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Optimized Hyperspectral Image Classification Using Tabu Search for Band Selection and Hyper3DNet Lite Classifier

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ABSTRACT
Hyperspectral imaging (HSI) is essential for capturing images across various spectral bands and providing in-depth spectral information. However, the high dimensionality of HSI data presents challenges, such as increased computational complexity and the curse of dimensionality. Band selection is a critical pre-processing step that addresses these challenges by identifying the most informative bands. This paper introduces a novel band selection method utilizing the Tabu Search algorithm (TSA), aimed at optimizing the selection of spectral bands to enhance classification performance. The proposed method assesses bands using a fitness function that maximizes variance and minimizes correlation among the chosen bands. Experimental results on Indian pine dataset and Pavia University Scenes, along with the K-Nearest Neighbor and Support Vector machine improves the classification accuracy while reducing computational demands.

Keyword--- Hyperspectral Imaging, Band Selection, Tabu Search, Feature Selection, Classification, Remote Sensing, Hyper 3D Net Lite

1. INTRODUCTION

Hyperspectral images (HSIs) play an important role in many applications such as remote sensing, urban planning[1], agriculture[2], medical imaging[3], food quality checking[4], environmental observation[5], Forensic Science[6] and natural resources[7] discovery. These applications demand the classification of HSI land cover and land use information. Hyperspectral sensors produce images with hundreds of bands, so that images are of high dimensionality[8]. Such high-dimensional images are difficult to visualize, store, and process; thus, they require dimensionality reduction techniques that can transform high-dimensional images into low-dimensional ones while retaining important information.

Band selection aims to improve computational efficiency, enhance classification performance, and minimize the impact of irrelevant or redundant information. In recent years, metaheuristic optimization techniques, such as Tabu Search[9], and Artificial Bee Colony (ABC)[10],Ant Bee Colony (ABC), Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), Cuckoo Search (CS) optimisation algorithm, Grey Wolf Optimisation (GWO), Differential Evolution (DE) and so on[11] have gained popularity for band selection due to their ability to explore large search spaces and avoid local optima.

In the analysis of hyperspectral imagery (HSI), dimensionality reduction (DR) techniques play a major role since several hundred bands are often available. The implementation of DR techniques allows for discarding redundant and noisy bands and producing a reduced representation of imagery. DR methods produce a set of derived features that are evaluated using different classification methods. For this reason, instead of selecting the lower number of bands to achieve a good trade-off between classification accuracy and computational costs, DR can be used to extract a higher-level feature representative of the input data, obtaining a better generalization of the classifier. Based on the selection strategy, DR techniques can be subdivided into two categories[11]: Individual band evaluation and band subset evaluation. Ranking methods and clustering methods are the examples of individual band evaluation. Exhaustive search, Greedy search and metaheuristic search are the examples of band subset evaluation.

Metaheuristic search algorithms, specifically population-based and neighborhood-based methods, are used to search for feature subsets. The neighborhood-based method focuses on identifying local optimal features using a single point at a time. Examples of neighborhood-based algorithms include Tabu Search (TS) and Simulated Annealing (SA).

Tabu Search (TS) is a metaheuristic optimization algorithm introduced by Glover in 1986[12]. Unlike traditional local search methods that can get trapped in local optima, TS employs a tabu list—a memory structure that records recent moves or solutions to prevent the algorithm from revisiting them. This mechanism allows TS to explore the search space more effectively and escape local optima.

A variety of machine learning classification algorithms have been proposed for HSIs, and the performance is further enhanced when the classifiers are combined into ensemble systems. Support Vector Machine (SVM)[13] is a powerful supervised learning algorithm used for classification and regression, which finds the optimal hyperplane that maximally separates classes in the feature space. It aims to maximize the margin between the closest data points (support vectors) and the hyperplane, ensuring robust classification. Random Forest (RF)[14] is an ensemble learning algorithm used for classification and regression that constructs multiple decision trees during training and combines their predictions to improve accuracy and reduce overfitting. For classification, it outputs the majority class (mode) from all the trees, and for regression, it outputs the average of the predictions. K-Nearest Neighbors (KNN)[15] is a simple, non-parametric algorithm used for classification and regression that classifies data points based on the majority class of their **k** nearest neighbors in the feature space. It computes distance (e.g., Euclidean) between data points and assigns the label based on the most common label among the closest neighbors.

Hyper3DNet Lite[16] is a lightweight deep learning architecture designed for hyperspectral image classification, focusing on efficiency and reduced computational cost. It combines 3D convolutions to capture spatial-spectral features and 2D convolutions for deeper feature extraction while maintaining a compact model size. The architecture is particularly suited for resource-constrained environments, achieving high classification accuracy with fewer parameters and less processing power.

2. BACKGROUND AND LITERATURE REVIEW

In order to process and analyse hyperspectral images, several advanced techniques are often required to overcome their associated challenges. One of the most important challenges when analysing hyperspectral images is their high dimensionality. This high dimensionality not only requires powerful and efficient techniques to process and analyse the data, but it also has a negative impact on the classification performance. Several techniques have been proposed to address this high-dimensional issue.

[17]This study introduces two hybrid metaheuristic search-based feature selection algorithms, namely ACTFRO (Ant Colony Optimization and Tabu Search with Fuzzy Rough set) and GATFRO (Genetic Algorithm and Tabu Search with Fuzzy Rough set), for cancer classification. These methods combine global and local optimal feature selection strategies, enhancing the selection of relevant features from microarray gene expression data. Using datasets like SRBCT, DLBCL, Breast cancer, and Leukemia, the proposed methods demonstrated superior performance in terms of classification accuracy, sensitivity, and computational efficiency, outperforming existing algorithms in the selection of optimal feature subsets

[9]This paper presents a novel dimensionality reduction algorithm combining tabu search optimization and the Compactness-Separation Coefficient (CSC). The algorithm effectively determines the optimal number of features. When integrated with classifiers like SVM and RVM, it demonstrates superior performance to Monte Carlo feature reduction method in terms of classification accuracy and computational efficiency. Using an SVM classifier, the method selected 95 bands with 30 training samples, achieving 96.98% accuracy. Increasing the training samples to 60 resulted in the selection of 97 bands and an improved accuracy of 98.29%. With an RVM classifier, the method selected 95 bands with 30 training samples, achieving 78.02% accuracy. Increasing the training samples to 60 resulted in the selection of 97 bands and an improved accuracy of 78.76%.

[18]This method combines a Genetic Algorithm (GA) with Tabu Search (TS) to enhance feature selection for object-based classification of high-resolution remote sensing images. This hybrid approach, known as GATS, aims to mitigate the premature convergence of GA by incorporating TS, which provides superior initial solutions and helps escape local optima. Experiments were conducted using WorldView-2 and QuickBird images, comparing the GATS method to standard GA, multistart TS, and the ReliefF method. The results demonstrated

that GATS improved classification accuracy, outperforming the other methods in terms of precision and efficiency [19]This method, Hyper3DNet, is a reduced-cost convolutional neural network designed for hyperspectral image (HSI) classification. It utilizes a combination of 3D convolutions for spectral feature extraction and 2D separable convolutions for spatial encoding, resulting in fewer parameters and lower computational costs than traditional models. The method was evaluated on various hyperspectral datasets, including Indian Pines, Pavia University, Salinas, EuroSAT, and Kochia leaves. In all cases, it achieved an accuracy rate exceeding 99%. Results indicated that Hyper3DNet achieved state-of-the-art classification performance with reduced complexity, making it a suitable choice for efficient HSI processing.

[16]This method consists of two main steps: first, a filter-based inter-band redundancy analysis (IBRA) is employed to evaluate the collinearity between spectral bands, effectively reducing redundancy and narrowing the search space. The second step involves a greedy spectral selection (GSS) that ranks the remaining bands based on their information entropy, followed by training a compact Convolutional Neural Network (CNN) to assess classification performance. The authors validate their approach using two datasets (Kochia and Indian Pines), demonstrating that their method yields better results than traditional feature selection techniques.

3. PROPOSED METHOD

The proposed methodology aims to address the joint classification and dimensionality reduction tasks on hyperspectral images by integrating Tabu Search optimization into the Hyper3DNet Lite classifier. The underlying algorithmic framework is built around the potential of exploiting the global search capabilities enabled by the implementation of a Tabu-based global optimizer, which is leveraged to guide the Hyper3DNet Lite classifier towards its optimal solution. Combining dimensionality reduction with classification can help to improve performance by reducing the impact of redundant information. The Tabu Search optimizer is iteratively applied to the subspace of the hyperspectral images to identify the most relevant spectral bands, effectively eliminating irrelevant features in the process.

A. Tabu Search Algorithm

Tabu search is a well-established method for solving optimization problems[18]. It iteratively improves the solution until an optimal one is found. It uses a list of forbidden moves to guide the search process effectively. By preventing revisiting and reusing unpromising solutions, it improves efficiency. Tabu search also selects successful moves as part of a group of high-performing solutions.

Tabu Search (TS) is a metaheuristic optimization algorithm for solving optimization problems. It iteratively improves the solution until an optimal one is found[12]. It uses a list of forbidden moves to guide the search process effectively. By preventing revisiting and reusing unpromising solutions, it improves efficiency. Tabu search also selects successful moves as part of a group of high-performing solutions.

Pseudocode

Step 1. Initialization: Randomly select an initial solution comprising a subset of bands.

Step 2. Neighbourhood Generation: Generate neighbouring solutions by swapping bands in the current solution with other bands not in the subset.

Step 3. Evaluation: Compute the fitness of each neighbouring solution using the fitness function.

Step 4. Selection: Choose the best non-tabu neighbour as the new current solution.

Step 5. Tabu List Update: Add the recent move to the tabu list to prevent cycling back to recent solutions.

Step 6. Termination: Repeat steps 2-5 until a maximum number of iterations is reached or convergence criteria are met.

Fitness Function

A crucial component of the Tabu Search algorithm is the fitness function, which evaluates the quality of a candidate solution (i.e., a set of selected bands). The fitness function provided aims to evaluate a subset of spectral bands in hyperspectral imaging by balancing two objectives

1. Maximizing the average normalized variance: Bands with higher variance contain more information and can better distinguish between different materials or classes.

2. Minimizing the average correlation: Reducing redundancy by selecting bands that are less correlated ensures that each band contributes unique information.

The fitness function can be mathematically expressed as:

$$Fitness(S) = \alpha.\bar{V}' - \beta.\bar{C}$$

where:
- S is the set of selected band indices.
- α and β are weighting coefficients (e.g., α = 0.8, β = 0.2).
- $\bar{V}'$ is the average normalized variance of the selected bands.
- $\bar{C}$ is the average correlation between pairs of selected bands.

I. Steps for computing Average Normalized Variance ($\bar{V}'$)

For each selected band s∊S:

1. Compute the variance V_s over all pixels:

$$V_s = \frac{1}{N}\sum_{i=1}^{N}(x_{i,s} - \mu_s)^2$$

- N is the total number of pixels (samples).
- $x_{i,s}$ is the spectral value of pixel i at band s.
- μ_s is the mean spectral value of band s:

$$\mu_s = \frac{1}{N}\sum_{i=1}^{N} x_{i,s}$$

2. Normalize the variances by the maximum variance among the selected bands:

$$V'_s = \frac{V_s}{\max_{s \epsilon S} V_s}$$

3. Compute the average normalized variance:

$$\bar{V}' = \frac{1}{|S|}\sum_{s \epsilon S} V'_s$$

-$|S|$ is the number of selected bands.

II. Steps for computing Average Correlation $\bar{C}$

For each unique pair of selected bands (s, t) where s, t ϵ S and s < t:

1. Compute the covariance between bands s and t:

$$Cov_{s,t} = \frac{1}{N}\sum_{i=1}^{N}(x_{i,s} - \mu_s)(x_{i,t} - \mu_t)$$

-μ_t is the mean spectral value of band t.

2. Compute the standard deviations of bands s and t:

$$\sigma_s = \sqrt{V_s}, \qquad \sigma_t = \sqrt{V_t}$$

3. Compute the correlation coefficient between bands s and t:

$$C_{s,t} = \frac{Cov_{s,t}}{\sigma_s \sigma_t}$$

4. Compute the average correlation across all unique band pairs:

$$\bar{C} = \frac{2}{n(n-1)}\sum_{\substack{s,t \epsilon S \\ s<t}} C_{s,t}$$

- n represents the number of bands and $\frac{n(n-1)}{2}$ is the number of unique pairs

The weighting parameters α and β control the relative importance of maximizing variance and minimizing correlation. This fitness function can be used within optimization algorithms (e.g., Tabu Search, Genetic Algorithms) to evaluate and select the optimal subset of bands that maximize information content and minimize redundancy.

B. Hyper 3DNet Lite Classifier

Hyper3DNetLite is a simplified, lightweight version of Hyper3DNet, designed for reduced computational cost and memory usage. It retains the dual structure of 3D feature extraction and 2D spatial encoding but with fewer layers and parameters. It's optimized for efficiency and suited for resource-limited devices, while the original Hyper3DNet offers higher performance at the expense of more resources. Hyper3DNet-Lite is designed for hyperspectral image classification using 3D convolutional kernels. To handle the large size of hyperspectral data, we used a chain of 2D convolutional neural networks, sharing parameters between layers. This design reduces the model's size, making it more efficient and avoiding the need for large input sizes during testing. As an exploratory study in hyperspectral classification, the Hyper3DNet Lite model performs relatively well compared to the U-Net model [9]. It is encouraged that the study of the Hyper3DNet Lite model be taken over by other researchers. For datasets with only a few spectral bands, the simpler design of Hyper3DNet-Lite works well. These simpler datasets don't need very complex models, so we can avoid using too many parameters, which helps prevent overfitting[20]

TABLE 1
HYPER3DNET-LITE ARCHITECTURE FOR THE IP DATA SET

Layer Name	Kernel Size	Stride Size	Output Size
Input	-	-	(1, 200, 5, 5)
Conv3D + ReLU	(3, 3, 3)	(1, 1, 1)	(16, 200, 5, 5)
Conv3D + ReLU	(3, 3, 3)	(1, 1, 1)	(16, 200, 5, 5)
Reshape	-	-	(3200, 5, 5)
SepConv2D + ReLU	(5, 5)	(1, 1)	(320, 5, 5)
SepConv2D + ReLU	(3, 3)	(1, 1)	(256, 5, 5)
SepConv2D + ReLU	(3, 3)	(1, 1)	(256, 5, 5)
Global Average Pooling	-	-	256
Dense	-	-	Classes (16 for IP Dataset)

The integration of the Tabu Search optimizer with the Hyper3DNet Lite classifier is expected to yield several benefits. First, the global search capabilities of Tabu Search can help guide the Hyper3DNet Lite classifier towards its optimal hyperparameter settings, potentially improving its classification accuracy. Second, the dimensionality reduction step facilitated by the Tabu Search optimizer can help reduce the impact of spectral redundancy and irrelevant features, leading to more efficient and robust classification performance.

4. DATASETS DESCRIPTION

The proposed method was evaluated on two widely used hyperspectral datasets, Indian Pines Contains 145×145 pixels and 220 spectral reflectance bands in the wavelength range 0.4–2.5 µm. After removing water absorption bands, 200 bands are used[21]. University of Pavia Consists of 610×340 pixels with 103 spectral bands covering the spectral range from 0.43 to 0.86 µm. The algorithm was configured to select 5 bands from each dataset[22]. The selected bands were used for classification using hyper3DNetLite Classifier.

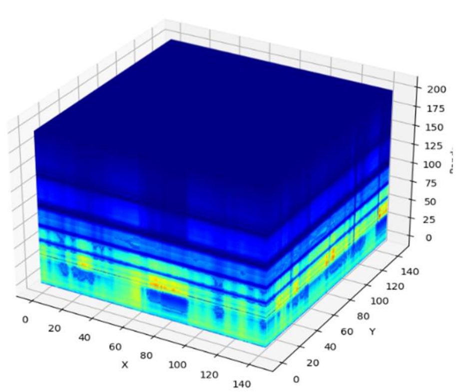

Figure 1: 3D Hyper spectral image of IP dataset

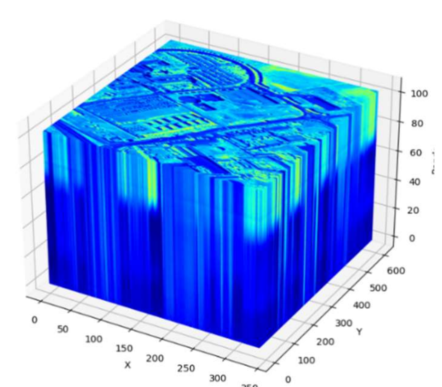

Figure 2: 3D Hyper spectral image of PU dataset

5. RESULTS AND DISCUSSION

In this work we analysis the performance of Tabu search algorithm for band selection and Hyper 3D Net Lite classifier for classification in two data sets IP and PU. We compare the performance of Hyper3D Net Lite classifiers with various classifiers namely SVM, RF and KNN. Tabu search algorithm identify the most relevant bands with the help of its fitness function. Here we use combination of variance and correlation to compute the fitness value. Variance is used to calculate the dependency of all pixels in the spectrum and the correlation is used to compute the relation among different spectrums. Variance measure helps to select bands with high information and correlation helps to avoid the redundancy among the spectral bands. The spectral behaviour of IP and PU are different thus we use two parameters α and β to control the fitness values of each group of bands.

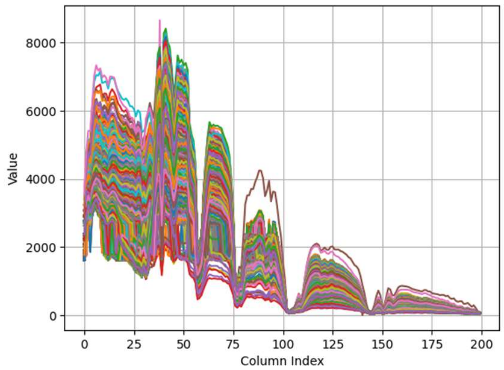

Figure 3: Pixel Representation Across All Bands of the Indian Pines (IP) Dataset

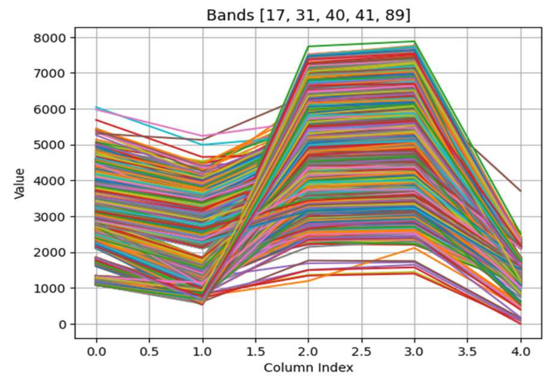

Figure 4: Pixel Representation Across Selected Bands of the Indian Pines (IP) Dataset

In the case of the IP dataset, the values of the fitness function parameters are set to $\alpha = 0.2$ and $\beta = 0.8$, indicating that more weight is given to the correlation components. As shown in Figure 3, the initial bands are more distributed, and the proposed method selects bands 17, 31, 40, 41, and 89.

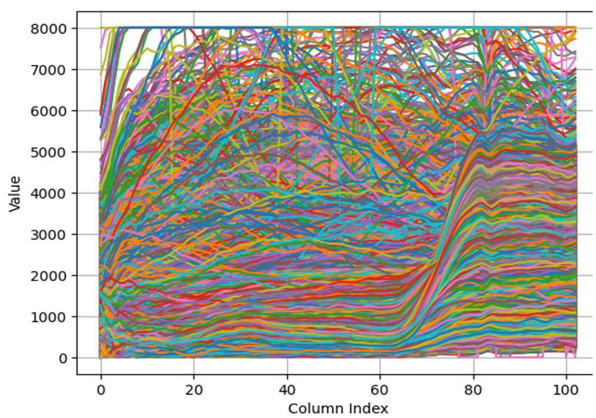

Figure 5: Pixel Representation Across All Bands of the Pavia University (PU) Dataset

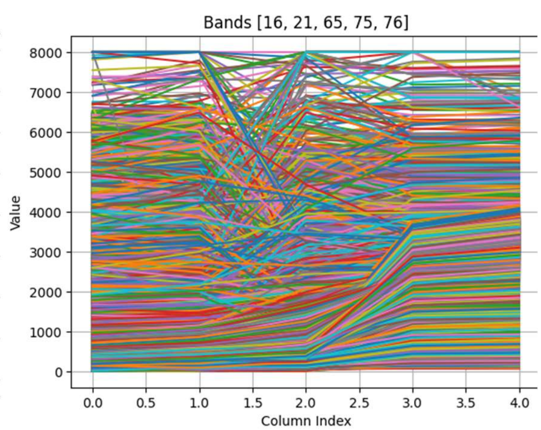

Figure 6: Pixel Representation Across All Bands of the Pavia University (PU) Dataset

Figure 2, illustrating the PU dataset, shows that all bands are equally distributed. Therefore, we set the fitness function parameters to $\alpha = 0.8$ and $\beta = 0.2$, giving more weight to the correlation components. The proposed method selects bands 16, 21, 65, 75, and 76.

TABLE 2
CLASSWISE CLASSIFICATION RESULT OF IP DATASET

Class	Class Name	Total Samples	SVM		RF		KNN		Hyper 3D Net Lite	
			Testing Samples	Success Test	Testing Samples	Success Test	Testing Samples	Success Test	Testing Samples	Success Test
1	Alfalfa	46	14	0	14	9	14	7	10	10
2	Corn-notill	1428	428	168	428	265	428	265	419	413
3	Corn-mintill	830	249	90	249	144	249	151	262	258
4	Corn	237	71	10	71	26	71	28	76	76
5	Grass-pasture	483	145	64	145	117	145	127	148	147
6	Grass-trees	730	219	210	219	208	219	211	222	222
7	Grass-pasture-mowed	28	8	0	8	5	8	6	8	8
8	Hay-windrowed	478	143	142	143	140	143	139	147	147
9	Oats	20	6	0	6	2	6	1	4	4
10	Soybean-notill	972	292	110	292	218	292	220	295	288
11	Soybean-mintill	2455	737	638	737	576	737	561	737	728
12	Soybean-clean	593	178	39	178	71	178	68	155	149
13	Wheat	205	61	58	61	55	61	59	59	59
14	Woods	1265	380	375	380	359	380	356	394	385
15	Buildings-Grass-Trees-Drives	386	116	18	116	56	116	40	111	110
16	Stone-Steel-Towers	93	28	23	28	24	28	23	28	28
	Total	10249	3075	1945	3075	2275	3075	2262	3075	3032

TABLE 3
CLASSWISE CLASSIFICATION RESULT OF PU DATASET

Class	Class Name	Total Samples	SVM		RF		KNN		Hyper 3D Net Lite	
			Testing Samples	Success Test	Testing Samples	Success Test	Testing Samples	Success Test	Testing Samples	Success Test
1	Asphalt	6631	1989	1802	1989	1785	1989	1753	1997	1989
2	Meadows	18649	5595	5547	5595	5318	5595	5283	5509	5493
3	Gravel	2099	630	173	630	348	630	364	631	624
4	Trees	3064	919	754	919	774	919	776	909	905
5	Painted metal sheets	1345	403	399	403	399	403	397	429	429
6	Bare Soil	5029	1509	399	1509	746	1509	724	1525	1469
7	Bitumen	1330	399	174	399	284	399	299	432	426
8	Self-Blocking Bricks	3682	1105	979	1105	899	1105	864	1115	1106

9	Shadows	947	284	284	284	283	284	284	286	286
	Total	42776	12833	10511	12833	10836	12833	10744	12833	12727

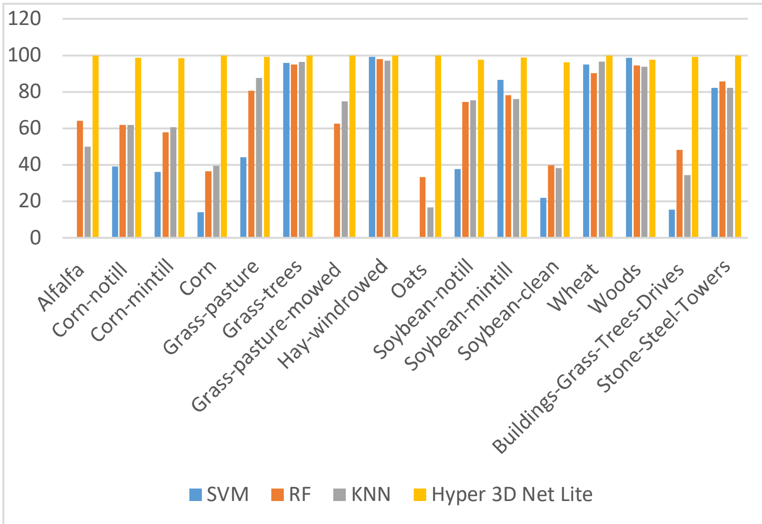

Figure 7: Class wise Classification Accuracy of IP Dataset

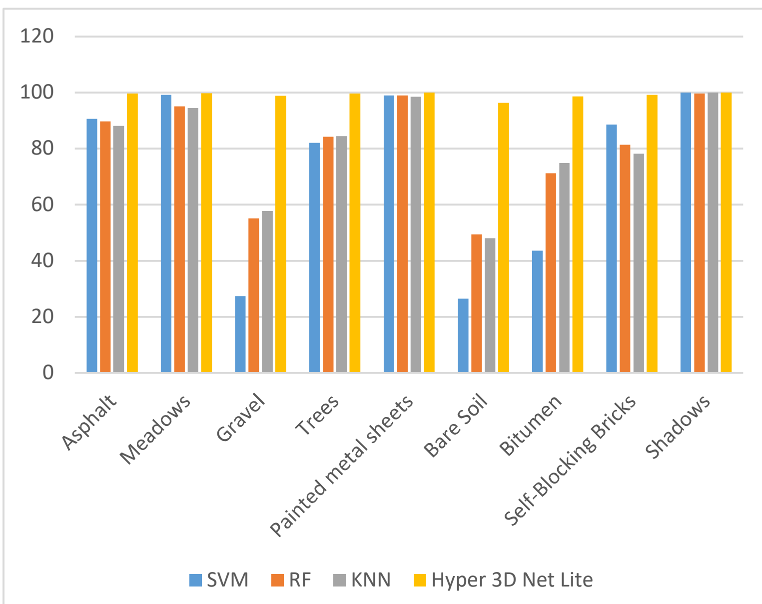

Figure 8: Class wise Classification Accuracy of PU Dataset

Table 2 and 3 shows the class wise classification accuracy of IP and PU data sets in various classifiers. The results show the proposed band selection method is good for Hyper 3d Net Classifier, it predicts most of the class very accurately in both data sets.

TABLE 4
CLASSIFICATION ACCURACIES OF SELECTED METHODS OF IP DATASET

	SVM	RF	KNN	Hyper3DNet Lite
Accuracy	63.25	73.98	73.56	98.6
Precision	64.13	73.48	73.17	98.8
Recall	63.25	73.98	73.56	99.1

F1 Score	59.72	73.37	72.81	98.94

TABLE 5
CLASSIFICATION ACCURACIES OF SELECTED METHODS OF PU DATASET

	SVM	RF	KNN	Hyper3DNet Lite
Accuracy	81.44	84.52	83.72	99.17
Precision	82.09	84.06	83.26	99.42
Recall	81.44	84.52	83.72	99.09
F1 Score	78.34	83.81	83.1	99.25

Tables 4 and 5 present the overall accuracy of the IP and PU datasets across various classifiers. The accuracy obtained by our proposed methodology supervised classification methodology exceeds the accuracy obtained by the baseline methods.

6. CONCLUSION AND FUTURE WORK

This study proposed a novel Tabu Search-based method for hyperspectral band selection and Hyper 3D Net Lite Classifier for classification. This method effectively balances variance maximization and correlation minimization, leading to improved classification accuracy and computational efficiency. Hyper3DNet-Lite is a computationally efficient classifier that maintains high accuracy despite its reduced complexity. The experimental results demonstrated that the proposed approach was very effective for image and spectral dimensionality reduction and that the classifier outperformed state-of-the-art spectral approaches in most cases. Two public datasets with different characteristics were used for evaluation, and all of the results were very promising. In the future, we intend to undertake a large-scale study with additional datasets to assess the effectiveness of our developed methodology. Finally, we will focus on extending this approach to other optimization criteria, such as incorporating spatial information in the selection process. This model is capable of providing consistent performances in shorter times could be used in real-world applications.

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