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Enhancing hyperspectral image object classification through robust feature extraction and spatial-spectral fusion using deep learning

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ABSTRACT

Hyperspectral imaging (HSI) has gained significant attention in recent years due to its broad applications across agriculture, environmental monitoring, urban planning, infrastructure management, and defense and security for object detection and classification. Despite its potential, current methodologies face challenges such as insufficient feature extraction, noise interference, and inadequate spatial-spectral fusion, limiting classification accuracy and robustness. This study reviews advancements in HSI object detection and classification methodologies, emphasizing the role of machine-learning (ML) and deep-learning (DL) techniques. Hence, this work proposes a novel framework to address these challenges, prioritizing robust feature extraction, effective spatial-spectral fusion, and comprehensive noise removal mechanisms. By integrating DL techniques and training with HSI noisy data, this framework aims to enhance classification accuracy and robustness. The findings suggest that the proposed approach significantly improves the reliability and performance of HSI-based object classification systems. This research provides a pathway for future development in the domain, promising to elevate the effectiveness of HSI applications in real-world scenarios.

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1. INTRODUCTION

Hyperspectral-Imaging (HSI) are emerging as a powerful technology in remote-sensing and various fields because of its capability of capturing detailed information across hundreds of narrow spectral-bands [1]. The overall process of how the hyperspectral image is taken is shown in Figure 1. Unlike traditional imaging techniques that capture data in three spectral bands (RGB), hyperspectral sensors acquire data in numerous contiguous bands, offering a wealth of spectral information [2]. The extensive spectral data obtained through HSI allows scientists to distinguish and identify various objects and materials by analyzing their distinct spectral signatures. This makes HSI a crucial instrument for classifying and detecting objects [3]. Further, object classification using HSIs involves the process of identifying and categorizing objects or materials within a hyperspectral image based on their spectral characteristics [4]. Each material or object exhibits a distinct spectral signature due to its unique chemical composition and physical properties, which can be exploited for accurate classification [5]. By analyzing the spectral reflectance patterns across multiple bands, machine-learning (ML) and deep-learning (DL) algorithms can be trained to differentiate between various objects and classify them into predefined classes or categories [6].

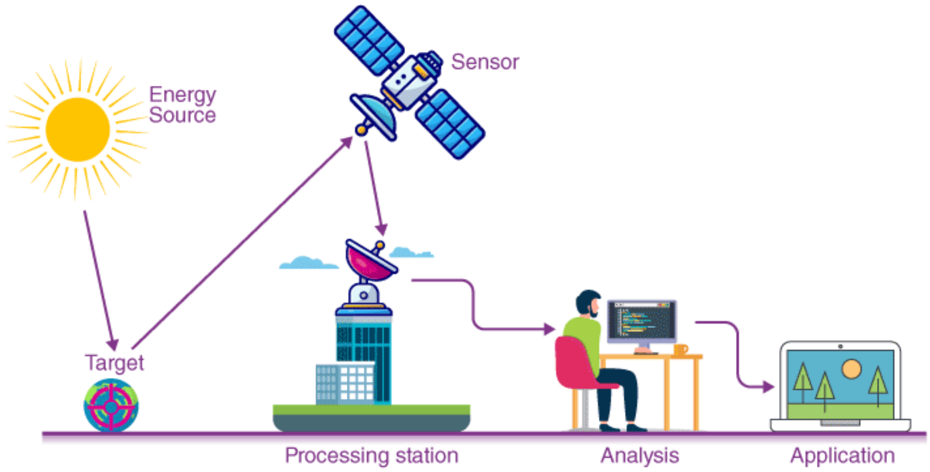

Figure 1. Process of capturing HSIs

The applications of HSIs in the current real world are diverse and extensive. They are widely used in agriculture for crop health monitoring, disease detection, and yield prediction [7]. In environmental monitoring, HSIs are utilized for vegetation mapping, water quality assessment, and land cover classification [8]. In urban planning and infrastructure management, HSIs aid in identifying land use patterns, monitoring pollution levels, and assessing geological features [9]. Additionally, HSIs play a crucial role in defense and security applications such as target detection, camouflage analysis, and surveillance HSIs help in identifying objects by exploiting their spectral signatures [10]. Each pixel in a HSI consists of spectral data across multiple bands, representing the unique reflectance properties of the corresponding area on the ground [11]. In HSIs, as seen in Figure 2, using the reflectance and wavelength, the space and spectral dimension are identified and using that a single band image is obtained. By analyzing these spectral signatures and extracting relevant features, ML and DL algorithms can distinguish between different materials and objects [12]. ML approaches like support-vector-machine (SVM) [13], random-forest (RF) [14], and K-nearest-neighbors (k-NN) [15] are the widely utilized approaches for object classification based on extracted spectral features.

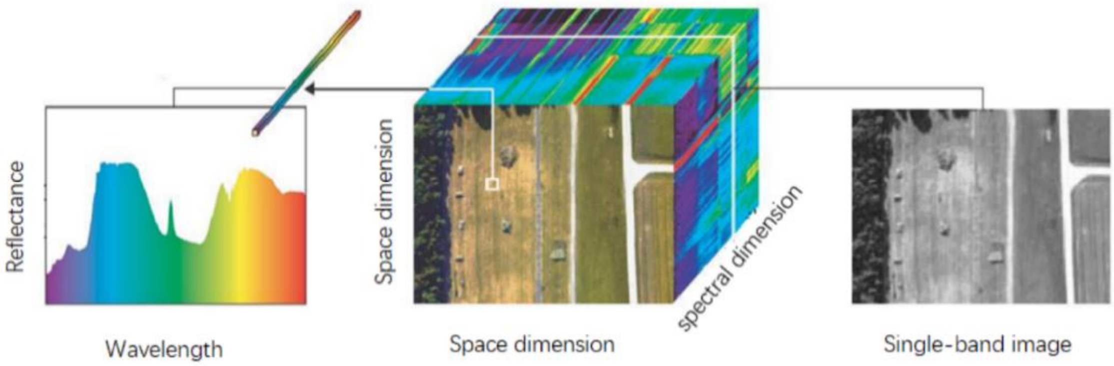

Figure 2. HSI image extraction

However, while ML and DL approaches have shown promising results in HSI object detection and classification, they face several limitations. One major limitation is the lack of emphasis on noise removal and feature extraction from hyperspectral data [16]. Many existing models focus on directly detecting or classifying objects without adequately preprocessing the data to remove noise and extract discriminative features [17]. This can lead to suboptimal performance and reduced accuracy in classification tasks. Moreover, the spatial-spectral fusion technique, which combines spatial and spectral information for enhanced feature representation, has only recently gained attention in HSI analysis using ML and DL [18]. Spatial-fusion feature fusion techniques aim to improve the quality of detected objects and enhance classification accuracy by incorporating spatial context along with spectral information. Recently, there is an important shift in the direction of utilizing DL methods for HSI object detection and classification [19]. DL models, particularly recurrent-neural-networks (RNNs) [20] and convolutional-neural-networks (CNNs) [21], have achieved superior performance because of their ability to learn complex spectral and spatial patterns from HSI data. RNNs, specifically, offer improved performance in collecting temporal relationships in sequenced information. This characteristic proves advantageous when evaluating spectrum sequences in HSIs. This study aims at addressing existing issues, challenges and limitations in HSI object classification approaches. Further, this work presents a novel framework that focuses on noise removal, feature extraction, and spatial-spectral fusion using advanced ML and DL techniques. The proposed framework main aim is to improve accuracy and provide robustness for HSI object classification by using spectral and spatial information from HSI data. The contribution of the work are as follows

– The study evaluates the current recent approaches used for HSI object detection and classification. This evaluation includes assessing the strengths and weaknesses of existing ML and DL techniques applied to HSI data.
– Through the evaluation process, the study identifies the key issues and challenges faced by the existing approaches in HSI object detection and classification.
– The study proposes a novel framework designed specifically to address the identified issues and challenges in HSI object classification. This framework introduces innovative methods, i.e., noise removal, feature extraction, and spatial-spectral fusion, aiming to enhance the accuracy and robustness of object classification results.
– The primary contribution of the study is to provide a better HSI object classification approach compared to existing methods. The novel framework tries to addresses the limitations of current approaches and can improve accuracy and reliability in classifying objects within hyperspectral images.

The manuscript is organized in the following way. In section 2, literature survey is discussed, where different approaches to HSI are discussed. Further, in section 3, issues and challenges are discussed from the above literature survey. Then, in section 4, a novel framework is presented for efficient HSI object detection and classification. Then in section 5, conclusion of the work is presented.

2. LITERATURE SURVEY

In this section, various ML and DL approaches for HSI object detection and classification are discussed. A novel dual-interactive graph-convolutional-network (DIGCN) was designed by Wan *et al.* [22]. This graph-convolutional-network (GCN) incorporated two distinct GCN branches for capturing spatial data at various scales. The GCN branches allowed refinement of graph data by leveraging multiscale-spatial data. Further, by combining features represented from two GCN branches, the edge data was improved. Moreover, by merging edge data from two GCN branches allowed generation of better feature descriptions in a single branch. Therefore, the DIGCN representational capability was improved with the updated graph data. In addition to speeding up the process of convolution, the DIGCN automatically acquires a discriminatory region-induced-graph that eliminates the drawbacks of the traditionally generated graph. Indian-Pines [23], Pavia-University (PU) [24], Salinas (SA) [25], and Houston (HU) [26] were used for evaluation. Evaluation was done using Average-Accuracy (AA), Overall-Accuracy (OA) and Kappa-Coefficient (KC). For IP, they achieved OA of 94.16%, AA of 94.41% and KC of 0.9334. For PU achieved OA of 93.24%, 93.76% of AA and KC of 0.9114. For SA achieved 97.61% of OA, 96.94% of AA and 0.9734 of KC. For HU achieved 91.72% of OA, 92.52% of AA, and 0.9103 of KC. Moreover, this work has considered to remove noise before evaluation. Jiang *et al.* [27] introduced a labeled noise cleaning technique that relied on Spectral-Spatial-Graphs (SSGs). The development of an affinity-graph in SSGs was a key finding of this work. The graph relied on both spectral-spatial similarities, where pixels within an identical region were obtained through super-pixel segmentation approach. The created affinity-graph was utilized for regularization and for removal of noise. For exploiting the spatial data, they presented multiscale-segmentation-based multi-layer SSGs (MSSGs). Evaluation was done using OA, AA, and KC on IP and PU. They have also conducted experiments on noise removal. Findings show they achieved 83.71% of OA, 97.55 of AA and 0.7903 of KC for IP dataset and for SA dataset, achieved 91.42% of OA, 95.41% of AA and 0.9045 of KC for SA dataset.

Gao *et al.* [28] introduced a new technique called spectral-band non-localization (SBNL). This technique allows exploration of non-local-spectral inter-band correlations using convolutional-kernels that have restricted field receptivity. They also developed an innovative multi-scale-share inception-block (MSIB) for utilizing cross-relationships between the multi-scale features. For effectively utilizing spatial-spectral features, presented a Plug and Play Adaptive-Feature-Fusion approach. By combining both the approaches they presented their novel technique which was called as adaptive-spectral-spatial feature-fusion-network (AS2F2N) for classification of HSI. The evaluation was conducted using IP, PU and HU. Evaluation was done using OA, AA, and KC. Findings show 98.11% of OA, 93.62% of AA, and KC of 0.978 for IP dataset. Further, for PU dataset achieved 98.65%, 96.81% and 0.983 of OA, AA and KC respectively. Finally, for HSI dataset achieved 89.77%, 90.89% and 0.8894 of OA, AA and KC respectively. He *et al.* [29] introduced a new object detection approach called S2ADet which utilized good use of the HSI abundant spatial-spectral features. Their suggestion was to use a two-stream network for aggregating spatial-spectral features. In addition, they annotated a large dataset called HOD3K, which included three object classes and 3242 HSIs taken from various real-world scenarios, in order to overcome the shortcomings of current datasets. The images encompassed 16 bands between 470 and 620 nm and had a pixel-resolution of 512×256. Extensive testing on two datasets proved that S2ADet outperformed current state-of-the-art approaches. Islam *et al.* [30], presented a DL approach which reduced the dimension and resampled the HSI image during preprocessing. For streamlining feature extraction and selection while keeping redundancy to least, their approach utilized a unique sub-group based dimension reduction approach. Furthermore, for solving class imbalance issue, the resampled data. After preprocessing, the data went through a hybrid CNN approach where the spatial-spectral features were extracted. By resampling, the achieved better performance even in the existence of noise. Evaluations were conducted using kennedy-space-center (KSC) [31] SA and PU dataset. The approach achieved OA of 99.46%, 99.94% and 99.98% for KSC, SA and PU respectively. F. Feng *et al.* [32], presented a low-rank-limited attention-enhanced-multiple feature-fusion-network (LAMFN). They performed spectral features preprocessing to identify a small number of features which can be characterized utilizing the initial data set and covariance data. Then extracted deep features utilizing a lightweight attention-enhanced 3D-Convolution approach, and to add to the position-sensitive data, a 2D coordinates-attention network was employed. Four HSI dataset, i.e., WHU-HongHu (WHU) [33], IP, HU and PU were considered. They achieved 78.15% for IP, 97.18% for PU, 81.35% for HU and 87.93% for WHU respectively.

Dang *et al.* [34], presented novel double-branch feature-fusion transformer approach for classifying HSI. They developed two attention-modules which dynamically changed the weights assigned to different spectrum bands and pixels in classifying HSI. Four datasets, i.e., KSC, SA, PU, and HU were utilized for evaluation. According to the KSC dataset, the OA was 98.64%, the AA was 97.13%, and the KC was 0.9849. For the SA dataset OA was 98.50%, AA was 99.18%, and KC was 0.9833, respectively. For the PU dataset, achieved OA of 98.76%, AA of 97.71%, and KC of 0.9836. According to the HU dataset, the OA was 90.08%, the AA was 90.55%, and the KC was 0.8927. Wan and Chen [35], proposed multi-strategy-fusion (MSF) framework that relied on bi-exponential edge-preserving-smoother (BEEPS). A SVM classifier was subsequently employed to determine the pixels soft classification probability. In addition, BEEPS was used to round off the subsequent processing of soft classified probability maps; this was done to enhance HSI's classification accuracy substantially by taking context-aware data related to all labeled classes into account. Using three HSI datasets, i.e., IP, KSC, and HU and randomly selecting 1%, 6%, and 5% of the samples to be labeled for training, MSF achieved OA of 99.47%, 99.52%, and 94.25%, respectively. Yan and Hong [36], presented a novel method which combined the best features of the two models, i.e., multi-layer perceptron (MLP) and CNN. For classification, they utilized merged spatial-spectral features data directly into MLP architecture after first using CNN. Furthermore, they presented a minimalistic approach to remove the effect of unnecessary spectrum frequencies. Evaluation was done on IP, PU and SA. The OA, AA, and KC achieved for IP dataset was 99.28%, 98.82% and 0.9918. The OA, AA, and KC achieved for PU dataset was 98.98%, 98.74% and 0.9865. The OA, AA, and KC achieved for SA dataset was 99.30%, 99.34% and 0.9922. Gu *et al.* [37], presented a multi-scale spatial-spectral attention-network with frequency-domain lightweight-transformer (MSA-LWFormer) for classification of HSI. Both the frequency-domain fused classifier and spectral-spatial extracted feature modules were enhanced by the technique's incorporation of Transformer, attention mechanisms, along with CNN. In order to acquire the shallow spectral-spatial characteristics along with capturing long-range spectral dependencies, the spectral-spatial feature retrieval modules used a Multi-Scale 2D-CNN integrating multi-scale spectral-attention (MS-SA). Experiments were done on PU, IP and SA. Evaluation was done using OA, AA, and KC. Findings show 98.87% of OA, 98.68% of AA and KC of 0.9871 for IP dataset, 99.79% of OA, 99.68% of AA and KC of 0.9973 for PU dataset, and 99.96% of OA, 99.95% of AA and KC of 0.9995 for SA dataset.

Zhang *et al.* [38], presented a novel 3D-2D hybrid-convolution and graph-attention-mechanism (3D-2D-GAT) based end-to-end HSI classification. To achieve higher classification accuracy, the technique made use of the combined efforts of the GAT component along with the hybrid convolutional extracted features module. GAT was used to learn spatial relationships across vast distances and to differentiate between samples with comparable and various stages of variation within each class. The suggested method outperformed previous state-of-the-art methods in terms of classification accuracy, according to findings from experiments on the IP, PU, and SA datasets. Findings show 99.19% of OA, 99.3% of AA and KC of 0.9907 for IP dataset, 99.73% of OA, 99.58% of AA and KC of 0.9964 for PU dataset, and 99.43% of OA, 99.52% of AA and KC of 0.9937 for SA dataset. Arshad *et al.* [39], presented hybrid convolution-transformer where visual transformer along with a residual 3D CNN structure were key components of their approach. To further prevent overfitting problems caused by insufficient training data, it employed an ordering aggregating layer. During the process of feature extraction, their suggested remaining attention-channel module preserved spectral features and acquired more comprehensive spatial-spectral complementary data. They ran tests on the SA and KSC datasets in addition to the Xuzhou dataset [40]. The model achieved 99.75% of OA, 99.71% of AA, and 0.996 of KC for SA, 99.46% of OA, 99.44% of AA and 0.9931% of KC for Xuzhou dataset and 99.95% of OA, 99.96% of AA and 0.9995 of KC for KSC dataset. Ali *et al.* in [41], presented TBMSSN, a two-branch multi-scale spectral-spatial feature-extraction-network for classifying HSIs. With the goal of enhanced feature representations, they developed the multi-scale-spatial feature-extraction (MSAFE) and multi-scale-spectral feature-extraction (MSEFE). They improved feature extraction, reduced the vanishing-gradient issue, and achieved maximum effectiveness and efficiency by densely connecting series of MSAFE or MSEFE modules in a two-branch architecture, respectively. They achieved 99.32% of OA, 98.26% of AA, 0.9922 of KC for IP dataset, 99.86% of OA, 99.73% of AA and 0.9981 of KC for PU dataset.

Huang *et al.* [42] developed a DL approach for identifying oil emulsions using a spectral-spatial feature-fusion. They used the conventional deviation approach for filtering out feature-bands which could differentiate among different oil and sea water. The evaluation was done using their airborne-visible infrared-imaging-spectrometer (AVIRIS) dataset. They achieved OA of 91.80%, KC of 86% with feature selection. Sigger *et al.* [43], presented DiffSpectralNet method a hybrid of diffusion and transformer approaches. The diffusion technique improved HSI classification by extracting various and significant spectral-spatial features. Utilizing a pre-trained denoising U-Net for classification, they developed an unsupervised training structure employing the diffusion system to extract high and low-level spatial-spectral features. They achieved 99.06%, 99.74% and 99.87% of OA for IP, PU and SA respectively. Further for AA, achieved 98.00%, 99.18% and 99.82% for IP, PU and SA respectively. Finally, for KC achieved 0.9893, 0.9965 and 0.9986 for IP, PU and SA respectively. Ashraf *et al.* [44] presented attention-3d-central-difference-convolutional dense-network (3D-CDC Attention-DenseNet). They used a dense approach that included pixel-wise combination alongside a spatial attention system to combine low-rank frequency characteristics and direct characteristic tuning in their 3D-CDC method, which relied on manipulating local built-in intricate patterns within the spectral-spatial features maps. The approach achieved OA of 97.93% for HU, 99.89% for PU and 99.38% for IP dataset. Goswami *et al.* [45] presented a HSI using a mix of three techniques: CNN, stationary-wavelet-transformations (SWT) and principal-component-analysis (PCA). After reducing dimensionality and extracting spatial-spectral features with SWT and PCA, the suggested method uses CNN for classification. With an OA of 98.2% on the IP dataset, 99.86% on the SA dataset, and 99.80% on the PU dataset, the results show that the suggested SWT-PCA-CNN method outperforms the traditional techniques.

3. FINDINGS

The above findings from the literature survey have been identified which is presented in Table 1. The findings from the above review shows most of the work considered for hyperspectral image object identification have used DL instead of Machine Learning. Further, it has been seen that all the works have considered similar metrics for evaluation, i.e., OA, AA and KC. Also, the datasets used in their work shows that most of the work have used IP, PU, SA, KSC and HU dataset. Very less work has considered different dataset like [29] has considered HOD3K, [39] has considered Xuzhou dataset and in [42] have considered an oil dataset.

From the above literature survey, it is seen that several novel approaches have been proposed for hyperspectral image (HSI) classification, each offering unique strengths and advancements in the field. The approaches presented in [22], [27], i.e., DIGCN and MSSGs respectively are mainly focused on removing noise and object detection. Further, the novel spectral-spatial aggregation (S2ADet) method by He *et al.* [29] stands out for its focus on spectral-spatial aggregation in hyperspectral object detection, featuring a hyperspectral information decoupling (HID) module, a two-stream feature extraction network, and a one-stage detection head. This approach showcases robust and reliable results, particularly outperforming existing methods on the HOD3K dataset. Another noteworthy contribution is the low-rank constrained attention-enhanced multiple feature fusion network (LAMFN) by Feng *et al.* [32], which leverages factor analysis for spectral feature preprocessing, a lightweight attention-enhanced 3D convolution module for deep feature extraction, and low-rank second-order pooling for convolutional feature selectivity. Despite limited training data, LAMFN achieves significant improvements in OA on datasets like IP, PU, HU, and WHU. Additionally, the double-branch feature fusion transformer (DBFFT) introduced by Dang *et al.* [34] excels in handling spectral sequence characteristics, achieving high OA, AA, and KC scores across datasets like KSC, SA, PU, and HU. These methods, along with others like the multi-strategy fusion (MSF) Framework by Wan and Cheng [35], the oil emulsion deep-learning identification model by Huang *et al.* [42], DiffSpectralNet by Sigger *et al.* [43], and 3D-CDC Attention DenseNet by Ashraf *et al.* [44], collectively contribute to advancing the state-of-the-art in HSI classification by integrating innovative techniques such as diffusion, transformer, attention mechanisms, and feature fusion to achieve remarkable performance gains across various evaluation metrics and datasets. In the next section, issues and challenges are discussed.

Table 1. Findings from above literature review

Reference	Methodology	Performance metrics	Dataset
[22]	Deep Learning (DIGCN)	OA, AA, KC	IP, SA, PU, HU
[27]	Deep Learning (MSSGs)	Noise Removal, OA, AA, KC	IP, PU
[28]	Machine Learning (AS2F2N)	OA, AA, KC	IP, PU, HU
[29]	Deep Learning (S2ADet)	OA, AA, KC	HOD3K
[30]	Deep Learning (Hybrid CNN)	OA, AA, KC	SA, PU, KSC
[32]	Deep Learning (LAMFN)	OA, AA, KC	IP, PU, HU, WHU
[34]	Deep Learning (DBFFT)	OA, AA, KC	KSC, SA, PU, HU
[35]	Machine Learning (MSF)	OA, AA, KC	IP, KSC, HU
[36]	Deep Learning (CNN + Transformer)	OA, AA, KC	IP, PU, SA
[37]	Deep Learning (MSA-LWFormer)	OA, AA, KC	IP, PU, SA
[38]	Deep Learning (3D–2D-GAT)	OA, AA, KC	IP, PU, SA
[39]	Deep Learning (Hybrid Convolution Transformer)	OA, AA, KC	SA, Xuzhou, KSC
[41]	Deep Learning (TBMSSN)	OA, AA, KC	IP, PU
[43]	Deep Learning (DiffSpectralNet)	OA, AA, KC	IP, PU, SA
[44]	Deep Learning (3D-CDC Attention DenseNet)	OA, AA, KC	HU, PU, IP
[45]	Deep Learning (SWT-PCA-CNN)	OA, AA, KC	IP, SA, PU

4. ISSUES, CHALLENGES AND SOLUTION

The issues and challenges for the work identified from the above literature survey is as follows:

- Limited focus on feature extraction: Many existing works in hyperspectral image (HSI) analysis have placed less emphasis on robust and effective feature extraction techniques. This lack of attention can lead to suboptimal performance in classification tasks and hinders the ability to fully exploit the rich information present in hyperspectral data.
- Sparse consideration of spatial-spectral fusion: Spatial-spectral fusion is a critical aspect of HSI analysis as it combines information from both spatial and spectral domains, enhancing the discriminative power of features. However, very few works have thoroughly explored and leveraged spatial-spectral fusion techniques, resulting in missed opportunities for improved classification accuracy and feature representation.
- Neglect of noise in HSI data: Noise is an inherent challenge in HSI, affecting the quality and reliability of extracted features. Unfortunately, many existing approaches have overlooked the issue of noise in HSI data, leading to potential inaccuracies and reduced robustness in classification models.
- Insufficient attention to preprocessing techniques: Preprocessing plays a crucial role in enhancing the quality of hyperspectral data for feature extraction. However, there has been relatively little focus on comprehensive preprocessing techniques such as noise removal and normalization, which are essential for improving the reliability and effectiveness of feature extraction processes.

To solve the above issues and challenges, this work presents a novel framework for HSI. Figure 3 illustrates the proposed framework, which encompasses several key steps. Initially, the framework considers input, which consists of HSIs. Following this, the object classification process starts. Initially, relevant features related to reflectance are extracted to enhance spatial-spectral feature fusion, a crucial step in the object classification pipeline. Subsequently, a DL technique is employed for object classification, facilitating the identification of objects within the HSIs. The final step involves evaluating the output in terms of OA, AA, and KC metrics commonly used to assess classification performance. To enhance the classifier's training and improve robustness, HSI noised data is utilized during the training phase, contributing to more reliable and accurate classification outcomes. By utilizing this approach, the classifier can be trained for achieving better outcomes and can solve the current problems faced by the DL approaches. In the next section, the conclusion and future work is discussed.

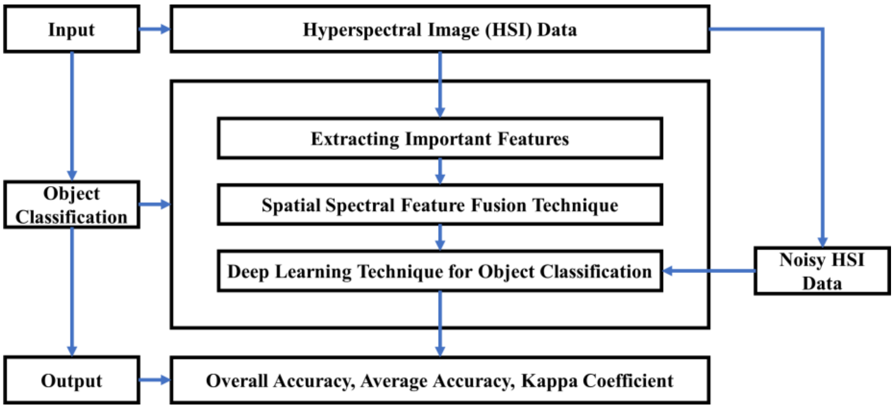

Figure 3. Proposed framework for HSI object classification

5. CONCLUSION

This work delved into the realm of HSI object detection and classification, exploring existing approaches, challenges, and limitations. Through a comprehensive review, we identified key issues such as limited focus on feature extraction, noise removal, and spatial-spectral fusion in current HSI classification models. We also noted the predominant shift towards DL techniques due to their recurrent networks, which offer improved results compared to traditional ML approaches. To address these challenges, we proposed a novel framework designed to enhance HSI object classification. Our framework prioritizes feature extraction, spatial-spectral fusion, and noise removal, thus addressing critical gaps in existing methodologies. By utilizing DL techniques for object classification and incorporating HSI noised data during training, our framework aims to deliver more robust and accurate classification outcomes. Through rigorous evaluation using metrics like OA, AA, and KC we anticipate demonstrating the efficacy and superiority of our proposed framework. We believe that this work contributes significantly to the advancement of HSI object detection and classification methodologies, offering a promising avenue for future research and development in this domain. In the future work the object classification pipeline will be further enhanced to achieve better outcomes.

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