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# Band Selection Methods for Hyperspectral Imagery Analysis – A Critical Comparison

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**Abstract:** Dimensionality Reduction (DR) encompasses a multifaceted array of techniques essential for addressing the challenges inherent in high-dimensional data, particularly evident in the analysis of Hyperspectral Images (HSI). The "Curse of Dimensionality" presents a formidable obstacle, rendering the utilization of all spectral bands computationally daunting. DR in HSI endeavors to preserve pertinent information while alleviating computational burdens, often through Band Selection methods. This analysis consolidates the contributions of researchers in the past 10 years, categorizing methodologies into nine distinct categories. Notably, clustering-based and optimization-based techniques emerge as frontrunners, consistently yielding superior accuracy. Experimentation across 19 real-time HSI datasets, including several highly-cited examples, underscores the efficacy of clustering-based methodologies in achieving optimal accuracy. In conclusion, while all DR methods merit appreciation, clustering-based approaches stand out for their demonstrated effectiveness in preserving data fidelity while reducing dimensionality.

***Keywords:*** *Dimensionality Reduction, Curse of Dimensionality, Band Selection, Band Subset*

## 1. Introduction

**H**YPERSPECTRAL imagery, a technology akin to giving our eyes superpowers, goes beyond the limitations of visible light to reveal the intricate spectral tapestry of our world. Imagine having a camera that perceives not just colors, but a vast spectrum of information hidden within them, like chlorophyll content in plants, mineral composition of rocks, or even the presence of pollutants in water. Hyperspectral remote sensing dives deep into the world of light, not simply the vibrant hues we perceive, but the entire spectrum of electromagnetic radiation. Hyperspectral sensors hone in on specific portions of this spectrum, capturing hundreds, even thousands of narrow spectral bands. Unlike a regular camera's three broad RGB bands, hyperspectral data unlocks a detailed fingerprint of light for each pixel in the image. 1

Unlike regular RGB images, which capture only three broad colour bands, hyperspectral sensors capture hundreds of narrow spectral bands, providing a wealth of information about the chemical and physical properties of objects in the scene. This makes it a valuable tool for various applications:

**Environmental Monitoring:**

*Tracking deforestation and forest health*: Hyperspectral data can reveal subtle changes in vegetation, allowing for early detection of deforestation and monitoring of forest health.

*Mapping water quality*: By analysing the spectral signatures of pollutants, hyperspectral imagery can identify and map water pollution, ensuring clean water resources.

*Monitoring air quality*: Tracking the presence and concentration of airborne pollutants like ozone and nitrogen dioxide can be achieved through hyperspectral imaging, improving air quality management.

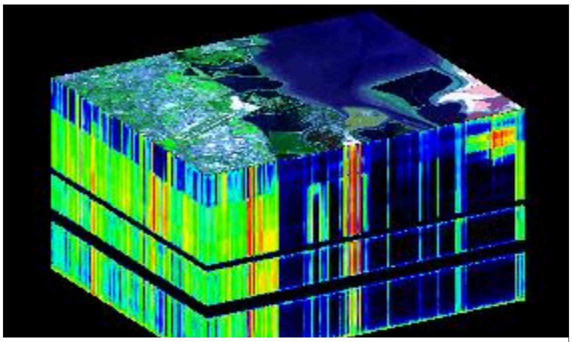

**Fig 1 AVIRIS hyperspectral data cube over Moffett Field, CA**

**Agriculture:**

*Precision agriculture*: Hyperspectral data can be used to assess crop health, identify nutrient deficiencies, and optimize fertilizer and water usage, leading to increased agricultural efficiency and sustainability.

*Disease and pest detection*: Early detection of crop diseases and pest infestations can be achieved by analysing changes in the spectral reflectance of plants, minimizing crop losses, and ensuring food security.

*Yield prediction:* Accurately predicting crop yields can be

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facilitated by hyperspectral data, allowing farmers to optimize their resources and make informed decisions.

**Mineral exploration:**

*Mineral Identification:* Hyperspectral data reveals the unique spectral signatures of various minerals, allowing geologists to pinpoint mineral deposits like iron ore, copper, gold, and even rare earth elements.

*Mapping and Delineation:* The detailed spectral the information helps in accurately mapping the extent and depth of mineral deposits, leading to more efficient resource extraction and minimizing environmental impact.

*Lithological Mapping:* Understanding the composition of rocks becomes a breeze with hyperspectral imagery, enabling the identification of rock types often associated with certain mineral deposits, and narrowing down exploration areas.

Beyond these sectors, hyperspectral image analysis finds applications in diverse fields like Target detection, health care, cultural heritage, forensic studies, etc.

Apart from having rich spatial and spectral information, the following major challenges are observed in hyperspectral data analysis:

- *High data volume:* The immense amount of data generated requires advanced processing and storage capabilities.
- *High dimensionality:* Hyperspectral data cube provides abundant spectral information in more bands or features or dimensions which can pose significant obstacles in analysis and interpretation.
- *Cost:* Hyperspectral sensors and software can be expensive, limiting their accessibility.
- *Data interpretation:* Extracting meaningful information from complex data requires expertise in spectral analysis.

Clustering is a process of identifying natural groups in the data based on some similarity measure such that the intracluster similarity is more and inter-cluster similarity is less. Clustering is a key technique in data analysis and plays a crucial role in remote sensing research. Clustering algorithms group pixels in satellite or aerial images based on their spectral reflectance, texture, and other features. This helps in identifying and mapping different land cover types, such as forests, water bodies, urban areas, and agricultural land. It helps in uncovering hidden patterns and structures within vast amounts of Earth observation data, providing valuable insights into various environmental and geographical phenomena. Major applications of Clustering in remote sensing include Land Cover Classification, Change Detection, Object Detection and Segmentation, Anomaly Detection, etc. Clustering is also popularly used for dimensionality reduction in hyperspectral images. This article focuses on dimensionality issues in hyperspectral data analysis and how this problem is addressed using clustering techniques.

## 2. DIMENSIONALITY REDUCTION PROBLEM

Hyperspectral data provides rich spectral information and hence it has been considered a powerful tool for vegetation classification, mineral classification, target detection and many other applications. As per the Hughes phenomenon, the classification accuracy decreases if the number of dimensions grows beyond a threshold. Dimensionality reduction in hyperspectral imagery can be achieved either by band selection or band extraction.

### 2.1. Band Extraction

Band extraction in hyperspectral data focuses on extracting spectral data that is most relevant or informative for a particular analysis. The goal is to reduce the dimensionality of the data while retaining the essential spectral information. There are several methods for band extraction in hyperspectral data: Principal Component Analysis (PCA), Independent Component Analysis (ICA), Kernel PCA (KPCA), etc.

### 2.2. BAND SELECTION

Band selection in hyperspectral data involves choosing a subset of bands that are most relevant for a particular task, such as classification or analysis. These band selection approaches are preferable when the application needs the original spectral information to be preserved.

Various Band Selection methods can be categorized into eleven groups: Clustering, Classification, Statistical Measures, Decomposition, Optimization (including Particle Swarm Optimization and Genetic Algorithms), Framework based Approaches, Ranking, Deep Learning, and Other Measures. These categories encompass diverse techniques, providing a systematic overview of approaches utilized for enhanced multispectral/hyperspectral data analysis.

All these categories and the author's contributions are described in the next sections.

### 2.3. Clustering-Based Approaches for Band Selection

There are a lot of contributions to this type of approach by the authors (Datta et al.,2015) proposed a method that is a three-step procedure in which the first step attributes of each band are determined, in the second step clustering is applied upon the bands with clustering. As a result of clustering redundant bands form a cluster and an exemplar band from each cluster is chosen for the band subset, the subset is applied with third step ranking method which removes the uncorrelated bands from the subset where the cardinality of the bands from subset are compared with original HSI bands. These ranking of bands are done according to the equation Cardinality of the $P^{th}$ band concerning to complete

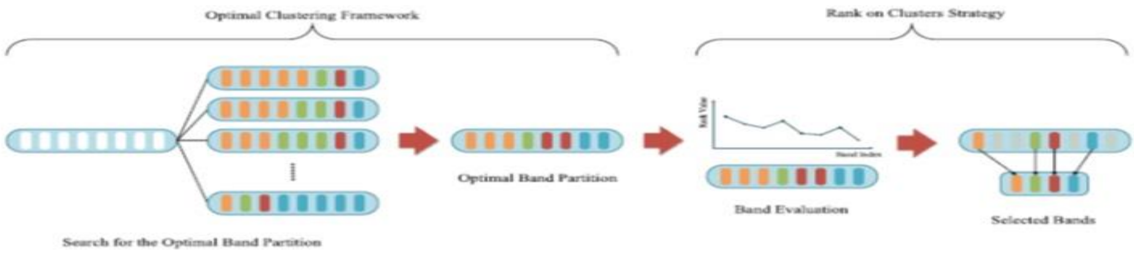


**Fig 2** Optimal Clustering Framework (Qi wang et al.,2018)

HSI Image is represented in equation1 which is Kullback-Leibler Divergence in which $g_{ki}$ is the point probability of total HSI image CD is the cardinality of a band, and thereafter the first top listed 'k' bands are selected as band subset.

$$CD(P_k, G_k) = KLD(P_k||G_k) + KLD(G_k||P_k)$$
$$= \sum_i P_{ki} * \log(P_k i/G_{ki}) + \sum_i G_{ki} * \log(G_{ki}/P_{ki}) \quad (1)$$

In another contribution by (Qi Wang et al., 2018) proposed a framework for band selection "Optimal Clustering Framework (OCF)" which is depicted in Figure 2. As per Qi the methodology multiple band subsets are formed an optimal subset partition is examined and later the best subset partition from where the better representative bands are chosen for the band subset. To implement this method *Dynamic Programming* proposed by *R.Bellman et al., 1951* is utilized for band selection which is breaking down the complete band set into smaller group band subsets and solving the optimal subset to be chosen. Second the usage of Continuous Band Indexes Constraint (CBIC) according to which the band with closer wavelengths produces similar reflectance, and also this is used for clustering the bands so that similar bands are grouped into one cluster. Third the ranking of cluster-formed bands where from each cluster a band is chosen for the band subset this is the optimal band subset.

In another approach by (Huang et al., 2022) proposed a novel method called "Structural Subspace Clustering(STSC)" for band selection, where STSC depends on self-representation properties of a band and structural prior information to know the shape of the cluster which are clustered. The complete method comprises of four parts *Structural Subspace Clustering, Structural Regularization, Estimation of Number of Bands, and Optimisation*. The Structural Subspace Clustering method builds a combined matrix with related coefficients matrix and sparse coefficient matrix which is decomposed into the coarse coefficient matrix, which helps us understand the representation of original bands in lower dimensional space and later adopted by adjusting the matrix.

Structural Regularization is to build and adjust the coarse coefficient matrix structural regularisation is utilized, which gives us the prior information related to bands locally and globally. The matrix representation reveals that high similarities occur mostly on the diagonal of the matrix, wherein there is also the possibility that the band far away from the diagonal also has high similarities which shows the global property of bands. For the local property, it is clear that band that are nearer to one another has similar kinds of local properties, so considering local property $l_{2,1}$ norm which on a jointly taken lead to column sparsity of difference matrix L and guarantees that neighboring columns in L are close. The number of bands estimation is done with the help of Laplacian graphs, and finally, optimization of the band's subset is done using the alternating direction method of multipliers (ADMMS).

Another approach is proposed by (Motiyani et al., 2023)

where in the proposed work there is initial utilization of the 'k- means' algorithm for segmentation of HSI data set. Later the segmented image of each segment is calculated with Shannon's Entropy and arranged in Ascending order, which is applied with a method called Multiple Feature (band) subset selection which identifies the top band for each segment with the help of $\gamma$ by evaluating $\beta$ and Shannon Entropy. From the before step bands with the highest Shannon Entropy are considered as band subsets which show more variation in bands, later the remaining segments are applied with clustering consisting of the top bands using pairwise distances between them.

(Wang et al., 2022) proposed another method called *Hypergraph Spectral Clustering Band Selection (HSCBS)* where first a hypergraph is constructed to prioritize the bands later a Laplacian matrix is constructed from the hypergraph. The Hypergraph is constructed to represent the high within-class similarity and the low between-class similarity. The process constructs the hypergraph from all the bands of HSI utilizing the three band selection criteria called Information Entropy(IE) for entropy, Maximum Variance Principal Component Analysis(MVPCA) for variance, and Enhanced Fast Density Peak Clustering(EFDPC) for data structure. The process of Hypergraph construction difference from the normal graph is represented in figure 3, where it symbolizes that hypergraph hyperedge may contain one or more vertices and one vertex can belong to one or more hyperedge. In figure 3 e1,e2 are hyperedges and v1,v2,v3,v4 and v5 are vertices.

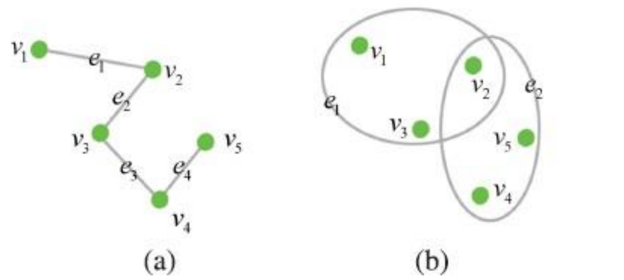


**Fig 3 Hypergraph Clustering (Wang et al.,2022)**

Another achievement in this category is (wang et al.,2020) introduced a method "*Fast Neighbourhood Grouping for Band Selection (FNGBS)* " represented in Figure 4, where the band selection was made using clustering by a *coarse-fine* strategy which selects more informative and relevant bands also with two factors called local density (LD), Information Entropy(IE). The process also determines the number of bands to be selected with the help of the determinantal point process (DPP), the process is implemented as the first step the adjacent bands are grouped into many subgroups as the adjacent bands have large similarities. second step calculating the two factors LD and IE of the formed groups, there is a selection of band from each group with the highest weight of the product of the two factors LD, IE. Third, there is a minimum number of bands to be selected determined by the DPPs, when the condition of minimum bands to be selected is achieved the final optimal band subset is given as output.

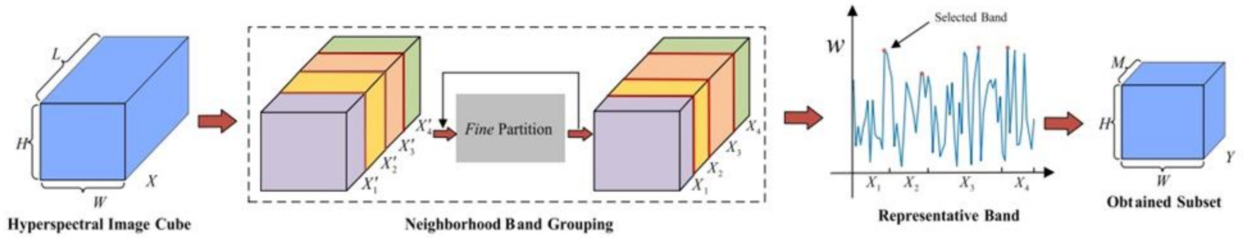


Fig 4 Fast Neighborhood Grouping (Wang et al.,2020)

The contribution by (Moussa et al., 2020) proposed a new method that combines two methods first extracting automatically spectrally variable endmembers using a linear spectral unmixing strategy second dissimilarity values vector are calculated between samples of extracted endmembers in the first step and segmenting using clustering process with the help of Mahalanobis distance. This clustering is called sequential clustering from each cluster formed in the second step is chosen as a band subset.

In another contribution of clustering-based band selection (Jia et al., 2016) proposed an improvement to the existing algorithm '*Fast Density Peak Clustering (FDPC)* ' and made '*Enhanced Fast Density Peak Clustering(E-FDPC)* ', where the author emphasizes that FDPC introduces a combination of ranking bands with different metrics and clustering bands would lead to similar band groups for selecting band subset. In FDPC ranking of bands is done by computing normalized local density and intra-cluster distance rather than simply taking into consideration for band subset, and a cutoff threshold is used for selecting an optimal band subset in E-FDPC. In FDPC each band image is decided by two factors local density and intra-cluster distance which depend on the similarity matrix, and a cutoff is used to know the nearest local dense point thus the cluster centers are determined by the highest distance value and the interesting point in this method is that cluster centers can determine the nonspherical data points which lead to a band subset. While coming to the point of E-FDPC it generates the intra-cluster distances using square product of distance and local density.

In 2022 (Baisantry et al.,) proposed a method that is a supervised learning-based clustering utilizing loadings of the components from Principal *Component Analysis (PCA)*, combined with a novel super-pixel-based graph Laplacian. This method tries to combine the two strategies Band Selection and Feature Extraction, the significance of each band is estimated using component loadings of PCA which are judged based on an objective functionality consisting of data fidelity, classification error, and spatial prior. The spatial relationship between bands is measured using the novel super pixel-graph method, and the procedure is something like initially bands are applied with k-means clustering and from each cluster-wise supervised method Discriminative Spectral Spatial PCA(DSS-PCA) is applied. Later bands selected from each cluster loadings are extracted, then selection of bands with the highest loadings from each cluster which is the final optimal band subset.

In a different approach by (Mali et al., 2023) proposed a new method for band selection where segmentation is applied with k-means clustering and the segmented image is considered as cluster. Arrange all clusters in the order of Gini Impurity, and choose the top segments that contain a number of pixels > 5 and for each segment calculate Gini Impurity, delta which signifies the variability in the band that makes is more significant. Now calculate the delta by exposing those bands whose Gini is greater than band j and by finding the maximum distance among the bands whose Gini is greater than band $j^{th}$ band. Evaluate the score and arrange all the bands in descending order of score parameter, select the top 'k' significant bands as optimal band subset, and utilize it for clustering.

(He et al., 2022) proposed another method for band selection called '*unsupervised multitask artificial bee colony (ABC) BS algorithm based on variable-size clustering (MBBS-VC)'*. As per He first the worst variable size band clustering is applied based on the worst decomposition upon this band selection is achieved as a multitask optimization problem. Later multitask multi-micro bee colony algorithm is induced with variable coding length, for searching multiple optimal band subsets with different sizes in parallel. Moreover, for the improvement of MBBS-VC bidirectional neighbouring learning and multi-measure integration judgement are implemented for increasing the accuracy of optimal band subset and increase the classification of HSI.

(Li et al., 2023) proposed a band selection algorithm 'block diagonal representation learning (BDRLA)', that gives high-quality utilization in which affinity matrix is generated. The spectral band similarity matrix is generated that has a clear diagonal structure, using it as a block diagonal similarity matrix with ordered partition points based upon $l_2$ -norm. The obtained similarity matrix is then processed with clustering without indicators and a dictionary learning is employed to select the represented bands from each cluster.

(Tang et al., 2023) proposed a new method for band selection called 'spatial and spectral structure preserved self-representation model for unsupervised hyperspectral band selection without using any label information($S^4P$)', which takes into consideration spatial and spectral features of the bands. According to $S^4P$ each band of HSI is transformed into a feature vector and applied with PCA, later segmentation(clustering) is applied upon the PCA transforming HSI into different super-pixels which reflects the spatial structure of different homogeneous regions. Each super pixel-level feature vector taken for the self-representation model is utilized for learning spectral correlation between bands. An adaptive and weighted multiple graph fusion is taken for generating similarity graph between super pixels, which enables us to capture spatial structure in the self-representation space.

(Sun et al.,2019) proposed a method '*Weighted Kernel Regularization for Band Selection (WKR-BS)* ' where the bands are transformed in to matrix X, vector y. Later model the non-linear relationships between X and y, into WKR problem that considers non-linear structures of HSI using WKRR (WKR with Ridge Regression). Now construct $L_1$-norm regularisation term on weights of all bands, the $L_1$ penalty considers variable contributions from different bands in describing the nonlinear relationships and to achieve sparsity between bands to be selected. WKR implements the *KerNel Iterative-based Feature Extraction (KNIFE)* algorithm for estimating the proper band weights, the KNIFE transforms the nonlinear kernel to reduce computational cost and minimize the 2 convex problems for solving sample coefficients and band weights. The top 'k' bands with larger weights and larger dissimilarity with other bands are considered as optimal band subsets.

**2.4. Classification-Based Band Selection**

Various classification approaches for band selection have been explored in recent studies. Author (Mehdi et al. 2023) applied an Anisotropic Gaussian kernel to Support Vector Machines, resulting in a notable 5% improvement in classification accuracy. On a different front, (Cao et al. 2016) introduced Automatic Band Selection (ABS), a novel technique integrating classification and clustering. ABS utilizes classifiers such as kNN and SVM to categorize bands within a represented Band Label vector. The labeled vectors are subsequently clustered, and bands from each cluster are considered based on a threshold to ensure non-repetitiveness. Additionally, noteworthy contributions by (Dey et al. 2023) involve the incorporation of statistical information, such as Mutual Information of Bands, combined with the neighborhood principle. This method is employed to rank bands based on their similarity/dissimilarity, resulting in the selection of an optimal band subset.

**2.5. Statistical Measures Based Band Selection**

The author's contribution of Statistical measures is encouraged by (Sun et al., 2019), who proposed a method named Correntropy-based sparse spectral clustering (CSSC) to select the proper band subset. The proposed method constructs an affinity matrix with the help of Correntropy measurement which considers the non-linear characteristics of every band of HSI.

In another contribution by (Adolfo et al., 2007) they proposed a method for dimensionality reduction dependent upon Statistical measures and hierarchical clustering, that maximizes the inter-cluster variance and minimizes intra-cluster variance. The proposed method utilizes Kullback-Leibler divergence to reduce data redundancy and unnecessary information among HSI bands. The procedure is implemented using 2 stages i) Calculating the Dissimilarity Measures between bands and 2) performing the Variance-Reduction Clustering Strategy. In the first stage, various dissimilarity measures are calculated between the bands to build a matrix like Shannon entropy, Normalised Mutual Information, Kullback-Leibler Divergence, etc. In the second stage, the observed dissimilarities are clustered using a hierarchical clustering procedure for optimal band subset selection.

As per (Jain et al., 2022) the band selection is done based on the "Mutual Information based Dependence Index (MIDI)", which is an unsupervised band selection method that is competent enough to identify the non-linear relationships between bands. The MIDI will first calculate the MIDI score between all the bands of HSI, later sort the band with decreasing order and those bands with null values are rejected for further process. Repeat the process of band selection until the required number of bands is selected, for a new band to be included in the band subset calculate the $i^{th}$ distance from the sorted array if both the bands are already in the selected list then move to the next step or else any one of the bands is rejected already then go to next band. If both bands are not present in the selected list then calculate the sum of distances between the band under consideration, and the remaining unselected bands whichever is greater is considered for the band subset. Iterate through this process until the optimal band subset with the required number of bands is obtained.

According to (Ehsan et al., 2022) the proposed work called "Joint-Conditional Mutual Information for Selecting Informative Feature (JCIF)", is purely based information theoretic feature selection approach that gives a band subset with the help of the maximum of the minimum approach. First, calculate the Mutual Information (MI) of each band in the HSI, and later select the band subset from these HSI bands that have maximum MI, these selected bands are then calculated with the difference between relevance and redundancy. The minimum difference bands are calculated with conditional entropy those bands with maximum conditional entropy are selected as optimal band subsets.

In another contribution by (Chug et al., 2023) proposed an approach called "Spectrally Optimized Feature Identification (SOFI)", which is based on a statistically optimal band selection strategy. The proposed method is applied in 2 stages first there is Feature Reduction, and second is Feature Selection. In the first stage, the bands that exhibit more Fisher ratio are only selected and the ones that show less are discriminated against, whereas in the second stage Genetic Algorithms are used for selecting the optimal band subset which is passed by the first stage that leads to optimal band subset.

### 2.6. Deep Learning Based Band Selection

Limited contributions have been made in the field of decomposition, where (Qi et al., 2023) introduced a novel approach using tensor-based decomposition on feature vectors (bands) of hyperspectral imagery (HSI). Their method involves applying clustering to streamline calculations, reducing computational complexity as the features are transformed into a lower-dimensional space. Another method proposed by (Zang et al., 2023) focuses on leveraging the spectral differences between water and other ground elements in an HSI dataset. By calculating the spectrum differences with various elements, this approach selects representative features by identifying the highest difference between HSI bands with pure water and the lowest difference between HSI bands with land cover. These contributions aim to enhance the efficiency and accuracy of decomposition techniques in HSI analysis.

Another method proposed by (Dou et al., 2020) "Attention-Based Auto Encoders for Band selection" where there is a utilization of a category of Auto Encoders for Band selection which is an unsupervised neural network model. These Encoders can output bands as the number of input bands, using this model raw HSI data is provided as input and after attaining the optimization of the model the column vectors of the model are used with K-Means clustering. The final optimal band subset consists of the bands selected from each cluster as a representative band.

In the approach by (Bao et al., 2022) "Similarity-based band selection using Deep Reinforcement Learning" where their model is developed based on a double deep Q-network (DDQN). The DDQN introduces more rewards and helps in adopting fixed targets, and DQN targets make the training samples unstable because the rewards are produced which is being solved by fixing the targets. The targets are fixed based on the parameters passed to Q-networks, as DQN suffers from over-estimation, a new target function is proposed as DDQN which fixes the problem of selecting the optimal band subset.

In their 2023 contribution, Liu et al. introduced a pioneering model, the Triple Constraints and Attention Network for Band Selection (TCANet-BS), which combines deep learning principles with innovative methodologies for hyperspectral imagery (HSI) analysis. TCANet-BS systematically selects bands for inclusion in a band subset by leveraging band informativeness, representativeness, and correlation. Inspired by deep learning architectures, TCANet-BS utilizes an Attention Reconstruction network to calculate band representativeness, spectral information divergence, and orthogonal subspace projection for band informativeness, and inter-band correlation, respectively. To address the challenge of highly correlated bands, TCANet-BS employs constraint mechanisms and scoring functions, iteratively operating until the final required number of optimal bands is selected. This sophisticated approach represents a significant advancement in hyperspectral data analysis, offering improved efficiency and precision in band selection processes.

The contribution by (Zhou et al., 2023) proposed a new method called "Iterative Graph Auto Encoder for Band Selection (IGAEBS)", which captures the structure information using an automatic construction process. This model is a new unsupervised pretext task for training convolution neural networks to extract features, later these features are utilized for building a graph to represent systemic relationships among the bands. This graph structure is continuously improved and the model that does this is an iterative graph improvement, which forwardly improves the graph structure and this graph is utilized for building clusters. From each cluster, a representative band is selected into the optimal band subset.

As per (Francis et al., 2023) a new method has been proposed "A TENSOR NON-CONVEX LOW RANK AND SPARSE CONSTRAINED BAND SELECTION SCHEME" for band selection. An effective Tensor-based band selection scheme and a submodule clustering are applied to preserve the spatial structure of the spectral bands in the proposed framework. The self-expressive representation of spectral bands is optimized using a representation tensor which leads to the construction of a similarity matrix, from which the appropriate number of non-redundant bands are extracted using silhouette clustering evaluation. To better rank the bands and know the self-expressiveness of bands $l_{1/2}$ -induced Tensor Nuclear Norm and $l_{1/2}$norm regularisation are included. After clustering the bands, the bands closest to the clusters' centers are chosen for the optimal band subset.

Another contribution by (Das et al.,2022) proposed a "Sparsity Regularized Deep Subspace Clustering for Multi-criterion-Based Band Selection" that utilizes the deep subspace clustering process framework with multicriteria-based band selection. As per Das deep subspace clustering identifies the underlying non-linear subspace structure, and sparsity measure to identify self-representative bands. To obtain the deep subspace the auto-encoders are utilized which deduce the self-representative coefficient matrix, which represents self-expressive layers with pq-norm sparsity that also reduces the dimensionality. The reduced dimension data are then optimized so that self-representation is present in the subspace data and the bands from each cluster after subspace clustering are selected by looking at the structural information along with statistical similarity measures to obtain the optimal band subset.

### 2.7. Optimization Based Band Selection

Optimization-based techniques for band selection in HSI are divided into three sub-categories: a) Particle Swarm Optimisation (PSO) b) Genetic Algorithm Based Optimisation (GAO) c) Other Optimisation techniques (OT). This area's contributions are less shown in PSO compared to OT and GAO.

#### 2.7.1. Particle Swarm Optimisation (PSO)

In this category, (Zang et al. 2017) made notable contributions by introducing a hybrid approach, combining clustering (Fuzzy C-means) with the optimization technique Particle Swarm Optimization (PSO) for Band Subset Selection (PSO-FCM). Within this method, the fuzzy membership is updated by PSO, and for each cluster formed through PSO-FCM, a band is selected based on the maximum entropy, representing the cluster optimally.

Another significant method proposed by (Wan et al. 2023) involves the application of an innovative technique called Adaptive Multistrategy Particle Swarm Optimization for Band Selection (AMSPSO_BS). In this approach, the Particle Update Strategy (PUS) is categorized into five distinct strategies, and an adaptive self-adjustment strategy automatically selects and applies the appropriate update strategy. These contributions showcase advancements in optimization techniques for band selection, enhancing the adaptability and effectiveness of the selection.

#### 2.7.2. Genetic Algorithms Based Optimisation (GAO)

In the realm of Genetic approaches to band selection, (Paul et al. 2015) proposed a novel technique that integrates both clustering and Genetic algorithms for optimal band subset identification. The method initiates spatial clustering in the first phase, where each candidate is selected from a formed cluster. In the second phase, the Genetic Algorithm and Kullback–Leibler divergences are applied to refine the candidate solution set, eliminating adjacent bands and achieving the best band subset. On a different front, (Tong et al. 2023) introduced a hybrid approach by combining cross-genetic algorithms, incorporating both Artificial Bee Colony and Genetic Algorithm. After applying the Artificial Bee Colony procedure to each band candidate, the selected band subset undergoes Genetic crossover operations, mitigating potential disadvantages from the earlier procedure. Subsequently, the refined band subset is submitted to a 3D-CNN for improved classification accuracy.

In another innovative algorithm, (Yin et al. 2012) introduced the Immune Clonal Strategy for band subset selection. The method involves selecting a random band subset and arranging bands in decreasing order of affinity. Clonal proliferation of each band occurs in descending order of the affinity function, followed by hybrid mutation. This process iterates until an improved combination of band subsets is found, resulting in enhanced classification accuracy of hyperspectral imagery.

#### 2.7.3. Other Optimisation Based Techniques (OT)

In the realm of band subset selection procedures, (Alkithab et al. 2020) have made a significant contribution with their innovative Column Subset Selection (CSS) algorithm. This algorithm strategically reduces bands based on a minimum residual errors strategy, employing Singular Value Decomposition (SVD) and QR factorizations to yield a refined subset of bands. By doing so, Alkithab et al. present an effective methodology for band selection, demonstrating the efficacy of their approach in minimizing errors and enhancing the overall performance of the selected bands.

Wang et al. (2022) present a pioneering Hybrid Grey Wolf Optimizer (HGWO) technique distinguished by its adaptive decreasing convergence factor, a departure from traditional linear approaches. The algorithm, rooted in the

Grey Wolf Optimizer framework, treats bands as entities within a wolf pack. Designating a band as ' *alpha*' to represent the optimal solution across the entire band set, the algorithm strategically selects successors '*beta*' and '*delta*' at the ground level of the wolf pack hierarchy. This hierarchical mimicry guides the band selection process, ultimately leading to the identification of an optimal subset. The adaptive convergence factor plays a pivotal role in preventing premature convergence, ensuring the algorithm's effectiveness in navigating the solution space and yielding superior outcomes.

In the study by Wu et al. (2024), a novel algorithm is introduced, drawing inspiration from the 'Cuckoo Search (CS)' algorithm, renowned for its exceptional feature search capabilities despite facing challenges in initial iterations. To address the issue of late iterations, the authors innovatively integrate CS with a 'Match Filter (MF),' enhancing band selection through a filter-based comparison involving the noise ratio of bands within the CS-selected band subset. This hybrid approach not only mitigates the initial struggles of CS but also introduces a sophisticated MF mechanism to refine band selection further. Additionally, the model incorporates a Neighbourhood-based grouping strategy to diminish similarities between bands filtered by the MF, thereby augmenting the algorithm's overall performance in efficiently identifying relevant features. This integrated methodology demonstrates a comprehensive and effective solution to enhance the algorithm's search efficiency and feature selection capabilities.

In the research conducted by (Xu et al. 2023), a pioneering Dingo Optimization Algorithm (DOA) is introduced to identify an optimal band subset that accurately represents relevant features within hyperspectral imaging (HSI) datasets. The proposed methodology integrates Fuzzy C-Means (FCM) clustering to partition the dataset into 'C' clusters. Subsequently, the DOA is applied to optimize the objective function, a clever combination of Entropy and correlation of bands. The algorithm strategically selects 'K' bands from each cluster to form the final band subset. Notably, the band population is dynamically updated using a hunting strategy inspired by dingoes, ensuring a systematic exploration of the solution space. The optimization process continues until the band subset attains the best fitness value, at which point the algorithm ceases, underscoring its efficiency in achieving an optimal representation of relevant features within the HSI dataset.

In their work, Ou et al. (2023) present an innovative model centered around a Multi-Objective Cuckoo Search (MOCS) for band selection, building upon the foundation of the 'Cuckoo Search (CS)' algorithm. To address challenges in initial iterations, an adaptive strategy is incorporated, enhancing the algorithm's efficacy. This method leverages information-sharing through grouping and crossover operations to achieve a balance between global exploration and local exploitation, effectively tackling the issues encountered in initial iterations. The proposed algorithm introduces the use of dispersion coefficient and cross-correlation to optimize the band selection process, fostering a higher quantity of information and lower intercorrelation between bands. This strategic approach ultimately leads to the identification of a superior band subset from the original hyperspectral imaging (HSI) band set. By applying MOCS to evaluate fitness based on the dispersion coefficient and cross-correlation, the algorithm systematically refines the band selection process until an optimal band subset is obtained, demonstrating its capability to enhance the quality of selected bands in HSI data.

In their 2023 work, Yang et al. introduced the Multiobjective Optimization method for Adaptive Band Selection (MMOABS), a groundbreaking strategy to tackle the band subset selection problem. Employing a multitask multi-objective framework during subset selection, MMOABS identifies bands with high discrimination, information richness, and low redundancy, ensuring a well-balanced and informative band subset. The dual-task approach enhances the overall efficiency of the selection process. Subsequently, the selected bands are utilized in classification tasks, where MMOABS has demonstrated superior accuracy compared to alternative methods. This innovative technique represents a significant advancement in band selection methodologies, showcasing its effectiveness in addressing the complexities of the band subset selection problem and improving classification accuracy.

Another work by (Ma et al., 2023) proposed a work called spectral correlation-based diverse Band Selection (SCDBS), which considers the correlation weights for building of weighted sparse reconstruction based on which the band subset is chosen, this leads to a band subset with high correlation to the original HSI data set. Another study by (wang et al., 2023) introduced a structure-conserved and neighborhood-grouped evolutionary algorithm (SNEA), which is an un-supervised method where first there is an optimization in between all the spatial structures present in the HSI scene with the help of an affinity matrix. The next strategy is to select the bands based on the spatial structures not being disturbed by any band included in the subset. To eliminate the redundancy there is a neighborhood grouping strategy applied so that the offspring solution from the above said method will be non-redundant.

### 2.8. Framework-Based Band Selection

This category has the least contributions where the author(Hu et al., 2023) proposed a framework methodology, called "One-shot Neural Band Selection(NBS)" to achieve a band subset. The proposed framework converse to the traditional band selection strategies rather than searching with a random subset and finding the optimal Band subset this strategy helps us find the optimal band subset with gradient descent problem-solving search methodology.

### 2.9. Ranking and Other Functionality Based Selection

The significance of this category is underscored by (Yang et al.'s 2019) introduction of the Shared Nearest Neighbour Co-relation Analysis (SNNCA) method. This approach builds upon the principles proposed by (Qiang et al. 2019) in their "Shared Nearest Neighbour Clustering (SNNC)" theory. SNNCA relies on shared nearest neighbours to determine the local density of each band, reflecting their characteristics. The calculation involves a combined equation utilizing the Gaussian Kernel Function, Distance factor, and Information Entropy. Bands' local densities are then ranked in descending order, with the top bands serving as cluster centers in SNNC. In the case of SNNCA, the most representative bands, correlated within each cluster, are selected to form the band subset. This methodological refinement enhances the understanding and selection of key bands in the context of shared nearest-neighbour analysis.

In an additional contribution to this line of research, (Llaveria et al. 2022) have introduced the Sequential BS Ranking (SBSR) method for efficient Band Subset Selection in Hyperspectral Imaging (HSI). The innovative approach involves calculating the entropy of each band in the HSI, followed by reordering the bands in descending order of their entropy values. Subsequently, the method selects the band with the highest entropy, incorporating it into the initial band subset S! = Ɵ. The process iteratively continues as each band is evaluated using a scoring function, resembling a form of correlation, concerning the bands already included in subset 'S'. This stepwise procedure ensures the selection of bands in set S based on their compatibility with the existing subset, effectively optimizing the band subset until the desired number of bands is attained.

In their work, (Sun et al. 2020) have introduced a novel approach named fast and latent low-rank subspace clustering (FLLRSC), representing a distinctive ranking method in hyperspectral imaging (HSI) analysis. The methodology strategically employs Hadamard random projections to alleviate the computational complexities associated with higher-dimensional data. Initially, the HSI dataset undergoes Hadamard Random Projections, facilitating the extraction of representative bands within a low sparse representation. This transformation effectively moulds the original HSI into a low-rank structure, crucial for subsequent computations. The correntropy measure similarity is then calculated based on this low-rank representation, providing a robust measure of similarity. The ensuing similarity matrix is subjected to spectral clustering, resulting in 'k' clusters. Bands proximate to the normalized rows around cluster centers are identified, forming the selected band subset. Sun et al.'s FLLRSC method showcases a nuanced integration of Hadamard random projections, low-rank structures, and spectral clustering, contributing to a more computationally efficient and representative band subset selection in hyperspectral data analysis.

In their contribution, (Xu et al. 2020) propose an innovative algorithm termed Similarity-based Ranking-Structural Similarity (SR-SSIM), which offers a unique blend of ranking principles inspired by density-based clustering. This method prioritizes the selection of bands into the band subset based on both ranking and structural similarity considerations. Notably, the ranking strategy draws inspiration from Fast Density Peak Clustering (FDPC), wherein instead of employing density and similarity for each band, Xu integrates the similarity parameter $\alpha$ and dissimilarity parameter $\theta$. The determination of $\alpha$ involves a cut-off similarity score, while $\theta$ is computed using the equation $\theta = \sqrt{1 - \varphi_i}$, signifying the nearest band with a larger average similarity. In the proposed method, bands exhibiting both normalized $\alpha$ and $\theta$ are ranked according to the cross-product of the norm($\alpha$) X norm($\theta$). The top 'k' bands are then selected as the band subset according to the SR-SSIM algorithm. This intricate combination of density-based clustering principles and structural similarity metrics distinguishes Xu et al.'s SR-SSIM as a promising method for robust and nuanced band subset selection in hyperspectral data analysis.

Shuying Li et al.'s (2023) research introduces the Difference between Intergroups (DIG) method for band selection, incorporating two key strategies: Grouping-Strategy via Intragroup Similarity (GSIS) and Ranking-Strategy via Difference between Intergroup (RSDI). GSIS facilitates a more dispersed band selection by reducing similarity within groups through coarse and fine grouping. RSDI then leverages knowledge and similarity within each group, selecting the maximum local density-represented band. The proposed method involves applying GSIS first, followed by RSDI, and subsequently employing DIG to handle redundant bands within the same groups. Multiple band subsets are generated, and an evaluation function is applied to determine the optimal subset based on the achieved evaluation function value. This comprehensive approach aims to enhance band selection efficacy, and the research suggests potential improvements through a thorough evaluation and comparative analysis of results.

In their work, Datta et al. (2012) introduced an unsupervised band selection algorithm comprising three sequential steps. Initially, the algorithm extracts attributes from bands by treating each pixel as an attribute and clusters them using DBSCAN, producing initial clusters. From these clusters, mean representative points are derived, maintaining equal attribute representation, and a matrix is constructed. In the subsequent stage, the matrix undergoes another round of DBSCAN clustering to segregate representative bands and isolated clusters containing bands deviating significantly. The resultant intermediate band subset comprises a combination of representative and isolated bands. Finally, in the third stage, bands within the intermediate subset are ranked based on their discriminatory power, quantified by their non-Gaussianity. This ranking, determined by Information Divergence, yields a list of bands ordered according to their discriminatory capability, from which the top 'k' bands are selected as the optimal band subset, enhancing the efficiency and effectiveness of hyperspectral data analysis.

In the realm of band selection, Chang et al. (2023) proposes an unsupervised RDF-based band subset selection (RDFBSS) method, employing the Radial Bias Function (RBF) for optimal band selection. The methodology comprises two distinct types: SQ-RBFBSS-MIN and SC-RBFBSS-MIN, both inspired by the N-FINDR algorithm to iteratively enhance band selection. In SQ-RDFBSS-MIN, bands are selected based on the difference in RDF curve scores, utilizing a Spectral Angle Mapper (SAM) and Spectral Information Divergence (SIDAM). The distortion matrix, calculated through SAM and SIDAM, is combined with the entropy of each band and processed using Blahut's rate-distortion algorithm to normalize RDF over hyperspectral imagery (HSI) data, ultimately yielding an optimal band subset. If the threshold value is not surpassed, the iterative process continues within the specified limit, refining the band subset further. The SC-RDFBSS-MIN process follows a similar functionality with initial conditional changes, presenting an innovative approach to unsupervised band selection using RDF and RBF.

In their 2021 work, Zhu et al. introduced a novel approach for band selection utilizing Improved Affinity Propagation (IAP), a technique akin to clustering. The method involves calculating the information entropy for each hyperspectral band, followed by the permutation of bands in decreasing order to construct a similarity matrix with itself. This permutated matrix is then partitioned into 'k' blocks, with the constraint that the value of 'k' should be greater than 1 and less than the square root of the total number of bands $\sqrt{L} \div 2$ , where L represents the bands in hyperspectral imagery (HSI). The submatrices obtained from this process are subsequently employed in the Affinity Propagation (AP) algorithm, and their combination forms the availability matrix for AP, yielding exemplars. These exemplars are transformed into the format of an identical matrix with only diagonal elements available. The resultant intermediate matrix undergoes entropy calculation, culminating in the selection of band subsets represented by the output exemplars, showcasing an innovative method for effective band selection using IAP and entropy considerations.

Another contribution by (Meenakshi et al., 2023) proposed a new method called Wavelet entropy-based Band Selection, where each band is calculated with a wavelet entropy and rank the bands based on entropy value. The first top 'k' bands are chosen as the optimal band subset.

### 2.10. Decomposition Based Selection

In the realm of hyperspectral image analysis, the contribution of methods addressing bottleneck-causing factors of graph regularization, particularly about correlations among bands and neighboring pixels, has been comparatively understated in comparison to optimization and ranking-based approaches. Herbenger et al. (2023) sought to address this gap by proposing a novel solution involving the utilization of spectral/spatial Laplacians and matrix CUR decomposition. The method commences with the construction of symmetrically normalized spectral and spatial Laplacians, subsequently optimizing these Laplacians through the alternating direction method of multipliers (ADMM) algorithm. This iterative process continues until convergence, resulting in a decomposed matrix of the original hyperspectral imagery (HSI), which is then transposed. The transposed matrix is further subjected to a classifier, such as Herbenger's chosen K-means, to identify optimal bands closely aligned with the cluster center. This method presents a significant advancement in mitigating graph regularization issues, showcasing its potential to contribute meaningfully to the broader field of hyperspectral image analysis.

In their contribution, Qi et al. (2023) introduced a groundbreaking method named the Tensor Decomposition-based Latent Feature Clustering (TDLFC) model designed for band selection. This innovative approach employs the CANDECOMP/PARAFAC (CP) tensor decomposition method to represent low-dimensional bands, effectively capturing both spatial and spectral information. To mitigate the risk of overfitting in the CP decomposition process, a regularization function is strategically applied. Following the decomposition, the resulting bands undergo 'K-Means' clustering, partitioning the dataset into 'n' clusters. Subsequently, representative bands are selected by identifying the points nearest to the centers of these clusters, forming an optimal band subset. The TDLFC model thus offers a comprehensive and sophisticated solution for band selection by leveraging tensor-based decomposition and latent feature clustering, showcasing its potential to enhance the extraction of meaningful information from hyperspectral data.

In the work presented by Zhang et al. (2024), a novel approach named Sparse Principal Component Analysis and Adaptive Multigraph Learning (SPCA-

AMGL) is introduced to address the challenge of achieving a low-dimensional representation of original hyperspectral data points. This method involves the projection of hyperspectral image (HSI) data points onto a low-dimensional space through Sparse Principal Component Analysis (SPCA). Subsequently, local manifold preservation is implemented to ensure that pixels belonging to the same class in the original dimensions also belong to the same class in the reduced-dimensional representation. Graph theory is utilized to represent the local manifold, constructing a graph based on the 'KNN' (K-nearest neighbors) principle, preserving the essential structure of the original HSI dataset in lower dimensions. The image classification process is then executed using adaptive multigraph learning, facilitating the exploration and learning of the similarity graph between bands. The SPCA-AMGL method offers a comprehensive solution for achieving an effective low-dimensional representation while preserving the local structure of hyperspectral data, showcasing its potential for accurate and meaningful image classification.

### 2.11. Other Game/Graph Theory Based Band Selection

In the domain of graph and game theory-based approaches, (Zhou et al. 2022) introduced a method grounded in the "maximum empirical volume (MEV) theory" principle. This innovative approach amalgamates the benefits of orthogonal projection and cross-entropy, relying on the Sequential Forward Selection (SFS) algorithm. The orthogonal projection involves the utilization of a hyperplane formed by the selected band subset. In a parallel contribution to this category, You et al. (2023) proposed the Global Affinity Matrix Reconstruction (GAMR) method. GAMR constructs pseudo labels for hyperspectral image (HSI) bands within the low-dimensional manifold space projected by the original data. The pseudo labels are intricately constrained by a graph regularization function formulated using a global affinity matrix reconstructed through the amalgamation of multiple predefined local similarities. Both methods showcase the potential of graph and game theory-inspired techniques in enhancing band selection processes, offering advanced strategies for maximizing empirical volume and constructing pseudo labels in a low-dimensional manifold space.

In this category of graph and game theory-based approaches, (Shang et al. 2023) introduced the Hypergraph Regularized Self-Representation (HyGSR) model for band selection, combining spectral similarity and band index to create a novel metric that normalizes the local structure of bands using Hypergraph. The utilization of an $l_2,_1$ -norm helps extract sparse properties of data, enhancing the efficiency of band selection. In a distinct contribution, (Jeenath et al. 2022) proposed an ensemble method that integrates strategic and competitive theory applications, incorporating Principal Component Analysis (PCA) for

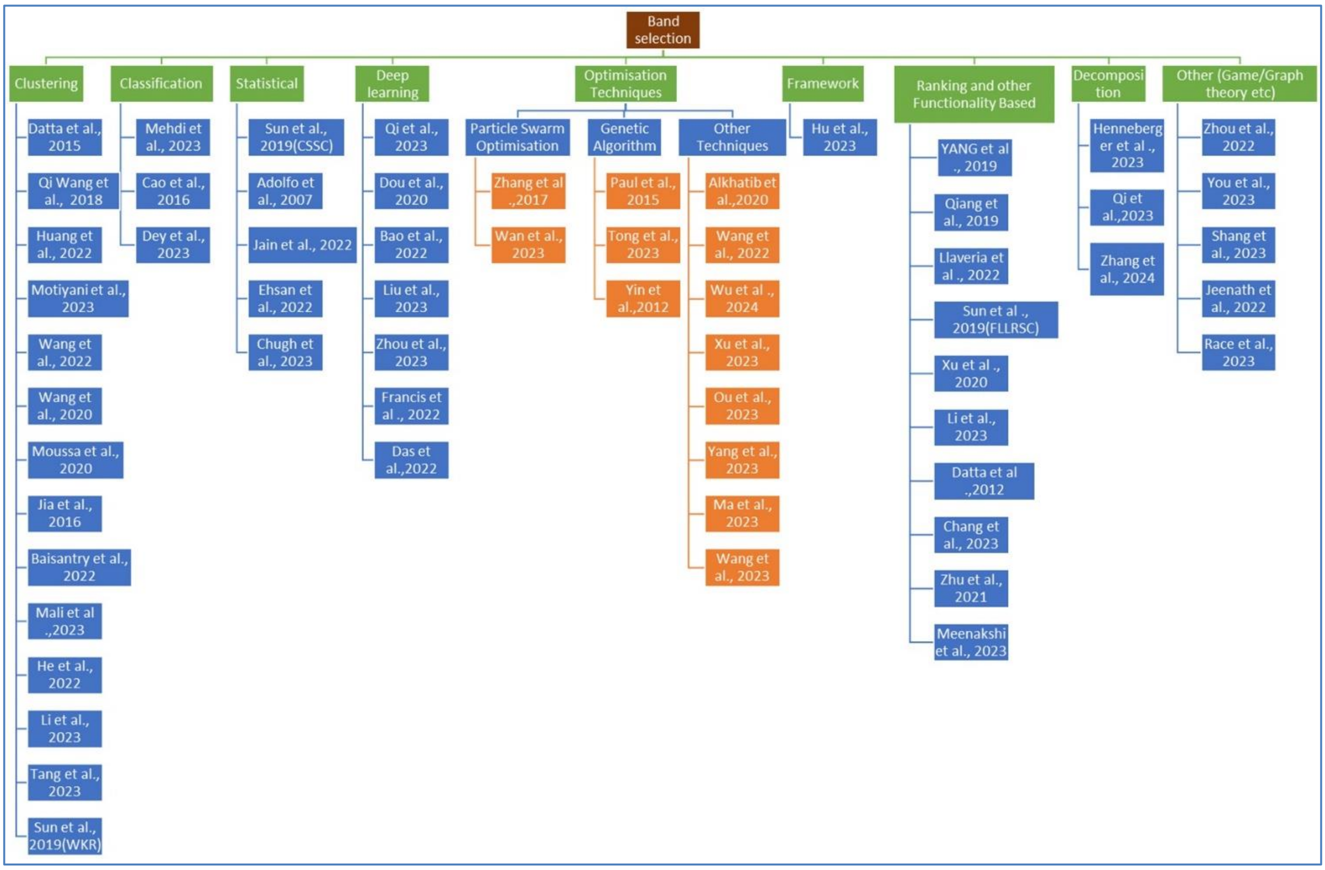


**Fig 4 Hierarchical Representation of Band Selection methods**

dimensionality reduction. Furthermore, (Race et al. 2023) provided a concise comparison of various dimensionality reduction methods, such as PCA, MNF, OSP, PPCA, revealing that faster techniques like PCA consistently yield superior accuracy compared to methods like PPCA. These advancements collectively underscore the diverse strategies within the graph and game theory-based approaches, showcasing their potential for refining hyperspectral band selection and dimensionality reduction processes.

## 3. Results

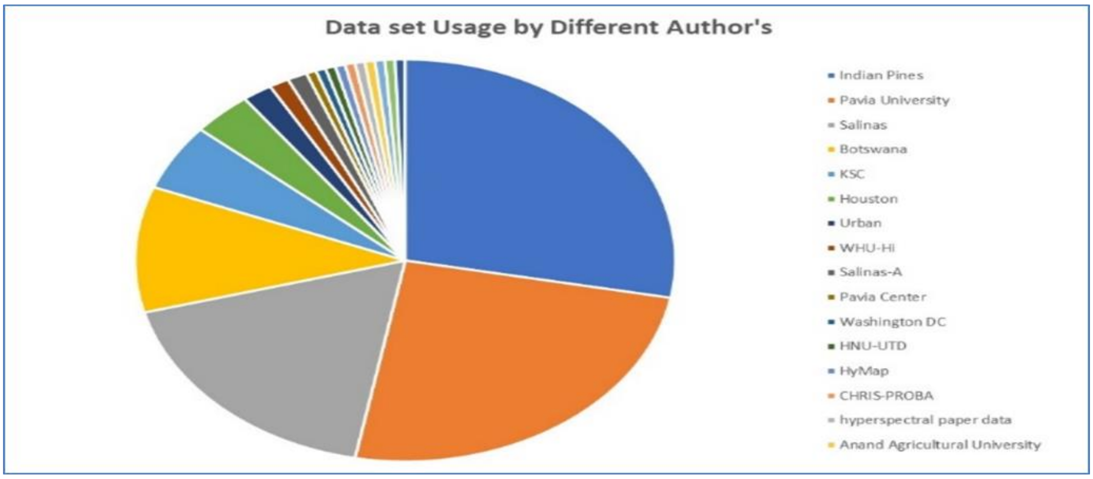


Fig 6 Contribution of Authors over HSI data sets used for Experimentation

Figure 5 categorizes literature-based Band selection techniques into nine groups, with a specific focus on optimization techniques, further classified into Particle Swarm Optimization (PSO), Genetic Algorithm Optimization (GAO), and Other Techniques (OT) as detailed in Section **2.7**. Figure 5 illustrates the author's contributions within these categories. Simultaneously, Figure 6 highlights dataset utilization, with Indian Pines being the predominantly used dataset, followed by Pavia University, Botswana, and KSC. Despite various datasets employed for methodological experimentation, the evaluation is based on five selected datasets. Clarifying the placeholders and providing specific details will enhance the overall coherence and completeness of the analysis.

The study's results underscore the supremacy of clustering-based methods in achieving high accuracy compared to the eleven band selection techniques assessed. These findings, applied to five widely used hyperspectral imaging (HSI) datasets available online, hold particular significance as these datasets align with those frequently utilized in the surveyed articles. The band selection process is standardized, ranging from 2 to 30 bands, allowing for flexibility across various literature methods. Notably, the results on the Indian Pines dataset, as depicted in Figure 7, highlight the effectiveness of author Qi Wang's contribution, the *Top Rank-Cut with Edge Preserving Filter (TC-EPF)*, a clustering approach, which achieved the highest Overall Accuracy (OA) of approximately 0.91. Furthermore, in the Pavia University dataset, the same methodology by Qi Wang et al., 2018 demonstrated exceptional performance with an impressive Overall Accuracy (OA) of 0.98 with ***Normalised-cut with Edge Preserving Filter (NC-EPF)*** shown in Figure 8.

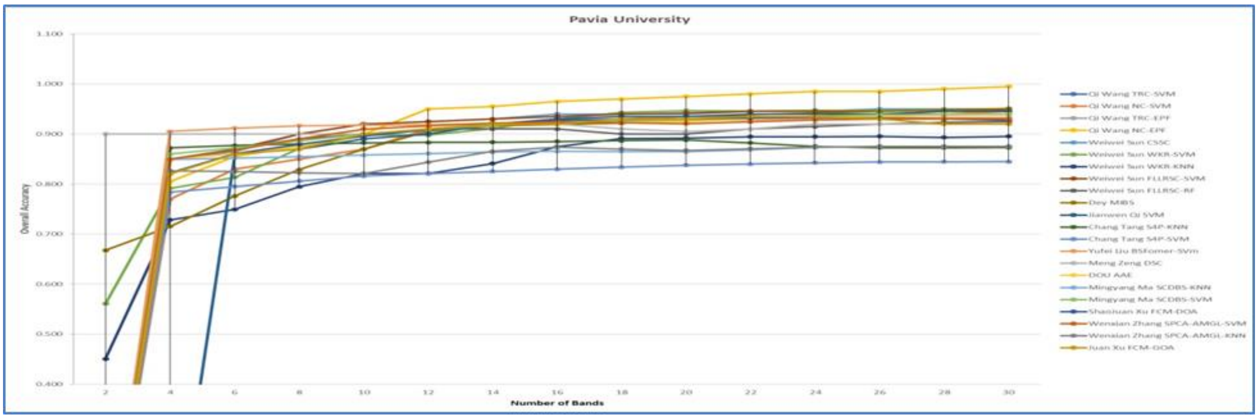


Fig 7 Overall Accuracy of Indian Pines Data set from top Band Selection Methods.

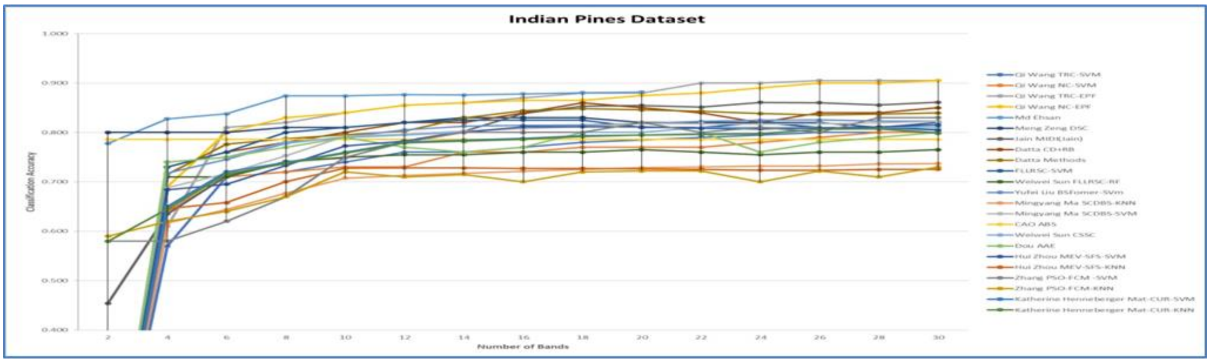


Fig 8 Overall Accuracy of Pavia University Data set from top Band Selection Methods.

The other end (Wu et al.,2024) proposed Heterogenous Cuckoo optimization search-based (\textbf{HCS-MF-EPF}) Band Selection has given better accuracy over Salinas data set figure \ref{fig:SA} with classification technique of SVM for HSI data set labeling. Botswana is applied by 16 different methods in the literature, which include Search optimization with clustering, and the filter-based approach is the best technique. Along with this figure \ref{fig:PIE} refers to the number of articles each of the data sets is being utilized to experiment with the author's methods, where the highest used HSI data set is Indian Pines. Among the Data sets used Pavia University, Salinas, Botswana, and Kennedy Space Center are at the top, so only these are utilized for study in the paper.

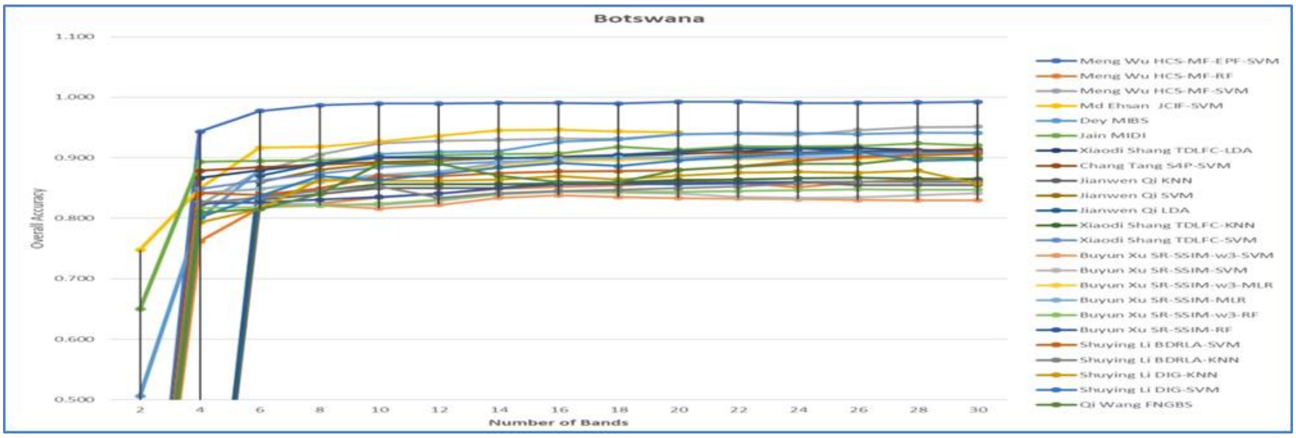


Fig 9 Overall Accuracy of Botswana Data set from top Band Selection Methods.

Figure 9 represents the top methods with 17 authors contributing to the survey providing the best accuracy with the **HCS-MF-EPF** method showing very high accuracy achieved mostly near 0.98, other than this (***JCIF-SVM***) proposed by (Ehsan et al., 2022) a combination of Statistical and clustering-based method for Band subset selection produced an accuracy of 0.942. And later talking about Figure 10 the contributions are only 9 for this data set, among which HCS-MF-EPF with SVM classifier is at the top with 0.99 OA. Then the next work which shows better classification accuracy is NC-EPF with an accuracy of 0.875. These outcomes affirm the efficacy and versatility of clustering-based techniques with optimization techniques resulting in best band subset selection for hyperspectral image analysis.

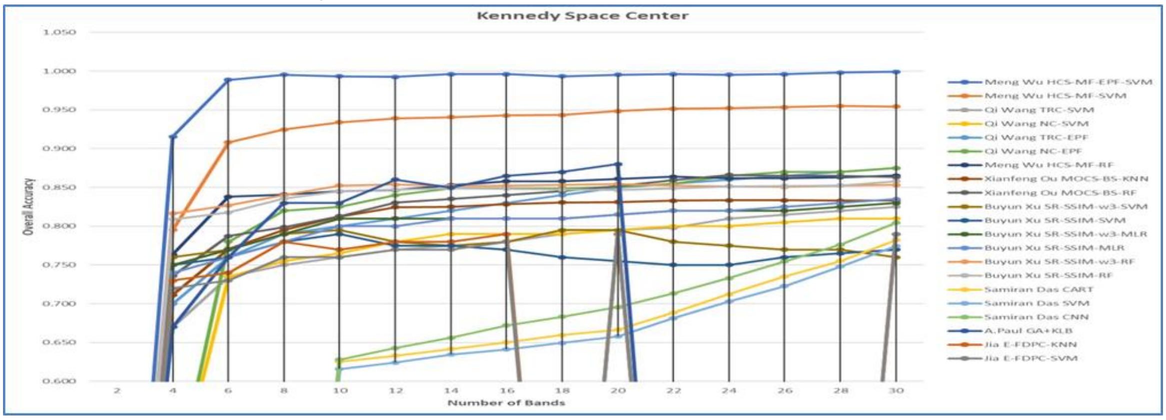


Fig 10 Overall Accuracy of KSC Data set from top Band Selection Methods

## 4. Conclusion

The author's pioneering work in the clustering mechanism stands out as the most effective among all eleven categories, with statistical approaches claiming the second position, closely followed by clustering in the third place. Particularly noteworthy are the clustering techniques that achieve top-tier accuracy through a neighbor grouping-based band subset selection framework. This framework meticulously selects a band subset using a threshold, seamlessly integrating the most representative bands. The result is a highly effective method for Hyperspectral Image Classification, showcasing the author's significant contribution to advancing this field. The predominant contributions lie within clustering techniques, with the least significant advancements originating from statistical theory-based optimization.

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