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REVIEW

Automated agricultural monitoring using deep learning: Crop type classification and farmland segmentation in Rwanda

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ABSTRACT

Agricultural monitoring is pivotal for optimizing crop management, resource allocation, and ensuring sustainable development. This study explores the application of advanced deep learning models for automated agricultural monitoring in Rwanda, focusing on two key tasks: crop type classification and farmland segmentation. Utilizing TensorFlow's MobileNet_V2 model, we achieved an overall classification accuracy of 76.13% in identifying various crop types from satellite imagery. Additionally, the Segment Anything Model (SAM) demonstrated promising results in farmland segmentation, effectively delineating agricultural fields within high-resolution satellite images. Despite challenges in quantitative evaluation due to the absence of ground truth data, the visual outcomes underscore SAM's potential for unsupervised segmentation tasks. The integration of these models offers a comprehensive approach to agricultural monitoring, facilitating informed decision-making for farmers, policymakers, and researchers. Future research directions include model optimization, enhanced data augmentation techniques, and the integration of multi-source data to further improve classification and segmentation performance.

KEYWORDS

Agricultural monitoring; Deep learning; Crop type classification; Farmland segmentation; MobileNet_V2; Segment anything model (SAM); Remote sensing; Tensor flow; Machine learning, Satellite imagery

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Introduction

Agriculture remains a cornerstone of Rwanda's economy, contributing over 30% to the country's GDP and employing approximately 70% of the population, primarily through smallholder farming [1,2]. Effective agricultural monitoring is essential for enhancing productivity, optimizing resource allocation, and promoting sustainable land management [3]. However, traditional methods, such as field surveys and manual data collection, are often labor-intensive, expensive, and limited in scalability [4]. As a result, there is a growing interest in leveraging modern technologies, particularly remote sensing and machine learning, to automate and scale agricultural monitoring [5].

In recent years, machine learning (ML) and deep learning (DL) techniques have made significant strides in improving agricultural processes, including crop classification, yield estimation, pest detection, and farmland segmentation [6]. Deep learning, especially Convolutional Neural Networks (CNNs), has gained prominence due to its capacity to analyze complex and large datasets such as satellite imagery with high precision, eliminating the need for manual feature engineering [7].

Importance of deep learning in crop monitoring and improvement

Crop type classification and farmland segmentation are crucial aspects of agricultural monitoring. They are vital for precision agriculture, resource management, and decision-making at both the farm and government levels [8,9]. Accurate crop type classification enables stakeholders to estimate agricultural productivity, optimize interventions, and monitor crop distributions [10]. Similarly, farmland segmentation helps delineate field boundaries, monitor land use, and assess changes in farming practices over time [11]. Together, these applications contribute directly to strategies aimed at improving crop management and production [12].

Recent advancements in ML and DL, particularly in using satellite imagery for agricultural tasks, show promising results in addressing challenges associated with traditional monitoring techniques [5]. CNN-based models like MobileNet_V2, designed for efficiency in resource-constrained environments, have been successfully used to classify crops with high accuracy [13]. MobileNet_V2's lightweight architecture enables it to be deployed on mobile and embedded devices, making it ideal for real-time agricultural monitoring [14].

In addition to crop classification, segmentation models such as the Segment Anything Model (SAM) have emerged as powerful tools for automating the delineation of agricultural fields. SAM's ability to perform unsupervised segmentation, even without extensive labeled datasets, makes it highly valuable for agricultural applications in developing regions like Rwanda [15]. This capability offers a much-needed solution for monitoring farmland and identifying changes in crop patterns and boundaries [11].

Literature Review

The integration of deep learning into remote sensing has led to transformative advances in various applications, including agricultural monitoring, land use classification, and environmental assessment. (CNNs), a subset of deep learning algorithms, have emerged as a powerful tool for these tasks due to their ability to automatically extract hierarchical features from raw data, significantly reducing the need for manual feature engineering.

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Deep learning in remote sensing

The use of CNNs in remote sensing for agricultural monitoring is well-documented. For example, Song et al. 2019, successfully applied CNNs to crop type classification using Sentinel-2 satellite imagery, highlighting the potential of deep learning in extracting relevant information from high-resolution data sources [7]. Similarly, Kamilaris and Prenafeta-Boldú in 2018, conducted an extensive review of deep learning techniques in agriculture, demonstrating how CNN-based models outperform traditional machine learning approaches in classifying crops and estimating yields, particularly when trained on large datasets [6].

MobileNet_V2, introduced by Sandler et al. 2018, is a CNN designed to be both efficient and accurate, particularly in scenarios with limited computational resources [14]. Its use of depth-wise separable convolutions makes it ideal for real-time applications, such as agricultural monitoring in remote or resource-constrained settings. Xu et al. 2019, tested MobileNet_V2 on crop disease classification, showing that the model achieved high accuracy while maintaining low computational costs, making it a suitable candidate for real-time, large-scale agricultural monitoring tasks [16]. By adapting this model, our study achieves a crop type classification accuracy of 76.13%, reinforcing its utility in Rwanda's context where computational resources are often limited.

Farmland segmentation techniques

Farmland segmentation, which refers to the delineation of agricultural plots from satellite or aerial imagery, plays a crucial role in precision agriculture, enabling effective land management and resource allocation. Traditional methods, such as those reviewed by Li et al. 2024, rely heavily on manual annotation and are therefore labor-intensive and prone to errors [17]. The emergence of deep learning models has reduced this reliance on manual input, allowing for automated, large-scale analysis.

The (SAM), although initially designed for more general image segmentation tasks, has shown promising potential in agricultural applications due to its ability to perform unsupervised segmentation. Kirillov et al. 2023, demonstrated SAM's versatility in segmenting diverse image datasets, suggesting its applicability in fields such as agriculture where labeled data is scarce [15]. In our study, SAM's performance in segmenting Rwandan farmlands underscores its potential for large-scale, automated agricultural monitoring, although challenges remain in terms of quantitative evaluation due to the lack of ground truth data.

Challenges in agricultural monitoring

Despite these advancements, several challenges persist. One of the key issues is the availability of labeled data, which is essential for training supervised machine learning models. Lary et al. 2016, noted that the lack of comprehensive, annotated datasets remains a major bottleneck in developing accurate remote sensing models [18]. In Rwanda, this is particularly pronounced, as data availability is often limited to specific regions or crop types.

Variability in agricultural landscapes also presents challenges for segmentation models. As noted by Bargoti and Underwood, the diversity in crop types, field sizes, and cultivation practices can reduce the accuracy of segmentation models [8]. This is particularly relevant in Rwanda, where smallholder farming is dominant, and field sizes can vary significantly even within short distances.

Finally, there is an increasing need for integrating data from multiple sources, such as combining satellite imagery with drone data or ground-based observations to improve model accuracy. Studies like those conducted by Huang et al. 2020, demonstrate the value of multi-source data in enhancing the robustness of deep learning models for crop classification [19]. This study aligns with these findings by emphasizing the potential for integrating multiple data sources in future iterations of the model to address data variability and improve classification accuracy.

Methodology

Data acquisition

Crop type classification data

The dataset for crop type classification was sourced from Radiant MLHub, a platform offering access to geospatial datasets tailored for machine learning applications. Specifically, three collections are available: rti_rwanda_crop_type_labels, rti_rwanda_crop_type_source, and rti_rwanda_crop_type_raw. For this project, only the first two collections were utilized:

Source Collection (rti_rwanda_crop_type_source): Contains input satellite images essential for training the machine learning model.

Labels Collection (rti_rwanda_crop_type_labels): Provides tags, classes, or labels corresponding to the images. These labels include crop types such as Banana, Maize, and Legume, as well as non-crop land cover types, such as Forest, Structure, and Other.

Access to these datasets was facilitated through the Radiant MLHub API, authenticated using a unique API key obtained upon registration. The data was downloaded and extracted into an organized folder structure to streamline subsequent processing steps.

Farmland segmentation data

High-resolution satellite imagery was acquired from Maxar, renowned for its detailed geospatial data. To enhance segmentation quality, the images were preprocessed by splitting them into smaller tiles (1000x1000 pixels) using the split_raster function from the SAMGeo library. This approach focused the segmentation efforts on manageable regions of interest, improving overall accuracy.

Data preprocessing

Crop type classification

Given the dataset's limited size (fewer than 2,606 images), data augmentation techniques were employed to expand and diversify the training data. The following augmentation methods were applied:

Random: Rotating images up to 10 degrees to introduce orientation variability.

Random zoom: Applying a 10% zoom to simulate different scales.

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Random horizontal shifts: Shifting images horizontally by 10% of their width.

Random vertical shifts: Shifting images vertically by 10% of their height.

These augmentations served as regularization techniques, enhancing the model's ability to generalize and reducing the risk of overfitting.

Model architecture and training

MobileNet_V2 for crop type classification

MobileNet_V2, selected for its efficiency and compactness, was adapted for the crop classification task. The model's architecture includes depthwise separable convolutions and inverted residuals with linear bottleneck layers, optimizing both performance and computational resource utilization.

Training parameters:

Batch size: 32

Epochs: 30

Loss function: Categorical cross-entropy

Activation Function: Softmax for probability distribution over crop classes.

Hyperparameters such as learning rate and dropout rate (set at 0.4) were fine-tuned to enhance model performance and prevent overfitting. The training process involved resizing and normalizing images, followed by applying data augmentation.

Segment anything model (SAM) for farmland segmentation

SAM was employed to generate segmentation masks for farmland areas within satellite imagery. Utilizing text prompts like "agricultural field," guided by Grounding DINO suggestions, SAM was applied to the preprocessed image tiles. Parameters such as box_threshold and text_threshold were optimized to improve segmentation accuracy.

Evaluation metrics

Crop type classification

Model performance was evaluated using the following metrics:

Overall accuracy: Percentage of correctly classified instances.

Precision: Proportion of true positives among predicted positives for each class.

Recall: Proportion of true positives among actual positives for each class.

F1-Score: Harmonic mean of precision and recall for each class.

Farmland segmentation

Due to the absence of ground truth data, quantitative evaluation of SAM's segmentation results was challenging. However, qualitative assessments through visual inspection were conducted to gauge segmentation accuracy and reliability.

Results

Crop type classification

Table 1. The MobileNet_V2 model achieved an overall accuracy of 76.13% on the test dataset.

Class	Precision	Recall	F1-Score	Support
Forest	0.92	0.88	0.90	307
Legumes	0.70	0.91	0.79	455
Other	0.53	0.49	0.51	133
Banana	0.89	0.81	0.85	545
Structure	0.60	0.48	0.53	270
Maize	0.91	0.83	0.87	117
Accuracy			0.77	1827
Macro Avg	0.76	0.73	0.74	1827
Weighted Avg	0.78	0.77	0.77	1827

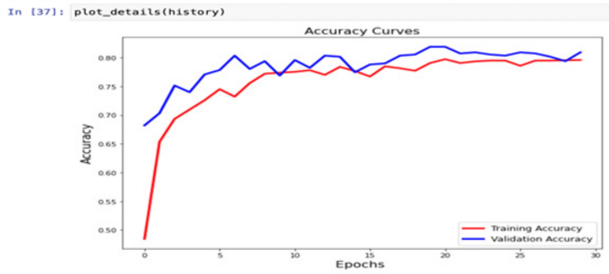

Figure 1. Overall Accuracy of MobileNet_V2 Model.

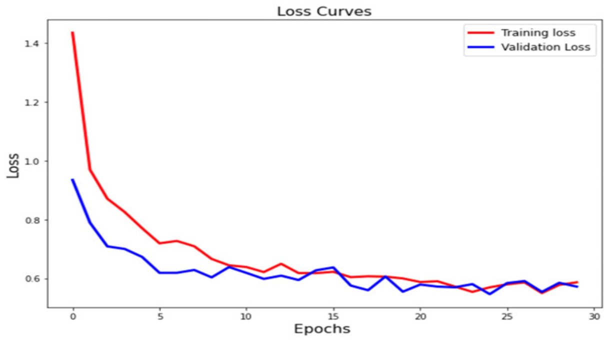

Figure 2. Accuracy and Loss Curves.

Farmland segmentation

SAM effectively generated segmentation masks for farmland areas within satellite imagery. Visual inspections revealed that SAM accurately delineated agricultural fields, demonstrating its potential for automated segmentation tasks. The following figures illustrate the segmentation results:

Figure 3. Original High-Resolution Image from Maxar.

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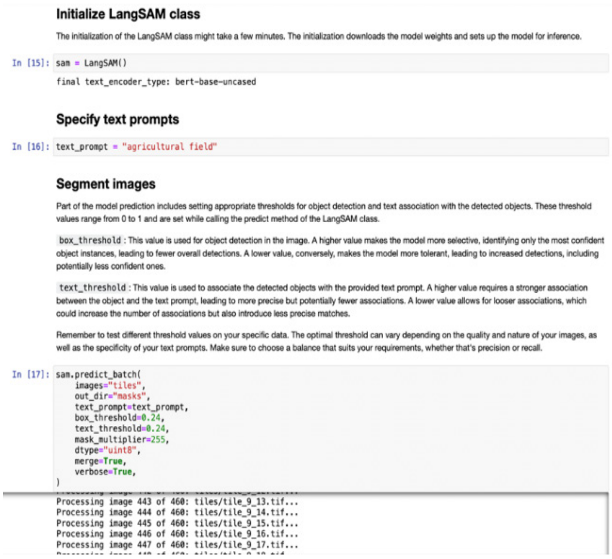

Figure 4. SAM Segmentation Initialization.

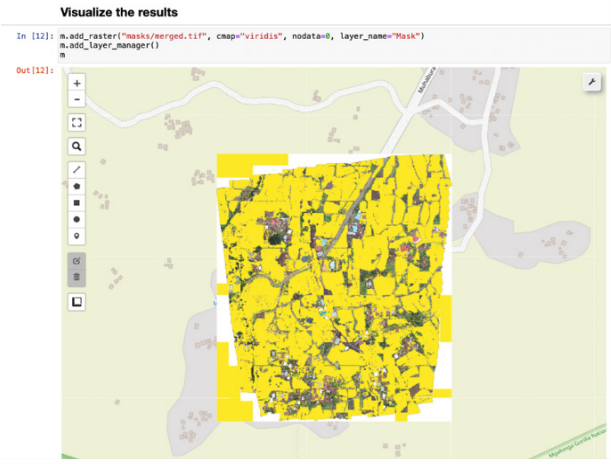

Figure 5. Segmentation Results.

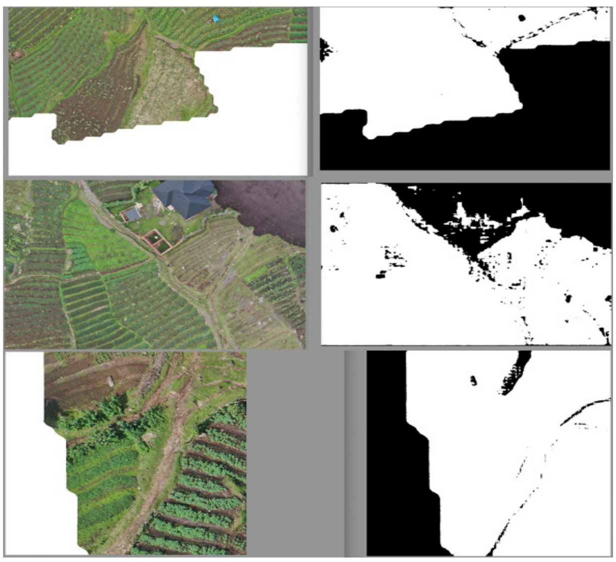

Figure 6. Tile vs. Mask Comparisons.

Challenges: The primary challenge in evaluating SAM's performance was the lack of ground truth data, which impeded the calculation of quantitative metrics such as Intersection over Union (IoU). Future studies should prioritize the collection of reference data to facilitate comprehensive performance assessments.

Discussion

Crop type classification

The MobileNet_V2 model demonstrated substantial efficacy in classifying various crop types within Rwanda's agricultural landscapes. High precision and recall values for classes like Forest, Banana, and Maize indicate the model's robustness in distinguishing these categories. However, moderate performance in classes such as "Other" and Structures suggests the need for further refinement, potentially through enhanced data augmentation or the inclusion of additional features. This aligns with findings from other studies that highlight the challenges of distinguishing between heterogeneous land cover types using deep learning models [13].

The model's compact architecture and efficiency make it suitable for deployment in resource-constrained environments, aligning with the practical requirements of agricultural monitoring systems. The balance between speed and accuracy achieved by MobileNet_V2 underscores its applicability in real-time monitoring scenarios, enabling timely decision-making for stakeholders [14].

Farmland segmentation

SAM's ability to generate accurate segmentation masks for farmland areas without extensive labeled data highlights its potential for scalable agricultural monitoring [15]. The qualitative success of SAM in delineating agricultural fields suggests that it can serve as a valuable tool in scenarios where manual annotation is impractical. Nevertheless, the absence of quantitative evaluation metrics necessitates a cautious interpretation of the results. Future research should focus on obtaining ground truth data to validate SAM's performance rigorously, following approaches used in similar segmentation tasks [20].

Integrated approach

Combining crop type classification with farmland segmentation offers a comprehensive framework for agricultural monitoring. While SAM provides an overview of cultivated areas, MobileNet_V2 offers detailed insights into specific crop distributions within these areas. This integrated methodology enhances the granularity and accuracy of agricultural analyses, supporting targeted interventions and optimized resource management [20,13].

Implications for agricultural policy and practice

The findings of this study have significant implications for agricultural policy and practice in Rwanda. Accurate crop classification and farmland segmentation enable:

Optimized resource allocation: Facilitating efficient distribution of water, fertilizers, and pesticides based on precise crop type distributions.

Informed decision-making: Empowering policymakers and farmers with timely data to respond to environmental challenges and optimize agricultural practices.

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Sustainable Land Management: Monitoring land use changes and assessing environmental impacts to support conservation efforts and sustainable development initiatives.

Conclusions and Recommendations

This study successfully demonstrated the application of deep learning models for automated agricultural monitoring in Rwanda. The MobileNet_V2 model achieved a commendable overall accuracy in crop type classification, while SAM showcased its potential in farmland segmentation. The integration of these models offers a robust framework for comprehensive agricultural monitoring, enhancing the precision and efficiency of land use analyses.

Based on the study's findings, the following recommendations are proposed for future research and practical applications:

Enhanced ground truth data collection: Implement comprehensive data collection strategies, including field surveys and participatory mapping, to obtain ground truth data essential for quantitative evaluation and model refinement.

Iterative model optimization: Continuously refine and optimize deep learning models through hyperparameter tuning, architectural modifications, and advanced data augmentation techniques to improve classification and segmentation performance.

Integration of multi-source data: Incorporate additional data sources such as drone imagery, weather data, and soil information to enrich input features and enhance model robustness.

Systematic model validation: Conduct systematic validation against established benchmarks and diverse datasets to assess model reliability and generalizability across different agricultural contexts.

Application in precision agriculture: Deploy the developed models in precision agriculture practices to enable targeted interventions, optimize resource utilization, and enhance crop monitoring at the farm level.

Capacity building and knowledge transfer: Facilitate training programs and workshops to empower stakeholders with the skills and knowledge required to utilize advanced machine learning and remote sensing technologies effectively. By embracing these recommendations, future endeavors can further advance the field of agricultural remote sensing, contributing to sustainable agricultural practices, enhanced food security, and informed policy making in Rwanda and beyond.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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