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The Application of Artificial Intelligence and Deep Learning in Extracting Agricultural Parcel Boundaries and Its Role in Enhancing Spatial Data Infrastructure (SDI)

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Abstract

Accurate delineation of agricultural land parcels is a key requirement for implementing precision agriculture, natural resource management, and the development of Spatial Data Infrastructures (SDI). Considering the diversity of planting patterns, vegetation changes, and challenges such as occlusions and manual interpretation methods lack sufficient efficacy. In recent years, deep learning models have emerged as innovative solutions for extracting parcel boundaries from satellite imagery and spatial data due to their high capability in extracting complex features and processing large-scale data. This study aims to investigate the role of deep learning models in accurately delineating agricultural land parcel boundaries based on the analysis of satellite images and spatial data within the framework of Spatial Data Infrastructure (SDI). The study focuses on analyzing various deep learning architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs). These models are evaluated from the perspectives of technical structure, input data types, performance metrics, and adaptability to operational challenges in precision agriculture. For comparative analysis, a set of recent studies and selected models are reviewed regarding accuracy, limitations, and compatibility with real-world conditions such as heterogeneous landscapes and scarce labeled data. The results indicate that CNN-based models perform well in processing satellite imagery but have limitations in capturing contextual dependencies, which can be improved by combining them with RNNs. Additionally, GAN models are effective in augmenting training data and generating synthetic images. The findings of this study can serve as a foundation for developing more intelligent and hybrid models in future SDI and smart agriculture systems.

Keyword: Deep Learning, Satellite Imagery, Smart Agriculture, Convolutional Neural Networks (CNN), Spatial Data Infrastructure (SDI).

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1. Introduction

In recent years, with significant advancements in information technologies and geographic tools, the use of Geographic Information Systems (GIS) and Spatial Data Infrastructure (SDI) in agriculture has become a fundamental pillar in resource management and agricultural development. One of the fundamental issues in this field is the precise delineation of agricultural land parcels, which plays a vital role in proper water resource planning, optimal resource allocation, and increasing agricultural productivity. Traditional methods for parcel boundary delineation, such as field surveying and processing of aerial photographs and satellite images, are often time-consuming, costly, and may not achieve the desired accuracy under certain conditions.

In this context, advanced machine learning techniques, particularly deep learning, have created a paradigm shift in this domain. Deep learning models, due to their capability to process complex data and hidden patterns in satellite imagery, artificial intelligence, and sophisticated simulations, enable more accurate identification and delineation of land parcel boundaries. These techniques are especially valuable in precision agriculture, where the need for accurate and timely data analysis is critical. They can enhance accuracy and efficiency in boundary delineation and agricultural resource management. This article examines the application of deep learning in delineating agricultural land parcels within the framework of Spatial Data Infrastructure (SDI), analyzing the challenges and benefits of using this technology to improve accuracy and agricultural productivity.

Accurate delineation of agricultural land parcel boundaries plays a crucial role in smart agriculture, water resource management, and land optimization. This process provides essential information for precision agriculture and helps farmers optimize resource consumption and increase crop yield (Dawn et al., 2023). However, traditional methods such as field surveying and the processing of aerial photographs and conventional satellite images face various challenges.

While field surveying is effective in some cases, it is time-consuming, expensive, and limited to recording fine details of parcel boundaries (Bennett et al., 2020). Additionally, conventional image processing methods, such as Object-Based Image Analysis (OBIA), heavily depend on segmentation techniques and often lack sufficient accuracy for extracting agricultural parcel boundaries (Xia et al., 2018).

Processing satellite images encounters multiple challenges affecting analysis accuracy and model performance. Key challenges include spatial and temporal variability of data, atmospheric conditions such as cloud cover or fog, varying resolution of images from different sensors, and noise and measurement errors. Furthermore, the large volume of data requires powerful storage, processing, and analysis capabilities, which can be time-consuming and costly without proper infrastructure. Accurate interpretation of features in heterogeneous areas or densely vegetated

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regions also presents a significant challenge in agricultural, natural resource, or disaster management applications. Moreover, the need for labeled data to train machine learning models is another common limitation in this field.

Artificial intelligence and deep learning have made significant advances in increasing the accuracy (e.g. Haery et a., 2024) and reducing the cost of delineating agricultural parcel boundaries. For example, models such as U-Net and RCF[1] have been used to extract hard and soft edges, respectively, enabling more precise identification of agricultural parcels (Xia et al., 2018). These methods leverage deep learning capabilities to better interpret images and extract boundaries.

Additionally, accurate delineation of agricultural parcel boundaries is key to monitoring crop health and growth. Inaccurate boundary delineation can lead to mixing data from adjacent fields in remote sensing analyses, such as vegetation indices (e.g., NDVI[2]), resulting in unreliable outcomes. This can negatively impact management decisions like irrigation scheduling (e.g. Mahpour and Shafaati, 2024), fertilization, or harvesting. Therefore, precise boundary extraction is a fundamental step in effective precision agriculture and intelligent crop monitoring. AI-based solutions have improved crop monitoring accuracy and health assessment by 30 to 50 percent and enhanced resource-based decision-making (Hoque & Padhiary, 2024). Deep learning models such as YOLOv5[3] have demonstrated successful performance in identifying and classifying agricultural products (Ram et al., 2023).

Overall, although traditional methods have limitations in accurate parcel boundary delineation, artificial intelligence and deep learning offer promising solutions. These technologies not only improve accuracy but also reduce time and costs, contributing to the optimization of smart agriculture.

2. Literature review

Convolutional Neural Networks (CNNs) have demonstrated remarkable success in processing satellite images for various tasks, including land boundary detection. CNNs excel at extracting high-level features from images, making them particularly effective for spatial data analysis. In the field of remote sensing, CNNs have shown strong capabilities in feature representation, leading to improved scene classification of satellite imagery (Liu et al., 2019).

Compared to other deep learning models, CNNs have both advantages and limitations. While CNNs are effective at processing local regions of images, they lack the ability to capture long-range contextual dependencies across different image areas (Zuo et al., 2016). Recurrent Neural

[1] Richer Convolutional Features
[2] Normalized Difference Vegetation Index
[3] You Only Look Once version 5

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Networks (RNNs), on the other hand, are designed to capture sequential dependencies and can be useful for encoding spatial dependencies in satellite imagery ((Zuo et al., 2015), (Zuo et al., 2016)). The combination of CNNs and RNNs, often referred to as Convolutional Recurrent Neural Networks (C-RNNs), has proven successful in learning spatial dependencies between image regions and enhancing feature discrimination within image representations ((Zuo et al., 2015), (Zuo et al., 2016)).

Generative Adversarial Networks (GANs) offer a different approach to satellite image analysis. Although GANs have not been directly compared with CNNs for land boundary detection, they have been explored in remote sensing applications to overcome challenges related to limited data availability (Logan et al., 2021). GANs can generate synthetic satellite images that potentially augment training datasets and improve model performance in scenarios with scarce data.

In summary, while CNNs perform well in processing satellite images for tasks such as land boundary detection, combining them with other deep learning models like RNNs can yield better results by capturing both local and contextual information. The choice of model depends on the specific task requirements, available data, and computational resources. Future research may focus on developing hybrid models that leverage the strengths of multiple architectures to optimize performance in satellite image analysis (Teixeira et al., 2023).

This section provides a comparative review of deep learning models presented in recent studies related to agricultural land segmentation. The focus is on evaluating the strengths, limitations, and real-world adaptability of these models, particularly in heterogeneous landscapes, noisy backgrounds, and limited labeled data scenarios. Table 1 summarizes the key characteristics of these models.

Table 1. Review of recent studies on deep learning methods for land parcel and vegetation segmentation from remote sensing images.

Article	Model	Strengths	Weaknesses	Real-World Compatibility	Reference
Local refinement mechanism for improved plant leaf segmentation in cluttered backgrounds	U-Net based model with local refinement mechanism	High accuracy in leaf segmentation in greenhouses; use of Gaussian and High-Boost filters	Sensitive to image blur and occlusion; requires precise labeled data	Performs well in greenhouse conditions; needs improvement for field conditions	Ma et al., 2023
Development of Semantic Maps of Vegetation Cover from UAV Images to Support Planning and Management in Fine-Grained Fire-Prone Landscapes	CNNs for shrub detection	Ability to detect vegetation cover in heterogeneous landscapes	Performance depends on quality of labeled data	General capability in complex landscapes but sensitive to input data quality	Trenčanová et al., 2022

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Article	Model	Strengths	Weaknesses	Real-World Compatibility	Reference
Enabling Multi-Part Plant Segmentation with Instance-Level Augmentation Using Weak Annotations	Weakly supervised learning and pseudo-labeling	Addresses object overlap issues; uses semi-automatic labeling	Time-consuming multi-part labeling; requires semi-labeled data	Suitable for low-labeled data areas; needs further optimization	Mukhamadiev et al., 2023
Improved random forest classification model combined with C5.0 algorithm for vegetation feature analysis in non-agricultural environments	Object-based Random Forest for forest classification	94.02% accuracy on aerial data; strong in vegetation discrimination	Designed for forests, not specific agricultural lands	Performs well in diverse vegetation cover landscapes	Wang, 2024
Improvement in Land Cover and Crop Classification based on Temporal Features Learning from Sentinel-2 Data Using Recurrent-Convolutional Neural Network (R-CNN)	CNN + RNN hybrid (Pixel R-CNN)	96.5% accuracy in crop classification using Sentinel-2 data	Focuses on crop classification, not boundary segmentation	Compatible with multi-temporal satellite images	Mazzia et al., 2019
A Futuristic Deep Learning Framework Approach for Land Use-Land Cover Classification Using Remote Sensing Imagery	Multi-spectral bands, topography, and texture fusion	89.43% accuracy in land use mapping	Not specifically designed for land parcel boundary detection	Capable of working with diverse data sources	Nijhawan et al., 2018
Deep Learning for Feature-Level Data Fusion: Higher Resolution Reconstruction of Historical Landsat Archive	GAN for spatial resolution enhancement	Improves resolution of historical Landsat data to Sentinel-2 quality	Focused on image reconstruction, not segmentation	Enhances input data quality for downstream models	Chen et al., 2021
Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data	Self-supervised learning combined with CNN	Detects crop types from Landsat-8 and Sentinel-1A data	Suitable for crop classification, not boundary segmentation	Performs well on multisensor data	Kussul et al., 2017
Convolutional Neural Networks enable efficient, accurate and fine-grained segmentation of plant species and communities from high-resolution UAV imagery	Analysis of high-resolution RGB UAV images	High accuracy in identifying specific plant species	Requires UAV data, which can be limited	Suitable for precise local-scale vegetation mapping	Kattenborn et al., 2019

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According to the table above, some models such as the U-Net-based approach with local refinement achieve precise leaf segmentation under greenhouse conditions (Ma et al., 2023). CNNs have shown good capability in detecting vegetation in heterogeneous landscapes (Trenčanová et al., 2022). Weakly supervised learning models are effective in overcoming object overlap challenges and reducing the need for fully labeled data (Mukhamadiev et al., 2023). Object-based Random Forest models also achieve high accuracy in forest classification (Wang, 2024).

On the other hand, limitations are evident in these studies. For example, some models perform poorly under image blur or occlusion conditions (Ma et al., 2023). Lack of sufficient labeled data reduces model accuracy, especially for tasks requiring multi-part or semi-automatic labeling ((Mukhamadiev et al., 2023), (Trenčanová et al., 2022)). Models like Pixel R-CNN, while successful in crop classification, are not specifically designed for agricultural land boundary delineation (Mazzia et al., 2019). Another challenge is adapting to complex landscapes and diverse vegetation covers. Although some models show general robustness, there remains a need for improvement to handle real-world heterogeneous data effectively ((Wang, 2024), (Kattenborn et al., 2019)).

Although the reviewed models have made significant advances in vegetation cover classification and agricultural land use mapping, most of them are not specifically designed for the delineation of agricultural plot boundaries. This gap highlights the need to develop models explicitly aimed at parcel boundary detection. Additionally, applying techniques such as weakly supervised learning, image super-resolution (Chen et al., 2021), and multimodal data fusion could enhance model performance under real-world conditions.

3. Theoretical Framework

Based on the butterfly model of Spatial Data Infrastructure (SDI), the agricultural cadastre is considered the primary source of spatial and descriptive data related to agricultural land parcels. These data include field boundaries, types and intensity of land use, ownership, and land use classifications. When integrated within the SDI framework, these data can be combined with other layers such as topographic maps, climate data, water resources, and agricultural infrastructure, thereby providing a unified platform for analysis, decision-making, and policymaking (Williamson et al., 2010).

Within this model, SDI acts as a bridge between cadastral data and land management systems. Through this infrastructure, the spatially enabled government can deliver various services such as land use planning, resource management, facilitation of public services, and monitoring of sustainable development based on geospatial data. Therefore, the agricultural cadastre is not only a tool for registering and maintaining parcel information, but within the SDI framework, it

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becomes a key instrument for sustainable agricultural development, more efficient resource utilization, and improved land governance.

Given the need for spatial data processing and analysis in agricultural cadastre, particularly in the automated delineation of parcel boundaries, the application of emerging technologies such as Artificial Intelligence (AI) and Deep Learning becomes crucial. These technologies are foundational to advancements in precision agriculture, especially in delineating field boundaries.

AI refers to the development of computer systems capable of performing tasks that typically require human intelligence (Sharma, 2021). In agriculture, AI is used for a range of applications including disease detection, plant classification, and smart irrigation (Ünal, 2020).

Deep Learning, a subfield of AI, uses artificial neural networks to uncover hidden patterns in unlabeled and unstructured data without human intervention (Ünal, 2020). Among these, Convolutional Neural Networks (CNNs) have shown remarkable ability in analyzing agricultural images obtained from satellites, aerial vehicles, and ground-based cameras (El Sakka et al., 2024).

Accurate delineation of field boundaries is critical for precision agriculture, as it enables farmers to optimize resource management, enhance crop health, and increase productivity (El Sakka et al., 2024), (Kujawa & Niedbała, 2021)). The significance of these technologies in precision farming lies in their ability to process vast amounts of data collected throughout the growing season, support decision-making systems, and optimize various aspects of agriculture (Wang, 2024). These technologies help develop smart agricultural systems that make agriculture more efficient and effective by utilizing advanced information technologies (Ünal, 2020). These capabilities are especially important in addressing global challenges such as population growth and limited agricultural land expansion (Sharma, 2021).

Therefore, AI, deep learning, and field boundary delineation are key components of precision agriculture, enabling farmers to make data-driven decisions, optimize resource use, and enhance overall productivity. As these technologies advance, their role in addressing food security challenges and promoting sustainable agriculture is expected to grow increasingly prominent ((Glady et al., 2024), (Padhiary & Kumar, 2025)).

This study's theoretical framework focuses on three major model categories, each with specific theoretical and technical foundations for spatial and image data analysis:

3.1. Convolutional Neural Networks (CNNs)

CNNs utilize architectures inspired by human vision and extract spatial and spectral features from images using convolutional layers. They are particularly effective in identifying objects, boundaries, and complex patterns in satellite imagery. Architectures such as U-Net, SegNet, and 2D/3D CNNs have proven highly effective for pixel-wise classification and delineation of agricultural features.

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CNNs have emerged as powerful tools in satellite image analysis for agricultural applications, playing a critical role in accurate boundary detection of land parcels. They have demonstrated exceptional performance in analyzing images from satellites, UAVs, and terrestrial cameras (El Sakka et al., 2024). By leveraging vegetation indices and multispectral imagery, CNNs enhance analytical capabilities and contribute to improved agricultural outcomes. Notably, hybrid 3D-2D CNN models have shown superior performance in extracting spatial and spectral features from high-resolution satellite images, achieving up to 95.6% classification accuracy for land cover, outperforming traditional machine learning algorithms such as SVM and RF (Saralioglu & Gungor, 2022).

Interestingly, although very deep CNNs are structurally complex and require extensive training data, some studies have proposed efficient and lightweight architectures that outperform well-known models like GoogleNet and SqueezeNet in classifying wetland areas (Jamali et al., 2021).

Consequently, CNNs—especially 3D/2D models and optimized architectures—are among the most effective tools for satellite image analysis in agricultural applications. These models outperform traditional methods in accurately identifying field boundaries by extracting high-resolution spatial and spectral features. Integrating CNNs with techniques such as data augmentation, transfer learning, and multimodal fusion further enhances their performance in tasks like crop classification and land use mapping (Teixeira et al., 2023).

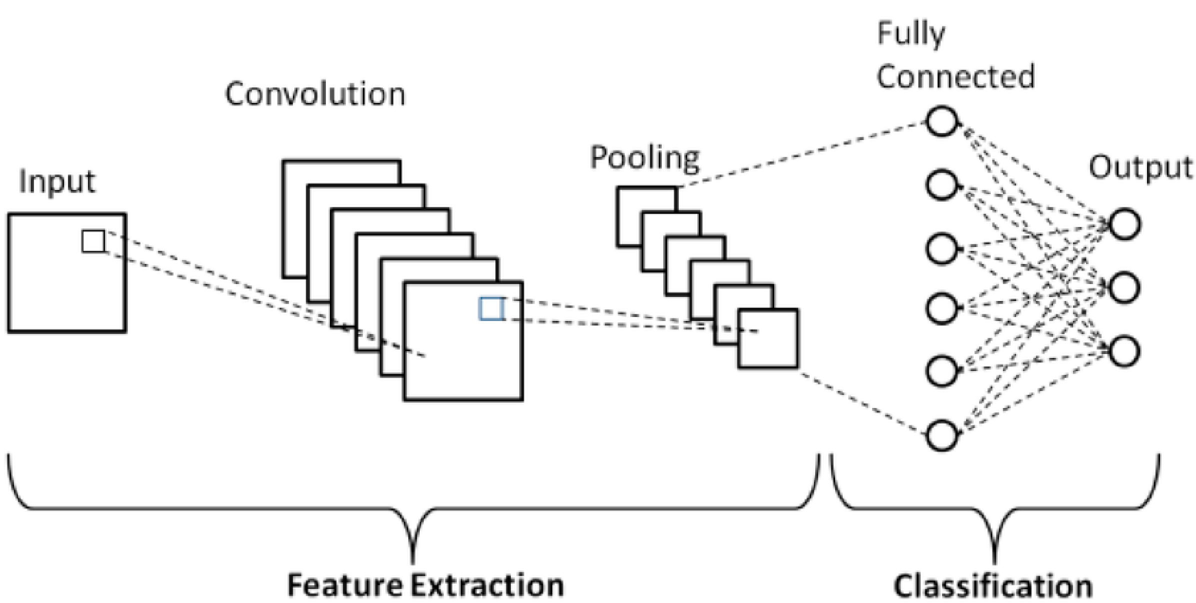

Figure 1. Basic structure of a convolutional neural network (CNN) for analyzing satellite images in precision agriculture. Adapted from (Phung & Rhee, 2019)

The basic CNN architecture image includes convolution, pooling, and fully connected layers designed to extract local features from images. CNNs, with their high ability to extract spatial features from satellite images, are an effective tool for identifying and determining agricultural

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land boundaries. Studies have shown that the use of CNNs in this field has higher accuracy than traditional methods.

3.2. Recurrent Neural Networks (RNNs)

RNNs are designed for processing sequential data such as text, speech, or time series. Their key feature is the ability to retain previous information through feedback loops, allowing them to model temporal dependencies in data. These networks are widely used in applications like machine translation, speech recognition, and sentiment analysis.

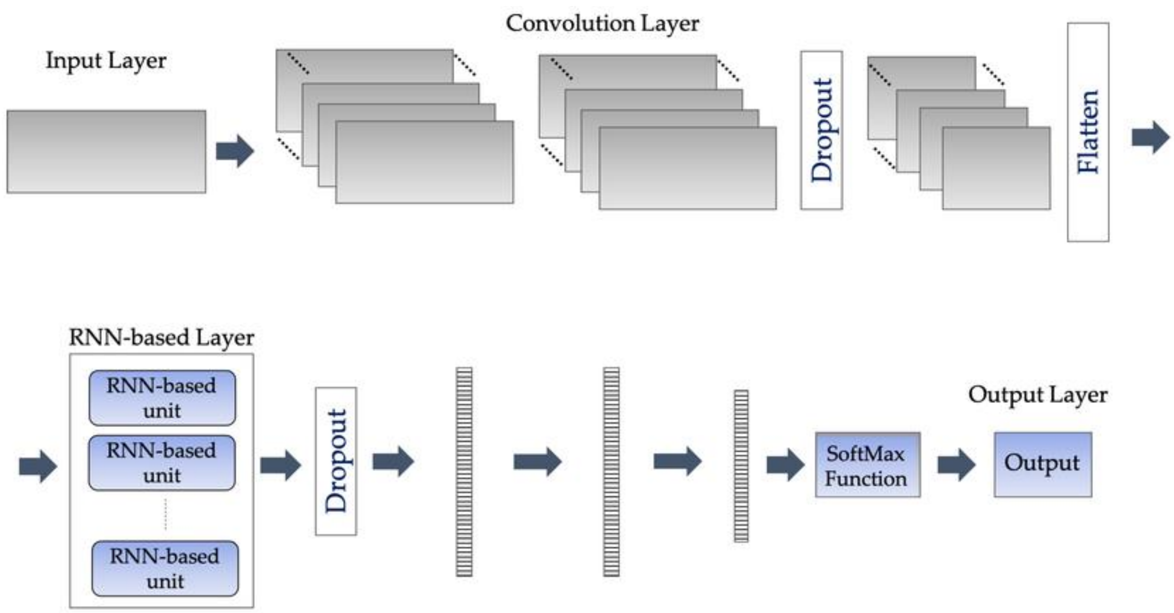

Figure 2. CNN-RNN Hybrid Architecture. Adapted from (Mekruksavanich & Jitpattanakul, 2021)

The architecture of the combined CNN-RNN model illustrates the integration of two types of neural networks: Convolutional Neural Networks (CNNs) for extracting spatial features from imagery, and Recurrent Neural Networks (RNNs) for modeling temporal dependencies within the data. In this framework, the CNN component initially extracts spatial representations from satellite images, which are subsequently processed by the RNN to capture temporal dynamics.

In the context of precision agriculture, delineating agricultural parcel boundaries is of critical importance. Multitemporal satellite imagery enables the observation of land cover changes over time. The hybrid CNN-RNN architecture leverages the spatial feature extraction capabilities of CNNs and the temporal modeling capabilities of RNNs, facilitating more accurate and stable boundary detection of agricultural fields.

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Consequently, the application of CNN-RNN hybrid architectures in satellite image analysis for agricultural parcel boundary extraction significantly enhances both the accuracy and efficiency of the process by jointly exploiting spatial and temporal information.

3.3. Generative Adversarial Networks (GANs)

GANs consist of two distinct neural networks: a generator that produces new data and a discriminator that attempts to distinguish real from generated data. Through this adversarial process, the quality of the generated data improves significantly. GANs are widely used for realistic image generation, data augmentation, and style transfer.

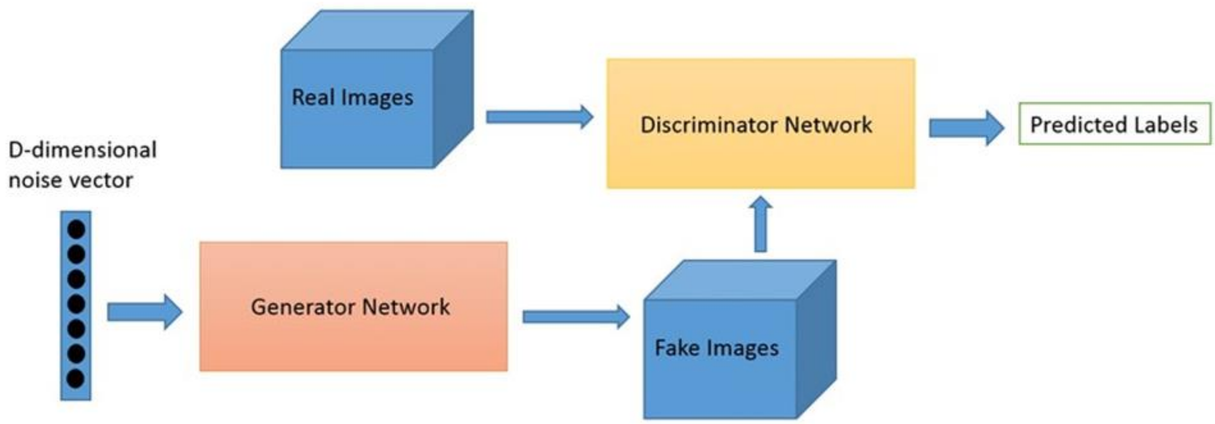

Figure 3. General Architecture of a Generative Adversarial Network (GAN). Adapted from (Alqahtani et al., 2019)

GANs can generate realistic synthetic images, which expand the training dataset—especially useful when real data are scarce. This capability contributes to improving the accuracy of boundary delineation models in agricultural land monitoring.

3.4. Deep Learning Strategies for Agricultural Parcel Boundary Delineation

Deep learning models, spatial data, and satellite imagery act synergistically to improve the accuracy and efficiency of agricultural field boundary detection. Research in this domain can be categorized into four main strategies:

1. **Complex Feature Extraction using CNNs**

   CNNs, due to their hierarchical structure, can detect spatial and spectral patterns at various levels. This makes them highly effective in delineating fine boundaries of land parcels. However, they may struggle with long-range dependencies and non-local contextual

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relations—especially in landscapes with similar vegetation types belonging to different parcels. Combining CNNs with LSTM or attention mechanisms can address these limitations and enhance boundary delineation performance ((Adegun et al., 2023), (Teixeira et al., 2023), (Zhang et al., 2020)).

2. **Multi-Branch Architectures for Complex Image Analysis**

   Multi-branch architectures use separate pathways to analyze local, contextual, and textural features, enabling them to better model the complexity of agricultural imagery (Khan & Basalamah, 2023).These models process data at multiple scales and effectively extract boundaries despite object overlap and varying shapes. Fusion mechanisms using attention improve accuracy significantly, especially in noisy or cluttered backgrounds.

3. **Multimodal Approaches using Diverse Data**

   Integrating various data types (spectral, spatial, biophysical, climatic) provides a more comprehensive view of agricultural landscapes. Such data, often from different sources and resolutions, pose challenges like alignment and spectral matching. Success in this domain relies on models' ability to extract meaningful features from heterogeneous data while minimizing noise and redundancy (Alipour et al., 2023).

4. **Accuracy Enhancement through Attention and Residual Structures**

   Models using attention mechanisms and residual structures—such as RAANet[4]—achieve high accuracy in land use classification from remote sensing data (Liu et al., 2022). These techniques enable the model to focus adaptively on important regions, improving classification while reducing network complexity. Despite their computational demands, such models are particularly effective in analyzing noisy or asymmetric agricultural plots.

Integrating deep learning models with data-centric frameworks like SDI offers new pathways for developing automated systems in agricultural cadastre. This contributes significantly to advancing precision agriculture and optimizing land management.

4. Research Methodology

This study is a review and analytical research conducted to examine the role and effectiveness of deep learning models in delineating the boundaries of agricultural land parcels based on satellite imagery analysis and geospatial data, within the framework of Spatial Data Infrastructure (SDI). Drawing on credible scientific sources, the research aims to analyze and explain the application of modern deep learning architectures in land parcel boundary extraction and their contribution to smart agriculture development.

[4] Residual ASPP with Attention Net

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The methodology adopts a descriptive-analytical approach using library and documentary resources. The main focus is on theoretical analysis of the structure of deep learning models, their advantages, limitations, types of input data, performance indicators, and accuracy levels in applications related to precision agriculture and land management. The study particularly examines models such as Convolutional Neural Networks (CNNs), multi-branch frameworks, and models equipped with attention mechanisms.

The research process began with the collection of scientific sources including peer-reviewed journal articles, technical reports, and empirical findings from prior studies. The selected models were then comparatively analyzed based on criteria such as technical structure, type of data used, relevance to boundary delineation, and performance evaluation metrics. Comparative tables were used to summarize key characteristics and illustrate the differences and similarities among the models.

Three widely-used deep learning models for delineating agricultural field boundaries are analyzed in this study:

- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs)
- Generative Adversarial Networks (GANs)

These models were selected based on criteria such as reported accuracy, adaptability to various conditions, availability of training data, and scalability. Due to their broad applicability, successful performance in remote sensing tasks, and interoperability with other architectures, these models were chosen as the central focus of this analysis. In the following sections of the paper, they are examined in the context of the theoretical framework and their integration with SDI.

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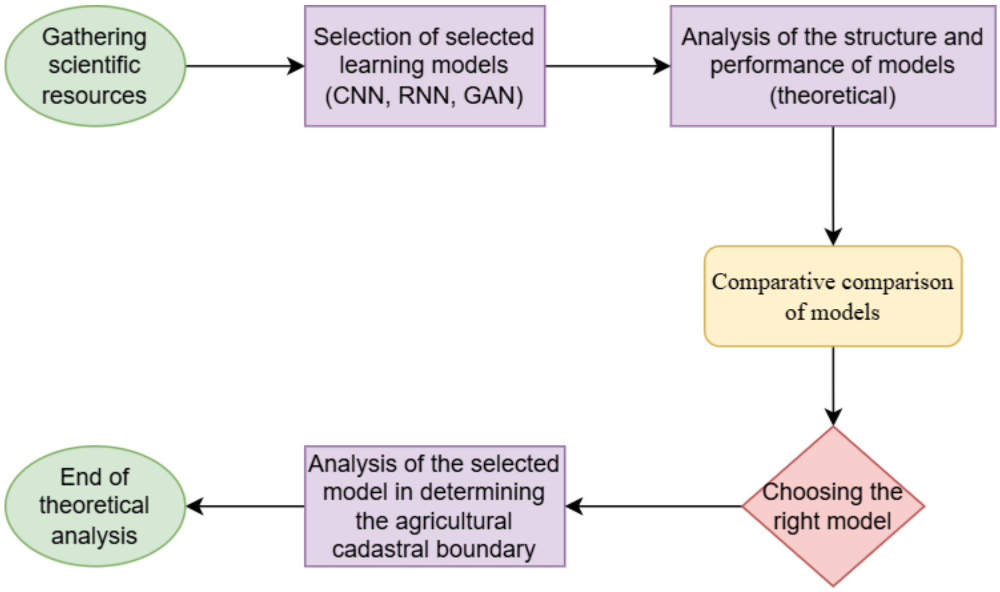

Figure 4. illustrates the overall workflow of the study, from literature collection to theoretical analysis of SDI and the selected deep learning models.

CNNs have demonstrated remarkable success in satellite image processing tasks, including land boundary detection. They possess strong capabilities for extracting high-level spatial features, making them particularly effective for geospatial data analysis (Liu et al., 2019). In remote sensing, CNNs have shown robust performance in object representation and have improved scene classification accuracy (Liu et al., 2019).

However, compared to other deep learning models, CNNs have both strengths and limitations. While CNNs are effective in processing local image regions, they often lack the ability to capture contextual dependencies between different parts of the image (Zuo et al., 2015). This is where RNNs can complement CNNs. Designed to learn sequential dependencies, RNNs can be beneficial for encoding spatial relationships in satellite imagery. The integration of CNNs and RNNs, known as Convolutional Recurrent Neural Networks (C-RNNs), has proven successful in learning spatial dependencies across image regions, enhancing object segmentation and boundary detection ((Zuo et al., 2015),(Zuo et al., 2016)).

GANs, on the other hand, offer a different approach to satellite image analysis. Although not directly compared with CNNs for land boundary detection, GANs have been explored in remote sensing to address limited data availability (Logan et al., 2021). GANs are capable of generating synthetic satellite images, potentially expanding training datasets and improving model performance in scenarios where labeled data are scarce.

In conclusion, while CNNs are effective in processing satellite images for boundary detection tasks, their combination with other deep learning architectures such as RNNs can yield improved outcomes by capturing both local and contextual information. Model selection should be tailored

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to the specific task requirements, data availability, and computational resources. Future research may focus on developing hybrid models that leverage the strengths of multiple architectures to optimize satellite image analysis (Teixeira et al., 2023).

Throughout this study, credible academic sources were reviewed to evaluate deep learning models in terms of structure, analytical capabilities, limitations, and suitability for geospatial data in smart agriculture. The findings provide valuable guidance for future research aimed at designing efficient and integrated models within the SDI framework and intelligent agricultural systems.

5. Evaluation and Validation of Results

5.1. Analysis of Core Deep Learning Models

Table 1 compares three main deep learning models—Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Generative Adversarial Network (GAN)—in terms of their strengths, limitations, and compatibility with real-world conditions for delineating agricultural land parcel boundaries using satellite imagery and geospatial data:

Table 2. Comparative analysis of CNN, RNN, and GAN deep learning models in terms of strengths, limitations, and real-world applicability for agricultural parcel boundary delineation

Deep Learning Model	Strengths	Limitations	Compatibility with Real-World Conditions
CNN (Convolutional Neural Network)	- High accuracy in extracting spatial and local features from satellite images- Strong performance in precise classification and boundary detection- Stable results with high-resolution data	- Inability to capture contextual and sequential dependencies across image regions- Reduced accuracy when dealing with heterogeneous and variable data- High dependency on labeled datasets	- Suitable for environments with high-quality and relatively uniform data- Less effective for diverse datasets or time-series data
RNN (Recurrent Neural Network)	- Captures temporal and contextual dependencies in sequential and time-series data- Enhances spatiotemporal analysis in satellite imagery- A complementary approach to CNN limitations	- Requires large and well-ordered sequential datasets- High computational complexity and training time- Sensitive to noise and disordered data	- Suitable for applications involving temporally and spatially sequenced data- Less effective in environments with limited or unstructured data
GAN (Generative Adversarial Network)	- Generates realistic synthetic data to augment training datasets- Reduces reliance on labeled data by increasing data diversity- Can improve the quality of hybrid models	- Complex training process requiring careful parameter tuning- Risk of generating unrealistic or inconsistent data if not properly trained- Indirect application in boundary extraction (mainly for data augmentation)	- Effective under conditions of data scarcity, enhancing model generalization- Requires strong computational resources and careful model supervision

5.2. Evaluation of Hybrid Models

Hybrid models, such as C-RNN and CNN-GAN combinations, have also been analyzed for their ability to improve accuracy under diverse conditions, including variations in vegetation types, parcel sizes, and data quality. Results suggest that hybrid models can reduce reliance on labeled data and provide more accurate performance in complex and heterogeneous environments.

5.3. Data Quality and Study Reliability

Given the nature of this study, which is based on a systematic review and comparative analysis of credible research in the field of agricultural parcel delineation using deep learning algorithms, the evaluation and validation process is analytical and grounded in scientific criteria. The datasets used in the analyzed studies are mainly derived from reputable remote sensing sources such as Sentinel-2, Landsat-8, and high-resolution imagery, contributing to the credibility of the findings. Consequently, the results of this review provide a reliable foundation for developing intelligent models within Spatial Data Infrastructure (SDI) frameworks for precision agriculture applications.

5.4. Proposed Analytical Framework

By identifying the strengths and limitations of the reviewed models, this study offers an analytical framework for selecting the most appropriate algorithm based on data conditions, land type, and specific goals in agricultural land management systems. This framework may serve as a foundation for future research on the development of localized models within SDI-based smart agriculture environments.

6. Conclusion and Summary

In recent years, the application of deep learning in analyzing satellite imagery, especially for the precise delineation of agricultural field boundaries, has witnessed significant growth. Challenges such as landscape heterogeneity, variability in cropping patterns, and the scarcity of labeled data have highlighted the limitations of traditional methods. In response, advanced deep learning models offer promising solutions to overcome these barriers.

Among various approaches, three major deep learning architectures have received the most attention:

Convolutional Neural Networks (CNNs)

Recurrent Neural Networks (RNNs)

Generative Adversarial Networks (GANs)

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The following table (Table 2) presents a comprehensive comparison of these architectures, clarifying their strengths, weaknesses, and specialized applications in the context of agricultural remote sensing and boundary extraction.

The combination of spatial data, satellite imagery, and advanced deep learning techniques leads to improved accuracy and efficiency in delineating agricultural land boundaries. This synergy enhances feature extraction, enables better handling of complex landscapes, supports effective data integration, and ultimately yields more reliable results in mapping and monitoring agricultural areas.

Table 3. Comparative Analysis of Deep Learning Models (CNN, RNN, and GAN) in Agricultural Land Parcel Boundary Delineation Using Satellite Imagery and Geospatial Data

Feature / Criterion	CNN (Convolutional Neural Network)	RNN (Recurrent Neural Network)	GAN (Generative Adversarial Network)
Appropriate Input Data	Images, especially 2D imagery such as satellite data	Sequential and time-series data with temporal dependencies	Image data, suitable for generating synthetic and augmented data
Feature Extraction Capability	High-level and local feature extraction (e.g., edges, textures)	Temporal and contextual dependency encoding between sequential data	Generation of new data samples similar to real data; data augmentation
Contextual Dependency Modeling	Limited to local features only	Strong; capable of capturing long-term and contextual dependencies	Capable of generating diverse data but not designed for dependency modeling
Primary Application in Remote Sensing	Scene classification, land boundary extraction, spatial data analysis	Complementary to CNN for modeling spatial/temporal dependencies	Augmentation of training data, generation of high-fidelity synthetic imagery
Limitations	Inability to model extended dependencies within images	Requires structured sequential data; complex training	Challenging training and convergence; requires quality initial data
Role in Hybrid Architectures	Foundation of image processing; core feature extractor	Complementary component for contextual encoding; enhances CNN models	Enhances data diversity; supports robust training of other models
Implementation in Precision Agriculture	Accurate boundary delineation, vegetation classification, texture analysis	Temporal-spatial change analysis, contextual encoding across land units	Data synthesis to mitigate limited labeled samples in agricultural datasets
Computational Requirements	Medium to high (depending on network depth)	High (depending on sequence length and network complexity)	Very high (due to simultaneous training of generator and discriminator)
Future Development Potential	Enhancement via integration with RNNs and other networks	Development of CNN-RNN hybrid models for improved spatial encoding	Advancement of more stable and spatially-aware GAN models for geospatial data

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In this study, the roles and applications of deep learning algorithms—specifically CNNs, RNNs, and GANs—in delineating the boundaries of agricultural land parcels using satellite imagery and geospatial data were reviewed. The findings from reviewed studies show that, especially when used in combination, these models have significantly improved boundary detection accuracy compared to traditional and even classical machine learning approaches.

Integrating these models within the Spatial Data Infrastructure (SDI) framework facilitates smart agriculture optimization, land and water resource management, and data-driven planning. Moreover, combining deep learning models with spatial databases can contribute to the development of intelligent decision-support systems in agriculture.

Overall, this research indicates that the development of hybrid, multi-architecture models using multi-source data provides an effective pathway to address current challenges in agricultural boundary delineation within the SDI environment. Future studies are encouraged to focus on lightweight, cost-effective hybrid models that are adaptable to diverse and localized spatial data. Such research directions could significantly contribute to the advancement of smart agricultural infrastructure and sustainable natural resource management.

Based on the comparative analysis, CNNs demonstrate strong performance in extracting local spatial features from satellite imagery, especially in accurately classifying objects and identifying field boundaries. However, their inability to capture global or sequential dependencies across image regions limits their interpretive capacity. RNNs, designed specifically to handle sequential and contextual relationships, effectively address this limitation. The combination of CNN and RNN (i.e., C-RNN) can significantly enhance the accuracy of feature identification in complex and heterogeneous landscapes.

On the other hand, while GANs are not directly designed for boundary extraction, they play a crucial role in augmenting training datasets by generating highly realistic synthetic images. This improves the performance of deep learning models by compensating for the lack of labeled training data.

In conclusion, no single model can be considered the optimal choice in all scenarios, as model selection depends on data characteristics, task requirements, and available computational resources. However, for the specific task of delineating agricultural boundaries using satellite imagery, C-RNN models—combining the spatial strength of CNNs with the contextual awareness of RNNs—stand out as a balanced and effective approach. In parallel, the use of GANs as a complementary tool for training data enhancement can further boost the performance of such hybrid models.

Thus, a forward-looking strategy in this domain involves the development and implementation of multi-stage, hybrid models that integrate deep learning, data generation, and advanced geospatial analysis into a unified framework.

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