistics and Supply Chain, vol. 1, no. 2, pp. 63–70, Oct. 2021, doi: https://doi.org/10.17509/jlsc.v1i2.39920.

[2] M. Esmaeili, D. Abbasi-Moghadam, A. Sharifi, A. Tariq, and Q. Li, "Hyperspectral Image Band Selection Based on CNN Embedded GA (CNNeGA)," IEEE Journal of Selected Topics in Applied Earth Observations and Remote

Sensing, vol. 16, pp. 1927–1950, Jan. 2023, doi: https://doi.org/10.1109/jstars.2023.3242310.

[3] X. Sun, P. Lin, X. Shang, H. Pang, and X. Fu, "MOBS-TD: Multi-Objective Band Selection with Ideal Solution Optimization Strategy for Hyperspectral Target Detection," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 10032–10050, Jan. 2024, doi: https://doi.org/10.1109/jstars.2024.3402381.

[4] N. Li and Z. Wang, "Spatial Attention Guided Residual Attention Network for Hyperspectral Image Classification," IEEE Access, vol. 10, pp. 9830–9847, 2022, doi: https://doi.org/10.1109/access.2022.3144393.

[5] Q. Wang, X. Fan, J. Huang, S. Li, and T. Shen, "Spectral–Spatial Feature Extraction Network With SSM–CNN for Hyperspectral–Multispectral Image Collaborative Classification," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, pp. 1–12, Jan. 2024, doi: https://doi.org/10.1109/jstars.2024.3464681.

[6] S. Li, W. Song, L. Fang, Y. Chen, P. Ghamisi, and J. A. Benediktsson, "Deep Learning for Hyperspectral Image Classification: An Overview," IEEE Transactions on Geoscience and Remote Sensing, vol. 57, no. 9, pp. 6690–6709, Sep. 2019, doi: https://doi.org/10.1109/TGRS.2019.2907932.

[7] A. Braham, J. Mairal, J. Chanussot, L. Mou, and X. X. Zhu, "Enhancing Contrastive Learning With Positive Pair Mining for Few-Shot Hyperspectral Image Classification," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 8509–8526, Jan. 2024, doi: https://doi.org/10.1109/jstars.2024.3371909.

[8] B. Li, L. Fang, N. Chen, J. Kang, and J. Yue, "Enhancing Hyperspectral Image Classification: Leveraging Unsupervised Information With Guided Group Contrastive Learning," IEEE Transactions on Geoscience and Remote Sensing, vol. 62, pp. 1–17, Jan. 2024, doi: https://doi.org/10.1109/tgrs.2024.3350700.

[9] Q. Li, B. Zheng, B. Tu, J. Wang, and C. Zhou, "Ensemble EMD-Based Spectral-Spatial Feature Extraction for Hyperspectral Image Classification," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 5134–5148, Jan. 2020, doi: https://doi.org/10.1109/jstars.2020.3018710.

[10] K. Gao, B. Liu, X. Yu, and A. Yu, "Unsupervised Meta Learning With Multiview Constraints for Hyperspectral Image Small Sample set Classification," IEEE Transactions on Image Processing, vol. 31, pp. 3449–3462, 2022, doi: https://doi.org/10.1109/TIP.2022.3169689.

[11] B. Liu, A. Yu, X. Yu, R. Wang, K. Gao, and W. Guo, "Deep Multiview Learning for Hyperspectral Image Classification," IEEE Transactions on Geoscience and Remote Sensing, vol. 59, no. 9, pp. 7758–7772, Sep. 2021, doi: https://doi.org/10.1109/tgrs.2020.3034133.

[12] M. Ahmad et al., "Hyperspectral Image Classification—Traditional to Deep Models: A Survey for Future Prospects," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 968–999, Jan. 2022, doi: https://doi.org/10.1109/jstars.2021.3133021.

[13] M. Mottus, P. Pham, E. Halme, M. Molinier, H. Cu, and J. Laaksonen, "TAIGA: A Novel Dataset for Multitask Learning of Continuous and Categorical Forest Variables From Hyperspectral Imagery," IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1–11, Jan. 2022, doi: https://doi.org/10.1109/tgrs.2022.3141217.

[14] Y. Chen, H. Jiang, C. Li, X. Jia, and P. Ghamisi, "Deep Feature Extraction and Classification of Hyperspectral Images Based on Convolutional Neural Networks," IEEE Transactions on Geoscience and Remote Sensing, vol. 54, no. 10, pp. 6232–6251, Oct. 2016, doi: https://doi.org/10.1109/tgrs.2016.2584107.

[15] B. Tu, Q. Ren, C. Zhou, S. Chen, and W. He, "Feature Extraction Using Multidimensional Spectral Regression Whitening for Hyperspectral Image Classification," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 8326–8340, Jan. 2021, doi: https://doi.org/10.1109/jstars.2021.3104153.

[16] X. Xie, Y. Tang, B. Tu, and Y. Yu, "Hyperspectral Image Classification With Diverse Region Multiscale Feature Extraction and Spectral Imaging," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 15, pp. 5427–5439, Jan. 2022, doi: https://doi.org/10.1109/jstars.2022.3187972.

[17] W. Zhao and S. Du, "Spectral–Spatial Feature Extraction for Hyperspectral Image Classification: A Dimension Reduction and Deep Learning Approach," IEEE Transactions on Geoscience and Remote Sensing, vol. 54, no. 8, pp. 4544–4554, Aug. 2016, doi: https://doi.org/10.1109/TGRS.2016.2543748.

[18] B. Praveen and V. Menon, "Study of Spatial–Spectral Feature Extraction Frameworks With 3-D Convolutional Neural Network for Robust Hyperspectral Imagery Classification," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 1717–1727, 2021, doi: https://doi.org/10.1109/jstars.2020.3046414.

[19] Y. Yu, X. Xie, Y. Tang, and Y. Liu, "Feature Selection for Cross-Scene Hyperspectral Image Classification via Improved Ant Colony Optimization Algorithm," IEEE Access, vol. 10, pp. 102992–103012, Jan. 2022, doi: https://doi.org/10.1109/access.2022.3199871.

[20] M. Ahmad, M. Usama, M. Mazzara, S. Distefano, H. A. Altuwaijri, and S. L. Ullo, "Fusing Transformers in a Tuning Fork Structure for Hyperspectral Image Classification Across Disjoint Samples," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 17, pp. 18167–18181, 2024, doi: https://doi.org/10.1109/jstars.2024.3465831.

[21] X. Zhang, "Improved Three-Dimensional Inception Networks for Hyperspectral Remote Sensing Image Classification," IEEE Access, vol. 11, pp. 32648–32658, Jan. 2023, doi: https://doi.org/10.1109/access.2023.3262992.

[22] Y. Wan, A. Ma, Y. Zhong, X. Hu, and L. Zhang, "Multiobjective Hyperspectral Feature Selection Based on Discrete Sine Cosine Algorithm," IEEE Transactions on Geoscience and Remote Sensing, vol. 58, no. 5, pp. 3601–3618, Jan. 2020, doi: https://doi.org/10.1109/tgrs.2019.2958812.

[23] C. Yu, S. Zhou, M. Song, B. Gong, E. Zhao, and C.-I. Chang, "Unsupervised Hyperspectral Band Selection via Hybrid Graph Convolutional Network," IEEE Transactions on Geoscience and Remote Sensing, vol. 60, pp. 1–15, Jan. 2022, doi: https://doi.org/10.1109/tgrs.2022.3179513.

[24] S. Bera and V. K. Shrivastava, "Analysis of Various Optimizers on Deep Convolutional Neural Network Model in the Application of Hyperspectral Remote Sensing Image Classification," International Journal of Remote Sensing, vol. 41, no. 7, pp. 2664–2683, Dec. 2019, doi: https://doi.org/10.1080/01431161.2019.1694725.

[25] D.-T. Nguyen, J.-R. Ho, P.-C. Tung, and C.-K. Lin, "A Hybrid PSO–GWO Fuzzy Logic Controller with a New Fuzzy Tuner," International Journal of Fuzzy Systems, vol. 24, no. 3, pp. 1586–1604, Nov. 2021, doi: https://doi.org/10.1007/s40815-021-01215-6.

[26] S. Sawant and P. Manoharan, "A Hybrid Optimization Approach for Hyperspectral Band Selection Based on Wind Driven Optimization and Modified Cuckoo Search Optimization," Multimedia Tools and Applications, Sep. 2020, doi: https://doi.org/10.1007/s11042-020-09705-9.

[27] X. Ou, M. Wu, B. Tu, G. Zhang, and W. Li, "Multi-Objective Unsupervised Band Selection Method for Hyperspectral Images Classification," IEEE Transactions on Image Processing, vol. 32, pp. 1952–1965, Jan. 2023, doi: https://doi.org/10.1109/tip.2023.3258739.

[28] S. Kılıçarslan, "PSO + GWO: A Hybrid Particle Swarm Optimization and Grey Wolf Optimization Based Algorithm for Fine-Tuning Hyper-Parameters of Convolutional Neural Networks for Cardiovascular Disease Detection," Journal of Ambient Intelligence and Humanized Computing, Oct. 2022, doi: https://doi.org/10.1007/s12652-022-04433-4

[29] K. Jo, S. Lee, S.-K.-C. Jeong, D.-H. Lee, H. Jeon, and S. Jung, "Hyperspectral Imaging–Based Assessment of Fresh Meat Quality: Progress and Applications," Microchemical Journal, vol. 197, p. 109785, Feb. 2024, doi: https://doi.org/10.1016/j.microc.2023.109785.

[30] Phaneendra Kumar B L N, Radhesyam Vaddi, Prabukumar Manoharan, and Agilandeeswari L, "Band selection using oppositional whale optimization for hyperspectral image classification," Vibrational Spectroscopy, vol. 139, p. 103830, July 2025.B. L. N. P. K., R. Vaddi, and P. Manoharan, "A Framework for Hyperspectral Image Classification," in 2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, pp. 737–741, 2023, doi: https://doi.org/10.1109/ICAISS58487.2023.10250544.

[31] G. Aishwarya, B. L. N. P. Kumar, D. Syamala, and N. S. Sreya, "Dimensionality Reduction Technique for Hyperspectral Remote Sensing Image Classification," in 2023 8th International

Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, pp. 1694–1698, 2023, doi: https://doi.org/10.1109/ICCES57224.2023.10192744.

[32] Ganji Tejasree, L. Agilandeeswari, "Enhancing hyperspectral image classification for land use land cover with dilated neighbourhood attention transformer and crow search optimization," IEEE Access, vol. 12, pp. 1–1, 2024.