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IMPROVED GREY WOLF OPTIMIZATION BASED BAND SELECTION FOR HYPERSPECTRAL REMOTE SENSING IMAGE CLASSIFICATION

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ABSTRACT

The selection of bands in hyperspectral imagery represents a significant challenge within the remote sensing discipline, attributable to the dataset's high dimensionality and the presence of redundant information across the various bands. This manuscript introduces a novel framework aimed at the classification of hyperspectral images. To identify the optimal set of bands, an enhanced grey wolf optimization technique employing a non-linear function is implemented, which iteratively refines the band configurations based on the optimal, suboptimal, and tertiary solutions, mirroring the roles of the "alpha," "beta," and "delta" wolves, respectively. Subsequently, the intrinsic information from the band set is extracted through a spatial filter that isolates the albedo component. A non-linear Support Vector Machine is trained with the extracted features. Empirical results derived from the Indian Pines and University of Pavia datasets confirm the effectiveness of the proposed framework in attaining superior classification accuracy over the state-of-the-art methods by accurately identifying appropriate bands and categorizing all varieties. The empirical quantitative and qualitative results validate the efficacy of the proposed framework. The proposed methodology holds significant relevance for land use analysis, environmental monitoring, and remote sensing applications, as it markedly reduces the number of bands utilized while maintaining classification performance.

Keywords: *Hyperspectral Images, Support Vector Machine, Grey Wolf Optimization, Band selection*

1. INTRODUCTION

The process of choosing the most useful spectral bands from a wide range of bands that collect data at different wavelengths is known as band selection in hyperspectral imaging. The most relevant bands are selected by focusing on information-rich wavelengths that significantly enhance tasks like categorization or detection. There are numerous ways to rank and choose the best bands, and these methods include filter methods, wrapper methods, and embedding methods. The process of classifying each pixel in a hyperspectral image into distinct classes according to its spectral signature is known as hyperspectral image classification. For this, methods like machine learning and deep learning are frequently employed. Applications for hyperspectral imaging (HSI) categorization are many including Crop Monitoring and Health Assessment [1], Monitoring deforestation [2], Mapping and Identifying Minerals [3], material identification and target detection [4], Urban planning [5], Tissue Analysis and Non-Invasive Diagnostics [6], Classification of Forest Species and Health Monitoring [7], Water Quality Assessment [8], Detection of Contaminants and Control of Food Quality [9], analyzation of cells and tissues [10]. These applications are given in Figure 1. The main limitations of Hyperspectral images are High dimensionality and redundancy, and it is sensitivity to noise. The main objective of this research is to propose an enhanced Grey Wolf Optimization (GWO)-based band selection model for hyperspectral remote sensing image classification. Unlike the traditional band selection methods, the proposed method emphasizes maximizing classification accuracy while reducing the numbers of selected bands and computational complexity. The respective outcome measures, such as overall accuracy, kappa coefficient, and per-class accuracy, clearly show the better performance of the proposed method on Indian Pines and

University of Pavia datasets, hence confirming novelty and efficiency of this work.

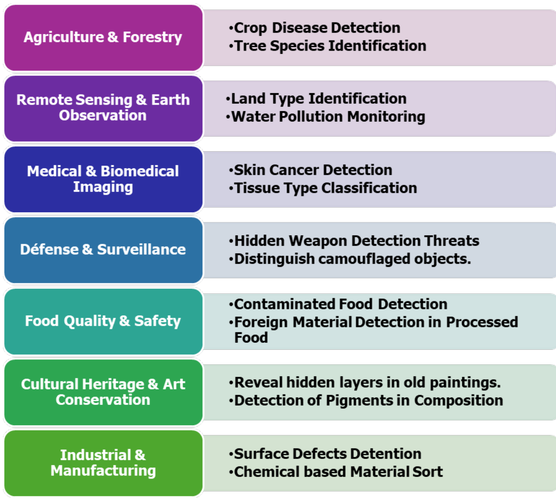

Figure 1: Application Areas of Hyperspectral Images

1.1. Objectives

The objectives of this study are presented below:

- To find optimal band set from Hyperspectral images using a novel band selection algorithm
- To extract spatial features which will enhance the classification accuracy
- To use a non-linear classification algorithm to classify the class labels of data sets.
- To test algorithms on at least two different benchmark datasets
- To use spectral spatial features on SVM classifier for quality classification maps.

1.2. Research Questions

The following research questions are framed:

- Is it possible to extract informative bands from nature inspired algorithm?
- How does spatial filter help in extracting the spatial features from the selected bands?
- How to train SVM Classifier to improve the classification Accuracy?
- Is it possible to check the efficacy of the band selection algorithm with varying number of bands, training samples?

2. LITERATURE REVIEW

In [11], a whale optimization algorithm to band subset selection has been introduced by utilizing humpback whale hunting behaviour to recover informative bands it can extract spatial features and a non-linear kernel support vector machine to classify data, benchmark datasets such as Indian Pines, University of Pavia, and Salinas. In [12], author used hybrid global optimization techniques combining with Cuckoo search and wind driven optimization. This approach initializes the population using the Chebyshev chaotic map, splits it into subgroups that are controlled separately by WDO and CS, and adaptively modifies the Levy flight step size in CS. In order to take advantage of self-equilibrium and symmetry, in [13], band selection has been done using hybrid rice optimization (HRO), which divides its population into three groups. Due to significant band correlation and redundancy, hyperspectral image (HSI) analysis in remote sensing poses a few challenges. In [14], for band selection author used modified whale optimization algorithm and multi resolution analysis is done using 3D discrete wavelet transform. Few algorithms are focused on target detection where only two objective functions are used which are not sufficient for selecting optimal bands subset, in [15], author proposed target-oriented Multi objective optimization of band selection (TOMOBS). In [16], research paper presents an unsupervised deep learning approach (DRA) based on particle swarm optimization (PSO) that selects bands based on spectral divergence and spatial gradient information. For reducing computational complexity and to remove spectral redundancy three band selection approaches are proposed in [17], which are Particle swarm optimization, Crowd search algorithm, Hybrid algorithm. For improving convergence speed and prevent local optima, in [18], paper presents a Hybrid Gray Wolf Optimizer (HGWO) for HSI BS. In [19], work presents an approach that leverages the efficient band decomposition of membrane computing and the predatory strategy of WOA to combine Wavelet SVM (WSVM) ensemble models with Membrane WOA (MWOA). In [20], paper suggests an enhanced genetic algorithm (GA) with a fitness function based on super pixel analysis and Fisher score for an unsupervised BS method. In [21] author addresses the difficulties in hyperspectral remote sensing and presents a semi supervised improved Levy flight (LF)-based genetic algorithm (GA) for band selection. A multicriteria semi-supervised model for band selection in hyperspectral images is presented in [22], It uses labelled samples to evaluate discrimination and assesses information and redundancy from unlabeled samples. In [23], presents a modified GWO (MGWO) that modifies band weights in accordance with fitness levels. In

[24], research suggests a hybrid method for hyperspectral band selection that combines genetic algorithms (GA) with deep learning autoencoders. For improving classification using a modified wavelet Gabor filter (Genet) convolutional neural network in [25], it sends flower pollination optimization (FPO) techniques for choosing ideal bands in aerial hyperspectral pictures. In [26], the Fruit Fly Optimization Algorithm (FOA) is presented as an application in this domain for spectral band selection in hyperspectral pictures. In [27], Farmers frequently underutilize recent agricultural technological developments because of equipment specificity and cost considerations author proposed fly optimization algorithm. In [28], research presents the Multitask Artificial Bee Colony Band Selection (MBBS-VC) method, which creatively finds many ideal band subsets of varying sizes concurrently by utilizing a Multi micro group Bee Colony technique together with variable-size clustering. In [29], paper suggests an algorithm called Golden Sine Spotted Hyena Optimization (GSSHO) that combines chaotic strategy, tournament selection, and Golden. In [30], author proposed binary grey wolf optimization-based hybrid CNN (BGWOHCNN) framework introduces a 2-D CNN to lighten computational burden and a 3-D CNN for joint feature extraction in order to improve efficiency and accuracy. By hybridizing PCA for dimensionality reduction with sequential convolutions in order to capture a range of spatial-spectral features, a multidimensional sequential CNN architecture (3D-1D-2D SCNN) was proposed for hyperspectral image classification in [31] and achieved higher accuracy on benchmark datasets. Through the integration of a particle reactivation module and simulated annealing in global updates, a more improved particle swarm optimization (PSO) algorithm was introduced in [32]. This upgraded algorithm enhanced population stability and diversity and performed better than both basic PSO and genetic algorithms in path planning problems. Unlike GA, ACO, and traditional PSO methods, the Ant Colony Natural Inspired Particle Swarm Optimization (ANPSO) in [33] realized notable improvements in PSNR, SSIM, and convergence rate for image enhancement through the integration of ACO and PSO with chaos theory and adaptive inertia weights. Adaptive inertia weight tuning and ant colony-based knowledge sharing were blended to develop the Colony Heuristic Particle Swarm Optimization (CHPSO) method in [34], which outperformed traditional image improvement algorithms for PSNR, SSIM, and convergence speed by 8.7%, 7.2%, and 9.4%, respectively. Through comparative analysis of fitness, feature count, and performance metrics, a wrapper-based feature selection method utilizing nine swarm intelligence algorithms including WOA, HHO, BOA, AOA, SSA, and others was proposed in [35] to find the best feature subsets. This method demonstrated improved classification accuracy across 12 benchmark datasets. By using adaptive weighted coefficients, 2-norm-based crowding distance, and a dual offspring generation strategy, a new multimodal multi-objective evolutionary algorithm (HREA-AWC) was proposed in [36] and was found to outperform the current algorithms in maintaining multiple Pareto Sets as well as convergence. By combining HR Net-SE, an improved attention mechanism, and Patch Fusion, a Swin Attention-HR Net model was presented in [37] for classification of remote sensing images. The model was able to outperform traditional CNN and Transformer-based models by 3.34% by utilizing contextual and global information more effectively. Utilizing NDWI, NDSI, and MODIS LST data for precise mapping and designing a post-disaster aggregate supply logistics route search system on the basis of satellites, satellite remote sensing and GIS technology were utilized in [38] to demarcate the tsunami-inundation zones and evaluate road damage in Miyagi Prefecture following the 2011 earthquake. For lung cancer classification from CT scan images, a hybrid AI-based approach combining ANN, SVM, KNN, and Decision Tree algorithms was proposed in [39]. ANN performed better than other models with highest accuracy (93.15% / 95.50%), precision, and recall across a broad range of dataset splits on the Lung Image Database. From the Plant Village dataset, a novel CNN-based model was proposed in [40] for the detection of early potato leaf disease. It outperformed the pre-trained models such as VGG16, ResNet50, and InceptionV3 with 99.67% test accuracy, less parameters, less overfitting, and improved early and late blight classification.

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]. New band selection strategies along with opposition-based learning are proposed in [30-33].

The major contributions of the paper are presented here for quick reference:

- An improved grey wolf optimization technique is introduced, incorporating a non-linear function that diminishes from 2 to 0 in a non-linear manner.
- The inherent information derived from the chosen spectral bands is obtained through spatial filtering and subsequently utilized in a non-linear support vector machine for the purpose of classification.
- The proposed framework was evaluated using benchmark datasets through both quantitative and qualitative methodologies, including performance metrics and classification maps.

3. PROPOSED METHODOLOGY

A thorough explanation of the methods used is given in this section. It uses a support vector machine classifier with a non-linear function and band selection based on the enhanced version of grey wolf optimization to extract spectral and spatial information. The general technique of the suggested approach is described in Figure 2.

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3.1 Grey Wolf Optimization

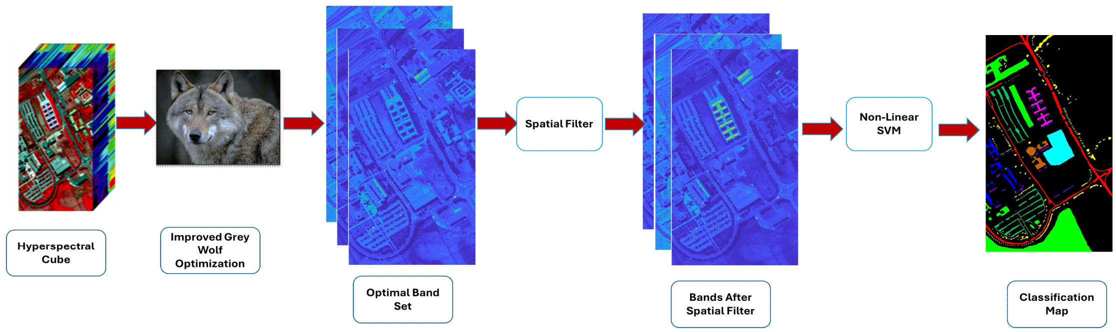

Figure 2: Framework of the Proposed Method

3.1.1. Hyperspectral image

A Hyperspectral image is cube which is in Three-dimensional dataset which stored spatial and spectral data over a wide range of wavelengths. Hyperspectral images contain hundreds of spectral bands which allow detailed analysis of material characteristics. The image cube consists of a spectral dimension (λ) with reflectance of radiance values at different wavelengths and two spatial dimensions (x, y). The spectral information gives precise identification and classification of objects based on their spectral signatures. Hyperspectral images are useful in fields like remote sensing, agriculture, mineral explorations, medical diagnostics and environmental monitoring.

3.1.2. Grey Wolf Optimization (GWO)

Grey wolf optimization algorithm is nature-based metaheuristic algorithm developed by Mirjalil et al.in 2014. In this there will be four wolves consists of alpha (α), beta (β), delta (δ), omega (ω) wolves. Alpha (α) is the leader, it represents the best solution and guides the search and hunting process for other wolves, and make decisions. Ensure exploitation of search space. Beta(β) is the second-best solution in the population, it helps alpha wolves in decision-making and hunting, maintains discipline and hierarchy, it leads delta and omega wolves, it helps balancing exploration and exploitation. Delta (δ) is the third best solution it acts as a bridge between the higher positions (α, β) and lower positions (ω) wolves. These are responsible for protecting and assisting the wolves. This guides omega wolves. Omega(ω) represents candidate solutions. It follows alpha, beta, omega wolves. It explores the solution space; it ensures diversification and global search. The hunting process in GWO has three major stages: encircling prey, hunting, and attacking or diverging to pursue optimal solutions. The algorithm mathematically represents the position updates of wolves by adaptive coefficient vectors, where an exploitation-exploration trade-off is achieved by slowly decreasing a controlling parameter (α). When |A|>1 wolves venture into new regions, whereas |A|<1 causes convergence close to the fittest solutions. The eventual position of a wolf is calculated by taking the average of its distances from the α, β, and δ wolves, such that a good balance is achieved between diversification and intensification. GWO is applied to feature selection.

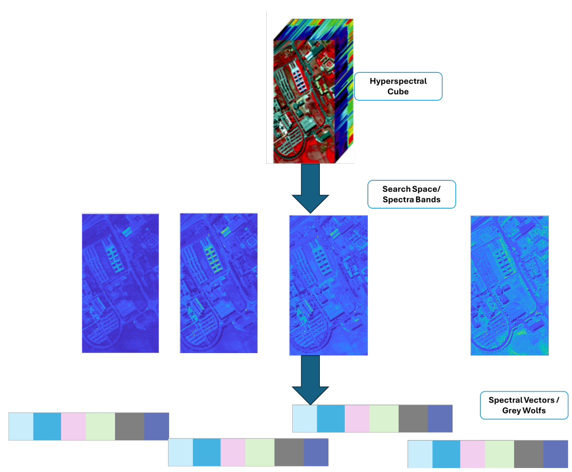

Figure 3: Creation Of Search Space of Spectral Vectors

The process of selecting the subset of the most useful spectral bands while removing unnecessary and redundant bands is called as band selection. The search space generation is given in Figure 3. Band selection involves few steps which are preprocessing of the hyperspectral image, Define the optimization problem, initialize the wolf population, define fitness function, applying GWO algorithm, stop the iterations when maximum number of iterations are reached, evaluate the selected bands.

3.1.3. Grey Wolf Optimization (GWO)

Algorithm

Input: Hyperspectral cube S
Output: Selected bands from S to identify classes
Step 1: Initialise search space and other parameters
Total search agents, Max_iterations, lower bound=0, upper bound=No.of bands in H
initialize alpha(α), beta(β), delta(δ) wolve
Population dimension = No. of search agents
Randomly initialise positions of search agents within search space
Step 2: Compute fitness function for each search agent
Initialise the constants and coefficients **a, A, C**
Step 3: Identify alpha(α), beta(β), delta(δ) wolves based on fitness function
Step 4: Update the position of each search agent using the following equations:

$$X1 = X\alpha - A1.|C1.X\alpha - X| \quad (1)$$

$$X2 = X\beta - A2.|C2.X\beta - X| \quad (2)$$

$$X3 = X\delta - A3.|C3.X\delta - X| \quad (3)$$

Compute new position as

$$X = (X1 + X2 + X3)/3 \quad (4)$$

Step 5: if (t< Max_iterations)
For each search agent:

- Revise a, A, C
- Determine fitness function
- Update X_α, X_β, X_δ if the new solution is better

End for
t=t+1 End if
Step 6: Return X, the collection of hyperspectral cube S most informative bands matched

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The nonlinearity is introduced in GWO in which the function also reduces from 2 to 0 over the iterations. The equation is given in equation (5). The same is shown in Figure 4.

$$a = 2 * (1 - (iter / Num\ Iterations)\ \hat{}2) \quad (5)$$

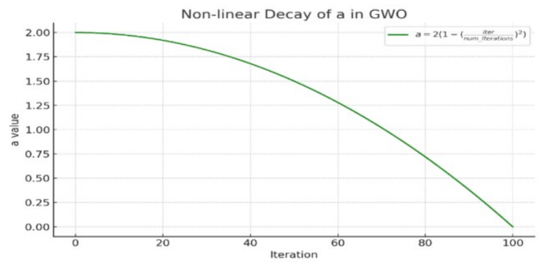

Figure 4: Non-linear decay used in GWO

The objective/fitness function formed is to select the informative bands by maximising the classifiers overall classification accuracy. During each optimisation the fitness function makes sure that the most informative bands are selected for best classification by assessing and updating accuracy at each optimisation
Maximize(x)=Maximise (OA), where OA is overall accuracy

3.2 Spatial Feature Extraction

A Spatial filter is a method to improve spatial features by analysing the neighbourhoods of pixels to decreases noise, edge preserving or extract structural data. While maintaining edge pixels, it determines the HSI image's Albedo structure, or average reflectance pixel. An HSI (Hyperspectral image) is composed of reflectance of light and illumination components, the reflectance known as albedo component. The mathematical representation of G.

$$Gi = Aj\ U\ Rj` \quad (6)$$

GWO adjusts albedo and shading coefficients dynamically to enhance feature separations. The optimization is guided by three leader wolves (Alpha (α), beta (β), delta(δ) which influences the search for best solution Using GWO, albedo represented as

$$A_i = \sum_{j \in N(i)} C_{ij} A_j \quad (7)$$

C_{ij} represents the adaptive coefficients optimized by gwo, N(i) is the adjacent of pixel I.

3.3 Support Vector Machine Classifier

The classifier used in proposed method is support vector machine. Classification is a machine learning technique which is used to categorize the data into predefined classes. SVM is widely used supervised learning algorithm it can handle high-dimensional data effectively. It finds and optimal decision boundary. SVM supports non-linear classification using tournament function which

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helps complex spectral patterns and maintain high classification accuracy. SVM is used as classifier for pixel wise because it is broadly applied to HSI classification provides sustainable perks with respect to accuracy, robustness and simplicity.

4. EXPERIMENTAL RESULTS AND ANALYSIS

In this section a detailed discussion about the benchmark datasets, spectral signatures of grey wolf optimization band set, and classification maps.

4.1 Dataset Summary

The figure 5 represents the dataset description, where Indian pines have 16 number of classes, bands of 220, wavelength of 0.4-2.5 µm, has AVIRIS sensor, and has spatial resolution of 145X145, whereas university of Pavia has 9 number of classes, 115 bands, 0.43-0.86 µm and uses ROSIS sensor and has spatial resolution of 610X340. The train and test samples are taken at the ratio of 30:70 percent.

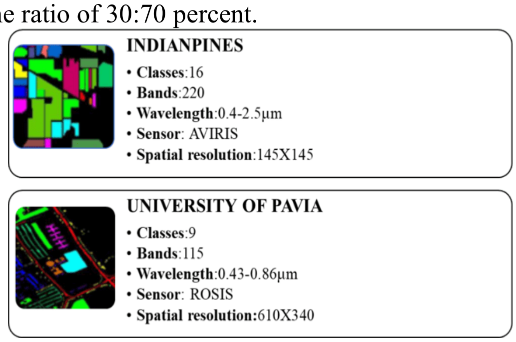

Figure 5: Data Set Description

4.2 Quantitative Analysis - Classification Accuracies

Table 1: Class wise accuracies of Indian pines

Class Name	Cuckoo search	IWO	CSO	GWO	Proposed
Class_1_Alfalfa	95.65	95.65	82.61	91.67	100
Class_2_Corn-notill	98.01	94.44	88.4	92.09	95.01
Class_3_Corn-mintill	94.75	92.83	93.57	95.81	96.6
Class_4_Corn	81.62	71.15	69.68	86.82	97.32
Class_5_Grass-pasture	96.29	95.82	97.29	96.25	99.4
Class_6_Grass-trees	99.13	99.3	99.65	98.62	99.65
Class_7_Grass-pasture-mowed	92.86	85.71	87.5	86.67	100
Class_8_Hay-windrowed	100	100	100	100	100
Class_9_Oats	90	90.91	100	90.91	100
Class_10_Soybean-notill	96.73	84.7	92.21	89.80	97.24
Class_11_Soybean-mintill	98.15	97.7	98.24	97.28	98.27
Class_12_Soybean-clean	95.33	92.03	92.98	94.54	97.95
Class_13_Wheat	100	96	96.08	95.96	97.06
Class_14_Woods	100	99.91	99.63	99.91	100
Class_15_Buildings-Grass-Trees-Drives	96.76	96.34	96.02	97.17	98.39
Class_16_Stone-Steel-Towers	88.24	97.83	97.87	97.44	95.65
OA	97.48	94.89	95.06	95.72	97.94
AA	95.22	93.14	93.23	94.43	98.28
Kappa	97.07	94.08	94.27	95.03	97.6

Overall accuracy (OA) means the percentage of all pixels that were correctly classified to all pixels in all classes. It informs you of how many total pixels were accurately classified out of all the pixels in the image. It is like receiving your overall score out of 100 in a test. Average Accuracy (AA) is the class average of each accuracy score. Then, the performance of the classifier on each class individually is assessed. Its average is then calculated. This is to ensure that all classes are given equal treatment, especially where some classes have fewer pixels than others. The effectiveness of the proposed method is discussed with other state of art methods by comparing. Table 1 depicts the comparison between different state of art methods for Indian pines dataset. The Indian pines dataset contains 16 classes, and proposed method has best accuracy compared to other methods like cuckoo search, improved whale optimization, crow search optimization, grey wolf optimization. From table 1 it shows that classification accuracies for classes Alfalfa, Grass_pasture_mowed, Hay windowed, oats, woods, has 100% whereas hay widowed, wheat, woods have 100% accuracy for cuckoo search method, but comparatively proposed method has more accuracy which is varying from average of 95%- 100%. And corn notill class has accuracy of 95.1 but in cuckoo search it has 98.01 though the accuracy is ,ore in other method but for the

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proposed method accuracy is better, corn class obtained an accuracy of 97.32 this was due to the albedo spatial filter, Soybean notill also obtained an accuracy of 97.24 which is more compared to other state of art methods, whereas Wheat class obtained an accuracy of 97.06 for proposed method but in cuckoo search its accuracy is 100% though its more but for proposed the accuracy is better this is obtained by using support vector machine, overall accuracy for proposed method is 97.94% which is more comparing to other state of art methods, average accuracy for proposed method is 98.28% and kappa coefficient is 97.6 which is more than other methods, and remaining classes also has accuracy approximately to 95%, this was obtained by using support vector machine and albedo spatial filter.

Table 2: Class Wise Accuracies of University of Pavia

Class Name	Cuckoo Search	IWO	CSO	GWO	Proposed
Class_1_Asphalt	99.28	98.92	99.41	99.04	99.78
Class_2_Meadows	99.82	99.82	99.87	99.75	99.95
Class_3_Gravel	97.08	95.57	98.76	96.48	98.5
Class_4_Trees	97.79	97.18	98.84	97.17	96.98
Class_5_Painted metal sheets	99.85	99.24	99.54	98.79	99.85
Class_6_Bare Soil	99.75	99.7	99.82	99.37	99.82
Class_7_Bitumen	94.78	96.53	95	98.18	99.69
Class_8_Self-Blocking Bricks	96.42	98.32	98.98	97.95	99.14
Class_9_Shadows	100	100	99.78	100	100
OA	99.15	99.17	99.52	99.14	99.61
AA	98.31	98.36	98.89	98.53	99.3
Kappa	98.78	98.81	99.31	98.77	99.4

The effectiveness of the proposed method is discussed with other state of art methods by comparing. Table 2 represents the comparison of state of art methods like cuckoo search, improved whale optimization, crow search optimization, grey wolf optimization. Table 2 shows comparison for university of Pavia data set. University of Pavia has 9 classes. In this dataset proposed method has high accuracy compared to other methods. From the table 2 it shows that classes that accuracy for classes Asphalt, meadows, painted metal sheets, bare soil, bitumen, self-blocking bricks has 99.95%, 99.85%, 99.82%, 99.69%, 99.14% respectively which is approximate to 100%, whereas class shadow has 100% accuracy and for class Gravel proposed method obtained an accuracy of 98.5% whereas crow search optimization tree has 96.98% obtained an accuracy of 98.76% but both are approximately same this is obtained due to the albedo spatial filter and class tree has got accuracy of 96.98% but for cuckoo search it got 97.79% but there is no big difference for both the methods this was achieved by support vector machine overall accuracy for proposed method has 99.61%, average accuracy is 99.3% and kappa coefficient is 99.4%, for the proposed method remaining classes also has accuracy on average of 96% , by this we can say proposed method is more effective and this accuracies for proposed method occurred by using support vector machine and albedo spatial resolution.

4.3 Qualitative Analysis - Classification Maps

Figure 6: Classification Maps for Indian Pines

Five different optimization-based feature selection methods—Cuckoo Search, Whale Optimization, Crow Search Optimization, Grey Wolf Optimization, and the Proposed Method are utilized to produce the classification maps of the Indian Pines hyperspectral dataset depicted in the above figure 6. In accordance with spectral signatures, each subfigure depicts how well the algorithms classify different crop and land cover classes**.** With few misclassified pixels and well-defined boundaries, the Proposed Method (e) generates the

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most correct and spatially consistent results of all of them. It effectively discards the noise and spectrum ambiguity introduced by other methods, especially in overlapping or blended areas. Grey Wolf and Whale Optimization provide slight lucidity, but the Cuckoo and Crow-based methods have scattered predictions. In complex hyperspectral environments, the Proposed Method is shown to have its enhanced ability to select discriminative bands and enhance class discrimination through presenting a purer map while preserving class integrity**.**

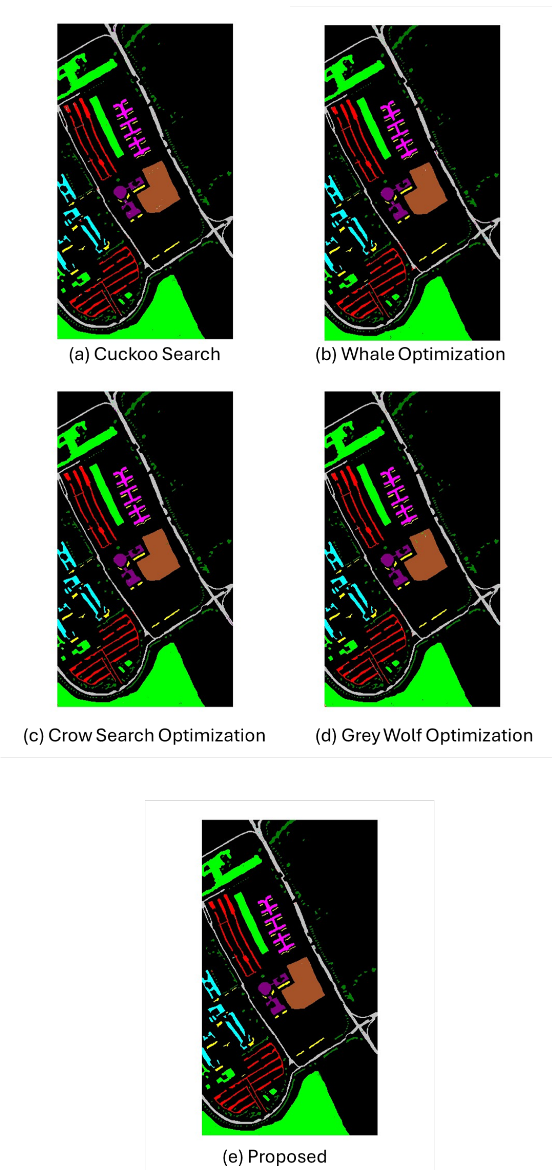

Figure 7: Classification Maps for University of Pavia

A Various optimization technique, such as Cuckoo Search, Whale Optimization, Crow Search Optimization, Grey Wolf Optimization, and the Proposed Method, are applied to display classification maps of the University of Pavia hyperspectral dataset in the above figure 7. Geographical categorization outcomes are shown in each subfigure, with colors representing different land cover classes. The Proposed Method has the best, most accurate segmentation visually, with minimal misclassifications and nicely preserved area boundaries. Especially on intricate areas like roads, structures, and vegetation, the suggested approach exhibits better spatial coherence, lower noise, and more distinct class boundaries compared to current methods. The Proposed Method offers better discrimination and homogeneous class labelling, while conventional methods are characterized by scattered misclassifications and overlaps between spectrally close classes. This shows clearly how effectively the proposed optimization technique performs to select spectral bands exactly and utilize spatial data to provide improved HSI classification results.

4.4 Performance Measure Analysis

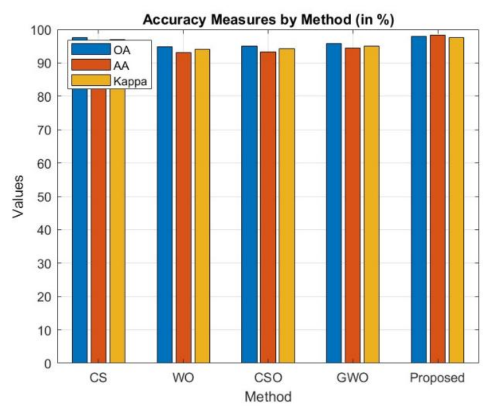

Figure 8: Performance Measures of Different Methods on Indian Pines

The above figure 8 represents the bar graph of different methods like cuckoo search, whale optimization, crow search optimization, grey wolf optimization and proposed method. In order to test the efficacy of proposed method three standard measures are to be computed which are overall accuracy (OA), average accuracy (AA), Kappa coefficient. From figure 8 the proposed method shows an overall accuracy (OA) of 97.94%, average accuracy (AA) of 98.28% and kappa has 97.6% which are high compared to other methods. This shows the effectiveness and robustness compared to other methods, this occurred because of using SVM, albedo spatial resolution.

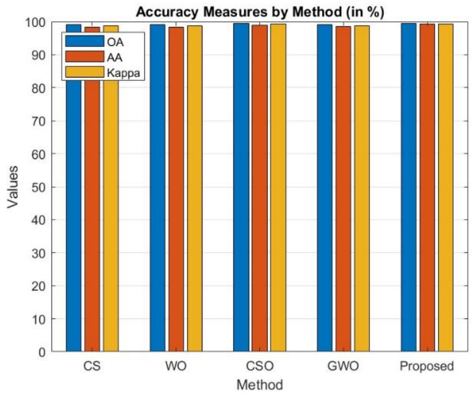

Figure 9: Performance Measures of Different Methods on University of Pavia

The above figure 9 shows the performance measures on university of Pavia. It can be seen that proposed method has OA of 99.61%, AA of 99.3%, kappa of 99.4 which is effective compared to other methods. This efficiency is due to SVM and albedo spatial resolution filter.

4.5 Sensitivity Analysis with Training Samples

The figure 10 represents the different training sample of Indian pines. It illustrates the relationship between percentage of training samples and overall accuracy achieved for proposed method. As shown in the figure 10 percentage of training samples increased from 10% to 40% there is an improvement in overall accuracy where the accuracy rises from 96.86% to 98.47%, whereas a slight decline is observed when training samples and overall accuracy achieved for proposed method.

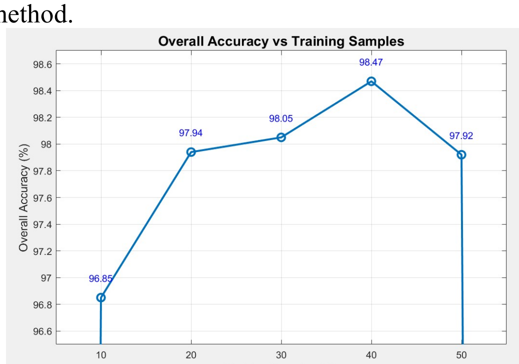

Figure 10: Sensitivity with Different Training Samples on Indian Pines Dataset

The graphical representation figure 10, entitled "Sensitivity Analysis with Varying Number of Bands on Indian Pines" delineates the relationship between the overall classification accuracy (OA) and the varying quantities of selected spectral bands. On the x-axis, the number of bands and on the y-axis, the OA are shown. The findings indicate a pronounced enhancement in OA as the quantity of bands progresses from 10 to 40, with the accuracy escalating from

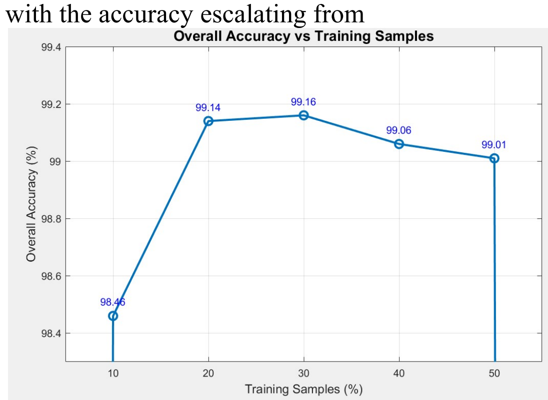

Figure 11: Sensitivity with Different Training Samples on University of Pavia Dataset

The figure 11 provides a depiction of the line graph variation of Overall accuracy to configuration of training data from university of Pavia. As shown in the figure 10% of training samples achieved accuracy of 98.46%, and for increase in training samples to 20% accuracy has 99.4%, for 30% it has 99.16%, whereas beyond 30% there is a decline at 40% has 99.06%, for 50 it has 99.01% but comparatively it has more efficiency even though it has declined for some samples as it ranges between 98%-99% which is best accuracy. It shows an optimal performance achieved by using SVM and albedo spatial resolution filter.

4.6 Sensitivity Analysis with Number of Bands

The graphical representation figure 12, entitled "Sensitivity Analysis with Varying Number of Bands on Indian Pines" delineates the relationship between the overall classification accuracy (OA) and the varying quantities of selected spectral bands. On the x-axis, the number of bands and on the y-axis, the OA are shown. The findings indicate a pronounced enhancement in OA as the quantity of bands progresses from 10 to 40, with the accuracy escalating from 98.47% to a zenith of 99.57%. Nevertheless, upon further increasing the number of bands to 50, the accuracy experiences a slight decline to 99.46%, implying that inclusion of additional bands beyond a specific threshold may engender redundancy or noise, resulting in minimal performance deterioration.

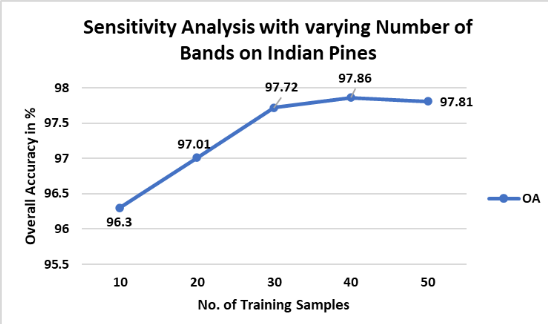

Figure 12: Performance Analysis vs Number of Bands on Indian Pines Dataset

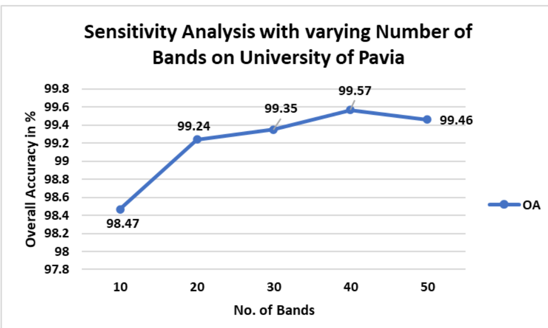

Figure 13: Performance Analysis vs Number of Bands on University of Pavia Dataset

Similarly, the graphical representation in figure 13 indicates a considerable enhancement in accuracy, escalating from 98.47% with 10 bands to 99.24% when utilizing 20 bands, followed by incremental improvements culminating in 99.57% at 40 bands, which signifies the zenith of performance on the University of Pavia dataset. Nonetheless, a minor reduction is noted at 50 bands, where the accuracy declines to 99.46%. This pattern implies that augmenting the number of bands initially enhances accuracy by facilitating the capture of more pertinent spectral information; however, exceeding a certain threshold may result in redundancy or the incorporation of extraneous features, thereby exerting a slight adverse impact on performance. Consequently, the analysis underscores the critical importance of optimal band selection for the efficient and precise classification of hyperspectral images within the University of Pavia dataset

5. CONCLUSION

In this article, a non-linear and improved band selection relying upon grey wolf optimization is proposed. The performance of the bands selected is tested with the non-linear kernel SVM on the benchmark data sets Indian pines and university of Pavia. It can be observed that the proposed sensitivity analysis the proposed method had high accuracies and efficient and more effective compared to others. In the proposed method support vector machine and albedo spatial filter plays a vital role by using these accuracies has been increased and it is more effective. The future work for this project is to implementing deep learning to enhance the classification accuracy and its performance.

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