Hyperspectral Image Classification - Traditional to Deep Models: A Survey for Future Prospects

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Abstract—Hyperspectral Imaging (HSI) has been extensively utilized in many real-life applications because it benefits from the detailed spectral information contained in each pixel. Notably, the complex characteristics i.e., the nonlinear relation among the captured spectral information and the corresponding object of HSI data make accurate classification challenging for traditional methods. In the last few years, deep learning (DL) has been substantiated as a powerful feature extractor that effectively addresses the nonlinear problems that appeared in a number of computer vision tasks. This prompts the deployment of DL for HSI classification (HSIC) which revealed good performance. This survey enlists a systematic overview of DL for HSIC and compared state-of-the-art strategies of the said topic. Primarily, we will encapsulate the main challenges of traditional machine learning for HSIC and then we will acquaint the superiority of DL to address these problems. This survey breakdown the state-of-the-art DL frameworks into spectral-features, spatial-features, and together spatial-spectral features to systematically analyze the achievements (future directions as well) of these frameworks for HSIC. Moreover, we will consider the fact that DL requires a large number of labeled training examples whereas acquiring such a number for HSIC is challenging in terms of time and cost. Therefore, this survey discusses some strategies to improve the generalization performance of DL strategies which can provide some future guidelines.

Index Terms—Hyperspectral Imaging (HSI), Hyperspectral Image Classification (HSIC), Deep Learning (DL), Feature Learning, Spectral-Spatial Information.

I. INTRODUCTION

Hyperspectral Imaging (HSI) is concerned with the extraction of meaningful information based on the radiance acquired by the sensor at short or long distance without making substantial contact with the object of interest [1]. In short, HSI provides detailed spectral information by sampling the reflective portion of the electromagnetic spectrum covering a wide range of 0.4 – 2.4 μm i.e. visible 0.4 – 0.7 μm to short wave infrared 0.7 – 2.4 μm in regions of narrow and contiguous spectral bands. HSI can also explore the emissive properties of objects in the range of mid to long infrared regions [2].

Despite the detailed information that provides many opportunities, it brings several challenges as well which includes, traditional techniques used to analyze monochromatic, RGB, and multispectral images that cannot be directly deployed to extract meaningful information captured by Hyperspectral sensor due to many reasons. For instance, HSI exhibits the unique statistical and geometrical properties of high dimensional spectral/spatial data, i.e. the volume of a hypercube and hypersphere concentrates on corners and outside shells respectively [2].

HSI has been utilized for several real-world applications including but not limited to the atmosphere, ecology, urban, agriculture, geology and mineral exploration, coastal zone, marine, forestry i.e. track forest health, water quality and surface contamination, inland waters and wetlands, snow and ice, biological and medical (A few applications have been shown in Figure 1). There are several military applications in camouflage, landmine detection, and littoral zone mapping. HSI has been used in space, air, and underwater vehicles to acquire detailed spectral information for a wide range of uses as well [3] - [5]. Therefore, it is quite important to detach the surface features where each feature has a different spectrum band. HSI can capture more than 200 spectral bands which helps practitioners to discriminate objects that were not possible before.

In this survey, we specifically focus on HSI data classification (HSIC), which has achieved a phenomenal interest of the research community due to its broad applications in the areas of land use and land cover [29] - [32], environmental monitoring and natural hazards detection [53], [54], vegetation mapping [55], [56] and urban planning. HSIC methodologies exploit machine learning algorithms to perform the classification task [57], [58]. These methods are outlined in various comprehensive reviews published.
Section V describes few commonly used types of layers and representations and basic machine learning strategies, respectively. In section III HSI data characteristics along with the advantages and limitations of DL that are faced while working with HSI. The main task of HSIC (HSI Classification) is to assign a unique label to each pixel of an HSI cube based on its spectral or spectral-spatial properties. Mathematically, an HSI cube can be represented as $X = \{x_{1,1}, x_{2,1}, \ldots, x_{B,1}\}^T \in \mathbb{R}^{B \times (N \times M)}$, where $B$ represent total number of spectral bands consisting of $(N \times M)$ samples per band belonging to $Y$ classes where $x_{i} = [x_{1,i}, x_{2,i}, x_{3,i}, \ldots, x_{B,i}]^T$ is the $i^{th}$ sample in the HSI cube with class label $y_{i} \in \mathbb{R}^{Y}$. The classification problem can be considered as an optimization one, in which a mapping function $f_{c}(\cdot)$ takes the input data $X$ and after applying some transformations over it, obtains the corresponding label $Y$, to reduce the gap between obtained output and the actual one.

$$Y = f_{c}(X, \theta)$$

where $\theta$ is certain parameter that may be required to apply transformations on input data $X$ such that $f_{c} : X \rightarrow Y$.

In literature, substantial work has been done on HSIC and there is a growing trend in the development of such techniques as shown in Figure 2. Most HSIC frameworks seemed to be influenced by the methodologies used in the computer vision domain. Traditional machine learning-based HSIC approaches use hand-crafted features to train the classifier. These methods generally rely on utilizing engineering skills and domain expertise to design several human-engineered features, for instance, shape, texture, color, shape, spectral and spatial details. All these features are basic characteristics of an image and carry effective information for image classification. Commonly used hand-crafted methods include : texture descriptors such as Local Binary Patterns (LBPs) [51], Histogram of Oriented Gradients (HOG) [52], Global Image Scale-invariant Transform / Global Invariant Scalable Transform (GIST) [53], Pyramid Histogram of Oriented Gradients (PHOG), Scale-invariant Feature Transform (SIFT) [54], Random Forests [55] and kernel-based Support Vector Machine (SVM) [56].

Color histograms are simple and effective handcrafted features used for an image classification task. They are easy to compute and invariant to small changes in images i.e. translation and rotation. The major drawback of a color histogram is that it does not provide spatial contextual information, hence it becomes difficult to distinguish between objects of the same color but different distribution. Moreover, color histograms are sensitive to variance in illumination. HOG features represent the histogram of edge orientations of spatial sub-regions. It can effectively extract the edge and local shape details and have been utilized in various remote sensing related works [32], [57], [58].

Scale-invariant Feature Transform (SIFT) is a broadly used robust feature descriptor applied to image classification tasks [59]–[62]. The advantage of the SIFT descriptor is that it is invariant to the changes in image scale, rotation, illumination, and noise. SIFT is used to extract local features that describe a specific point in the image. The disadvantage of SIFT is that it is mathematically complex which increases its computational cost.
GIST represents the global description of important aspects of an image that is the scales and orientations (gradient information) of various subregions of an image. GIST basically builds a spatial envelope in terms of different statistical properties like roughness, openness, and ruggedness, etc [63]. Texture descriptors such as local binary patterns (LBPs) are used for remote sensing image analysis [51]. LBPs are used to describe the texture around each pixel by choosing pixels from the square neighborhood and gray level values of all neighborhood pixels are thresholded with respect to the central pixel.

The color histograms, GIST, and texture descriptors are global features that represent the certain statistical characteristics of an image like color, texture [64], [65], and spatial structure [53]. While HOG and SIFT are local features that describe geometrical information. Usually they are used to construct bag-of-visual-words (BoVW) models [30], [31], [34], [62], [66]–[71] and HOG feature-based models [32], [72]. Some popular feature encoding or pooling strategies to enhance the performance of BoVW are Fisher vector coding [51], [73], [74], Spatial Pyramid Matching (SPM) [75], and Probabilistic Topic Model (PTM) [71], [76]–[78]. A single feature is insufficient to represent the whole image information, hence a combination of these features is used for image classification [30], [66], [76], [78]–[84].

Hand-crafted features can effectively represent the various attributes of an image, hence work well with the data being analyzed. However, these features may be insubstantial in the case of real data, therefore it is difficult to fine-tune between robustness and discriminability as the set of optimal features considerably vary between different data. Furthermore, human involvement in designing the features considerably affects the classification process, as it requires a high level of domain expertise to design hand-crafted features.

To mitigate the limitations of hand-crafted feature designing, a deep feature learning strategy was proposed by Hinton and Salakhutdinov in 2006 [85]. Deep learning (DL) based methods can automatically learn the features from data in a hierarchical manner, to construct a model with growing semantic layers until a suitable representation is achieved. Such models have shown great potential for feature representation in remote sensing image classification [86], [87].

DL architectures can learn the behavior of any data without any prior knowledge regarding the statistical distribution of the input data [88] and can extract both linear and non-linear features of input data without any pre-specified information. Such systems are capable of handling HSI data in both spectral and spatial domains individually, and also in a coupled fashion. DL systems possess a flexible architecture in terms of types of layers and their depth, and adaptive to various machine learning strategies like supervised, semi-supervised, and unsupervised techniques.

B. Hyperspectral Data Characteristics and DL Challenges

Despite the above discussed DL potentials, there are still some challenges that need to be considered while applying DL to HSI data. Most of these challenges are related to the characteristics of HSI data i.e. hundreds of contiguous and narrow spectral channels with very high spatial resolution throughout the electromagnetic spectrum coupled with limited availability of training data. Although the pixels with rich spectral information are useful for classification purposes however, the computation of such data takes a lot of time and resources.

Furthermore, processing such high dimensional data is a somewhat complex task due to an increased number of parameters. This is known as the curse of dimensionality which considerably influences the classification performance especially in the case of supervised learning [89]. Since the size of training data is not adequate/insufficient and/or not reliable (i.e. the training samples may not provide any new information to the model or may have similar patterns/structures) to properly train the classifier which may lead the model to overfit. This is known as Hughes phenomena [90] which occurs when labeled training data is significantly smaller than the number of spectral bands present in the data. Lack of labeled HSI data is a major issue in HSIC as labeling of HSI is a time consuming and expensive task because it usually requires human experts or investigation of real-time scenarios.

In addition to high dimensionality, HSIC suffers from various other artifacts like high intra-class variability due to unconfined variations in reflectance values caused by several environmental interferers and degradation of data caused by instrumental noise while capturing the data [91]. Furthermore, the addition of redundant bands due to HSI instruments affects the computational complexity of the model. Spectral mixing is another challenge related to the spatial resolution of HSI. HSI pixels with low to average spatial resolution cover vast spatial regions on the surface of earth leading to mixed spectral signatures which result in high inter-class similarity in border regions. As a result, it becomes difficult to identify the materials based on their spectral reflectance values [92]. Following are some main challenges that come across when DL is applied to HSIC:

- **Complex Training Process**: Training of Deep Neural Network (DNN) and optimization by tuning parameters is an NP-complete problem where the convergence of the optimization process is not guaranteed [93]. Therefore, it is assumed that training of DNN is very difficult [88] especially in the case of HSI when a large number of parameters need to be adjusted/tuned.
- **Limited Availability of Training Data**: As discussed above, supervised DNN requires a considerably large amount of
training data otherwise their tendency to overfit increases significantly [94] leads to the Hughes phenomena. The high dimensional characteristic of HSI coupled with a small amount of labeled training data makes the DNNs ineffective for HSIC as it demands a lot of adjustments during the training phase [50].

- **Model’s Interpretability**: The training procedure of DNNs is difficult to interpret and understand. The black box kind of nature is considered as a potential weakness of DNNs and may affect the design decisions of the optimization process. Although, a lot of work has been done to interpret the model’s internal dynamics.

- **High Computational Burden**: One of the main challenges of DNNs is dealing with a big amount of data that involves increased memory bandwidth, high computational cost, and storage consumption [95]. However, advanced processing techniques like parallel and distributed architectures [96], [97] and high-performance computing (HPC) [92] make it possible for DNNs to process large amounts of data.

- **Training Accuracy Degradation**: It is assumed that deeper networks extract more rich features from data [99], however, this is not true for all systems to achieve higher accuracy by simply adding more layers. Because by increasing the network’s depth, the problem of exploding or vanishing gradient becomes more prominent [99] and affects the convergence of the model [98].

### III. HSI REPRESENTATION

Hyperspectral data is represented in the form of a 3D hyperspectral cube, \(X \in \mathbb{R}^{B \times (N \times M)}\), which contains 1D spectral and 2D spatial details of a sample where \(B\) represents the total number of spectral bands and \(N\) and \(M\) are spatial components. The HSI cube is shown in Figure 4.

![Hyperspectral Cube](image)

**Fig. 4: Hyperspectral Cube**

#### A. Spectral Representation

In such representations, each pixel vector is isolated from other pixels and processed based on spectral signatures only which means the pixel is represented only in spectral space \(x_i \in \mathbb{R}^B\). Where \(B\) can either be the actual number of spectral channels or just relevant spectral bands extracted after some dimensionality reduction (DR) method. Usually, instead of using original spectral bands, a low dimensional representation of HSI is preferred for data processing in order to avoid redundancy and achieve better class separability, without considerable loss of useful information.

Dimensionality Reduction (DR) approaches for spectral HSI representation can either be supervised or unsupervised. Unsupervised techniques transform the high dimensional HSI into a low dimensional space without using the class label information, for example, Principal Component Analysis (PCA) and locally linear embedding [100]. On the other hand, supervised DR methods utilize labeled samples to learn the data distribution i.e. to keep data points of the same classes near to each other and separate the data points of different classes. For instance, linear discriminant analysis (LDA), local Fisher discriminant analysis (LFDA) [101], local discriminant embedding (LDE) [102] and nonparametric weighted feature extraction (NWFE) [103]. LDA and LDFA provide better class separability by maximizing the inter-class distance of data points and minimizing the intra-class distance. However, due to the spectral mixing effect, in which the same material may appear with different spectra or different materials may have the same spectral signatures, it becomes difficult to differentiate among different classes based on the spectral reflectance values alone.

#### B. Spatial Representation

To deal with the limitations of spectral representation, another approach is to exploit the spatial information of the pixels, in which pixels in each band are represented in the form of a matrix, \(x_i \in \mathbb{R}^{N \times M}\). Due to high spatial correlation, neighboring pixels have higher probabilities to belong to the same class. Therefore, in the case of spatial representation, neighboring pixels’ information is also considered and the neighborhood of a pixel can be determined using kernel or pixel central window [104]. Some common methods to extract spatial information from HSI cube are morphological profiles (MPs), texture features (like Gabor filters, gray-level co-occurrence matrix (GLCM), and local binary pattern (LBP), etc.) and DNN based methods. Morphological profiles are capable of extracting geometrical characteristics. Few extensions of MPs include extended morphological profiles (EMPs) [105] and multiple-structure-element morphological profiles [106].

The texture of the image provides useful spatial contextual information of HSI. For instance, a Gabor filter, a texture analysis technique, can efficiently obtain the textural information at various scales and orientations. Similarly, LBP can provide rotation-invariant spatial texture representation. The GLCM can effectively determine the spatial variability of HSI by exploiting the relative positions of neighborhood pixels. The DNNs can also extract spatial information of HSI by considering the pixel as an image patch instead of representing it as a spectral vector. The spatial information contained in HSI can also be extracted by combining various of the afore discussed methods. For instance, combined Gabor filter and differential morphological profiles [108] to extract local spatial sequential features for a recurrent neural network (RNN) based HSIC framework.

#### C. Spectral-Spatial Representation

This representation jointly exploits both spectral and spatial information of data. In such approaches, a pixel vector is processed based on spectral features while considering the spatial-contextual information. The strategies that simultaneously use both spectral and spatial representations of HSI, either concatenate the spatial details with spectral vector [44], [109] or process the 3D HSI...
cube to preserve the actual structure and contextual information.

In literature, all these HSI representations are widely exploited for HSIC. Most of the DNNs for pixel-wise classification utilized the spectral representation of HSIs. However, to mitigate the limitations of spectral representation, many efforts have been made to incorporate the spatial information. Recently, joint exploitation of both spectral and spatial features has gained much popularity and led to improved classification accuracy. These HSI feature exploitation approaches, for HSIC, are further discussed in the following sections.

IV. LEARNING STRATEGIES

Deep learning models can adopt various learning strategies that can be broadly categorized into the following:

A. Supervised Learning

In a supervised learning approach, the model is trained based on the labeled training data which means training data is comprised of a set of inputs and their corresponding outputs or class labels. During the training phase, the model iteratively updates its parameters in order to predict the desired outputs accurately. In the testing phase, the model is tested against the new input/test data in order to validate its ability to predict the correct labels. If trained sufficiently, the model can predict the labels of new input data. However, supervised learning of DNNs requires a lot of labeled training data to fine-tune the model parameter. Therefore, they are best suited to scenarios where plentiful labeled data is available. The details of various supervised learning techniques for DNNs will be explained in the respective sections.

B. Unsupervised Learning

In contrast to the supervised learning approach, unsupervised learning techniques learn from the input data with no explicit labels associated with it. These approaches try to identify the underlying statistical structure of input representations or patterns in the absence of corresponding labels. As there is no ground truth available for the training data so it might be difficult to measure the accuracy of the trained model. However, such learning strategies are useful in the cases where we want to learn the inherent structure of such datasets which have a scarcity of training data. The principal component analysis (PCA) is an unsupervised learning technique that can be used to learn a low dimensional representation of the input. Similarly, k-means clustering is another unsupervised learning method that groups the input data into homogeneous clusters.

C. Semi-supervised Learning

The semi-supervised learning technique is half-way between unsupervised and supervised approaches. It learns from the partially labeled datasets that are a small amount of labeled training data can be utilized to label the rest of the unlabeled data. These techniques effectively utilize all available data instead of just labeled data, therefore, these techniques have gained much popularity among the research community and are being widely used for HSIC. The details of these methods are briefly described in section X.

V. DEVELOPMENT OF DNNs (TYPES OF LAYERS)

In the following, we review recent developments of some widely used DNN frameworks for HSIC. We specifically surveyed the literature published from 2017 onward. DNNs exhibit a great variety of flexible and configurable models for HSIC that allow the incorporation of several types of layers. Few widely used types of layers are explained in the following subsection.

A. Fully Connected Layers

A fully connected (FC) layer connects every neuron in the lower layer to every neuron in the upper/next layer. Mostly, they are used as the last few layers of a model usually after convolution/pooling layers. FC takes the output of the previous layer and assigns weights to predict the probabilities for class labels. Due to a large number of connections, a large number of parameters need to be adjusted which significantly increases the computational overhead. Moreover, due to a large number of parameters, the model becomes more sensitive to overfitting. However, to mitigate the effect of overfitting, a dropout method is introduced in.

B. Convolutional Layers

The convolutional (CONV) layer convolve the input data or feature maps from a lower layer with the filters (kernels). The filter contains weights whose dot product is calculated with the subset of input data by moving it across the width, height, and depth of the input region. The output of the filter is known as a feature map. CONV layer provides spatial invariance via a local connectivity approach in which the neuron in the feature map connects to a subset of input from the previous layer rather than connecting to every neuron. This reduces the number of parameters that need to train. To further reduce the number of parameters, the CONV layer uses the mechanism of parameter sharing in which the same weights are used in a particular feature map.

C. Activation Layers

Activation layers are assumed to be a feature detector stage of DNNs. FC and CONV layers provide linear representations of input data or it can be said that they work similarly to linear regressors and data transformed by these layers is considered to be at the feature extraction stage. Therefore, to learn non-linear features of data, an activation layer must be used after FC and CONV layers. In the activation layer, feature maps from previous layers go through an activation function to form an
Some commonly used activation functions are sigmoid, hyperbolic tangent (tanh), rectified linear unit (ReLU), and softmax. However, in HSI analysis, softmax and ReLU are widely employed activation functions [50]. Figure 5 presents a graphical representation of a few commonly utilized activation functions.

**D. Pooling or sub-sampling layers**

The pooling layer, also known as the sub-sampling or down-sampling layer, takes a certain input volume and reduces it to a single value as shown in Figure 6. This provides the invariance to small distortions in the data. The pooling layer helps the model to control overfitting as the size of data and model’s parameters both are reduced which also leads to a decrease in the computational time. The commonly used down-sampling operations are max-pooling, average-pooling, and sum-pooling. Recently, a pooling technique, wavelet-pooling is introduced in [125] whose performance is commensurable to max-pooling and average-pooling. Alternatively, [126] proposed another trend in which the pooling layer is replaced by the CONV layer of increased filter stride.

The FE network consists of multiple hierarchically stacked CONV, activation, and pooling layers. The CONV layer extracts the features from input data by convolving a learned kernel with it. On each CONV layer, the kernel is spatially shared with whole input data which reduces the model’s complexity and the network becomes easier to train as the number of parameters that need to be fine-tuned is reduced. Convolved results are then passed through an activation layer which adds nonlinearities in the network to extract non-linear features of the input. This is achieved by applying a non-linear function to the convolved results. Afterward, the resolution of the feature map is reduced by applying a pooling operation to achieve shift-invariance. Generally, the pooling layer is added with every CONV layer followed by the activation function.

The classification stage consisting of FC layers and a Softmax operator gives the probability of input pattern belonging to a specific class based on the feature maps extracted at the FE stage. FC layer connects every single neuron in the previous layer to every neuron in the current layer. In [130] and [131], the authors proposed that the FC layer can be disregarded by using a global average pooling layer. Softmax is commonly used for classification tasks [132]–[134] however, many works have also utilized SVM [135], [136] for this purpose.

In the following, we reviewed three types of CNN architectures for HSIC: i) Spectral CNN, ii) Spatial CNN and iii) Spectral-spatial CNN. Figure 7 illustrates the general architecture of these three frameworks.

**A. Spectral CNN Frameworks for HSIC**

Spectral CNN models only consider 1D spectral information \((x_i \in \mathbb{R}^B)\) as input, where \(B\) could either be the original number of spectral bands or the appropriate number of bands extracted after some dimensionality reduction method. In [137], a CNN structure was proposed to mitigate the overfitting problem and achieved a better generalization capability by utilizes \(1 \times 1\) convolutional kernels and enhanced dropout rates. Moreover, a global average pooling layer is used in place of a fully connected layer in order to reduce the network parameters. To reduce high correlation among HSI bands [131] proposed a CNN architecture for HSIC which fully utilized the spectral information by transforming the 1D spectral vector to a 2D feature matrix and by cascading composite layers consisting of \(1 \times 1\) and \(3 \times 3\) CONV layers, the architecture achieved the feature reuse capability. Similar to [137], [131] also utilized the global average pooling layer to lower the network’s training parameters and to extract high dimensional features.

In [138] authors presented a hybrid model for HSIC in which the first few CONV layers are employed to extract position invariant middle-level features and then recurrent layers are used to
extract spectral-contextual details. Similarly, [111] used a hybrid architecture for classifying healthy and diseased Wheat heads. For the input layer, they transform spectral information into a 2D data structure. In [139] CNN proved to be more effective as compared to SVM and KNN for the spectral based identification of rice seed’s variety. A similar application of CNN was explored in [112] where various varieties of Chrysanthemum were identified using spectral data of the first five PCs of Principal component analysis (PCA). PCA is a dimensionality reduction method that is widely used in many DL applications to handle/preprocess high dimensional data. In [140] PCA was utilized to preprocess medical HSI and then the fusion of CNN kernels with Gabor kernels using dot product is used for classification.

The study [141] analyzed another dimensionality reduction technique Dynamic Mode Decomposition (DMD) which converted 3D HSI data to 2D and then this data is fed to vectorized CNN (VCNN) for classification. To overcome the noise effect in pixel-wise HSIC, a method of averaged spectra is used in [142] where an averaged spectra of a group of pixels belonging to bacterial colonies is extracted for further analysis.

B. Spatial CNN frameworks for HSIC

Spatial CNN models only consider spatial information and to extract the spatial information from HSI data, dimensionality reduction (DR) methods are employed on spectral-domain to lower the dimensionality of original HSI data. For instance, [143] used PCA to extract the first PC with refined spatial information and fed it to a fully CNN framework for classification. Similarly, [144] trained a spatial-based 2D-CNN with one PC. In [145], PCA whitened input data considering three PCs is fed to a random patches network as a 2D-CNN classification framework.

The method proposed in [146] cropped the patches from 2D input images (i.e. images from the different spectral bands) to train a 2D-CNN architecture that learns the data-adaptive kernels by itself. Furthermore, some authors also proposed the utilization of handcrafted features along with the spectral domain reduction. For example, [147] combined the Gabor filtering technique with 2D-CNN for HSIC to overcome the overfitting problem due to limited training samples. The Gabor filtering extracts the spatial details including edges and textures which effectively reduce the overfitting problem. The work [148] proposed a deformable HSIC network based on the concept of deformable sampling locations which can adaptively adjust their size and shape in accordance with HSI’s spatial features. Such sampling locations are created by calculating 2D offsets for every pixel in the input image through regular convolutions by taking into account three PCs. These offsets are able to cover the locations of similar neighboring pixels possessing similar characteristics. Then structural information of neighboring pixels is fused to make deformable feature images. Regular convolution employed on these deformable feature images can extract more effective complex structures.

C. Spectral-Spatial CNN frameworks for HSIC

Spectral-spatial pixel-wise HSIC can be achieved by integrating spatial features into spectral information. For instance, [149] presented an improved pixel pair feature (PPF) [150] approach called spatial pixel pair feature which is different from traditional PPFs with respect to two main aspects: one is the selection of pixel pair that is only the pixel from the immediate neighborhood of central pixel can be used to make a pair, second is the label of pixel pair would be as of central pixel. An efficient deep 3D-CNN framework was proposed in [151] that simultaneously exploits
both spectral and spatial information for HSIC. Similarly, to reflect the variations of spatial contexture in various hyperspectral patches, [152] implemented an adaptive weight learning technique instead of assigning fixed weights to incorporate spatial details.

The work [152] proposed a two-stage framework for joint spectral-spatial HSIC which can directly extract both spectral and spatial features instead of independently concatenating them. The first stage of the proposed network is comprised of a CNN and softmax normalization that adaptively learns the weights for input patches and extracts joint shallow features. These shallow features are then fed to a network of Stacked Autoencoder (SAE) to obtain deep hierarchical features and final classification is performed with a Multinomial Logistic Regression (MLR) layer. A 3D-CNN model was introduced in [153] to jointly exploit spectral-spatial features from HSI and to validate its performance comparison is performed with spectral based DBN, SAE, and 2D-spatial CNN for HSIC.

The work [154] proposed a deep multiscale spectral-spatial feature extraction approach for HSIC which can learn effective discriminant features from the images with high spatial diversity. The framework utilizes the Fully Convolutional Network (FCN) to extract deep spatial information and then, these features are fused with spectral information by using a weighted fusion strategy. Finally, pixel-wise classification is performed on these fused features.

In [155] a dual-channel CNN framework was implemented for spectral-spatial HSIC. In the proposed approach, 1D-CNN is used to hierarchically extract spectral features and 2D-CNN to extract hierarchical spatial features. These features are then combined together for the final classification task. Furthermore, to overcome the deficiency of training data and to achieve higher classification accuracy, the proposed framework is supported by a data augmentation technique that can increase the training samples by a factor of 6. In [156], a multiscale 3D deep CNN is introduced for end-to-end HSIC which can jointly learn both 1D spectral and 2D multiscale spatial features without any pre-processing or post-processing techniques like PCA, etc. In order to reduce the band redundancy or noise in HSI, [157] explored a novel architecture for HSIC by embedding a band attention module in the traditional CNN framework. The study [158] proposed an HSIC architecture in which PCA transformed images are used to obtain multi-scale cubes for handcrafted feature extraction by utilizing multi-scale covariance maps which can simultaneously exploit spectral-spatial details of HSI. These maps are then used to train the traditional CNN model for classification.

The work [159] combined CNN with metric learning-based HSIC framework which first utilizes CNN to extract deep spatial information using the first three PCs extracted by PCA. Then, in a metric learning-based framework, spectral and spatial features are fused together for spectral-spatial feature learning by embedding a metric learning regularization factor for classifier’s training (SVM). Similarly, [160] combines multi-scale convolution-based CNN (MS-CNN) with diversified deep metrics based on determinantal point process (DPP) [161] priors for (1-D spectral, 2-D spectral-spatial, and 3-D spectral-spatial) HSIC. Multiscale filters are used in CNN to obtain multi-scale features and DPP based diversified metric transformation is performed to increase the inter-class variance and decrease intra-class variance, and better HSI representational ability. Final classification maps are obtained by using a softmax classifier.

In recent work, [162] an HSIC framework is proposed to extract multi-scale spatial features by constructing a three-channel virtual RGB image from HSI instead of extracting the first three PCs through PCA. The purpose of using a three-channel RGB image is to utilize existing networks trained on natural images to extract spatial features. For multi-scale feature extraction, these images are passed to a fully convolutional network. These multi-scale spatial features are fused together and further joined with PCS extracted spectral features for final classification via SVM.

A two-branch (spectral and spatial) DNN for HSIC was introduced in [163]. The spatial branch consists of a band selection layer and a convolutional and de-convolutional framework with skip architecture to extract spatial information of HSI, and in the spectral branch, a contextual DNN is used to extract spectral features. The paper [164] introduced an adaptive band selection based semi-supervised 3D-CNN to jointly exploit spectral-spatial features. Similarly, in [165] spectral-spatial features are simultaneously exploited in an unsupervised manner using a 3D convolution autoencoder. A hybrid 3D − 2D-CNN architecture was presented by [166] in which 3D-CNN is first used to extract joint spectral-spatial features and then 2D-CNN is further used to obtain more abstract spatial contextual features. The study [167] proposed a Bayesian HSIC architecture that combines CNN with Markov random field. The CNN first extracts joint spectral-spatial features and then a smooth MRF prior is placed on class labels to further refine the spatial details.

D. Future directions for CNN-based HSIC

In the preceding section, we have reviewed the recent developments of CNNs for HSIC. Although CNNs’ based HSIC frameworks have achieved great success with respect to classification performance, there are still many aspects that need further investigation. For instance, there is a need to further work on such models that can jointly employ spatial and spectral information for HSIC. Many of the above-surveyed frameworks use dimensionality reduction methods to achieve better spectral-spatial representation but such approaches discard useful spectral information of HSI. Hence the development of robust HSIC approaches that can preserve the spectral information is required. However, processing of such approaches increases the computational burden, and the training process becomes slower, therefore, parallel processing of such networks using FPGAs and GPUs is desired in order to achieve the computationally fast models, that can even be suitable for mobile platforms, without the performance degradation. Moreover, as the CNNs are becoming deeper and deeper, more labeled training data is required for accurate classification, and as discussed before, there is a lack of labeled training data in HSI. In order to overcome this issue, more research is required to integrate the CNN with unsupervised or semi-supervised approaches.

VII. AUTOCODEC (AE)

Autoencoder (AE) is a popular symmetrical neural network for HSIC due to its unsupervised feature learning capability. AE itself does not perform a classification task instead it gives a compressed feature representation of high-dimensional HSI data. AE consists of an input layer, one hidden or encoding layer, one reconstruction or decoding layer, and an output layer as shown in Figure 8. AE is trained on input data in such a manner to
encode it into a latent representation that is able to reconstruct the input. To learn a compressed feature representation of input data, AE tries to reduce the reconstruction error that is minimizing the difference between the input and the output.

Whereas, the Stacked Autoencoder (SAE) is built by stacking multiple layers of AEs in such a way that the output of one layer is served as an input of the subsequent layer. Denoising autoencoder (DAE) is a variant of AE that has a similar structure as of AE except for the input data. In DAE, the input is corrupted by adding noise to it, however, the output is the original input signal without noise. Therefore, DAE, different from AE, has the capability to recover original input from a noisy input signal.

To learn high-level representation from data, the work [168] proposed a combination of multi-layer AEs with maximum noise fraction which reduces the spectral dimensionality of HSI, while a softmax logistic regression classifier is employed for HSIC. The study reported in [169] combined multi-manifold learning framework proposed by [170] with Counteractive Autoencoder [171] for improved unsupervised HSIC. The work [172] jointly exploited spectral-spatial features of HSI through an unsupervised feature extracting framework composed of recursive autoencoders (RAE) network. It extracts the features from the neighborhood of the target pixel and weights are assigned based on the spectral similarity between target and neighboring pixels. A two-stream DNN with a class-specific fusion scheme is used to extract spectral features and the second stream is implemented to extract spatial information using Convolutional Neural Network (CNN), while final classification is performed by fusing the class prediction scores obtained from the classification results of both streams.

Another work proposed a hybrid architecture for multi-feature based spectral-spatial HSIC which utilizes Principle Component Analysis (PCA) for dimensionality reduction, guided filters [174] to obtain spatial information and sparse AE for high-level feature extraction. The framework proposed in [175] exploited both spectral and spatial information for HSIC by adopting batch-based training of AEs and features are generated by fusing spectral and spatial information via a mean pooling scheme. Another work [176] developed a spectral-spatial HSIC framework by extracting appropriate spatial resolution of HSI and utilization of stacked sparse AE for high-level feature extraction followed by Random Forest (RF) for the final classification task.

Similarly, [177] also used stacked sparse AE for various types of representation that is spectral-spatial and multi-fractal features along with other higher-order statistical representations. A combination of SAE and extreme learning machine was proposed in [178] for HSIC, which segments the features of the training set and transform them via SAE, after transformation, feature subsets are rearranged according to the original order of training set and fed to extreme learning machine-based classifiers, while Q-statistics is used for final classification result. This processing of feature subsets helps to improve variance among base classifiers [178]. Similarly, in a recent work [179] implemented a computationally efficient multi-layer extreme learning machine-based AE which learns the features in three folds, as proposed in [180] for HSIC.

To overcome the issue of high intra-class variability and high inter-class similarity in HSI, [181] developed a stacked Autoencoder (SAE) based HSIC which can learn compact and discriminative features by imposing a local fisher discriminant regularization. Similarly, in the latest work [182] a k-sparse denoising AE is spliced with and spectral–restricted spatial features that overcome the high intra-class variability of spatial features for HSIC. The study [183] proposed an HSIC architecture that first makes the spectral segments of HSI based on mutual information measure to reduce the computation time during feature extraction via SAE, while spatial information is incorporated by using extended morphological profiles (EMPs) and SVM/RF is used for final classification. Recently, [184] used SAE for the classification of an oil slick on the sea surface by jointly exploit spectral-spatial features of HSI.

A. Future Directions for AE-based HSIC

In the above section, we have surveyed the recent developments of AEs based techniques for HSIC. Although such frameworks provide powerful predictive performance and show good generalization capabilities, more sophisticated work is still desired. Many of the discussed approaches do not fully exploit abundant spatial information so further techniques need to be developed that can fully employ joint spatial and spectral information for HSIC. Moreover, the issue of high intra-class variability and high inter-class similarity in HSI also hinders the classification performance. Many of the above-reviewed works have addressed this issue but
and second is linked with the sparsity and selectivity of training process may result in two problems: first, multiple hidden fine-tuning with the help of labeled samples. However, this pre-training with unlabeled samples and the second is supervised learning process of DBN involves two steps: one is unsupervised comparison with some other classification approaches. The usual classification by combining spectral-spatial information and made a of HSIC. For instance, [187] used DBN for land cover classification.

A detailed overview of RBM can be found at [186]. To extract more comprehensive features from input data, the hidden unit of one RBM can be fed to the visible units of other RBM. This type of layer by layer architecture builds a DBN, which is trained in a greedy manner and can capture deep features from HSI. The architecture of three-layer DBN is shown in Figure 9.

![Fig. 9: Basic architecture of RBM](image)

In literature, several works implemented DBN for the purpose of HSIC. For instance, [187] used DBN for land cover classification by combining spectral-spatial information and made a comparison with some other classification approaches. The usual learning process of DBN involves two steps: one is unsupervised pre-training with unlabeled samples and the second is supervised fine-tuning with the help of labeled samples. However, this training process may result in two problems: first, multiple hidden units may tend to respond similarly [188] due to co-adaptation [189] and second is linked with the sparsity and selectivity of activations neurons that are some neurons may always be dead or always responding [190]. To mitigate these two problems, [191] introduced a diversified DBN model through regularizing the pre-training and fine-tuning process by imposing a diversity prior to enhancing the DBN’s classification accuracy for HSI.

To extract efficient texture features for the HSIC, the work [192] proposed a DBN based texture feature enhancement framework which combines band grouping and sample band selection approach with a guided filter to enhance the texture features, which are then learned by a DBN model and final classification results are obtained by a softmax classifier. The work [193] implemented a parallel layers framework consisting of Gaussian-Bernoulli RBM which extracts high-level, local invariant and nonlinear features from HSI and a logistic regression layer is used for classification.

To improve the classification accuracy, some works are considered to jointly exploit the spectral and spatial information contained in HSI. For instance, [194] introduced a DBN framework with the logistics regression layer and verified that the joint exploitation of spectral-spatial features leads to improved classification accuracy. Similarly, [195] proposed a spectral-spatial graph-based RBM method for HSIC which constructs the spectral-spatial graph through joint similarity measurement based on spectral and spatial details, then an RBM is trained to extract useful joint spectral-spatial features from HSI, and finally, these features are passed to a DBN and logistic regression layer for classification.

### Future directions for DBN-based HSIC

In the preceding section, we have reviewed the latest developments of DBN-based HSIC frameworks. We have observed that relative to other DNNs, very few works have utilized the DBNs for the purpose of HSIC. Therefore, there is a need to further explore the DBN-based robust techniques that can jointly employ spatial and spectral features for HSIC. In addition, another research direction can be the regularization of the pretraining and fine-tuning processes of DBN to efficiently overcome the issue of dead or potentially over-tolerant (always responding) neurons.

### IX. RECURRENT NEURAL NETWORK (RNN)

The architecture of the Recurrent Neural Network (RNN) (Shown in Figure 11) comprises loop connections, where the node activation of the next step depends on the previous step [196]. Therefore, RNNs are capable of learning temporal sequences. RNN models process the spectral information of HSI data as time sequence considering the spectral bands as time steps [197]. There are three basic models of RNN a) Vanilla, b) Long-Short-Term Memory (LSTM) and c) Gated Recurrent Unit (GRU).

Vanilla is the simplest RNN model and leads to information degradation while processing high dimensional data. LSTM models composing of two states overcome this issue by controlling the information flow through three gates: input, forget, and output gates. It learns the relevant information over time by discarding the extraneous information. However, the gate controlling strategy makes the LSTM a considerably complex approach. GRU variant of LSTM enjoys the simplicity of the Vanilla model and provides high performance similar to LSTM. GRU is a simpler version of LSTM which modifies the input and forget gate as an update ($z_t$) and reset ($r_t$) gate and removes the output gate. A comparison of LSTM and GRU’s internal architecture is presented in Figure 12.
For the first time, [198] proposed an RNN based HSIC framework with a novel activation function (parametric rectified tanh) and GRU, which utilizes the sequential property of HSI to determine the class labels. In [107] a local spatial sequential (LSS) method based RNN framework was introduced which first extracts low-level features from HSI by using Gabor filter and differential morphological profiles [108] and then fuse these features together to obtain LSS features from the proposed method, these LSS features are further passed to an RNN model to extract high-level features, while a softmax layer is used for final classification.

Keeping in view the usefulness of spatial information to achieve improved classification accuracies, [199] proposed a spectral-spatial LSTM based network that learns spectral and spatial features of HSI by utilizing two separate LSTM followed soft-max layer for classification, while a decision fusion strategy is implemented to get joint spectral-spatial classification results. Similarly, [200] proposed a patch-based RNN with LSTM cells that incorporate multi-temporal and multi-spectral information along with spatial characteristics for land cover classification.

In literature, several works proposed Convolutional Neural Network (CNN) based hybrid RNN architectures (CRNN) for HSIC. For instance, [138] implemented a convolutional RNN in which the first few CONV layers are employed to extract position invariant middle-level features, and then recurrent layers are used to extract spectral-contextual details for HSIC. Similarly, [201] utilized such a model for semi-supervised HSIC by using pseudo labels. The study [202] suggested an HSIC framework in which CNN is used to extract spatial features from HSI, then these features are passed to a GRU based fusion network which performs feature level and decision level fusion.

Similarly, Luo, et.al., [203] exploited both spectral and spatial information contained in HSI by combining CNN with parallel GRU based RNN which simplifies the training of GRU and improves performance. Bidirectional Convolutional LSTM (CLSTM) was proposed in [118] to jointly exploit spectral-spatial feature of HSI for classification. In [204] combined multiscale local spectral-spatial features extracted by 3D-CNN with a hierarchical RNN which learns the spatial dependencies of local spectral-spatial features at multiple scales. Recurrent 2D-CNN and recurrent 3D-CNN for HSIC was proposed in [205] and along with an interesting comparison of these frameworks with their corresponding 2D and 3D-CNN models, which validates the superiority of recurrent CNN. The work [206] integrated CNN with CLSTM in which a 3D-CNN model is used to capture low-level spectral-spatial features and CLSTM recurrently analyzes this low-level spectral-spatial information. Recently, [207], introduced a cascade RNN for HSIC which consist of two layers of GRU-based RNN, the first layer is used to reduce the redundant spectral bands and the second layer is used to learn the features from HSI, furthermore, few convolutional layers are employed to incorporate the rich spatial information contained in HSI.

A. Future directions for RNN-based HSIC

In the above section, we have surveyed the recent developments of AEs based techniques for HSIC. Although RNN-based HSIC frameworks have attracted considerable attention to the remote sensing community and achieved great success with respect to classification performance, there are still many aspects that need further investigation. For instance, the construction of sequential input data for RNN. Most of the surveyed methods considered HSI pixel as a sequential point that is the pixel from each spectral band that forms a data sequence. However, This increases the length of RNN’s input sequence considerably large which can lead to an overfitting issue. Moreover, processing such large data sequences increases the computational time and the learning process becomes slower. Therefore, the use of parallel processing tools needs to be further investigated to achieve good generalization performance of RNN-based HSIC. In addition, approaches like a grouping of spectral bands to decrease the data sequence length and utilization of the entire spectral signature to better discriminate between various classes can further be explored to construct the sequential input of the RNN model. Another interesting future direction may involve the implementation of RNN-based HSIC frameworks in a real multi-temporal HSI context.

X. STRATEGIES FOR LIMITED LABELED SAMPLES

Although DNNs have successfully exploited for the task of HSIC however, they require a considerably large amount of labeled training data. However, as discussed earlier, the collection of labeled HSI is very critical and expensive due to numerous factors that either demand human experts or exploration of real-time scenarios. The limited availability of labeled training data hinders the classification performance. To overcome the aforesaid issue, many effective strategies have been proposed in the literature. In this section, we will briefly discuss some of these strategies while focusing on active learning algorithms.

A. Data Augmentation

To combat the issue of limited training samples, data augmentation is proven to be an effective tool for HSIC. It generates new samples from the original training samples without introducing...
additional labeling costs. Data augmentation approaches can be categorized into two main strategies as i) data wrapping; ii) oversampling [208]. Data wrapping usually encodes several invariances (translational, size, viewpoint, and/or illumination) by conducting geometric and color based transformations while preserving the labels, and oversampling based augmentation methods inflate the training data by generating synthetic samples based on original data distributions. Oversampling techniques include mixture based instance generation, generative adversarial networks (GAN), and feature space augmentations [208].

Referring to HSIC literature, several data augmentation based frameworks have been employed to improve the classification performance by avoiding potential overfitting, which is generally caused by the limited availability of training data. For instance, [209] enhanced the training data by using three data augmentation operations (flip, rotate, and translation), and then this enhanced data is exploited to train CNN for HSIC. The paper [210] presented a comprehensive comparison of various extensively utilized HSI data augmentation techniques and proposed a pixel-block pair-based data augmentation that utilized both spectral and spatial information of HSI to synthesis new instances, to train a CNN model for HSIC. The work [132] compared the classification performance of their diverse region-based CNN framework with and without data augmentation techniques and demonstrated that the data augmentation leads to higher classification accuracies. Similarly, in another comparison [211], data augmentation based CNN exhibited a 10% increase in HSIC accuracy when compared to a PCA based CNN model.

The above-discussed methods utilize offline data augmentation techniques that increase the training data by creating new instances during/before the training process of a model. Recently, a novel data augmentation framework for HSI is proposed in [212] which, rather than inflating the training data, generates the samples at test time, and a DNN trained over original training data along with a voting scheme is used for the final class label. To improve the generalization capability of DNN models, [212] also proposed two fast data augmentation techniques for high-quality data syncretization. A similar PCA based online data augmentation strategy is proposed in [213] which also synthesis new instances during the inference, instead of training.

B. Semi-supervised/Unsupervised Methods

Semi-supervised learning (SSL) approaches learn data distribution by jointly exploiting both labeled and unlabeled data. These techniques expand the training data by utilizing unlabeled samples along with labeled ones in order to construct a relationship between feature space and class labels. Several SSL-based HSIC frameworks have been proposed in the literature that can mainly be categorized as follows: i) Co-training, ii) Self-training, iii) Generative adversarial networks (GANs), iv) Graph-based SSL models and v) Semi-supervised SVM. A recent comprehensive survey on these SSL techniques can be found in [214]. Moreover, another in-depth survey of SSL approaches is also presented in [215].

The SSL-based HSIC techniques are briefly summarized in [216], where authors also made a detailed comparison of these methods. The method presented in [207] used pseudo or cluster-labeled samples to pre-train a CRNN for HSIC and small-sized labeled data is used to fine-tune the network. Similarly, [120] proposed a semi-supervised HSIC framework that exploits PCA and extended morphological attribute profiles to extract pseudo-labeled samples which are fed to a CNN-based deep feature fusion network. The work [217] proposed a dual strategy co-training approach based on spectral and spatial features of HSI. Similarly, [218] separately pre-trained two SAEs, one using spectral and the other using spatial features of HSI, and fine-tuning is achieved via a co-training approach. [219] proposed a region information based self-training approach to enhance the training data. A graph-based self-training framework was developed in [220] where initial sampling is achieved through subtractive clustering. Recently, [121] improved the HSIC performance by pseudo-labeling the unlabeled samples through a clustering-based self-training mechanism and regulate the self-training by employing spatial constraints.

Generative Adversarial Networks (GANs), proposed by [221], are comprised of two neural networks, one is known as a generator and the other is known as discriminator (Figure 13). GANs can learn to replicate the samples by exploiting the data distribution details. The work [222] proposed a spectral feature-based GAN for SSL-based HSIC. Similarly, [223] proposed a GAN-based spectral-spatial HSIC framework. Similarly, [224] developed a CNN-based 1D-GAN and 3D-GAN architectures to enhance the classification performance.

![Fig. 13: A general architecture of generative adversarial network (GAN)](image)

C. Transfer Learning

Transfer learning enhances the performance of a model by using prior knowledge of a relevant primary task to perform a secondary task. In other words, information extracted from the relevant source domain is transfered to the target domain to learn unseen/unlabeled data. Therefore, transfer learning can be effectively employed in domains with insufficient or no training data. Based on the availability of labeled training instances, transfer learning frameworks can further be categorized as supervised or unsupervised transfer learning. Generally, both source and target domains are assumed to be related but not exactly similar. However, they may follow different distributions as in the case of HSIC where categories of interest are the same but data in two domains may vary due to different acquisition circumstances.

In DNN based HSIC, the model learns features in a hierarchical manner, where lower layers usually extract generic features, when trained on various images. Therefore, the features learned by these layers can be transferred to learn a new classifier for the target dataset. For instance, [225] pertained a two branch spectral-spatial CNN model with an ample amount of training data from
other HSIs and then applied the lower layers of the pre-trained model to the target network for the robust classification of target HSI. To learn the target specific features, higher layers of the target network are randomly initialized and the whole network is fine-tuned by utilizing limited labeled instances of target HSI. Similarly, [226] proposed a suitable method to pre-train and fine-tune a CNN network to utilize it for the classification of new HSIs. The study [227] combined data augmentation and transfer learning approaches to combat the shortage of training data in order to improve HSIC performance.

As discussed before, data in source and target domain may vary in many aspects, for instance, in the case of HSIs, the dimensions of two HSIs may vary due to the acquisition from different sensors. Handling such cross-domain variations and transferring the knowledge between them is known as heterogeneous transfer learning (a detailed survey of such methods can be found in [228]). In HSIC literature, several works have been proposed to bridge the gap for transferring the knowledge between two HSIs, with varying dimensions and/or distributions.

For example, [229] proposed an effective heterogeneous transfer learning-based HSIC framework that works well with both homogeneous and heterogeneous HSIs, and [230] used an iterative re-weighting mechanism-based heterogeneous transfer learning for HSIC. Similarly, a recent work [231] proposed a band selection based transfer learning approach to pre-train a CNN, which retains the same number of dimensions for various HSIs. Furthermore, [232] proposed an unsupervised transfer learning technique to classify completely unknown target HSI and [233] demonstrate that the networks trained on natural images can enhance the performance of transfer learning for remote sensing data classification as compared to the networks trained from scratch using smaller HSI data.

D. Active Learning

Active Learning (AL) iteratively enhances the predictive performance of a classifier by actively increasing the size of training data, for each training iteration, by utilizing an unlabeled pool of samples. In each iteration, AL enhances the training dataset by actively selecting the most valuable instances from the pool of unlabeled data and an oracle (Human or machine-based) assigns the true class labels to these instances. Finally, these useful instances are added to the existing training dataset and the classifier is retrained on this new training dataset. The process continues until a stopping criterion, that maybe the size of the training dataset, the number of iterations, or the desired accuracy score, is achieved. A general framework of AL is illustrated in Figure 14.

The selection of the most useful/effective samples is made in such a way that the samples should be informative and representative of the overall input distribution in order to improve accuracy. Based on the criteria of adding new instances to the training set, AL frameworks can be designated as either stream-based or pool-based. In stream-based selection, one instance at a time is drawn from an actual set of unlabeled samples and the model decides whether to label it or not based on its usefulness. While in pool-based strategy, samples are queried from a pool/subset of unlabeled data based on ranking scores computed from various measures to evaluate the sample’s usefulness. The work [234] found that streamed-based selection gives poorer learning rates as compared to pool-based selection as the former tends to query extra instances. In pool-based selection, it is important to incorporate diversity in the pool of samples, in order to avoid redundancy within the pool of samples. Generally, the following three aspects are focused on while selecting/querying the most valuable samples: heterogeneity behavior, model’s performance, and representativeness of samples. A brief introduction of these sampling approaches is given below:

1) Heterogeneity-based selection: These approaches select the samples that are more heterogeneous to the already seen instances with respect to model diversity, classification uncertainty, and contention between a committee of various classifiers. Uncertainty sampling, expected model change, and query-by-committee are examples of heterogeneity based models.

- **Uncertainty Sampling**: In this approach, the classifier iteratively tries to query the label of those samples for which it is most uncertain while predicting the label. The selection of new instances is based on ranking scores against a specified threshold and the instances with scores closest to that threshold are queried for labels. One simple example of such a scheme could be implementing the probabilistic classifier on a sample in a scenario of binary classification and query its label if the predicted class probability is close to 0.5.

- **Query-by-Committee**: Such heterogeneity based approaches perform the sampling process based on the dissimilarities in the predictions of various classifiers trained on the same set of labeled samples. A committee of various classifiers trained on the same set of training data is used to predict the class labels of unlabeled samples and the samples for which classifiers differ more are selected for querying labels. The committee of different classifiers can either be built by using ensemble learning algorithms like Bagging and Boosting [235] or by changing the model parameters [236]. Generally, a less number of diverse classifiers is adequate for constructing a committee [235], [237].

- **Expected Model Change**: Such a heterogeneity based approach chooses the instances which result in a significant change from the current model in terms of the gradient of the objective function. Such techniques attempt to query the label for those instances that are considerably different from the current model. These sampling techniques only fit the models which follow gradient-based training procedures/optimization.
2) **Performance-based Selection**: Such methods consider the effect of adding queried samples to the model performance. They try to optimize the performance of the model by reducing variance and error. There are two types of performance-based sampling:

- **Expected Error Reduction**: This approach is interrelated to uncertainty sampling in such a way that uncertainty measures maximize the label uncertainty of the sample to be queried for the label while expected error reduction reduces the label uncertainty of the queried sample. Referring to the already discussed example of the binary classification problem, the expected error reduction approach would choose the samples with probability far away from 0.5 in order to reduce the error rate. Such techniques are also known as the greatest certainty models [236].

- **Expected Variance Reduction**: Reducing the variance of the model is guaranteed to reduce future generalization error [238]. Therefore, expected variance reduction techniques attempt to indirectly reduce the generalization error by minimizing the model variance. Such approaches query the instances that result in the lowest model variance. The Fisher information ratio is a well-known variance minimization framework.

3) **Representativeness-based selection**: Heterogeneity-based models are prone to include outlier and controversial samples but performance-based approaches implicitly avoid such samples by estimating future errors. Representative sampling tends to query such instances that are representative of the overall input distribution, hence, avoid outliers and unrepresentative samples. These approaches weight the dense input region to a higher distribution, hence, avoid outliers and unrepresentative samples. Similarity [19] mentioned the importance of representative samples in the context of AL.

A multiview AL (MVAL) framework was proposed in [246] that analyzes the object from various views and measure the informativeness of the sample through multiview Intensity-based query criteria. Similarly, [247] also exploited the concept of multiview learning using the Fisher Discriminant Ratio to generate multiple views. In another work, [248] proposed a novel adaptive MVAL framework for HSIC which jointly exploits the spatial and spectral features in each view. Recently, [249] proposed an MVAL technique that utilizes pixel-level, subpixel-level, and superpixel-level details to generate multiple views for the purpose of HSIC. Moreover, the proposed method exploits joint posterior probability estimation and dissimilarities among multiple views to query the representative samples.

In the HSIC literature, several works have combined the AL and DNN. For instance, [250] joined autoencoder with AL technique and [251] proposed a DBN-based AL framework for HSIC. Similarly, [252] coupled Bayesian CNN with AL paradigm for the purpose of spectral-spatial HSIC. Recently, [253] proposed a CNN-based AL framework to better exploit the unlabeled samples for HSIC.

Many works integrated AL with transfer learning for the purpose of HSIC. For example, [254] proposed an AL-based transfer learning framework that extracts the salient samples and exploits high-level features to correlate the source and target domain data. Another work, [255] proposed a stacked sparse autoencoder based active transfer learning technique that jointly utilizes both spectral and spatial features for HSIC. Another work [256] combined domain adaptation and AL methods based on multiple kernels for HSIC.

AL-based HSIC offers some sophisticated frameworks to enhance the generalization capabilities of models. For instance, [19] proposed a fuzziness-based AL method to improve the generalization performance of discriminative and generative classifiers. The method computes the fuzziness-based distance of each instance and estimated class boundary, and the instances having greater fuzziness values and smaller distance from class boundaries are selected to be the candidates for the training set. Recently, [257] proposed a non-randomized spectral-spatial AL framework for multiclass HSIC that combines the spatial prior Fuzziness approach with Multinomial Logistic Regression via a Splitting and Augmented Lagrangian classifier. The authors also made a comprehensive comparison of the proposed framework with state-of-the-art sample selection methods along with diverse classifiers.

XI. CONCLUSION AND FUTURE DIRECTIONS

The rich information contained in HSI data is a captivating factor that constitutes the utilization of HSI technology in real-world applications. Moreover, advances in machine learning methods strengthen the deployment potentials of such technologies. In this work, we surveyed recent developments of hyperspectral image classification (HSIC) using state of the art deep neural networks (Auto-encoder (AE), deep belief network (DBN), recurrent neural network (RNN), and convolutional neural network (CNN)) in a variety of learning schemes (specifically, supervised, semi-supervised and unsupervised learning). In addition, we also analyzed the strategies to overcome the challenges of limited availability of training data like data augmentation, transfer learning, and active learning, etc.

Although the current HSIC techniques reflect a rapid and remarkable sophistication of the task, further developments are
still required to improve the generalization capabilities. The main issue of deep neural network-based HSIC is the lack of labeled data. HSIC data is infamous due to the limited availability of labeled data and deep neural networks demand a sufficiently large amount of labeled training data. Section discussed some widely used strategies to combat the aforesaid issue but significant improvements are still needed to efficiently utilize limited available training data. One direction to solve this problem could be to integrate the exploration of various learning strategies discussed in section to cash in the joint benefits. One more way is to exploit a few-shot or K-shot learning approaches that can accurately predict the class labels with only a few labeled samples. Moreover, there is a need to focus on the joint exploitation of spectral-spatial features of HSI to complement classification accuracies achieved from the aforementioned HSIC frameworks. Another future potential of HSIC is computationally efficient architectures. Therefore, the issue of the high computational complexity of deep neural networks is of paramount importance and it is crucial to implement parallel HSIC architectures to speed up the processing of deep neural networks to meet the computational stipulation of time-critical HSIC applications. In this direction, high-performance computing platforms and specialized hardware modules like graphical processing units (GPUs) and field-programmable gate arrays (FPGAs) can be used to implement the parallel HSIC frameworks.

Hence, to assimilate aforesaid aspects in the development of a new hyperspectral image classification framework is to appropriately utilize the limited training samples while considering joint spectral-spatial features of HSI and maintaining the low computational burden.

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