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Leveraging Deep Learning in Remote Sensing: A Novel Approach for Agricultural Greenhouse Detection and Innovation Management

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Abstract

Innovation management plays a pivotal role in harnessing advanced technologies to drive progress across diverse fields. In this context, integrating deep learning models within remote sensing technologies presents transformative potential for monitoring, change detection, analysis, and decision-making in fields such as agriculture, urban planning, and environmental studies. This study examines the role of sophisticated deep learning approaches in analyzing high-resolution satellite imagery to improve the detection of agricultural greenhouses. Using MMSegmentation (DeepLabv3Plus) with multispectral data at 0.7-meter resolution, the research addresses the limitations of traditional methods by substantially enhancing detection accuracy and efficiency. To address data scarcity and increase model robustness, advanced data augmentation techniques—such as rotations, scaling, and flipping - expand dataset diversity, fostering adaptability and performance under diverse conditions. The study also assesses the impact of environmental factors, including seasonal variations and weather, on model performance. Suggested improvements include expanding the dataset to encompass a wider variety of greenhouse types and conditions, incorporating high-resolution or hyperspectral imagery for finer details, and building multi-temporal datasets to capture dynamic environmental changes. The findings underscore the importance of advanced innovation management in enhancing remote sensing applications, offering actionable insights for agricultural management in Albania and similar regions. This research contributes to the broader field of innovation management by showcasing how deep learning can revolutionize practical applications in agriculture.

1. Introduction

Innovation in agriculture stands as a key enabler for shaping more responsive and impactful government policies, fostering the development of digital tools and techniques that enhance both agricultural productivity and the quality of life [1]. Deep Learning [2, 37] offers a distinct paradigm within the broader landscape of Machine Learning algorithms. Although it is a subset of Machine Learning, Deep Learning diverges in its capabilities, particularly through the deployment of Artificial Neural Networks [3], which possess the ability to autonomously learn and make intelligent decisions. Unlike traditional Machine Learning models, which can perform adequately with varying data volumes, Deep Learning architectures require vast datasets to achieve optimal performance. Furthermore, Deep Learning requires high-performance computing resources, such as GPUs, to efficiently execute its computationally intensive algorithms.

The integration of Deep Learning with satellite imagery has revolutionized the field of Remote Sensing, providing unprecedented capabilities for the monitoring and analysis of land use patterns and environmental changes [4].

Among its diverse applications, object detection in satellite imagery has emerged as a crucial tool for evaluating agricultural practices, managing natural resources, and informing urban development strategies.

This comparative study [5] critically examines the performance of various Deep Learning models in the detection [4] of greenhouses within satellite images. Leveraging high-precision data from two satellites, the study incorporates diverse topographical features and climatic conditions across regions, presenting a comprehensive case study to assess the robustness and adaptability of Deep Learning models in remote sensing applications.

2. Related Work

Deep learning techniques have accelerated satellite imagery analysis, making it more reliable and efficient than conventional approaches. One of the main benefits of implementing deep learning techniques is their ability to enhance satellite image interpretation, particularly in fields like agriculture and disaster management [6].

As a result, obstacles such as converting satellite imagery into meaningful, high-quality maps, while not new, have become more manageable with advancements in deep learning [7]. Traditionally, producing top-quality maps was time-consuming and prone to errors. Thanks to new datasets and advancements in computer vision, automation is now achievable, particularly through hybrid model [8] and deep learning model applications [9]. For remote sensing, models like U-Net and Mask R-CNN are commonly employed [8]. These models primarily identify specific objects, including vegetation, from satellite images. They are especially critical in converting raw satellite data into usable maps with high accuracy, achieving a Mean Average Precision (mAP) score of up to 0.79 for computers [9]. Utilizing these models, researchers have demonstrated how deep learning enhances the annotation of satellite images, which is of great importance in areas such as urban planning and disaster management.

In agriculture, deep learning has been applied to monitor land use and management, especially on a large scale, such as mapping paddy fields. Conventional data collection methods like field surveys and expert assessments are expensive and time-consuming especially when cloud coverage obscure critical information [10]. Spectral channels, while rich in information, complicate image processing due to adversarial environmental conditions like cloud cover and seasonal crop variations [11].

Researchers have shown that using multi-temporal, high-resolution classification techniques with deep neural networks can effectively tackle these challenges. This approach improves the ability to monitor and analyze changes over time, particularly in areas like environmental monitoring and agriculture. Studies highlight that these methods enhance accuracy and help interpret complex data sets [6,12]. Moreover, deep learning's versatile Convolutional Neural Networks (CNNs) [13] and Recurrent Neural Networks (RNNs) enable the processing of large amounts of satellite data, capturing various spatiotemporal patterns [10]. This capability is essential for agricultural applications, where monitoring crop cycles and predicting yields depend on temporal changes in satellite imagery.

Object and change detection [14] in remote sensing images has been a significant research focus in recent years. Optical remote sensing, coupled with computer vision, has led to dynamic advancements in Earth observation. However, challenges such as insufficient variation in datasets, limited object categories, and fluctuating imaging conditions have hindered progress in object detection [15]. To address these issues, datasets like DIOR (Dataset for Object Detection in Optical Remote Sensing Images) have been developed [16]. DIOR offers valuable insights, though it faces drawbacks such as the need for higher spatial resolution and challenges related to lighting, weather, seasons, and image quality [16]. These datasets open new avenues for studying trends in agriculture, urban planning, and environmental protection. DIOR provides a large-scale benchmark, essential for advancing deep learning approaches and improving remote sensing applications through aggregate multi-scale context [17]. In disaster management, the dataset's adaptability is crucial for detecting small, overlapping objects such as buildings and vehicles in challenging environments. DIOR's diverse object classes, along with its spatial and temporal variability, make it an invaluable tool for evaluating the potential of object detection models [16].

The Remote Sensing Super-Resolution Object Detection (RSSOD) dataset [18] is another significant achievement, providing high-resolution imagery for detecting small objects in highly overlapping contexts. Identifying minor objects, such as small structures, is vital for satellite imagery, especially in urban and agricultural planning. Researchers have observed that many datasets lack small object categories [19], leading to poor performance of object detection algorithms in these areas. The integration of super-resolution techniques with object detection has been a breakthrough. The Multi-class Cyclic Generative Adversarial Network [20] with Residual Feature Aggregation (MCGR) model is a novel approach that enhances object detection by improving image quality. Researchers have shown that enhancing image resolution before detection leads to better results, particularly for small objects, which are challenging to detect in low-resolution images. The MCGR model has outperformed state-of-the-art detectors [20] such as YOLOv5 [21], EfficientDet, and Faster R-CNN [22], producing a higher mAP. Due to the availability of large-scale datasets, advancements in object detection have the potential to transform remote sensing. High object variability and resolution, particularly in small, distinctive objects, are essential for applications such as disaster response, agricultural monitoring, and urban planning. These versatile datasets allow for more effective training of object detection models, improving accuracy in detecting crowded, differently sized objects under various imaging conditions.

While deep learning has made remarkable strides [23] in enhancing the accuracy and efficiency of remote sensing image classification, it is important to recognize that several significant challenges still exist. Addressing these challenges will be essential for realizing the full potential of this technology and advancing the field further. One major bottleneck is the complexity and diversity of patterns in remote sensing data, making feature extraction difficult. Recent advances in deep neural networks, particularly in deep feature learning, have improved scene classification. However, the challenge of processing large-scale and high-dimensional remote sensing data persists [24,36]. Moreover, deep learning models require large, annotated datasets for effective training, but such datasets are often limited in remote sensing. Although benchmark datasets exist, they are typically domain specific and lack the necessary variation for broader applications. Additionally, the cost of acquiring and annotating remote sensing data is high, further complicating efforts to build large, diverse datasets [24].

This study will evaluate the performance and suitability of deep learning models for satellite imagery analysis. It will also examine how variations in image data such as resolution, quantity, and shape affect model effectiveness. Through this comparative analysis, the research aims to contribute to the optimization of object detection techniques [25], thereby enhancing agricultural monitoring and environmental management in Albania, as well as in similar regions worldwide.

2.1. Model Comparison for Agricultural Monitoring

This section evaluates three widely used deep learning models: YOLO, Mask R-CNN, and DeepLabv3Plus to determine the most suitable approach for agricultural monitoring. Each model's segmentation type, strengths, and limitations are analyzed, with a focus on their ability to address the complexities of large-scale agricultural applications, as presented in Table 1: Comparative Evaluation of Deep Learning Models

Table 1: Comparative Evaluation of Deep Learning Models

Model	Type of segmentation	Strength	Limitation
YOLO	No segmentation (object detection only)	Real-Time detection and classification of objects	Cannot provide pixel-level information or classify all regions.
Mask R-CNN	Instance segmentation	Distinguishes individual objects with precise boundaries	Does not classify all pixels; focuses on specific objects
DeepLabv3Plus	Semantic segmentation	Classifies all pixel in an image into meaningful categories, creating a complete scene map	Cannot separate individual objects within the same category

From this comparative analysis, DeepLabv3Plus emerges as the most suitable model for agricultural monitoring. Its semantic segmentation capability ensures pixel level classification, allowing for the creation of comprehensive maps that are crucial for tasks such as crop type identification, field boundary delineation, and land-use classification. This model's robustness to environmental variability, such as cloud cover and seasonal changes, further enhances its applicability in diverse agricultural contexts.

While YOLO provides speed and efficiency, its lack of pixel-level granularity restricts its application to broader object detection tasks rather than detailed scene analysis. Mask R-CNN, though effective in object-specific segmentation, is less practical for large-scale agricultural landscapes requiring holistic mapping.

In contrast, DeepLabv3Plus offers the optimal balance of scalability, accuracy, and contextual understanding, making it the preferred choice for addressing the intricate demands of agricultural monitoring and decision-making.

3. Methodology

This study presents an innovative methodology that integrates advanced deep learning techniques with high-resolution multispectral satellite imagery to enhance the precision and efficiency of agricultural greenhouse detection. The segmentation approach is selected to be applied based on the successful application of alternative models, such as 3D-CNNs, in similar agricultural contexts [26]. At the core of this approach is the MMSegmentation [27] framework, which uses the DeepLabv3Plus model well-suited for semantic segmentation tasks [28]. This model has proven highly effective in identifying the subtle structural differences that define greenhouses, even in complex environments. By utilizing multispectral imagery with a spatial resolution of 0.7 meters, the methodology extracts detailed spectral data, allowing the model to better distinguish greenhouses from surrounding land features.

A key innovation in this approach is the use of data augmentation techniques, such as rotation, flipping, and scaling. These techniques help make the model more robust by artificially increasing the diversity of the training data, which in turn helps the model perform better in real-world applications. Fine-tuning the model further ensures that it adapts to the specific characteristics of the study area, improving the accuracy of greenhouse detection. To make the process more efficient, the methodology incorporates the ArcGIS Pro Geoprocessing Tool, specifically the "Classify Pixel Using Deep Learning" tool. This integration automates much of the pixel classification, reducing the need for manual intervention and speeding up the overall workflow.

To assess the model's performance, several key metrics are used, including precision, recall, and the F1 score [29-30]. These metrics help evaluate different aspects of the model's ability to identify greenhouses. Precision measures how accurately the model identifies positive instances (greenhouses), while recall looks at how well the model captures all relevant greenhouse structures. The F1 score combines both precision and recall into a single measure, offering a balanced assessment of the model's overall performance, especially when there may be imbalances in the data.

Support which refers to the number of actual instances in each class adds further context to these evaluations. A confusion matrix [30], also helps clarify the model's decision-making process by showing how many instances were correctly or incorrectly classified as true positives (TP), false positives (FP), false negatives (FN), and true negatives (TN) [31].

In summary, the methodology presented here provides a robust, scalable framework for the automatic detection of agricultural greenhouses. By combining advanced deep learning models with high-resolution satellite imagery and geospatial analysis, the approach ensures both accuracy and practical applicability. The process follows a series of well-defined steps: starting with the management of high-resolution satellite images (70 cm pixel), preparing training samples manually, training the DLPK model, executing the model, generating the final results, and evaluating the model's performance. This structured approach helps ensure reliable and consistent greenhouse detection results.

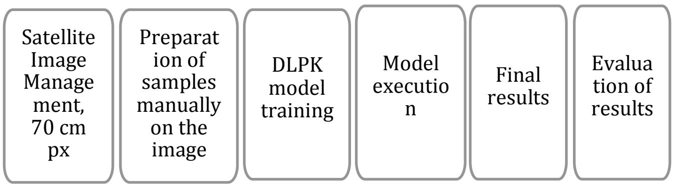

Figure 1. Methodology Workflow for Agricultural Greenhouse Detection Using Deep Learning

The diagram visually illustrates the key steps in the methodology, from satellite image management to final evaluation.

4. Results

When training a deep learning model for image analysis, the output generated by the Train Deep Learning Model tool [32, 39] includes a file titled model_metric.html. This file provides comprehensive information regarding the performance of the trained model, detailing key metrics such as the learning rate, training and validation losses [33], and the average precision score [34]. These metrics are critical for evaluating the model's accuracy and effectiveness, offering valuable insights into its training dynamics and predictive performance.

Occasionally, the training loss may exceed the validation loss, which could indicate that the model is underfitting. Underfitting occurs when the model fails to adequately capture the underlying patterns in the training data, resulting in significant prediction errors. As shown in Figure 2, Model 1 exhibits a higher training loss, suggesting the model's inability to generalize effectively. This elevated training loss points to the need for additional training iterations to address the discrepancy. Alternatively, enhancing the dataset by incorporating a larger sample size could improve the model's capacity to generalize, thus leading to better performance. The performance metrics [13] for Model 1, including precision, recall, and F1 score, are summarized in Table 1 below.

Model 1 Specifications:
Collected samples: 348
Model Type: MMSegmentation
Model Name: deeplabv3plus

Table 2. Model 1 Performance Metrics

Metric	Result
precision	0.884234
recall	0.939886
f1 score	0.911211

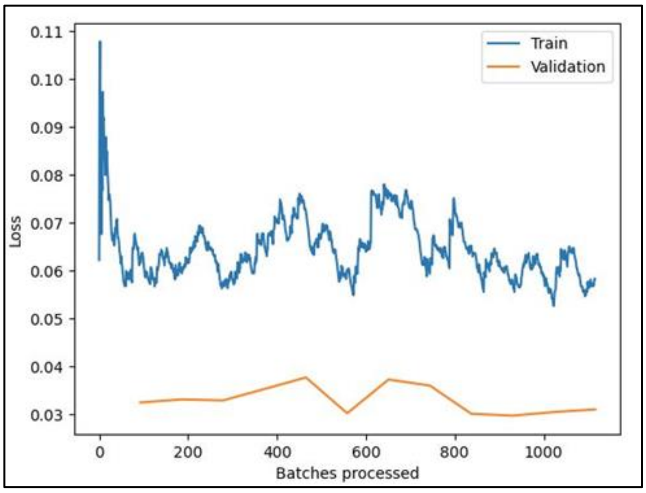

Figure 2. Training and Validation loss - Model 1

In Model 2, the training loss consistently exceeds the validation loss, as shown in Figure 3. This pattern typically suggests overfitting, where the model fails to generalize to unseen data. Despite performing well on the training dataset, the model shows poor generalization on the validation set. Notably, the validation loss initially declines but eventually rises, indicating the onset of overfitting. This can occur due to an excessively complex model relative to the dataset or prolonged training duration. A common remedy for this issue is early stopping, terminating training once the loss stabilizes at a low value. Early stopping, along with other regularization techniques, is crucial for improving model generalization and preventing overfitting. Performance metrics for Model 2, including precision, recall, and F1 score, are provided in Table 2 below.

Model 2 Specifications:
Collected samples: 914
Model Type: MMSegmentation
Model Name: deeplabv3plus

Table 3. Model 2 Performance Metrics

Metric	Result
precision	0.908052
recall	0.912206
f1 score	0.910124

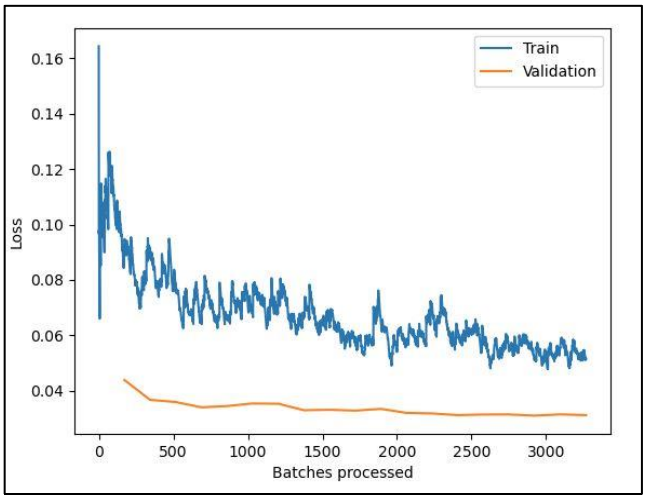

Figure 3. Training and Validation loss - Model 2

In Model 3, as depicted in Figure 4, both the training and validation losses progressively decline before stabilizing, suggesting that the model has achieved an optimal fit. This pattern indicates a well-balanced state, where the model successfully avoids both underfitting and overfitting, effectively generalizing to new data while minimizing prediction errors. The performance metrics for Model 3, such as precision, recall, and f1 score, are presented in Table 3 below.

Model 3 Specifications:
Collected samples: 3401
Model Type: MMSegmentation
Model Name: deeplabv3plus

Table 4. Model 3 Performance Metrics

Metric	Result
precision	0.928721
recall	0.927120
f1 score	0.927920

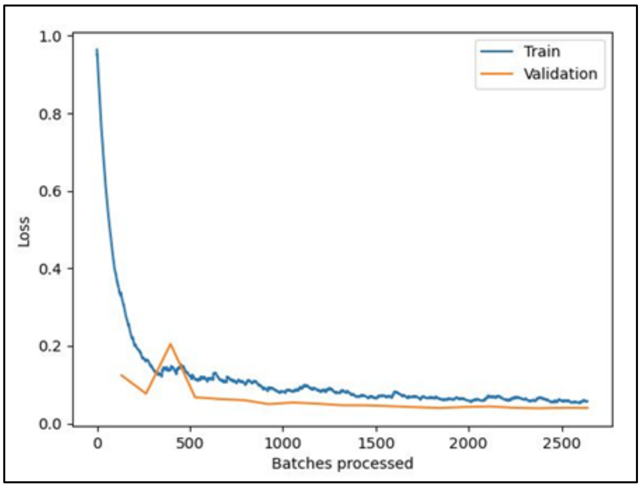

Figure 4. Training and Validation loss - Model 3

4.1. Discussion

The results of the greenhouse detection process are systematically presented through a series of figures, each illustrating the distinct contributions of Models 1, 2, and 3. Figure 5 provides an initial overview of the area of interest, establishing the context for the subsequent analysis. Figures 6, 7, and 8 present the detection outcomes from each model, highlighting their respective strengths and limitations in identifying greenhouses within satellite imagery. These figures reflect the models' varying abilities to navigate complex agricultural landscapes, accounting for diverse environmental and topographical conditions.

Figure 9 offers a comparative analysis of the three models' performance, facilitating a direct evaluation of their relative efficacy. The results demonstrate that Model 3 outperforms the other models in terms of both accuracy and reliability, detecting greenhouses with higher precision and fewer false positives. This suggests that Model 3 is the most robust and effective approach for agricultural monitoring, particularly in challenging contexts where environmental variables may impact detection accuracy.

The performance enhancement observed in Model 3 can be attributed to the fine-tuning process. Initially, the model was trained using pre-trained weights from a large-scale object detection model, followed by systematic optimization of key hyperparameters, including the learning rate, batch size, and number of epochs. Additionally, data augmentation techniques such as random rotations, scaling, and flips were employed to expand the variability of the training dataset. This strategy aimed to improve the model's ability to generalize across diverse agricultural landscapes, ultimately resulting in improved accuracy and detection reliability, as evidenced in Figure 10.

Despite the advancements made, several challenges persist. The use of ArcGIS [38] Geoprocessing tools for data preprocessing, while effective, can introduce certain inconsistencies, particularly when dealing with large and complex datasets. These inconsistencies, often related to geographical feature alignment and data quality, necessitate careful attention during preprocessing and validation stages. While Model 3 demonstrated robust performance, further refinement is needed to address the detection of smaller or overlapping greenhouses, which remain challenging in certain conditions.

In addition to accuracy, it is important to consider other performance metrics, such as precision, recall, and F1-score, to provide a more nuanced evaluation of the model's capabilities. These metrics would offer deeper insights into the model's ability to balance true positive detection with the minimization of false positives and false negatives. Moving forward, enhancing the model's robustness to handle variations in environmental conditions, such as lighting, weather, and seasonal changes in satellite imagery, will be crucial for optimizing its practical application in agricultural monitoring.

In conclusion, while the results of this study demonstrate the significant potential of deep learning models, particularly Model 3 in agricultural monitoring, continued fine-tuning and testing with additional datasets are essential for further improving the model's reliability. The findings suggest that with further optimization, deep learning models can provide highly effective solutions for agricultural monitoring, offering the potential for more precise and scalable applications in real-world settings.

Figure 5. Area of Interest

Figure 6. Greenhouses detection – Model 1

Figure 7. Greenhouses detection – Model 2

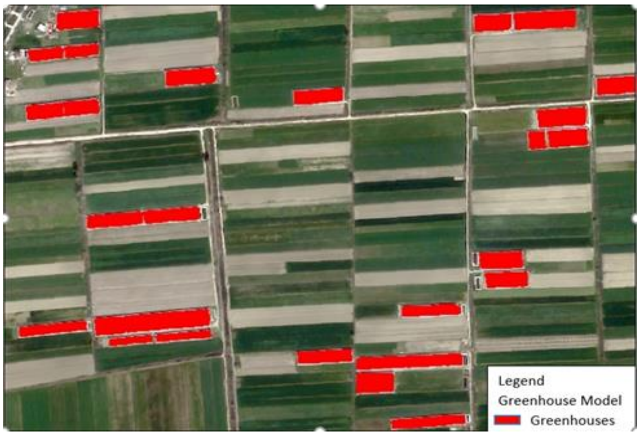

Figure 8. Greenhouses detection – Model 3

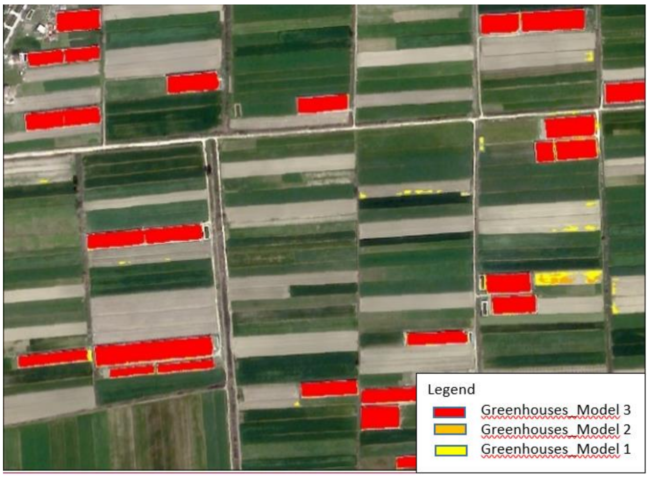

Figure 9. Greenhouses detection – Model 1,2,3

Figure 10. Greenhouses detection – Model 3 (Final)

5. Conclusions and future research

This study demonstrates the significant potential of deep learning models, specifically MMSegmentation (DeepLabv3Plus), for the automated detection of agricultural greenhouses using high-resolution multispectral satellite imagery. The methodology successfully identifies greenhouse structures, offering improvements in both accuracy and scalability. The integration of deep learning models with high-resolution imagery, with a spatial resolution of 0.7 meters, proved essential for distinguishing greenhouses from other agricultural features. The results confirm that MMSegmentation, when coupled with a robust fine-tuning process, can address the complexities inherent in greenhouse detection, particularly in environments where conventional detection methods fall short.

In addition to the technical contributions, this study underscores the importance of innovation management in the development and deployment of AI-driven solutions. The successful application of deep learning for greenhouse detection highlights the need for effective innovation management strategies that bridge the gap between cutting edge technology and practical implementation in agricultural monitoring.

By fostering cross-disciplinary collaboration and aligning technological advancements with the needs of agricultural stakeholders, innovation management ensures that these technologies are scalable, sustainable, and adaptable to diverse environmental conditions.

While the approach presented in this study shows promising results, several limitations were identified that must be addressed to further enhance the model's performance. A key challenge is the limited scope of the dataset, which primarily focuses on agricultural regions in Albania.

This restriction in geographic coverage hampers the model’s ability to generalize to other regions with different environmental conditions, such as varying vegetation types, landforms, and seasonal fluctuations.

In future research, it is critical to expand the dataset to include imagery from diverse regions with different topographies and climatic conditions. This will enable the model to be tested across a wider range of agricultural environments and improve its generalizability and robustness.

Datasets from various geographical regions, including areas with varying climates [35] and agricultural practices, would offer valuable insights into how the model performs under different conditions, ultimately improving its adaptability and accuracy in detecting greenhouses worldwide. The role of innovation management will be crucial in facilitating the collaboration needed to gather diverse datasets and implement these technological advancements in new contexts.

Another limitation lies in the environmental challenges, including shadowing, lighting variability, and cloud cover, which affected the model’s detection capabilities. These environmental factors introduce inconsistencies in the satellite imagery, making it difficult for the model to consistently identify greenhouses, especially in regions with frequent cloud cover or in areas with significant seasonal variations in lighting.

While these challenges were briefly mentioned in the study, the solutions to address them were not fully explored. To enhance the model’s performance, future research should investigate advanced shadow removal algorithms, such as those based on deep learning, which can effectively eliminate the effects of shadows and lighting inconsistencies.

Moreover, the development of spectral indices that are designed to mitigate the effects of lighting variability, such as those based on the Normalized Difference Vegetation Index (NDVI) or other vegetation indices, could help to improve the accuracy of greenhouse detection, particularly in regions with fluctuating light conditions. Implementing these techniques will make the model more resilient to the environmental factors that currently pose significant challenges. Here, innovation management will be essential for integrating such advancements into the existing workflow, ensuring their successful adoption and practical application in agricultural monitoring.

Furthermore, while this study focused on a single-resolution imagery (0.7 meters), exploring the integration of higher resolution or hyperspectral imagery could offer even more detailed information for greenhouse detection. Hyperspectral imagery, which captures a broader range of wavelengths beyond the visible spectrum, has the potential to provide additional spectral information that could further differentiate greenhouses from surrounding land features, improving detection accuracy in complex agricultural environments.

Future research could explore the incorporation of such high-resolution and hyperspectral data to enhance the model’s performance and expand its applicability. The incorporation of innovation management principles will be key in ensuring that such high-resolution data is accessible, analyzed effectively, and integrated into decision-making processes across various agricultural sectors.

In terms of model performance, the study primarily relied on precision, recall, and F1-score metrics to evaluate the detection accuracy. While these metrics provided valuable insights into the model’s ability to correctly identify greenhouses, future research should consider incorporating additional performance measures that can offer further insights into the model's ability to discriminate between different classes.

Additionally, it would be beneficial to evaluate the model's performance in a real-world setting, where the conditions of satellite imagery can vary due to atmospheric disturbances, seasonal changes, or other factors that are not always represented in training data. Innovation management will play a pivotal role in facilitating the real-world deployment of these models, ensuring they are adapted to practical use cases and addressing the challenges posed by varying environmental conditions.

Future research should focus on several key areas to enhance the applicability and performance of the model. First, the development of multi-temporal datasets that capture imagery from different seasons, weather conditions, and times of day will be crucial in addressing the challenges posed by environmental variability. These datasets will help the model better adapt to changes in the landscape and improve its ability to generalize over time. Second, integrating advanced techniques for handling environmental challenges, such as shadow removal, lighting correction, and cloud detection, will improve the model's robustness. Third, expanding the dataset to include regions with different geographical features, climates, and agricultural practices will enhance the model's ability to generalize across diverse agricultural landscapes.

To facilitate this, future research will leverage data from the Copernicus program, which provides access to a wide range of high-resolution satellite imagery from various geographical regions. This will allow for the expansion of the geographical scope of the study, enabling the model to be tested across diverse topographies and climates. Finally, exploring the integration of hyperspectral imagery could offer more precise spectral data, leading to further improvements in greenhouse detection. The integration of innovation management into these research directions will ensure that these technological advancements are efficiently implemented and scaled, with a focus on sustainability and impact.

By addressing these challenges and expanding the scope of the research, future studies can build on the findings of this study to create more scalable, accurate, and reliable geospatial AI solutions for agricultural monitoring. This will not only improve greenhouse detection but also contribute to more effective agricultural management and monitoring practices, both in Albania and in other regions with diverse environmental conditions. Furthermore, innovation management will be essential in ensuring that the advancements made in AI and satellite imagery are effectively translated into practical solutions that drive innovation in agricultural practices. Future studies should explore how innovation management can facilitate the adoption of AI technologies, ensuring that they meet the needs of agricultural stakeholders and contribute to more sustainable, efficient, and data-driven agricultural systems.

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Author contributions

Vilma Tomço: Conceptualization, Methodology, and Writing – Original Draft Preparation.
Erika Grabocka: Simulation of Three Deep Learning Models, Data Curation, and Validation.
Miranda Harizaj: Investigation and Writing – Review and Editing of the Manuscript.

Conflicts of interest

The authors declare that they have no conflicts of interest.

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