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SEMI-AUTOMATIC DATA ENRICHMENT FOR OPEN STREET MAP (OSM) USING DEEP LEARNING ALGORITHMS

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Abstract

It is crucial to obtain continuous data on unplanned urbanization regions in order to develop precise plans for future studies in these regions. An unplanned urbanization area was selected for analysis, and road extraction was performed using very high-resolution unmanned aerial vehicle (UAV) images. In this regard, the Sat2Graph deep learning model was employed, utilizing the object detection tool integrated within the deep learning package published by ArcGIS Pro software, for the purpose of road extraction from a very high-resolution UAV image. The high-resolution UAV images were subjected to analysis using the photogrammetry method, with the results obtained through the application of the Sat2Graph deep learning model. The resulting road extraction was employed for the purpose of data enhancement on OpenStreetMap (OSM). This will facilitate the expeditious and precise implementation of data updates conducted by volunteers. It should be noted that the recall, F1 score, precision ratio/uncertainty accuracy, average producer accuracy, and intersection over union of products were automatically extracted with the algorithm and determined to be 0.816, 0.827, 0.838, 0.792, and 0.597, respectively.

Keywords GIS, OpenStreetMap, Deep learning, Data enrichment, Photogrammetry

OPEN STREET MAP (OSM) İÇİN DERİN ÖĞRENME ALGORİTMALARI KULLANARAK YARI OTOMATİK VERİ ZENGİNLEŞTİRME

Özet

Plansız kentleşme bölgeleri hakkında sürekli veri elde etmek, bu bölgelerde gelecekte yapılacak çalışmalar için kesin planlar geliştirmek açısından büyük önem taşımaktadır. Analiz için bir çarpık kentleşme alanı seçilmiş ve çok yüksek çözünürlüklü insansız hava aracı (İHA) görüntüleri kullanılarak yol çıkarımı yapılmıştır. Bu bağlamda, çok yüksek çözünürlüklü İHA görüntüsünden yol çıkarımı amacıyla ArcGIS Pro yazılımı tarafından yayınlanan derin öğrenme paketine entegre edilmiş nesne tespit aracı kullanılarak Sat2Graph derin öğrenme modeli kullanılmıştır. Yüksek çözünürlüklü İHA görüntüleri, Sat2Graph derin öğrenme modelinin uygulanmasıyla elde edilen sonuçlarla birlikte fotogrametri yöntemi kullanılarak analize tabi tutulmuştur. Elde edilen yol çıkarımı OpenStreetMap (OSM) üzerinde veri iyileştirme amacıyla kullanılmıştır. Bu, gönüllüler tarafından gerçekleştirilen veri güncellemelerinin hızlı ve hassas bir şekilde uygulanmasını kolaylaştıracaktır. Geri çağırma, F1 puanı, kesinlik oranı/belirsizlik doğruluğu, ortalama üretici doğruluğu ve ürünlerin birleşimi üzerindeki kesişimin algoritma ile otomatik olarak çıkarıldığı ve sırasıyla 0,816, 0,827, 0,838, 0,792 ve 0,597 olarak belirlendiği belirtilmelidir.

Anahtar Kelimeler: CBS, OpenStreetMap, Derin öğrenme, Veri zenginleştirme, Fotogrametri

Cite

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1. Introduction

The monitoring of environmental conditions has emerged as a pivotal area of development in recent years. The studies conducted in this direction have primarily examined the changes occurring on Earth and their impact on urban and environmental scales. Consequently, the monitoring of urban development represents a crucial aspect of the creation of smart cities. In this regard, the utilisation of high-resolution unmanned aerial vehicles (UAVs) and aerial photography has become a significant area of interest [1, 2]. Up until this point, satellite imagery has typically been employed for the monitoring of urban development. However, with the advent of UAVs in recent years, these processes have begun to be conducted with more sensitive data. Despite the enhanced accessibility of sensitive data through the advancement of data collection techniques, the resulting products have frequently exhibited inconsistencies and ambiguity. It is therefore imperative to extract meaningful results from the data obtained from UAV images. While the manual extraction process has evolved over time with the advent of semi-automatic methods, the detection of objects from dense data has become a fully automatic process in recent years, enabled by the advent of deep learning algorithms.

The issue of object detection has emerged as a pivotal concern in the domains of remote sensing and photogrammetry in recent years. Currently, however, the utilisation of deep learning methodologies is becoming increasingly prevalent. It is particularly challenging to gather data in regions experiencing unplanned urbanization, underscoring the importance of automated data collection using deep learning algorithms in such contexts. In consequence of these developments, the advancement of image detection sensors and the power of deep learning algorithms is occurring on a daily basis, thereby maintaining object detection as one of the most important research areas. The development of deep learning algorithms has facilitated the automation of urban development monitoring, enabling the rapid extraction of data from vast areas. These methods have transformed object detection, facilitating the analysis of vast quantities of data with remarkable speed and precision, even in intricate urban environments. These developments are especially advantageous in rapidly urbanizing regions, where conventional manual data collection techniques are inadequate due to time and resource limitations. The combination of high-resolution sensors and cutting-edge deep learning models enables the precise identification of diverse urban features, including infrastructure elements and vegetation.

The collection of data via automated processes and the provision of solutions for rapidly urbanizing areas are becoming increasingly important, as is the availability of open-source data delivery platforms. One such data provider is OpenStreetMap, a voluntary project initiated by Steve Coast in 2004 (5). The principal objective of the project is to create and disseminate free geographic data. However, the veracity of the data entered into OSM is contingent upon the geographic information provided by the user entering the data. Despite the efforts of numerous volunteers, it is not possible to assert that the data in OSM is 100% accurate. Accordingly, the use of high-resolution images and data generated automatically by deep learning algorithms is preferable. Such advanced techniques offer more reliable and precise data that can be regularly refreshed and validated against ground-truth information.

1.1 Related Work

The application of deep learning to object detection in high-resolution images represents a significant area of research activity in recent years. The selection of the methodology is undoubtedly a crucial aspect, yet it is equally important to utilize high-resolution data to substantiate the efficacy of the methodology. While such studies employ high-resolution aerial photographs (7), analogous studies are conducted with high-resolution satellite images (8, 9). The selection of data is dependent upon the intended application. Although the utilisation of commercial software for object detection is a prevalent approach, the employment of deep learning algorithms has become a standard practice in recent years (10-12).

In addition to the type of data utilized, the selection of a deep learning algorithm is also a crucial consideration. While the majority of these algorithms are open source, they also have commercial applications. While convolutional neural networks (CNN) are a prevalent tool for object detection (13, 14), other approaches, including part-based convolutional neural networks (15), critical feature capturing networks (16), the Attention Scale Pyramid Deformable (17), and the Frequency Extraction Network (18), are also employed for this purpose. Recently, transformer-based models such as Vision Transformers (ViT) have demonstrated considerable promise in extracting spatial relationships and detailed features, particularly in complex scenes. Moreover, YOLO (You Only Look Once) models, including the latest YOLOv5 and YOLOv7 versions, are widely employed for real-time object detection due to their optimal balance between speed and accuracy. The integration of convolutional neural networks (CNN) with recurrent neural networks (RNN) has gained prominence in the domain of sequential data analysis, particularly in the context of video-based detection, where it offers enhanced tracking capabilities. Another recent development is Meta's "Segment Anything" model, which demonstrates proficiency in segmentation tasks by facilitating flexible and precise delineation of objects across diverse contexts without the necessity for specific training for each target object. These advances in deep learning algorithms are further enhancing the precision and adaptability of detection in a range of urban and environmental contexts, thereby facilitating more robust data extraction from diverse and high-resolution datasets.

In their study, Abdullahi et al. [19] conducted an exhaustive review of the literature on deep learning algorithms for road extraction. Zhu et al. [20] put forth the Global Context-aware and Batch-independent Network (GCB-Net) approach for road extraction in the study. The GCB-Net method employs global context-aware and multi-parallel dilated convolution techniques to enhance the spatial relationship. The proposed method was evaluated on the DeepGloba Roads and SpaceNet Roads datasets. In their study, Li et al. [21] proposed a road extraction method that employs an ensemble learning model in the post-processing stage. The results of the experiments demonstrate that the proposed method yields superior outcomes compared to other models. In their study, Lian and Huang trained a convolutional neural network (CNN) model using point annotations. As a consequence of the application, it was determined that the sensitivity of the method in question was high. Xu et al. [11] proposed a novel approach for road extraction using remote sensing images. To validate the method, a dataset obtained from Google Earth was employed, and it was observed that the method yielded effective results.

Open Street Map has always been an interesting research topic due to the data collected by volunteers [23-26]. Although there have been several studies on OSM, the enrichment of OSM data is the subject of this study. Mobasheri et al [27] used multiple GPS tracks collected from wheelchair users to collect information about people's travel experiences and used data mining methods to create road geometries from these data. In his study, Mobasheri [28] developed a rule-based topological relationship detection algorithm using external matches such as data attributes and classifications to improve the system's information retrieval capabilities and increase data richness. Zhao et al [29] leveraged OSM data for geographic object detection by integrating it with high-resolution imagery, and used the enriched dataset to generate urban scenes.

Other researchers have explored the use of machine learning techniques to enrich OSM data by integrating it with external datasets to improve spatial accuracy and completeness. For example, Memduhoglu and Basaraner [34] used geospatial data integration and ontological inference to semantically enrich building features within OSM to provide a more nuanced understanding of urban areas. Similarly, Jokar Arsanjani et al [35] used spatial statistics to enrich OSM data with land use classification, creating a richer dataset for urban and environmental applications. These studies demonstrate the potential of integrating OSM with advanced data sources and techniques to improve spatial detail and data usability in various domains.

In this study, road extraction was performed using the object detection method using a high-resolution UAV image of Mersin, Turkey and the Sat2Graph deep learning algorithm. The main motivation of this work is to semi-automatically insert high-fidelity data obtained from a high-resolution image into a volunteer-based platform such as OSM. In this way, enriching the data in OSM will quickly present users with current data. According to other studies, the difference here is to provide a semi-automated data transfer using high-resolution UAV imagery to a platform that provides volunteer-based data such as OSM. Detailed information will be provided in later stages of the study.

2. Material and Method

2.1. Study Area

This study was conducted in a neighborhood in Mersin, Turkey, where I obtained high-resolution UAV imagery (Figure 1). The selected area, characterized by dense and irregular development patterns, serves as a prime example of the unplanned urbanization commonly found in rapidly growing cities in Turkey. This urbanization pattern includes narrow streets, mixed-use buildings, and a lack of green spaces, underscoring the urgency of urban transformation initiatives.

In addition, the complex layout of the neighborhood, with winding streets and varying building heights, presents unique challenges for automated mapping and street extraction. The distinct spatial characteristics of the study area make it an ideal test case for evaluating the performance and accuracy of the deep learning algorithm used for road extraction. By analyzing road networks in such irregular environments, this research aims to improve the reliability of automated detection models and assess their adaptability to unstructured urban landscapes.

Figure 1. Study Area.

2.2. Method

This study used high-resolution UAV imagery of an unplanned urban area in Mersin, Turkey, processed using photogrammetry and deep learning techniques to enrich OpenStreetMap (OSM) data.

This methodology aimed to improve the spatial accuracy of OSM data in areas of dense, unplanned urbanization and provide a reliable alternative to volunteer-driven updates. This section provides detailed information on the processing of the resulting data, as shown in Figure 2.

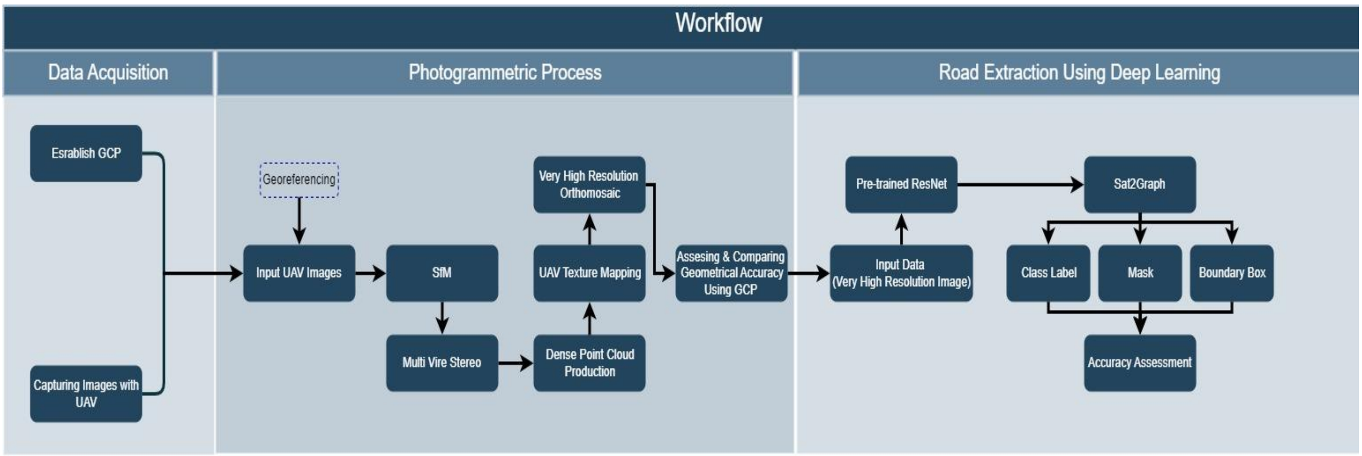

Figure 2. Workflow.

A Sensefly Ebee Plus UAV with an integrated 20 MP camera was used for the photogrammetric research. It is integrated with a remote flight control and a real-time kinematic (RTK) system. The main field activities were carried out in three steps: (1) flight mission, (2) ground control point (GCP) placement and acquisition, and (3) flight operation and aerial image collection. In flight planning, the equivalent of a GSD of ~7 cm/pixel is ~260 m in the S.O.D.A. camera. In addition, the UAV was equipped with satellite positioning systems (GPS/GLONASS) and all collected images were geo-located in a WGS84/UTM36N metric coordinate system.

2.2.1. Image Processing

Agisoft Metashape software was used to process the obtained images and the model was created using the Structure from Motion (SfM) algorithm. Projection errors between images are optimized according to point positions. In addition, the self-calibration method provided by the software was preferred in the project. Using the SfM algorithm, this software first aligns the images, performs preliminary adjustments, and generates a point cloud [30]. To do this, the algorithm performed automatic positioning between images [31].

Then, image alignment was performed using Agisoft Metashape software and the first point cloud generation was completed using key points in different images (citation). For this step, a low-density 3D coordinate point cloud is generated. Then, the multi-view stereo algorithm is used to generate the dense point cloud. This algorithm divides the overlapping images into subsets and reconstructs the 3D point data independently of these subsets (citation). In the last step, a high-resolution orthomosaic image, which will be used in this study, was produced from the generated 3D data.

2.2.2. Deep Learning Method

This study used the Sat2Graph deep learning method developed by He et al. [32]. The deep learning toolbox published by ArcGIS Pro developers was used to apply this method.

Sat2Graph is a new approach that can encode a road network graph into a 3D tensor. This graph is called GraphTensor Encoding (GTE) and has been developed using a non-repetitive neural network model to convert the input image directly into the road network. G = {V, E} is a road network covering an area of W meters by H meters, where V are vertices and E are edges. GraphTensor Encoding uses Wλ x Hλ x (1 + 3Dmax) to encode the graph, where λ is the spatial resolution that limits the encoded graph and Dmax is the maximum edge that can be encoded [32]. This method combines the advantages of segmentation and graph-based approaches and provides more effective results, especially in complex urban environments. Sat2Graph was chosen for this study because its graph-based approach allows it to capture intricate road topologies, which is essential in the unplanned, dense urban environment of the study area. Unlike pixel-based CNN segmentation models, which can struggle in areas with overlapping roads or dense intersections, Sat2Graph's tensor encoding enhances connectivity and continuity in road networks, making it ideal for updating OpenStreetMap (OSM) data.

While traditional CNN-based models, such as UNet or Mask R-CNN, are commonly used in road extraction studies, they can face challenges in preserving network connectivity in complex urban layouts. UNet, for example, is effective at pixel-based segmentation, but may fail to maintain continuity at intersections or occlusions.

Transformer-based models, such as Vision Transformers, improve feature extraction but lack the graph-specific structure essential for accurate road network representation. In contrast, Sat2Graph's graph encoding is specifically designed for road network connectivity, making it highly suitable for enriching OSM with accurate data.

The captured high-resolution imagery was processed in Agisoft Metashape using Structure from Motion (SfM). This method aligns images to produce a three-dimensional point cloud, which captures the spatial configuration of the study area. Subsequently, a multi-view stereo algorithm generated a dense point cloud, providing precise spatial data essential for the Sat2Graph road extraction. Photogrammetry furnished a highly accurate, georeferenced orthomosaic image, which augmented the overall road extraction accuracy, ensuring that the results closely reflected the physical configuration of the study area.

In this study, the Deep Learning tool, which is an add-on to ArcGIS Pro, was utilized for the Sat2Graph application. The pre-trained deep learning model package, "Road Extraction - Global," was selected for use in this study. In order to utilise this package via ArcGIS Pro, a minimum version of 2.9 is required. To utilize this package, a 7 cm/pix resolution orthomosaic was employed, the creation of which was previously delineated.

2.2.3. Assessment Method

The method is currently employed for the assessment of the precision of a range of object detection algorithms, including the calculation of recall, F1 score, precision ratio/uncertainty accuracy (UAcc), producer accuracy (Pacc), and manual detection. In order to evaluate the efficacy of our aforementioned accuracy evaluation method, it is first necessary to define the following terms.

The true positive (TP) value represents the number of roads that are correctly identified by the algorithm. The false positive (FP) is the number of roads that are not roads, but are misidentified by the algorithm. The false negative (FN) is the number of roads not detected by the algorithm. The actual number of roads in the images is represented as N.

The recall rate is an important measure of algorithm performance. It is defined as follows:

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

The F1 score is a single metric that combines precision and recall into a single value. This value is calculated as the harmonic mean of the two combined metrics:

$$F1 \text{ score} = \frac{2\text{*TP}}{2\text{*TP+FN+FP}} \quad (2)$$

Precision represents another crucial evaluation metric, determining the number of vehicles identified as truly positive across all detection instances:

$$\text{Precision (UAcc)} = \frac{\text{TP}}{\text{TP+FP}} \quad (3)$$

$$\text{Pacc} = \frac{\text{TP}}{N} \quad (4)$$

In addition to the aforementioned metrics, the intersection over union (IoU) was also calculated to provide a more detailed assessment of the model's ability to accurately delineate road segments. The IoU is particularly useful in road extraction tasks, as it measures the overlap between the predicted and ground-truth road areas, thereby providing a robust indication of the model's segmentation accuracy. The IoU is defined as follows:

$$IoU = \frac{Area\ of\ Intersection}{Area\ of\ Union} \quad (5)$$

The area of intersection represents the portion of the predicted road segment that is in common with the ground-truth road segment. The area of union is the total area covered by both the predicted and ground-truth segments.

3. Results and Discussion

The issue of urban development is of significant importance and requires further study. The use of Earth observation methods allows for the monitoring of urban development. The extraction of roads can prove an efficacious solution to a significant issue, particularly in urban areas characterised by intricate structural configurations. In regions where unplanned urbanization is prevalent, the updating and tracking of roads represents a significant challenge.

The objective of this study is to utilize the Sat2Graph deep learning method to infer pathways in an unplanned urbanization region of Mersin and to enhance the OpenStreetMap (OSM) data set. To this end, a very high-resolution (7 cm/pixel) UAV image was employed.

In this study, road extraction from the high-resolution image was performed using the object detection method of the recently developed deep learning tool within Esri ArcGIS Pro. The tool employs the Sat2Graph algorithm and a pre-trained deep learning package. Further details about this tool can be found in the documentation provided by Esri [33]. Given that the region under study is one of rapid unplanned urbanization, it is crucial to obtain results in a context where the distinction between roads is challenging. Figure 3 illustrates the area in which the path inference is conducted and the resulting output.

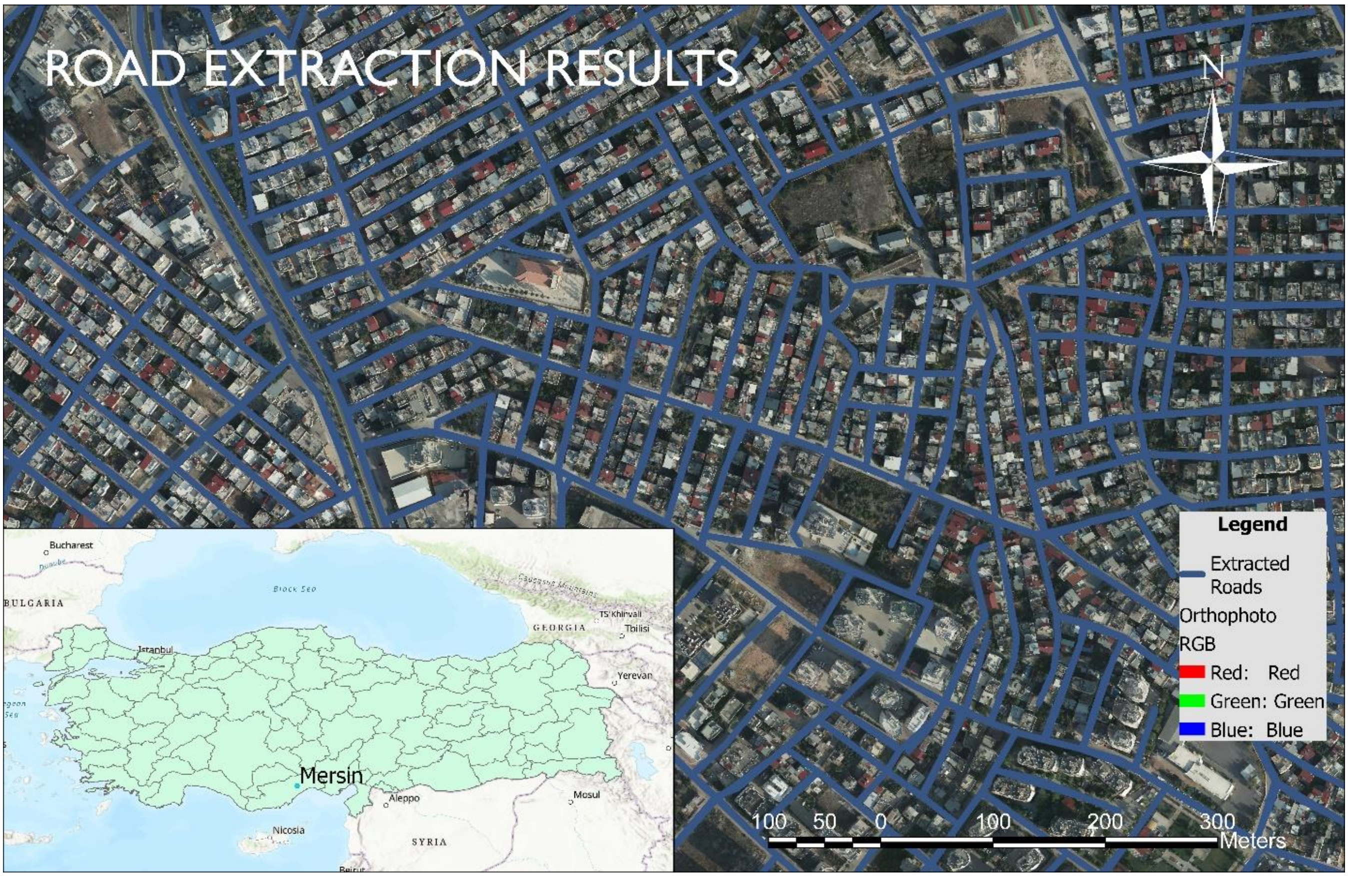

Figure 3. Road Extraction Results.

As illustrated in Figure 3, the prevalence of unplanned urbanization has resulted in the occurrence of topological inconsistencies, including overlap, overshoot, and undershoot, in the extracted road results.

Topological errors are a common occurrence in the process of road extraction within unplanned urban areas, which are typified by irregular road layouts, narrow streets, and high building density. These errors frequently emerge due to the irregular nature of urban structures, wherein roads exhibit a lack of consistent patterns, thereby rendering it challenging for the model to discern between roads and other urban features. This ultimately leads to instances of overlap or excessive expansion. Furthermore, complex intersections and narrow roads increase the probability of segmentation errors, as the model may identify roads as multiple disconnected segments or generate redundant paths. This phenomenon is illustrated in Figure 4 (first row, second column), where the road is erroneously extracted as two lines due to inadequate boundary differentiation in narrow spaces. The inability of deep learning models, such as Sat2Graph, to maintain continuity in dense urban environments where roads are obscured or intersect with other objects also results in the loss of data. To address these challenges, advanced post-processing techniques, such as edge snapping and node merging, can enhance the precision of road alignment, reducing the occurrence of overlaps and expansions. The integration of segmentation with boundary-aware object detection in hybrid models could facilitate the differentiation of narrow road boundaries, ensuring the representation of roads as single, continuous lines. Additionally, the augmentation of datasets with diverse examples from dense urban areas could enhance the model's ability to recognize complex road structures, thereby reducing errors in similar environments.

While the objective is to obtain results with greater accuracy, the results obtained are also sufficient for the intended use of the study. The objective of this study is to enhance the OSM data set. Consequently, as illustrated in Figure 4, there is a dearth of path data within the OSM data set, which has been obtained through path inference from the extant UAV data. Consequently, the automatically obtained path extraction results were employed to manually enrich the OSM data. The application of these methods facilitates the expeditious and precise updating of OSM data.

Figure 4. Comparison of OSM Roads and Extracted Roads.

As illustrated in Figure 4, the volunteer-entered OSM data can be expeditiously updated and augmented with data obtained from the road extraction. This study offers a more expedient data collection methodology, employing unmanned aerial vehicle (UAV) imagery in lieu of the GPS tracker data collection utilized in previous studies. However, this approach is more contemporary, as it employs the deep learning method.

In this regard, the results of road extraction were analyzed by comparing the ground truth values and the paths obtained through deep learning (Table 1). As illustrated in Figure 4, a comparison of the data yielded the results presented in Table 1.

Table 1. Road extraction results for the very high-resolution UAV images using Sat2Graph

	Total	**TP**	**FP**	**FN**	**Recall**	**F1 Score**	**Precision (UAcc)**	**Pacc**	**IoU**
Sat2Graph	427	301	58	68	0.816	0.827	0.838	0.792	0.597

FN = false negative; FP = false positive; Pacc = producer accuracy; TP = true positive; UAcc = user accuracy; IoU = intersection over union.

The results of the analysis demonstrate that the Sat2Graph algorithm was able to effectively identify road networks within the complex and unplanned urban environment of Mersin, Turkey. The high recall score indicates that the algorithm was successful in detecting the majority of road features. The F1 score and precision demonstrate a balanced performance in detecting true road segments without generating an excessive number of false positives. The IoU of 0.597 serves to illustrate the degree of overlap between the predicted and ground-truth road networks, reflecting moderate segmentation accuracy and suggesting potential avenues for improvement in dense urban contexts.

A comparison of these results with findings from other studies provides a basis for evaluating the performance of Sat2Graph. For example, Abdullahi et al. reported F1 scores of approximately 0.75-0.80 for convolutional neural network (CNN)-based road extraction models applied to urban areas with complex structures. This is comparable to the F1 score achieved by Sat2Graph in this study, indicating its competitive performance despite the challenges of unplanned urban areas. Zhu et al.'s study on GCB-Net, a global context-aware network, achieved slightly higher IoU values around 0.65, although their study utilized cleaner and less intricate urban datasets, which may account for the difference.

The findings illustrate that the Sat2Graph approach offers a viable approach for augmenting OSM data in urban settings, particularly through the automation of road extraction from high-resolution UAV imagery. The high recall and F1 scores indicate that the model is capable of effectively detecting road networks in complex urban environments, thereby supporting its potential application in the updating and enrichment of OSM data. However, it is important to consider the limitations of this approach. In densely developed, unplanned urban areas, the model demonstrated a tendency to produce topological errors, including overlaps, excessive expansions, and instances of missing data. These issues have the potential to reduce the precision of extracted road networks. These issues primarily arise due to the irregular patterns and complex intersections common in unplanned urban settings, which may present a challenge for the model in distinguishing roads from other structures. Moreover, the model's performance may be contingent upon the resolution and quality of the input imagery. Lower-resolution images may result in less precise road delineations. A further limitation is that Sat2Graph does not include intrinsic mechanisms to address these topological errors, necessitating additional post-processing for refinement. These limitations indicate that while Sat2Graph is beneficial for semi-automated data enhancement in OSM, supplementary preprocessing and post-processing procedures may be necessary to achieve optimal precision in dense urban environments.

Upon examination of the analysis results and Figure 4, it becomes evident that the Sat2Graph method does not yield a particularly high level of accuracy. However, it is sufficient to enhance the quality of the OSM data, which represents the primary objective of this study. The generation of the data is a relatively straightforward process, as the results are obtained using commercial software. Furthermore, the resulting accuracy can be employed to enrich the OSM data. Moreover, the deep learning tool developed by Esri can be utilized to address engineering challenges without the necessity of programming expertise.

4. Conclusion

This study achieved the enrichment of OpenStreetMap (OSM) data through the integration of high-resolution UAV imagery with advanced deep learning algorithms, specifically employing the Sat2Graph model to improve road network accuracy in urban areas. The study employed a three-phase approach. Initially, very high-resolution UAV data was collected and processed to create an orthomosaic at a 7 cm/pixel resolution, thereby capturing the detailed spatial characteristics of the study area. The aforementioned orthomosaic was then utilized in the second phase, wherein path inference was conducted through the application of the Sat2Graph deep learning model within the ArcGIS Pro software. In the assessment phase, multiple accuracy metrics, including recall, F1 score, user accuracy (UAcc), and producer accuracy (Pacc), were employed to evaluate the model's performance. The resulting scores of 0.816, 0.827, 0.838, and 0.792, respectively, indicate a robust capability to identify road networks in complex and irregular urban environments.

However, the study also revealed challenges associated with the application of deep learning in dense, unplanned urban areas, where topological inconsistencies such as overlaps, excessive expansions, and missing data were observed. These findings highlight the limitations of current deep learning models in handling the variability and irregularity of road networks in urban settings with minimal planning. To address these limitations, incorporating post-processing techniques, such as edge snapping and node merging, could improve connectivity and reduce segmentation errors in the extracted road networks, enhancing data quality.

Future research may benefit from a multi-faceted approach, with an emphasis on the integration of advanced graph-based corrections and hybrid deep learning models, with the objective of further reducing topological errors. The implementation of hybrid models that combine segmentation and boundary-aware detection may facilitate the differentiation of road boundaries in dense environments, thereby enhancing the continuity and accuracy of extracted road networks. Furthermore, augmenting the training dataset with a more diverse range of urban scenarios, encompassing both unplanned and irregular layouts, may enhance the model's adaptability and robustness across diverse urban landscapes, ultimately increasing its reliability and precision.

Comparative studies involving other object detection algorithms, such as Mask R-CNN or Vision Transformers, may provide solutions into the most effective models for road extraction in complex environments, especially when coupled with high-resolution data. By testing and comparing different deep learning algorithms and integrating the findings into a unified approach, future studies could establish guidelines for selecting the most suitable algorithms for enriching OSM data in diverse settings.

This study's semi-automated data enrichment approach provides a means of rapidly updating OSM data with greater accuracy, particularly in dynamic urban areas where frequent changes can rapidly render map data obsolete. As urban areas continue to expand and evolve, the use of high-resolution imagery and deep learning for map data enrichment can facilitate urban planning and sustainable development efforts by ensuring the reliability and currency of information on infrastructure provided by public mapping platforms like OpenStreetMap (OSM).

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