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# CNN Based Hyperspectral Image Classification Enhanced by Dimensionality Reduction Techniques

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***Abstract:*** **-** Hyperspectral imaging (HSI) is a powerful technique for capturing high-density 3D images across multiple spectral bands. HSI is used for various tasks across different domains and several algorithms with diverse approaches have been applied to process HSI data. However, these algorithms often face significant challenges due to high computational costs associated with complex dimensionality. In this study, we adopt two strategic approaches to implement a novel method for HSI classification. The dimensionality reduction using metaheuristic optimization is implemented based on the initial solution derived by Principal Component Analysis (PCA). The Metaheuristic search algorithm- Tabu Search enhanced by the Naïve Bayes (TSNB) fitness method is used for the dimensionality reduction process. This research aims to apply a Convolutional Neural Network (CNN) with dimensionality reduction techniques to simplify the classification process. We utilize our approach to demonstrate successful results in the HSI classification process. Our method shows promising results on the Indian Pine dataset compared to four other leading band selection techniques.

***Keywords:*** Hyperspectral Imaging, HSI Classification, Band Selection, Tabu Search, Principal Component Analysis, CNN Classifier, Hyper3DNet Lite

## 1. INTRODUCTION

Hyperspectral Imaging acquires both spectral and spatial information, which significantly enhances its utility in remote sensing applications. Hyperspectral Images (HSI) are multidimensional data cubes, encompassing highly dense spectral and special information about the scene captured. Each pixel in an image represents a vector that contains data from multiple contiguous spectral bands, resulting in higher dimensionality. Dimensionality reduction [3] is essential to overcome challenges such as the presence of noise, redundancy and heavy computational cost. The unique spectral signatures of these bands can be used to identify different objects based on their reflectance characteristics.

Metaheuristic search algorithms provide a novel method for dimensionality reduction facilitating optimized datasets with relevant features from hyperspectral data. The Metaheuristic algorithm, Tabu search [4] provides an effective method for feature extraction and classification process in hyperspectral datasets. Tabu search is a neighborhood-based algorithm that maintains a memory structure called Tabu list [5] to keep the most recent solutions. It avoids the problem of getting stuck in local optima by revisiting recent solutions. The fitness function [4] plays a significant role in guiding the search process to ensure the quality of the result by avoiding the local optima. Dimensionality Reduction of hyperspectral image gives way to the significant improvement in image classification and feature extraction process. A precise selection process results in a compact dataset with

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sufficient labels that are prominent in attaining efficient classification. Our method implements dimensionality reduction through Tabu Search enhanced by Naïve Bayes (TSNB) fitness evaluation.

The Convolutional Neural Networks (CNN) [13,14] have revolutionized the HSI classification process with high accuracy and automated extraction of discriminative features. Especially, the 3D CNN with the convolutional filters extended to three dimensions is applied to capture spatial relationships and patterns [16] in 3D data cubes. The spatial and spectral dimensions in hyperspectral imaging are best processed using 3D CNNs, as 2D CNNs struggle to handle spectral relationships effectively. The capabilities of 3D CNN models [16] provide a novel method for overcoming challenges and complexities in the HSI classification process.

## 2. SIGNIFICANCE OF THE STUDY

HSI contains a vast collection of intricate information across various spectral bands that highlight the distinct characteristics of observed objects. Accurate classification methods [14] offer an abundance of information with the potential for a wide range of applications. Effective classification methods facilitate the extraction of valuable information for versatile uses in areas such as agriculture and environmental surveillance [13,14].

High-resolution imagery identifies factors such as water quality, pollution sources, and the health of ecosystems, [14] which helps in operations such as pinpointing areas of concern, monitoring changes, and assessing environmental management techniques. This information is crucial for preserving ecosystem health, protecting biodiversity, and minimizing environmental risks. In agriculture, high-resolution data supports crop monitoring, disease detection and yield estimation. High-resolution spatial data enhances precision agriculture by providing insights into soil composition, nutrient levels and plant health, thus optimizing resource utilization for improved productivity.

Various machine learning methods have been utilized for the HSI classification process, including Decision Trees, Logistic Regression, K-Nearest Neighbors (K-NN), and Support Vector Machines (SVM) [14]. These ML classifiers struggle to handle the spatial data and give only successful results for spectral information. Deep learning methods efficiently handle HSI data, integrating spectral and spatial information. Convolutional Neural Network (CNN) classifiers represent a cutting-edge approach in the classification of hyperspectral images (HSI), demonstrating superior performance and accuracy in this specialized domain. This study focuses on CNN-based classification for HSI utilizing benchmark datasets for evaluating the performance.

## 3. REVIEW OF LITERATURE

Hyperspectral images contain numerous spectral bands that provide essential and valuable information. However, higher dimensionality of HSI raises computational complexity resulting in degraded performance of the entire system [1]. Hence, dimensionality reduction is necessary for efficient processing of HSI. The FNGBS [17] divides the HSI cube into multiple groups by adopting a coarse-fine method that clusters the bands with high similarity as a single group. The algorithm focuses on HSI band selection by utilizing a quick neighborhood grouping method. It combines local density and information entropy as criteria for selecting the band subset. The determinantal point process automates the evaluation of the minimum number of bands needed to adequately represent the entire spectrum. Band selection is a typical method for dimensionality reduction and the studies [18] focus on band selection based on the Similarity-Based Ranking Method. The SR-SSIM employs a structural similarity indexing method to assess the similarity between band pairs. Pre-processing with the band selection method shows promising results for experiments on the CNN classifier. Band selection without affecting the original content [19] can be achieved by the Optimal Clustering Framework (OCF) method. The algorithm implements a framework for achieving optimal results for specific objective functions with reasonable constraints. Band selection is made from the existing clustered structures based on rank assigned using the clustering method. The minimum number of bands required to represent the distinctive features is estimated based on the correlation reduced band-power ratio. The HAGRID [20] aims at dimensionality reduction by implementing histogram-assisted feature selection. The histogram indicates the wavelengths associated with the peak distribution point that are identified using a univariate Gaussian mixture model. This approach yields a subset of informative bands that are more effective than methods like partial least squares discriminant analysis. The correlated multispectral data can be transformed into an uncorrelated format through the effective feature selection of principal components [1], enhancing the quality and usability of the data. The studies [2] focus on the application of Principal

Component Analysis for band selection to reduce the computational cost of sensor data from UAV (Unmanned Aerial Vehicles). Dimensionality reduction can be achieved through principal component feature extraction from HSI. PCA generates a reduced set of uncorrelated data that represent a linear combination of the actual values. The study [3] points out that PCA-based dimensionality reduction is a highly effective method to eliminate redundant data from hyperspectral images. Tabu Search [6] offers an enhanced approach to address the demands of big data processing, yielding superior results in generating clusters that demonstrate impressive quality and computational efficiency. Tabu search provides results [4] with more global possibility eliminating the chance of failing in local optima. The main advantage of Tabu search [5] lies in creating small local neighborhoods that minimize the chance of revisiting recent solutions. HSI classification [13] is a well-established method in remote sensing, and deep learning models are capable of managing the complexity and nonlinearity inherent in HSI data. The CNN model is a reliable option in the complex classification process. CNN architecture [14] provides optimal results in managing the complexities of HSI classification by extracting both spectral and spatial information.

## 4. PROPOSED SYSTEM

The proposed method implements the HSI classification based on dimensionality reduction techniques for efficient and faster results. Principal Component Analysis (PCA) is a valuable technique employed for the initial selection of bands, helping to enhance the efficiency and effectiveness of subsequent analyses. The selected bands are given as seeds to the Tabu search optimization, generating informative bands for the classification process. The Naïve Bayes method serves as the fitness function for evaluating the quality of Tabu candidate selection. The CNN-based classification method gives significant spectral band information as the final result.

### 4.1 Construction of Initial Solution

The metaheuristic optimization algorithms start from an initial solution that acts as the first candidate solution for succeeding explorations. The feature selection using Principal Component Analysis is implemented to create the initial solution. The PCA method works on the concept [2] that the neighboring bands of HSI images are highly correlated carrying redundant information about the object. The statistical properties of HSI bands [1] are taken into account to transform the original bands into a set of uncorrelated bands.

The one-dimensional vector $X = [x_1, x_2, \cdots x_n]$ represents the HSI data [1], where $x_i$ is the band vector of the $i^{th}$ band .

The mean vector in X-space is calculated as

$$\mu = \frac{1}{n}\sum_{i=1}^{n} X_i$$

The covariance matrix C**x** is computed as:

$$\mathbf{C(x) = E\{(x- \mu)(x- \mu)^T\}}$$

The expectation operator is applied, and the transposition is performed on the expected values. The covariance matrix **C** is decomposed into eigenvectors and eigenvalues.

C = V * Λ * V^T

The eigenvector matrix is represented by V and Λ is the diagonal matrix of eigenvalues [2].

The eigenvectors corresponding to the largest eigenvalues are selected to get the principal components with the most variance. Sort the eigenvalues in descending order and the top eigenvectors are selected that correspond to the largest eigenvalues. Eigenvectors represent the principal components [2] that capture the greatest amount of variance in the data. Now the data X is projected onto the space defined by the principal components.

Principal Components (PC) are obtained as,

$X_{\mathbf{selected}} = X_{\mathbf{centered}} * V$

$X_{\mathbf{selected}}$ is the sub of bands that serves as the initial solution for the dimensionality reduction.

The following algorithm performs principal component analysis on the feature set.

***Step 1:*** Find the bands with the highest principal component.

***Step 2:*** Sort the indices by the absolute value of the component.

**Step 3:** Get the nearest bands from the dataset.

### 4. 2. Dimensionality Reduction

Dimensionality reduction is essential for improving the efficiency of hyperspectral image classification by reducing noise in the hyperspectral image data. Traditional algorithms are not effective in HSI due to problems such as local optima. The metaheuristic optimization method, Tabu Search can be effectively applied for HSI zand selection.

#### 4.2.1 Initial Solution

Construction of the initial solution [4] is the first phase in the Tabu search algorithm which affects the outcome of the entire process. This study applies bands selected using PCA as the starting solution for the Tabu search operation. Search as the whole operation starts with an assumption that the initial solution is the current solution that represents the best outcome of the process.

#### 4.2.2 Neighborhood Formation

Neighborhood defines a candidate list of solutions [5,7] that are neighbors to the current solutions. Neighborhood construction is a significant process because an inappropriate neighborhood may mislead the search operation to unpromising spectral space. The pairwise interchange method is adopted for neighborhood generation in which each neighbor is generated by changing the members in the current solution list.

#### 4.2.3 Evaluate Solutions

Rate the neighbors through evaluation [4] in order to reach the next solution. The Gaussian Naïve Bayes classification [8,10] method is applied to identify the likelihood of neighboring solutions. The likelihood P(S|H) is computed using the probability density function [9] given below.

$$\mathrm{P}(S_i|H) = \frac{1}{\sqrt{(2\pi\sigma^2}} * \exp\left(-(S_i - \mu)^2 \,/\, (2\sigma^2)\right)$$

where $S_i$ is the spectral value of the $i^{th}$ band, μ represents the mean value for the $i^{th}$ band and σ is the variance of the $i^{th}$ band for class H. The class with the maximum probability represents the most relevant spectral bands contributing significantly to the classification process. From this, the beast non-Tabu member is selected as the current solution.

#### 4.2.4 Update the Tabu List

The Tabu list decisively identifies the solutions [5] that must not be revisited in future iterations, effectively eliminating local optima. The Tabu list update is intended to avoid the chance of sticking to the recent moves.

#### 4.2.5 Termination

The neighborhood generation process is repeated for several iterations, evaluating the quality of selected bands [6] and updating the best solution derived. Moreover, the convergence criteria are assigned to check whether the consecutive iterations are not significantly contributing to the updating best solution.

### 4.3 Spectral Classification

Convolutional Neural Networks (CNNs) demonstrate outstanding performance in the classification of 3D images. The architecture provides effective results for hyperspectral imaging, enabling simultaneous classification of both spectral and spatial information. The spectral bands selected by the Tabu search operation are given for further classification through the CNN model. This allows the CNN to operate on HSI with reduced dimensionality that avoids the chance of overfitting. The Hyper3DNet Lite [11,12] is a CNN architecture that provides an effective classification of HSI at lesser computational expense. The 3D convolutional filters are applied for the classification of both spectral and special information. A chained set of layers identifies different classes in the HSI data. It reduces input size, significantly simplifying the testing process.

## 5. EXPERIMENTAL RESULTS

In this section, we rigorously compare our method's (TSNB) performance against leading state-of-the-art algorithms, demonstrating its superior effectiveness and efficiency. The Indian Pine (IP) scene is taken as the test dataset. It consists of 220 bands with 0.4–2.5 $\mu$m as range of wavelength and each band is of size 145x145 pixels. Five principal components are selected as the initial solution for the dimensionality reduction. From this initial solution, the Tabu search algorithm selects the significant bands for further classification through the Hyper3DNet Lite classifier. Table 1 displays the classification results for each class.

**Table-1**
**Classwise classification result of IP Dataset**

| Class | Class Name | Number of Samples | Testing Samples | Success Test | Accuracy |
|---|---|---|---|---|---|
| 1 | Alfalfa | 46 | 16 | 15 | 0.94 |
| 2 | Corn-notill | 1428 | 709 | 675 | 0.95 |
| 3 | Corn-mintill | 830 | 436 | 422 | 0.96 |
| 4 | Corn | 237 | 123 | 120 | 0.97 |
| 5 | Grass-pasture | 483 | 231 | 228 | 0.98 |
| 6 | Grass-trees | 730 | 372 | 370 | 0.99 |
| 7 | Grass-pasture-mowed | 28 | 14 | 14 | 1 |
| 8 | Hay-windrowed | 478 | 240 | 240 | 1 |
| 9 | Oats | 20 | 12 | 8 | 0.66 |
| 10 | Soybean-notill | 972 | 502 | 482 | 0.96 |
| 11 | Soybean-mintill | 2455 | 1213 | 1185 | 0.97 |
| 12 | Soybean-clean | 593 | 283 | 274 | 0.96 |
| 13 | Wheat | 205 | 98 | 98 | 1 |
| 14 | Woods | 1265 | 640 | 631 | 0.98 |
| 15 | Buildings-Grass-Trees-Drives | 386 | 191 | 178 | 0.93 |
| 16 | Stone-Steel-Towers | 93 | 45 | 45 | 1 |
| | Total | 10249 | 5125 | 4985 | 0.97 |

The TSNB method selected [0, 35, 39, 75, 98] bands from the IP dataset. The figure-1 shows the Classwise Representation of selected bands.

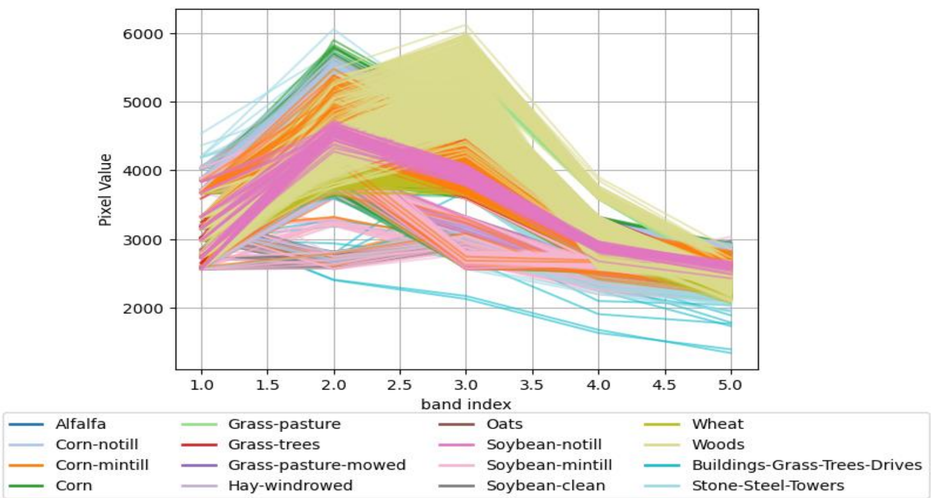


**Figure-1** Classwise Representation of selected bands

We have compared the performance of our algorithm with the FNGBS (Fast Neighborhood Grouping Method for Hyper Spectral Band Selection), SSIM (Structural Similarity Index Method), OCF (Optimal Clustering Framework), and HAGRID (Histogram Assisted Genetic Algorithm for Reduction in Dimensionality). Table-2 shows the classwise accuracy comparison, and it is clear that our method gives outstanding results in this process.

**Table -2**
**Classwise accuracy of different band selection methods(IP)**

| Class | FNGBS | SSIM | OCF | HAGRID | TSNB |
|---|---|---|---|---|---|
| Alfalfa | 0.93 | 0.93 | 1 | 0.81 | 0.94 |
| Corn-notill | 0.94 | 0.95 | 0.94 | 0.94 | 0.95 |
| Corn-mintill | 0.94 | 0.96 | 0.96 | 0.96 | 0.97 |
| Corn | 1 | 0.98 | 0.97 | 0.99 | 0.97 |
| Grass-pasture | 0.99 | 0.98 | 1 | 0.98 | 0.98 |
| Grass-trees | 0.98 | 1 | 0.98 | 0.98 | 0.99 |
| Grass-pasture-mowed | 1 | 0.92 | 1 | 0.92 | 1 |
| Hay-windrowed | 1 | 1 | 1 | 1 | 1 |
| Oats | 1 | 0.75 | 0.67 | 1 | 0.66 |
| Soybean-notill | 0.97 | 0.96 | 0.967 | 0.97 | 0.96 |
| Soybean-mintill | 0.97 | 0.97 | 0.98 | 0.97 | 0.97 |
| Soybean-clean | 0.98 | 0.94 | 0.94 | 0.94 | 0.96 |
| Wheat | 0.98 | 1 | 0.98 | 1 | 1 |
| Woods | 0.97 | 0.96 | 0.97 | 0.97 | 0.98 |
| Buildings-Grass-Trees-Drives | 0.93 | 0.91 | 0.94 | 0.92 | 0.93 |
| Stone-Steel-Towers | 0.97 | 1 | 1 | 1 | 1 |

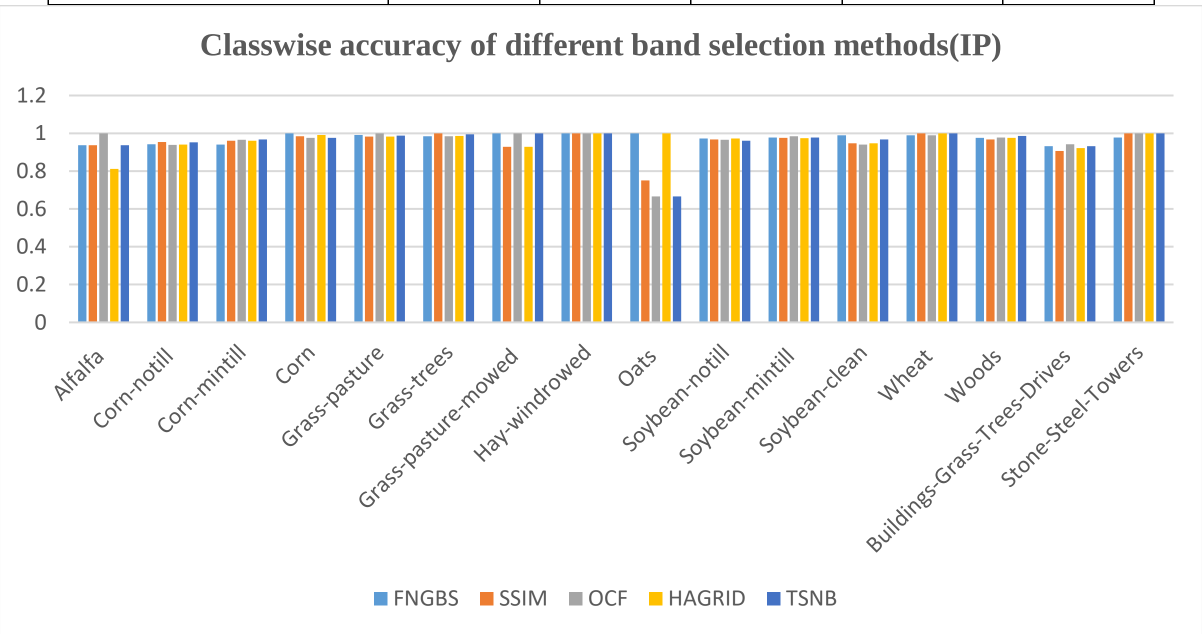


**Figure-2 Classification accuracies of selected Methods in IP Dataset**

Figure-2 illustrates the classification accuracy of all four methods on the IP dataset and it indicates that our method gives good results for the HSI classification process.

## 6. CONCLUSION

Hyperspectral image analysis is a broad area that finds application in different sectors. Balancing computational expense and accuracy is the major challenge in the HSI analysis. We have considered the application of dimensionality reduction techniques for designing a novel method for HSI classification. The PCA method is applied to derive an initial solution for band selection which acts as the seed for the Tabu search algorithm. Band selection is achieved by the Tabu search method based on Gaussian Naïve Bayes fitness evaluation. On the selected bands, the CNN classifier Hyper3DNet Lite performs the classification giving promising results at reduced computational complexity. This system provides outstanding results on test datasets and through further testing process, it can be customized for real-world applications.

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