AI-Driven Digitization of Cadastral Maps: A Review

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***Abstract*—Cadastral maps that are accurate and current are very important for land management, city-planning and property control. The old techniques for making cadastral maps are mostly based on manual mapping and field survey which makes the process very slow, costly and hard to keep up to date in areas where activities are changing quickly. The current innovations in the fields of artificial intelligence and high-resolution satellite imagery have opened the way to automating the digitization of the cadastral map which would enhance the efficiency and the accuracy at the same time. This paper discusses an AI-based approach to detecting the constraints of the cadastral areas with the aid of drone-captured images and the U-Net deep learning model. The primary objective of the study is to delineate the land parcels visibly and to check their concordance with the official cadastral reference data. The UAV images taken at a high resolution bring out the boundary features very clearly; and on the other hand, the masks that are annotated by the experts and represent the visible cadastre boundaries serve as the ground truth. A U-Net convolutional neural network is then trained to perform pixel-wise semantic segmentation on these features. In order to provide a complete assessment, the performance of the model is measured using a pixel-based confusion matrix that categorizes predictions as true positives, false positives, true negatives, and false negatives. From this data, metrics like precision, recall, Intersection over Union (IoU), and F1-score are calculated to assess the completeness and correctness of the boundaries. Additionally, a comparative analysis is performed to measure the impact of image resolution by contrasting the results obtained from UAV with that from satellite imagery. The results obtained from the experiments show that the use of deep learning with UAVs outperforms the satellite images in terms of recall and F1-scores, indicating better boundary detection. The results also prove that the use of AI for cadastral mapping is technically practical and provides boundary accuracy as a benefit, making it easier for modern land administration systems to accept it.**

Keywords—Artificial Intelligence; Cadastral Mapping; Deep Learning; Geospatial Digitisation; Land Boundary Detection; Segmentation.

I. INTRODUCTION

The digitisation of cadastral maps using AI-based boundary line detection is transforming land management by improving the accuracy and efficiency of map processing. Traditional cadastral maps, which document property boundaries, were often drawn by hand, leading to inaccuracies due to human error and map degradation over time. Manually digitising these maps is a time-consuming and error-prone process, especially with the complex features they often include, such as roads, rivers, and buildings. This is where AI plays a critical role, particularly in Convolutional Neural Networks (CNNs). CNNs, a powerful type of deep learning model, can be trained to automatically detect boundary lines in these maps, significantly enhancing the precision and speed of the digitisation process. By learning from large datasets of labelled maps, CNNs can identify patterns that distinguish boundary lines from other features, overcoming the challenges posed by map distortions, varying line thickness, and other inconsistencies that arise in traditional methods.

The use of AI for digitising cadastral maps offers numerous advantages. It automates what was once a manual and tedious task, dramatically reducing the time and resources required to process large volumes of maps. Additionally, AI models like CNNs can adapt to different types of cadastral maps from various regions, improving the scalability of the digitisation process.

The resulting digital maps are more accurate, consistent, and easier to update and manage, allowing land administration bodies to improve land registration systems, reduce boundary disputes, and enhance transparency in land transactions. Furthermore, the integration of these AI-generated digital maps with Geographic Information Systems (GIS) opens up new opportunities for advanced land use analysis and planning.

This study is theoretically grounded on the geo-spatial intelligence framework, where remotely sensed data act as spatial evidence, deep learning models act as intelligent interpreters, and cadastral systems act as legal-administrative outputs. UAV imagery provides spatial truth, U-Net based CNNs transform this truth into parcel boundaries, and GIS converts these outputs into legally usable cadastral maps. This chain establishes a logical scientific bridge between sensing, intelligence and land governance.

II. PROBLEM STATEMENT

Cadastral maps, which record the boundaries, ownership, and dimensions of land parcels, are essential for land administration, urban planning, property taxation, and resource management. Despite their importance, many regions face significant challenges in the creation, maintenance, and utilisation of cadastral maps, impeding effective land governance and economic development. One key issue is the lack of accuracy and consistency in cadastral records. In many developing nations, existing maps are often outdated, incomplete, or inaccurate due to manual surveying methods and a lack of updated data. This discrepancy can lead to land disputes, overlapping claims, and inefficient land use, further straining the legal and administrative systems.

Another critical problem is the digital divide in cadastral mapping. While modern Geographic Information Systems (GIS) offer sophisticated tools for mapping and managing land data, many regions lack the technological infrastructure and expertise to fully digitise and integrate their cadastral systems.

This not only hampers efficient land management but also limits transparency, accessibility, and public participation in land-related decision-making. Additionally, there is often a lack of coordination among various stakeholders, including government agencies, private sector actors, and local communities. Without clear communication and collaboration, cadastral updates are often delayed, and the maps produced may not reflect actual land use or ownership changes.

In summary, the primary issues facing cadastral mapping today include outdated records, insufficient technological infrastructure, and weak institutional collaboration. These problems hinder effective land administration, exacerbate land conflicts, and limit the potential for sustainable development. Addressing these challenges requires the modernisation of cadastral systems through technological upgrades, capacity building, and better coordination among stakeholders.

Although deep learning models have been applied to cadastral boundary detection, existing studies are limited by region-specific training, lack of transferability evaluation, and poor integration with GIS-based cadastral workflows. Most previous works focus on image-level segmentation without validating legal parcel accuracy. Therefore, a major gap exists in evaluating AI-generated boundaries against real cadastral records and converting them into legally usable vector maps."

III. RELATED WORKS

The digitisation of cadastral maps has received increasing attention in recent years due to the need for improved land administration, property management, and urban planning. Traditional paper-based cadastral systems are gradually being replaced by digital cadastral databases integrated with Geographic Information Systems (GIS), enabling improved accuracy, accessibility, and efficient updating of land records [5], [9]. These digital platforms support better spatial data management; however, conventional digitisation methods still rely heavily on manual interpretation, limiting scalability and consistency.

Recent advancements in Remote Sensing (RS), Global Navigation Satellite Systems (GNSS), and Unmanned Aerial Vehicles (UAVs) have significantly enhanced the precision and efficiency of cadastral surveys. High-resolution satellite imagery and UAV-based mapping techniques provide faster and cost-effective solutions for large-scale land parcel mapping, particularly in regions with complex terrain [2], [4], [6]. Despite these benefits, traditional image-based methods require substantial human involvement for boundary delineation, motivating the adoption of automated approaches.

Artificial intelligence and deep learning techniques have emerged as effective tools for automating cadastral boundary extraction and parcel delineation. Several studies have demonstrated the use of convolutional neural networks for detecting visible land boundaries from UAV imagery with improved accuracy compared to conventional methods [2], [3], [4]. Dataset-driven approaches further enable supervised learning for cadastral applications, facilitating large-scale digitisation while reducing manual effort [1], [14]. Comparative analyses indicate that AI-driven methods can outperform manual mapping in terms of efficiency, although their performance is highly dependent on the availability of annotated training data and regional generalisation capability [6], [8].

Crowdsourcing has also been explored as a participatory approach to cadastral mapping, particularly in informal settlements and data-scarce regions. Community-contributed spatial data, combined with satellite imagery and AI-assisted validation, can enhance cadastral coverage and inclusivity [7], [9]. However, concerns related to data accuracy, legal reliability, and standardisation necessitate additional verification mechanisms before integration into formal cadastral systems.

The integration of three-dimensional (3D) cadastral models is gaining importance in urban environments where complex, multi-level property rights exist. Machine learning-based techniques have been investigated for 3D cadastral mapping and indoor localisation to better represent vertical land use and underground infrastructure [11], [12]. While these approaches offer improved spatial representation, challenges related to interoperability, data complexity, and implementation cost remain.

Overall, existing studies highlight the growing role of AI, UAVs, and digital platforms in cadastral map digitisation. However, most research focuses on specific tasks such as boundary detection or dataset development, with limited emphasis on comprehensive, scalable AI-driven frameworks. Addressing issues related to data dependency, generalisation, and system integration remains a key research challenge in modern cadastral digitisation.

IV. METHODS AND MATERIALS

A. *Existing Methods:*

Conventional approaches to cadastral map digitisation primarily involve converting analogue cadastral maps into digital vector formats. A commonly used method includes scanning paper-based cadastral maps into raster images, followed by vectorisation to enable manipulation within GIS environments. In this process, raster images are manually or semi-automatically digitised using software such as ArcGIS or AutoCAD, where parcel boundaries are traced to generate vector layers.

However, the accuracy of such digitised outputs is highly dependent on the quality and currency of the original maps. Distortions, ageing, and outdated survey information often result in positional inaccuracies. Geographic Information System (GIS)-based cadastral digitisation is another widely adopted approach that facilitates the integration of spatial data layers such as land parcels, infrastructure, and topography. GIS platforms enable efficient storage, visualisation, and updating of cadastral information, often using precise geographic coordinates obtained from surveying techniques such as GPS or GNSS. Despite these advantages, traditional GIS-based methods still rely heavily on manual intervention, limiting scalability and automation.

B. *Data Collection and Preprocessing:*

Imagery Source: Recent studies emphasise the use of high-resolution UAV imagery for detailed cadastral boundary mapping, particularly in rural and agricultural regions. Persello et al. [1] highlight that UAV platforms such as the DJI Phantom series provide imagery with fine ground sampling distance (GSD), enabling improved visibility of parcel boundaries and physical features.

Ground Truth Generation: Accurate ground truth data is essential for training and validating deep learning models. In existing studies, cadastral boundaries are manually annotated by domain experts using GIS tools, and the annotations are converted into binary or multi-class masks representing boundary locations. These labelled datasets provide reliable reference information for supervised learning and ensure precise model training.

(a)

(b)

(c)

Fig. 1. Example result of the proposed U-Net–based boundary detection framework showing (a) input satellite image, (b) generated binary mask, and (c) extracted land boundaries overlaid on the original image.

(a)

(b)

(c)

Fig. 2. **a**) Cadastral boundaries; **b**) manually vectorised visible boundaries and (**c**) predicted visible boundaries with a customised CNN; (**a**–**c**) overlaid on UAV imagery.

C. Deep Learning Models and Architecture:

Model Selection: Among various deep learning architectures, U-Net has emerged as a widely adopted model for image segmentation tasks due to its encoder–decoder structure and ability to capture both spatial context and fine-grained details. Several studies employ customised U-Net variants with reduced convolutional depth to suit cadastral boundary detection tasks, achieving efficient performance while controlling computational complexity.

Training Setup: Training is typically performed on fixed-size image patches, such as 256 × 256 pixels, to preserve boundary detail while maintaining computational efficiency. Models are trained using UAV-based cadastral datasets and, in some cases, standard boundary detection datasets to enhance feature learning. Data augmentation techniques are often applied to improve robustness and reduce overfitting.

D. Boundary Detection and Post-Processing:

- Visible Boundary Detection: After training, the model detects visible boundaries in the test imagery. Further processing techniques like edge detection and morphological transformations can refine boundary lines, removing noise and enhancing the visual clarity of boundaries.
- Vectorisation of Boundaries: For practical applications, rasterised boundary detections are converted into vector format using GIS tools. This process makes the data compatible with cadastral systems and supports integration with existing maps and geographic databases (MDPI, 2022).

E. Model Evaluation and Validation:

Evaluation Metrics: Model performance is commonly assessed using standard segmentation metrics, including precision, recall, Intersection over Union (IoU), and F1-score. High F1-scores reported in prior studies indicate effective boundary identification and segmentation accuracy.

Testing for Transferability: To evaluate generalisation capability, models are tested across different geographic regions and land-use patterns. Studies such as Grift et al. [1] emphasise that regional diversity significantly influences model performance, highlighting the importance of transferability testing for practical cadastral applications.

V. PROPOSED METHODS

For AI-driven cadastral mapping and land boundary delineation, a structured methodology is proposed that builds upon existing deep learning approaches while addressing current limitations identified in the literature. High-resolution UAV imagery is considered the primary data source due to its ability to capture fine spatial details of cadastral boundaries, particularly in rural and semi-urban environments [1]. In addition, the integration of complementary data sources such as multispectral imagery and LiDAR is proposed to enhance boundary detection in areas with irregular terrain or limited visual contrast.

For model development, convolutional neural network-based architectures such as U-Net and Fully Convolutional Networks (FCNs) remain suitable due to their proven capability in preserving spatial features essential for accurate boundary extraction. To address limitations related to long-range spatial dependency and model generalisation, transformer-based architectures such as Vision Transformers (ViTs) are considered as an extension to conventional CNN models. These architectures enable global context learning across images and may improve boundary continuity in large or complex parcels. Furthermore, self-supervised or semi-supervised learning strategies are proposed to reduce dependency on extensive annotated datasets and improve adaptability across diverse geographic regions.

Boundary refinement is achieved through the integration of deep learning outputs with classical image processing techniques. Edge detection methods such as Canny or Sobel filters are applied to refine segmented boundaries and improve continuity. In addition, graph-based modelling techniques, including graph neural networks (GNNs), are proposed to capture spatial relationships among boundary pixels, enabling smoother and more topologically consistent boundary representations.

For practical integration into cadastral systems, raster-based boundary outputs are converted into vector formats compatible with GIS platforms. Incorporating raster-to-vector conversion as part of the automated workflow enables seamless integration with existing cadastral databases and supports legal and administrative use. Direct generation of vector boundaries within the modelling pipeline is considered to improve processing efficiency and support near real-time applications.

Model performance evaluation is conducted using standard segmentation metrics such as Intersection over Union (IoU) and F1-score. In addition to accuracy assessment, transferability testing across datasets from different geographic regions is emphasised to evaluate robustness and applicability in real-world cadastral scenarios. To further enhance generalisation, synthetic data generation using generative adversarial networks (GANs) is proposed to simulate diverse boundary conditions and land-use patterns [1].

Finally, deployment within a cloud-based framework is considered to facilitate scalability, enable continuous model updating through user feedback, and support practical adoption by cadastral agencies. This proposed methodology integrates established techniques with emerging AI strategies to provide a scalable and adaptable solution for modern cadastral map digitisation.

VI. ARCHITECTURE DIAGRAM

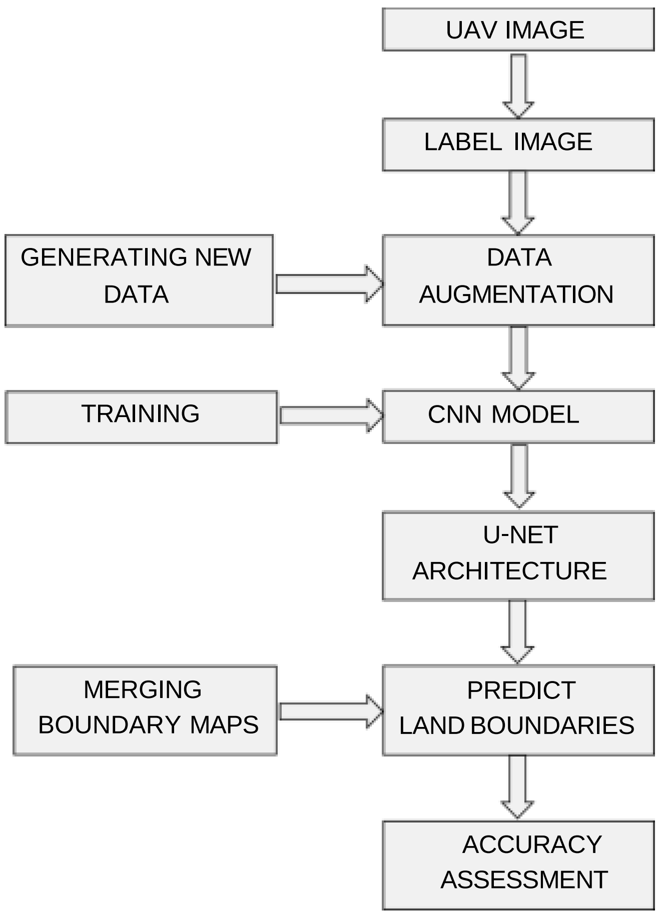

Fig.5 The workflow of creating a model and verifying the accuracy of its predicted images.

VII. RESULT

	Precision	Recall	F1-Score	PoLiS (m)
S2 (from scratch)	0.42	0.36	0.38	27.0
S2 (pre-trained)	0.48	0.33	0.39	26.7
GM Images	0.47	0.52	0.49	20.3

The average F1-score of the GM experiment is 0.49. The high spatial resolution of the GM results in an average PoLiS value of 20.3 m, which is significantly better than the average PoLiS value of 26.7 m obtained using S2 data.

Cadastral Maps				
	Boundary Map	Recall	precision	F1 Score
Odranci	Manually	0.372	0.627	0.467
	Predicted	0.207	0.491	0.291

Table 2. Assessment of the overlap between cadastral boundaries and land visible boundaries, Odranci [3]

The confusion matrix is employed to assess how effectively the system detects visible land boundaries and how well those detected boundaries align with the official cadastral lines. In this context, each pixel is categorised as either a true positive (TP), false positive (FP), true negative (TN), or false negative (FN).

Using these pixel-level classifications, two key performance metrics are derived:

- Recall = TP / (TP + FN)
- Precision = TP / (TP + FP)

Here, recall reflects the completeness of boundary detection, while precision indicates its accuracy or correctness. Both metrics are essential for evaluating the reliability of cadastral boundary extraction. To provide a balanced measure that considers both recall and precision, the F1 score is calculated using the formula:

F1 Score = 2 × (recall × precision) / (recall + precision)

The assessment presented in Table 1 and Table 2 demonstrates quantitative validation of the AI-generated boundaries. The UAV-based model achieves an F1-score of 0.49 and PoLiS distance of 20.3 m, confirming superior boundary localisation. The overlap analysis with cadastral records (Table 2) provides legal-level validation.

1. To extract cadastral boundaries using deep learning.
2. To evaluate segmentation accuracy using F1-score and IoU.
3. To validate AI boundaries against cadastral maps.

Objective-1 is achieved through U-Net segmentation (Fig.5). Objective-2 is satisfied using F1-score and PoLiS (Table 1). Objective-3 is achieved by overlap analysis with official cadastral maps (Table 2).

VIII. CONCLUSION

AI-driven cadastral maps represent a transformative shift in land administration and management. By integrating artificial intelligence (AI) with geospatial technologies, these systems offer unprecedented levels of accuracy, automation, and scalability. AI can automatically process satellite imagery, recognise land parcel boundaries, and identify land use patterns, significantly reducing the time and labour required for manual mapping. Furthermore, AI-powered tools such as machine learning and computer vision enhance the precision of cadastral data, allowing for a more accurate representation of land parcels, even in complex environments such as urban areas or informal settlements. However, challenges remain in implementing AI-driven cadastral systems, especially in regions with limited technological infrastructure, insufficient data quality, and a lack of skilled personnel. Moreover, ethical concerns such as data privacy and the risk of algorithmic bias must be addressed to ensure equitable outcomes. In summary, we can conclude that AI- driven cadastral maps hold the potential to revolutionise land governance by improving efficiency, accuracy, and accessibility. With proper technological, institutional, and ethical frameworks in place, they can play a critical role in sustainable land management, economic development, and resolving land tenure issues.

REFERENCES

[1] AI4SmallFarms: A Dataset for Crop Field Delineation in Southeast Asian Smallholder Farms, Claudio Persello, Jeroen Grift, Xinyan Fan, Claudia Paris, Ronny Hänsch, Mila Koeva; 2023

[2] Bujar Fetai, Matej Raˇciˇc and Anka Lisec." Deep Learning for Detection of Visible Land Boundaries from UAV Imagery", Remote Sens. 2021, 13, 2077.

[3] Bujar Fetai, Dejan Grigillo and Anka Lisec." Revising Cadastral Data on Land Boundaries Using Deep Learning in Image-Based Mapping, Published: 4 May 2022".

[4] Xue Xia, Claudio Persello and Mila Koeva. "Deep Fully Convolutional Networks for Cadastral Boundary Detection from UAV Images", 2019

[5] Julius M. Knopp, Gregor Levin, and Ellen Banzhaf. Aerial Data Analysis for Integration Into a Green Cadastre-An Example From Aarhus, Denmark, IEEE JOURNAL OF SELECTED TOPICS IN APPLIED EARTH OBSERVATIONS AND REMOTE SENSING, VOL. 16, 2023.

[6] Emmanuel Nyandwi, Mila Koeva, Divyani Kohli and Rohan Bennett, Comparing Human Versus Machine-Driven Cadastral Boundary Feature Extraction, Published: 12 July 2019.

[7] Fatma Betül Yidiz, İsmail Ercüment Ayazli, Hidayet Takci, Generating temporal cadastral parcels with artificial intelligence algorithms within the scope of cadastre 2034, 2nd Intercontinental Geoinformation Days (IGD) – 5-6 May 2021.

[8] Jelena Ignjatić, Bojana Nikolić, Aleksandar Rikalović, Deep Learning for Historical Cadastral Maps Digitisation: Overview, Challenges and Potential, CSRN 2803.

[9] Toshboeva Robiya Sobirovna. Artificial Intelligence in the Cadastral System of Uzbekistan: Application Problems and Solutions, ISSN: 1827-7160 Volume 28 Issue 1, 2024.

[10] Jeroen Franken, Wim Florijn, Maarten Hoekstra, and Eric Hagemans. Rebuilding the Cadastral Map of The Netherlands: The Artificial Intelligence Solution", 21– 25 June 2021.

[11] Alireza Hajiheidari, Mahmoud Reza Delavar, and Abbas Rajabifard. Smart Urban Cadastral Map Enrichment—A Machine Learning Method, ISPRS Int. J. Geo-Inf. 2024, 13, 80.

[12] C. Potsiou, N. Doulamis, N. Bakalos, M. Gkeli, C. Ioannidis. "INDOOR LOCALIZATION FOR 3D MOBILE CADASTRAL MAPPING USING MACHINE LEARNING TECHNIQUES", Volume VI-4/W1-2020.

[13] Ramon Espinel, Gricelda Herrera-Franco, Luis Rivaa Gdeneirarcia and Paulo Escandon-Panchana. Artificial Intelligence in Agricultural Mapping: A Review.

[14] Remi Petitpierre, Paul Guhennec. Effective annotation for the automatic vectorisation of cadastral maps, Digital Scholarship in the Humanities, 2023, 38, 1227–1237.