Review on Advancement in Machine Learning and Deep Learning Techniques for Crop Classification

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Crop classification is a fundamental task for agriculture monitoring and management to optimize resource allocation and ensure food security. With the advancement of Artificial Intelligence(AI) Algorithms and Remote Sensing Technology, improved accuracy and efficiency in crop classification processes can be attained. This paper presents a comprehensive review of the various Remote Sensing technologies and AI algorithms used for crop classification. First, we will discuss the role of various remote sensing techniques used for capturing imagery, including Unmanned Aerial vehicles (UAVs) and satellites, followed by various fusion technologies for integration images from different platforms. Second, various models and techniques implemented in the literature, including both machine learning (SVM, Random Forest, Decision Tree) and deep learning (CNNs, RNNs, and Neuarl Networks) have been reviewed. Third, as conclusion , this paper finds that CNN-based models utilizing hyperspectral and mutitemporal fused imagery from various remote sensing sources are prevalent in the classification field. This paper has highlighted key challenges in areas such as data availability, scalability, model generalization, and integration of multi-source imagery. Additionally, it offers potential solutions and proposes various methods and techniques for further exploration in crop classification.

Keywords: Crop Classification, Deep Learning, Remote Sensing, Satellite Imagery, UAVs, Unmanned Aerial Vehicles.

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1 Introduction

Agriculture has always held immense importance in sustaining human society. From being the backbone of any economy to providing food security and self-sufficiency, agriculture is essential for global wellbeing and a sustainable future. Farmers and other stakeholders must decide wisely on several linked issues to maintain and improve agricultural production. crop classification is crucial for many reasons, including yield prediction [1], growth monitoring, fertilizer application, weed management [2], disease control [3], etc. Traditionally, field surveys and other methods were used for collecting ground data for crop identification, which was inconvenient, laborious, and time-consuming. The task becomes more difficult if the area under consideration significantly increases, say at the district or state level. Remote sensing technologies like satellites, UAVs and other aerial photographs etc. have enabled capturing of vast areas without actual intervention. These technologies have enabled monitoring of crops over large agricultural areas and assessing crop health, which is vital for food security and sustainable farming practices.

Machine learning and deep learning algorithms have enabled processing and analyzing vast amounts of remote sensing data efficiently, identifying patterns and features. These tools have improved accuracy in classifying crop types, detecting diseases, and predicting yields. The ability to learn from data makes deep learning algorithms suitable for crop classification task and provide a scalable solution for modern agriculture.

The aim of this paper is to perform a bibliometric analysis of application of satellite or UAV imageries for crop classification using different Machine Learning and deep learning techniques. Further, we examine the changing research landscape that combines artificial intelligence and image processing to manage large agricultural areas. Different remote sensing technologies for agricultural purposes will be explored, along with various AI algorithms for classification.Section 2 provides an in-depth overview of the existing literature on the remote sensing techniques in this field. Section 3 delves into the comparison of the various deep learning and Machine Learning Algorithms employed in crop identification has been done, along with the Evaluation Metrics utilized to assess their performance. In the subsequent Section 4, as discussion we will present different challenges and research gaps observed during the study followed by the scope of future work that can be undertaken.

2 Literature Review of Remote Sensing Technology in Crop Classification

An immense development in the field of agriculture has been seen during the last two decades and has been made possible due to remote sensing technologies. Remote Sensing Technologies provide non-destructive and non-intrusive way to capture imagery for agriculture monitoring and provide finer details across wide areas over a period of time.

The availability of high spatial, temporal, spectral, and radiometric resolution imagery from satellites has significantly enhanced its application scope in agriculture by improving precision and accuracy.

For classifying crops over an area, image data is being obtained from satellites, UAVs, manned devices, IoT devices, autonomous robots and smartphones, etc. Recent years have also seen an increase in the use of integration techniques for fusing images from these sources. The availability of different types of sensors enables RS technologies to provide rich features for precision agriculture. High-resolution remote sensing images can offer detailed texture information. Spectral and temporal information from images can be utilized to extract features for classification.Several work have addressed the use of remote sensing technologies in agriculture. Satellites provides global coverage, capturing the image over a wider area while UAVs range is very much limited when compared to satellites. But in terms of spatial resolution, UAVs have better spatial resolution as the images captured by them have higher ground-spatial distance (GSD). Also, in terms of availability, UAVs have proven to be a more portable, handy, flexible, and near real-time option if coverage area under consideration is limited. However, spectral resolution of the satellites is significantly better, as most of satellite imagery has atleast 4 bands (Red, Green, Blue and Near-IR). Both UAVs and satellite imageries have their own features and challenges e.g both are impacted by the weather conditions, including clouds, cloud shadows, wind, rain, humidity etc.

The integration of remote sensing techniques with machine learning and artificial intelligence has enhanced their ability to analyze large and complex datasets. This has further helped in making more accurate predictions about crop yields and resource needs. Across all the studies for the task of crop identification, data has been obtained from various sources including UAVs (Unmanned Aerial Vehicles), satellites (both Landsat and Sentinel), aircraft, hand-held devices like cameras, and other wall-mounted devices. Different types of images may have varying levels of complexity and distinct features that can impact the accuracy of a classification model. For example, images with clear and well-defined objects may be easier to classify accurately compared to images with cluttered backgrounds or ambiguous shapes.

Additionally, the diversity and variability of images in a dataset can also affect classification accuracy. A dataset with a wide range of images representing different classes can help improve the model's ability to generalize and make accurate predictions on unseen data. Therefore, it is important to consider the types of images being used when evaluating the performance of a classification model and to ensure that the dataset is representative of the real-world scenarios the model will encounter.

To initiate a classification process, the acquired dataset needs to undergo preprocessing. This preprocessing step involves cleaning the data, handling missing values, scaling or normalizing the features, encoding categorical variables, and splitting the data into training and testing sets. These steps are essential to ensuring that the data is in a suitable format for the classification algorithm to learn from and make accurate predictions. Broadly analysing, the classification process is carried out into two phases :

Feature Learning and Classification. Feature learning involves Convolution function, followed by pooling. Classification involves flattening, Fully Connected layer and Softmax layer. Now, let us have a look at how the use of these remote sensing technologies is being done for crop classification.

2.1 UAV Imagery in Crop Classification

Unmanned Aerial Vehicles (UAVs), popularly known as drones, have become an indispensable tool in surveying applications across various fields such as land surveillance, geographic studies, agriculture, and security. The use of UAVs in agriculture has revolutionized the process of crop monitoring and identification through high-resolution images. UAVs are increasingly being used to gather valuable data for precision agriculture, including crop and plant recognition. Basics components of UAVs include the airframe or physical structure, propulsion system, control system and the communication systems. Both fixed wing(the Arator 5b of the company XMobot) and rotary wing drones (the Phanton 4 from the DJI manufacturer) are available for the surveying purpose. Rotary-wing are preferred for precision agriculture due to lesser cost, more area coverage in shorter time given its low maneuverability, searching for more detailed or larger images of the area to be monitored, autonomous flights without the need for human interaction for either take-off, landing or battery recharging [4]. Control system of UAVs include the stabilisation during flight, navigation system equipped with GPS and communication system include the control and data transmission with the ground centre.

Although, many studies have used satellites in the field of crop classification [5], [6], [7], [8]. But they have their own drawbacks/ limitations, like low spatial and temporal resolution, that impact the data quality and predictions. Unlike remote sensing based on satellites or manned aircraft, UAVs can capture images at low altitudes. UAVs, therefore, can provide data with high spatial, spectral and temporal resolution [9] and enable accurate assessment. Due to their agility, they can cover large areas swiftly by providing real-time data. Other applications of UAVs in agriculture include the identification of cereal crops, precision agriculture, weed management, pests and diseases management, as well as nutrients and fertilizer requirements. Additionally, they are being used to assess physical characteristics under changing environmental conditions to identify favorable genotypes and phenotypes.

Now a days, various types of cameras and sensors are being used on Unmanned Aerial Vehicles (UAVs)platforms. The most commonly used sensors are Red-Green-Blue (RGB) cameras which capture images in three primary wavebands: red, green, and blue [10], [11], [12]. They are preferred due to their low cost, lightweight design, flexibility, and ease of data analysis. Multispectral sensors capture images in multiple narrow spectral bands beyond the visible spectrum, i.e., red, green, blue, and near-infrared (NIR). Multispectral data is useful in assessing crop health, detecting stress, and identifying specific vegetation characteristics. RGB imaging is unable to capture spectral information beyond the visible spectrum, which is important for characterizing chemical and physical proprieties of a target. Hyperspectral sensors capture images in numerous narrow and contiguous spectral bands. Unlike multispectral cameras, hyperspectral cameras provide detailed information across a wide range of wavelengths and are valuable for precise crop classification [13] [9] and assessing crop health. Thermal sensors detect infrared radiation emitted by objects and help monitor temperature variations in crops, identify stress, and assess water availability [14].

To achieve the goal of timely classification, with low operating cost, high flexibility, and the ability to provide real-time data, UAV-borne hyperspectral systems have become an important data source for remote sensing-based agricultural monitoring. The images captured are pre processed using various techniques like radiometric calibrations, geometric correction [15], ortho-rectification, mosiacking [16], [11], labelling etc. before being used as input for classification model. Preprocessing steps vary on the basis of dataset being used and learning model being used for classification. These can be further explored with different techniques to optimize performance and accuracy. Some of the common techniques used in preprocessing have been summarized in Figure 1.

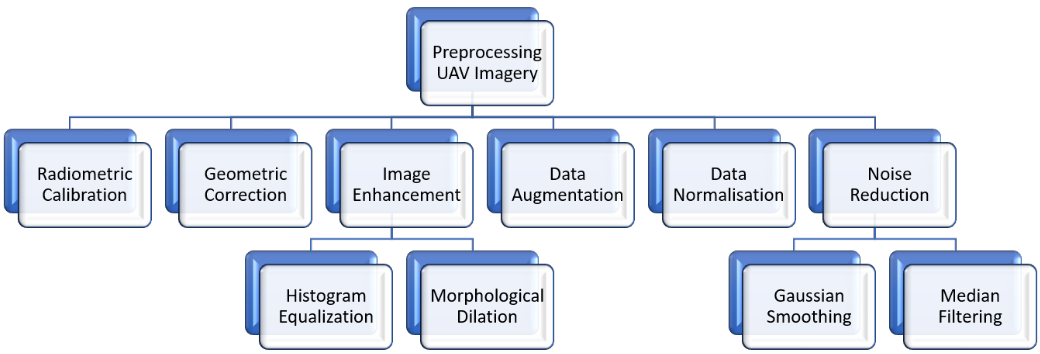

Figure 1: Preprocessing of UAV images

However, utilizing UAVs presents certain challenges such as vegetation diversity, soil patterns, terrain variability, processing high-resolution data, flight permissions and policies, and occasionally high equipment costs. Researchers and policymakers rely on satellite data for making informed decisions and efficient resource management. Synoptic View and Multi-Temporal Coverage provided by satellites during the growing season make them ideal for evaluating crop dynamics and detecting abnormalities. There are numerous open-source tools such as QGIS (Quantum GIS) and GRASS GIS software that aid in UAV data processing and analysis with advanced features. Commercial options like ENVI, Pix4D, Agisoft Metashape, and cloud-based platforms such as Google Earth Engine and Microsoft Azure AI also provide services for analyzing geospatial data from UAV imagery. Moreover, integrating various UAV-derived data types (e.g., RGB, multispectral, LiDAR) with deep learning methods can improve classification accuracy. Some of the datasets, like WHU-Hi [13],WeedMap [18] are available publicly.

Studies have proved that high classification accuracy have been achieved with UAV data due to its high resolution and the ability to capture detailed spectral and spatial information. [19] reported an accuracy of 89% using SegNet and FCN-AlexNet on UAV images.A number of ML and DL techniques have been applied on UAV data for crop classification, demonstrating the versatility of these methods. [20] used MobileNetv2 feature extractor and ConvLSTM model for classification, achieving an accuracy of 97.43%. Integration of UAV data with advanced DL models like CNNs, RNNs, and attention mechanisms has shown promising results. Using an attention-based recurrent convolutional neural network, [11] achieved an overall accuracy of 92.80%. Studies has proved that the UAVs imagery has proved effective in case of multicrop classification [11], trees canopy [12], forest and other sturcture also [10].When it comes to monitoring crops at various growth stages, UAVs provide flexibility in data capture by enabling frequent and focused data collection [11] and [21]. The integration of UAV data with advanced models like CNNs, RNNs, and attention mechanisms has shown promising results. For example, [11]) achieved an overall accuracy of 92.80% using an attention-based recurrent convolutional neural network.

2.2 Satellite Imagery in Crop Classification

Satellites have been utilized for agricultural monitoring since the 1970s. The LANDSAT-1 and LANDSAT-2 satellites, MODIS, Sentinel-1,Sentinel-2 [6], and GaoFen [5] , SPOT6 [22]are some of the widely used satellites in agricultural programs. The growing availability of data from recurring and long-term satellite observations has prompted a strong desire by the agricultural community to use satellite data in creating crop maps over large geographic areas. The utilization of satellites has transformed global agriculture. Their extensive perspective, multitemporal coverage, and cost-efficiency have rendered them as indispensable tools in various field including agriculture.

Like UAVs, the satellites are equipped with a variety of sensors that allow researchers to monitor crop types, crop health, and other conditions from space. Multispectral sensors used in satellite like Sentinel-2, LandSat-2, and Gao Fen, capture data across multiple spectral bands, facilitate the analysis of vegetation health, crop types, and land cover. Hyperspectral Sensors such as Hyperspectral Imaging Spectroradiometer (HSI) and EnMAP (Environmental Mapping and Analysis Program) help differentiate subtle differences in crop types, soil properties, and stress conditions. Synthetic Aperture Radar (SAR) used in Sentinel-1 operates independently of the availability of sunlight and can penetrate cloud cover to capture images [23]. Thermal infrared sensors like MODIS (Moderate Resolution

Table 1: Research Work on Crop Classification using UAVs Imagery

Article	Imagery Source	Crop Type	Work Done	Result
[13]	Hyper spectral UAV	Three Regions of study: LongKou: 9 classes HanChuan : 16 HongHu :23	CNN with Conditional Random field Classifier used for crop classification and model compared with Benchmark CNN, SVM(Support Vector Machine), FNEA-OO and SVMFMC.	OA – 93.95% Kappa-0.9290 AA-92.69%
[29]	High-resolution UAV imagery	To identify weeds in two crops Pea and Strawberry	Improved faster R-CNN and compared with YOLO-V3 and K-Nearest Neighbour (KNN), SVM	AA- 95.3%, OA- 94.73% Kappa-0.89.
[11]	Multi-Temporal Unmanned Aerial Vehicle imagery (RGB) for time period (Sep-Nov 2019)	Chinese cabbage, carrot, leaf mustard, Turnip. potherb. spinach, kohlrabi	Attention-based Recurrent Convolutional neural network and compared with SVM, RF, and MLC	overall accuracy-92.80% Kappa-0.9206
[10]	UAV Images	Banana, Maize, Legume, Forest, Structure and other categories	Deep Neural Network VGG16 model for feature extraction	OA-0.86 Precision-0.86 Recall-0.86 Kappa-0.82 F1 score-0.86
[12]	UAV images	3 species of palm trees in the Amazon Forest region	ResNet-18 incorporated into the DeepLabv3+ architecture. [encoder module-convolutional block- Atrous Spatial Pyramid Pooling (ASPP)- softmax classifier]	Average Accuracy-87.8%
[17]	UAV images	Rice and Corn	SegNet and FCN-AlexNet and Adam Optimizer	accuracy - 89% Inference Speed-0.7s
[20]	UAV Imagery	(Banana, Maize, and Legume), two additional non-cropland cover types (Forest and Structure)	The technique employs adaptive bilateral filtering for image preprocessing, MobileNetv2 feature extractor with Bayesian optimization for parameter optimization, and convolutional long short-term memory (ConvLSTM) model for crop classification.	Accuracy-97.43 Precision-89.02 Recall 85.03 F score 86.74
[21]	UAV Imagery (Hyperspectral and Multispectral) (2013 and 2014.)	6 varieties of weeds in sorghum fields	1. Hyperspectral data and Stepwise Linear discriminant analysis (SLDA) used to identify the most significant spectral bands for discriminating weeds from sorghum. 2. Multispectral images and object-based image analysis (OBIA) to detect weeds	Use of fewer bands and high spatial resolution improves weed classification
[27]	UAV Images (High Resolution)	Beet, Parsley, and Spinach along with weed	1. Vision Transformer (ViT) model using self-attention paradigm for plant classification of weeds and crops. 2. Compared with EfficientNet and ResNet.	Highest accuracy of 99.8% in plant classification. Stability of ViT on variation of the dataset size asserted.

Imaging Spectroradiometer) [8] and Landsat 8 Thermal Infrared Sensor (TIRS) measure thermal radiation emitted by objects and can easily assess crop stress, water availability, and temperature variations. LiDAR (Light Detection and Ranging) data can be used to complement optical and radar imagery. Airborne LiDAR systems are capable of capturing detailed elevation information, aiding in monitoring crop health, canopy structure analysis, and 3D modeling. Table 2 summarises some of the work in the area of crop classification using of satellite imagery.

Table 2: Research Work on Crop Classification using Satellite Imagery

Article	Imagery Source	Crop Type	Work Done	Result
[5]	Satellite imagery :GaoFen-I(RGB, IR) Time Period : (Mar- Sep)	Five area in China with multiple crops(20);	1.Classification approach for multi-scenario (Full-season crop classification, in-season crop classification, few-sample crop classification) 2. Two-step classification: Transformer (to capture the features) + Convolution and compared with RF, CNN, SIFT BERT	The Cropformer model worked at par with other models in terms of accuracy. However, the model can learn generalized features using limited labeled data and performed good in multi-scenario classification.
[6]	Satellite imagery: Sentinel – 2 combined with agriculture machine operation	Corn crop	1. Positive Unlabelled (PU) classification using SVM. 2. DL based NN with 4 Convolutional layers 3. Triplet Loss Siamese network to learn sample representations. 4. Contrastive Learning with data augmentation (10 .	Triplet Loss Siamese Network performed best with Accuracy-97.47% F1-weighted-97.47% F1-Neg-95.77% F1-Pos- 98.19% MCC- 0.94
[7]	Satellite Data	8 Crops including maize, wheat, soybeans, sunflower, winter barley, rapeseed, sugarbeet and peas.	1. Sparse Autoencoder and neural network for fine-tuning. 2. Translated satellite data into unified hyperspace for analysis.	Overall Accuracy- 91.0%(1st experiment) 85.9%(2nd experiment)
[8]	Satellite Imagery (Multi-spectral and Multi-temporal)	corn, cotton, soy, spring wheat, winter wheat, and barley	1. Multimodal deep learning classification solution with two-stream architecture that combines spatial-spectral and phenological properties. 2. fusion of spatial and temporal streams is explored using late fusion techniques, improving the accuracy. 3. Hyperparameter optimization is performed using grid search on validation dataset.	The proposed model reduced the prediction error by 60% compared to traditional methods. 2. Out performs the other methods in terms of accuracy and F1-score.

2.3 Integrating UAVs and Satellite Data for Improved Crop Insights

Many studies have used the fusion of data from more than one source like combining UAV and Satellite [8] and [15], fusion of data from different satellites [23], SAR (Synthetic Aperture Radar) and optical imagery [24] and [25], Multispectral and SAR imagery [22]. In [22], used a data fusion method, DTW(Dynamic Time Warping) to extract high similarity time series feature index. [23] have demonstrated processing UAV imagery involving pixel-level fusion, feature-level fusion, and decision-level fusion. Pixel-level fusion combines multi-sensor input data through compression and dimensionality reduction methods. Feature-level fusion merges extracted features from various sensors to create a multi-source feature stack. Decision-level fusion integrates the classification results of individual sensor features according to predetermined rules or decisions [6]. Utilizing UAVs and satellites also addresses the problem of acquiring data over large agricultural regions for efficient crop monitoring. Fused data has shown significantly improved accuracy compared to the original UAV data [16] [15]. Data fusion from different sources like optical, SAR, UAVs provide complementary information like spectral reflectance, texture, moisture content and enhance the ability to discriminate between crop types [26]. This information enables the extraction of more robust features. Further, data fusion reduces the restriction on capturing images due to atmospheric conditions like cloud, rain, humidity and wind. Optical imagery may be impacted by cloud cover, however SAR can penetrate through the clouds, thus avoid the temporal gaps in capturing the images [22]. Temporal variability, caused by factors such as the growing season, weather changes, or disease infections, can lead to changes in crop appearance, making it a challenging feature. With timeseries data from Sentinel-1 and Sentinel-2 satellites has significantly enhanced the precision in capturing crop dynamics [23].

3 Deep Learning and Machine Learning Techniques in Crop Classification

AI algorithms have proven to be effective tools for crop classification, providing enhanced accuracy, automated feature extraction, scalability, adaptability to various conditions, and innovative applications. Deep Learning algorithms, particularly CNNs (Convolutional Neural Networks) have emerged as the state-of-the-art method for computer vision applications since they have proven to be effective tools for image processing tasks and have produced more accurate outcomes.Their expertise in extracting intricate patterns and characteristics from remote sensing data leads to enhanced accuracy in recognizing and categorizing crop varieties [13]. CNNs have the ability to capture both local and global patterns in image and are less computationally inexpensive [10]. A CNN architecture consists of mainly three stacked layers namely Convolutional layer and the Pooling layer (for recognizing the patterns in the images) followed by fully connected

Table 3: Research Work on Crop Classification using fused imagery

Article	Imagery Source	Crop Type	Work Done	Result
[32]	Fusing UAV images and Sentinel -2A data	10 categories including rice, corn, soybean, buckwheat	1. UAV and Sentinel-2A images fused using Gram-Schmidt transformation for crop distribution mapping. 2. Random Forest Algorithm for classification.	Fused images achieved higher classification accuracies, ranging between 10.58% and 16.39%
[16]	The Fusion of Satellite and Unmanned Aerial Vehicle(UAV) Imagery	honeysuckle, maize, peanut and tree, Roads and buildings	1. Data fusion of UAV images and satellite multispectral images is performed. 2. Compared the performance of Support Vector Machine (SVM), Artificial Neural Network (ANN) and Maximum Likelihood (ML) on using the fused images.	1. Improved classification accuracy of the fused image compared to the original UAV image (OA was over 80%) 2. ANN method with the highest accuracy followed by SVM and ML.
[23]	Fusion of Sentinal-1 and Sentinal-2 Data	Banana, Maize, and Legume, two additional non-crop land cover types (Forest and Structure)	1. Impact of using optical and SAR data and their fusion on crop classification accuracy evaluated. 2. Two fusion approaches: feature stacking and decision fusion. 3. Investigated the influence of feature Selection, parcel size and optical data availability on classification and accuracy. 3. Random Forest (RF) used for classification.	1. SAR datasets outperform optical datasets and optical-SAR combination outperformed single sensor predictions. 2. The feature selection strategy (group-wise forward feature selection - gFFS) did not improve the accuracy.
[24]	Sentinel SAR-optical fusion (Apr-Oct 2018, Columbia)	soybean, corn, sorghum, Sudan grasss witch grass Three varieties of weeds (foxtail, ragweed, and cocklebur)	1. Impact of using optical-SAR data fusion, coupled with virtual constellation and 3-D deep learning network on crop classification accuracy evaluated. 2. Compared the performance of DL networks 3D UNet, SegNet, 2D Unet and RF.	1. 3D UNet achieved the highest accuracy. (OA = 0.912 for SAR(OA = 0.937 for optical data, SAR/optical fused data (OA = 0.941) 2 fusion of multi-temporal SAR and optical data improves accuracy.
[25]	Satellites Sentinel-1 and Sentinel-2: Optical and SAR data	Maize, Soyabean and other crops	1. DL approach using optical and SAR data for reducing the temporal gaps in data capture. 2. Ensemble learning framework combining different DL models to balance the imbalanced class distribution. 3. Fused multitemporal Sentinel-1 polarimetric feature and Sentinel-2 Surface Reflectance Data.	1. OA – 91.7% Kappa coefficient -85.7% F1 Score : maize- 93.7%, Soybean- 92.2%, Wheat- 90.9% 2. Best performing model 3D-ConvSTAR

Table 4: Research Work on Crop Classification using fused imagery

Article	Imagery Source	Crop Type	Work Done	Result
[22]	SPOT6 Satellite and Sentinel-1A (Multi-Temporal Data Fusion in MS and SAR Images	Paddy rice	1. Data fusion method to extract high similarity time series feature index through integration of MS and SAR images. 2. Dynamic Time Warping to integrate different image data sources, data of different lengths, and generation information with time characteristics. 3. Comparison done on SVM, Neural Networks, and Decision Tree with and without DTW index.	Decision Tree(DT) performed best with OA- 94.71%, Kappa-0.81; and without DTW OA- 93.26%, Kappa-0.76; proving the effectiveness of Fusion method
[31]	LandSat Imagery	Corn, Soybean, Barley, Spring Wheat, Dry Beans, Sugar Beets, And Alfalfa.	1. Classification workflow using Deep Neural Networks (DNN) based on LandSat imageries, historical crop maps and ground measurements. 2. Created processing workflows to automate the preprocessing, training, testing, and postprocessing steps. 3. Tested the hybrid solution on new images.	The model achieved an overall accuracy exceeding 82% and can achieve better accuracy in multiple time of growth cycle in large farmlands

layer (for classification). However, Convolutional Neural Networks only consider local spatial information and can often get stuck in local optima, leading to gaps or isolated areas in the classification maps. To overcome this, [13] proposed the deep convolutional neural network with a conditional random field classifier (CNNCRF) framework. A deep CNN was used to extract detailed spectral and spatial features, while a Mahalanobis distance boundary constrained CRF model was implemented to integrate spatial-contextual information and reduce isolated regions in the classification maps.The CNNCRF model achieved an overall accuracy of 93.95%, 98.91% and 93.74% over the three regions under study. The model performed better on the dataset compared to SVM and Benchmark-CNN.

Various other Deep learning models used across the studies include DeepCNN, Neural Networks, DeepNet, YOLO LSTM(Long Short-'Term Memory Networks [20], Transformers [27], U-Net, etc and pretrained model like SegNet, ResNet, VGG16. Machine algorithms include SVM, k-Nearest Neighbors, Random Forest. Apart from the above algorithms, transfer learning has been applied where the acquisition of a large labeled dataset is impractical and also speeds up the learning phase of the model. Crop Segmentation requires extensive labeled datasets to train ML models. In [20], transfer learning has been used on drone images to leverage pre-trained models and optimize hyperparameters to enhance the accuracy of crop classification algorithms. In [10], pretrained VGG16 model was used for feature extraction and a DNN with fully connected layer, a drop out layer followed by Adam Optimiser for classification. The model shows good accuracy for banana, forest and maize but accuracy is reduced for legumes due to high interclass heterogeneity. A multimodal deep learning approach that combines spatial-spectral and phenological characteristics has been utilized for crop type identification in the study by [8]. The proposed solution used a two stream architecture : spatial stream with CNN and temportal stream with LSTM and reduced the prediction error by 60%. In [28], Decision Trees have been used for multicrop recognition using high spatial and temporal NDVI (Normalised Difference Vegetation index)signatures extracted from multispectral imagery and enhanced overall accuracy and kappa value. NDVI values are crucial in early-to-mid session for crop classification. [22]. Ensemble techniques that combine diverse classification models, such as Decision Trees, Random Forest, Naive Bayes, and Support Vector Machines (SVM), are used to implement crop classification. Ensemble techniques have been demonstrated in [25], wherein multi-temporal Sentinel-1 polarimetric features are integrated with Sentinel-2 surface reflectance data, has outperformed alternative techniques and achieved the highest mean F1 scores demonstrating the effectiveness in enhancing the accuracy.

Broadly, the image classification task for crop identification has been categorized into two approaches:Object-based Classification [29] and Pixel-based Classification [23]. To deal with the challenge of a limited data set and variable target sizes, optimized Faster R-CNN was used for identification of weeds and crops in strawberry and pea field for precision agriculture sprayer [29]. YOLOv3, an object based classification model attained a better average weed identification accuracy compared to developed Faster RNN developed. YOLOv3 predicts an objectness score for each bounding box using logistic regression [30]. The general workflow for any AI classification algorithm is depicted in Figure 2.

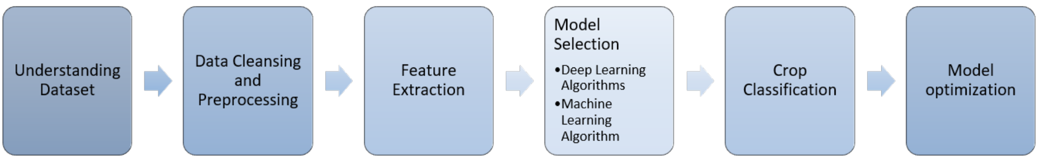

Figure 2: Workflow for a Crop Classification Model

To evaluate a crop classification model, it's essential to use appropriate metrics to assess its performance. The choice of metrics depends on the context, purpose, and relative importance of the errors. Several metrics have been used for the evaluation of deep learning models to assess their effectiveness. Some of these metrics are confusion matrix, accuracy, precision, recall, F1 score and kappa value. The confusion matrix gives a detailed insight of true positives, true negatives, false positives, and false negatives. It may be considered the fundamental tool for understanding the model's effectiveness and performance. F1 is the harmonic mean of precision and recall and is generally used for imbalanced datasets.

4 Conclusion

After conducting the study of the articles on remote sensed data for crop classification, it can be concluded that deep learning techniques which use CNNs as base model are used for crop classification. However, when classification is performed on temporal data or fused data, LSTM based models are preferred. The Random Forest machine learning model has also demonstrated high classification accuracy compared to other models. To overcome the limitation of labeled datasets, data augmentation techniques, transformer models, multimodal fusion and transfer learning have proven to be effective. For mapping larger areas, agriculture imagery from various sources like satellites, UAVs(Unmanned Aerial Vehicles), Manned Aircraft, high-resolution cameras, etc. can be fused to provide high spatial, spectral, and temporal resolution data and have proved to boost the classification accuracy. Hyperspectral images capture data across hundreds of narrow spectral bands, thus provide better data for extraction of features(NDVI, EVI etc.) when compared to RGB sensors. For capturing multitemporal data, UAVs and satellites have both proven to be reliable sources. Factors like spatial resolution, spectral resolution, temporal resolution, patch size, sample quality and image annotation have been found to impact the accuracy.

While reviewing the literature, it has been found that crop segmentation has still many areas that need to be further explored. Multiple crop classification is yet to be worked upon further. Some crops have similar visual characteristics that make them difficult to distinguish [10]. Scalability is yet remains a less explored area in crop segmentation. There is scope of working on evaluating the scalability of model to larger areas for multicrop classification [5] and [25]. Further research could explore the generalization of models trained on a specific region or crop type to incorporate domain adaptation. Several studies have indicated the challenges posed by the scarcity of labeled datasets and its impact on the robustness and generalization capabilities of the model [20]. The study by [13] emphasizes the importance of training and testing time as the efficiency of the model.

Future work is suggested on data fusion and sensor integration techniques [10], [15] for exploring the optimal spatial resolution to enhance the accuracy. Extracting robust features from spectral information with the help of multispectral and hyperspectral imagery can enhance accuracy. Variabliability in timeseries data and impact of different growth stages, environmental conditions like moisture content [11] is another crucial work to be undertaken for further study. To improve the robustness and accuracy of models, especially for minority crops and in complex cropping systems can be key area of future work. Studies [31] indicate that the models still remain underfit and needs integration with more high-performance computational platforms. Other ensemble methods or fine-tuned models trained on diverse datasets may offer a solution. Deploying these models in real-world scenarios to monitor vast agricultural areas for efficient inference and real-time analysis necessitates the creation of a lightweight model, a distributed computation system, and integration with edge AI. In summary, this study will help different researchers and policymakers understand different remote sensing technologies and integration with DL and ML techniques to use them in crop monitoring, yield prediction, crop health monitoring, early disease detection, finding compatible crops, crop cycles, etc.

References

[1] Jiaxuan You, Xiaocheng Li, Melvin Low, D. Lobell, and Stefano Ermon. Deep gaussian process for crop yield prediction based on remote sensing data. In *AAAI Conference on Artificial Intelligence*, 2017.

[2] Yanbo Huang, Krishna N. Reddy, Reginald S. Fletcher, and Deana D. Pennington. Uav low-altitude remote sensing for precision weed management. *Weed Technology*, 32:2 – 6, 2017.

[3] Leninisha Shanmugam, A. L. Agasta Adline, N. Aishwarya, and Gokulnath Krithika. Disease detection in crops using remote sensing images. *2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR)*, pages 112–115, 2017.

[4] Yanbo Huang, Steven J. Thomson, Wesley Clint Hoffmann, Yubin Lan, and Bradley K. Fritz. Development and prospect of unmanned aerial vehicle technologies for agricultural production management. *International Journal of Agricultural and Biological Engineering*, 6:1–10, 2013.

[5] Hengbin Wang, Wanqiu Chang, Yu Yao, Zhiying Yao, Yuanyuan Zhao, Shaoming Li, Zhe Liu, and Xiaodong Zhang. Cropformer: A new generalized deep learning classification approach for multi-scenario crop classification. *Frontiers in Plant Science*, 14:1130659, March 2023.

[6] Eduardo Nascimento, John Just, Jurandy Almeida, and Tiago Almeida. Productive Crop Field Detection: A New Dataset and Deep Learning Benchmark Results. *IEEE Geoscience and Remote Sensing Letters*, 20:1–5, 2023. arXiv:2305.11990 [cs].

[7] Mykola Lavreniuk, Nataliia Kussul, and Alexei Novikov. Deep Learning Crop Classification Approach Based on Coding Input Satellite Data Into the Unified Hyperspace. In *2018 IEEE 38th International Conference on Electronics and Nanotechnology (ELNANO)*, pages 239–244, Kiev, April 2018. IEEE.

[8] Krishna Karthik Gadiraju, Bharathkumar Ramachandra, Zexi Chen, and Ranga Raju Vatsavai. Multimodal Deep Learning Based Crop Classification Using Multispectral and Multitemporal Satellite Imagery. In *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, pages 3234–3242, Virtual Event CA USA, August 2020. ACM.

in: *Advancements in Communication and Systems*. Ed. by Ashish Kumar Tripathi and Vivek Shrivastava. Computing and Intelligent Systems, SCRS, India., 2023, pp. 593–610. DOI: https://doi.org/10.56155/978-81-955020-7-3-53

[9] Telmo Adão, Jonáš Hruška, Luís Pádua, José Bessa, Emanuel Peres, Raul Morais, and Joaquim João Sousa. Hyperspectral imaging: A review on uav-based sensors, data processing and applications for agriculture and forestry. *Remote Sensing*, 9(11), 2017.

[10] Robert Chew, Jay Rineer, Robert Beach, Maggie O'Neil, Noel Ujeneza, Daniel Lapidus, Thomas Miano, Meghan Hegarty-Craver, Jason Polly, and Dorota S. Temple. Deep Neural Networks and Transfer Learning for Food Crop Identification in UAV Images. *Drones*, 4(1):7, February 2020.

[11] Quanlong Feng, Jianyu Yang, Yiming Liu, Cong Ou, Dehai Zhu, Bowen Niu, Jiantao Liu, and Baoguo Li. Multi-Temporal Unmanned Aerial Vehicle Remote Sensing for Vegetable Mapping Using an Attention-Based Recurrent Convolutional Neural Network. *Remote Sensing*, 12(10):1668, May 2020.

[12] Matheus Pinheiro Ferreira, Danilo Roberti Alves De Almeida, Daniel De Almeida Papa, Juliano Baldez Silva Minervino, Hudson Franklin Pessoa Veras, Arthur Formighieri, Caio Alexandre Nascimento Santos, Marcio Aurélio Dantas Ferreira, Evandro Orfanó Figueiredo, and Evandro José Linhares Ferreira. Individual tree detection and species classification of Amazonian palms using UAV images and deep learning. *Forest Ecology and Management*, 475:118397, November 2020.

[13] Yanfei Zhong, Xin Hu, Chang Luo, Xinyu Wang, Ji Zhao, and Liangpei Zhang. WHU-Hi: UAV-borne hyperspectral with high spatial resolution (H2) benchmark datasets and classifier for precise crop identification based on deep convolutional neural network with CRF. *Remote Sensing of Environment*, 250:112012, December 2020.

[14] Zheng Zhou, Yaqoob Majeed, Geraldine Diverres Naranjo, and Elena M.T. Gambacorta. Assessment for crop water stress with infrared thermal imagery in precision agriculture: A review and future prospects for deep learning applications. *Computers and Electronics in Agriculture*, 182:106019, 2021.

[15] Licheng Zhao, Yun Shi, Bin Liu, Ciara Hovis, Yulin Duan, and Zhongchao Shi. Finer Classification of Crops by Fusing UAV Images and Sentinel-2A Data. *Remote Sensing*, 11(24):3012, December 2019.

[16] Yujiao Zou, Guangming Li, and Shuai Wang. The Fusion of Satellite and Unmanned Aerial Vehicle (UAV) Imagery for Improving Classification Performance. In *2018 IEEE International Conference on Information and Automation (ICIA)*, pages 836–841, Wuyishan, China, August 2018. IEEE.

[17] Yang, Ming Der and Tseng, Hsin Hung and Hsu, Yu Chun and Tseng, Wei Chen. Real-time Crop Classification Using Edge Computing and Deep Learning. In *2020*

IEEE 17th Annual Consumer Communications & Networking Conference (CCNC), pages 1–4, Las Vegas, NV, USA.

[18] Inkyu Sa, Marija Popović, Raghav Khanna, Zetao Chen, Philipp Lottes, Frank Liebisch, Juan Nieto, Cyrill Stachniss, Achim Walter, and Roland Siegwart. Weedmap: A large-scale semantic weed mapping framework using aerial multispectral imaging and deep neural network for precision farming. *Remote Sensing*, 10(9), 2018.

[19] Ming-Der Yang, Hsin-Hung Tseng, Yu-Chun Hsu, and Hui Ping Tsai. Semantic Segmentation Using Deep Learning with Vegetation Indices for Rice Lodging Identification in Multi-date UAV Visible Images. *Remote Sensing*, 12(4):633, February 2020.

[20] Mohammed Altaf Ahmed, Jaber Aloufi, and Suleman Alnatheer. Satin Bowerbird Optimization With Convolutional LSTM for Food Crop Classification on UAV Imagery. *IEEE Access*, 11:41075–41083, 2023.

[21] Nik Norasma Che'Ya, Ernest Dunwoody, and Madan Gupta. Assessment of Weed Classification Using Hyperspectral Reflectance and Optimal Multispectral UAV Imagery. *Agronomy*, 11(7):1435, July 2021.

[22] Tsu Chiang Lei, Shiuan Wan, You Cheng Wu, Hsin-Ping Wang, and Chia-Wen Hsieh. Multi-Temporal Data Fusion in MS and SAR Images Using the Dynamic Time Warping Method for Paddy Rice Classification. *Agriculture*, 12(1):77, January 2022.

[23] Aiym Orynbaikyzy, Ursula Gessner, Benjamin Mack, and Christopher Conrad. Crop Type Classification Using Fusion of Sentinel-1 and Sentinel-2 Data: Assessing the Impact of Feature Selection, Optical Data Availability, and Parcel Sizes on the Accuracies. *Remote Sensing*, 12(17):2779, August 2020.

[24] Jarrett Adrian, Vasit Sagan, and Maitiniyazi Maimaitijiang. Sentinel SAR-optical fusion for crop type mapping using deep learning and Google Earth Engine. *ISPRS Journal of Photogrammetry and Remote Sensing*, 175:215–235, May 2021.

[25] Niantang Liu, Qunshan Zhao, Richard Williams, and Brian Barrett. Enhanced crop classification through integrated optical and SAR data: a deep learning approach for multi-source image fusion. *International Journal of Remote Sensing*, pages 1–29, July 2023.

[26] Shuting Yang, Lingjia Gu, Xiaofeng Li, Tao Jiang, and Ruizhi Ren. Crop classification method based on optimal feature selection and hybrid cnn-rf networks for multi-temporal remote sensing imagery. *Remote Sensing*, 12(19), 2020.

[27] Reenul Reedha, Eric Dericquebourg, Raphael Canals, and Adel Hafiane. Transformer Neural Network for Weed and Crop Classification of High Resolution UAV Images. *Remote Sensing*, 14(3):592, January 2022.

[28] Muhammad Ahsan Latif. Multi-crop recognition using UAV-based high-resolution NDVI time-series. *Journal of Unmanned Vehicle Systems*, 7(3):207–218, September 2019.

[29] Shahbaz Khan, Muhammad Tufail, Muhammad Tahir Khan, Zubair Ahmad Khan, and Shahzad Anwar. Deep learning-based identification system of weeds and crops in strawberry and pea fields for a precision agriculture sprayer. *Precision Agriculture*, 22(6):1711–1727, December 2021.

[30] Joseph Redmon and Ali Farhadi. Yolov3: An incremental improvement, 2018.

[31] Ziheng Sun, Liping Di, Hui Fang, and Annie Burgess. Deep Learning Classification for Crop Types in North Dakota. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13:2200–2213, 2020.

[32] Zhong, Liheng and Hu, Lina and Zhou, Hang Deep learning based multi-temporal crop classification. *Remote Sensing of Environment*, 221:430–443, 2019.