College of Social Sciences

A Semi-Automated Technique for Cadastral Boundary Extraction from UAV Images Using Deep-Learning and Geospatial Techniques

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A Thesis Submitted to the Department of Geography and Environmental Studies in Partial Fulfilment of the Requirements for the Degree of Master of Arts in Geography and Environmental Studies (Specialization in GIS, Remote Sensing, and Digital Cartography)

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Addis Ababa, Ethiopia
June, 2024

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This is to certify that the Thesis prepared by Binyam Zeray Abrham, entitled: A Semi-Automated Technique for Cadastral Boundary Extraction from UAV Images Using Deep-Learning and Geospatial Techniques and submitted in partial fulfilment of the requirements for the degree of Master of Arts in Geography and Environmental Studies (Specialization in GIS, Remote Sensing, and Digital Cartography) complies with the regulations of the University and meets the accepted standards with respect to the originality and quality.

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Declaration

I declare that this Thesis is originally prepared by me. It is based on my work, with acknowledgments of other sources, and has not been submitted in whole or part for any other professional qualification.

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Dedicated to my father Zeray Abrham

"Why Should I become someone's shadow I want to create my own identity If I have to become a shadow Then I will become as great as my father" A. Kumar C

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Abstract

The 2030 Agenda for Sustainable Development acknowledges the crucial role of land in advancing and accomplishing the Sustainable Development Goals across the globe. Nevertheless, a large portion of land rights worldwide are still unregistered in government-sanctioned systems. To address this issue, the Fit-for-Purpose (FFP) approach to land administration has been introduced. This approach aims to streamline cadastral mapping and minimize the expenses and time associated with conventional surveying methods. This study examines the progress and possibilities of using Unmanned Aerial Vehicle (UAV) imagery and Deep learning techniques, particularly Convolutional Neural Networks (CNNs), which are employed for the extraction of cadastral boundaries. CNNs have demonstrated their effectiveness in accurately and efficiently extracting boundaries, as they are capable of extracting high-level features without the need for human expertise in feature engineering. The study tested the BDCN and HED deep learning models for cadastral boundary extraction from UAV datasets. The BDCN model achieved an average precision of 0.68, a recall of 0.80, and an F-score of 0.73. It had an average precision of 0.88 and an overall IoU of 0.85. The HED model performed slightly better achieving an average precision of 0.66, a recall of 0.68, and an F-score of 0.67. It also demonstrated an average precision of 0.98 and an overall Intersection over Union (IoU) of 0.88. The results indicate that these deep learning models can effectively extract cadastral boundaries in vector polygon format, which can be directly used in mapping for rural cadaster with post-processing and field verification. The study highlights the potential of using UAV imagery and deep learning techniques to support more efficient and cost-effective cadastral boundary mapping, aligning with the goals of the Fit-for-Purpose land administration approach.

Keywords: Land administration, Cadastral mapping, Unmanned Aerial Vehicle (UAV), Deep learning techniques

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Acronyms and Abbreviations

AFE:	Automatic Feature Extraction
CNN:	Convolutional Neural Networks
BDCN:	Bi-Directional Cascade Network
FFP:	Fit-For-Purpose
FFPLA:	Fit-For-Purpose Land Administration
FCN:	Fully Convolutional Neural
GCP:	Ground Control Point
GIS:	Geographic Information System
GPS:	Global Positioning System
HED:	Holistically-Nested Edge Detection
UAV:	Unmanned Aerial Vehicles

Chapter One

1 Introduction

1.1 Background

Land is the foundation of all life, and its availability is essential to which all life on Earth depends on (Williamson, 2001). According to the 2030 Agenda for Sustainable Development, land plays a crucial role in advancing and attaining the Sustainable Development Goals (SDGs) across the globe. Unfortunately, a significant portion of land rights worldwide are not officially recorded in government-sanctioned systems. The registration process is often sluggish in numerous countries, with only approximately 30% of global land rights being acknowledged and registered within formal registration systems (Dyli, 2016). According to (Zevenbergen, 2004), the challenges in developing countries include delays, inefficiencies, and lack of transparency. The implications of these issues are far-reaching, affecting land administration, property rights, and overall economic development.

Creating cadastral maps using traditional ground surveying methods is a time-taking and costly process that needs a substantial amount of manual labor (Enemark & Mclaren, 2017). In many developing countries, there is a struggle to address land-related challenges that can lead to disputes, discourage investment, and hinder economic growth, ultimately obstructing their ability to reach their full potential (Metaferia et al., 2023).

The current attempts to enhance land administration systems have relied on outdated approaches, lacked coherence, and ultimately failed to bring about the necessary widespread changes and advancements on a large scale (Enemark et al., 2016). New solutions are needed to ensure security of tenure for everyone, while also being affordable and capable of being developed and improved quickly over time in small increments (Metaferia et al., 2023). The FFP/FFPLA approach strives to offer affordable, efficient, and progressively enhanced land administration solutions that can guarantee the security of tenure for all. This is in contrast to traditional, expensive, and time-consuming surveying methods. Notably, this method can be utilized for both the initial stages and continuous maintenance of the system (Enemark et al. 2016).

Fit-for-purpose approaches are crucial for providing immediate and cost-effective land surveying solutions. In accordance with (Enemark & Mclaren 2017). these approaches prioritize four principles: utilizing general boundaries for land delineation, particularly in rural and semi-urban areas, employing high-resolution satellite and aerial imagery based on purpose rather than technical standards, and allowing for opportunities to update, upgrade, and improve. In alignment with this perspective, it is vital to utilize inexpensive technologies that cater to current societal needs for surveying purposes. Among these technologies, high-resolution satellite imagery is particularly suitable as a data source for capturing cadastral boundaries due to its convenience and efficiency. Photogrammetric techniques offer straightforward and comprehensive solutions to the aforementioned mapping problems (Hashmi et al., 2021). These techniques allow for the extraction of property boundaries with a certain tolerance level, without the need for labor-intensive field work (Bennett et al., 2021). With the widespread availability of remote-sensing technology, acquiring remote-sensing images for indirect surveying has become easier and more affordable (Bennett et al., 2021). Different techniques are available for acquiring cadastral data depending on the concept of the boundary. Aerial photography is the most cost-effective option when considering a large area for systematic adjudication. Aerial photographs meet tolerable measurement requirements to produce cadastral maps at rural and urban scales (Tuladhar, 2004) Currently, Unmanned Aerial Vehicles (UAVs) or drones are being used to capture high-resolution data, opening up new possibilities for gathering comprehensive spatial data. Numerous studies have been conducted using UAVs with varying spatial resolutions, tailored to specific needs (Kachamba et al., 2016).

According to (Tuladhar,2004) UAVs can deliver high-resolution photographs and point cloud data for specific parcels of land, outperforming traditional surveying methods. This makes UAVs a valuable tool in land administration and the Fit-for-Purpose (FFP) approach. The use of UAVs for small areas is an efficient, flexible, transparent, and participative way to acquire high-quality geospatial data and information at a low cost, UAV deployment is preferred (Zevenbergen, 2004). This approach is feasible for obtaining consistent boundary information; though, it is important to recognize that it is a time-consuming, resource-intensive, and challenging endeavor. (Fetai et al., 2019). furthermore, it may deliver inconsistent outcomes among different experts by the time of digitization (Metaferia et al., 2023). Recent advancements in computer vision and digital image processing enabled to delivery of these extraction procedures automatically or semi-automatically (Carrio et al., 2017). Automated image extraction is the preferred solution over manual techniques for the task of reducing the workload in image analysis. The development of convolutional neural networks (CNNs) has introduced a new approach to semantic segmentation and edge detection of remote sensing images (Luo et al., 2021).

This study aims to investigate the progress and potential of utilizing UAV images for extracting cadastral boundaries with Deep learning techniques, particularly Convolutional Neural Networks (CNNs), which have shown impressive results. Their effectiveness in achieving precise and efficient extraction. In fact, experimental results have shown that CNNs offer superior precision and accuracy in boundary extraction. Overall, the motivation of the study is to improve existing approaches to cadastral boundary mapping, which often suffer from limitations in terms of time, cost, and labor.

1.2 Problem Statement

The research is initiated with a literature review in relation to the objective. This review helped to identify the challenge in cadastral mapping. For example, the review highlighted that formal land administration systems in many parts of Africa, such as those described by (Burns & Dalrymple, 2008), face several challenges, including high costs for updating and maintenance, as well as inefficiency. These challenges primarily arise from limited financial, human, and technical resources. To tackle these issues, the fit-for-purpose land administration (FFPLA) framework was developed, with a specific focus on the development of modern cadastres, particularly in the field of land measurements (Enemark & Mclaren, 2017). In Ethiopia, the land certification program was implemented in two phases (Deininger et al., 2008). The first phase involved registering over 20 million rural land parcels using local land measurement techniques like rope or tape, as well as traditional methods known as timad (Bezu & Holden, 2014). However, a major issue with this phase was the limited positional accuracy (Persha et al., 2017). To address this limitation, the second phase of land certification was introduced. This phase utilized modern technologies such as satellite imagery, orthophoto, and the Global Navigation Satellite System (GNSS) (Bezu & Holden, 2014). The second phase was planned to last for 5.5 years, starting in March 2014, with the aim of completing approximately 14 million parcels for second-level certification (Milindi et al., 2020). However, the process of land certification in Ethiopia is still ongoing, and the desired outcome has not yet been achieved (Persha et al., 2017). Overall, the two-phase land certification program in Ethiopia made significant progress in rapidly registering land rights for millions of smallholder farmers (Milindi et al., 2020). However, the program also encountered persistent challenges related to technical, institutional, and financial limitations, which underscore the need for a more comprehensive and sustainable approach to land administration. This approach is exemplified by the fit-for-purpose land administration (FFPLA) framework (Mclaren et al., 2016). This study primarily focuses on addressing technical issues, particularly in enhancing cadastre measurements. One suggested method to bridge the gap in cadastral survey is through automatic feature extraction (AFE), which is considered a viable alternative within the FFPLA framework for mapping and updating cadastral boundaries (Enemark & Mclaren, 2017).

Previous research on this topic, such as the study by (Metaferia et al., 2023) in Ethiopia, has explored semi-automated feature extraction based on traditional segmentation using aerial images. However, there have been only a few studies on the use of automated methods for identifying visible cadastral boundaries from UAV imagery. More research is needed to evaluate the precision and reliability of UAV-based cadastral mapping in different contexts and land tenure systems. Additionally, the findings of most studies are limited in their generalizability due to their focus on specific case studies or restricted regions. Therefore, it is important to give further attention to standardizing data acquisition, processing techniques, and accuracy assessment methods in UAV-based mapping. Moreover, exploring the integration of UAV imagery and advanced deep learning methods for automatic feature extraction, as well as the development of interoperable cadastral systems, is necessary.

1.3 Objectives

1.3.1 General Objective

The main objective of the study is to test the applicability of semi-automatic cadastral boundary extraction using a deep learning approach to support general boundaries from high-resolution UAV imagery.

1.3.1.1 Specific Objectives

- To choose the most suitable deep learning model and define its parameters for the purpose of extracting cadastral boundaries.
- To apply feature extracting deep learning model on the selected testing dataset.
- To analyze the applicability of the semi-automated feature extraction method for cadastral boundary mapping.

1.4 Research Questions

The following research questions developed aligning with each specific objective.

Corresponding to objective 1:

- What are the possible semi-automatic cadastral boundary extraction deep learning approaches?
- Which deep learning method is suitable for cadastral boundary extraction purposes?
- How to get the finest hyperparameters of the model to extract cadastral boundaries?

Corresponding to objective 2:

- What are the standard metrics used for evaluating predicted polygon parcels?

Corresponding to objective 3:

- What are the contributions of the deep learning approach for semi-automatic feature extraction for general cadastral boundary mapping?

1.5 Scope of the Study

The scope of the study is to develop and implement a deep learning-based method for semi-automated extraction of cadastral features from UAV (Unmanned Aerial Vehicle) imagery. The goal is to create cadastral boundaries that are accurate, up-to-date, and suitable for their intended use, such as land administration, and urban planning.

1.6 Significance of the Study

The study on semi-automatic feature extraction for cadastral boundary extraction from UAV images using deep learning in Ethiopia's case has significant implications for increasing cadastral mapping's precision, effectiveness, and economy. It can help initiatives for sustainable development, improve land administration systems, and advance the field's technological capabilities. Ultimately, the outcomes of this study can benefit various stakeholders involved in land management and contribute to the socio-economic development of Ethiopia.

1.7 Limitations of the Study

This study has a few limitations that should be taken into account. Firstly, the performance of the deep learning model is affected by the size and diversity of the training dataset. This limitation impacts its ability to generalize to a wider range of UAV images and types of parcels. Furthermore, variations in sensor quality and environmental factors like weather and lighting conditions can also affect the model's performance. Additionally, accurately delineating parcels becomes challenging when there is occlusion or overlapping parcels.

Moreover, the computational process involved in training and running the deep learning model can be time-consuming. This can limit the practical deployment of the model in real-time or large-scale applications. The training data for the farm parcel identification model was specifically created using information from rural cadasters. The focus was on capturing the unique characteristics and attributes of farm parcels in rural settings. This targeted approach enables the model to learn the distinctive patterns of land use in rural areas, specifically those dedicated to agriculture. As a result, the model is highly effective at accurately identifying farm parcels within rural regions, excluding urban settings. It is important to consider these limitations when interpreting the findings of this study and when planning future research or applications of the developed deep-learning approach for parcel extraction from UAV images.

1.8 Organization of the Thesis

This thesis consists of five chapters. In Chapter One, the background of the study is discussed, and the problem statement identifies the research objectives and questions, scope, significance, limitations, and organization of the study presented**.** Chapter two presents an extensive literature review on Cadaster and the various types of measuring, UAV types, and their use. In Chapter Three the proposed deep learning models BDCN and HED are discussed in detail. Additionally, a description of the datasets and the methods used to prepare them are provided, along with accuracy assessments of the models. Chapter four presents the results. The final chapter deals with the conclusions and recommendations.

Chapter Two

2 Literature Review

2.1 Cadastral System

The cadastral system is a tool for land management and administration. It aims to establish a secure and reliable system for registering real property. This parcel-based system contains up-to-date information about the land, including records of rights, restrictions, and responsibilities (McLaren et al., 2010) It usually consists of a geometric description of land parcels, as well as additional records that describe the type of interests in the land, ownership or control of those interests, and occasionally even the value of the parcel and its improvements (Al-ruzouq & Dimitrova, 2006).

Parcel objects are essential components of a cadastral system. In real life, a parcel of land refers to a continuous and distinct piece of land that possesses specific legal and usage characteristics (Zevenbergen, 2004). According to (Mclaren et al., 2016) land parcel, known as a cadastre, refers to a piece of land that has been officially delineated from a larger area. Parcel boundaries can be either natural or artificial, and they can be represented by visible features on the ground, lines on a map, or coordinates.

Cadastral Boundary and Mapping

The significance of cadastral maps in land administration cannot be emphasized enough. These maps play a pivotal role as essential reference documents that precisely depict the geographical location and extent of a property (Williamson, 2001). The creation of cadastral maps can be achieved through two primary methods: direct and indirect, depending on the data collection process.

Direct Surveying

In direct surveying, surveyors employ instruments such as GNSS (Global Navigation Satellite System), Electronic Distance Meters (EDM), theodolites, or measuring tapes directly on the unknown property to observe and measure its boundaries with meticulous precision. This traditional method has long been utilized by surveyors to determine property boundaries (Corlazzoli & Fernandez, 2004). These techniques are well-recognized and accurate. However, there are instances when they are not favorable. Surveying a very large area, for example, could be excessively time-consuming and costly (Tuladhar, 2004). By employing these instruments and techniques, surveyors can ensure that property boundaries are established with meticulous precision. This level of accuracy is crucial in land administration as it provides a solid foundation for property rights, land management, and decision-making processes (Zevenbergen, 2004). The direct surveying method remains a trusted and effective approach in the field, enabling surveyors to deliver reliable and accurate cadastral information that is essential for various applications within the realms of land administration and beyond.

Indirect Surveying using Semi-Automated Feature Extraction

Indirect surveying involves gathering data from remote sources such as satellites, aircraft, or unmanned aerial vehicles (UAVs). This method allows surveyors to extract boundaries by digitizing features manually from aerial or satellite images (Corlazzoli & Fernandez, 2004). While indirect surveying may not offer the same level of precision as direct surveying, it presents a cost-effective and efficient approach to acquiring cadastral data over vast areas(Tuladhar, 2004). Cadastral boundaries can be further classified into general or fixed boundaries, depending on their definition. Fixed boundaries are delineated with greater precision and are often marked with permanent constructions or monuments on the ground. These physical features provide clear and enduring demarcation of property limits (Zevenbergen, 2004). In contrast, general boundaries are defined in a manner that leaves the precise location undescribed, relying instead on physical features such as fences, hedges, waterways, or tracks to indicate the boundary (Luo et al., 2017). The choice of boundary concept determines the techniques employed for acquiring cadastral data. Aerial photography, for instance, emerges as a cost-effective option when considering systematic adjudication over a substantial area (Tuladhar, 2004). Orthorectified aerial photographs have long been indispensable in the creation of cadastral maps, as they satisfy the necessary measurement requirements for producing accurate rural and urban-scale cadastral maps (International Association of Assessing Officers, 2016). Although this approach is feasible for obtaining accurate boundary information, it has a few drawbacks. The digitization process is time-consuming and requires a significant number of resources. Additionally, it is less accurate compared to other methods. Moreover, if revisions are needed, repeating the digitization process becomes challenging (Enemark & Mclaren, 2017).

2.2 Fit For Purpose for Land Administration

Fit-for-purpose land administration refers to the design and implementation of land administration systems that are specifically tailored to meet the needs and challenges of a particular country or region (Mclaren et al., 2016). It emphasizes the importance of addressing current land issues effectively, rather than simply following advanced technical standards (Enemark & Mclaren, 2017). This approach recognizes that different contexts require different solutions and that land administration systems should be flexible and adaptable to local conditions (Barry, 2018).

According to Mclaren et al., 2016 the fit for purpose for land administration has three key components: spatial, legal, and institutional frameworks. These components of the framework are interconnected and create a conceptual nexus that is supported by the essential means of capacity development. It is important for each of the frameworks to be flexible enough to meet the varying needs of the country across different geographical, judicial, and administrative contexts (Enemark & Mclaren, 2017) .

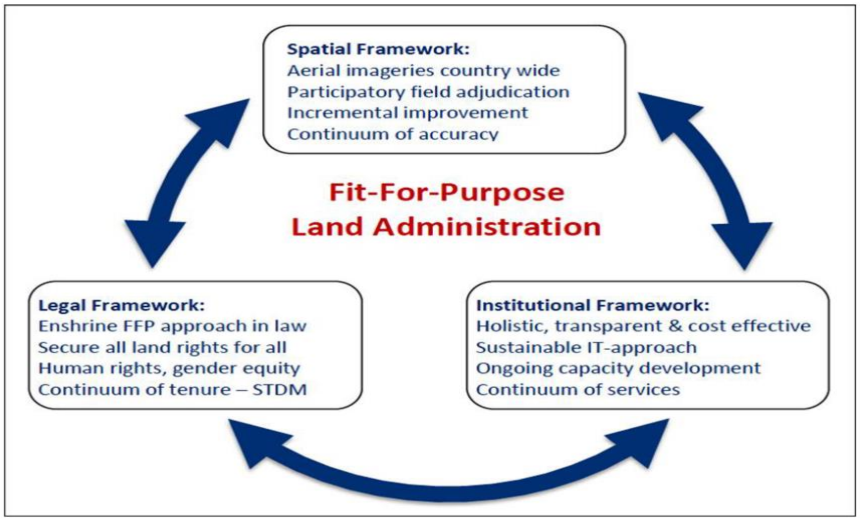

Figure 2-1 Fit-for-purpose land administration (Mclaren et al., 2016)

The spatial framework aims to represent how land is occupied and used. The representation's scale and accuracy should be sufficient to support the security of different legal rights and tenure forms, as well as the management of these rights and the use of land and natural resources through the institutional framework (Mclaren et al., 2016). Therefore, the FFP approach should be incorporated into land laws, and the institutional framework should be designed in an integrated, transparent, and user-friendly manner to administer this regulatory setup. To achieve this, reliable and up-to-date land information is necessary, which is provided through the spatial framework (Enemark & Mclaren, 2017).

The FFP concept encompasses a dynamic interaction among the spatial, legal, and institutional frameworks to achieve the overall land policy objectives and outcomes for society and communities. Each framework can be incrementally improved over time. These dependencies need to be carefully coordinated to ensure that the frameworks mutually reinforce each other (Mclaren et al., 2016).

The FFPLA executions and the implementation practice in Nepal are identified as the best practices, for it successfully executed the FFPLA fundamental framework key principles and satisfied the FELA pathway goals. The FFPLA implementations in Uganda, Mozambique, and Benin were also successful and possessed experiences that could be expanded to other countries (Metaferia et al., 2023). By leveraging the best practices and experiences from Nepal, Uganda, Mozambique, and Benin, Ethiopia can potentially strengthen its land administration system and work towards more effective, inclusive, and sustainable land governance. However, the adaptation process should be carefully tailored to the country's unique context and requirements.

2.3 Application of UAV Images in Cadastral Mapping

Unmanned aerial vehicle (UAV) platforms are being used to collect valuable data for various purposes such as surveillance, mapping, and inspection. They are now considered a cost-effective alternative to other aerial photogrammetry methods (Nex & Remondino, 2014). Unmanned aerial vehicles (UAVs) are becoming increasingly popular in remote sensing due to their ability to quickly and inexpensively collect high-resolution data for land administration. The high-resolution ortho-mosaics produced by UAVs are currently being used for boundary delineations in countries like Rwanda and Ethiopia (Crommelinck et al., 2016).

Different types of UAV platforms are currently being used for various purposes. These platforms can be categorized as fixed-wing, multirotor, or hybrid. These tools can be utilized to map extensive areas of land, spanning over 150 hectares. The boundaries can be digitized manually from orthophotos or automatically extracted (Blessing, 2022).

Figure 2-2 Types of Drones (source: inxee.com)

In addition, the use of UAV images in cadastral mapping has been explored in several studies (Eisenbeiss, 2011). Both found that UAVs can achieve high accuracy in mapping arable land, reporting a ground accuracy of 1.7 cm and a height accuracy of 0.6 cm. Crommelinck focused on the extraction of visible boundaries, with (Fetai et al., 2019) using high-resolution optical sensors on UAVs and achieving an 80% accuracy in boundary extraction and proposed a workflow for automatic boundary delineation from UAV data, which could potentially raise the efficiency of mapping procedures. These studies collectively demonstrate the potential of UAV images in Enhancing the precision and effectiveness of cadastral mapping.

2.4 Fully Automated Feature Extraction Using a Deep Learning Approach

Various researchers have utilized automatic feature extraction algorithms for a range of purposes, including road network extraction, river coastline extraction, the extraction of residential building roofs, and the delineation of valley boundaries are just a few examples of the numerous tasks involved in this project. One is Cadastral boundary extraction is a critical task in land administration and management. The advent of Unmanned Aerial Vehicle (UAV) technology has opened up new possibilities for accurate and efficient boundary extraction(Crommelinck et al., 2016). There are key findings and developments in using UAV images for cadastral boundary extraction. Here, some of the approaches developed for linear feature extraction are explained below the first study by (Fetai et al., 2019) shows a comparative study to evaluate different automated methods for cadastral boundary extraction using UAV images. They compared various algorithms such as edge detection, object-based classification, and machine learning techniques. The study concluded that machine learning algorithms, particularly deep learning models, show great potential in accurately extracting boundaries from UAV images. The other finding was made by (X. Xia, 2019). proposed a deep learning-based approach for automated cadastral boundary extraction from high-resolution UAV images. They utilized a fully convolutional network (FCN) trained on a large dataset of annotated images. The results depicted that the FCN model achieved higher accuracy compared to traditional methods, demonstrating the effectiveness of deep learning in boundary extraction. The other comparative study made by (Crommelinck et al., 2019) assesses different image analysis techniques for cadastral boundary extraction from UAV images. They compared traditional computer vision algorithms, machine learning methods, and deep learning approaches. The findings indicated that deep learning methods, particularly convolutional neural networks (CNNs), outperformed other techniques in terms of accuracy and efficiency.

The literature review demonstrates the growing interest in using UAV images for cadastral boundary extraction. Deep learning techniques, such as FCNs and CNNs, have shown superior performance compared to traditional methods. Integration of image segmentation, geometric algorithms, and contextual information has also contributed to improved extraction accuracy. However, several gaps exist. Firstly, there is a need for further research to evaluate the generalizability of these methods across different geographic areas and boundary types. Most studies have focused on specific case studies or limited regions, hindering the broader applicability of the proposed techniques. Additionally, the robustness of the models in handling various UAV image qualities, lighting conditions, and complex boundary shapes needs further investigation. Lastly, more research is required on the practical implementation and integration of these automated methods into existing land administration systems. The literature review highlights the advancements and potential of utilizing UAV images for automated cadastral boundary extraction. Deep learning techniques, particularly CNNs and FCNs, have shown promising results in achieving high accuracy. Integration of image analysis techniques and contextual information further improves extraction accuracy. This study is planned to see added values of automatic feature extraction algorithms from UAV images for cadastral general boundary mapping purposes. This is where the novelty of the study lies.

In conclusion, the semi-automated technique for cadastral boundary extraction using UAV images offers a timesaving, accurate, and efficient solution for land surveying. By combining the capabilities of UAVs and image-processing algorithms, this technique provides a versatile and accessible approach to extracting cadastral boundaries. With further advancements in technology and continued research, the potential for future developments in this field is promising.

2.4.1 The Bi-Directional Cascade Network of CNN

The BDCN model utilizes a cascade of convolutional layers that process the input image in both forward and backward directions (Zeng et al., 2016). This bi-directional approach allows the model to capture contextual information from multiple scales, leading to more accurate edge detection. It employs a bi-directional cascade structure. The model's ability to capture fine details and intricate structures in images is enhanced by this feature. This makes BDCN particularly suitable for parcel extraction, where precise boundary delineation is crucial (Zeng et al., 2016).

BDCN has demonstrated remarkable performance in parcel extraction tasks. Its ability to accurately detect edges and delineate boundaries makes it an invaluable tool for urban planners, agricultural analysts, and environmental scientists. By providing precise parcel boundaries, BDCN facilitates better decision-making and resource management (Zeng et al., 2016).

A range of studies have explored the use of bi-directional cascade networks in various applications. (Luo et al., 2021) proposed a bi-direction transformer network (BDTNet) for road extraction in remote sensing images, achieving high accuracy(Zhong et al., 2021) integrated a bi-directional feature pyramid network (BiFPN) into a cascade region-based CNN for live object tracking and detection, significantly improving performance. (Zeng et al., 2016) introduced a gated bi-directional CNN (GBD-Net) for object detection, which effectively integrated local and contextual visual cues. In addition (Hashmi et al., 2021) further improved the cascade network by incorporating a deformable composite backbone for detecting formulas in scanned document images. This enhancement has resulted in achieving state-of-the-art performance. These studies collectively demonstrate the potential of bi-directional cascade networks in various image-processing tasks (Xia et al., 2021).

2.4.2 The Holistically-Nested Edge Detection (HED) Model of CNN

The Holistically-Nested Edge Detection (HED) model is another state-of-the-art approach to edge detection. It employs a deep learning framework that integrates hierarchical features from multiple layers of a convolutional neural network (CNN) (Xia et al., 2015). This holistic approach enables HED to detect edges with high accuracy and robustness. Similar to BDCN, HED is trained in an end-to-end manner, optimizing all parameters simultaneously. This results in a cohesive model that performs well across various edge detection tasks (Zeng et al., 2016).

The Holistically-Nested Edge Detection (HED) model, developed by (Xie & Tu, 2015), is a significant advancement in edge detection, achieving high accuracy and speed. This model has inspired further research, such as the Dense Extreme Inception Network proposed by Poma in 2019 and Soria in 2020, which both show improvements in edge detection performance. The Holistically-Nested Edge Detection (HED) Model has been applied to various tasks, including parcel extraction. (Xie & Tu, 2015) used a high-resolution network and a farmland edge postprocessing method to achieve precise farmland edge detection. Similarly, (Xia et al., 2018.) proposed a method called a deep-edge guided approach to extract cropland parcels, with a specific focus on their boundaries. (Hong et al., 2021) developed a futures extraction algorithm for regularly arranged agricultural areas, achieving high correctness and completeness.

2.5 Conceptual Framework

Based on the literature sources mentioned above, it is clear that there is a significant research gap in the use of semi-automatic feature extraction, specifically deep learning methods, in conjunction with UAV images for cadastral mapping. Recognizing this gap and the importance of automatic feature extraction using deep learning techniques, this study aims to explore the role of deep learning approaches for automatic feature extraction in general cadastral boundary mapping. The primary objective of this research is to enhance understanding and provide comprehensive insights into the capabilities and limitations of automatic feature extraction using deep learning algorithms in cadastral mapping. By evaluating the performance and applicability of these methods, the study aims to contribute to the advancement of cadastral mapping practices.

To achieve this objective, the conceptual framework for this study consists of three key components. The first component is the literature review, which examines deep learning methods for feature extraction in various domains, analyzes the use of UAV images in cadastral mapping and their advantages, evaluates the fit-for-purpose spatial framework (FFP-LA) and its relevance to cadastral mapping, and discusses the cadastral boundary principle and its significance in parcel boundary delineation.

The second component is the methodological approach, which includes UAV image acquisition and preprocessing, selection of appropriate deep learning models for feature extraction, application of deep learning models to extract relevant features from UAV images, integration of the fit-for-purpose spatial framework (FFP-LA) and cadastral boundary mapping, and performance evaluation and analysis of the deep learning-based feature extraction techniques.

The third component is the expected outcomes of the study, which include enhanced understanding of the capabilities and limitations of deep learning-based feature extraction in cadastral mapping, insights into the integration of deep learning, the FFP-LA framework, and improved cadastral mapping practices, and contributions to the advancement of cadastral mapping through the application of innovative deep learning techniques.

By incorporating these key elements, this conceptual framework provides a comprehensive and balanced representation of the study. It addresses the gaps identified in the literature and aligns the methodological approach with the research objectives.

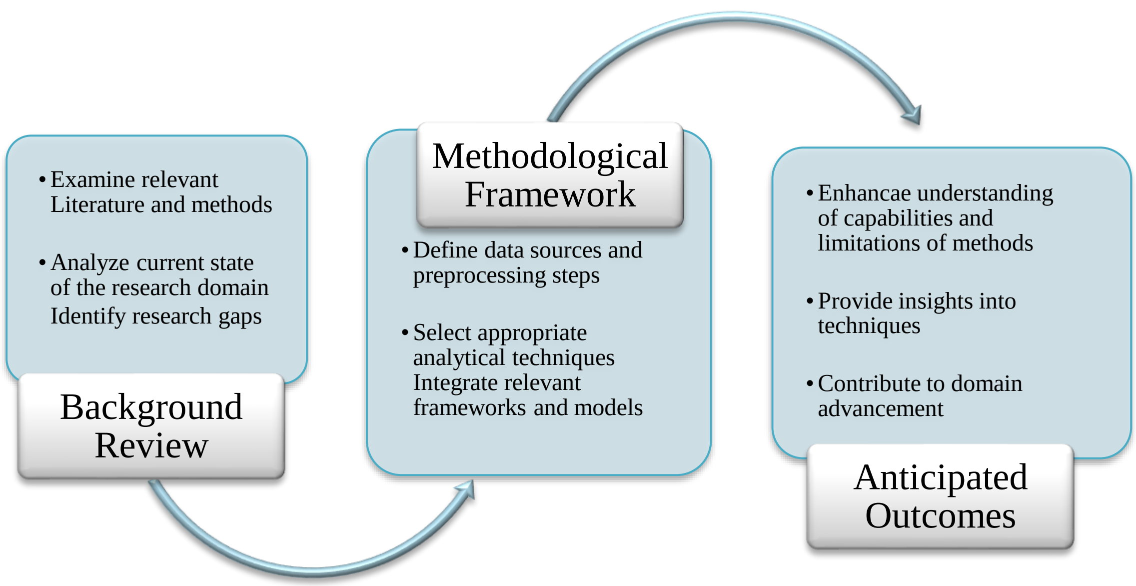

Figure 2-3 Conceptual framework

Chapter Three

3 Research Methodology

3.1 Description of the Study Area

The study was conducted in the Sodo Woreda, East of Central Ethiopia, specifically in, between Firsha keble and Bue town. Geographically, it lies between 8°26'5.6"N and 38°36'43.56"E, the area coverage is 487.81 ha. Sodo Woreda consists of 59 kebeles, with 54 being rural and 5 being urban. The administrative centers are Buee and Kella towns. Among these towns, Buee, Kella, Suten, and Tiya have access to electricity, while the remaining rural kebeles rely entirely on biomass energy, such as firewood and animal dung, for domestic fuel and lighting (Tadesse et al., 2020).

Approximately 85% of the people in the study area rely on crop-livestock mixed farming systems as their primary source of livelihood. Agriculture in the area is mainly rain-fed, but around 25% of farmers who live along the Meki River practice small-scale irrigation to grow vegetables for local markets. The majority of landholdings in Sodo are less than 2 hectares, with 53.1% of households owning 0.5-2 hectares and 25% owning less than 0.5 hectares. Additionally, 7.4% of households are reportedly landless (Berhanu, 2021). Crop and livestock production are closely integrated to generate income, mitigate environmental variability and risks, and meet household consumption needs. The major annual crops grown are Maize, Wheat, and Teff, while enset is a perennial staple crop. The outputs from these crops and livestock are primarily used for household consumption, with some being sold in markets to generate cash income. Wheat, teff, and maize are the main cash crops (Berhanu, 2021).

The selection of the study area is based on the availability of UAV images. In addition, the farm plot is small in size, and this helps to explore the applicability of automatic feature extraction.

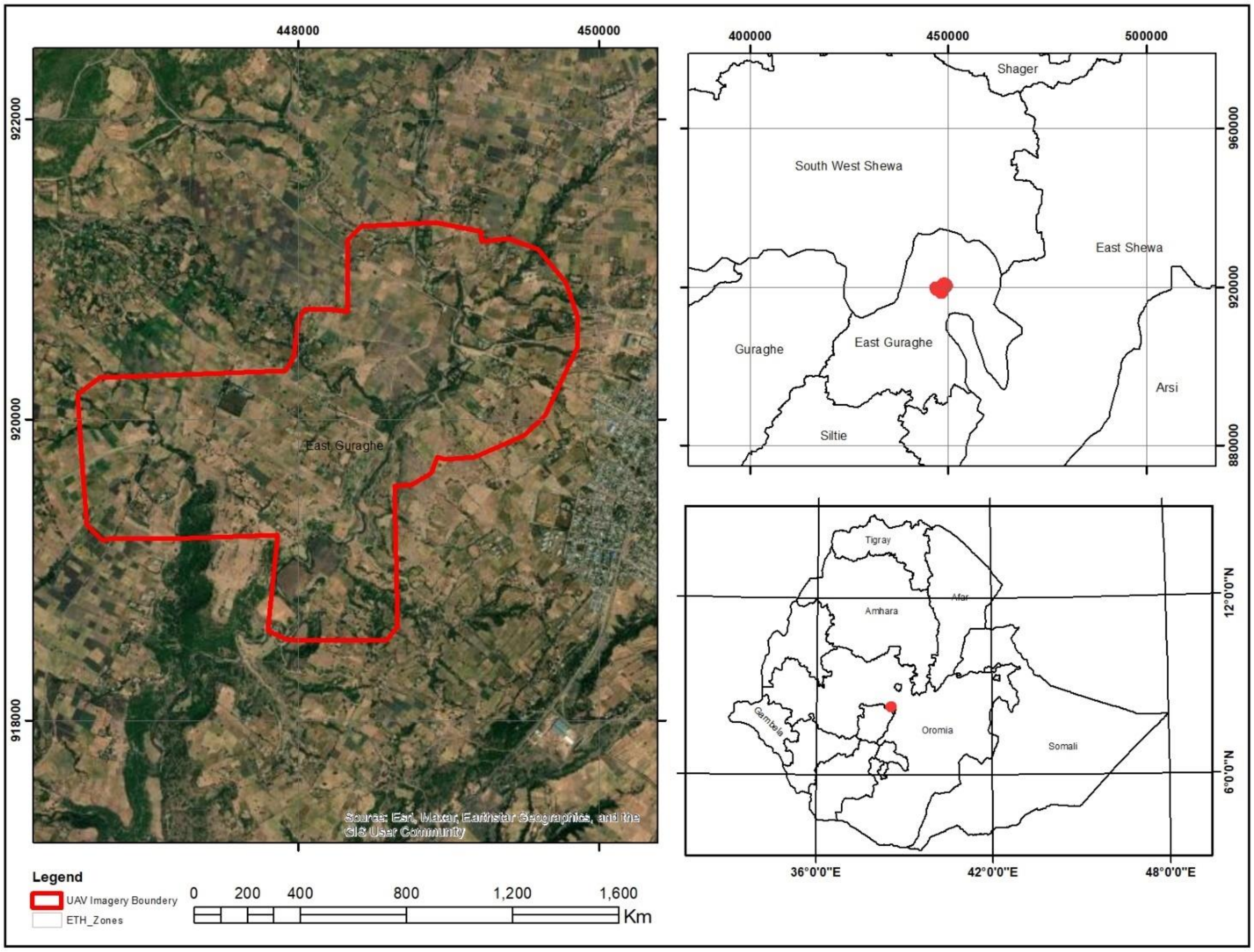

Figure 3-1 Location map of the study area.

3.2 Research Philosophy

3.2.1 Research Design

This study used a quantitative research design to develop and evaluate a deep learning model for automatically extracting features in cadastral boundary extraction. The research process consisted of the following:

To begin with, the research commences by conducting a literature review that is relevant to the objective. This review aids in identifying the most appropriate deep-learning architecture for the task of extracting cadastral boundaries.

The main reason for using the UAV imagery for this deep learning task is the availability and suitability of the data. Compared to other sources of remote sensing data, the UAV imagery stands out for being high-resolution, flexible, cost-effective, and temporally relevant. These qualities make it an excellent choice for performing deep learning-based parcel extraction. The level of detail and control over data acquisition the UAVs can greatly improve the performance and applicability of deep learning models used for this task.

. The image captured by the Space Star UAV is processed to create an orthorectified image. This process involves using 20 Ground Control Points (GCPs) to generate an accurate orthophoto and The Deep Learning (DL) model has been trained using the prepared UAV image through the image tiling technique. This technique involved dividing the images into smaller tiles, which were used as input for the DL model during the training process.

The third step involved conducting several experiments to determine the optimal hyperparameters for the model. These parameters were used to train the model, and a polygonization method was applied to extract the polygons in a vector format. The results of the model were evaluated using the accuracy assessment method.

Lastly, in the analysis part, the predicted polygons obtained from the UAV image were compared to assess their consistency and accuracy and validate the precision, recall, F1score, and IOU of extracted boundaries by overlaying them with the existing cadastral boundaries from the study area.

In summary, the research methodology of this study involved a systematic literature review, data preparation through orthorectification and tiling, model training with optimized hyperparameters, polygon extraction using BDCN and HED CNN model, and evaluation of the results by comparing predicted polygon from the UAV image and validated the correctness and completeness of extracted boundaries.

The detailed description of procedures followed during cadastral boundary extraction from UAV imagery is described as follows (Figure 5).

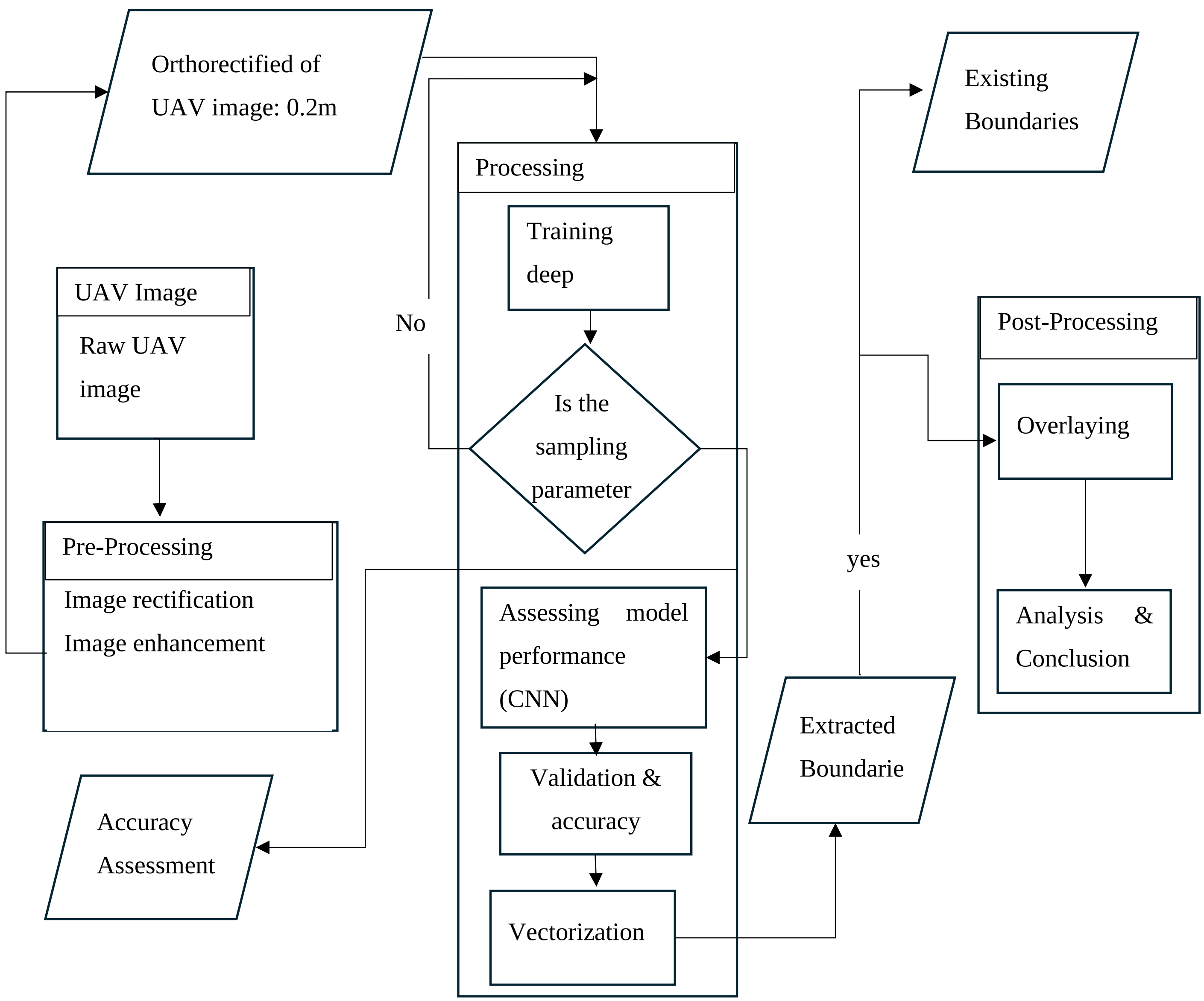

Figure 3-2 Research design workflow

3.2.2 Data Preparation

The UAV images used in this research were acquired by the Ethiopian Construction Design and Supervision Works Corporation (ECDSWC) by Space Star drone on January 15 2023 a flight altitude of 100 m in 80 percent overlap and 40 percent side lap A total of 1056 images were taken to cover the entire study area most of the land is covered by diverse farm parcels. The images were taken, under clear skies. The orthophoto process was carried out using PIX4D software using a distribution of 20 ground control points (GCPs).

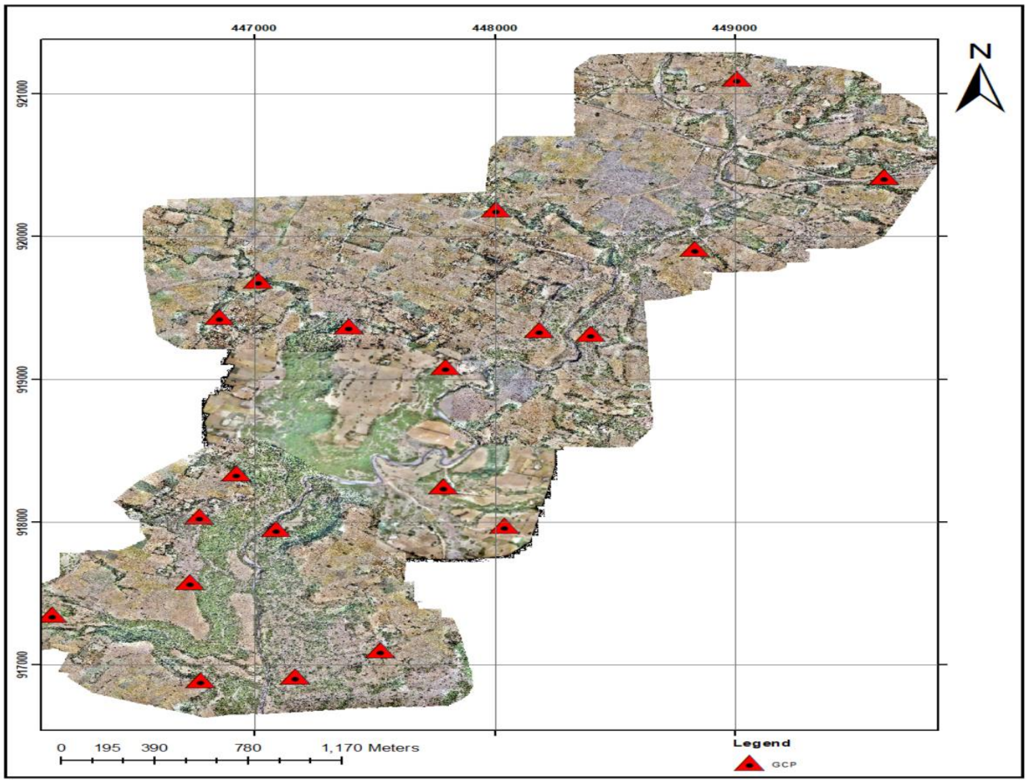

Figure 3-3 GCP point distribution over the project area

These orthophoto images have 3 bands (RGB). The spatial resolution was high-resolution (20 Cm by 20 cm) and contained cadastral boundaries and covered a diverse range of cadastral features. Considering the balance between accuracy and processing time and flight that took place following the farm harvest with the objective of establishing clear boundaries.

The digitized data was acquired by ECDSWC manual digitization. The reference data that has been obtained is in the form of polygons presented in a shapefile format, which depict land parcels. In order to train the deep learning model, these polygons are transformed into lines. Instead of directly rasterizing these lines, a buffer of 0.5 meters is applied on both the left and right sides to accurately detect the edge of the farm parcel. This is done by measuring the orthophoto and taking into account the average farm edge, which is approximately 1 meter in width.

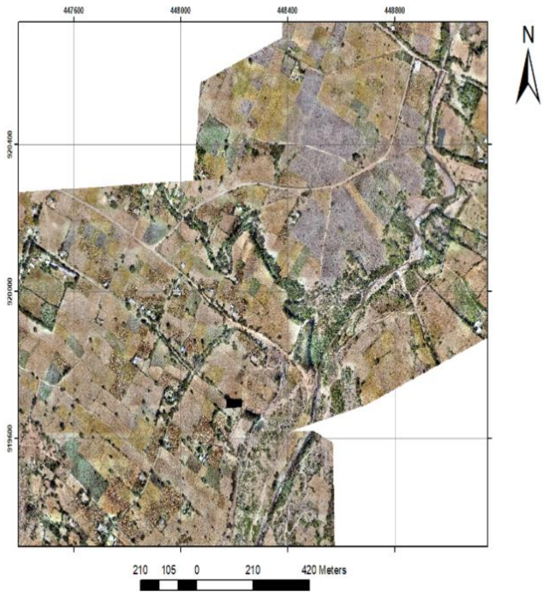

Figure 3-4 Orthophoto data set

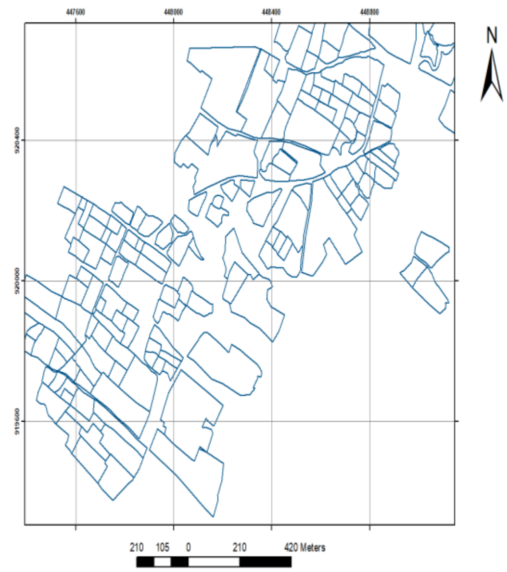

Figure 3-5 Digitized referenced dataset

3.2.3 Parcel Annotation:

High-quality image datasets are crucial for effective neural network training in the field of deep learning to comprehend segmented targets more effectively. So far there is a lack of publicly available semantic segmentation datasets for agricultural plots, as most existing datasets focus on road traffic, buildings, or natural scenes (Qi et al., 2024).To create ground truth data for training the BDCN and HED model, manually annotated the parcel boundaries in the images by using ArcGIS Pro3.02. Used a custom annotation tool that allowed them to edit Digitized referenced datasets. The annotations were carefully reviewed and cross-checked to ensure accuracy and consistency.

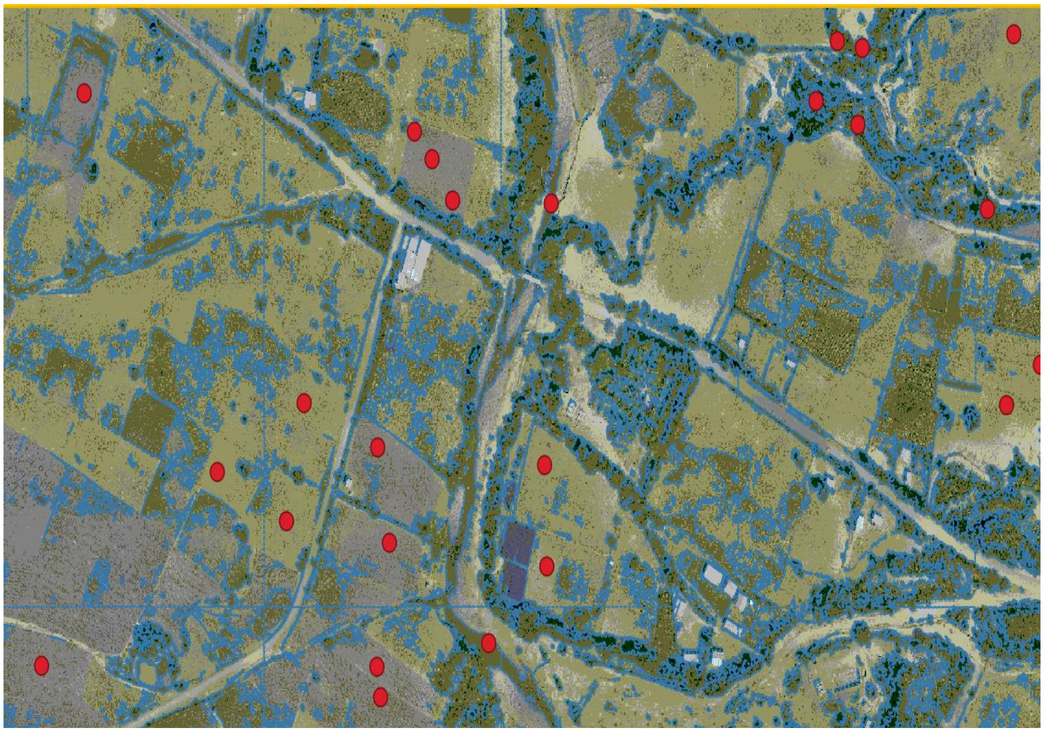

Figure 3-6 Parcel Annotation

3.2.4 Tile Preparation

In order to enhance the efficiency of the next processing step, it is crucial to consider the image size or tile size (Wudye, 2022). The study areas' UAV orthoimages are divided into 512 × 512-pixel tiles. In total, there were 595 original tiles, Label images, also known as ground truth images, were created for each UAV image. These label images were grayscale 512 × 512 × 1 in size and were generated from manually digitized reference boundaries, originally in vector format. To enhance generalization and increase the number of training samples, the reference boundaries were buffered to 50 cm and then rasterized using ARCGISPRO 3.02. The UAV tiles were also rotated, flipped, and scaled. This technique, called data augmentation in deep learning, is used to supplement the original training data. Rasterio is a popular Python library that integrated with ArcGIS API for reading and writing geospatial raster datasets, was used to manipulate raster data. It provides a simple and efficient way to manipulate raster data, Rasterio is built on top of the GDAL (Geospatial Data Abstraction Library) library, which gives it the capability to work with a wide range of raster file formats. Once the data preparation and augmentation were completed, the next step was to train the BDCN and HED models.

Figure 3-7 The Training set is paired with its corresponding ground truth labels.

3.2.5 Automation Process BDCN and HED models architecture-based CNN

After evaluating various CNN models, it has been determined that the BDCN and HED models are the most suitable for extracting farm parcels. According to Crommelinck In deep learning, CNNs can be trained in two approaches, from scratch or via transfer learning. Training a model from scratch for cadastral boundary extraction is a well-suited approach for working with specialized datasets and tasks. This involves preparing mask data and determining the optimal number of training epochs, as well as carefully tuning relevant hyperparameters (Dumoulin & Visin, 2016). The unique characteristics of land parcels and property boundaries may not be adequately represented in pre-trained models, making a from-scratch training strategy more appropriate (Crommelinck et al., 2019). By creating custom masks and having full control over the training process, it can tailor the model to the distinct nuances of cadastral data, potentially leading to higher accuracy in boundary detection (Crommelinck et al., 2019). While this method requires more computational resources and a larger, meticulously prepared dataset compared to transfer learning, the trade-off is the opportunity to develop a highly specialized and accurate model for the cadastral boundary extraction task at hand. In this study, the BDCN and HED models were trained from scratch using UAV imagery to capitalize on this advantage.

3.2.5.1 BDCN Model Architecture

The BDCN model utilizes a cascade of convolutional layers that process the input image in both forward and backward directions. This bi-directional approach allows the model to capture contextual information from multiple scales, leading to more accurate edge detection. It employs a bi-directional cascade structure that enhances the model's ability to capture fine details and intricate structures in images(Zeng et al., 2016).

These approaches promote the acquisition of multi-scale representations across various layers, allowing for the detection of well-defined edges corresponding to their respective scales. The model was trained using UAV data as input and manually digitized ground truth data as a mask.

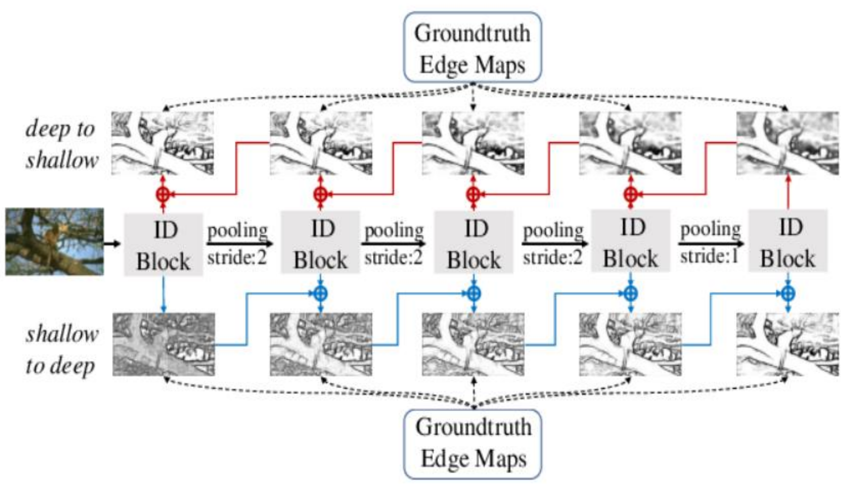

Figure 3-8 BDCN model architecture (source: semantic.scholar.org)

3.2.5.2 HED Model Architecture

The HED algorithm uses fully convolutional neural networks and deeply-supervised nets to predict images from images. It learns hierarchical representations with the help of deep supervision of side responses. This approach is effective in dealing with the difficulty of detecting edges and object boundaries accurately. It tackles two key challenges in edge detection: holistic training and prediction of images, as well as learning features at multiple scales and levels(Xie & Tu, 2015).

The model was trained using UAV data as input and manually digitized ground truth data as a mask.

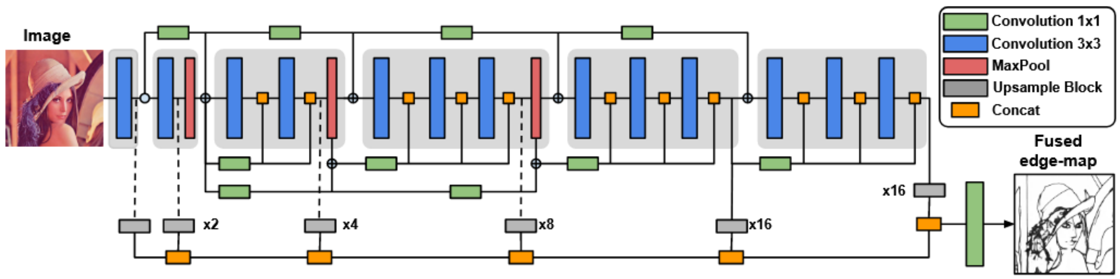

Figure 3-9 HED model architecture (source: semantic.scholar.org)

3.2.6 Polygonization Method

Considering the various methods available for polygonization, geospatial techniques this is convert rasterized edge detection results into vector polygons. after that simplifies polygon outlines by removing unnecessary vertices, while still preserving the essential shape and simplifies the boundary or footprint of building polygons, while maintaining their essential shape and size. These techniques accurately identify the boundaries of farm parcels and generate polygons based on these detected boundaries.

3.2.7 Accuracy Assessment

The accuracy assessment in this study investigates two aspects these are the evaluation of the BDCN and HED model and the evaluation of the detection quality of the visible land boundaries for the test UAV data.

Table 3-1 displays the confusion matrix, which contains the values for true positive (TP), true negative (TN), false positive (FP), and false negative (FN). This matrix is used to assess the detection quality of the visible land boundaries.

Table 3-1 Confusion matrix

Ground Truth			
		Boundary	No Boundary
Prediction	Boundary	TP	FP
	No boundary	FN	TN

The accuracy of detecting visible land boundaries was evaluated by calculating the F1 score using the confusion matrix. The F1 score, obtained from the test UAV data, represents the combined measure of recall and precision (Equations (2) and (3)). Higher values indicate a higher level of accuracy.

Equation (1) Recall $\text{Recall} = \frac{\text{TP}}{\text{TP+FN}}$

Equation (2) Precision $\text{precision} = \frac{\text{TP}}{\text{TP + FP}}$

The recall is determined by dividing the number of accurately predicted visible boundaries by the total number of reference cadastral boundaries.

Precision, on the other hand, is considered by dividing the number of correctly predicted visible boundaries by the total number of predicted positive visible boundaries. The F1 score includes precision and recall, and it is calculated using the following equation: Equation (4)

$$\text{F1 score1 score} = 2 * \frac{\text{recall * precision}}{\text{recall + Precision}}$$

Equation (3) F1 score

The other measurement is **Intersection over Union (IoU)**: The IoU dealings the degree of overlap between the predicted segmentation and the ground truth segmentation. Given a prediction mask area of overlap and the reference data mask area of union, the IoU is simply calculated as:

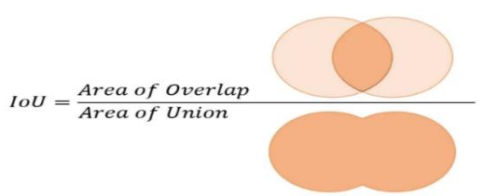

Figure 3-10 IoU formula (source medium.com)

The overall methodology described in Figure 3-11 appears to be a process for training and evaluating a CNN model to predict visible cadastral land boundaries using UAV imagery. Moreover, it provides a clear overview of the end-to-end methodology used in this study, outlining the key processing steps and model evaluation components.

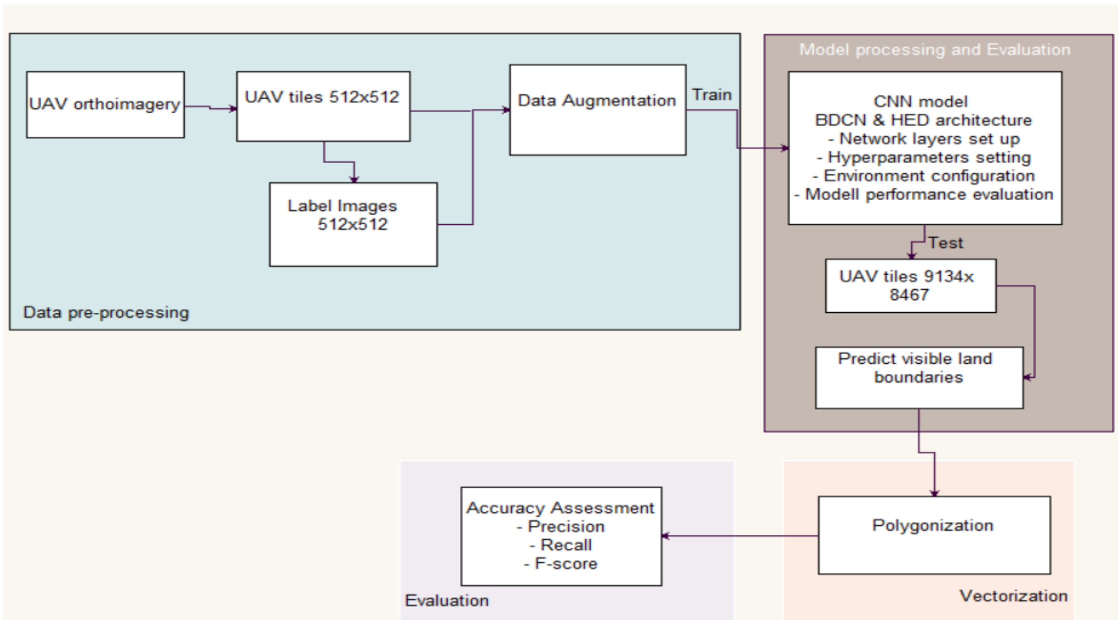

Figure 3-11 Overall methodology

Chapter Four

4 Results and Discussion

4.1 Models’ Performance

Edge detection is a well-known problem in computer vision, and various algorithms have been developed to address it. These algorithms differ in their success rates and often utilize established filters or operators. One popular technique is Canny Edge Detection, which involves multiple stages such as Gaussian blurring, gradient filtering, and non-maxima suppression (Canny, 1986). Additionally, some techniques rely on manually crafted features to detect edges(Xie & Tu, 2015). In Wassi's study, he found that applying Canny Edge Detection to satellite images yielded an overall accuracy of 19.47 Based on his findings, he decided to use mean shift segmentation and Leilei Xu Using a single-task edge semantic segmentation model, the edge features of farmland performs 11.31% and 11.72% on two study area the result in terms of IoU. However, more recent algorithms like Structured Forest for Fast Edge Detection have gained popularity. These algorithms combine machine learning with hand-crafted features, resulting in higher accuracy and faster processing speeds compared to previous methods(Xie & Tu, 2015). In recent years, with advancements in deep learning, many CNN-based models have been developed to solve edge detection problems. Yusen Xie used LinkNet and D-LinkNet to use a deep learning model that is optimal in all indicators, with IoU and F1 scores obtaining 0.7398 and 0.8505, respectively. When employing these deep learning models, edge detection can be considered a special case of pixel classification. This study explores the promising results of BDCN and HED models, which will be further discussed. However, Before running models, there are several important considerations to keep in mind. These are model selection, choice of architecture, computational performance, and time. By considering the BDCN and HED models selected for this study, the performance and result are presented in Table 4-1.

Table 4-1 Models Performance

Types of the model	Backbone model	Learning rate	Number of epochs	Batch size	Data augmentation	Accuracy of the model
BDCN	vgg11_batch normalized	'2.29e-03', '	20	8	On the Testing process	8.11
HED	vgg11_batch normalized	3.02e-04	20 it stops learning in 14	8	On the Testing process	8.28

The table presents a comparison of the performance of the BDCN and HED models on a cadastre-related task. According to (Thakkar et al., 2018). batch normalization has been proven to enhance the performance of deep learning models, especially those utilizing the VGG architecture. Therefore, this study adopts the vgg11_batch_normalized backbone architecture for both models. Various options were tested, but ultimately the vgg11_batch_normalized model was selected due to its superior results compared to Resnet34 and ImageNet. Whereas both models differ in their learning rates, number of epochs, and data augmentation strategies. The BDCN model has a relatively high learning rate of '2.2909e-03' and achieves an accuracy of 8.11 after training for 20 epochs with a batch size of 8 and applying data augmentation during the testing process. In contrast, the HED model has a lower learning rate of '3.0200e-04' and achieves a slightly higher accuracy of 8.28, also after 20 epochs of training with a batch size of 8 and data augmentation applied during testing. Interestingly, the HED model stops learning after 14 epochs, suggesting that it may have reached a limit in its training. Overall, the HED model appears to perform marginally better than the BDCN model for this particular task, perhaps benefiting from the lower learning rate that helped the model converge more effectively. However, the performance difference is relatively small, and further experimentation with different hyperparameters could potentially lead to even better results for both models. (Bar 2022) proposed a method for predicting the performance of semantic segmentation, which could be useful for comparing ground truth and prediction images. The following figure shows side-by-side, BDCN and HED models.

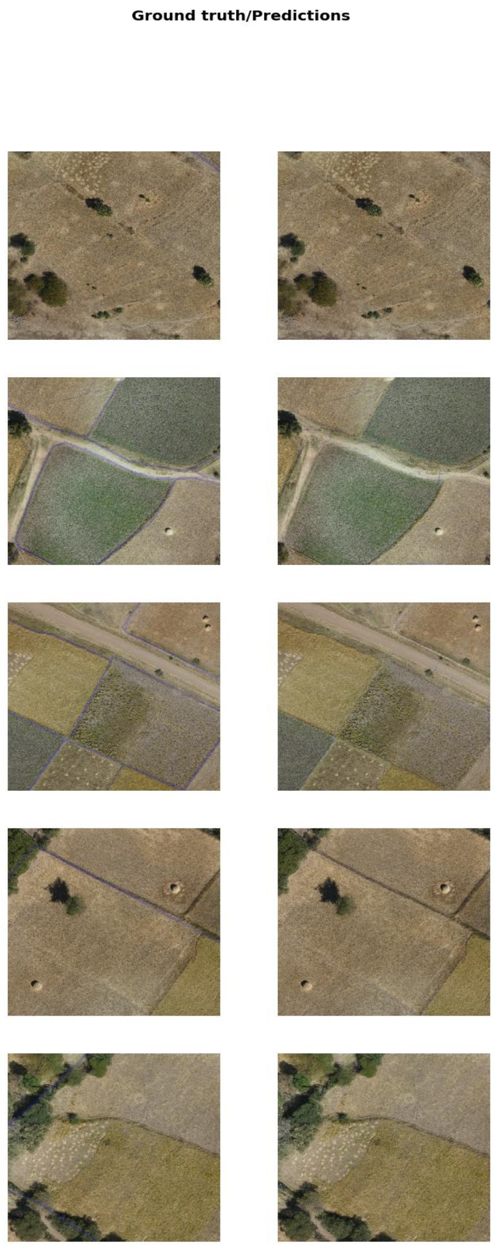

Figure 4-1 Ground truth with predication BCDN model

Figure 4-2 Ground truth with predication HED model

In the "Ground truth/Predictions" section, the left column shows the ground truth images, while the right column displays the predictions made by the models.

The BDCN model appears to capture the general layout and structures in the images quite well, with its predictions closely matching the ground truth. The model seems to accurately identify the roads, fields, and other features in the landscape. However, there are some instances where the BDCN model's predictions deviate slightly from the ground truth, such as in the fourth row, where the predicted image does not fully align with the ground truth. On the other hand, the

HED model's predictions demonstrate a more precise alignment with the ground truth across the majority of the images. The model's predictions closely match the shape, size, and placement of the various elements in the landscape, such as the roads, fields, and buildings. This suggests that the HED model may have a more accurate and detailed understanding of the spatial features in the images compared to the BDCN model.

Overall, both the BDCN and HED models show impressive performance in predicting the ground truth, with the HED model appearing to have a slight edge in terms of the accuracy and precision of its predictions. This comparison provides valuable insights into the respective strengths and capabilities of these two models in the context of UAV image analysis and understanding.

4.2 Training loss and Validation loss

In parcel extraction, training loss, and validation loss are important metrics used to assess the performance of a machine-learning model. These metrics provide to understanding of how well the model is learning from the training data and how well it simplifies to unseen data (Zhong et al., 2020). Training loss refers to the error or discrepancy between the predicted outputs and the actual outputs of the model during training. It quantifies how accurately the model fits the training data. On the other hand, validation loss measures the error on a separate validation dataset that the model has not encountered during training. It provides an estimation of the model's performance

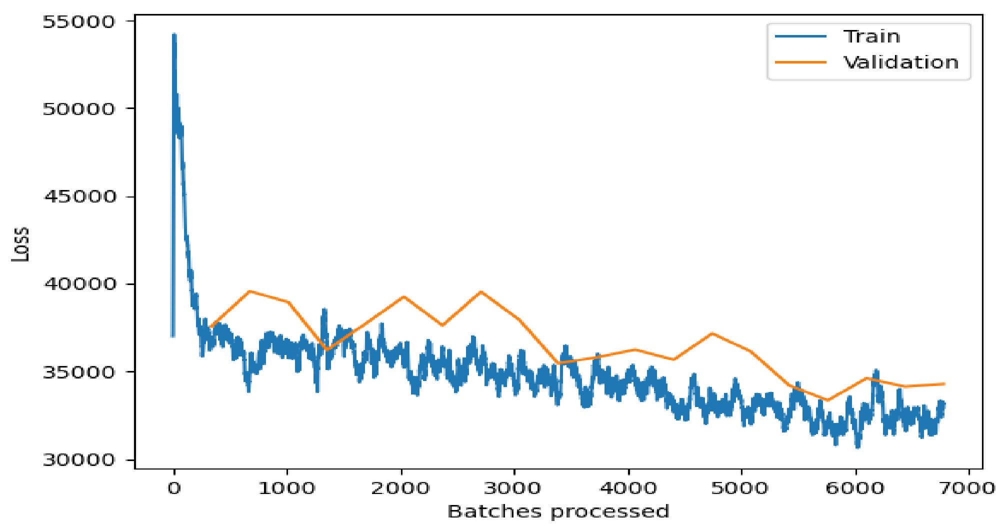

Figure 4-3 BDCN Model result

on new, unseen `data. Monitoring both training loss and validation loss is a common practice during the training process to evaluate the model's performance.

The graph displays the results of the BDCN Model. The blue line represents the training loss, while the orange line represents the validation loss. Initially, both the train and validation loss values are relatively high, indicating poor initial learning of the model. However, as the number of epochs and batches increases, the training loss significantly decreases, suggesting that the model is effectively learning to fit the training data.

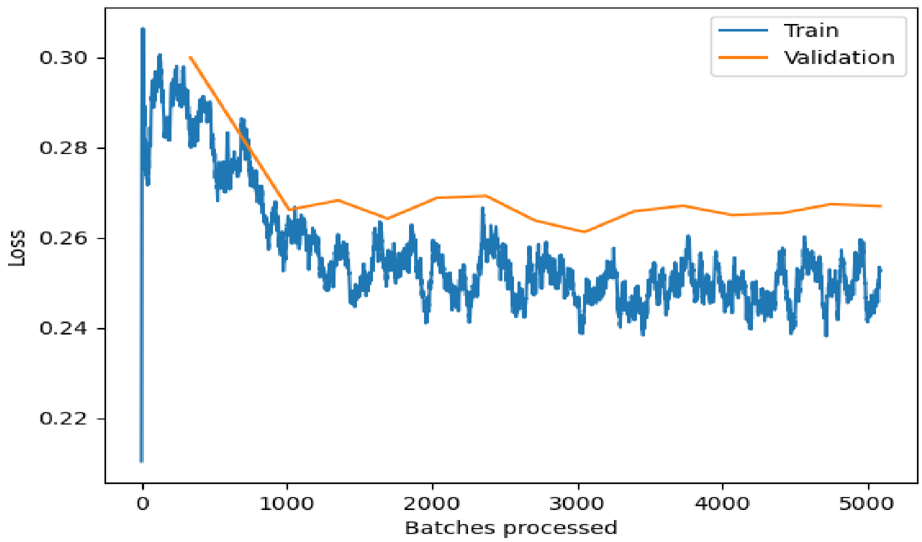

Figure 4-4 HED Model result

The graph illustrates the HED model, with the blue line representing the training loss and the orange line representing the validation loss. Initially, the training and validation loss curves start to converge, indicating a balance between fitting the training data and generalizing it to the validation data. As the training process nears its end, the training and validation loss values stabilize, suggesting that further training may not greatly enhance performance. To enhance the results, post-processing should involve data augmentation.

4.3 Training Epoch

Epoch refers to a complete pass of the entire training dataset through the neural network(Hong et al., 2021). The number of epochs is a crucial hyperparameter that determines how many times the neural network will encounter the entire training dataset during the training process.

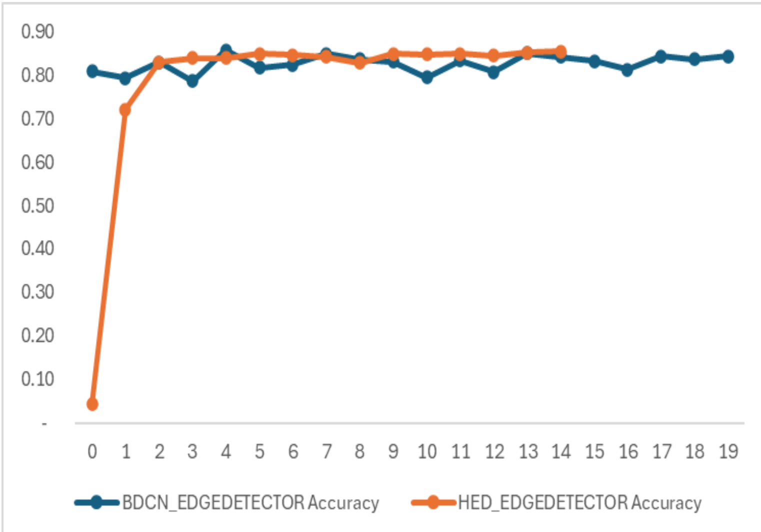

Figure 4-5 BDCN and HED training epoch

The graph displays the epoch number on the X-axis and the accuracy of the model on the Y-axis. BDCN and HED Models, over the course of 20 epochs. Both models demonstrate good edge detection performance, with the HED model showing consistently higher accuracy throughout the training process compared to the BDCN model. The BDCN model, however, shows a clear trend of improving accuracy over the training epochs, indicating that it is effectively learning to detect edges in the data. The HED model stops learning in 14 epochs and does not show any further improvement, indicating it may have reached the limits of its learning capacity. Whereas BDCN didn’t stop learning.

4.4 Accuracy Assessment

This study evaluates the accuracy of the BDCN and HED models in detecting visible land boundaries for UAV data. The accuracy assessment is based on metrics such as precision, recall, F1 score average precision, and overall IOU. These statistical metrics are used to assess the accuracy and performance of machine learning models.

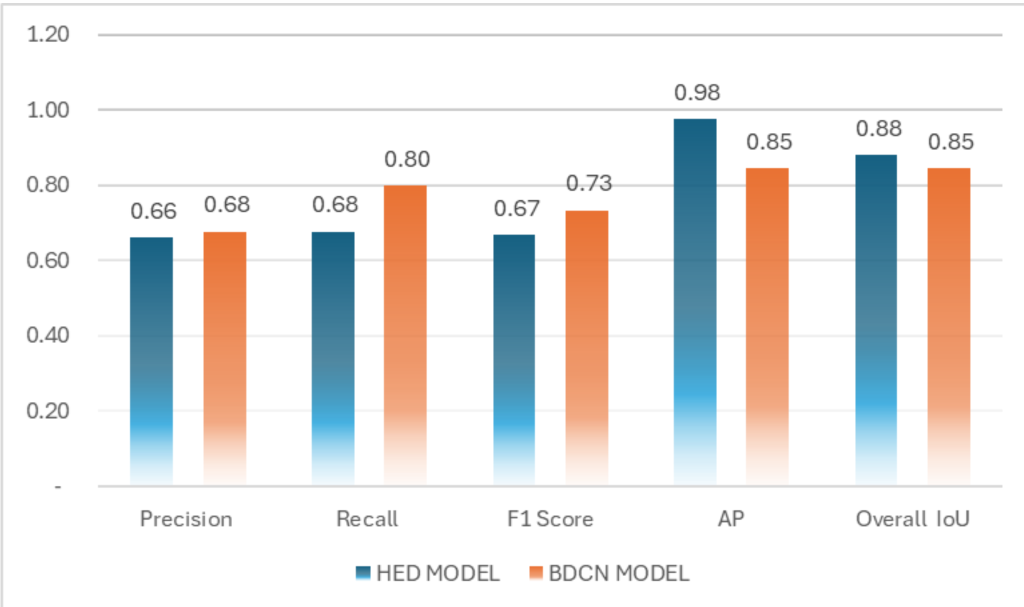

Figure 4-6 Accuracy of the BDCN and HED model

When comparing the performance of the two models, the key observations are: The BDCN model achieved an average precision of 0.68, meaning that 68% of the boundaries it extracted were correct. This indicates that the model accurately identified the boundaries in the UAV imagery. A higher precision score suggests a lower rate of false positives, meaning it is less likely to mistakenly identify non-boundary areas as boundaries. Additionally, the BDCN model had a recall of 0.80, measuring its ability to correctly identify actual boundaries in the dataset. It successfully identified 80% of the true boundaries. A higher recall score indicates a lower rate of false negatives, meaning it is less likely to miss actual boundaries.

The F-score of 0.73 provides a balanced evaluation of the BDCN model's performance, considering both precision and recall. It is calculated using the harmonic mean of precision and recall, giving equal weight to both measures. A higher F-score indicates a better balance between precision and recall.

Moving on to the HED model, it achieved an average precision of 0.66, slightly lower than the BDCN model. However, it still demonstrates a high level of accuracy in identifying boundaries in the rural cadaster. The HED model had a recall of 0.68, correctly identifying 68% of the actual boundaries. The F-score of 0.67 suggests a balanced performance similar to the BDCN model.

In terms of Intersection over Union (IoU), the BDCN model achieved an average of 0.85, while the HED model achieved an average of 0.88. IoU measures the overlap between the predicted boundary and the ground truth boundary. A higher IoU indicates a better alignment between the predicted and actual boundaries. Both models achieved high IoU scores, indicating their ability to accurately capture the boundary area.

According to Maxwell et al. (2021), who conducted a comprehensive review of over 100 papers on deep learning applications in remote sensing, certain performance metrics emerge as common benchmarks in binary classification studies. The review established average ranges for key metrics:

Recall: 71%

Precision: 61%

F1 score: reported in 59% of studies

Intersection over Union (IoU): often around 0.65

This study compares the performance of two prominent models, the Bi-Directional Cascade Network (BDCN) and Holistically-Nested Edge Detection (HED), against these benchmarks. Both models demonstrated strong performance, particularly in IoU, with BDCN and HED achieving 0.85 and 0.88 respectively, surpassing the average. In terms of recall, BDCN outperformed the average with 0.80, while HED fell slightly below at 0.68. Both models exceeded the average F1 score, with BDCN reaching 0.73 and HED 0.67. Overall, the BDCN model consistently performed above average across all metrics, while the HED model excelled in IoU and F1 score but showed room for improvement in recall.

Overall, the BDCN model consistently outperformed the established benchmarks across all the evaluated metrics, making it a particularly promising choice for cadastral boundary extraction tasks. The HED model also showed strong performance, especially in IoU and F1 score, but may benefit from further enhancements to improve its recall. These findings highlight the potential of deep learning techniques, such as BDCN and HED, to drive advancements in cadastral mapping and land management applications within the remote sensing domain.

4.5 Geometrical Comparison

One of the validations for automatic parcel extraction is comparing with reference data in terms of area coverage which indicates the data correctness and completeness. Randomly 20 parcels were selected based on their shape and completeness in the three data sets.

Table 4-2 Comparison of area coverage

No	DIGITIZE	HED	Dizitize-HED	BDCN	Dizitize-BDCN
1	5,492.17	5,208.73	283.44	5,150.85	341.32
2	9,997.41	9,736.55	260.87	9,216.08	781.33
3	9,512.66	8,860.68	651.99	8,951.55	561.11
4	3,380.84	3,169.28	211.55	3,081.47	299.37
5	2,723.03	2,382.89	340.14	2,422.55	300.48
6	2,592.31	2,217.46	374.85	2,192.27	400.03
7	13,383.08	12,582.48	800.60	12,724.81	658.28
8	12,614.26	11,855.35	758.91	11,881.42	732.84
9	1,427.04	1,196.90	230.14	1,237.25	189.79
10	1,716.33	1,312.00	404.32	1,408.39	307.94
11	3,218.07	3,093.67	124.40	3,014.47	203.60
12	5,157.80	4,564.13	593.67	4,653.23	504.57
13	4,994.30	5,273.81	-279.51	5,541.31	-547.00
14	7,475.63	7,475.63	-	7,011.18	464.45
15	2,825.80	2,521.01	304.79	2,462.62	363.18
16	21,074.02	20,174.70	899.32	20,184.98	889.04
17	7,067.86	6,693.55	374.31	6,483.89	583.97
18	3,015.87	2,889.80	126.07	2,790.72	225.15
19	905.23	754.10	151.13	815.25	89.98
20	6,997.64	6,771.01	226.63	6,949.30	48.34
Average Differennce HED 341.88 m2				Average Differenc BDCN 369.89m2	

The table compares the results of the two models with the reference digitized data. When evaluating the effectiveness of models for land administration purposes, it is important to consider the Fit for Purpose (FFP) rule. According to the International Association of Assessing Officers (IAAO, 2015), in urban areas, the horizontal spatial accuracy for cadastral maps is typically 0.3 meters or less, while in rural areas, an accuracy of 2.4 meters is considered sufficient. In an urban environment, accuracies of 1 foot or less (0.30 meters) are usually desired or necessary, whereas in rural areas, it may be sufficient to specify an accuracy of 8 feet (2.4 meters). However, the FFP approach promotes flexibility in terms of accuracy to better meet social needs (Crommelinck et al., 2016).

The comparison of the BDCN and HED model results with the digitized reference data provides interesting insights regarding their effectiveness for fit-for-purpose cadastral mapping. The minimum area coverage difference between BDCN and digitized is 48.34 m2, the maximum is 781.34 m2, and the average difference in 20 parcels is 369.89 m2. In contrast, the HED model has a minimum area coverage difference of 124 m2, a maximum of 899 m2, and an average difference of 341.88 m2 when compared to the digitized reference. The lower minimum difference for the BDCN model suggests its ability to accurately capture parcel boundaries in certain cases, which is crucial for fit-for-purpose land administration. On the other hand, the smaller overall average difference for the HED model indicates that it may have better overall performance in aligning the extracted parcel areas with the digitized reference.

4.6 Qualitative Analysis

To further assess the model's effectiveness, it is recommended to evaluate its performance on a separate test set or real-world data to ensure that it can make accurate predictions in practical scenarios. By using the test data, the deep learning models can predict and extract the cadastral features that they have learned during the training phase.

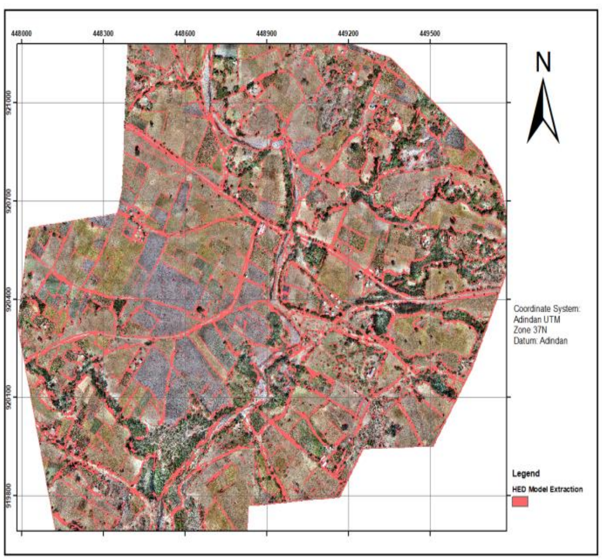

Figure 4-7 HED model extraction

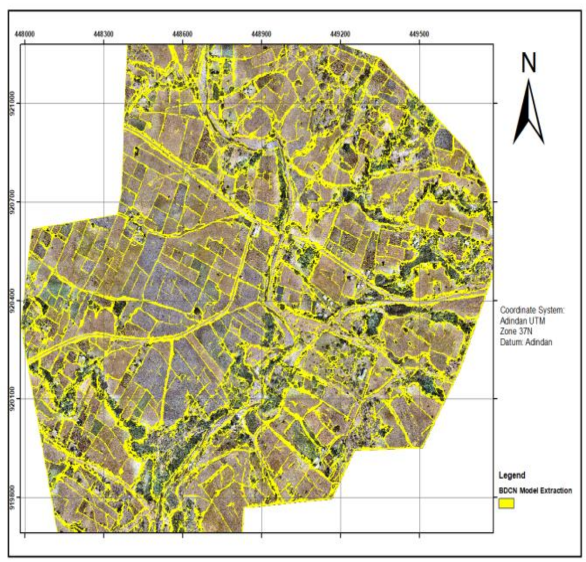

Figure 4-8 BDCN model extraction

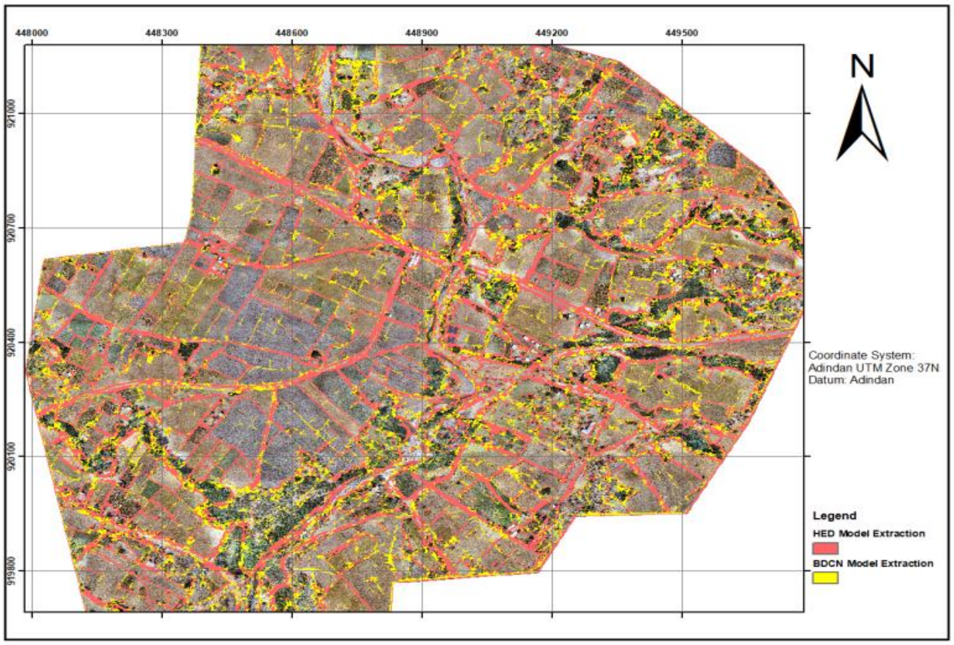

Figure 4-9 BDCN and HED model Extraction overlay

Figures 4-7, the HED, Figure 4-8, the BDCN model predicted on test data, and Figure 4-9, the overlay of extraction both result in the BDCN and HED model.

Figure 4-9 shows the predicted edges for both models on a test image. The BDCN model prediction is shown in yellow, while the HED model prediction is shown in red. As the figure shows, the BDCN model has identified more detailed edge features compared to the HED model. The BDCN model prediction is more comprehensive, with more edges detected, especially in the areas of the image with complex structures. The HED model, on the other hand, has detected fewer edges, and the edges it has detected are less detailed and sparser but in terms of finding the real edge is better. The overlay of the two models' predictions, shown in the bottom-right corner of the figure, highlights the differences between the two models. The yellow areas indicate where the BDCN model has detected edges that the HED model has not, As the overlay shows, the BDCN model has detected more edges in the image, especially in the areas with complex structures.

Figures 4-10, Figure 4-11, and Figure 4-12 present a comparison of manual digitization and automated feature extraction using the HED and BDCN models. Based on visual inspection, it can be observed that the delineation of parcels shows similarity between the digitized and extracted boundaries. The results indicate that the automated approaches provide reliable outcomes in terms of accurately demarcating the boundaries of most parcels.

Figure 4-10 Overview Digitized Parcels

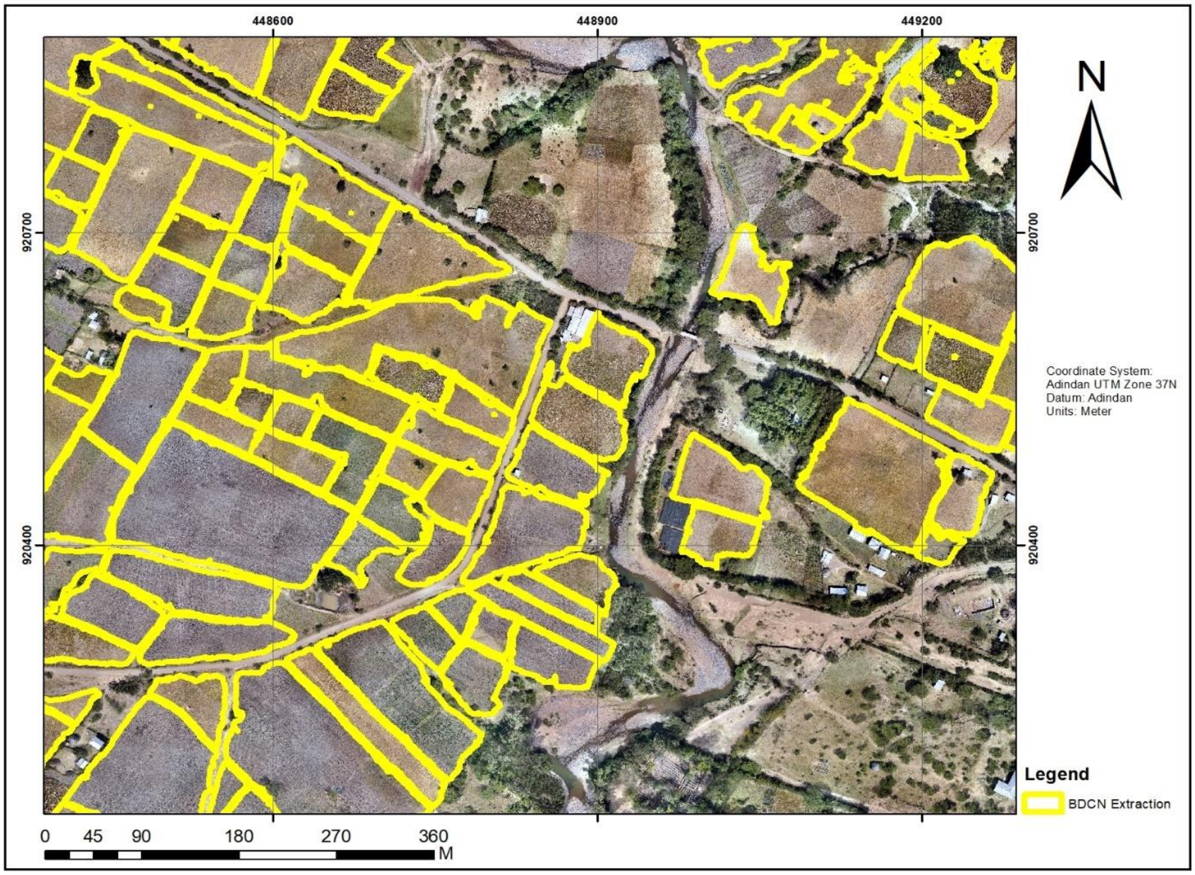

Figure 4-11 Overview of BDCN automatic parcels extraction

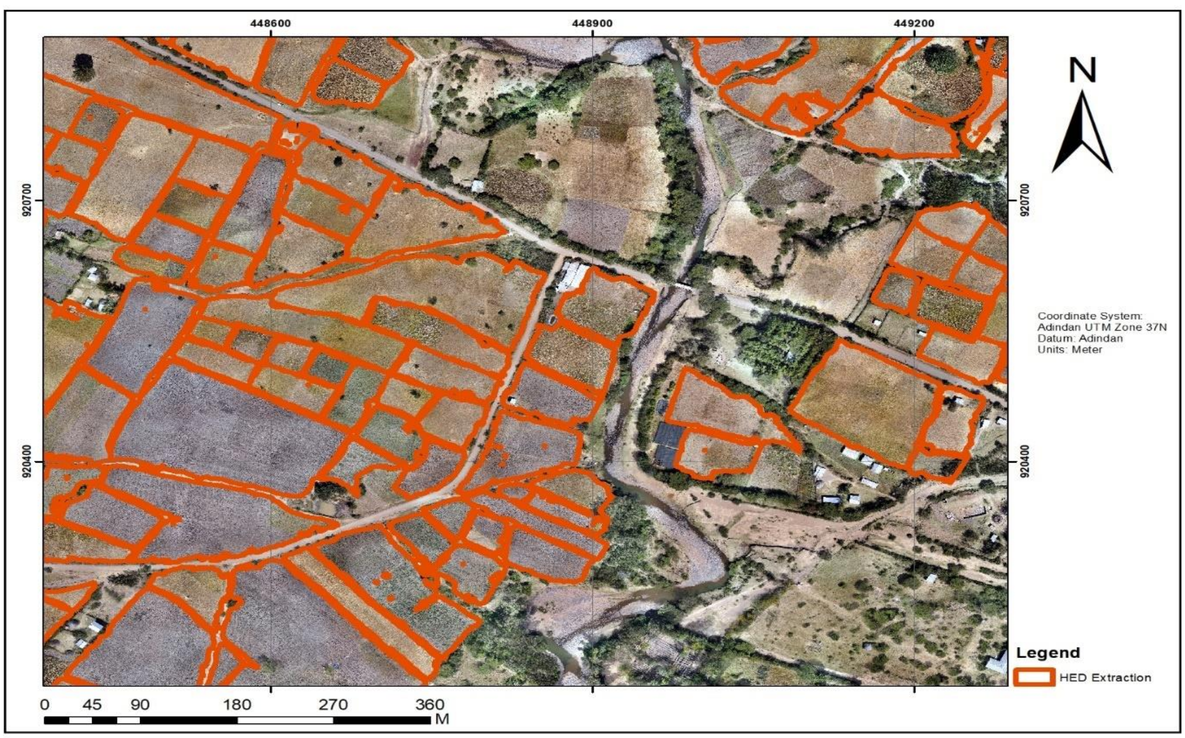

Figure 4-12 Overview of HED automatic parcels extraction

Figure 4-13 shows the manually digitized parcels, while Figures 4-14 and 4-15 depict the parcel boundaries extracted using the BDCN and HED models, respectively. The high level of alignment between the automated extractions and the manual digitization suggests that the developed models are effective in accurately capturing individual parcels, even at the single parcel level.

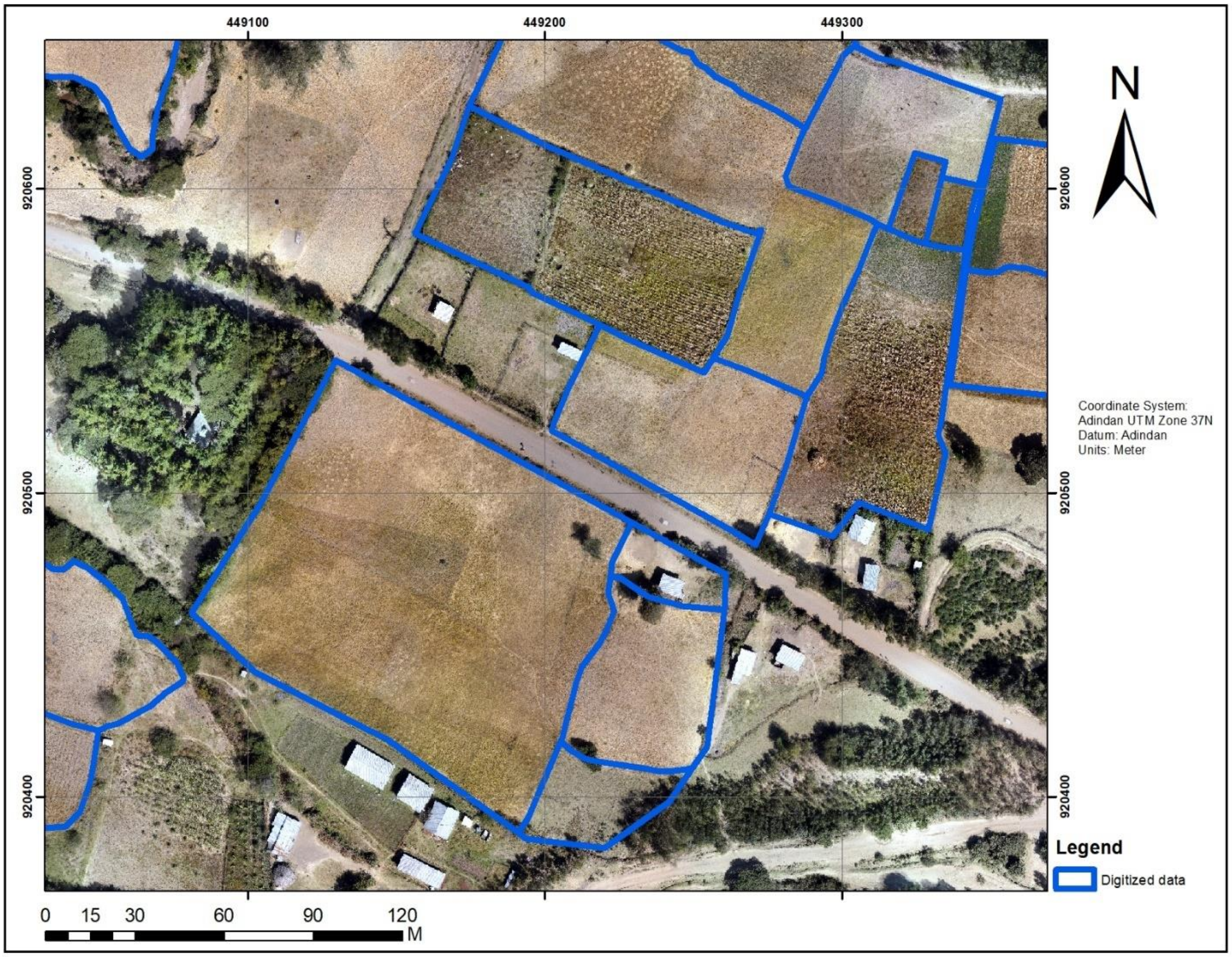

Figure 4-13 Digitized parcels

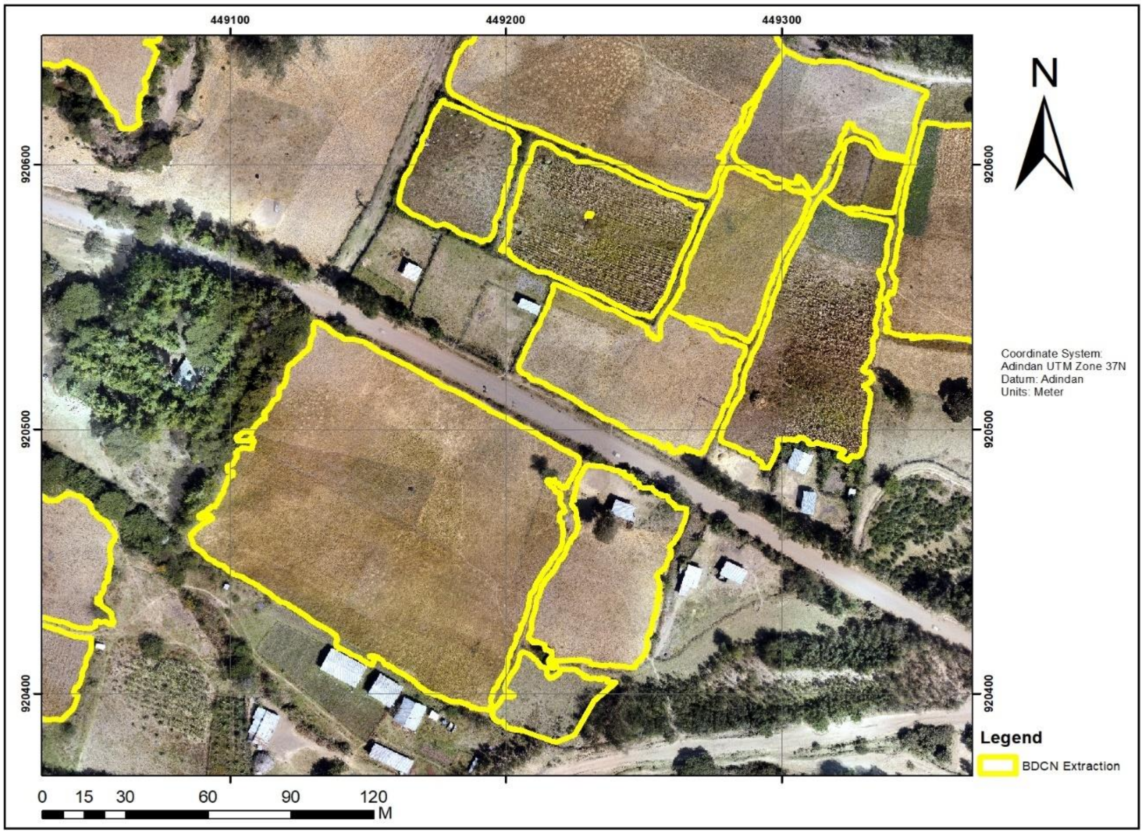

Figure 4-14 BCDN model extraction

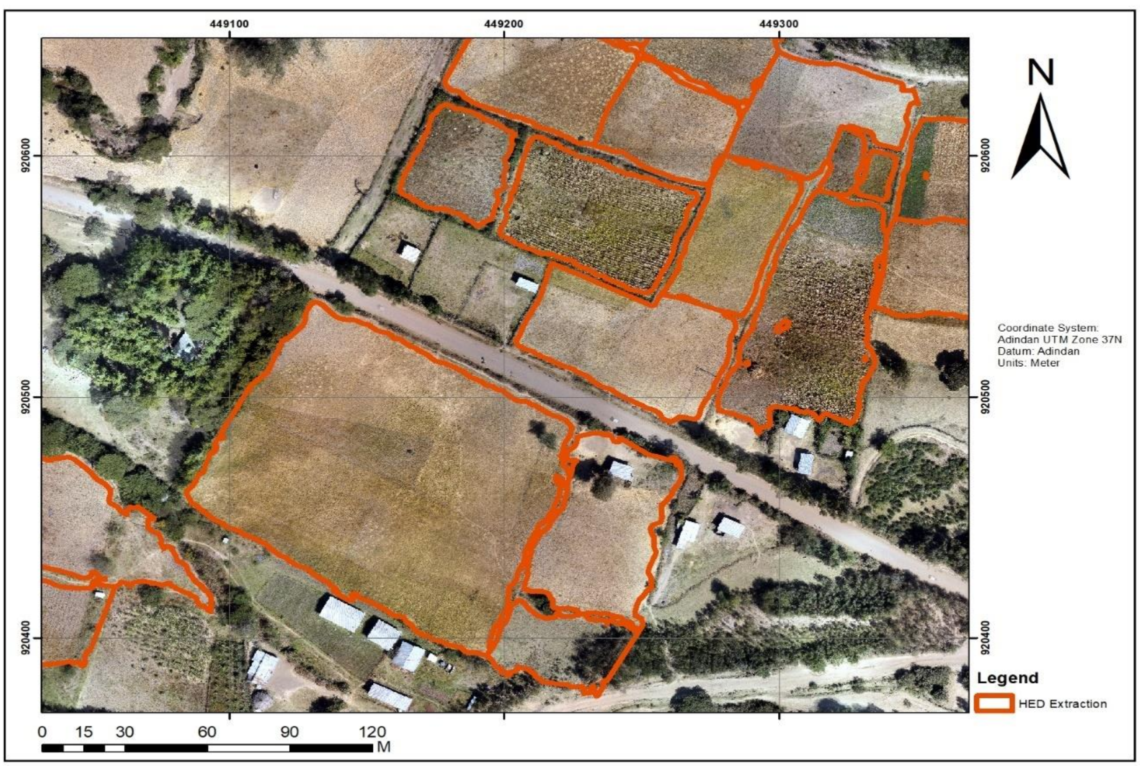

Figure 4-15 HED model extraction

4.7 Enhancing Cadastral Digitization Through Interactive

On-screen digitization is a conventional interactive process used in geographic information systems to create a digital map from multiple image sources The progress in computer processing capabilities and machine learning algorithms has improved the traditional on-screen digitization method, allowing for more accurate and precise identification and delineation of cadastral boundary lines (Metaferia et al., 2023).

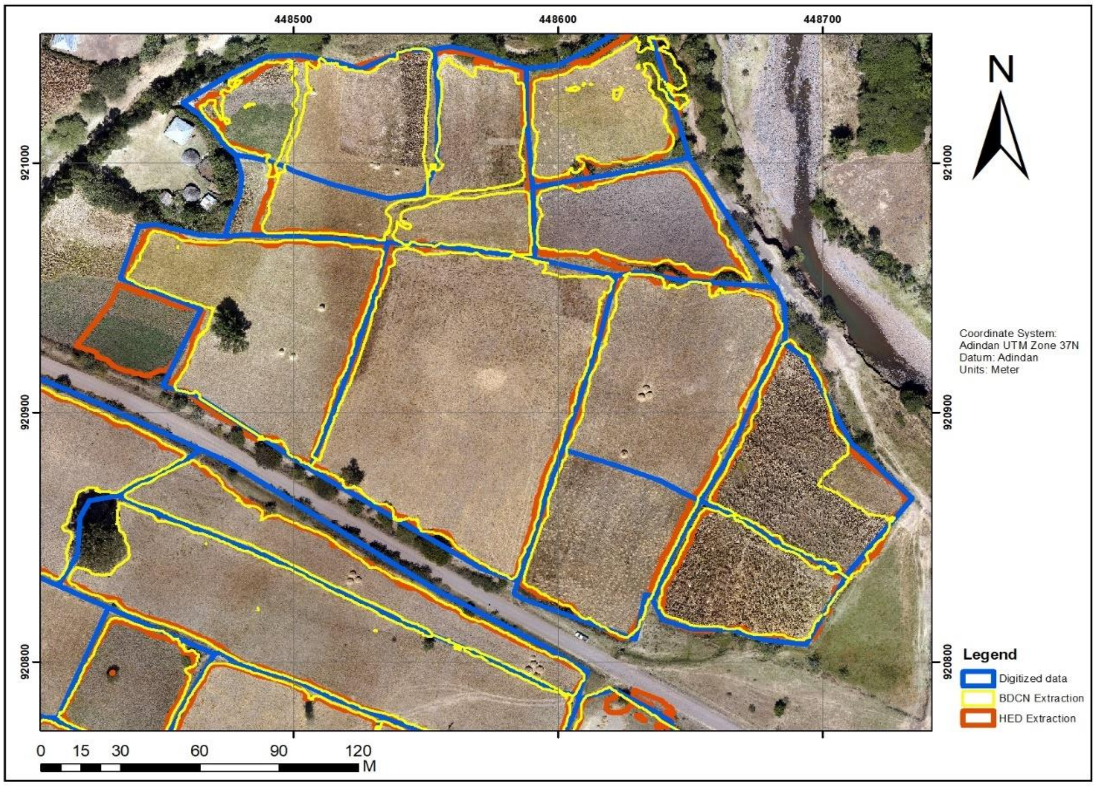

Figure 4-16 Overlay of Digitized, BDCN, and HED models

According to IAAO 2015 Parcel areas, as generated and stored in the parcel polygon, should be compared to areas stored in tabular databases for review and correction of significant differences. Parcel polygons should be viewed with ortho imagery and older scanned maps, based on the above concept the extracted parcels overlay with digitized and orthophoto in Figure 4-16 shows that the blue color represents the ground truth, the red color represents the HED extraction, and the yellow color represents the BDCN extraction. To compare these extractions with the cadaster boundary rule, we need to consider the accuracy and alignment of the boundaries. By visually analyzing the overlay, we can determine how well the HED and BDCN extractions align with the ground truth and the expected cadaster boundary rule. When comparing the alignment of the extracted model results with the digitized ones, observed that the BDCN result far from the digitized parcel had a measurement of 1.24m, while the HED result had a measurement of 1.52 m. According to the International Association of Assessing Officers (IAAO, 2015) both result lies within the tolerable limits. It is important to note that the accuracy and reliability of the extractions can vary depending on factors such as the quality of the input data, the performance of the models, and the complexity of the parcels.

According to the International Association of Assessing Officers (IAAO, 2015), cadastral maps should not have overlapped or missing parcel polygons. The results obtained from this study show that the parcel polygons extracted are closed and do not have any gaps or inaccuracies. These findings suggest that the boundaries of the parcels are in compliance with the cadastral requirements. It is also feasible to make edits to the boundaries and include additional attribute information. The figure demonstrates that there are no overlaps or gaps between the parcel polygons in the extracted boundaries.

When comparing the Digitized method with automatic future extraction using deep learning methods, scalability, and efficiency favor automatic feature extraction, as it can handle large datasets and reduce human effort. Conversely, manual digitization requires skilled personnel, training, and significant time investment. Additionally, considerations such as cost, expertise, data updates, error analysis, and integration with other processes should be taken into account when deciding between the two methods. In summary, through visual inspection, it is evident that automatic feature extraction offers consistency in parcel boundary demarcation. However, there are instances where the automated approach falls short of fully extracting certain parcels. The choice between manual digitization and automatic feature extraction depends on factors such as project requirements, available resources, desired accuracy, and the specific characteristics of the dataset. Evaluating these factors will help determine the most appropriate approach for achieving accurate and reliable parcel boundaries.

According to (Wassie 2016). investigation, the current approach used in Ethiopia allows a digitizer to digitize approximately 40 parcels per day. This means that, on average, it takes about 20 minutes for a digitizer to manually digitize one parcel. Additionally, he discovered that it takes around 3 months for four digitizers to digitize one kebele Based on these findings, when we compare the two models, once they are trained, they are able to extract features from over 300 parcels in just under an hour. In contrast, manual digitization requires 7.5 days per person.

4.8 Strengths and Limitations of the Model

The conventional method for cadastral boundary mapping has been known to be slow, require a lot of manpower, and be susceptible to mistakes. However, in recent years, a new approach utilizing edge detection deep learning has gained popularity as a more promising option. This technique seeks to automate the identification of parcel boundaries from UAV imagery, making the cadastral mapping process more efficient. By assessing the strengths and limitations of this approach, valuable insights can be gained to support decision-making in cadastral mapping situations.

Strength

Deep learning models have revolutionized the field of UAV image analysis by combining high-level representation and end-to-end learning. These models, such as BDCN and HED, offer several advantages over traditional feature extraction methods. These models can extract high-level features from the input images and learn to make predictions directly from the raw data, eliminating the need for manual feature engineering. This led to an end-to-end learning approach that enables the models to automatically learn and adapt to different scenarios, improving their performance over time. The integration of high-level representation and end-to-end learning in deep learning models for UAV image analysis holds great potential for advancing the capabilities of UAVs in various domains, particularly in cadastral mapping.

Limitation

Deep learning models for feature extraction, such as BDCN and HED, can be sensitive to image quality, including factors like resolution, noise, and lighting conditions. Lower-quality UAV images may result in reduced accuracy and reliability of the feature extraction process Some feature extraction techniques may struggle with generalizing well to different types of UAV images or varying environmental conditions. This limitation can affect the overall performance and applicability of the models and feature extraction often requires significant computational resources, including high-performance GPUs, to process large amounts of data efficiently. This can pose challenges in terms of computational requirements and time constraints for real-time or large-scale applications.

To conclude the strengths and limitations edge detection deep learning approach for cadastral boundary mapping hold significant promise in streamlining and improving the traditional cadastral mapping process. While the method has its strengths, such as increased automation and potential for higher accuracy, it also faces challenges related to data availability, model complexity, and generalization. By considering the strengths and limitations developing strategies to address its limitations. Ongoing research and collaboration between domain experts and machine learning specialists will be crucial in further advancing this technology for effective and reliable cadastral mapping.

4.9 Challenge in Future Extraction

Despite the overall consistency, there are cases where the automatic feature extraction process falls short of fully capturing the boundaries of certain parcels. This can occur due to various factors such as the complexity of parcel configurations, occlusions within the imagery or data source, limitations of the extraction algorithm, or challenges in interpreting the available information. The main challenges are:

Over and Under Segmentation

There are cases where the automatic feature extraction process falls over and under prediction capturing the boundaries of certain parcels. This occurs because the crops within a single plot of land can vary, resulting in the model producing over-segmented and under-segmented parcels.

Figure 4-17 Over segmentation

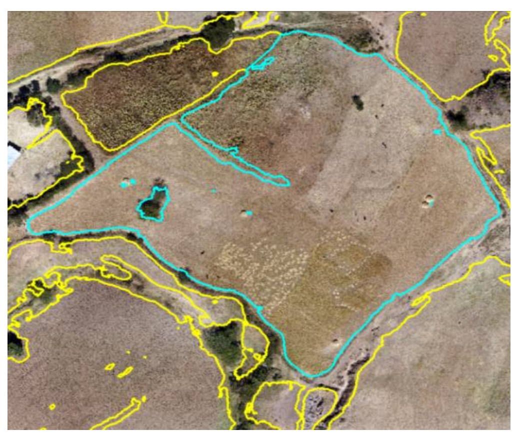

Figure 4-18 Under segmentation

Complex Parcel Boundaries

Some land parcels may have irregular or complex boundaries like different crop in one plot and the pattern of the parcel making it challenging for algorithms to accurately detect and segment them.

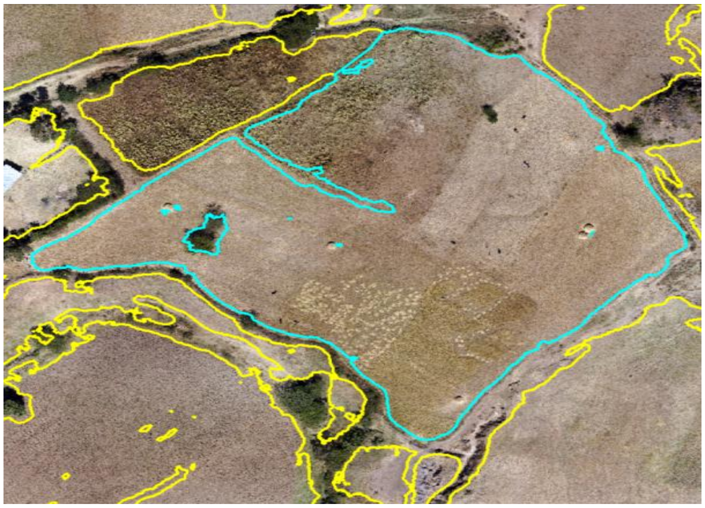

Figure 4-19 Complex Parcel Boundaries

Shadows and Occlusion

Shadows cast by buildings, trees, or other objects, as well as occlusions, can affect the performance of the extraction algorithms.

Figure 4-20 Shadows cast by trees

Chapter Five

5 Conclusion and Recommendation

5.1 Conclusion

In this study, semi-automatic Cadesteral boundary extraction using deep learning models has been discovered and evaluated to delineate cadastral boundaries of farm parcels using UAV images to obtain a vector format.

The proposed methods employed BDCN (Bi-Directional Cascade Network) and HED (Holistically Nested Edge Detection) models to perform edge detection on the test images, subsequently extracting the edges of farm parcels.

The models were tested on UAV orthophotos 9134*8467 dimension with a 20cm resolution. The HED model achieved an average precision of 0.66 (67% correctness), a recall of 0.68 (68% completeness), and an F-score of 67. It also demonstrated an average precision of 0.98 and an overall Intersection over Union (IoU) of 0.88 (88%). The BDCN model performed slightly better, with an average precision of 0.68 (68% correctness), a recall of 0.80 (80% completeness), and an F-score of 67%. It also had an average precision of 0.84 and an overall IoU of 0.84 (84%). According to the quantitative results, the parcel prediction HED model has higher similarity with the reference digitized polygons compared to the polygons predicted by the BDCN model. However, in terms of completeness or recall, the BDCN model has a better result of 0.8, while the HED model is 0.67. This suggests that the BDCN model is able to extract more of the cadastral edges compared to the HED model.

The quality of the predicted boundaries has been affected by several factors. These include the complexity of parcel configurations, the presence of shadows and occlusions, invisible boundaries, confusing features like terraces that intersect parcels, and the quality of the digitized reference cadastral data.

In conclusion, both the BDCN and HED models were capable of extracting cadastral boundaries from other UAV datasets. Their performance can be further improved through transfer learning by increasing the number of epochs. The test data demonstrated that these models can extract cadastral boundaries in vector polygon format, which can be directly used in mapping for rural cadaster with post-processing and field verification.

5.2 Reflection on the Research Objective

The main objective of this thesis is to create a deep learning method that can extract cadastral boundaries in a vector format using UAV images. This method aims to decrease the time and cost associated with collecting data on the ground. In the following section, it presents a concise summary of the answers to the sub-objectives posed in Chapter One.

1) To choose the most suitable deep learning model and define its parameters for the purpose of extracting cadastral boundaries.

In order to choose a semi-automated deep learning model for detecting and mapping cadastral boundary series systematic literature review has been conducted on previous studies that implemented deep learning algorithms to extract cadastral boundary UAV images. The review found that fully convolutional networks (FCN) are highly effective for semantic segmentation and edge detection. Among the FCN models, BDCN and HED models have been found to outpace others. When developing the models hyperparameter tuning is considered this includes learning rate backbone selection, batch size, and data augmentation are tested to increase the diversity of the training data and improve the model's generalization. Both models reach maximum accuracy for BDCN is 8.11 (81%) and for the HED model 8.28 (83%). Moreover, it is important to ensure that the predicted cadastral boundaries and the ground truth data have similar feature representations, indicating the model's ability to accurately extract and represent the relevant information.

2) To apply feature extracting deep learning model on the selected testing dataset.

Both deep learning models were tested on a diverse UAV dataset that contained various types of parcels. The parcels were extracted using the ArcGIS Pro 3.02 Deploying model, which employed a tool to classify pixels using deep learning. The results were then converted into vector data by extracting the farm edges and farm parcels.

3) To analyze the applicability of the semi-automated feature extraction method for cadastral boundary mapping.

To check the applicability of the model, different accuracy metrics of machine learning are applied. These metrics include the F1 score, precision, recall, IOU, and geometrical comparison.

Additionally, a qualitative analysis is conducted by comparing the model's results with reference digitized data. The overall results suggest that the approach is more effective in extracting boundaries of cadastral features, particularly farm parcels. However, the effectiveness of the model is affected by the complexity of parcel configurations, as well as the presence of shadows and occlusions. In general, deep learning models BDCN and HED are proven to an effective approach to supporting the current cadastral boundary mapping. The method can be implemented in an integrated way with existing boundary mapping approaches.

5.3 Recommendation

This study was intended to test the applicability of semi-automatic feature extraction using a deep learning approach to support general boundaries from high-resolution UAV imagery in a vector polygon format. Both the deep learning models BDCN and HED models proved to work on the test dataset, evaluated, and have a promising result, though this result could work in a similar dataset as far as the issue of cadastral boundary mapping is concerned more issues need also be considered. Future studies should focus on improving the training of the BDCN and HED models by increasing the number of epochs and incorporating more diverse datasets. This can help with better generalization and accuracy of the models.

Using multi-temporal data to avoid shadow and occlusion. Incorporating additional features such as spectral information, texture, and elevation data could potentially improve the accuracy of boundary detection. This would involve using multi-spectral or LiDAR data alongside UAV images.

Exploring transfer learning techniques to adapt the models to different regions and types of agricultural fields can enhance their applicability. Fine-tuning the models with region-specific data can improve their performance in varied environments.

Implementing robust field verification and post-processing techniques to validate and refine the extracted boundaries.

Participatory mapping approaches where local farmers and stakeholders contribute to the identification and validation of parcel boundaries.

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Annex

Accuracy assessment report

Accuracy Assessment Report

Disclaimer

The confidence range of the detected features is [0.000000, 0.000000]. If features with small confidences were filtered out (e.g., by a threshold in the model inference), caution is advised when comparing the results below to other results based on the full confidence range [0, 1].

Average Precision averaged across these 10 IoU thresholds [0.5, 0.55, ..., 0.95] and all classes

mAP @ IoU [0.5 : 0.95] @ All_Classes = 0.845771.

IoU >= 0.5000

IoU >= 0.5000	Precision	Recall	F1 Score	AP	True Positive	False Positive	False Negative
All Classes	0.6766	0.8000	0.7332	0.8458	136.0000	65.0000	34.0000
0	0.6766	0.8000	0.7332	0.8458	136.0000	65.0000	34.0000

Accuracy Assessment Report

Disclaimer

The confidence range of the detected features is [0.000000, 0.000000]. If features with small confidences were filtered out (e.g., by a threshold in the model inference), caution is advised when comparing the results below to other results based on the full confidence range [0, 1].

Average Precision averaged across these 10 IoU thresholds [0.5, 0.55, ..., 0.95] and all classes

mAP @ IoU [0.5 : 0.95] @ All_Classes = 0.879310.

IoU >= 0.5000

IoU >= 0.5000	Precision	Recall	F1 Score	AP	True Positive	False Positive	False Negative
All Classes	0.6609	0.6765	0.6686	0.9770	115.0000	59.0000	55.0000
0	0.6609	0.6765	0.6686	0.9770	115.0000	59.0000	55.0000

Figure HED model Accuracy assessment report

Quality Report

Quality Report

Generated with Pix4Dmapper version 4.5.2 Preview

Important: Click on the different icons for:

Help to analyze the results in the Quality Report

Additional information about the sections

Click here for additional tips to analyze the Quality Report

Summary

Project	New_Phase_3
Processed	2022-12-21 23:11:30
Camera Model Name(s)	DSC-RX1RM2_35.0_7952x5304 (RGB)
Average Ground Sampling Distance (GSD)	2.02 cm / 0.80 in
Area Covered	2.567 km^2 / 256.6852 ha / 0.99 sq. mi. / 634.6112 acres

Quality Check

Images	median of 39484 keypoints per image
Dataset	734 out of 735 images calibrated (99%), all images enabled
Camera Optimization	0.06% relative difference between initial and optimized internal camera parameters
Matching	median of 15962.8 matches per calibrated image
Georeferencing	yes, 5 GCPs (5 3D), mean RMS error = 0.002 m

Preview

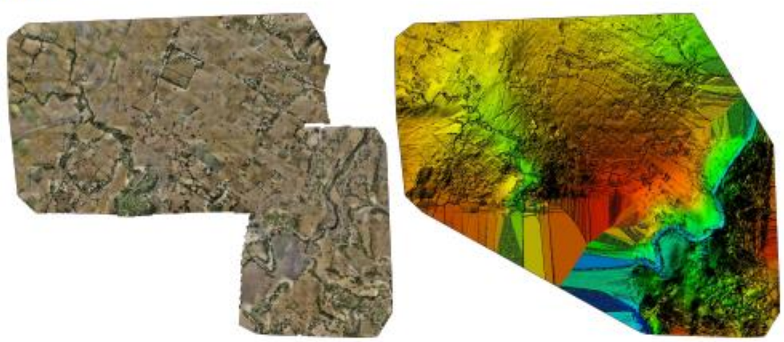

Figure 1: Orthomosaic and the corresponding sparse Digital Surface Model (DSM) before densification.

Figure Quality Report

Quality Report

Generated with Pix4Dmapper version 4.5.2 Preview

Important: Click on the different icons for:

Help to analyze the results in the Quality Report

Additional information about the sections

Click here for additional tips to analyze the Quality Report

Summary

Project	fINAL_TEST
Processed	2022-12-07 23:11:38
Camera Model Name(s)	DSC-RX1RM2_35.0_7952x5304 (RGB)
Average Ground Sampling Distance (GSD)	2.29 cm / 0.90 in
Area Covered	2.500 km^2 / 250.0278 ha / 0.97 sq. mi. / 618.1520 acres

Quality Check

Images	median of 44125 keypoints per image	✔
Dataset	1056 out of 1056 images calibrated (100%), all images enabled	✔
Camera Optimization	0.6% relative difference between initial and optimized internal camera parameters	✔
Matching	median of 12431.4 matches per calibrated image	✔
Georeferencing	yes, 5 GCPs (5 3D), mean RMS error = 0.001 m	✔

Preview

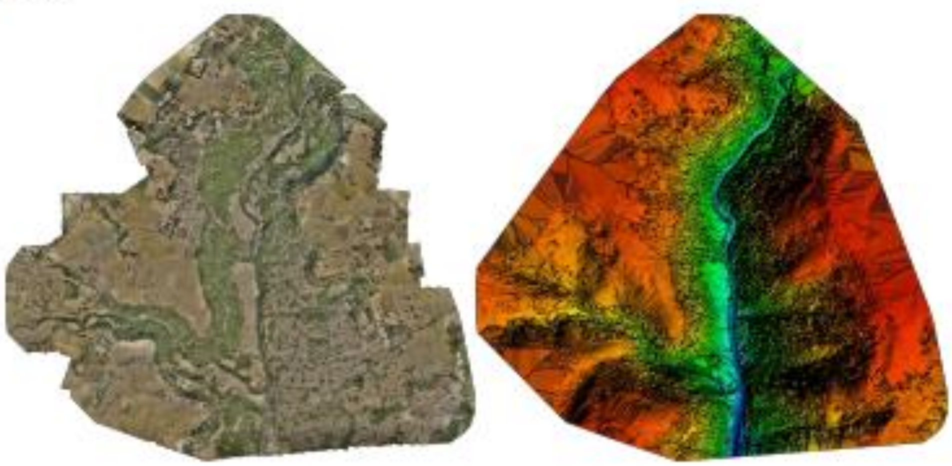

Figure 1: Orthomosaic and the corresponding sparse Digital Surface Model (DSM) before densification.

Image preprocessing code

```
import os
from itertools import product
import rasterio as rio
from rasterio import windows

in_path = r'D:\GIS and Remote Sensing MA Program@AAU\mosaicccc'
input_filename = 'finalmasp1.tif'

out_path = r'C:\Users\binyam\Desktop\Project_DL\resized'
output_filename = 'tile_{}-{}.tif'

def get_tiles(ds, width=256, height=256):
    nols, nrows = ds.meta['width'], ds.meta['height']
    offsets = product(range(0, nols, width), range(0, nrows, height))
    big_window = windows.Window(col_off=0, row_off=0, width=nols, height=nrows)
    for col_off, row_off in offsets:
        window = windows.Window(col_off=col_off, row_off=row_off, width=width,
height=height).intersection(big_window)
        transform = windows.transform(window, ds.transform)
        yield window, transform

with rio.open(os.path.join(in_path, input_filename)) as inds:
    tile_width, tile_height = 256, 256

    meta = inds.meta.copy()
    meta.update({
        'driver': 'GTiff',
        'count': 3,  # Set the number of output bands to 3 (RGB)
        'dtype': 'uint8',  # Set the data type to unsigned 8-bit
        'photometric': 'RGB',  # Set the photometric interpretation to RGB
```

```
        'nodata': 0  # Set the nodata value to 0
    })

    # Read the RGB bands (assuming they are the first three bands)
    rgb_bands = inds.read([1, 2, 3])

    for window, transform in get_tiles(inds, tile_width, tile_height):
        print(window)
        meta['transform'] = transform
        meta['width'], meta['height'] = window.width, window.height
        outpath = os.path.join(out_path, output_filename.format(int(window.col_off),
int(window.row_off)))
        with rio.open(outpath, 'w', **meta) as outds:
            # Write the RGB bands to the output tile
            outds.write(rgb_bands[:, window.row_off:window.row_off + window.height,
                        window.col_off:window.col_off + window.width], indexes=[1, 2, 3])
```

code with normalization

```
import os
from itertools import product
import rasterio as rio
from rasterio import windows
import numpy as np

in_path = r'D:\GIS and Remote Sensing MA Program@AAU\mosaicccc'
input_filename = 'finalmasp1.tif'
```

```
out_path = r'C:\Users\binyam\Desktop\Project_DL\real'
output_filename = 'tile_{}-{}.tif'

def get_tiles(ds, width=512, height=512):
    nols, nrows = ds.meta['width'], ds.meta['height']
    offsets = product(range(0, nols, width), range(0, nrows, height))
    big_window = windows.Window(col_off=0, row_off=0, width=nols, height=nrows)
    for col_off, row_off in offsets:
        window = windows.Window(col_off=col_off, row_off=row_off, width=width,
height=height).intersection(big_window)
        transform = windows.transform(window, ds.transform)
        yield window, transform

with rio.open(os.path.join(in_path, input_filename)) as inds:
    tile_width, tile_height = 512, 512

    meta = inds.meta.copy()
    meta.update({
        'driver': 'GTiff',
        'count': 3,  # Set the number of output bands to 3 (RGB)
        'dtype': 'uint8',  # Set the data type to unsigned 8-bit
        'photometric': 'RGB',  # Set the photometric interpretation to RGB
        'nodata': 0  # Set the nodata value to 0
    })

    # Read the RGB bands (assuming they are the first three bands)
    rgb_bands = inds.read([1, 2, 3])

    for window, transform in get_tiles(inds, tile_width, tile_height):
        print(window)
        meta['transform'] = transform
        meta['width'], meta['height'] = window.width, window.height
```

```
        outpath = os.path.join(out_path, output_filename.format(int(window.col_off),
int(window.row_off)))
        with rio.open(outpath, 'w', **meta) as outds:
          # Get the tile for normalization
          tile = rgb_bands[:, window.row_off:window.row_off + window.height,
                  window.col_off:window.col_off + window.width]

          # Normalize the tile
          normalized_tile = tile.astype('float32') / 255.0

          # Write the normalized tile to the output tile
          outds.write(np.uint8(normalized_tile * 255), indexes=[1, 2, 3])
```

image enhancment rotation

```
import os
from itertools import product
import rasterio as rio
from rasterio import windows
import numpy as np
from skimage import exposure
from sklearn.model_selection import train_test_split
from torchvision.transforms import (
  Compose,
  RandomRotation,
  RandomHorizontalFlip,
  RandomVerticalFlip,
  ToTensor,
)
from PIL import Image

in_path = r'D:\GIS and Remote Sensing MA Program@AAU\mosaicccc'
input_filename = 'finalmasp1.tif'
```

```
out_path = r'C:\Users\binyam\Desktop\Project_DL\datpre1'
output_filename = 'tile_{}-{}.tif'

def get_tiles(ds, width=512, height=512):
    nols, nrows = ds.meta['width'], ds.meta['height']
    offsets = product(range(0, nols, width), range(0, nrows, height))
    big_window = windows.Window(col_off=0, row_off=0, width=nols, height=nrows)
    for col_off, row_off in offsets:
        window = windows.Window(col_off=col_off, row_off=row_off, width=width,
height=height).intersection(big_window)
        transform = windows.transform(window, ds.transform)
        yield window, transform

with rio.open(os.path.join(in_path, input_filename)) as inds:
    tile_width, tile_height = 512, 512

    meta = inds.meta.copy()
    meta.update({
        'driver': 'GTiff',
        'count': 3,  # Set the number of output bands to 3 (RGB)
        'dtype': 'uint8',  # Set the data type to unsigned 8-bit
        'photometric': 'RGB',  # Set the photometric interpretation to RGB
        'nodata': 0  # Set the nodata value to 0
    })

    # Read the RGB bands (assuming they are the first three bands)
    rgb_bands = inds.read([1, 2, 3])

    # Lists to store image paths and their corresponding labels
    image_paths = []
    labels = []
```

```
    for window, transform in get_tiles(inds, tile_width, tile_height):
        print(window)
        meta['transform'] = transform
        meta['width'], meta['height'] = window.width, window.height
        outpath = os.path.join(out_path, output_filename.format(int(window.col_off), int(window.row_off)))
        with rio.open(outpath, 'w', **meta) as outds:
            # Get the tile for normalization
            tile = rgb_bands[:, window.row_off:window.row_off + window.height,
                             window.col_off:window.col_off + window.width]

            # Normalize the tile
            normalized_tile = tile.astype('float32') / 255.0

            # Apply histogram equalization to enhance the tile
            enhanced_tile = exposure.equalize_hist(normalized_tile)

            # Scale the enhanced tile back to the 0-255 range
            scaled_tile = np.uint8(enhanced_tile * 255)

            # Write the enhanced tile to the output tile
            outds.write(scaled_tile, indexes=[1, 2, 3])

            # Add the image path and label to the lists
            image_paths.append(outpath)
            labels.append(0)  # Replace 0 with the appropriate label for your task

    # Split the data into training and validation sets
    train_paths, val_paths, train_labels, val_labels = train_test_split(image_paths, labels, test_size=0.2, random_state=42)
```

```
# Data augmentation transformations
data_transforms = Compose([
    RandomRotation(20),
    RandomHorizontalFlip(),
    RandomVerticalFlip(),
    ToTensor(),
])

# Apply data augmentation to training data
train_data = []
for path, label in zip(train_paths, train_labels):
    image = data_transforms(Image.open(path))
    train_data.append((image, label))

# Apply data augmentation to validation data
val_data = []
for path, label in zip(val_paths, val_labels):
    image = data_transforms(Image.open(path))
    val_data.append((image, label))

# Train your deep learning model using the augmented data
# ...
# Your deep learning model training code here
# ...
```