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Remote Sensing and Deep Learning-Based Image Classification for Precision Agriculture

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***Abstract*—This Precision agriculture has become an essential approach to modern farming, aiming to optimize resource use, improve crop productivity, and ensure sustainability. A cornerstone of precision agriculture is the ability to collect, analyze, and interpret spatial and temporal information about agricultural fields. Remote sensing (RS) provides cost-effective, large-scale, and repetitive observations of crop conditions, while recent advances in artificial intelligence, especially deep learning (DL), have significantly improved the accuracy of image classification and interpretation. Integrating RS with DL techniques has therefore become a key driver of innovation in agricultural monitoring and decision support.**

The aim of this study is to demonstrate how satellite data can be used to detect and map heterogeneity within fields and differences in crop growth, with particular emphasis on the application of advanced classification methods. In this study, I analyzed the spatial variability of intensively cultivated agricultural fields using several machine learning and deep learning-based algorithms (Cluster, k-means, SVM, k-NN). The results of the different classification methods were compared to identify the most effective approach for assessing crop development anomalies and supporting precision agriculture.

***Keywords*—Remote Sensing, Sentinel2, Deep Learning, Image Classification, Agriculture**

I. INTRODUCTION

This Precision agriculture has become an essential approach to modern farming, aiming to optimize resource use, improve crop productivity, and ensure sustainability. A cornerstone of precision agriculture is the ability to collect, analyze, and interpret spatial and temporal information about and within agricultural fields. Remote sensing (RS) provides cost-effective, large-scale, and repetitive observations of crop conditions, while recent advances in artificial intelligence, especially deep learning (DL), have significantly improved the accuracy of image classification and interpretation. Integrating RS with DL techniques has therefore become a key driver of innovation in agricultural monitoring and decision support.

The application of remote sensing and deep learning in precision agriculture has gained significant attention over the past decade due to its potential to enhance crop monitoring, improve yield predictions, and optimize resource use. Remote sensing technologies, including multispectral, hyperspectral or radar (SAR) sensors, provide high-resolution, temporally-rich data that can capture crop characteristics, stress conditions, and those variability within fields [1, 2]. Remote sensing represents a robust and objective source of information for precision agriculture, providing essential data to support the assessment of within-field variability, the detection of plant stress conditions, and the planning of site-specific management interventions. The analysis of multitemporal satellite imagery facilitates the monitoring of crop development, identification of sowing irregularities, detection of pest infestations, and evaluation of spatial variations in water and nutrient availability [3]. Nevertheless, the reliability and accuracy of such analyses are influenced by several factors, including the characteristics of the imagery and spectral indices applied, the timing of data acquisition [3], and the phenological stage of the observed crop. In addition to these factors, the choice of image classification method plays a critical role in determining the quality of the derived information. Advanced machine learning and deep learning algorithms—such as Support Vector Machines (SVM), Random Forest (RF), and Convolutional Neural Networks (CNN)—have been shown to significantly improve classification accuracy and enhance the interpretation of complex agricultural landscapes. The application of these techniques enables more reliable discrimination of crop types and stress levels, thereby strengthening the decision-support capacity of precision farming systems.

One of the studies investigated the potential of using Sentinel-2 satellite imagery combined with automatic, unsupervised classification methods to map crop heterogeneity within arable fields. The study encompassed both vegetated and non-vegetated periods and was conducted on intensively cultivated farmland. The results indicate that automatic classification can be effectively employed to identify within-field variability: spectral data clusters serve as reliable indicators of heterogeneous zones, and their statistical characteristics corroborate the presence of underlying physical differences [4, 5]. The choice of classification method significantly influences the accuracy and reliability of the derived information, thereby impacting the effectiveness of precision farming interventions.

Recent advancements in unsupervised classification techniques have further enhanced the mapping of agricultural landscapes. For instance, a multi-source unsupervised classification model (MUCCM) based on multi-scale feature aggregation networks was proposed for unsupervised crop mapping using time-series Sentinel-2 images, demonstrating improved classification performance in complex agricultural areas [6]. Additionally, a study employing time-series data and quality control procedures highlighted the effectiveness of these approaches in enhancing crop classification in complex environments ScienceDirect. These developments underscore the critical role of classification methods in precision agriculture, influencing the accuracy and reliability of information derived from remote sensing data.

Several studies have demonstrated the effectiveness of convolutional neural networks (CNNs), fully convolutional networks (FCNs), and U-Net architectures for pixel-level and semantic segmentation of agricultural fields [7, 8]. These models are particularly adept at identifying subtle differences between crop and weed species or detecting field boundaries, outperforming traditional machine learning approaches such as support vector machines (SVM) or random forests (RF) when sufficient labeled data are available. However, model performance can vary depending on the network architecture and the specific classification task, highlighting the need for careful selection of model type based on the target crop or phenomenon.

Temporal information from multi-date satellite imagery has been shown to significantly improve classification accuracy. Recurrent-convolutional networks, which combine CNNs with recurrent layers such as LSTMs, effectively capture phenological dynamics of crops, enabling differentiation between species with similar spectral characteristics but differing growth cycles [9]. Moreover, hybrid architectures such as CNN-LSTM or CNN-GRU models demonstrate robustness to missing data due to cloud cover or sensor gaps, maintaining high classification accuracy (>85%) under realistic conditions [10].

The fusion of multispectral and SAR imagery further enhances classification performance, particularly for crops with complex structures or when optical data are limited due to atmospheric conditions [1]. Additionally, hyperspectral imaging, when combined with deep learning models, enables early detection of crop stress, nutrient deficiencies, and disease onset, exploiting subtle spectral signatures that are not easily discernible in traditional multispectral bands [2].

Despite the promising results, challenges remain in terms of data availability, annotation quality, and computational resources. Many studies highlight the need for large, accurately labeled datasets to train deep learning models effectively. Approaches such as transfer learning, data augmentation, and multi-scale feature fusion have been successfully employed to mitigate these limitations [8]. Overall, the integration of remote sensing and deep learning represents a powerful tool for precision agriculture, enabling more informed decision-making, improved crop management, and increased sustainability.

The aim of this study is to demonstrate how satellite data can be used to detect and map heterogeneity within fields and differences in crop growth, with particular emphasis on the application of advanced classification methods. In this study, I analyzed the spatial variability of intensively cultivated agricultural fields using several machine learning and deep learning-based algorithms (CLUSTER, KMEAN, SVM, k-NN, Random Forest). The results of the different classification methods were compared to identify the most effective approach for assessing crop development anomalies and supporting precision agriculture.

II. MATERIALS AND METHODS

A. Study area

Mapping of within-field heterogeneity was carried out on arable land using both supervised and automatic classification methods across several agricultural fields. However, in the present study, the analyses conducted on one representative field (Fig. 1) are presented as an example. The studied agricultural field is located in Komárom-Esztergom County, Hungary (47.595170, 18.701629). Based on precision soil sampling repeated every five years and subsequent laboratory analyses, the humus (organic matter) content varies between 1.58 % and 2.99 %. Lower organic matter content is typical of the higher, erosion-prone parts of the field, whereas higher humus content is observed in slightly sloping or flat areas.

The soil texture index (Arany-type soil plasticity index, KA) characterizes the soil's physical texture and particle-size distribution, from which its water retention and permeability can be inferred. In the examined area, the KA values range between 37 and 45, indicating the presence of sandy loam (37), loam (38–42), and clay loam (43–45) soil types.

According to the Hungarian Soil Classification System (HSCS), the dominant soil type in the area is brown forest soil. The field is cultivated under a crop rotation system, alternating between autumn and spring arable crops. Topography has a considerable influence on land management: based on the topographic map, the highest point of the field lies at 276 m, while the lowest point is at 205 m above sea level. The area also includes slopes with gradients between 12 % and 17 %.

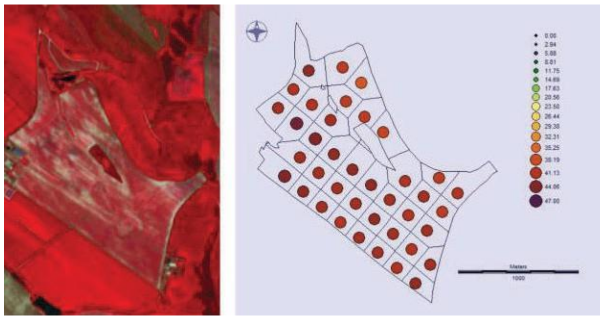

Fig. 1. Study area on satellite image (Sentinel2, 2025 June 30th) and soil sampling zones.

B. Data

Sentinel-2 comprises two satellites, Sentinel-2 A and Sentinel-2 B, which provide high spatial resolution (up to 10 m) and temporal resolution (up to 5 days) images freely. The data is available at various levels of pre-processing, including TOA and BOA. In this study Copernicus Sentinel-2 Collection 1 MSI Level-2A (L2A) Bottom of Atmosphere Reflectance Products were used. This work collected the cloud free images covering the study area in 2025 to obtain the spectral features of crops. Specifically, 6 bands including Green, Red, Near-Infrared (NIR), Short wave infrared (SWIR) 1 and SWIR2 were selected for feature extraction and classificatin. Behind spectral features I also selected some widely used indexes calculated from the Sentinel-2 images: the Normalized Difference Vegetation Index (NDVI) Green Vegetation Index (VIgreen) and Normalized Difference Water Index (NDWI).

The selection of satellite images was preceded by an analysis of the entire vegetation period (Fig. 2). This study focuses on the period between May and September 2025, during which 30 high-quality images (with cloud cover below 30%) were available. Time-series analysis enables the monitoring of crop development throughout the growing season. Fig. 2 shows the average NDVI values calculated for the study area. To analyze within-field heterogeneity, the period corresponding to the maximum vegetation index values (June 7–22) was selected. During this period, six high-quality Sentinel-2 images were acquired.

Ground references data included harvest (combine yield) maps, soil data, and topographic information from previous years.

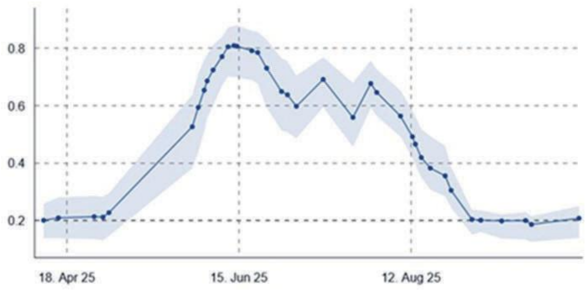

Fig. 2. Changes in the average NDVI value measured during the growing season (2025, Sentinel2)

III. Machine Learning in Image Processing

Machine learning plays an increasingly important role in remote sensing and image analysis, as it enables the extraction of meaningful information from complex and high-dimensional datasets. In this context, image features—such as spectral, spatial, and textural characteristics—serve as input data for algorithms that perform image classification, pattern, and shape recognition. The machine learning process generally involves two main stages: training and evaluation. During the training phase, algorithms learn the relationships between input features and target classes based on reference (labeled) data. In the evaluation phase, the trained model is tested on unseen data to assess its accuracy and generalization ability.

Selecting an appropriate machine learning approach depends on several factors, including the research objective, the size and quality of the available dataset, and the statistical properties of the features. Machine learning algorithms are typically divided into two main categories: supervised and unsupervised learning methods. Supervised learning relies on labeled data, where the correct class of each training sample is known, while unsupervised learning identifies natural groupings or patterns in the data without prior labeling.

In this study, both supervised and unsupervised classification methods were applied to analyze spatial variability within agricultural fields. Specifically, two supervised algorithms—k-Nearest Neighbors (kNN) and Support Vector Machine (SVM)—and two unsupervised clustering approaches—the general clustering (CLUSTER) method and k-means algorithm—were used for image classification. The combination of these techniques allows for a comprehensive comparison of classification performance and supports the identification of the most effective method for detecting field heterogeneity and crop condition differences.

A. *Results of Mapping Field Heterogeneity by Using Unsupervised Classification*

Prior to executing the algorithm for automatic, rule-based classification, several key parameters must be defined.

- Calculation of point-to-point distances: In this study, distances are interpreted in the intensity space, and the Euclidean distance was employed to quantify them.
- Calculation of distances between clusters (classes): The simplest approach considers the average of all possible pairwise distances between points belonging to two clusters. Alternatively, distance measures derived from the probability distributions of the clusters can be used to capture more complex relationships.
- Definition of a clustering criterion: This criterion evaluates the quality of correspondence between intensity vectors and clusters. It generally favors classifications in which intra-cluster distances are minimized, while inter-cluster distances are maximized, ensuring optimal separation of spectral feature groups.

In this study, both k-means and general clustering algorithms were applied for unsupervised classification of satellite imagery. The k-means algorithm partitions data into a predefined number of clusters by iteratively assigning points to the nearest centroid and updating centroids until convergence. It is simple, computationally efficient, and widely used in remote sensing, but requires prior knowledge of the number of clusters and is sensitive to initial centroid placement. In contrast, the general clustering algorithm identifies natural groupings without predefining the number of clusters by evaluating inter-point distances and optimizing cluster assignment based on a criterion that minimizes intra-cluster variance and maximizes inter-cluster separation. While more flexible and adaptive to heterogeneous data distributions, general clustering can be computationally intensive and sensitive to parameter settings. Both methods provide complementary approaches for mapping spatial heterogeneity and extracting meaningful features from multispectral imagery.

The clustering process was carried out according to these specifications. The results of the unsupervised classification are presented in Fig. 3 where, based on the chosen parameter settings, six distinct data clusters were identified in the first step of the analysis.

Subsequently, the statistical characteristics of each cluster—such as the spectral indices and mean reflectance values of individual bands—were analyzed to support thematic interpretation. Based on this analysis, spectrally similar or small clusters were merged to form broader, thematically meaningful categories. As a result, the study area was classified into three distinct categories: average productivity, above-average productivity, and below-average productivity. In addition, the forested section within the field was delineated as a separate land-cover category.

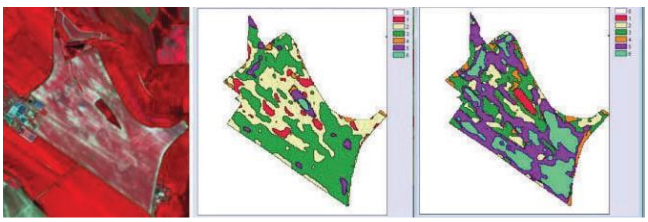

Fig. 3. Sentinel-2 image (input) and the results of two clustering procedures. The colors represent the identified clusters and do not correspond to specific thematic categories.

In the CLUSTER-based classification, two dominant clusters (72 and 99 ha) and four smaller ones (1.2–10.9 ha) were identified. The largest cluster exhibited wide internal variability (NDVI 0.25–0.51), indicating that further subdivision would have been appropriate. Moreover, parts of the forested area were misclassified together with the best-performing vegetation zones. By contrast, the k-means algorithm produced clusters whose size and spatial distribution more accurately reflected field heterogeneity. Comparison with combine harvester yield data confirmed that k-means provided a more consistent and realistic representation of the productivity patterns.

B. Results of Mapping Field Heterogeneity by Using Supervised Classification

The second part of the analysis involved supervised classification using k-Nearest Neighbors (k-NN) and Support Vector Machine (SVM) algorithms within an object-based image analysis (OBIA) framework. Prior to classification, the imagery was segmented into meaningful objects at two levels: a coarse "chessboard" segmentation defining super-level objects, and a multiresolution segmentation producing sub-level objects for finer spatial detail. From these objects, spectral, textural, and structural features were extracted, including layer values and calculated vegetation indices (e.g., NDVI, EVI, NDWI), to serve as classification attributes. Training samples (Fig. 4) were defined for three categories: average, higher than average, and lower than average crop performance.

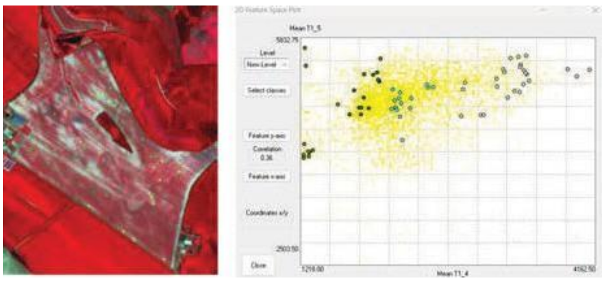

Fig. 4. The samples and theirs location in the feature space created by using NIR, RED bands.

Both k-NN and SVM algorithms (Fig. 5) then assigned objects to these classes based on their feature vectors. The k-NN classifier identifies the class of an object according to the majority class among its nearest neighbors, while SVM constructs an optimal hyperplane that maximizes the margin between classes in the multidimensional feature space. This supervised OBIA approach enables precise delineation of intra-field heterogeneity and provides reliable information for precision agriculture decision-making.

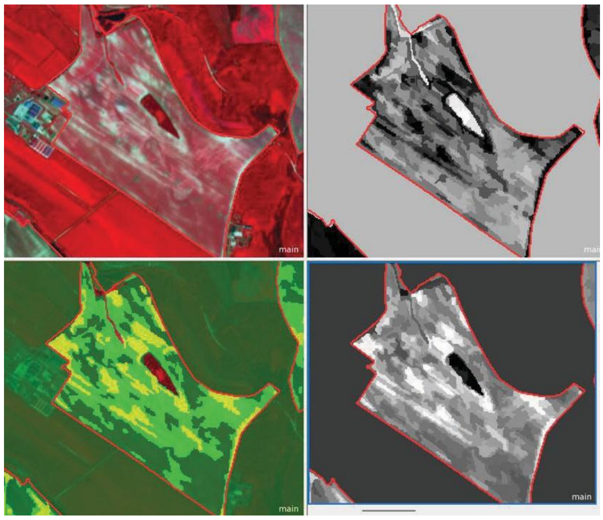

Fig. 5. Sentinel-2 image, representative grayscale feature layers used in the classification process, and the resulting land-cover map generated using the SVM algorithm.

The accuracy of supervised classification is influenced by several factors, including the outcome of the segmentation, the representativeness of the training areas, the relevance of the selected features for describing the categories, and the classification algorithm itself. In the present study, segmentation parameters were determined based on prior experience, and the results of the unsupervised classification were used to select the training areas. Features commonly applied in vegetation mapping, such as spectral indices and band values, were calculated to describe the categories. By comparing the results of multiple traditional and advanced classification approaches and harvest data (Fig. 6) it can be concluded that supervised classification provides more accurate outcomes.

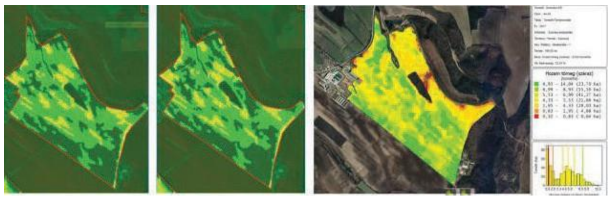

Fig. 6. Land-cover map generated using the k_NN and SVM algorithm, and harvest map

Furthermore, the spatial distribution and size of the categories showed low variability, and comparison with reference data indicated that the Support Vector Machine (SVM) algorithm yielded the most precise results.

Support Vector Machines (SVM) are supervised, non-parametric learning methods widely used in remote sensing and other fields for classification and, occasionally, regression. The principle of SVM is to represent the training objects as points in a multi-dimensional feature space and then determine the optimal hyperplane that best separates the classes. The optimal hyperplane is defined as the separating surface that maximizes the margin between objects belonging to different classes (Fig. 7).

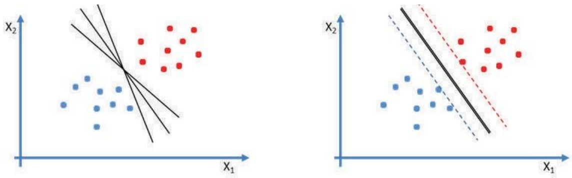

Fig. 7. Possible decision boundaries for a linear SVM (left), and the optimal decision boundary that maximizes the margin between the two categories (right)

Importantly, the classification outcome is not determined by all training points but only by those located closest to the decision boundary, known as the support vectors. This property makes SVM highly efficient, as a representative subset of the training data is sufficient to define the decision boundary accurately. equations consecutively.

IV. Conclusion

The overall classification workflow integrates both unsupervised and supervised approaches to maximize the detection of intra-field variability. Initially, unsupervised clustering was applied to identify natural groupings in the spectral data and explore patterns of heterogeneity without prior knowledge. These results provided preliminary insights into field variability and informed the selection of meaningful training samples for the subsequent supervised, object-based classification. By combining the exploratory power of unsupervised methods with the precision of supervised OBIA using k-NN and SVM, the workflow ensures both robust class separation and accurate mapping of crop performance across the study area. This supervised OBIA approach enables precise delineation of intra-field heterogeneity and provides reliable information for precision agriculture decision-making.

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