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ADVANCED SOFT COMPUTING PARADIGM FOR CROP MAPPING USING REMOTE SENSING AND ARTIFICIAL INTELLIGENCE: A REVIEW

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SUMMARY

High-precision crop type mapping is fundamental for agricultural monitoring, food security assessment, and sustainable land management. Recent breakthroughs in Earth observation and machine learning (ML) have greatly enhanced the potential for satellite data to capture crop phenology, spatial variability, and temporal variations. This paper conducts a systematic review of over 30 satellite-based crop type mapping studies, covering satellite data sources, multi-sensor fusion techniques, and classification models. The quantitative meta-analysis of the reviewed studies indicates that the fusion of optical and synthetic aperture radar (SAR) data can enhance overall classification accuracy by 0.2% to 0.6%, especially in areas with high spatial variability and frequent cloud cover. In addition, ensemble learning and deep learning models have been found to outperform conventional classifiers, with substantial improvements in both accuracy and robustness for various agro-ecological zones. Pixel-level fusion methods have been found to be the most effective means of enhancing crop type discrimination and area estimation.

Key words: *satellite crop classification, multi-sensor data fusion, optical–SAR integration, time-series vegetation indices, deep learning in remote sensing, cloud-based crop monitoring.*

INTRODUCTION

High-precision crop type mapping is an essential component of modern agriculture, allowing for efficient crop phenology monitoring, food security analysis, and sustainable land use. During the last decade, the Earth observation (EO) technology development has led to a significant increase in the availability, variety, and temporal resolution of satellite imagery [1]. Classical classifiers, such as Support Vector Machines (SVM) and Random Forests (RF), have shown high performance in high-dimensional feature spaces, while deep learning models, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and attention models, are highly effective in modeling spatial, temporal, and multi-sensor relationships [2]. Furthermore, cloud computing platforms, such as Google Earth Engine, have facilitated large-scale and near-real-time crop mapping, allowing for applications ranging from field to global scales [3].

Recent studies have demonstrated the advantages of multi-sensor fusion, especially the combination of optical and SAR images, which improves crop type classification accuracy and overcomes the limitations of cloud contamination. However, there are still challenges in sensor fusion, model transferability, ground truth scarcity, and the trade-off between model complexity and practicability [4]. This review systematically integrates more than 30 recent studies on crop mapping, analyzing sensor data sources, feature representation techniques, fusion techniques, and machine learning algorithms [5]. Following are the main contributions:

- Systematic integration of more than 30 recent studies on crop type mapping, comparing different sensors, fusion schemes, and machine learning techniques.
- In-depth analysis of fusion and classification schemes, with a special focus on pixel-level fusion and its practicability.
- Research gap identification, including sensor fusion, ground truth scarcity, and model transferability.

The rest of this paper is structured as follows. Section 2 presents a literature review on crop images, focusing on radar and optical satellite data. Section 3 introduces a new Review Methodology section. Section 4 presents an overview of data fusion techniques and machine learning methods, while Section 5 offers a comparative assessment of accuracy levels and new trends. section 6 presents a comparative evaluation of the proposed model with existing state-of-the-art techniques to assess its effectiveness and reliability. Section 7 addressing these gaps and challenges will pave the way for developing more efficient systems in future research. Finally, Section 8 concludes this paper by summarizing the main findings and future research avenues for crop mapping applications.

SATELLITE DATA SOURCES

Radar and Optical Data

Its effectiveness stemmed from the correlation between plant physical characteristics, phenology, sensor measurements, making it valuable for crop analysis. With the advent of radar data, researchers have turned their attention to the synergies between the two sources and the connection between backscattering and crop attributes [6].

(Table 1) Sentinel-1 SAR and Sentinel-2 multispectral data are the two most used satellite datasets as they can sense different aspects of crop monitoring with their simultaneous high temporal rates of return and open access provision [7]. Pixel-level fusion is the most common method because it combines spectral, backscatter and texture features in an efficient way. Regarding classifiers, Random Forest is the most adopted algorithm, being robust with high-dimensional features and lack of training samples followed by Support Vector Machines and more recently deep learning models [8]. These results illustrate a tradeoff between methodological reliability, data richness, and operational feasibility in large scale crop mapping [9].

Table 1. List of satellite datasets and methods used

Author (Year)	Method/Approach	Satellite Dataset(s) / Sensor(s)
Cai et al., 2018	Time-series analysis with machine learning	Landsat 5, 7, 8
Mansaray et al., 2017	Optical and microwave remote sensing analysis	Sentinel-1A (VV, VH polarization), Landsat 8 (OLI)
Kussul et al., 2018	SAR and optical imaging over multiple time periods	Landsat-8, Sentinel-1A (C-band, 2015–2016), Sentinel-2
Forkuor et al., 2015	Sequential masking classification	TerraSAR-X, RapidEye, Sentinel-1A SAR
Foerster et al., 2012	Phenological data and spectral-temporal profiling	35 Landsat images
Skakun et al., 2016	Multi-temporal crop classification	Landsat 8, Radarsat-2 (C-band)
Zheng et al., 2015	Time-series NDVI analysis	24 scenes from Landsat 5 TM and 7 ETM
Sarzynski et al., 2020	Combination of radar and optical imagery via GEE	Landsat 8, SAR
Hu et al., 2021b	Random Forest supervised classification	Sentinel-1 and Sentinel-2
Sun et al., 2022	Deep learning	Sentinel-1 and Sentinel-2
Kaplan et al., 2023	Estimation of vegetation variables	Sentinel-1 and Sentinel-2
Habibie et al., 2024	Land cover classification using GEE and CNN1D	Sentinel-1 and Sentinel-2

REVIEW METHODOLOGY AND FEATURE EXTRACTION

NDVI is a valuable indicator of the presence of photosynthetically active plant life. Traditional approaches of parametric and nonparametric classification from an image had produced inefficient outputs [10]. As a result, phenological data is required to create a unique growth model for each crop type based on spectral temporal profiles [11]. They enable the extraction of physiologically relevant measures.

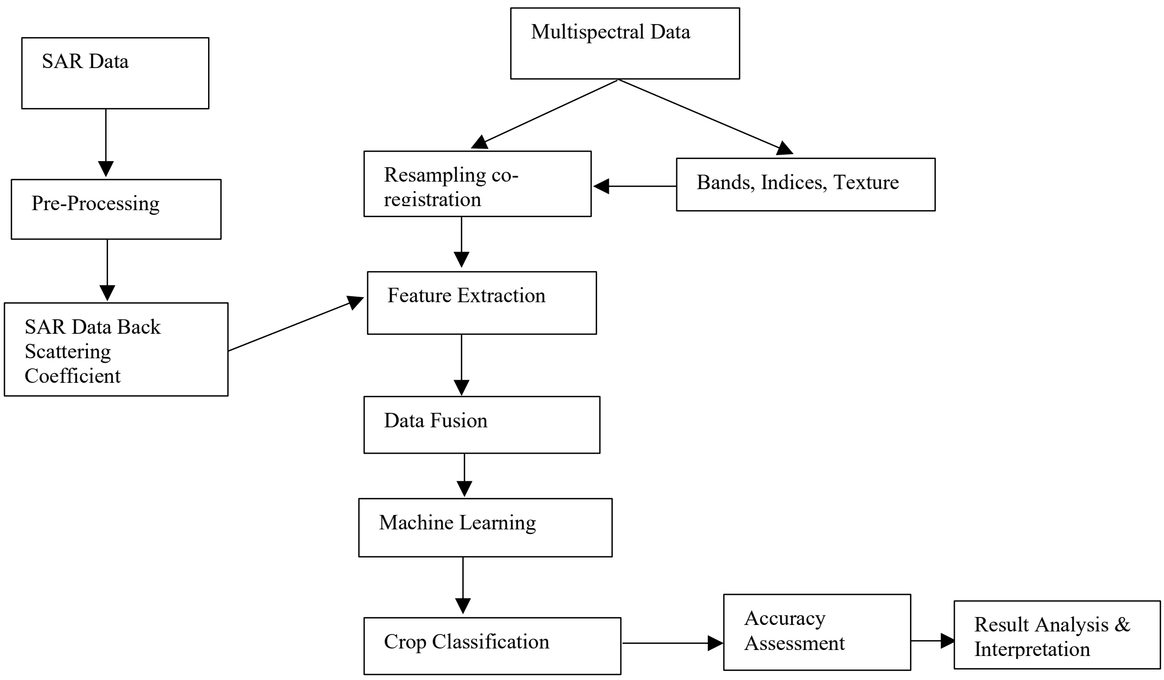

Figure 1. Overall architecture of the proposed soft computing-based crop mapping framework

Phenological properties have been used to characterize cultures in several recent research [12]. for example, exploited spectral features at specified dates to derive phenological metrics that revealed interior physiological properties. These variables allow decision rules to be built to do an autonomous crop extraction. (Figure 1) The methodology flowchart presents a logical organization guiding the review from data collection to synthesis. The review initially describes the sources used, such as SAR and multispectral datasets to provide a knowledge about sensor performance and limitations [13]. The review then discusses feature extraction, involving spectral indices, backscatter and texture features that allow efficient depiction of the information. Based on these data fusion inputs, different strategies of data fusion are systematically surveyed focusing on pixel-level methods to combine multiple sources of information [14]. The structure then leads the discussion to classification and machine learning solutions that directly depend upon feature quality and fusion strategy. Lastly, the review concludes with accuracy comparison of different studies, trend-pattern identification, and research gap recognition [15][16][17][18][19][20].

Vegetation Indices

The spectral variations in vegetation response across various bands are exploited by NDVI which are described in (1) – (3):

$$NDVI = (NIR - IR) / (NIR + IR) \quad (1)$$

$$SAVI = (1 + L) * (NIR - R) (NIR + R + L) \quad (2)$$

$$MSAVI = [2 * NIR + 1 - \sqrt{} (2 * NIR + 1)2 - 8 * (NIR - RED]/2 \quad (3)$$

The crop cycle is statistically represented by the indices that display temporal fluctuations [21]. For charting agricultural phenological development, the NDVI is still the most often used indicator the Enhanced Vegetation Index defined in Equation (4).

$$EVI = 2.5 * ((NIR) - (R) / NIR + 6 * R - 7.5 * B + 1 \quad (4)$$

The models that follow concentrate on biomass productivity and vegetation height. Crop-specific phenological dynamics are captured using the Rice Mapping Index described in Equation (5):

$$RMI(NIR) = NIR1(Harvest) - NIR1(transplanting)NIR1 + NIR1(transplanting) \quad (5)$$

[22] derived RVI for cotton crop growth phenology. Structural crop growth characteristics derived from SAR backscatter are represented by the Radar Vegetation Index in Equation (6):

$$RVI = \frac{4\sigma_{vh}}{\sigma_{vv} + \sigma_{vh}} \quad (6)$$

PIXEL-LEVEL DATA FUSION

Based on a pixel basis, image fusion combines optical and radar data to improve textural and spatial resolution while preserving spectral accuracy [23]. Principal component analysis, intensity-hue-saturation, wavelet transforms, and hybrid approaches are the most used fusion techniques. These methods have been categorized based on component substitution, multi-resolution, and hybrid techniques. Further this enhances its improved fusion methodologies [24].

Component Substitution Techniques

PCA is a commonly used method for pixel level data fusion that effectively minimizes data redundancy while preserving key information [25].

In agricultural areas, HPF fusion performs better than other pixel-level fusion approaches. In another study by [26], it was found that while the HPF method improves wheat classification accuracy, it doesn't enhance vineyard classification accuracy. Based on the combination of Landsat and RADARSAT images reveals finer landscape details compared to using each dataset independently [27]. Specifically, employing the BT approach results in an image that effectively distinguishes between forested areas and cultivated rice fields [28].

Multi-Resolution Analysis

Each level of the pyramid is linked to a channel with reduced resolution and corresponding spatial characteristics. Wavelets and curvelets are two of the most utilized multi-resolution analytic tools. The fusion method based on wavelets combines spatial information from SAR imaging with optical images, minimizing distortion of spectral information. PALSAR data. could be a very viable technique for urban regions, but not for rural areas. While the implementation of DWT enhances the identification of wheat fields in contrast to different land cover categories like residential or pasture, its impact on the overall accuracy is relatively minimal with alternative [29].

The benefit of image-fusion approaches in agricultural remote sensing is highly dependent on similarity of crops, atmospheric limitations, resolution of sensor and heterogeneity of landscape. When crop classes are spectrally similar (e.g., cereals at similar phenological stages), feature-level and model-based fusion, more precisely deep learning based on spectral–temporal signatures can outperform pixel-level fusion by capturing subtle textural and temporal variation. In the case of persistent cloudy conditions, SAR–optical fusion and spatiotemporal fusion methods are more effective since radar data provides all-weather continuity while optical data maintains crop biophysical sensitivity. For high spatial detail demands (field-scale management), separation methods (including pan-sharpening and spatial–spectral fusion) work well in relatively homogeneous landscapes, and object-based or deep neural fusion is better for complex, heterogeneous landscapes when mixed pixels dominate. In general, pixel-level fusion can adapt to uniform high-quality image conditions where the traditional pixel level is suitable for crop mapping [30].

MACHINE LEARNING & DEEP LEARNING MODELS

Various categorization algorithms are used in crop mapping. Support Vector Machine, Decision Tree (DT), and Random Forest (RF) classifiers have been the primary options for identifying remote sensing images in recent years [31] had improved the crop classification accuracy of multiple algorithms such as weighted KNN subspace KNN (ensemble classifier) cubic SVM quadratic SVM Median Gaussian SVM. To generate spatial-spectral embedding for each date pixels undergo processing by shared consecutive MLPs. It obtained an overall accuracy of 0.93. [32] used Decision Tree Classifier and Random Forest algorithm to classify crop type.

Random Forest and Deep Neural Networks to employ deep learning methods in modelling the early and late sowing of cotton and soybean crops. [33] utilized LSTM and BiLSTM models, which demonstrated significantly faster processing speeds with GPU acceleration compared to the methods of traditional machine learning classification. In a UNet model trained in Arkansas using CDL and Landsat data was transferred to US and China locations to map corn and rice. They discovered that spectral values differed for the same crops among regions, making direct model transfer difficult. They developed an approach to improve data consistency and thereby effective transfer of models for crop mapping globally, by adjusting windows to better match up sow and growth phases specifically in target areas of interest [34].

High-resolution reflectance dataset for the Huaihe basin by combining Sentinel and Landsat data using Google Earth Engine (GEE). Using this dataset, the accuracy was 88.87% (Kappa 0.78; Mean Kappa 0.775) and a phenological type-based crop intensity map was developed. This dataset has the potential to improve grain yield prediction and assessment of ecosystem impacts on a regional scale. A method of contrastive learning was introduced to combine the representations. To instill a more compact model, the partial weight-sharing principle has been introduced and built a more efficient late feature-level fusion network. This approach facilitated better feature discrimination for different input sizes over conventional supervised approaches. A study analyzed deep learning techniques in wheat farming to suggest an ontology-centered knowledge management platform. This system aims to facilitate the cataloging of objectives investigated, preprocessing methods, models used, datasets employed, and outcomes obtained. They conclude that deep learning provides a cost-efficient, robust, and accurate alternative in the measurement of wheat traits compared to traditional methods and a step forward in high-throughput phenotyping for future research. [35] evaluated three vegetation detection methods: two were deep learning-based models and one was an object-based NDVI-ML method combining computer vision and machine learning. Their results further indicated NDVI-ML approach provided superior performance compared with deep learning models including DeepLabV3+ with RGB bands. However, they found that the differences in types of images of training and testing data made it hard for deep learning approaches to achieve good results. Nevertheless, a comprehensive analysis of deep learning techniques for environmental RS has been released. MODIS, which has a higher temporal resolution than Landsat (a 16-day cycle) and can penetrate clouds, is noted as the preferred RS sensor and NDVI is the most used feature.

Equally important is the deployment of existing technological tools. Integrating Sentinel-1 backscatter GRD into GEE streamlines the process by removing the need for humans to handle and store large datasets and allowing algorithms to work directly with the data.

An overall accuracy 91% with a kappa coefficient 0.90 was achieved at Coalville, UK study area. In another study by [36], corn and soy were the identified crops.

PERFORMANCE COMPARISON

The findings underscored the advantages of utilizing Shortwave Infrared (SWIR) bands instead of the commonly used v Near Infrared (NIR) and visible bands in crop classification and it exhibits a 10 to 15% increase in accuracy [37]. The optimal band combination was determined to be the green band. In, crop classification included Mature Rubber, Shrub/Orchard, Forest, Mangrove, Palm Oil, Paddy field and Built-up area. Compared to Landsat data alone, which produced accuracy between 91.20% and 91.93%, the combination of Landsat and SAR data produced the best unbiased worldwide accuracies, ranging from 92.96% to 93.83%. (Ajadi et al., 2021), focused on soybean and corn classification classified cotton crop combining Sentinel1 and Sentinel2.

Table 2. Comparative analysis of existing methods

Literature Survey	Model / Method	Overall Accuracy (%)	COE (%)
Yang et al., 2021	SVM	85.98	14.02
Jayatrao Mohite et al., 2020	RF		13.55
Jayatrao Mohite et al., 2020	DNN	89.15	10.85
Ramalingam et al., 2019	Unsupervised Classification	76.24	23.76
Kaplan & Rozenstein, 2021	Linear Regression	70.00	30.00
Luo et al., 2021	RF	89.75	10.25
Ge et al., 2021	U-Net	87.00	13.00
Yuan et al., 2023	Self-Supervised Learning	88.17	11.83
Fu et al., 2023	ML (TWDTW) Method	90.74	9.26
Habibie et al., 2024	CNN 1D	78.00	22.00

RESEARCH GAPS & CHALLENGES

In general, the literature in Table 2 reflects a trend of performance enhancement from conventional statistical and classical machine learning methods to deep learning models. Conventional approaches like linear regression (70%) and unsupervised classification (~76%) have a limited ability to capture the complex, non-linear relationships that exist in satellite time series data. Supervised machine learning algorithms like SVM (85.98%) and RF (86.45-89.75%) provide better performance, especially when adequate training data and proper feature representation are considered [38].

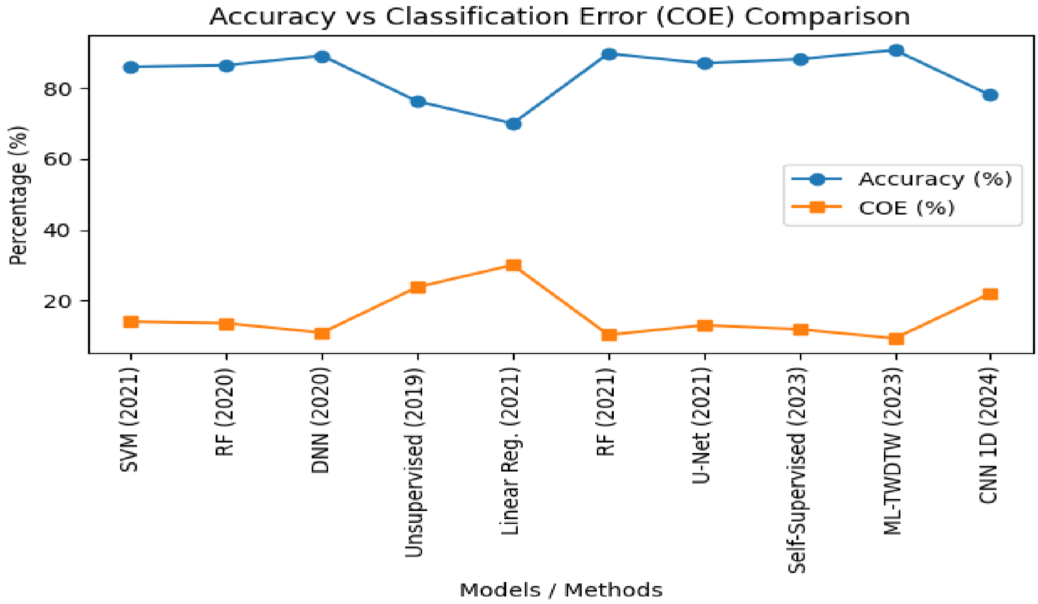

Figure 2. Comparative performance analysis: accuracy Vs error comparison

Deep learning models further improve the classification accuracy by exploiting spatial, spectral, and temporal relationships in multi-source data. Models like DNN (89.15%), U-Net (87%), self-supervised learning (88.17%), and TWDTW-based ML (90.74%) always perform better than most traditional methods. However, the improvement in accuracy over optimized RF and SVM models may be marginal in homogeneous landscapes and simple classification problems. However, the relatively poor performance of CNN-1D in some studies clearly indicates that the benefits of deep learning are still highly sensitive to model architecture, data requirements, and the size of the training dataset [39]. Figure 2 is a comparative graphical representation of the overall classification accuracy (%) of different machine learning and deep learning models as reported in the literature. The comparison also encompasses traditional methods like Linear Regression (70%) and Unsupervised Classification (76.24%), ensemble learning techniques such as Random Forest (85.98-89.75%), deep learning techniques including DNN (89.15%), U-Net (87%), and CNN 1D (78%), and advanced techniques such as Self-Supervised Learning (88.17%) and the ML-based TWDTW approach (90.74%). The Classification Error (COE), calculated for different machine learning and deep learning techniques [40]. Lower values of COE represent better classification accuracy, and the TWDTW-based ML technique has the lowest error rate (9.26%), followed by Random Forest and deep learning techniques

CONCLUSION

This review illustrates a ranking of crop classification accuracy, emphasizing the evolution from conventional statistical and machine learning techniques to sophisticated deep learning models. Traditional approaches, such as linear regression and unsupervised classification, indicating a lack of ability to capture complex relationships in satellite imagery. Supervised machine learning algorithms exceed 88% accuracy with some studies reporting accuracies above 90% in multi-sensor or dense time-series crop classification tasks. The importance of multi-sensor fusion is illustrated to be essential for accurate crop mapping in challenging scenarios like cloud-contaminated areas or heterogeneous regions. Pixel-level fusion enables efficient processing of large-scale crop classification datasets. Despite such achievements the variability of model performance based on regions and seasons, and the trade-off between accuracy, interpretability, and efficiency. Future studies should focus on providing standardized benchmark datasets and statistically sound evaluation methodologies, as well as efficient and interpretable deep learning models. Moreover, self-supervised and transfer learning methods can alleviate the need for large amounts of labeled data, especially in data-scarce areas. Cloud-native platforms with multi-sensor fusion and real-time analytics capabilities will play a critical role in the development of scalable crop monitoring systems for sustainable agricultural practices and global food security.

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