Significant Classes of Operations Towards Classification of Hyperspectral Images

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ABSTRACT
With the advent of advanced technological penetration towards remote sensing applications, hyperspectral image (HSI) has been a pivotal point of focus in the development of spectroscopic investigation toward further modernizing remote sensing applications. The outcome is only the identification and classification of the sensed object leading to the generation of a classification map. However, various approaches are available with a diverse focus on different problems. It is, therefore, essential to understanding the best-suited process. Therefore, this manuscript reviews different significant approaches to understanding the strength and weaknesses associated with processing HSI. The study's outcome highlights that machine learning is the most suitable approach to be considered for classification in the future direction of work, which can address various weaknesses and bridge the research gap explored in existing approaches of HSI.

Keywords: Hyperspectral Image; Remote Sensing Application; Object Classification; Processing HSI; Machine Learning

INTRODUCTION

Hyperspectral Image (HSI) consists of massive information of the spectrum in order to identify and classify different objects [1]. Currently, various optical analysis techniques carry out detecting an object in HSI. It should be noted that the human eye can identify only three bands of colors, i.e., red, green, and blue, while HSI offers a greater number, available in hundred bands of colors [2]. The capturing process of HSI is carried out using imaging spectrometers, while sensing technologies, i.e., spectroscopy and remote imaging, are prominent technologies [3]. Hyperspectral image processing is carried out using two prominent analysis techniques, i.e., spectral analysis and image analysis. In this case of spectral analysis, the sample image is initially subjected to image correction followed by extraction of spectral information. The pre-processing operation removes the artifacts present, followed by model calibration and validation to generate a simplified model. On the other hand, in the case of image analysis, the sample image is subjected to a correction process followed by pre-processing operation. Feature extraction is one essential approach in this scheme which is further followed by the calibration of the model. Finally, the calibrated model undergoes validation.

The outcome of both the standard approach is applied for model application in order to generate a predictive map [4]. The existing study found that research is carried out in three different directions toward solving problems associated with i) unmixing, ii) classification, and iii) target detection. The unmixing process has various further schemes, i.e., spatial-spectral [5], sub-pixel mapping [6], end-member extraction, and sub-pixel mapping [7], which all come under linear process. There are also wide ranges of studies on classification problems where the investigated solutions are mainly classified into two types, viz. i) spatial-spectral and ii) pixel-wise. The spatial-spectral classification schemes are mainly found to use feature extraction [8], supervised feature learning [9], unsupervised feature learning [10], and semi-supervised learning [11]. In contrast, the pixel-wise classification approach is mainly classified into a transfer learning scheme [12][13], a band selection scheme [14][15], and dimensional reduction [16]. Various schemes are also found for target detection, mainly using spatial and spectral approaches. The most frequently found techniques are deep learning, clustering, gaussian model, logistic regression, linear

regression, support vector machine, directed graphical models, ensemble learning, latent linear model, gaussian mixture model, and sparse linear models.
However, it is found that there is scattered work on the approaches in HSI, and a more structured and updated report is required to highlight the most prominent approach. This paper discusses frequently adopted operations toward classification to understand its underlying issues. The paper's organization is as follows: Section II discusses the essentials of HSI, followed by a discussion of the operation of HSI with different perspectives in Section III. Section IV discusses the classification approaches of HSI, Section V discusses study findings while discussion while Section VI discusses the research gap, while Section VII summarizes the conclusion and future work.

Essentials of HSI

The conventional camera captures only three channels of color, i.e., red, green, and blue, while the HSI captures more detailed information about the image. HSI is the final capture of remote sensing, which has three essential components, i.e., processing approach, sensors, and scene. Scene modeling consists of various factors, e.g., clouds, shadow effect, contiguity factors, transmittance, etc., in HSI. Sensor modeling will consist of calibration error, quantization noise, thermal noise, shot noise, etc. The processing algorithm will use various approaches of data distribution, linear transformation, atmospheric compensation, etc. While treating HSI, some common operations are i) identifying and rectifying the geometric distortion, ii) performing calibration of the image concerning the visual sensor, and iii) usual image calibration. With the aid of a hyperspectral sensor, the light intensities of hundreds of channels are captured concerning the infrared and visible spectra. It will eventually mean that a hyperspectral image has more detailed information as compared to the normal image-capturing device (Fig.1). The usage of HSI is reported in environmental protection, agriculture, land mapping, etc. HSI can do the tracing of CO_2 as well as other harmful pollutants. Different irrigation levels, the presence of plant disease, and the identification of the type of remote crop are significant contributions of HSI over precision agriculture. Apart from this, the detection of different object classes with higher accuracy can be carried out by HSI.

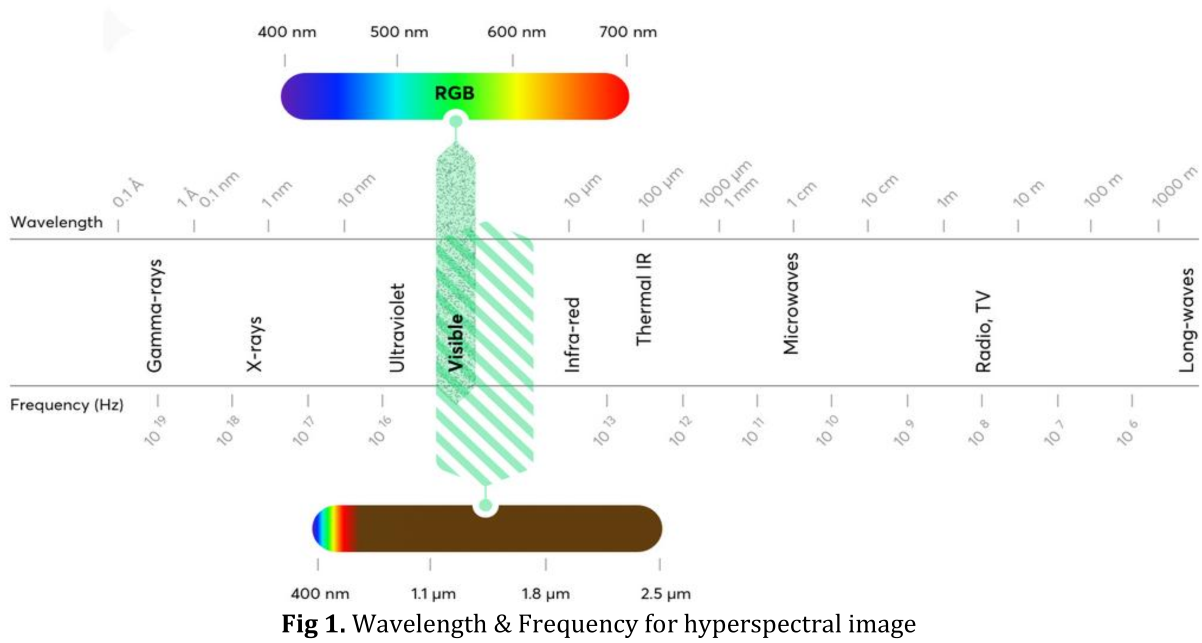

Fig 1. Wavelength & Frequency for hyperspectral image

There are two standard types of analysis methods for HSI data, viz. i) Pure pixel method [17] and ii) mixed pixel method [18]. The pure pixel method considers that a set of the same pixel corresponding to one band represents one object and are indexed as distinct signatures. They are further classified into statistical methods [19] and vegetation index [20]. The mixed pixel method is based on the non-inclusion of the theory that there are no limiting factors of resolution of sensed HSI and no complexity associated with the field. There are two forms of mixed pixel method, i.e., the linear mixture method [21] and the non-linear mixture method [22]. Fig.2 highlights the classification schemes. Various essential factors significantly affect the application of the above-mentioned standard analysis scheme, viz defining the class as well as the number of pixels required to be trained[61]. Despite such beneficial facts, HSI is associated with various challenges; hence, they are not widely used commercially. The first biggest challenge in using HSI is its dependency on the higher cost of satellites. The second bigger challenge is its hyperspectral technologies which require a special skill set and command over most advanced imaging technologies. Apart from this, there is also inadequate standardized data that are labeled and could be used for training.Moreover, there is no uniform standard for constructing such sensors to capture HSI. Another significant challenge is the massive size of data within such hyperspectral images[62]. When HSI generates such higher dimensional data, it offers a potential challenge to reposit the data in one place. Transmitting such massive data over limited bandwidth is another secondary issue, while processing is a tertiary issue connected with HSI. It should be noted that a normal hyperspectral image is a hundred times bigger in size compared to a normal colored image with R, G, and B in it and hence developing an application that can instantly perform processing (like on normal images) on the go is something which cannot be done on the hyperspectral image[63]. All this will eventually affect the classification performance, which is one of the essential features of HSI to detect and classify the object[64]. This report will discuss different forms of processing approach and their strength and weakness associated with them. The next section discusses the frequently adopted operation in HSI and the classification techniques being investigated.

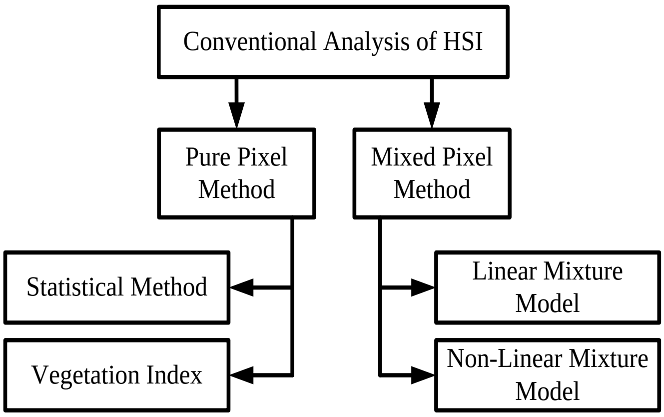

Fig 2. Classifcation of Conventional Analysis of HSI

Review of Operations on HSI

There are currently 5456 conference papers, 2825 Journals, 251 early access articles, 55 magazines, and four books published in IEEE Xplore digital library. Different approaches focus on solving variants of associated issues. This section discusses the observation being carried out towards different approaches over HSI concerning the following categories:

Study Towards Processing HIS Data

Various processing techniques applied on HSI have been witnessed to mainly cater to the demand of making the input image suitable for the specific application. The work by Martel et al. [23] aimed to develop a comprehensive unmixing hyperspectral image considering a Graphic Processing Unit (GPU). The prime assumption of this study is to consider the negligible effect of any secondary reflection or scattering to formulate the unmixing of HSI in the linear form. The study has implemented a simplified unmixing mechanism using GPU to achieve parallelism using an Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) dataset. The study outcome shows that the proposed system offers a lower clock frequency for the Tesla K40c GPU compared to GTX 680, while it offers a better time of execution too. Although the study is a dedicated attempt toward practical processing enhancement; however, its outcome is limited to the GPU being used. The adoption of HSI is also used in micro-spectroscopy, as seen in the work of Ahmed et al. [24], where the study aims to extract specific information from the massive number of noisy infrared bands. The author has developed a pixel classification mechanism using a semi-supervised learning approach. The core aim of the study was then oriented toward dimension reduction as well as the clustering of the pixel. The study assumes that recognizing the cluster is easier when it corresponds to the specific sub-cellular component. The study outcome shows that the presented scheme is better than the supervised scheme in the presence of large variation in the intra-class. Fan et al. [25] have aimed to develop a database system for HSI. The process of the database design is considered by an external source of the spectral data, which is subjected to the exporting towards land class spectral data that is finally imported towards processing HSI system. Further, the pixel spectral data is extracted from the HSI system towards the built database. The system also performs requests of the operation from the HSI system. Spectral library files are also used, which assists in read and write operation. However, the approach has a constraint towards using compatible spectral library files. The contribution observed in the study is that it facilitates observing and comparing, followed by resampling. It can also facilitate spectra importing and exporting. The work carried out by Prasad et al. [26] has addressed the problems associated with the high dimensionality of HSI using the sparsity-based method. The study has emphasized the usage of the reflectance feature. The study assumes that processing HSI can be improved by identifying the suitable components for effective sparse representation. Therefore, the methodology adopted is mainly of morphological segregation of different object shapes, assisting in classification. The study outcome shows that the presented scheme offers enhanced accuracy in the range of 88.7-92.6% compared to existing approaches. One of the unique contributions of the study is that its outcome is compliant with rotation invariance assessed on three different datasets of hyperspectral images. Wei et al. [27] have processed HSI towards a super-resolution scheme where the emphasis is given to the mosaicking method of RGB image exclusively meant for HSI. The study assumes that adopting a conventional mechanism could lead to error-free demosaicing. The presented scheme adopts a methodology in which a regularization method using local low ranks could enrich higher correlation over available spectra and offer significant unique patterns. The study also develops an iterative mechanism towards super-resolution using essential properties of HSI. Assessed over real and synthetic data, the proposed system shows better signal quality than the existing system. Apart from this, there are also studies carried out towards multi-GPU based processing (Florimbi et al. [28]), change detection-based processing (Marinelli et al. [29]), selection of progressive band (Song et al. [30]), dual processing (Wang et al. [31]). Table I. summarizes the approaches mentioned above for processing HSI.

Table 1. Summary of Exisitng Approaches Towards processing HSI

SI.No.	Authors	Research Focus	Methods, Methodology, Tools Used	Research Findings	Conclusions Drawn	Limitations of Study
1	Martel et al.	Unmixing HSI	GPU-based, NVIDIA, GEFORCE	Tesla K40c offers a lower clock frequency than GTX 680	Offers higher parallelism with Tesla K40c	Outcome specific to GPU
2	Kumar et al.	Segmentation	Sem-supervised	F1 score of 71.18%	Better approach compared to random forest & support vector machine	Outcome based on 20 test images only
3	Fan et al.	Database design	Experimental approach	Simpler to access and use hyperspectral data	Facilitates safety inspection	Constraint of using spectral library files
4	Prasad et al.	Decoupling sparsity factor	Morphological segregation of data.	Increased classification accuracy	Offers noise robustness	Iterative scheme would lead to memory consumption
5	Fu et al.	Super-resolution	Resist error propagation	Highly resistive of any level of noise	Supportive of both high and low-resolution input image	Affects the quality of high resolution HSI

Study Towards Pre-processing HIS Data

There is a higher likelihood of artifacts in HSI during the capturing stage. If such images are taken from moving aerial bodies, the chances of the presence of artifacts are higher. Hence, existing literature has introduced various pre-processing approaches to address this problem. This section discusses various ranges of pre-processing approaches being carried out over HSI. The work carried out by Teng et al. [32] addresses the problem associated with the degradation of an image when attempting to recover it from

mixed noise. The study assumes that spatial and spectral information can be used to construct band-based relevance attributes. This study introduces a unique restoration scheme where information is fused while adaptive morphological filtering is applied. The study aims to eliminate mixed noise while it targets to retain the complete spatial data. According to this work, edge information is extracted, followed by obtaining a clustering kernel by applying the edge-growing algorithm. The study uses majority voting and a Gaussian filter as a pre-processing operation, followed by k-means clustering, to obtain adaptive structuring elements. The significant contribution of the study is that it assists in the extraction of restored HSI as well as a class map with the aid of this filtering method. The study outcome shows significantly lower computational time and higher signal quality in contrast to the existing filtering method.
Image denoising is another significant approach toward pre-processing HSI. Work carried out by Meng et al. [33] suggests that better detection and classification performance can be obtained by applying a denoising scheme. According to the author, obtaining two-dimensional data from high-dimensional HSI leads affects the image quality. In order to address this problem, this work combines PCA with the Tucker decomposition method to carry out the denoising of HSI. The study outcome shows a lower error rate for the Indiana dataset than the PaviaU dataset.Jimenez et al. [34] have conducted a study where the end-member of both spatial and spectral types are considered using GPU owing to its low cost. The study assumes that both spectral and spatial information possess sensitive information, and prioritizing them will hamper certain information. The study's methodology relates to using pre-processing level operation where Multiscale Gaussian filtering is used, followed by calculating spatial homogeneity and purity index of spectral. The study has used Principal Component Analysis (PCA) for this purpose. The essential contribution found for this study is that it does not prioritize information (either spatial or spectral) and treats both equally. The analysis uses the AVIRIS dataset, NVIDIA, and GTX 580 to observe the mean spectral angle distance. The study outcome shows PCA contributes towards enhanced results concerning computation time. A study emphasizing pre-processing in HSI is witnessed in Rasti et al. [35], where the author has worked on image restoration techniques. The study assumes that the l1-least square method is suitable for a signal with unknown knowledge. The study has used a sparse low-rank model where risk estimation is carried out to generate an involuntary approach for image restoration. The result analysis shows that the presented scheme offers better pre-processing performance with cost-effective computational processing. The work carried out by Du et al. [36] has also aimed towards evolving with a unique denoising scheme considering matrix factorization of low rank. According to the study findings, it is claimed that white Gaussian noise usually pollutes HSI. The study also improves the noise estimation mechanism to leverage its efficiency. This work assumes that additive white Gaussian noise of independent and identical nature can corrupt the band of HSI if their standard deviations are different. Using the Washington DC Mall dataset, the study incorporates low-ranking matrix factorization as a noise model. The study outcome shows that the presented scheme performs better accuracy than the existing system. The study offers validated outcomes to prove its accuracy and efficiency. Apart from this, the other pre-processing approaches are CNN-based pre-processing (Maffei et al. [37], Yuan et al. [38], Liu and Lee [39]) and PCA-based optimized pre-processing (Dong et al. [40]). Table 2 summarizes the above-mentioned approaches toward pre-processing HIS

Table 2. Summary of Exisitng Approaches Towards Pre-processing HSI

SI.No.	Authors	Research Focus	Methods, Methodology, Tools Used	Research Findings	Conclusions Drawn	Limitations of Study
1	Teng et al.	Image restoration	Morphological filtering, k-means clustering	Classification accuracy of 98.83%	There is no significant difference between majority voting approach and proposed approach on classification accuracy	Availability of Reference color image
2	Meng et al.	Image denoising	PCA, tucker decomposition	Higher PSNR	Could increase computational complexity	Could lead to higher response time
3	Jimenez et	Pre-	GPU, extraction	PCA	Supports	Outcome

	al.	Processing	of end-members from spatial & spectral, multiscale Gaussian filtering, spatial homogeneity, Principal component Analysis, spectral purity index	improves outcome	parallelism, faster processing	specific to GPU
4	Rasti et al.	Image restoration	Sparse and low rank, l_1-least square	Reliable pre-processing	Computationally less expensive	Frequent change in model parameters demanded
5	Du et al.	Image denoising	Low rank matrix factorization	Patching offers better noise modelling	Inconsistent outcome of accuracy concerning various images	Could lead to computationa l complexity

Study Towards Dimensional Reduction In HSI

The shape and size of the HSI are quite larger, and it imposes various challenges when it comes to storage followed by performing any form of processing over it. Due to a larger number of spectral bands, applying analysis becomes less effective. Hence, the existing system has introduced various approaches toward reducing the dimension of the HSI without affecting the essential information within it. Such approaches target minimizing the computational complexity and filtering the redundancy from the essential features. This section briefly of some of the existing schemes studied toward dimensional reduction. Dong et al. [41] have addressed the problem of dimensional reduction in HSI using a distance metric learning scheme that introduces distinct information in abundance. The study introduces an ensemble learning scheme over local metrics and deals with the data. The presented implementation also targets performing subspace learning in order to retain maximum samples over the same class and keeps away samples from different classes. An ensemble metric is built from this learned class. The presented study carries out only less assumption of data unlikely any existing approaches. The analysis is carried out over the Indian Pines dataset, where SVM and KNN classifiers are used to find that the presented scheme offers better accuracy than other approaches. The problems associated with dimension reduction while performing classification in HSI are addressed in the work of Wang and Liu [42]. The prime aim of the study is to look for a subspace with a low rank to address the degradation in performance owing to applying linear discriminant analysis. This study has integrated a dictionary-based mode function with the weighted low-rank mechanism to characterize the degree of equivalency among the samples with a target of retaining HSI's local and global structure. The work carried out by Berman et al. [43] has addressed the problems associated with the HSI dimension identity, which is used for estimating error factors during the pre-processing operation. The study aims to evaluate the process of estimating dimension and find the possible impact on it owing to band error. The presented study assumes that the banding error is of Gaussian distribution. The study also assumes that white noise exists at a specific variance in the wavelet coefficient. The study's outcome shows that spectral estimators, especially using regression, offer better performance in contrast to existing wavelet-based spatial estimators. Compressive sensing is another uniquely adopted scheme for dimension reduction in HSI. The work of Liu et al. [44] has aimed to accelerate the quality of the reconstructed image obtained from compressive sensing considering the structure of high dimensional data. The study also assumes that significant information is not considered while performing compressive sensing, which could further affect the accuracy. The study has applied a rank minimization approach over the compressed snapshot image, thereby representing it as a non-convex problem. The study constructs an algorithm in order to address this issue along with solving the computational complexity issue as well. The simulated outcome of the study shows that it offers better signal quality than existing schemes. The outcomes are found to offer consistency in all forms of test cases and datasets considered.Yan et al. [45] conducted a study towards dimension reduction, aiming to use non-negative matrix factorization by considering the geometric structure of the HSI data. The study assumes that mutual correlation between tasks could facilitate better adoption of the graph regularization scheme. The feature weight attributes are allocated automatically to harness the additional value-added information associated with spectral and spatial data without any dependency on extra attributes. Therefore, the study addresses the dimension reduction problem by integrating non-negative matrix factorization with a graph regularization scheme in an adaptive fashion. An analysis is being carried out using the Indian Pines, University of Pavia, and Pavia Center datasets to exhibit that the presented system offers better accuracy in object detection than the existing system. The other approaches towards dimensional reduction are neural network-based (Liu and Lee [46]), sparse regularization (Ma et al. [47]), and enhanced path-based technique approach (Feng et al. [48]). Table 3 summarizes the above-mentioned approaches toward dimension reduction in HSI.

Table 3. Summary of Exisitng Approaches Towards Dimension Reduction In HSI

SI.No.	Authors	Research Focus	Methods, Methodology, Tools Used	Research Findings	Conclusions Drawn	Limitations of Study
1	Dong et al.	Dimensional reduction and classification	Ensemble learning, local discriminative distance metric	10% higher accuracy than existing methods	Effective learning scheme	Selection of feature
2	Wang and Liu	Dimension reduction	Weighted low rank representation, linear discriminant analysis	Better accuracy	Size of dictionary has an effect towards performance of dimension reduction	Preservation of lower structures is time consuming
3	Berman et al.	Band error influencing estimation of dimension	Comparative analysis of estimation methods	Regression is superior	Doesn't offer consistency in performance	Doesn't emphasize over unmixing process or extracting significant features much
4	Liu et al.	Improve signal quality of reconstructed image	Minimization approach, block matching, aggregation , projection	Enhances the image quality	Technique is robust to noise	Time of block matching will increase with increase of streams of signal
5	Yan et al.	Dimension reduction	Non-negative matrix factorization, SVM	Enhanced overall accuracies	No extra attribute required for allocation of feature weight	Study outcome differs in accuracy for two different dataset

Classification Approaches In HSI

The conventional camera captures only three channels of color, i.e., red, green, and blue, while the HSI captures hundreds of bands. HSI can be represented as a three-dimensional data cube consisting of one-dimensional information associated with the spectral bands and two-dimensional information associated with spatial data of image attributes. The disparity is connected with the image attributes, e.g., shape and land covers, due to the assignment of fine wavelength for each spectral band. From the viewpoint of the remote sensing application, the classification mechanism is harnessed for representing the assignment process for individual pixels towards the set of specific classes. This process generates a classification map as shown in Fig.3. There are two explicit classification categories, i.e., supervised, and unsupervised approaches of classifiers. In the supervised approach, the training samples are used for classifying the input data for all classes.However, various inevitable challenges are associated with applying a supervised classification scheme toward loss of balance between inadequate accessibility of training samples and high data dimensionality. Apart from this, combining the significant part of spectral and spatial information is necessary to offer beneficial information to the analysis. Classifying HSI has witnessed various evolving approaches and techniques, i.e., i) kernel method, Bayesian method, support vector machine, neural network architecture, and maximum likelihood method.

There is an increasing proliferation of convolutional neural networks and deep learning in classifying HSI. Irrespective of potential advantages, adopting deep learning gives rise to the overfitting problem. One of the prime reasons is the HSI's complex nature compared to the natural image.On the other hand, learning the abstract feature of higher order is permitted in CNN and its deep structure. Hence, CNN is reported to offer a better contribution toward classification performance. CNN also performs training for non-separable data. However, there are also certain complexities associated with the CNN approaches too. Hence, this report discusses some potential approaches toward classifying the HSI.Five hundred six journals, 512 conferences, 87 early access articles, and four magazines published in the last decade towards classification in HSI in IEEE Xplore digital library. A nearly similar trend is also observed in other reputed publications. This section discusses most related work associated with classification techniques:Aptoula [49] aims to perform classification concerning morphological profiles. The author has discussed the usage of the attribute profile and has extended them to perform better classification performance. This method ensures the aggregation of geometric and spectral properties, offering further scope for performing multi-variate functions. The study assumes connectivity for eight neighborhood grayscale with iso-intensity. Analyzed with Pavia and Salinas dataset, the study has used PCA for dimension reduction where the classification accuracy ranges between 90-99%. An in-depth analysis shows that the presented scheme challenges classification in the presence of shadows.A similar approach to using attribute profiles is also seen in the work of Xia et al. [50]. The paper addresses problems associated with modeling spatial information and dimension reduction. The study develops a framework for training classifiers consisting of spatial data. A random subspace ensemble learning approach is used for dimension reduction, while spatial information modeling uses attribute profiles of multiple forms. Adopting an extreme learning machine and decision tree are used as the base classifier. The study outcome was assessed using overall accuracy and diversity as the performance parameter to show that the presented scheme provides higher accuracy.

Zhang et al. [51] have conducted a study to address the computational complexity associated with the existing representation-based approach. All the samples are assumed to reside in low-dimensional subspace if they belong to the equivalent class. The study presents a sparse representation method and different learning approaches for classification. The representation vector is obtained from different forms of features (texture, shape, and spectral) while using joint sparsity over the coefficient of representation. The study also uses a parallel orthogonal matching scheme to optimize. Further, the study also uses information on contextual neighborhoods connected to each feature. The study outcome exhibits that it offers satisfactory classification performance concerning overall accuracy. It is observed that the model offers better accuracy outcomes for multifeatured methods in contrast to single feature methods.Falco et al. [52] have discussed a study that aims to classify HSI in a supervised manner. The idea of the implementation is to emphasize spectral analysis by using Independent Component Analysis (ICA) for reducing features. This process also positively controls the redundancy in data. The study selects the potential representative component by reducing the error due to the reconstruction process while computation is carried out from training samples. Spatial features are extracted, followed by assessing the contextual information associated with each field. This is done by determining the optimal level of representation. The study outcome shows that the proposed system offers accuracy ranging from 96-99.08% for different HSI databases.

The work carried out by Li et al. [53] has developed an approach for performing classification with more emphasis on spectral unmixing of HSI. The study assumes the number of end members to be equivalent to the number of classes. The author aims to develop a semi-supervised approach for classifying HSI where adequate fractions of the end-members are generated using a conventional spectral unmixing approach. The discriminative classification approach represents the pixels characterized by maximum confidence. One of the unique contributions of this study is to integrate the information obtained from spectral unmixing and classification adaptively. The study outcome shows that the proposed system offers better accuracy than the supervised technique, techniques with only unmixing, and a semi-supervised approach. It does all this operation without any dependency on weighted parameters. The work carried out by Wang et al. [54] aimed to develop a system that selects the unsupervised band for assisting in the classification process. Apart from this, the selection of band also assists in mitigating dimension reduction issues in HSI. The study has derived the correlation matrix from investigating the underlying bands. Selection is carried forward for different band combinations using a clustering algorithm. Haut et al. [55] have conducted a study aiming to develop an architecture for power consumption while performing the classification of HSI. The study mainly targets improvising the onboard computing capabilities with a deep learning mechanism. The study assumes that deep learning architecture harnesses its effective optimal search scheme for the best solution, and this concept is applied for better resource conservation in hardware. Using an experimental approach, the study outcome shows that the presented scheme offers higher accuracy of 97.95% while energy consumption is kept lower around 0.0893 wH. The processing time is also controlled within 75.04 s. However, the study does not emphasize on memory perspective.

Feng et al. [56] discussed a unique classification scheme where the study aimed to use a different form of network to classify HSI. The study uses an adversarial network of generative form to extract the samples using a discriminator. However, this scheme cannot be directly applied to HSI; therefore, the presented scheme introduces spectral and spatial attributes to generate samples and define the samples of multiple classes. The study outcome shows that the scheme offers 99% overall accuracy in classifying nine classes of the HSI dataset. Apart from this, the training time and testing time are also found to be satisfactorily reduced. In short, the scheme assists in enhancing the discriminative ability of multi-class. The work carried out by Jia et al. [57] has aimed to develop HSI classification using a fusion concept of a superpixel, which is a representation scheme. The study assumes that including texture information can enhance the classification performance for spatial characteristics of HSI. The study first achieves the extended multi-attribute profiles from input HSI followed by convolving it with Gabor filters. The utilization of the extracted Gabor features is further boosted by using a collaborative classification scheme based on representation. The number of the extracted superpixel is confirmed over multiple scales using a heuristic approach. Despite the higher accuracy obtained in this strategy, the presented scheme has to carry out a higher number of voting operations to decide the class label; thereby, complexity may arise.

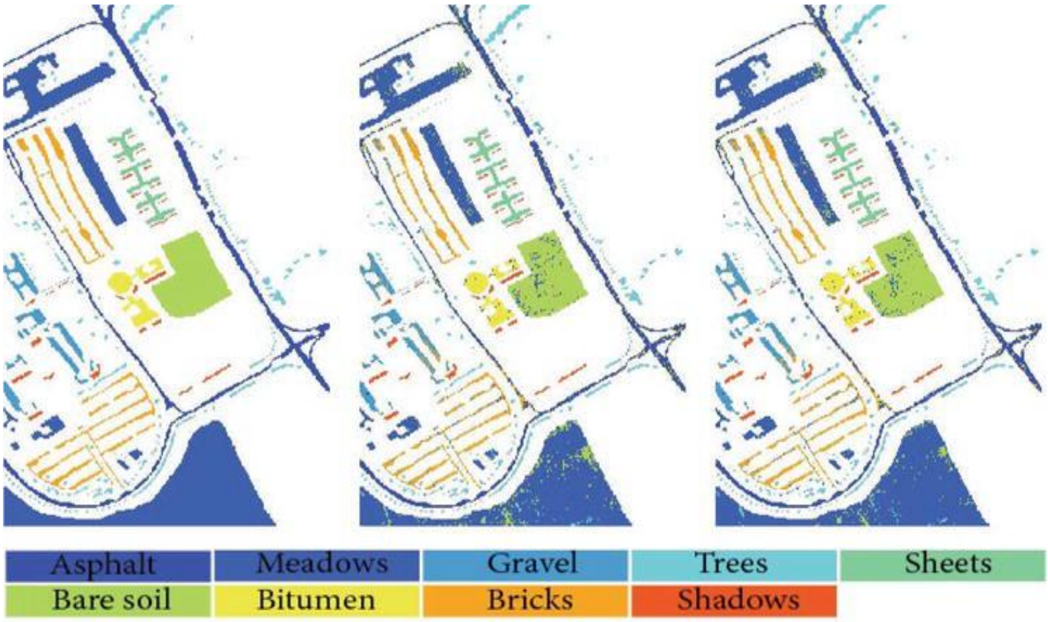

Fig 3. Classifcation outcome in HSI

Song et al. [58] have conducted a study that aimed to select a band of HSI based on class information. The presence of different forms of weight over the specific class of interest can be determined using class information, which is the prime assumption of the study. Using probability concept, the present scheme computes inter and intra-class information criteria. Class entropy is further computed in this study using self-class information. A unique contribution of this method is that it can determine the required training samples for each class, reducing the computational complexity. The model also assists in estimating the weightage of significance associated with each class during the classification operation. The study outcome shows approximately 95% of overall accuracy. The study encourages the usage of different class information, which can be used for effective classification performance. Sun et al. [59] have presented a work toward classifying HSI where spectral and spatial factors are used to construct an attention network. The author has discussed the problems associated with using CNN towards the edge information of the land area, whose pixel information differs from the center pixel. This problem is addressed by implementing an attention network that uses spectral and spatial information. In this model, all the modules involve a few three-dimensional dimensional operations associated with activation and convolution. This simplifies the system for converging in the presence of smaller sets of a sample of training. The study outcome shows the overall accuracy as 92.46%. Apart from this, the study contributes towards mitigating the problems of such interfering pixels. Chang et al. [60] have conducted a study aiming to improve sampling operation for better classification performance. The study addresses the problems associated with the inconsistency in classification due to arbitrary sampling process. When considered with k times, such arbitrary samples could offer better classification accuracy. This paper has discussed an iterative scheme where a specific value of the K is considered to minimize the ambiguity associated with arbitrary sampling. The core idea of the topic is to add the classification map of the spatial filter associated with the image cube. An iterative operation is carried out considering the selection of the newly generated image sample. The summary of above discussed approaches is given Table 4

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Table 4 . Summary of Exisitng Approaches Towards Classifcation Approaches in HSI

Sl.No.	Authors	Research Focus	Methods, Methodology, Tools Used	Research Findings	Conclusions Drawn	Limitations of Study
1	Aptoula	Classification	Extended attribute profiles, PCA	90-99% of accuracy	Ensure homogeneity of distribution of pixel value	Performance degrades in the presence of shadow
2	Xia et al.	Modeling spatial information	Morphological attribute profiles	90-99% overall accuracy	Classification based on spectral and spatial offers better performance	The increased computational complexity for rotational subspace
3	Zhang et al.	Multifeatured learning	Sparse representation, contextual neighborhood	97.78% overall accuracy	The multifeatured method offers higher accuracy	The study depends upon the training dictionary
4	Falco et al.	Classification of spectral & Spatial data	ICA, morphological attribute profiles	The overall accuracy of 96-99.08%	Effective extraction of class-based features,	The inclusion of highly iterative steps could lead to computational complexity.
5	Li et al.	Spectral unmixing	Developing discriminative classifier	Higher accuracy	Competitive classification performance	It does not deal with computational complexity issue
6	Wang et al.	Selection of band	Block diagonal sparsity	Higher overall accuracy	Effective data grouping by trace Lasso normalization	Performance significantly different in a different dataset
7	Haut et al.	Controlling power consumption during classification	Deep learning, convolution neural network	JETSON offers better performance than XEON	Satisfactory accuracy of 97.95% and reduced energy consumption of 0.0893 wH	Memory constraints not considered
8	Feng et al.	Classification of HSI	Spectral-spatial multi-class approach, adversarial	Addresses problems associated with	Effectively generate real multi-class samples	The system is an extensively memory-dependent

			network	smaller sample size		solution
9	Jia et al.	Classification of HSI	Collaborative representation, Gabor Filter, Heuristic strategy, Super-pixel fusion	92-100% accuracy obtained	The technique supports different sizes of HSI,	Focuses only on spatial resolution
10	Jia et al.					
11	Song et al.	Classification of HSI	Selection of band based on class information, probability modeling	95% of overall accuracy	Performs intra and interclass analysis	Response time gets affected by increasing inclusion of classinformation
12	Sun et al.	To suppress interfering pixel	Attention network using spectral and spatial information	92.46% of overall accuracy	Simple to converge due to lesser activation of three-dimensional convolution	The model does not encode the orientation and object position.
13	Chang et al.	Classification of spectral-spatial sample	Random training sample in an iterative manner	Increased rate of classification	Highly extensive model as it can be used with any classifier	This could lead to computational complexities with increasing iteration

RESEARCH FINDINGS AND DISCUSSION

Summary of Operations in Hyperspectral Image

After reviewing the trends of the existing approaches towards hyperspectral images, it is seen that there are prominently three categories of research work, i.e., approaches towards processing, pre-processing, and dimension reduction. Following are the learning outcomes of the review of literature:

- The primary problem is associated with the higher dimensional data in HSI, which significantly challenges implementing supervised classification techniques. The sophisticated structure of HSI data and restricted training sample availability are the biggest impediments in this case.
- Not all the implemented solution has considered both spatial and spectral information, while both are essential to apply an unsupervised mechanism of processing HSI data.
- Another significant observation is that few studies focus on achieving parallelism toward implementing its algorithm. Processing HSI demands higher computational resources and needs to boost the algorithm processing time, which is less emphasized in the existing approach. Such approaches are unsuitable for time or mission-critical applications as they are highly inclined towards regular computation.
- Support Vector Machine is one of the most frequently adopted classifiers in processing HSI data. However, the most challenging aspect is to adopt a higher iterative process to opt for samples (patterns in the proximity of unlabeled marginal bound) and a specific number of labeled samples. Other associated issues are performing multi-class extension, regularization parameter selection, and constructing threshold criteria.
- The pre-processing approach can be considered a significant contribution in existing times that deals with making the HSI input highly suitable and error-free so that it can be subjected to different levels of analytical processing. The accuracy significantly increases by applying pre-processing; however, not all standard approaches consider pre-processing, which is the first step. Assuming that pre-processing exists, the next level of work could anticipate more accuracies while performing classification operations.

Apart from this, one common observation is that all the studies on HSI have been carried out toward achieving classification accuracy by addressing various related problems. This fact concludes that further understanding the impact of different approaches toward classification performance is necessary. The classification in HSI data is a sophisticated process to identify specific objects from the given data, followed by structuring them to analyze the data more effectively. Hence, irrespective of the existing trend towards evolving out-processing, pre-processing, and dimension reduction-based methods, they directly contribute to the final goal of classification. Under this classification process, each pixel is assigned a class label for better study objects. The existing study on processing spectral data offers a precise environment for supervised classification. Various applications can be designed in this direction, e.g., management of resources, detection of the target, surveilling changes in land, etc. There is wider availability of supervised classification technique that has already been used in existing approaches, e.g., SVM, random forest, decision tree, maximum likelihood, etc. However, such approaches can be applied only over labeled data to carry out classifier training. Apart from this, existing studies have also focused on using the KNN classifier. Although they are used in sorting out dimension reduction problems, they are essentially used for classification. It is already known that classification based on the pixel is not possible in a massive size of HSI; therefore, it is essential to perform classification based on the allocation of specific classes of an object. However, it is noticed that irrespective of using existing pre-processing and processing followed by dimensional reduction, the problems associated with a lesser degree of interclass variability in the existing system remain unaddressed. On the other hand, adopting spatial information can benefit classification based on the pixel, while spectral information offers richness. Hence, it can be concluded that there is a need to perform a study towards understanding the technical effectiveness of solving classification-based problems with consideration that existing approaches towards processing, pre-processing, and dimensional reduction could be further complimentary towards supporting better classification performance.

Summary of Operations in Hyperspectral Image

- The existing system frequently uses the supervision classification approach (maximum likelihood function, decision tree, artificial neural network, support vector machine). Most studies claim benefits for adopting SVM due to lower dependencies towards training samples. However, it should be noted that they are not yet been proven to solve problems associated with multi-classification.
- Deep learning is another frequently adopted technique used in classifying HSI owing to its inclusion of both spectral and spatial processes. Although it originated from an artificial neural network, the deep learning-based classification approach claims to be robust.
- There are also approaches associated with the unsupervised classification approach, which usually considers the similarity of spectral features of HSI. It will mean that it enables the clustering method without dependency on apriori information. Hence, such approaches are mainly based on assumption and construct clusters using various classification processing along with the inclusion of an iterative process. Adopting this classification approach reduces the possibility of human-based errors; however, they demand extensive post-processing to prove the higher reliability of their overall accuracies. It also lacks consistency.
- The next approach is a semi-supervised classification which has evolved owing to issues with the supervised approach (higher accuracy depends upon an increasing number of trained data). The classifiers are trained using unlabeled and labeled data in a semi-supervised approach to classification. The success factor of using this method is good, but unfortunately, not much work is carried out.
- Another classification approach is the self-training approach. Although it offers a simple classification scheme, it also has an issue. Achieving higher accuracy is quite challenging in this approach owing to a limited number of training samples. When labeling is carried out over unlabeled samples, there is a higher probability of noise sample inclusion. Apart from this, it also includes higher iteration with an accumulation of more errors causing an unreliable classification process.

Research Gap

At present, different schemes of classifications exist. It is observed that researchers in existing times encourage the usage of supervised and unsupervised schemes most dominantly owing to their various beneficial outcomes; however, there are also associated limitations with this. It is observed that supervised classification schemes have a potential dependency on the information of apriori condition, whereas adding human intervention will positively influence the classification performance. Hence, depending upon various demands of existing and upcoming applications of remote sensing using HSI, integrated with the extraction of HSI, there is an emergent need to integrate multiple techniques in a hybrid form for better classification performance. Apart from this, the theory used in the classification approach in HSI has reported issues that are not much to be addressed in the reviewed literature. Hence, machine learning schemes require more amendments to address such issues. The significant research problems associated with the existing approaches of machine learning approaches towards data processing are as follows:

- Most of the existing machine learning approaches have been implemented by considering a specific dataset, which does not offer a higher-end complexity. The impact of complex data for processing, although it exists, has never been investigated.
- There was also not much focus on extracting specific traits or representation of any unique attribute as there was a lack of complexity consideration of data.
- Most of the machine learning approaches implemented were highly recursive, focusing less on the quality of processed data.
- There was no typical consideration of data processing where all the existing systems take the input data and subject it to training. The possibility of efficient data processing is missing in the existing system.Dynamic and real-time data can have a significant stochastic characteristic which will pose a challenge in identifying any significant or unique attribute within it; hence it may also pose an impediment to another level of data processing.

CONCLUSION AND FUTURE DIRECTION

This paper discusses various techniques that are associated with various analyses and processing for HSI. All the reported approaches have been claimed for beneficial outcomes; the paper contributes towards carrying out an exhaustive review to extract the strengths and weaknesses of existing approaches. There is an emergent need to evolve with better computational modeling that leads toward an effective classification performance in HSI. Hence, the future direction of the work will be towards adopting machine learning to optimize classification performance. The prime aim of future research will be to develop a novel framework of object classification of the hyperspectral image with more emphasis on data processing using a cost-effective and highly efficient novel design of a machine learning approach. The future study will target accomplishing an optimal computational classification model with stochastic data processing and effective validation technique to showcase its applicability in real-life situations.

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