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TOPICAL REVIEW

An Overview of Integrating Deep Learning Methods With Close-Range Hyperspectral Imaging for Agriculture

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ABSTRACT Hyperspectral imaging combines spectroscopy with imaging, thus capturing both spectral and spatial features. This makes it a useful technology in several application areas such as remote sensing and smart agriculture. Extracting spatial-spectral information of objects-of-interest from hyperspectral images requires sophisticated computational methods. The last decade saw the rapid advancement of deep learning methods due to their superior automatic feature extraction capability from images, and hence it is no surprise that these methods have been adapted and used for hyperspectral image analysis. Yet, while deep learning methods have achieved some success for hyperspectral remote sensing, it has been less explored in close range (or proximal) hyperspectral imaging, which is likely because at this range, it is more akin to spectroscopy with spatial information, rather than the case of remote sensing, which is more akin to imaging with higher spectral resolution. Close-range HSI allows for fine-scale analysis of plant health, nutrient levels, disease detection, and crop quality, which is very important in precision agriculture. In light of the new computational methods in deep learning, this review article provides an in-depth analysis and comparisons of such methods when applied to proximal hyperspectral imagery, with a particular emphasis on unsolved challenges (e.g., limited availability of annotated datasets, the need for robust models under real-world conditions, and the integration of spatial and spectral information) and potential future research directions for agricultural applications. The review emphasizes the importance of further explorations and has provided recommended directions for future research that could elevate close-range hyperspectral imaging technology from research to industry use for smart agriculture applications.

INDEX TERMS Hyperspectral imaging, deep learning, machine learning, precision agriculture, crops.

NOMENCLATURE

AE	Auto-Encoder.
AL	Active Learning Sampling.
CapsNets	Capsule Networks.
CLSTM	Conv. Long-Short Term Memory Analysis.
CNNs	Convolutional Neural Networks Machine.
DBNs	Deep Belief Networks Networks.
DL	Deep Learning.
FHS-DBNs	Firefly Harmony Search Deep Belief Networks.
GANs	Generative Adversarial Networks Auto-Encoder.
GCNs	Graph Convolutional Networks Learning.
HSI	Hyperspectral Imaging.
LSTM	Long-Short Term Memory.
MI	Mutual Information Vehicle.
miniGCNs	mini-batch Graph Convolutional Networks.

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ML	Machine Learning.
MUS	Maximum Uncertainty.
MV	Multi-View.
PCA	Principal Component.
RBM	Restricted Boltzmann.
RNNs	Recurrent Neural.
RS	Random Sampling.
SAE	Stacked Auto-Encoder.
SSAE	Stacked Sparse.
SSL	Semi-Supervised.
SVM	Support Vector Machine.
TL	Transfer Learning.
UAV	Unmanned Aerial.

I. INTRODUCTION

A griculture is crucial for food security and sustainability [1]. Challenges such as population growth and climate change require understanding plant responses for maximizing crop yield. To address such challenges, there is a growing need for technologies that provide rapid and accurate insights into plant health and functionality. In turn, this has driven the now widespread adoption of sensor technologies for non-destructive assessment in plants. Indeed such a need is not new, as agrarian communities, which often pass down wisdom through proverbs, have advice that states: "*the difference between a good farmer and a great farmer is two days*". This proverb highlights the importance of the farmer's experience in predicting weather conditions, detecting pests and disease early enough to mitigate damages, determining the optimal harvest time for the best crop quality and quantity, and sensitivity to food pricing. Contemporary research aspires to replicate the insights of great farmer through technology, and this is where Hyperspectral Imaging (or HSI) plays a pivotal role.

HSI combines imaging with spectroscopy, which makes it a viable sensing option for non-destructive and rapid measurement of plant structural and physiological dynamics at close range. Combining this system with the latest deep learning algorithms allows us to have many "great farmers" everywhere, thus ensuring sustainable and consistent food production globally. While human expertise is valuable, this technology is essential because visual inspections are subjective [2], [3], [4]). Automating agricultural processes is a longstanding objective, and the use of HSI systems can minimize dependence on manual human observations by gathering the spectral response from plants to provide insights into their chemical composition and linking them to the plant's physiology. This enables a comprehensive analysis of surfaces or objects, providing a more thorough understanding of their absorption, transmission, and reflection bands under specific conditions. In recent work, HSI obtained from drones and satellites have been successfully employed in remote sensing applications [5].Because of the large number of available datasets in remote sensing, a multitude of methods have been developed to effectively extract the abundant information contained within these images.

Proximal hyperspectral images are valuable for agriculture and food science. However, research progress in this area is slower due to limited dataset availability [6]. Generating ground-truths for hyperspectral images could be challenging due to the high cost of analysis [7]. Unlike remote sensing applications whereby the ground truth for the hyperspectral image can be annotated by human vision (i.e., labeling large swaths of land and water), proximal hyperspectral imaging is more akin to spectroscopy with spatial information, whereby the spectral responses of each "pixel" can be considered a point spectroscopy measurement linked to the plant's chemical composition. Ground truths for these types of images require analytical chemical tests to be performed on the plant, which is a costly endeavor.

Even though the cost of attaining ground-truths remains high, hyperspectral imaging devices are becoming more affordable [8]. It should be noted that other imaging technologies are available, such as RGB, SAR cameras, thermal sensors, and LiDAR. Compared to RGB cameras, HSI is preferred as it preserves the spectral information of pixels in an image which enables the quantification of nutritional deficits, illnesses, and drought conditions [9]. Recent research has also shown that HSI provides valuable spectral and spatial information for crop variety identification, stress, and disease detection, plant growth monitoring, and assessment of soil properties like moisture, organic matter, and nutrient content [10]. Yet, despite such capabilities, the repeatability, reproducibility, and replicability of HSI systems pose challenges in terms of instrument setup and calibration, data processing, analysis, and interpretation. Figure 1 depicts the distinction between hyperspectral and RGB images. [2].

Figure 2 shows the four key computational steps involved in the use of HSI measurement systems: imaging, data processing, data analysis, and decision-making. HSI data processing and mining tools are continually advancing, incorporating machine learning and deep learning methods to predict or estimate plant traits. While standard data preprocessing techniques can help address some of these challenges, there is a demand for a more efficient approaches. Therefore, extracting useful information from the raw hyperspectral data is a challenging task and has motivated researchers to explore alternative methodologies. While empirical methods [29], [30], and traditional machine learning techniques [17], have demonstrated some success in the past, these methods largely depended on complex feature engineering, thus inhibiting their widespread adoption [15]. Nonetheless, as summarized by Table 1, these methods are still being explored to this date.

Since 2012, Deep Learning (DL) gained widespread popularity due to its inherent capability to autonomously learn features, detect patterns, and capture spatial relationships [31], completely bypassing the feature engineering problem faced by traditional ML. DL offers notable advantages such as adaptability, high performance, and scalability, rendering it

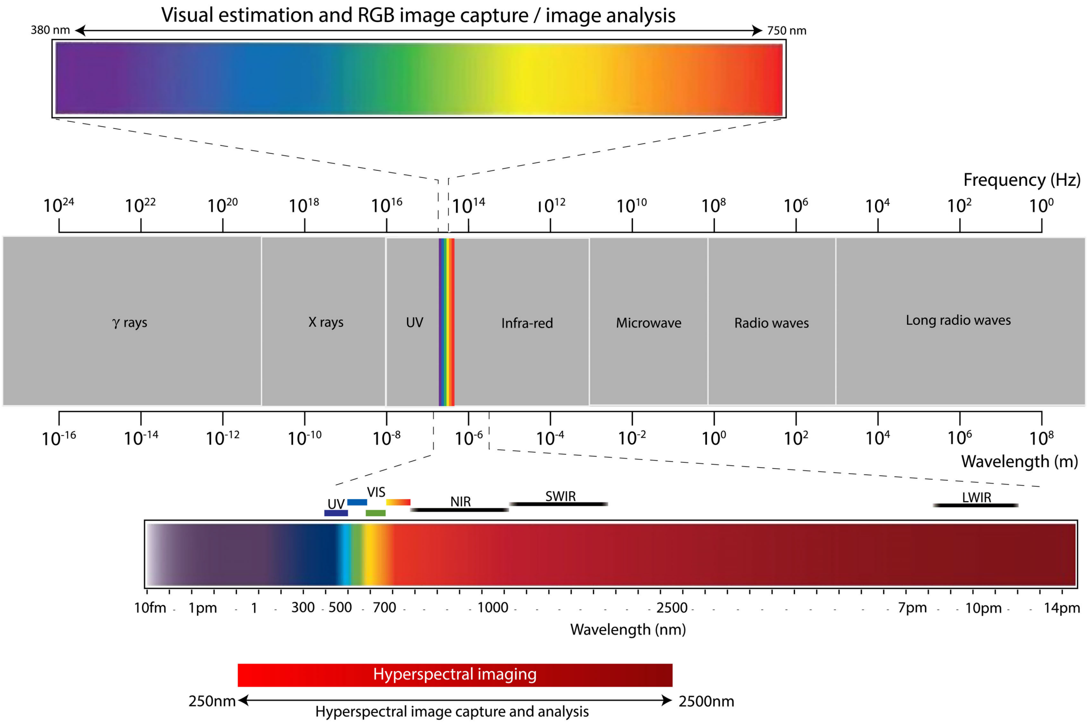

FIGURE 1. RGB and hyperspectral images cover different ranges of the electromagnetic spectrum [2]. RGB images portray the visible spectrum by utilizing three color channels, while hyperspectral images can encompass hundreds of wavebands.

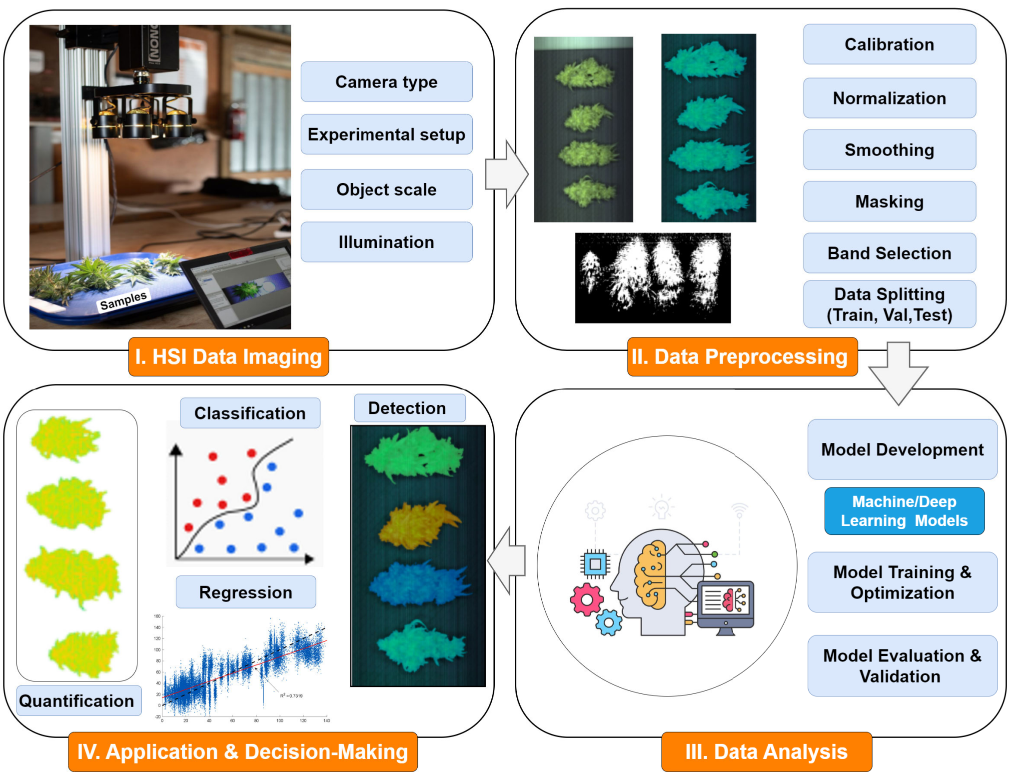

FIGURE 2. Generalized process of hyperspectral imaging.

well-suited for HSI analysis, especially in remote sensing. Yet close-range agricultural HSI analysis continues to encounter challenges due to limited model interpretability, the need for extensive high-quality labeled data, and problems associated

TABLE 1. Articles reviewing hyperspectral imaging and machine learning in plant image analysis.

Reference	Theme
2019 [11]	Application of near-infrared HSI with ML methods to identify geographical origins of dry narrow-leaved oleaster fruits
2019 [12]	Detection of nutrition deficiencies in plants using proximal images and ML: A review
2020 [13]	ML and digital images for crop/weed discrimination
2020 [14]	HSI combined with ML as a tool to obtain high-throughput plant salt-stress phenotyping
2020 [4]	HSI combined with ML for the detection of fusiform rust disease incidence in loblolly pine seedlings
2021 [15]	ML techniques for analysis of HSI to determine the quality of food products: A review
2021 [16]	Plant trait estimation and classification studies in plant phenotyping using machine vision: A review
2021 [17]	ML applied to HSI in agriculture
2022a [18]	Determination of viability and vigor of naturally-aged rice seeds using HSI with ML
2022b [19]	Tea category identification using wavelet signal reconstruction of HSI and ML

TABLE 2. Articles reviewing hyperspectral imaging and deep learning in plant image analysis.

Reference	Theme
2019 [20]	Deep Learning Meets Hyperspectral Image Analysis: A Multidisciplinary Review
2020 [21]	Deep Learning Applications for Hyperspectral Imaging: A Systematic Review
2021 [22]	A review of deep learning used in the hyperspectral image analysis for agriculture
2021 [23]	Critical insights into modern hyperspectral image applications through deep learning
2021 [24]	Review on Convolutional Neural Networks (CNN) in vegetation remote sensing.
2022 [25]	A systematic review of hyperspectral imaging technology with a machine and deep learning methodology for agricultural applications
2023 [26]	A review of the combination of deep learning techniques with proximal hyperspectral images in agriculture
2023 [27]	Machine Learning and Deep Learning Techniques for Spectral Spatial Classification of Hyperspectral Images: A Comprehensive Survey
2024 [28]	A research review on deep learning combined with hyperspectral Imaging in multiscale agricultural sensing

with training DL models from highly variable HSI data [22]. There is a limited number of reviews that specifically address the research and challenges involved in integrating HSI technology with DL methods for plant image applications, as shown in Table 2. To this end, the main objective of this review article is to examine the advancements and obstacles in utilizing deep learning methods for analyzing proximal hyperspectral imaging (HSI) in smart agriculture. It provides an overview of different DL models employed in agricultural HSI analysis while also shedding light on their inherent limitations.

The literature search was conducted in August 2024 using Scopus and Google Scholar, which cover a wide range of relevant bibliographic databases. The search terms were completed using two pairs of keywords. The initial set consisted of the specific keywords "hyperspectral", "deep learning", and "agriculture." Two more general keywords ("hyperspectral", "image", "deep learning") were used to make sure that all relevant papers were found. Moreover, a few specific review articles' reference lists were also examined. It included exclusively those studies that were published in a peer-reviewed journal. In such context, the aims of this review are three-fold: (a) to provide a comprehensive characterization of the current state-of-the-art in hyperspectral imaging using deep learning, with a specific focus on the challenges highlighted in the existing literature; (b) to identify notable study gaps and methodological limitations that could impede the practical implementation of proposed methods in real-world scenarios; (c) to recommend the roadmap for future research directions.

II. ANALYSIS OF PLANT IMAGES USING DEEP LEARNING MODELS AND HYPERSPECTRAL IMAGING: APPLICATIONS AND LIMITS

Using DL to analyze hyperspectral imaging datasets have the opportunity to greatly improve prediction accuracy. This section covers a wide range of applications where HSI-DL has been used in plant trait analysis, from disease detection to nutrient estimation, highlighting meaningful limitations and challenges. Their understanding is necessary for advancing the field and realizing areas that require further development. Specifically, it is useful to compare and understand the HSI camera wavelengths of each specific study, their area of application, the evaluation metrics used in that study, and when the study was performed. These are summarized in Table 3, and each subsection breaks them down by their agricultural objectives.

A. STRESS IDENTIFICATION AND QUANTIFICATION

Stress identification and quantification play a vital role in supporting decision-making and farm management. Abiotic stresses such as drought and herbicide, and biotic such as diseases and pests have been studied using hyperspectral images Table 3. Notably, hyperspectral images can identify stress conditions before visible symptoms become apparent, thus serving as a cost-effective and time-efficient substitute for labor-intensive laboratory analysis [14]. They are also particularly valuable in the early detection of diseases and contaminants in seeds. Additionally, hyperspectral images facilitate high-throughput phenotyping, enabling rapid evaluation of stress resistance across multiple samples [32],

[33], [34]. Early detection of stress faces a significant issue due to the subtle nature of signs and symptoms that are not easily discernible using hyperspectral imaging (HSI) data. Existing research primarily concentrates on investigating isolated stress factors within controlled environments and monitoring temporal changes in stress levels while maintaining consistent environmental variables. However, interaction effect of multi-plant species and multi-stress factors, as well as environmental factors, will be result in compounded plants' spectral responses, thus potentially confounding the stress detection with other plant factors.

B. PRODUCTS QUALITY

The quality control of the agricultural products involves the selection of the best crop batches and determination of shipment quantity and pricing based on consumer demand [35], as depicted in Table 3. Variations in product quality can result from physical, biological, and chemical effects, which can impact intrinsic quality, pricing, fruit maturity, seed vigor, and appearance. Manual methods of inspection are both time consuming and prone to error [36]. Hyperspectral imaging offers a cost-efficient option for evaluating hidden quality factors that are not visible to the naked eye [37]. Fast product sorting requires quick response times, and deep learning can function efficiently with minimal resources [38]. Nevertheless, adjusting models to varied product features can be difficult, sometimes requiring separate models for individual types [39]. Furthermore, identifying crop quality, even under controlled environments, is complex because the spectrum differs among various types and batches, necessitating distinct models for each, which limits generalizability.

C. CONTAMINANTS AND IMPURITIES DETECTION AND QUANTIFICATION

The detection of contaminants and impurities is important regarding the quality of the product and for health and safety reasons [40], [41]. While visual screening can be subjective and unreliable, laboratory analysis is often time-consuming and expensive. Hyperspectral images provide a promising high-throughput solution for detecting heavy metals [42], [43], 2020b [44] Table 3. Screening for dangerous items and chemicals generally necessitates time-consuming and costly laboratory analysis. Many nations have legal restrictions on impurities and pollutants, therefore systems that utilizes hyperspectral imagery and deep learning must prioritize compliance. Detecting alien items and chemicals is challenging, especially when trying to fulfill strict regulatory requirements, and typically involves accounting for uncertainty and sensitivity of processes and equipment to justify the detection ranges and thresholds of acceptable and unacceptable limits for a variety of contaminants.

D. PLANT MATURITY DETERMINATION

Knowing the optimal harvest time is said to be the holy grail of farming as it ensures maximum profits for the farmer. Hyperspectral images can detect slight spectral differences in the fruit that will indicate different maturity stages and offer an objective and effective method superior to human eye inspections and traditional laboratory analyses [11], [45], [46]. Hyperspectral images have been used since at least the early 2010 decade for estimating maturity and ripeness Table 3. While current methods focus on individual fruit maturity, implementing this technology on a larger scale is still in progress [6]. Although optimization of the harvest timing can be challenging and selection of an area to harvest may be tough, a robotic platform for mapping maturity has much potential for increasing yield and reducing fruit drop.

E. NUTRITIONAL STATUS

Monitoring nutritional parameters is crucial for achieving maximum agricultural yield and optimizing fertilization, but traditional methods pose several challenges to surveying large fields. Hyperspectral images identify alterations in chemicals before symptoms are observable, hence enabling UAV nutrition monitoring [47]. Although hyperspectral imaging for nutrition monitoring is not widely adopted, nitrogen has become one of the most studied elements and can be shown in Table 3. While field estimation is practical, most research is conducted in the laboratory setting [48]. Spectral changes similar to other stresses may obscure the accurate detection of nutrition problems; thus, additional data are needed. Limited literature has been placed on the sensitivity that hyperspectral-based systems provide toward detecting nutrition problems.

F. OTHER APPLICATIONS

Many applications have been studied involving the combination of deep learning and hyperspectral imaging. These categories are summarized by the studies in Table 3.

- **Product Varieties Differentiation:** Different varieties have specific characteristics, and their accidental mix may lead to adverse effects on quality and economic parameters. Efficient screening techniques urgently need to be developed to prevent fraudulent practices [49]. However, current techniques for variety discrimination are often costly, time-consuming, and limited in their applicability [19]. Accurately classifying seeds and crops based on their variety poses challenges due to subtle differences at the chemical level [50]. This challenge increases in difficulty if the crop is faced with a great number of potential varieties [51]. Although high accuracies have been achieved under ideal conditions, replicating such success in real-world settings remains a challenge [52].
- **Object Segmentation:** Enabling harvest automation is the main goal of this study. [53], suggested a low-cost method by modifying an RGB sensor with a filter to

resemble hyperspectral characteristics. Complex-valued neural networks were employed to improve robustness against variation in illumination [54].
- **Plant Species Recognition** Plant species recognition is difficult because of seasonality and variations in spectral patterns. [55], Observed that a more sophisticated multitemporal strategy should be employed to model changing class separability. Moreover, with different growth stages, the task gets more difficult [56].
- **Pests Disease Detection and Classification:** Continuous pest and disease surveillance around the crop cycle is very important to maximize yield and quality [58], [59], [60]. Recent advances in deep learning, such as the attention-based lightweight models for early potato disease detection using RGB images [61], show the potential of the deep learning model in disease detection, which could be enhanced by integrating hyperspectral imaging techniques. Hyperspectral imaging is a non-destructive and efficient way to check crop health. Different pest and disease stressors can be identified by utilizing vegetation indicators and machine learning techniques. However, current Hypersectral camera camera-based systems have hurdles due to a lack of high-resolution HSI data, which affects reliable identification, and the diverse agricultural environment requires flexible algorithms and large amounts of data.

Table 4 provides a summary of all the limitations, both application-specific and general, discussed in this review.

III. COMMONLY USED DEEP LEARNING NETWORKS FOR HYPERSPECTRAL IMAGING IN SMART AGRICULTURE

Recently, a number of well-known deep learning networks, such as convolutional neural networks (CNNs), deep belief networks (DBNs) autoencoders (AEs), recurrent neural networks (RNNs), capsule networks (CapsNet), graph convolutional networks (GCNs), morphological neural networks (MNNs), and transformer architectures, have been widely and successfully used in the hyperspectral image analysis tasks. An overview of these cutting-edge deep learning networks is shown in Figure 3.

A. CONVOLUTIONAL NEURAL NETWORKS

Convolutional neural networks (CNNs) are a kind of feed-forward neural networks capable of automatically identifying features in applications like voice and image processing [68]. Through back-propagation, convolution filters, and pooling, fully connected layers are trained. One advantage of CNNs is their insensitivity to transformations such as image translation and rotation, which mitigates the requirement manual feature extraction [69]. When applied in HSI applications, CNNs can extract spectral-spatial features for processing [70]. As in Figure 4, there are three types of CNN-based HSI frameworks: spectral, spatial, and spectral-spatial feature models [71].

1D-CNNs: The 1D-CNN models for hyperspectral images primarily focuses on the 1-dimensional spectral data of every pixel when analyzing the discriminative features in the spectral domains [72]. It either considers originally determined bands of spectrum or selects crucial bands obtained via various dimensionality reduction techniques [34]. Even with fewer hyperspectral images, large training sets can be built up because every single pixel is treated as a distinct sample [33], which means that every pixel is treated as a point spectroscopy. Methods for averaging spectra in regions help to correct noise, but such methods result in smaller spectra and finally lead to poor performance due to the complete ignorance of spatial information, particularly in cases of isospectral heterogeneity [32].

2D-CNNs: Traditional spectral feature-based 2D-CNN models of hyperspectral imaging utilizes 2D spatial information to determine the spatial patterns in a given hypercube [73]. To enhance the efficiency of the network, several techniques of dimensionality reduction are applied in the spectral domain. However, inappropriate methods for reduction may result in a loss of information and poor performance regarding the selection of features [7]. Patch cropping is one of the most common ways out to address limited training samples [64]. While 2D-CNNs capture the spatial content, they often fail to model spectral information. This may introduce spectral distortion and can lead to poor extraction of significant spectral features.

3D-CNNs: The 3D-CNN model, which is based on spectral-spatial characteristics, simultaneously processes 2-dimensional spatial features and 1-dimensional spectral features in the hyperspectral image [74]. These models utilize 3D kernels for learning relationships between the spectral and spatial dimensions of hypercubes, which can be used for quantification or categorization [45]. Even though the techniques mentioned above may reveal an abundance of information from hyperspectral images, as training data increases, this increases the computing load and model complexity [75]. Thus, certain studies have combined CNNs and dimensionality-reducing techniques to minimize the dimensions of HS data [74].

Despite CNN models achieved very promising results in HSI analysis, there is still a need for more effective algorithms that use HSI's spectral-spatial features while retaining effectiveness.

B. DEEP BELIEF NETWORKS

DBNs are a type of neural network proposed by Hinton in 2009 with multiple hidden layers, as shown in Figure 3b. This architecture gives them the capability of extracting the hierarchical features of hyperspectral data [76]. Each hidden layer functions as a Restricted Boltzmann Machine (RBM), and its parameters are optimized using supervised learning techniques [77]. The features extracted from DBNs are very helpful in various tasks related to classification, target detection, and anomaly detection [78], [79]). Moreover, DBNs

TABLE 3. Articles dealing with different characteristics of each type of application of HSI. The "Application" column uses letters B, Q, and M for binary classification, quantification, and multi-class classification, respectively. In the "Accuracy" column, the metrics are represented as follows: "Acc." the percentage of correctly classified samples, "F1" for F1-score, "IoU" for Intersection over Union, "r" for Correlation coefficient, and "r^2" for Coefficient of determination.

Reference	Application	DL Model	Bands	Accuracy
Articles on Stress Identification and Quantification.				
Reference	**Application**	**DL Model**	**Bands**	**Accuracy**
2019 [34]	Estimation of plant cold damage levels (Q)	CNN (1D)	450-885	0.82 ^{r}
2020 [14]	Salt-stress phenotyping (Q)	CNN(3D)	380-1030	0.59-0.94 ^{IoU,r}
2020 [33]	The relative water content of maize plants (Q)	1D CNN (1D)	370-1030	0.87 $^{r^2}$
2020a [35]	Detection of FHB in wheat kernels (Q)	Self-search Deep net (3D)	400-1000	0.97 $^{Acc.}$
Articles on Products Quality Control				
Reference	**Application**	**DL Model**	**Bands**	**Accuracy**
2018 [36]	Estimation of soluble solids content and firmness of tomatoes (Q)	CNN (1D)	400-1000	0.97 $^{r^2}$
2021b [38]	Estimation of micro-components in flowers (Q)	CNN (1D)	874-1734	0.60-0.93 $^{r^2}$
2021 [40]	CNN (1D)	Prediction of sugar and pH levels in grapes (Q)	N/A	0.66-0.95 $^{r^2}$
2021a [39]	Determination of pomelo fruit quality (Q)	RBF-PLS (1D)	1000-2500	0.90-0.92 ^{r}
2022a [37]	Prediction of oil content in maize kernels (Q)	Attention-Based CNN (1D)	866.4-1701.0	0.92 $^{r^2}$
Articles on Contaminants and Impurities Detection and Quantification				
Reference	**Application**	**DL Model**	**Bands**	**Accuracy**
2019 [41]	Cadmium content estimation in lettuce leaves (Q)	DBN (1D)	431-961	0.92 $^{r^2}$
2022 [42]	Detection of lead in lettuce (Q)	WT-SAE (1D)	480.5-1001.6	0.95-0.98 $^{r^2}$
2020 [43]	Prediction of cadmium residue in lettuce (Q)	SAE (1D)	380-1030	0.95 $^{r^2}$
2020a [44]	Prediction of lead in lettuce (Q)	WT-SAE (1D)	380-1030	0.96 $^{r^2}$
2020b [45]	Detection of heavy metals in lettuce (Q)	SAE (1D)	400.7-1001.6	0.94 $^{r^2}$
Articles on Plants Maturity Determination				
Reference	**Application**	**DL Model**	**Bands**	**Accuracy**
2018 [6]	Maturity Estimation of Mangoes (Q)	CNN (1D)	411.3-867.0	0.97 $^{r^2}$
2020 [46]	Maturity Evaluation of Strawberries (Q)	Several CNN Model (3D)	380-1030	0.55-0.84 $^{1,r^2}$
2021 [47]	Papaya Maturity Estimation	CNN (3D)	400-900	0.90 ^{F1}
2021 [11]	Estimation of strawberry ripeness	CNN (3D)	370-1015	0.98 $^{Acc.}$
Articles on Nutritional Status				
Reference	**Application**	**DL Model**	**Bands**	**Accuracy**
2018 [58]	Prediction of Nitrogen in oilseed rape (Q)	SAE-FNN (1D)	380-1030	0.90 $^{r^2}$
2021b [48]	Nitrogen Prediction in Maize (Q)	SSD CNN (3D)	450-900	0.73 $^{r^2}$
2021 [49]	Estimation of Leaf Nitrogen content in wheat (Q)	CNN (3D)	360-1025	0.86 $^{r^2}$
2022b [51]	determination of Zn content in Rape Leaves (Q)	Modified SAE (1D)	431-962	0.96 $^{r^2}$
Articles on Other Applications				
Reference	**Application**	**DL Model**	**Bands**	**Accuracy**
2020 [55]	Semantic segmentation of plants (B)	U-Net (2D)	407-997	0.96^{IoU}
2021 [52]	Hybrid okra seed identification (M)	SSAE, CNN (1D)	948.2-1649.2	$0.94-0.98^{Acc.}$
2022 [53]	Discrimination of tea varieties (M)	VGGNet CNN (1D)	874-1734	$0.89^{Acc.}$
2021 [54]	Green pepper segmentation (B)	GAN (1D)	400-1000	$0.91^{Acc.}$
2021 [56]	Tree species classification (M)	5-layer network	400-1000	$0.85-0.96^{Acc.}$
2022 [57]	Discrimination between corn and weeds (B)	Lightweight-3D-CNN (3D)	400-1000	$0.98^{Acc.}$
2022b [50]	Identification of rice seed varieties (M)	CNN (1D)	900-1700	0.86 $^{Acc.}$
2022b [19]	Tea type classification (M)	MobileNetV2 + SVM (3D)	908-1735	$0.99^{Acc.}$

have demonstrated promise in semi-supervised learning (SSL) contexts, effectively tackling the problem of limited labeled data [80]. In many applications, both the Firefly xi Harmony Search DBN model and PCA-based data reduction techniques have turned out to be efficient [81]. Furthermore, DBNs were used very successfully for the identification of lead contamination in lettuce plants, outperforming previously developed traditional methods [82]. However, there are some problems associated with DBNs: these involve a computationally intensive procedure, interpretability, and optimization of parameters. Recently, research has focused on resolving initialization challenges and explaining manifold structure issues. [83].

C. AUTO-ENCODING NETWORKS

Autoencoders (AEs) are primarily an unsupervised learning model that include decoder and encoder stages [84]. Whereas AEs were initially proposed for unsupervised learning scenarios, they have also been proven useful for semi-supervised and supervised learning tasks [85], [86]. A stacked autoencoder (SAE) comprises of several AEs that may be trained layer-by-layer for feature learning and generative model generation [87]. As in Figure 3c, SAE learns the hidden patterns of hyperspectral data, hence reducing the load of manually designing features [88]. In the case of agricultural HSI, spectralÂ signatures from every pixel are supplied onto the encoding unit and then rebuilt by the decoding unit,

TABLE 4. Summary of limitations by application in hyperspectral imaging research.

Application	Limitations
Stress Identification and Quantification	• Early stress detection is challenging due to subtle signs not easily discernible with HSI data. • Research primarily focuses on isolated stress factors in controlled environments. • Complex interactions between plant varieties, stressors, and environmental factors lead to spectral response variations.
Product Quality Control	• Real-time product sorting requires low latency, feasible with efficient deep learning models. • Identifying crop quality in labs is complicated by spectrum differences across various kinds, batches, and sources. • Separate models for each variety, batch, and source are necessary, hindering results.
Contaminant and Impurity Detection and Quantification	• Screening for dangerous items and chemicals typically involves costly laboratory analysis. • Ensuring adequate sensitivity of processes and equipment is crucial. • Developing appropriate detection thresholds requires datasets with a wide range of contamination levels.
Plant Maturity Determination	• Optimizing harvest timing and selecting specific areas for harvesting is challenging. • Robotic platforms designed to map plant maturity show promise in increasing yield and reducing fruit drop.
Nutritional Status	• Most research occurs in labs despite the practicality of field estimation. • Detecting nutrition issues accurately is complex due to spectral alterations resembling other stresses, requiring additional data. • The sensitivity of hyperspectral based systems in detecting nutrition problems requires further exploration, with limited literature attention.
Other Applications	• Accurately classifying seeds and crops by variety is challenging due to subtle chemical differences. • Complexity rises when dealing with numerous potential varieties. • High accuracies achieved under ideal conditions are difficult to replicate in real-world settings.
General Limitations	• Challenges include illumination effects, complex plant geometry, and the need for calibration and denoising methods. • High technology costs hinder widespread adoption, necessitating more affordable options. • Advanced techniques and models: Some studies lack the exploration of advanced deep learning and pattern recognition models. • Certain papers lack concrete solutions for handling illumination variations and may be limited in scope. • Scarcity of benchmark hyperspectral datasets is noted, affecting comparative analysis and real-world applicability. • High data complexity, redundancy, and dimensionality pose challenges. • Challenges include handling variations in lighting conditions.

which enables spectral feature extraction [41]. In order to improve the learning ability, lots of upgraded AE models are present, such as Stacked Sparse Autoencoders (SSAE), denoising autoencoders, and Compact and Differentiated Stacked Autoencoders [89]. Models integrating AEs with downscaling, CNN, a 2D self-encoder, and a 3D convolutional operator enable fusion of spatial-spectral features [90]. However, more work needs to be done in terms of optimizing the use of spatial features, dealing with intra-class variation and inter-class similarities, co-training, pre-training, and adaptive neural networks. Furthermore, it is crucial to develop training procedures that are faster and able to handle larger datasets.

D. RECURRENT NEURAL NETWORKS

Recurrent Neural Networks (RNNs) are neural networks with feedback connections that process data in sequence [91]. It takes the previously sampled instant's output as an input for the current instant, as shown in Figure 3d. RNN analyzes HSI data efficiently by considering spectral information as a time series dataset [92]. The traditional RNNs have difficulties like the vanishing and exploding gradient; they only concentrate

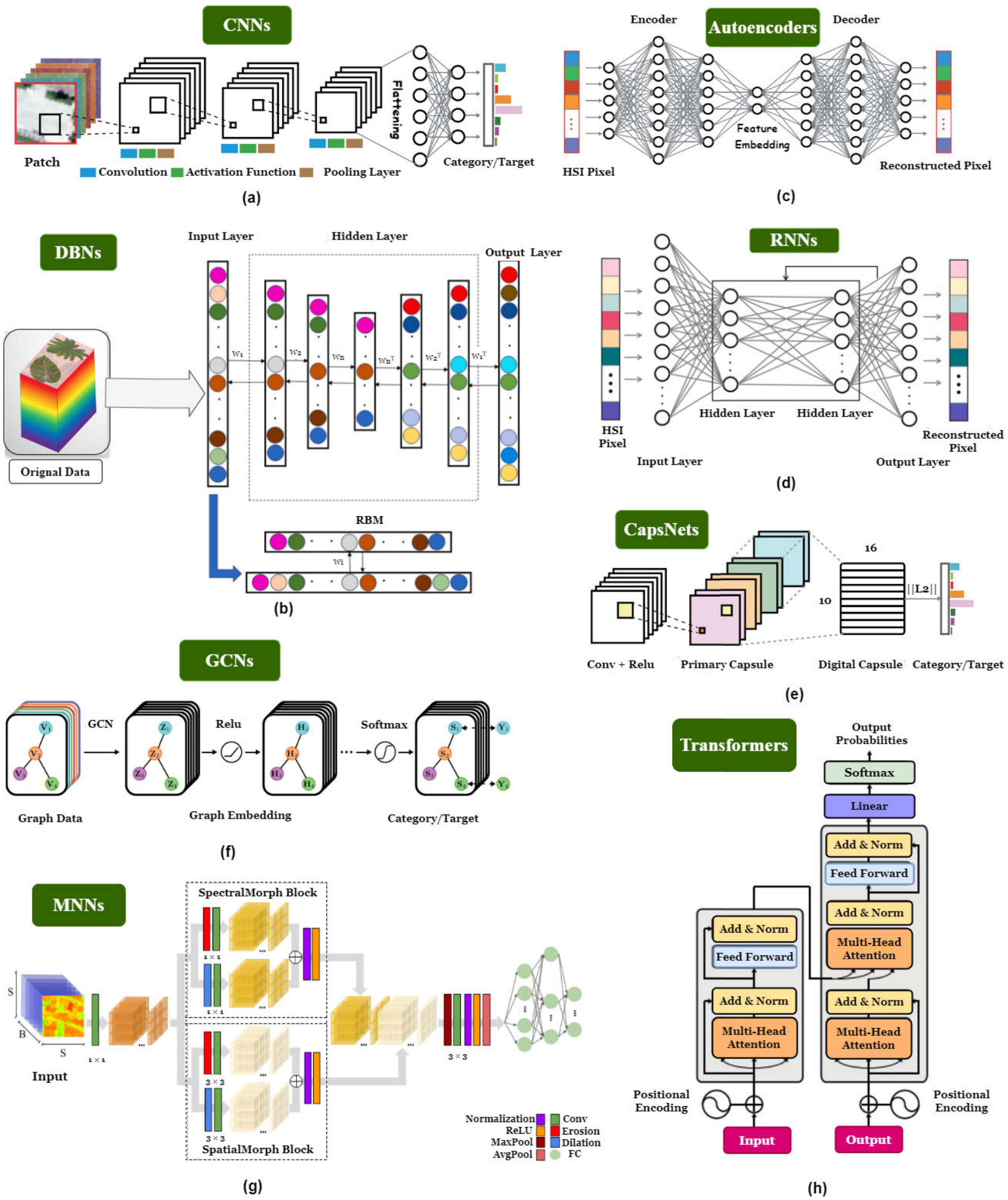

FIGURE 3. An overview of deep learning networks utilized in the HS image analysis, such as (a) CNNs [62], (b) DBNs [63], (c) AEs [26], (d) RNNs [26], (e) CapsNet [64], (f) GCNs [65], (g) MNNs [66], and (h) Transformer Neworks [67].

on the spectral features, which makes it difficult for them to learn long-term spectral dependencies [93]. Automatic learning of spatial-spectra characteristics from hyperspectral data has been accomplished via bidirectional convolutional long and short-term memory networks (Bi-CLSTM) in order to optimize the performance of models and effectively

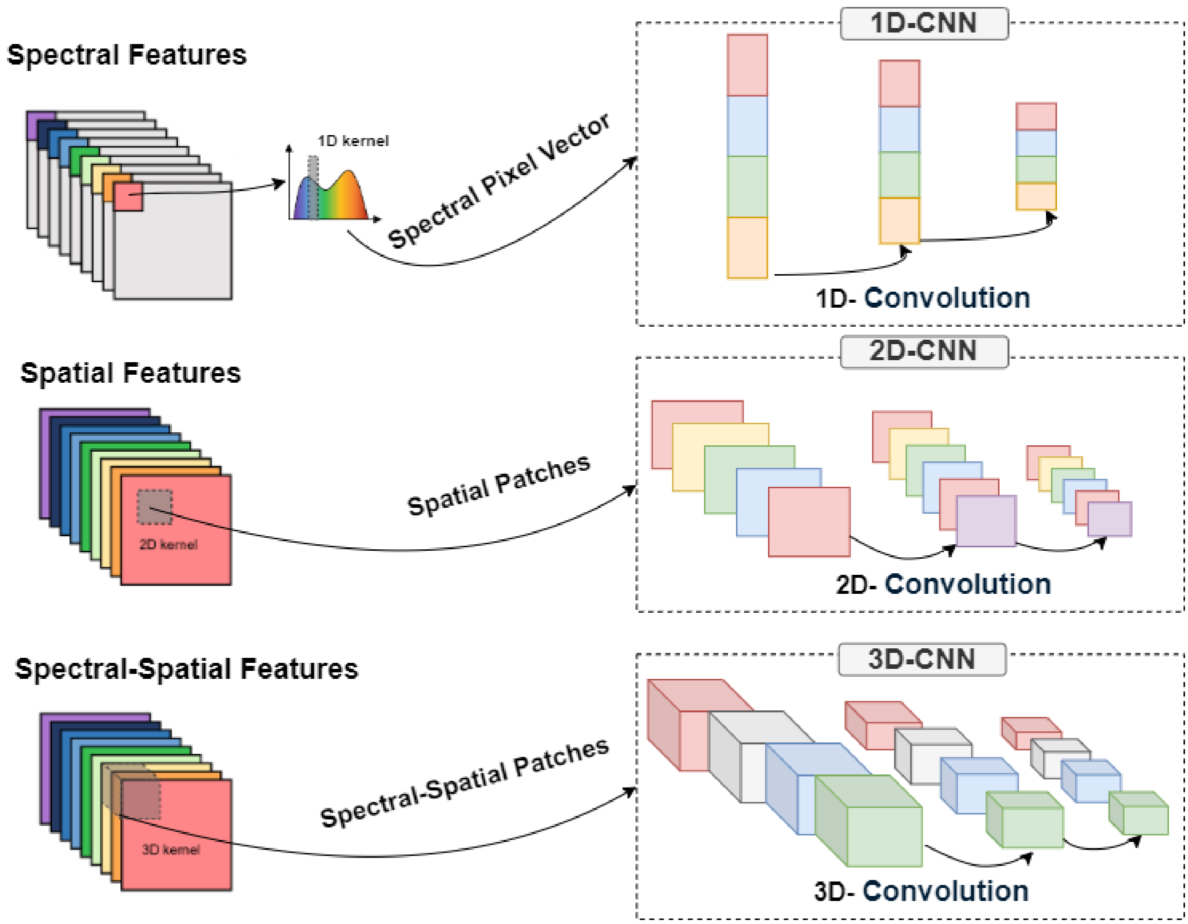

FIGURE 4. The 1D, 2D, and 3D CNN convolution architecture for hyperspectral image analysis.

leverage spatial features [94]. In the spatial-spectral LSTM models, CNN and PCA are used for feature extraction [34]. Combining CNNs and RNNs results in integrated spatial-spectral characteristics. Future study should focus on enhancing RNN model data creation, resolving overfitting, and shortening input sequence lengths. It is critical to build models for unstructured settings that can manage data unpredictability in weather, soil conditions, and plant growth phases.

E. CAPSULE NETWORKS

Capsule Networks (CapsNets) is an alternate method for capturing specific features in HSI data [95]. CapsNets model associations in data with activity vectors, unlike the standard procedures relying on scalar values. The length of these vectors represents the probability of an object's presence, while their orientation represents the object's pose parameters [64]. Furthermore, modified a CNN-based model by incorporating a spectral-spatial capsule unit, resulting in an efficient classification framework for HSI images while reducing network design complexity [64], as depicted in Figure 3e. However, despite the advantages of learning spectrum characterizations (such as equivalence, robustness, long-term relevancy in data), they can be intrinsically ineffective for accurately modeling sequential features.

F. GRAPH CONVOLUTIONAL NETWORKS

Numerous studies have explored the use of CNNs and graph convolutional networks (GCNs) for hyperspectral image categorization. Recent study has introduced novel GCN architectures to alleviate the working difficulty with large graphs in this domain. For example, mini-batch GCNs (miniGCNs) have been proposed to handle large-size graphs in GCNs and achieved the state-of-the-art performance in hyperspectral image classification [65] as shown in Figure 3f. Additionally, an attention-based GCN has been developed which draws features from hyperspectral imagery by paying attention to spectral information, resulting in significant increases in the accuracy of classification [96]. However, the representation capacity of many existing GCN-based approaches remains restricted due to the limited availability of labeled pixels [97].

G. MORPHOLOGICAL NEURAL NETWORKS

Morphological Neural Networks (MNNs) have been an important architecture for hyperspectral image processing and analysis since it provides a way of involving non-linear morphological operations like erosion and dilation [66], as shown in Figure 3g. Unlike traditional CNNs and RNNs, MNNs make use of morphological transformations to process and analyze the spatial structures in hyperspectral data [98]. These operations enable MNNs to model and enhance local contextual features efficiently, which is very important in detailed image analysis. Although MNNs are very good at preserving and highlighting the local spatial characteristics, they may not have the inherent ability to deal with long-term dependencies or global contextual information effectively [99].

H. TRANSFORMER NETWORKS

The Transformer networks (TNs) have recently gained significant popularity as one of the major backbone architectures, mainly for problems involving sequential or time-series data and include hyperspectral image processing and analysis. In contrast to traditional deep learning models such as CNNs, DBNs, and RNNs, transformers leverage self-attention mechanisms that enable efficient processing and analysis of sequential data [67], as illustrated in Figure 3h. This makes transformers well-suited for hyperspectral image analyses tasks, as the self-attention block in transformers is known for its ability to globally capture sequential information through positional encoding [100]. Although transformers have the advantage of being able to address long-term dependencies within spectral signatures. However, they lack the ability to capture local contextual or semantic characteristics very well, which is a strength of CNNs and RNNs [101].

Recent lightweight Vision Transformer (ViT) variations, notably TinyViT [102] and MobileViT [103], use architectural improvements to achieve computational efficiency on portable devices. However, high spectra dimensionality, the inherent spectral–spatial complexity, and hardware constraints on edge devices usually used in agricultural settings limit its adoption in proximal HSI.

The comparative summary of the performance, advantages, and limitations of different deep learning methods for hyperspectral imaging in agriculture is provided in Table 5.

The computational characteristics of deep learning models for hyperspectral imaging are highly dependent on network depth, dataset size, and the number of spectral channels in the dataset. The deeper networks and larger datasets tend to mean longer training times, greater hardware requirements, and higher energy consumption. A general overview of the computational complexity, training time, inference time, hardware requirements, and energy consumption for the various deep learning models used in HSI analysis is given in Table 6. This comparison highlights the varying resource demands of various architectures, an important aspect for real-world deployment.

Figure 5 illustrates the distribution of the indicative average accuracies of various deep models such as 1D-CNN, 2D-CNN, 3D-CNN, Autoencoders, RNNs, and other advanced models. These were obtained by averaging reported accuracies from the research articles summarized in Tables 3 and 2.

Overall, traditional deep learning algorithms such as CNNs, DBNs, and RNNs in HSI for precision agriculture face major difficulties related to data loss and various issues of dimensionality. The transformers that can handle the long-term dependencies within the spectral signature still struggle to capture the local contextual features, which CNNs and RNNs handle well. In this respect, a combined transformer with other deep learning models could provide a more holistic approach for HSI analysis. While most of these studies focus on the classification of remote sensing with a limited number of available datasets, further studies are required to be performed for the exploration of these networks in terms of quantification and regression tasks related to proximal hyperspectral imaging across diverse agricultural datasets.

IV. COMMON ISSUES AND SOLUTIONS FOR DEEP LEARNING MODELS IN AGRICULTURAL HSI ANALYSIS

A. DATA SCALE AND VARIABILITY

Currently, agricultural hyperspectral imaging datasets for deep learning are in short supply [104]. Data collection on various agricultural missions requires a variety of procedures that are both expensive and time-consuming [105]. The scarcity in its availability and poor quality of the acquired dataset further restricts the development of DL-HSI techniques [106]. Methods such as semi-supervised learning, transfer learning, active learning, and data augmentation have been adopted to further enhance data utilization efficiency and performance. In addition, an effort is made to develop large-scale, standardized, high-quality, annotated agricultural hyperspectral datasets.

1) DATA AUGMENTATION

Data augmentation approaches create new training samples with no additional labeling expenses [31]. They include data wrapping, which performs geometric and color modifications while leaving labels intact [107], and oversampling, which guarantees that fresh samples have comparable feature distributions to the original data [108]. Oversampling methods include hybrid instance generation, GANs, and feature space augmentation [109]. Data augmentation helps models in learning data distribution and characteristics, resolving sample imbalance and overfitting as depicted in Figure 6a.

Existing HSI data augmentation approaches frequently use techniques from RGB images without fully grasping HSI's spectral and spatial characteristics [110], particularly when they are working outside the visible spectrum where the ground truth is costly and complex to obtain. Nonetheless, approaches based on HSI spectral and spatial information have been proposed with samples generated during testing, followed by the application of trained models and voting schemes [111]. The challenges with performing

TABLE 5. A comparative summary of different deep learning networks for HSI in smart agriculture.

Model	Performance	Advantages	Limitations
CNN	High spatial feature extraction accuracy; widely used for HSI classification.	Effectively captures spatial characteristics; excellent for detecting local features in hyperspectral data.	Limited in ability to capture long-range spectral dependencies; large labeled datasets are required.
DBN	Effective for feature extraction in classification, target detection, and outlier detection; demonstrated success in semi-supervised learning (SSL) for limited labeled data.	Extracts hierarchical features; works well with limited labeled data; combines unsupervised pre-training (RBMs) with supervised fine-tuning.	Difficult to interpret and optimize; struggles with scalability for large datasets.
AE	Excel in spectral feature extraction, useful for semi-supervised and supervised tasks; advanced versions (SSAE, denoising) and hybrid models enhance spatial-spectral fusion.	Manual feature engineering is reduced by unsupervised learning; SAE enables hierarchical feature learning; hybrid models enhance spatial-spectral representation.	Suboptimal spatial feature extraction, requiring further optimization; sensitive to intra-class variation and inter-class similarities; requires co-training, pre-training, and adaptive neural networks for better performance.
RNN	Effectively handles sequential HSI data by treating spectral information as a time series; Bi-CLSTM and hybrid CNN-RNN architectures improve spatial-spectral feature learning.	Captures temporal and long-term spectral dependencies; improves spatial-spectral feature extraction.	Vanishing/exploding gradients; challenges in handling unstructured data.
CapsNet	Efficient for HSI data encoding with activity vectors representing data relationships, improving image classification.	Encode feature relationships through activity vectors; reduces network design complexity when employed together with spectral-spatial capsule units.	Not good at capturing sequential features correctly.
GCN	Achieves good performance on hyperspectral image classification, especially with miniGCNs and attention-based GCNs, which improves the classification accuracy.	Reduces computational cost with mini-batch GCNs; attention mechanisms enhance feature learning with a focus on spectral information.	Limited capacity of representation with insufficient labeled data; graph construction preprocessing is required.
MNN	Effective in hyperspectral image analysis, improving local spatial feature extraction through morphological operations like dilation and erosion.	Enhances regional contextual features, enhancing spatial understanding; morphological operations improve spatial pattern analysis in hyperspectral data.	Limited ability to capture long-term dependencies or global contextual information.
Transformer Network	State-of-the-art in spatial-spectral feature modeling; employed for both classification and regression. excels in capturing long-range dependencies in spectral data.	Model global sequential information using self-attention; effective for long-term dependency analysis in spectral data. Scalable to large datasets.	Struggling to keep local contextual or semantic information, compared to CNNs or RNNs.

data augmentation in HSI include preserving features, selecting augmentation techniques, handling limited numbers of data and samples, and consideration of domain knowledge together with computing capabilities.

2) SEMI-SUPERVISED LEARNING

The Semi-supervised learning trains models using a combination of labeled and unlabeled data [112]. It is useful for HSI analysis when labeled data is limited, and could be a viable approach for near-infrared HSI. In agricultural HSI analysis, many approaches such as self-training, co-training, GANs, graph-based, and semi-supervised SVM have been used [113]. Data quantity, quality, skewed distribution, noise, computational difficulty, and restricted generalizability are all challenges.

3) ACTIVE LEARNING

To increase the performance of models, Active Learning (AL) automatically chooses informative data for labeling [114]. Figure 6b, highlights diverse behaviour, model performance,

TABLE 6. Computational characteristics* of deep learning networks for HSI in smart agriculture.

Model	Computational Complexity	Training Time	Inference/Testing Time	Hardware Requirements	Energy Consumption
CNN	Moderate -to- High (based on kernel size and network depth)	Moderate -to- Long (based on network depth and dataset size)	Fast -to- Medium (performs well with small inputs)	GPUs necessary to train efficiently (for large datasets and complex models).	Moderate -to- High (based on model complexity and hardware)
DBN	High (due to deep-layered architecture and fine-tuning)	Long (Pre-training and fine-tuning require multiple iterations)	Moderate (inference is not too slow after training)	High-performance GPUs/TPUs required (Processing deep belief structures require high computation and memory power)	High (Multiple iterations and deep structures are power-consuming)
AE	Moderate -to- High (Stacking layers and reconstruction loss increases complexity)	Moderate -to- Long (Training involves learning hierarchical representations)	Fast -to- Moderate (learned compact representations make inference efficient)	GPUs needed for stacked models (Parallelization is necessary to handle large HSI datasets)	Medium -to- High (dependent on complexity of architecture)
RNN	High (Sequential data processing increases complexity due to dependencies)	Long (Backpropagation through time (BPTT) makes training slow)	Moderate (Inference needs sequential processing of dependencies)	GPUs/TPUs required for sequence processing (Memory-intensive operations for time-series learning)	High (due to recurring operations and memory utilization)
CapsNet	High (due to dynamic routing and vector representations)	High (because of iterative routing and complex computations)	High -to- Moderate (because of dynamic routing and capsule vector computations)	High-end GPUs/TPUs required (Higher memory and compute demand for vectorized feature extraction)	High (Computationally expensive due to complex routing operations)
GCN	High (Graph-based computations and neighborhood aggregation increase complexity)	High (scales with graph size and complexity)	Moderate (Efficient once trained but scales with graph size)	GPUs necessary for large graphs (Parallel computation necessary for spectral and spatial graph processing)	High (Graph convolutions are memory-intensive and require iterative updates)
MNN	Moderate -to- High (depends on structuring element size and morphological operations, which are less computationally intensive than convolutions)	Moderate (Training focuses spatial structures over deep feature hierarchies)	Fast (Efficient inference time due to simple operations like dilation and erosion)	Standard GPUs/CPUs (Does not require heavy computational resources)	Low -to- Moderate (Light operations make it power-efficient)
TN	Very High (Due to self-attention mechanisms and large models)	Very Long (Due to attention mechanisms and large dataset requirements)	Moderate (Inference has the benefit of parallelized attention but still requires high memory)	High-end GPUs/TPUs with high memory (Attention mechanisms demand high computational resources)	Very High (Multi-head attention and large tokenization require high power consumption)

**Note: The terms "Low," "Moderate," and "High" are qualitative estimations that depend on several kinds of factors, including the size of the dataset, the number of spectral bands, the model architecture (e.g., network depth, kernel size), and standard hardware requirements. These qualitative assessments provide general comparisons rather than serving as specific metrics.*

and sample representativeness [84]. AL decreases labeled samples, increasing learning efficiency when compared to usual semi-supervised algorithms [115]. Random sampling (RS), maximum uncertainty sampling (MUS), multi-view (MV), and mutual information (MI) sampling are all prominent AL approaches [116]. Some of the challenges in using AL to perform HSI analysis involve the optimization of sample selection, dealing with data variability, and label noise. To address such challenges, various techniques, including pre-processing, label correction, data augmentation, and semi-supervised learning, can be employed.

4) TRANSFER LEARNING

Transfer learning is the utilization of pre-trained models to resolve a novel issue, improve performance, or accelerate training [117], [118]. Figure 6c shows that it can use current models to improve the desired job's performance, especially when the dataset is limited [119]. TL's efficacy has made it frequently employed in agricultural hyperspectral image analysis [120]. Domain shift, task specificity, and model compatibility are some of the challenges encountered in transfer learning for hyperspectral imaging (HSI). Domain shift can be addressed through techniques like domain

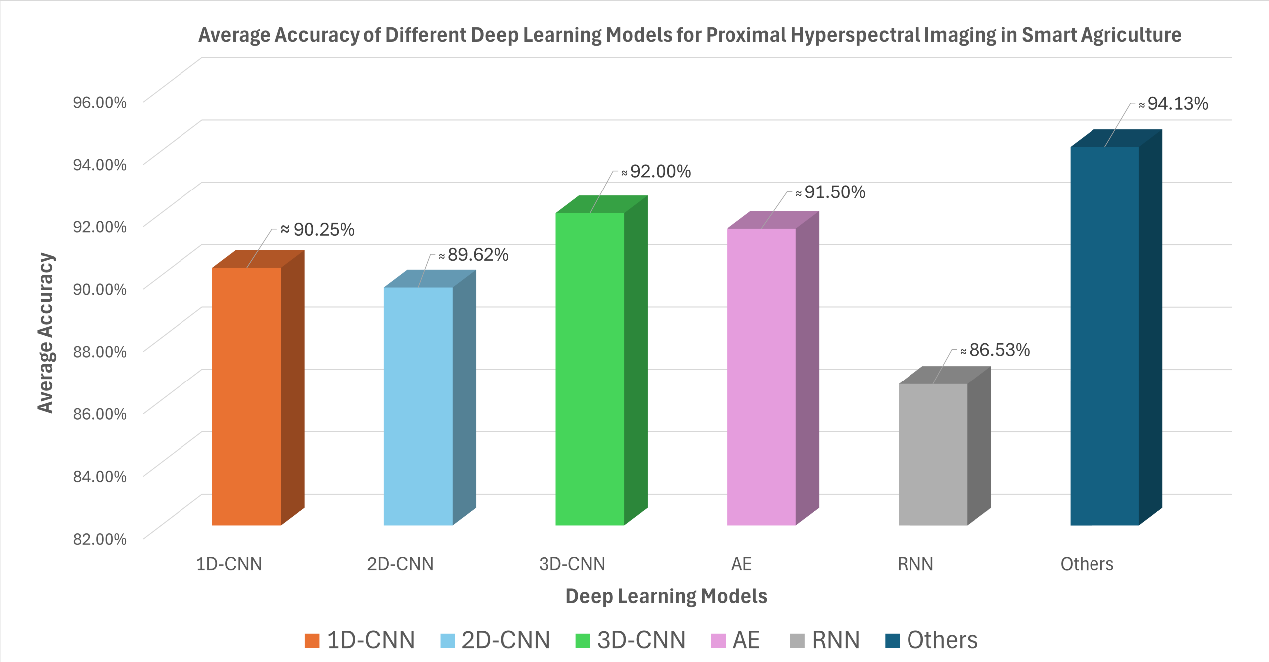

FIGURE 5. Indicative average accuracy** of various deep learning models over the last five years for proximal HSI in smart agriculture.

adversarial training or feature alignment. Multi-task learning techniques can be used to address task specificity. Furthermore, transformation or feature selection techniques can be used to increase model compatibility.

B. DATA BALANCE AND QUALITY

1) DATA BALANCE

Hyperspectral data is frequently imbalanced, with certain categories having fewer samples than others [111]. Several techniques are used to solve this, including data resampling, integrated learning, category weight alterations, data augmentation, anomaly detection, and domain adaptation. Data resampling uses strategies like under-sampling or oversampling to balance sample sizes [4]. Category weight adjustments emphasize specific categories in the loss function [121]. Integrated learning connects models to increase recognition performance in a select few categories. Anomaly detection considers minority groups separately. Data augmentation produces artificial data for minority groups. Domain adaptation modifies algorithms according to domain knowledge and features specific to minority categories.

2) DATA QUALITY

Different disturbances, noises, and environmental destruction, including light, shadows, air turbulence, and cloud cover, may have an impact on HSI data [6]. This can reduce data quality, thus compromising model accuracy and robustness [47]. To enhance the hyperspectral image quality, techniques such as super-resolution, reconstruction, restoration, and denoising are needed. Denoising techniques remove noise from the spectral range by either discarding noisy bands or adopting advanced noise removal techniques [52], including deep learning algorithms that improve image quality and accuracy [37]. Reconstruction techniques recover incomplete data of hyperspectral images [122], while super-resolution methods enhance image detail by mapping low-resolution data to high-resolution output to enhance clarity and precision [123]. Diffusion models have recently become highly effective generative models for denoising and reconstruction in HSI and remote sensing applications [124], [125], although their utilization in proximal HSI for smart agriculture is still largely unexplored.

C. FEATURES SELECTION AND COMPRESSION

HSI data are high-dimensional, with hundreds of spectral bands per pixel, resulting in storage and processing challenges [126]. Methods of features selection and compression could become necessary in such cases to reduce dimensions and computational expenses with no compromise on the important information. Such techniques include observations of spectral curves to identify the distinguishing wavelengths [30], Dimensionality reduction techniques include principal component analysis, factor analysis, and non-negative matrix decomposition [127]. Feature selection techniques, which try to identify most important or representative portion of features using mutual information, information gain, correlation coefficient analysis, and variance analysis based methods. Furthermore, attentional mechanisms are used to select hyperspectral bands that have the closest relationship to the categories of interest

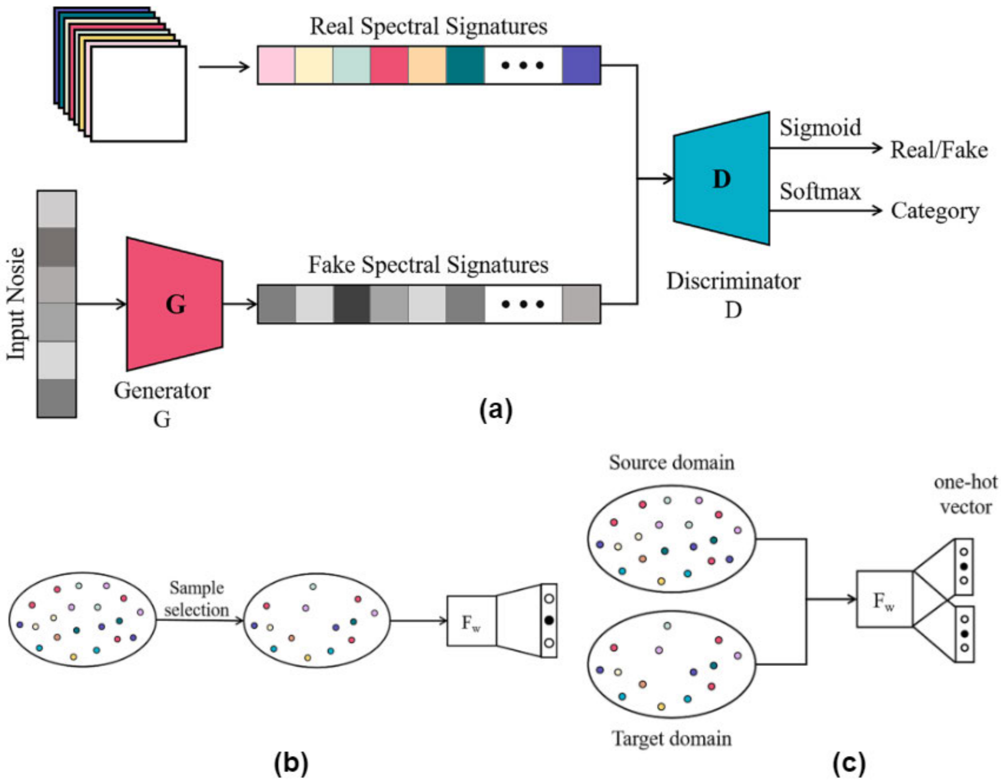

FIGURE 6. General architecture of (a) GAN, (b) active learning, and (c) transfer learning [26].

as characteristics [128]. Expertise in the domain, possibility of loss of information, and computational complexity while dealing with large-scale HSI are the problems associated with the issues of features selection and compression.

D. DATA LABELING AND ANNOTATION

Data annotation is difficult, especially in near-infrared HSI of a plant component which typically results in giving a single label to an entire image (i.e. getting a single chemical compound for the entire plant component) [129]. This technique, however, may not adequately represent unique characteristics in physiological parts of that plant component [121] and it raises the danger of overfitting due to the fewer labeled samples. Some researchers have labeled each row of the image to increase the number of labeled samples [130], but this approach has limits. Data annotation can be more challenging when patterns are too complex for human observers [131], necessitating the investigation of annotation criteria. Some researchers created labeled datasets based on alterations before as well as after artificial contamination, and the findings demonstrated that these labeling strategies are feasible [7].

E. EXPLORING MODEL INTERPRETABILITY

The interpretability of deep learning methods for analysis in HSI can be addressed via the following methods: visualization of heat maps, significance analysis of local features, and integrated modeling. Heat map visualization illustrate a model's focus on explicit locations, which is useful to know crucial features [106]. In contrast, local feature significance analysis helps to identify the vital characteristics by measuring the contribution to the prediction. Finally, integrated modeling incorporates deep learning models to enhance the performance and interpretability of results [8]. While these strategies improve dependability, problems remain due to model complexity, large parameter size, and HSI data quantity. In such a case, balancing the interpretability-performance tradeoff is sensitive; hence techniques should be developed for unique contexts. Some approaches could face scalability issues and would need optimization and acceleration to run on a large scale.

F. MODEL TRAINING PROCEDURE

The majority of the experiments in the literature employed supervised learning to train models using well annotated images. Data annotation is time-consuming and error-prone, frequently requiring human correction [129]. Although unsupervised and semi-supervised techniques can minimize labeling effort and mistakes, they may not be appropriate for hyperspectral images, requiring more study [31]. Data annotation becomes more difficult for complex visual patterns, typically resulting in a single label per image rather than pixel-level annotation, thereby missing spatial connections. Some studies mark each line in the image to rise the total amount of labeled samples [130]. Supervised learning separates datasets into training and test sets, frequently at random, which can result in skewed data distributions. Cross-validation, particularly with 5 or 10 folds, is advised to alleviate this problem, however it is not routinely used in many research.

G. EXTERNAL FACTORS

Lighting effects, such as shadows, reflections, and incidence angles, provide substantial obstacles, particularly in uncontrolled field situations [132]. While certain mitigating measures exist, maintaining dataset representativeness is critical. Noise in spectral bands, which is generally concentrated near the band extremities, can influence model robustness. Noise reduction techniques may be useful, but focus must be employed to prevent deleting significant information. Outliers should also be handled to avoid training models with low data quality [133]. Sensor noise, including thermally induced strip noise and quantization-related noise, is related and requires complex filtering algorithms to maintain structural textural details.

V. CONCLUSION AND FUTURE WORK

This review article has highlighted the significant development in integrating proximal hyperspectral imaging with deep learning methods that recently achieved enormous success in agricultural applications, particularly in plant image analysis. Current literature consists mostly of initial proof-of-concept studies carried out under ideal conditions, and largely focus on classification in remote sensing applications with limited datasets. However, in reality, there are still significant challenges and unsolved issues that require extensive research efforts to propel this technology into the mainstream agricultural workflow. This review outlines that deep learning methods are highly adaptable for extracting complex information from hyperspectral images, while existing HSI technology currently still lacks the required level of sensitivity for several tasks, such as data generalization and model fitness. Nevertheless, this is a technology that keeps improving and we are closer than ever before to producing a prescient AI farmer with superhuman vision who can grow crops at unprecedented levels of efficiency and sustainability. DL methods suit the analysis of precision agriculture with HSI, and the studies discussed in this review article provide different ways to utilize the information present in HSI images. However, challenges still exist in acquiring more representative data and building models to perform robustly under real-world settings. Future research shall have to focus on improving precision perception in agriculture by improving model generalizability through uncertainty quantification and exploring self-supervised learning and diffusion models in limited data settings. The creation of publicly available proximal HSI datasets would enable benchmarking and accelerate research progress in the field. Moreover, federated learning frameworks could be investigated to assist grower confidentiality and data scarcity in multi-orchard studies by enabling privacy-preserving data sharing and collaboration across farms or research sites. Developing lightweight and hybrid DL models for field use can bridge lab research and real-world agricultural applications.

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