Enhancing Machine Learning Crop Classification Models through SAM-Based Field Delineation Based on Satellite Imagery

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Abstract*—Accurate crop classification is vital for various agricultural applications, including yield estimation, land use monitoring, and precision farming. Machine learning models trained on satellite imagery have shown promising results in this domain. However, the accuracy of these models heavily depends on the quality of input features, particularly the delineation of individual fields. Traditional methods for field delineation often face challenges in complex landscapes and heterogeneous agricultural patterns. In this study, we propose a novel approach to enhance machine learning crop classification models by integrating the Segment Anything Model (SAM) for field delineation by utilizing satellite imagery. The Segment Anything Model (SAM) algorithm is a versatile segmentation method capable of segmenting images into meaningful regions based on a wide range of features. By leveraging SAM, we aim to accurately delineate field boundaries from satellite imagery, providing more refined input features for machine learning models. The proposed methodology involves several key steps. First, we preprocess satellite imagery to enhance spectral signatures and differentiation between parcels. Next, we apply SAM to segment the imagery into distinct field boundaries based on various features, extracted from Sentinel-2 satellite imagery. These delineated fields serve as input features for training machine learning classification models. One of the primary advantages of SAM-based field delineation is its flexibility in segmenting diverse agricultural landscapes. SAM can adapt to different environmental conditions and crop types, effectively capturing the spatial variability present in satellite imagery. This comprehensive delineation enables machine learning models to learn more representative features, thereby improving classification accuracy. To evaluate the effectiveness of our approach, we conducted experiments on a diverse dataset comprising satellite imagery from various regions and crop types. We achieved 81 % accuracy in crop identification, while in this work we show the effectiveness of parcel-based filtering, which removes isolated misclassified pixels. Since multiple crops may be cultivated within the same cadastral unit, our field delineation parcels proved to be more effective for postprocessing (filtering) purposes compared to cadastral data, thus ensuring accurate attribution of crops to corresponding land parcels. Our results demonstrate significant improvements in crop classification maps when incorporating SAM-derived field boundaries into the training data. Our study highlights the potential of SAM-based field delineation techniques to enhance machine learning crop classification models using Sentinel-2 satellite imagery. By accurately delineating field boundaries, we provide more informative input features, leading to improved classification performance and better insights into agricultural landscapes. This research contributes to advancing the capabilities of remote sensing technologies for precision agriculture and land management applications.

***Index Terms*—field delineation, machine learning, Segment Anything Model (SAM), crop classification**

I. Introduction

Accurate crop classification is fundamental to various agricultural applications, such as yield estimation, land use monitoring, and precision farming. With the advantage of remote sensing technologies and the availability of high-resolution satellite imagery, machine learning models have shown significant promise in enhancing the accuracy and efficiency of crop classification tasks [1]. These models rely heavily on the quality of input features, particularly the precise delineation of individual fields, which serve as the foundation for accurate analysis and predictions.

Traditional methods for field delineation, such as manual digitization and classical image processing techniques, often struggle to maintain accuracy in complex landscapes characterized by heterogeneous agricultural patterns [2]. These challenges necessitate the development of more sophisticated and automated approaches to effectively delineate fields from satellite imagery.

In recent years, machine learning and deep learning techniques have emerged as powerful tools for image segmentation and object detection tasks [3]. One such advanced technique is the Segment Anything Model (SAM) [4], a versatile segmentation algorithm capable of dividing images into meaningful regions based on a wide range of features. SAM's ability to adapt to different environmental conditions and crop types makes it an ideal candidate for field delineation in agricultural landscapes.

This study proposes a novel approach to enhance machine learning crop classification models by integrating the SAM algorithm for field delineation using Sentinel-2 satellite imagery. By leveraging SAM, we aim to achieve more accurate delineation of field boundaries, which in turn provides more refined input features for training machine learning models.

Our methodology involves preprocessing satellite imagery to enhance spectral signatures, applying SAM to segment the imagery into distinct field boundaries, and using these delineated fields as input features for machine learning classification models.

The flexibility of SAM-based field delineation is particularly advantageous in handling diverse agricultural landscapes, effectively capturing the spatial variability present in satellite imagery. This comprehensive delineation enables machine learning models to learn more representative features, thereby improving classification accuracy. Our experimental results demonstrate significant improvements in crop classification maps when incorporating SAM-derived field boundaries into the training data.

By accurately delineating field boundaries, this research aims to enhance the capabilities of remote sensing technologies for precision agriculture and land management applications. The integration of SAM-based techniques into crop classification models not only improves classification performance but also provides better insights into agricultural landscapes, contributing to the advancement of precision farming practices.

II. Material and Methods

A. Data

In this research, we focused on the Vojvodina region in North Serbia, which is predominantly agricultural arable land. We utilized 6 Sentinel-2 images from the 2023 season to create a time series dataset for model training, consisting of 40,101 data points. The dates of Sentinel-2 image acquisition for this study are as follows: June 13, 2023; June 23, 2023; July 3, 2023; July 8, 2023; July 13, 2023; and September 6, 2023. We created patches of 256x256 pixels from these red, green, and blue bands images to prepare for machine learning model training. The dataset was divided into two parts: 70% for training and 30% for testing. The SAM was then employed to delineate parcel boundaries in vector format. These parcel boundaries were overlapped with a predefined pixel-based classification map [7] to extract labels. For object-based classification purposes, the data was converted into vector format to ensure that each parcel defined by SAM has only one class value. This integration of time series data, precise parcel boundaries, and unified class values per parcel enhances the accuracy and reliability of the final classification map. The results of the test dataset are presented in Table I, where the column "Support" indicates how many data points are of each crop type.

B. Method Overview

The method begins with the acquisition of satellite imagery from the Sentinel-2 satellite. This data is then processed using the Segment Anything Models (SAM) technique to derive parcel boundaries. While SAM also performs its own classification, it was found to be inconsistent across patches, often yielding an excessive number of different classes. Concurrently, information on crop type is derived from existing classification maps [7]. The parcel boundaries obtained from SAM are then intersected with the classification map and Sentinel-2 images to create a complete dataset. This dataset, which includes the spectral footprint and boundary information for each parcel and crop type, is fed into a machine learning classification model. For object-based classification, we utilized Random Forest (RF) [5] and Feed Forward Neural Network (FNN) [6] models. The models are trained to recognize patterns and make classifications based on the input data. The output from the machine learning models is a final classification map, providing a categorized representation of the area of interest. Additionally, an initial classification map may also be used at some stage of the process to refine or validate the results. This method effectively combines satellite imagery with machine learning to produce a detailed and accurate classification map, leveraging spectral information and parcel boundaries to enhance the accuracy of the classifications. All algorithms were implemented using the Scikit-Learn [8] Python and Keras [9] libraries. These libraries are free and widely used in everyday challenges for implementing artificial intelligence in various decision-support systems.

III. Results and Discussion

The output of SAM shown in Figure 2 represents successful parcel delineation achieved through the utilization of patches with dimensions 256x256 pixels and solely relying on the RGB bands extracted from Sentinel-2 images. This delineation process involves the identification and delineation of each parcel within the agricultural landscape.

The SAM algorithm effectively segments the input imagery into distinct regions corresponding to different parcels or fields. By processing only the red, green and blue bands, SAM focuses on capturing the spatial characteristics and patterns present in the Sentinel-2 imagery related to agricultural land cover.

Classification performance results are presented in Table I. Each row in the table corresponds to a specific crop type, and the columns represent various evaluation metrics: Precision, Recall, F1-Score, and Support.

The Precision metric measures the accuracy of positive predictions among all predicted positives. Recall, also known as sensitivity, indicates the proportion of actual positives that were correctly identified by the model. F1-Score is the harmonic mean of Precision and Recall, providing a balance between the two metrics. Support refers to the number of occurrences of each class in the dataset.

From the classification report, we can observe:

- Maize exhibits a balanced precision and recall, indicating good performance in both correctly predicting maize and capturing most maize instances.
- Wheat demonstrates the highest recall among all crops, suggesting that the model is particularly effective at identifying most of the wheat present in the dataset. Its high precision further indicates that predictions of wheat are usually accurate.
- Soybean has a lower recall compared to its precision, implying that the model misses a significant portion of

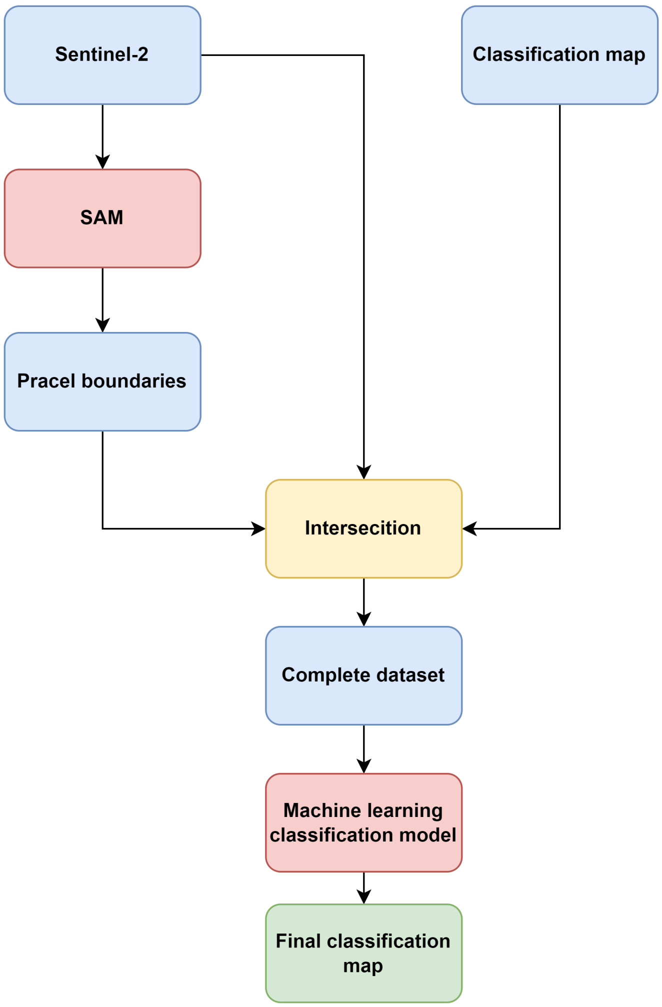

Fig. 1. A flowchart overview and example walk-through of the methods presented in this paper. The blue markers represent the data sources and raw inputs used in the method. These include the Sentinel-2 satellite imagery and the Parcel Boundaries. These markers indicate the foundational data required to initiate the process. The yellow marker represents the creation of an integrated dataset. The red markers signify operational processes and techniques applied to the data. The green marker represents the final output of the method.

soybean instances, although it is quite reliable when it predicts soybean.
- Sugarbeet and Sunflower have similar scores with respectable precision and recall, indicating a moderate level of accuracy and coverage in predictions.
- Oilseed rape shows strong precision but slightly lower recall, similar to soybean, indicating some missed true cases.
- Other crops display the lowest precision and recall, which might suggest difficulties in distinguishing these from other categories or a high variability within this category itself.

Regarding the confusion matrix we can conclude:

- High diagonal values (true positives) for most crops, especially wheat and oilseed rape, indicate strong correct predictions in these categories.
- Notable off-diagonal values highlight confusion between certain crops, such as other crops being frequently misclassified as wheat or maize, likely due to similar spectral signatures or overlapping features in the input data.
- Wheat has considerable misclassification with 'other crops', suggesting a potential overlap in characteristics or a large number of wheat samples skewing the model's training.

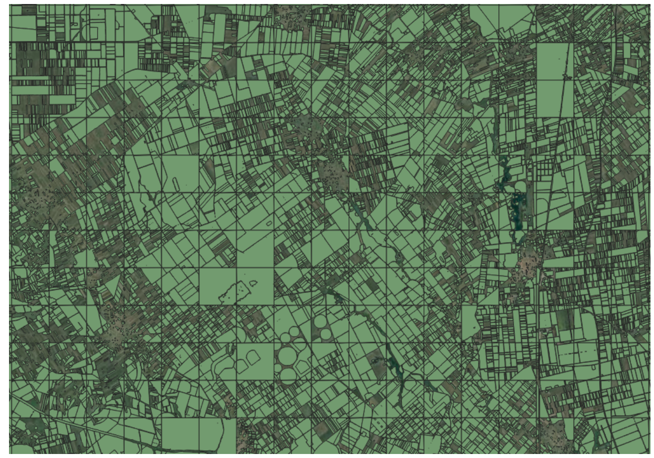

Fig. 2. Output of SAM represented as vector format of parcels boundaries

TABLE I
CLASSIFICATION REPORT OF FNN FOR CROPS IN VOJVODINA REGION ON TEST SET

Crop	Precision	Recall	F1-Score	Support
maize	0.78	0.80	0.79	1037
wheat	0.84	0.91	0.87	4460
soybean	0.80	0.57	0.66	444
sugarbeet	0.80	0.79	0.79	463
sunflower	0.81	0.79	0.80	1170
oilseed rape	0.83	0.80	0.81	929
other crops	0.74	0.69	0.71	2627

The FNN model performs well for crops like wheat and oilseed rape with high precision and recall. However, challenges remain in distinguishing soybean and 'other crops' effectively, as indicated by lower recall values and significant confusion with other crop types. Improving the model's ability to differentiate between these categories may enhance overall accuracy and reliability.

IV. CONCLUSION

In conclusion, the decision to perform object-based classification stemmed from the unique characteristics of the agricultural parcels in our study area. With very small parcels, the majority of pixels are located on the borders where spectral signatures are mixed, posing challenges for accurate classification using traditional methods. On the other hand, larger parcels exhibit anomalies such as isolated pixels caused by occurrences of weeds or pests, further complicating the

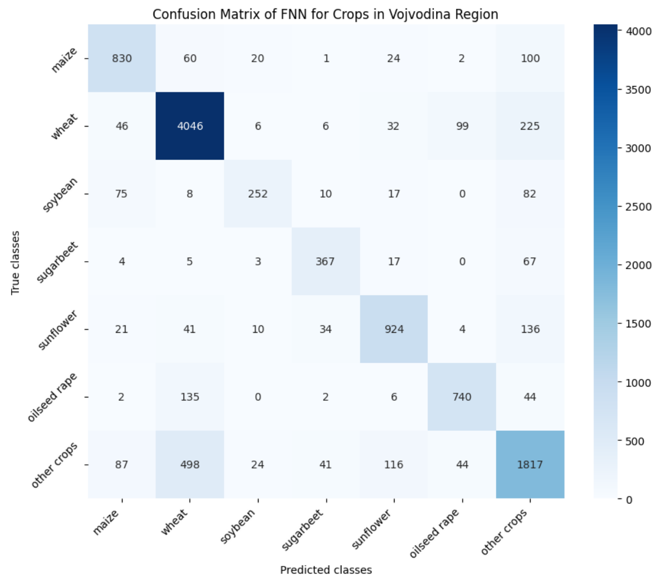

Fig. 3. Confusion Matrix of FNN for Crops in Vojvodina Region

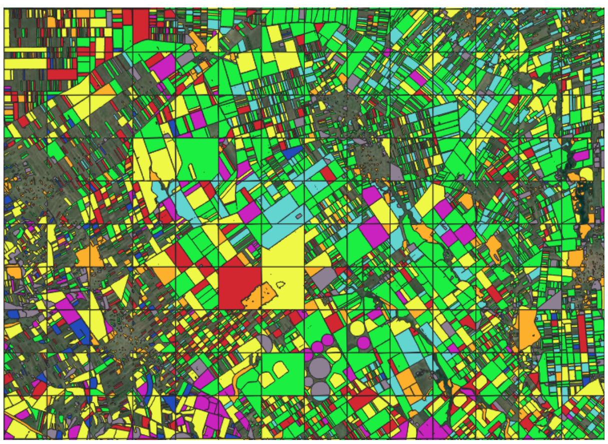

Fig. 4. Output of FNN represented as vector format of parcels classification

classification process. While the initial application of the SAM did not yield promising results, additional steps and algorithms were necessary to improve classification accuracy.

Looking ahead, future work will initially focus on expanding our dataset to include regions beyond Vojvodina, alongside leveraging a larger series of dates from Sentinel-2 imagery. This expansion aims to provide a more robust dataset for analysis. Additionally, we plan to incorporate the remaining spectral channels from Sentinel-2, moving beyond the current usage of only RGB channels. Concurrently, we intend to fine-tune the SAM model to achieve even better parcel delineation, which is crucial for precise agricultural mapping. Following these enhancements, the development and implementation of Convolutional Neural Network (CNN) algorithms for both image segmentation and classification tasks will take place. CNNs offer the potential to address the complexities and nuances present in agricultural parcel classification by leveraging their ability to learn hierarchical features directly from the data. By harnessing the power of deep learning techniques, we aim to enhance the precision and reliability of crop classification in our study area, ultimately advancing our understanding of agricultural landscapes and facilitating informed decision-making processes.

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