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A Comprehensive Satellite Review of Deep Learning Methods for Road Extraction from Satellite Images

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KEYWORDS:
Road extraction and detection, High-resolution remote sensing images, Satellite images, Deep learning.

ABSTRACT

Given the increase in demand for the use of satellite imagery in automated and accurate extraction of roads, high-definition satellite imagery has recently created an increase in the need for automated and accurate techniques for extracting road networks from remote sensing images using modern techniques. Due to the increase in the accuracy and capability of creating strong representations within a deep learning architecture that can automate many of the manual tasks of creating and maintaining maps, deep learning has become the most prevalent method to extract roads from remote satellite images. In this paper, we have provided a complete overview of methods that utilize deep learning architectures to extract roads from satellite images. The papers that we discussed in this overview are organized by the architecture of the network or models, such as CNN's, U-Net models, attention/implementation models, and transformer models. Performance comparisons for the extracted road data were performed based on the benchmarking datasets of DeepGlobe, SpaceNet, and the Massachusetts Roads Dataset using established performance metrics of Intersection Over Union (IoU), Precision, Recall, and F1 Score. Moreover, we discuss the strengths and weaknesses of the current techniques and methods used for extracting road data from these four types of models. We highlight common issues with extraction, such as road discontinuities, occlusion of roads, low contrast surfaces, and a lack of generalizability across datasets when using the former three types of networks, which cause similar performance issues. Finally, we propose several future research directions to develop better-performing systems that do not just rely on using deep learning with the aforementioned architectures but also on hybrid architectures, fusing multiple sensor data types and limiting the need to rely on collecting large sets of manually annotated satellite images in order to improve the performance of road extraction systems.

الكلمات المفتاحية:
استخراج الطرق واكتشافها، صور الاستشعار عن بعد عالية الدقة، صورالاقمار الصناعية، التعلم العميق .

الملخص

نظرًا للازدياد المستمر في الطلب على استخدام صور الأقمار الصناعية في الاستخراج الآلي والدقيق لشبكات الطرق، فقد أدت الصور الفضائية عالية الدقة في الآونة الأخيرة إلى زيادة الحاجة إلى تقنيات مؤتمتة ودقيقة لاستخراج شبكات الطرق من صور الاستشعار عن بُعد باستخدام الأساليب الحديثة. ومع التطور الكبير في دقة وقدرة معماريات التعلم العميق على بناء تمثيلات قوية قادرة على أتمتة العديد من المهام اليدوية المتعلقة بإنشاء الخرائط وصيانتها، أصبح التعلم العميق أكثر الطرق شيوعًا لاستخراج الطرق من صور الأقمار الصناعية.
في هذه الورقة، نقدم مراجعة شاملة للطرق التي تعتمد على معماريات التعلم العميق لاستخراج الطرق من الصور الفضائية. تم تنظيم الدراسات التي تمت مناقشتها في هذه المراجعة وفقًا لمعماريات الشبكات أو النماذج المستخدمة، مثل الشبكات العصبية الالتفافية (CNNs) ، ونماذج U-Net ، ونماذج الانتباه وتطبيقاته، ونماذج المحولات (Transformers). كما تم إجراء مقارنات الأداء لنتائج استخراج الطرق اعتمادًا على مجموعات البيانات القياسية DeepGlobe و SpaceNet ومجموعة بيانات Massachusetts Roads ، وذلك باستخدام مقاييس الأداء المعتمدة مثل معامل التقاطع على الاتحاد (IoU) ، والدقة (Precision) ، والاسترجاع (Recall)، ومعاملF1.

علاوة على ذلك، نناقش نقاط القوة والضعف للتقنيات والأساليب الحالية المستخدمة في استخراج بيانات الطرق ضمن الأنواع الأربعة من النماذج. كما نسلط الضوء على المشكلات الشائعة في عملية الاستخراج، مثل انقطاع الطرق، وحجب الطرق، والأسطح ذات التباين المنخفض، وضعف قابلية التعميم عبر مجموعات البيانات المختلفة عند استخدام الأنواع الثلاثة الأولى من الشبكات، مما يؤدي إلى مشكلات متشابهة في الأداء. وأخيرًا، نقترح عدة اتجاهات بحثية مستقبلية لتطوير أنظمة أكثر كفاءة، لا تعتمد فقط على التعلم العميق باستخدام المعماريات المذكورة أعلاه، بل تشمل أيضًا المعماريات الهجينة، ودمج بيانات متعددة من أنواع مختلفة من المستشعرات، وتقليل الاعتماد على جمع كميات كبيرة من صور الأقمار الصناعية المشروحة يدويًا، بهدف تحسين أداء أنظمة استخراج الطرق.

1. INTRODUCTION

Satellite images are a primary source of geospatial data, and these images have many uses, including in meteorology (weather forecasting), agriculture management, forest management, preserving biodiversity, and planning sustainable cities, with the advances in satellite photo technology allowing for the capture of extensive amounts of detailed imagery at high resolution. These developments have increased the amount of imagery available for analysis and, therefore, increased the demand for automated methodologies to extract this imagery, especially the task of identifying roads, which require detailed pixel resolution classifying methods to provide an accurate defining of a road network. Currently, roads are foundational infrastructure, linking rural to urban areas and creating avenues for generating economic development as well as managing tourism and emergency responses. As such, road extraction has an important function for urban examples, and those functions will impact urban traffic monitoring and environmental management, particularly with respect to any satellite imagery that may contain shadows or obstructions created by buildings or vegetation. As such, it is essential to deploy contemporary data analytic tools, such as Deep Learning algorithms, as a tool and guide for accurately extracting and classifying features from remote sensing satellite imagery while decreasing the potential of computational miscalculation and/or error. Convolutional Neural Networks (CNNs), Fully Convolutional Networks (FCNs), and Transformer-based models are widely applied in urban high-resolution image segmentation. While fully supervised models require extensive manually labeled datasets, semi-supervised and unsupervised approaches leverage unlabeled or partially labeled data to improve training efficiency and enhance model generalization. Figure 1 shows the precise classification of deep learning techniques for road extraction in remote sensing images. The deep neural networks consist of millions of features, and these features are organized into layers, and they were trained by repeat iteration with high accuracy. Road extraction continues to face challenges such as variations in illumination, seasonal changes, narrow or low-contrast roads, and the need to balance model accuracy with computational efficiency. Researchers typically evaluate performance using benchmark datasets such as DeepGlobe, SpaceNet, and Massachusetts Roads, employing metrics like Intersection over Union (IoU), Precision, Recall, and F1-score. Recent advances in network architectures—including attention mechanisms and multi-scale feature fusion further enhance model accuracy, automation, and reliability in road extraction from satellite images [4],[5],[6]. In the next section, the study aims to analyze state-of-the-art deep learning-based road extraction methods, classify them according to supervision type, discuss their advantages and limitations, and then outline future directions for improving the quality and accuracy of road detection in remote sensing applications. Finally, future works are suggested for further studies. Despite the growing use of deep learning for road extraction, many review studies lack a clear comparison between different model architectures and provide limited discussion of their generalization across datasets and regions. Moreover, common issues such as fragmented road predictions and high computational cost are often insufficiently addressed. Therefore, this paper presents a concise and structured review of recent deep learning-based road extraction methods, highlighting key challenges and future research directions.

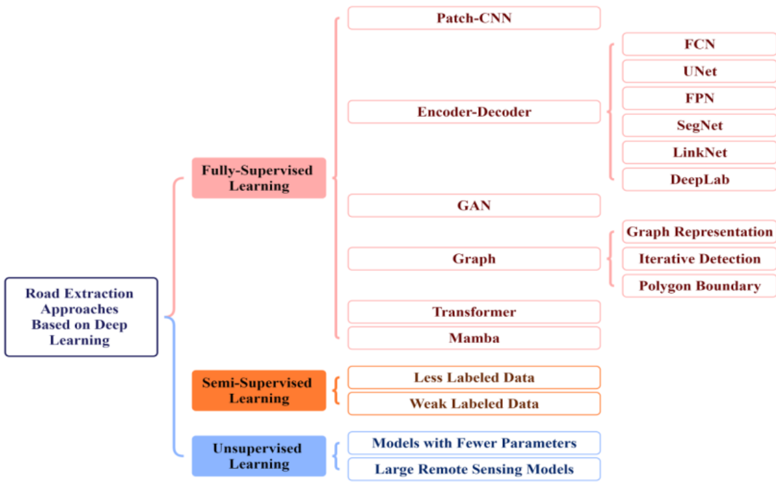

Figure 1. Classification of road extraction approaches based on deep learning.

2. RELATED WORK STUDIES

In 2020, Yeneng Lin proposed a Nested SE-Deeplab model for automatic road extraction from extremely high-resolution remote sensing imagery. Based on Deeplab v3, the proposed framework employs multi-scale up-sampling to effectively fuse shallow and deep features, while a Squeeze-and-Excitation (SE) module enhances channel-wise feature representation. The use of Dice loss further improves performance on imbalanced datasets. Experimental results on the Massachusetts Roads Dataset demonstrate that Nested SE-Deeplab surpasses the models (FC-DenseNet, Deeplab v3, SegNet, and UNet), confirming its superiority and robustness in fine-grained road extraction [7].

Many towns aim to automate the assessment of road damage, but they are constrained by budget, experience, and technological capabilities. In 2020, Deeksha Arya proposed a study that created a dataset of 26,620 photos, tested Japan's smartphone-based model abroad, and presented cross-country damage detection models along with suggestions for global data and model sharing. It proposes models capable of detecting and classifying road damage in more than one country [8].

In 2021, Dudu proposed an approach to facilitate intelligent highway management. This study uses an object-oriented image information extraction technique for road detection in remote sensing photographs. Road features are used for rule-based extraction, segmentation with suitable thresholds, and image enhancement. Optical satellite imagery was used as the dataset. The object-oriented approach successfully recovers road information with a reasonable level of segmentation and accuracy, according to the results [9].

In 2021, Christian proposed a methodology capable of detecting buildings and roads with sub-pixel width by fusing both Sentinel-1 and Sentinel-2 data (at 10 m) together with Open Street Map to train deep learning models for building and road detection at 2.5 m. Furthermore, a modified U-Net architecture is used to both segment the input images and increase the resolution of output masks. A dataset collected from 44 cities across the Spanish territory has been used and divided into training and testing cities. The quantitative and qualitative results indicate that high-resolution satellite imagery can be used for sub-pixel width building and road detection [10].

In 2021, Dejun Feng proposed a road extraction method that enhances precision and addresses the problem of occlusion-induced discontinuities in road networks. The approach combines an attention-based CNN for robust feature extraction with an emphasis on salient regions and noise suppression, and a heuristic connected-domain analysis technique that reconnects fragmented road segments. The study uses the DeepGlobe Road Extraction dataset to perform experiments and evaluate the proposed method. The proposed method demonstrates strong performance in extracting roads from complex and obstructed areas, confirming its effectiveness and robustness [11].

In 2021, Yuewu Hou introduced an approach for road extraction from high-resolution remote sensing images using a Complementary UNet (C-UNet). The method consists of four main steps: (1) an initial extraction of road information using a standard UNet, (2) removal of partial errors through a predefined threshold, (3) generation of a second segmentation using a Multi-scale Dense Dilated Convolution UNet (MD-UNet) to detect missing road regions, and finally, (4) fusion of the results from steps one and three to produce more accurate and complete outputs, Massachusetts Road dataset is used for road extraction of remote sensing Images[12].

In 2022, Yifang Yin proposed a paper, with 1,344 annotated images from Singapore, Grab-Pklot is the first high-resolution, context-enriched satellite imagery dataset for parking lot recognition. In contrast to other datasets that primarily concentrate on land use, buildings, and roads, Grab-Pklot incorporates multi-channel formatted contextual information on nearby buildings and roads in addition to car park annotations. The authors suggested a fusion-based segmentation method to verify its utility, demonstrating that predicting correlations between parking lots and adjacent geographic features enhances detection precision. In addition to highlighting new opportunities and obstacles in parking lot detection from satellite images [13].

In 2022, Kushagra Pal proposed the use of deep learning for ground detection in autonomous vehicles. In order to extract surface normal information from the KITTI road dataset under difficult circumstances, it contrasts three architectures: ResNet-50, Xception, and MobileNet-V2. All models achieved high segmentation accuracy, according to the results, with MobileNet-V2 providing a lightweight option, which makes it appropriate for edge deployment [14].

Lei He Proposed One-Stop-Road Model (the "D-DenseNet") in 2022. The new architecture shows better performance than the original model "D-LinkNet" regarding extracting roads from remote-sensing images. The D-DenseNet benefits from being able to see the global context of remote sensing imagery through its Stem Block and improvements in dilated convolution within its DenseNet Backbone. Compared to D-LinkNet, the D-DenseNet results show higher accuracy and efficiency in road extraction from remote sensing images. Therefore, we conclude that combining the D-DenseNet's D-Dense Block, Stem Block, and Dilated Convolutions significantly improves the performance of semantic segmentation in road extraction." [15].

In 2022, Varun Yerram proposed a project, the purpose of this project was to provide a methodology for measuring roadway area through Remote Sensing. The method consists of two parts: Road Extraction and Area Measurement. The proposed method was based on Advanced Deep Learning Models (U-net++, ResNeXt), combined with an Efficient Post-Processing Method to determine the Road Areas from satellite images with pixel resolution. The results indicated that the proposed approach was superior to other Unet-based approaches when tested on the Massachusetts Data Set in terms of Road Extraction Accuracy.[16].

In 2022, Shiwei Shao proposed a better road extraction network using U-Net. It adds helpful functionalities and focuses on what's important to get more precise segmentations. A residual dilated convolution module captures multi-scale road features, while residual densely connected blocks facilitate feature reuse and gradient flow. In addition, channel and spatial attention modules refine the use of spectral and spatial information. To evaluate the performance of the proposed method, comparative experiments were conducted using the Deep Globe Road Extraction dataset. Experimental results showed higher accuracy, fewer false detections, and better alignment with ground truth compared to other methods [17].

In 2022, Hamza Ghandorh proposed a new way for road detection from high-resolution satellite images by combining semantic segmentation and edge detection to produce an accurate segmentation map with obvious-road boundaries. Also, to deal with the highly imbalanced data set, a combination of weighted cross-entropy loss and the focal Tversky loss was used as the loss function. The proposed method was tested on two datasets, Saudi Arabia and the United States, showing that it can generate precise maps and detect road edges effectively, even in complex environments [1].

In 2023, Qianxiong Xu proposed P2CNet, a two-branch network for road extraction that blends satellite images with imperfect road data, like Open Street Map. The model incorporates a Gated Self-Attention Module (GSAM) to capture long-range semantics and fuse features, as well as a Missing Part (MP) loss to highlight absent road pixels. The datasets used in SpaceNet2 and OSM3 experiments reveal that P2CNet attains state-of-the-art accuracy, indicating its efficacy in enhancing road extraction [18].

In 2023, D. Madhumita and H. A. Bharath introduced The article underlines the importance of road networks for economic growth and emphasizes the need for advanced road stress mapping in maintenance planning. The type of dataset utilized optical remote sensing with very high resolution (VHR). Their study proposed an end-to-end approach that integrates a convolutional neural network (CNN) with GIS to extract and estimate distress from very high-resolution satellite images. By enhancing feature extraction, the model aims to overcome the limitations of previous methods and improve prediction accuracy [19].

In 2023, Hussein Ali Al-Iiedane proposed an automated technique for detecting roads in extremely high-resolution satellite data. The approach, which combined CNNs with transfer learning, performed better in the Deep Learning Challenge. Additional advantages of the method include faster convergence, efficient utilization of non-local blocks, and data augmentation. All things considered, it increases the accuracy and efficiency of road segmentation and provides a dependable substitute for manual inspection [20].

In 2023, Arezou Akhtarmanesh suggested a deep learning-based road extraction from aerial images for usage in autonomous cars, transportation, infrastructure, and disaster relief. A patched, rotated, and enhanced version of the DeepGlobe dataset was used to train the suggested model, a UNet with attention blocks in the decoder. Patching, rotating, removing background-only photos, and filtering photos with few road surfaces were all part of the preprocessing process; attention blocks served as soft attention, while patching and rotation served as hard attention. The study also uses precision-recall analysis to examine performance problems on difficult samples and suggests future research avenues [21].

In 2024, Indukumar Perla discussed the importance of Road extraction from satellite images, which is essential for infrastructure planning, emergency response, and navigation. The study proposed a deep learning-based road detection and image segmentation method using a U-Net architecture. The model is trained on publicly available datasets with optimizers and hyperparameters fine-tuned for improved performance. Comparative analysis with other techniques reveals significant improvements and highlights the potential advantages of the proposed paradigm [22].

In 2025, Ahmed Nabil proposed a hybrid road extraction framework that integrates Faster R-CNN with a Multi-Task Road Extractor (MTRE) model. The Faster R-CNN first identifies candidate road regions, which are then simultaneously segmented and classified by the MTRE using a shared encoder architecture. The SpaceNet satellite dataset was used to perform experiments showing very good results, demonstrating that the combination of object detection and multi-task learning works well for extracting roads in complex urban locations [23].

In 2025, Arpan Maharaj presented an improved DeepLabV3+ network for extracting roads from satellite images (road extraction). An ASPP is used to perform the typical approach for obtaining feature maps from satellite images, which was replaced in this case by DenseDDSSPP and SE modules. These changes enabled improved extraction of complicated road networks by improving the feature maps that are used in the extraction process. Results from testing indicate that this model achieves higher levels of accuracy and precision in performing road extraction. Mnih and Hinton originally created the first dataset, the Massachusetts road dataset. In the same way, the authors used the DeepGlobe dataset as a second dataset for testing. [24].

3. COMPARATIVE DISCUSSION

After reviewing some of the research findings that discuss the effectiveness of U-Net Inspired Architecture in road segmentation, it is observed that the primary factor contributing to its success is the use of pixel fusion through the implementation of skip connections. With this in mind, the development of transformer architecture will enable further increases in connectivity through spatially cohesive feature representation, in addition to global feature representation; however, both of these methods require significantly higher levels of computation and large training datasets, which would prohibit their use in real-time applications. The conclusion that no single architecture can effectively tackle all road extraction problems thus leads to the need to hybridize or develop lightweight solutions.

Table 1. Comparison of Previous Studies on Road Extraction Using Deep Learning

Author(s)	Year	Method / Approach	Dataset	Results	Key Contributions	Limitations
Yeneng Lin	2020	Nested SE-Deeplab	Massachusetts	Outperformed baselines	Improved fine-grained extraction via multi-scale features	Limited cross-dataset validation
Deeksha Arya	2020	Smartphone-based DL	Multi-country images	Accurate damage detection	Enabled cross-country damage detection	Not full road extraction
Dudu	2021	Object-oriented rules	Optical imagery	Reasonable accuracy	Used object-based features for segmentation	Limited robustness vs. DL
Christian Ayala	2021	Modified U-Net + fusion	44 Spanish cities	Sub-pixel accuracy	Enhanced detection via multi-source fusion	Region-specific validation
Dejun Feng	2021	Attention CNN + post-process	DeepGlobe	Better connectivity	Improved continuity under occlusion	Added post-processing overhead
Yuewu Hou	2021	C-UNet (fusion)	Massachusetts	More complete outputs	Reduced missing roads via complementary fusion	Higher computational cost
Yifang Yin	2022	Context-aware segmentation	Grab-Pklot	Higher precision	Leveraged contextual information	Focused on parking, not roads
Kushagra Pal	2022	ResNet/Xception/MobileNet	KITTI	High accuracy	Demonstrated lightweight efficiency	Not satellite-focused
Lei He	2022	D-DenseNet	HR imagery	Better than D-LinkNet	Improved segmentation with DenseNet	Limited generalization
Varun Yerram	2022	U-Net++ / ResNeXt	Massachusetts	Higher accuracy	Enhanced roadway area estimation	Needs post-processing
Shiwei Shao	2022	Attention U-Net	DeepGlobe	Fewer false detections	Improved accuracy using attention	Higher compute demand

Hamza Ghandorh	2022	Segmentation + edges	KSA & USA	Clear boundaries	Enhanced boundary detection	Complex pipeline
Qianxiong Xu	2023	P2CNet + OSM	SpaceNet/OSM	SOTA performance	Integrated partial maps for better extraction	Depends on external maps
D. Madhumita & H. Bharath	2023	CNN + GIS	VHR imagery	Better distress mapping	Automated road distress analysis	Not full network extraction
Hussein Al-Iiedane	2023	CNN + Transfer Learning	DL Challenge	Up to 97.6% acc.	Improved detection via transfer learning	Binary classification only
Arezou Akhtarmanesh	2023	Attention U-Net	Modified DeepGlobe	Better hard samples	Attention improved difficult cases	Added preprocessing cost
Indukumar Perla	2024	Optimized U-Net	Public datasets	Improved performance	Boosted U-Net via tuning	Limited novelty
Ahmed Nabil	2025	Faster R-CNN + MTRE	SpaceNet	Robust in urban scenes	Combined detection and segmentation	Less pixel-level focus
Arpan Mahara	2025	Enhanced DeepLabV3+	Mass./DeepGlobe	Higher precision	Strong multi-scale extraction	High data/computation needs

4. RESEARCH LIMITATIONS AND GAPS

Deep learning-based road extraction has achieved substantial progress; however, several important limitations remain unresolved:

- Both CNN-based and transformer-based models continue to struggle with low-contrast or shadowed roads.
- Generalization issues arise when models trained on DeepGlobe perform poorly on other datasets, such as SpaceNet or Massachusetts.
- Predicted road networks often remain fragmented, especially in rural regions or areas with significant occlusion.
- The high computational cost of transformer models limits their deployment in real-time systems.
- The lack of large, extensively annotated datasets restricts the training of robust models across diverse environments.
- Multi-sensor data fusion (e.g., LiDAR + optical imagery) is still insufficiently explored despite its strong potential to improve accuracy.

Addressing these limitations is essential for developing a more resilient, scalable, and reliable road extraction system.

5. CONCLUSIONS

The migration from traditional U-Net-based models to more sophisticated model types, such as DeepLabV3+, networks enhanced with attention, and transformer-like or similar technologies, which will be used for extracting road data from satellite imagery using deep learning, was the focus of this review of research progress. Although segmentation methods and state-of-the-art (SOTA) provide improved performance, many obstacles are associated with segmentation (i.e., occasion, light, variability, and generalizing across locations). While many approaches exist to resolve these challenges through the development of more robust segmentation techniques or deploying readily available models for new datasets, more evaluation of SOTA will be performed to identify the limitations of SOTA over existing methods and to provide additional insight into why SOTAs are superior to traditional segmentation techniques. This paper's comparative analysis shows that transformer models provide better contextual understanding at a higher computational cost, DeepLabV3+ offers robust multi-scale feature representation, and U-Net-based architectures continue to be effective for lightweight and fine-grained extraction. Future studies should concentrate on creating hybrid CNN-Transformer models that strike a balance between accuracy and efficiency, utilizing self-supervised and generative learning to lessen reliance on annotated datasets, and integrating multi-sensor and multi-temporal imaging. More scalable, accurate, and dependable road extraction systems that are appropriate for smart city applications, autonomous navigation, and disaster response are anticipated to be made possible by these directions.

Conflict of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Consent for publications

All authors have read and approved the final version of the paper for publication.

Availability of data and material

All data supporting the findings of this study are included within the paper.

Authors' contributions

E.A.F. designed the main idea of the study, prepared the dataset, conducted the experiments, and wrote the initial draft of the manuscript.
A.A.S. supervised the research, reviewed the methodology, and contributed to the revision and final editing of the manuscript.
Both authors have read and approved the final version of the article.

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