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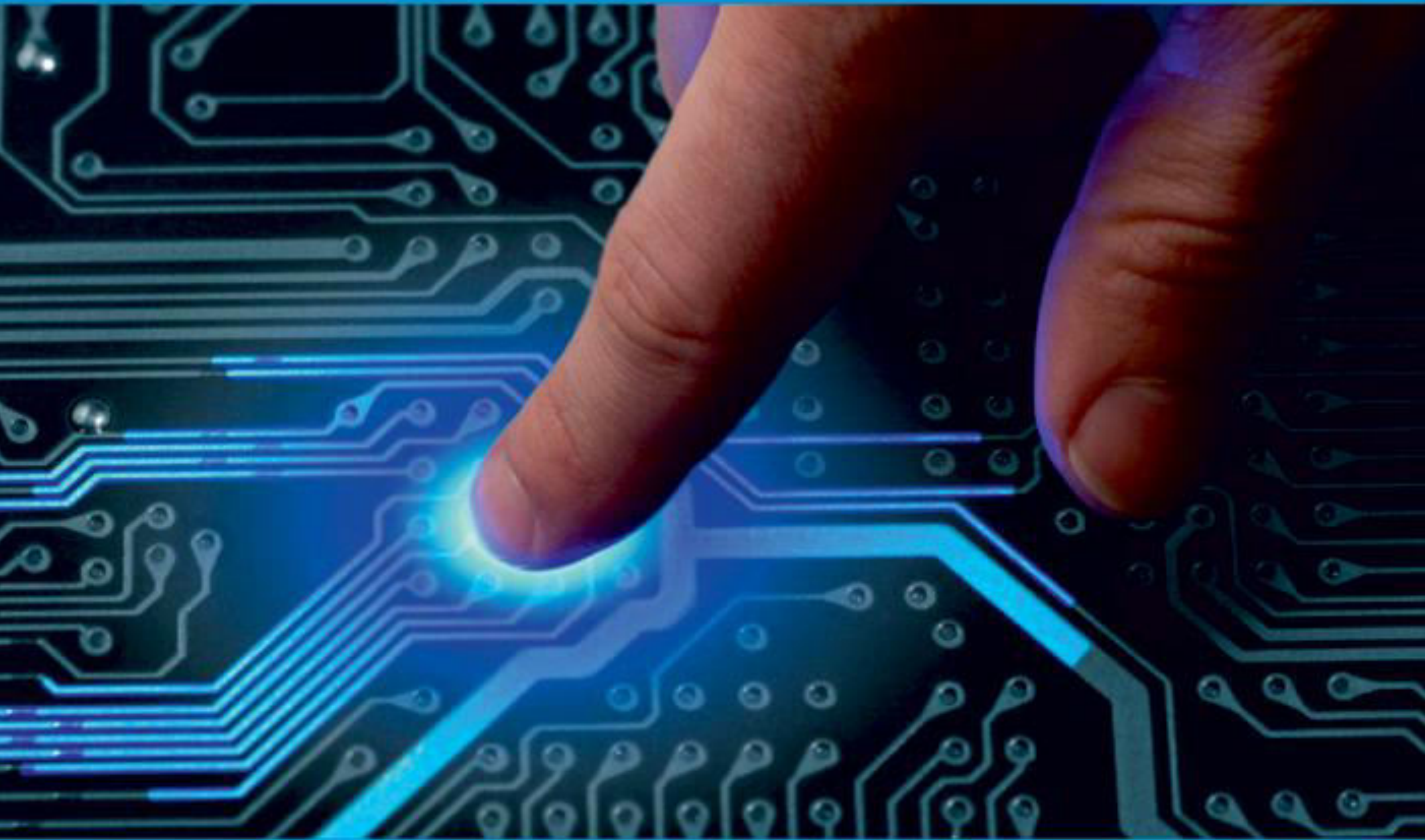

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An Overview of Deep Learning Techniques for Road Detection in High-Resolution Satellite Images

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ABSTRACT: One of the main and most difficult problems in computer vision research has been removing road networks from high-resolution remote sensing photos. Numerous applications, such as urban planning, traffic management, disaster response, and environmental monitoring, depend on the accurate identification of road networks. The field of artificial intelligence has witnessed tremendous advancements and advances in road extraction technology, especially in the area of deep learning. This research provides an extensive analysis of deep learning techniques for road extraction from remote sensing imagery, emphasizing how these technologies improve process accuracy and efficiency. Deep learning techniques are divided into fully supervised, semi-supervised, and unsupervised learning approaches, each having more focused subcategories, depending on the kind of annotated data that is used. The tenets, advantages, and disadvantages of these approaches are contrasted and examined. The review also provides an overview of the metrics applied to assess road extraction algorithms and the high-resolution remote sensing picture datasets used for these kinds of activities. In conclusion, we go over the main obstacles and potential applications of computational intelligence methods to enhance the precision, automation, and intelligence of road network extraction.

KEYWORDS: road extraction, high-resolution remote sensing images, deep learning, fully-supervised,semi-supervised, unsupervised.

I. INTRODUCTION

High-resolution satellite imagery is now widely available due to the quick development of remote sensing technology, providing previously unheard-of possibilities for a range of uses, including environmental monitoring, urban planning, and disaster relief. Among these uses, geographic information systems (GIS), navigation, and transportation planning heavily rely on the identification and extraction of road networks from satellite pictures.Conventional approaches to road detection in satellite imagery frequently depend on manually created features and traditional image processing methods. Although helpful, these techniques are often labor-intensive, time-consuming, and have a limited capacity to generalize across different geographical regions and imaging situations. A new paradigm has developed with deep learning, providing strong capabilities to improve and automate the road detection process.

Neural networks with several layers, or deep architectures, are used in deep learning, a type of machine learning, to learn representations of data with multiple levels of abstraction. This capacity has shown to be very successful in a number of computer vision tasks, such as semantic segmentation, object detection, and image categorization. Specifically, convolutional neural networks (CNNs) have demonstrated exceptional efficacy in obtaining spatial hierarchies from images, which renders them very suitable for the task of detecting roads in high-resolution satellite photography.

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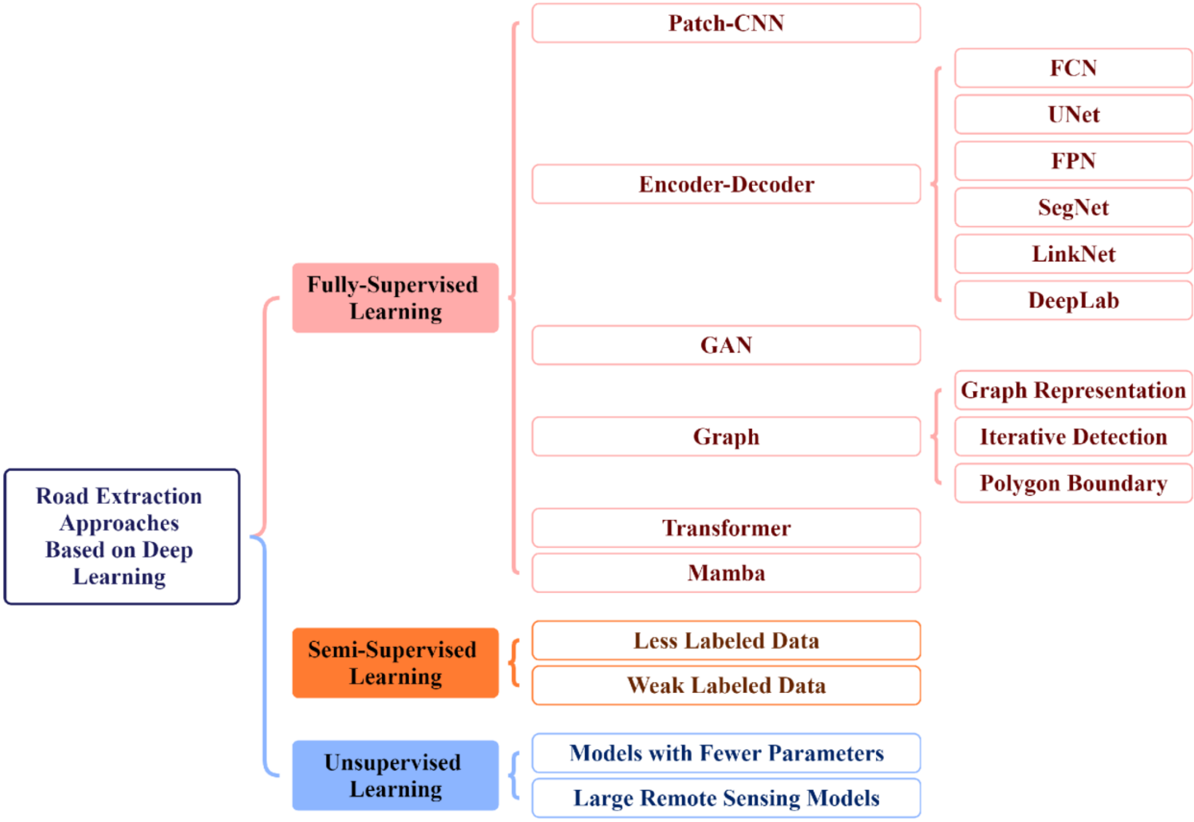

Figure 1. Classification of road extraction approaches based on deep learning.

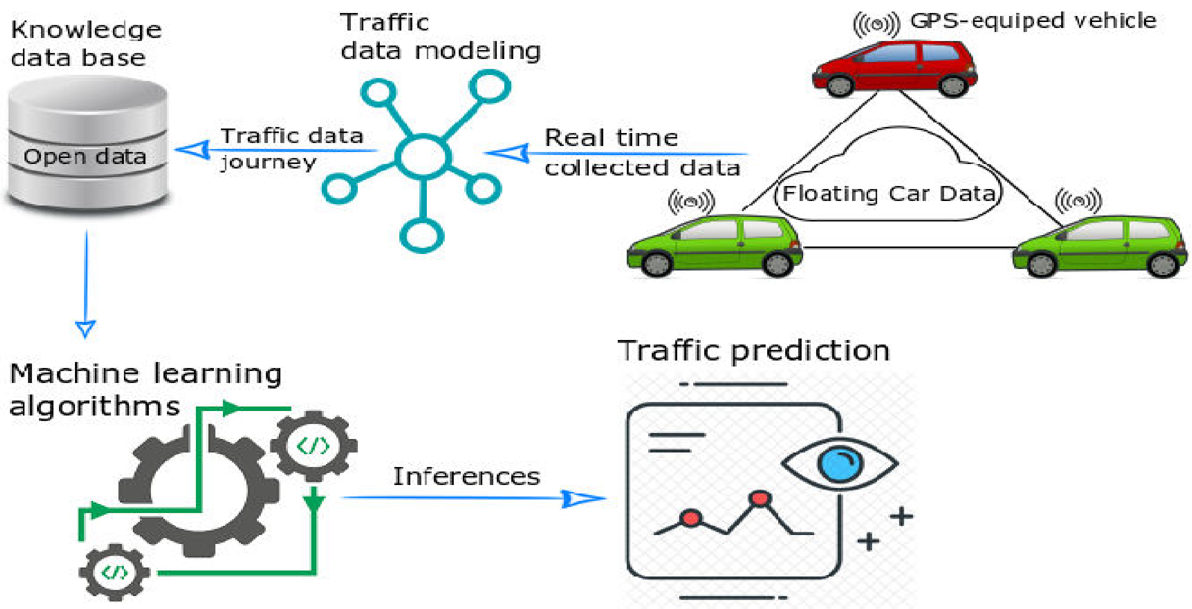

Figure 2 deep learning traffic prediction

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II. RELATED WORK

This section examines how deep learning techniques are being applied in computer vision, with a focus on how they can be used to extract road networks from high-resolution remote sensing photos. Figure 4 displays the sources of the examined literature, and Figure 3 provides a roadmap of the techniques covered in the literature.

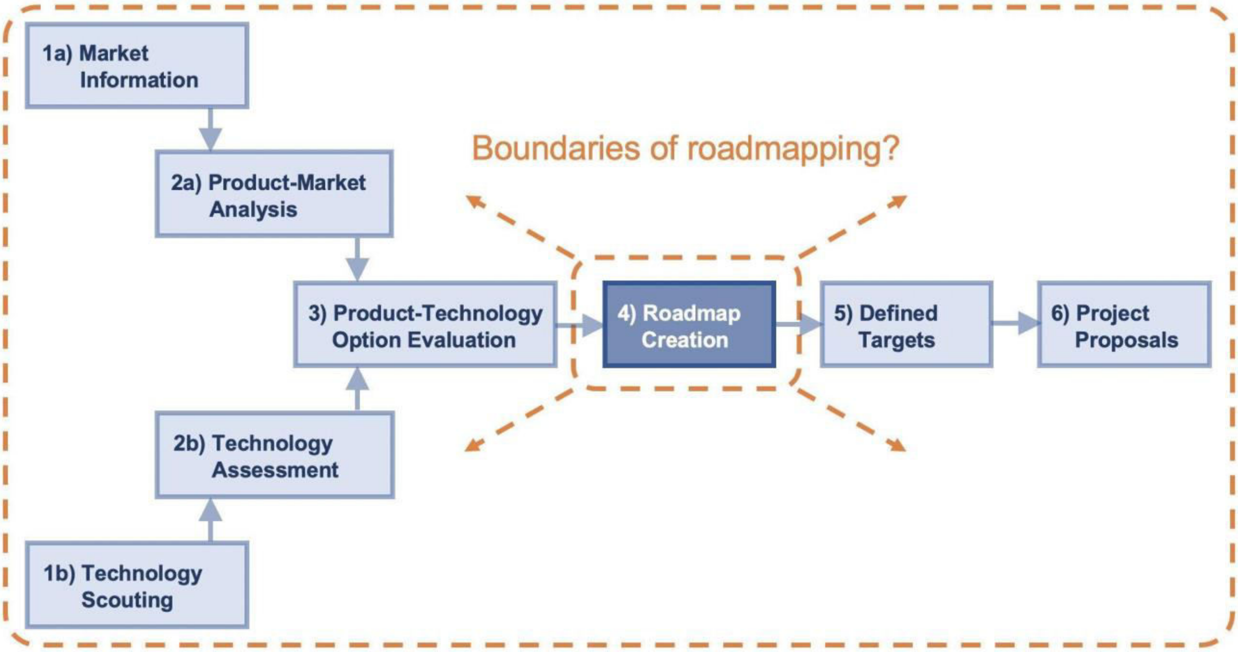

Figure 3 Road mapping as process

Generally speaking, road extraction techniques categorize each pixel in an image as "road" or "non-road." Road areas are frequently hidden by other objects,[4] such as vehicles, structures, and trees, which makes identification more difficult but also provide important context for identifying road sections in challenging situations.

Three primary phases may be distinguished in the development of road extraction techniques: deep learning approaches, manual feature-based methods, and morphological feature-based methods. The accuracy of traditional approaches is limited by their reliance on manual analysis, [2]which makes them time- and resource-intensive. These techniques are constantly being improved because to the development of deep learning technology, which raises the efficiency and accuracy of road extraction. As a result, the development of deep learning techniques for road extraction is highlighted in this section.

III. SUPERVISED TECHNIQUES FOR ROAD RECOVERY

The annotated datasets used in supervised road extraction methods are used[1] to identify each pixel as "road" or "non-road." These techniques take advantage of high-resolution remote sensing photos to discover intricate patterns and features related with road networks using a range of deep learning architectures. The most widely utilized architectures in this field are convolutional neural networks (CNNs), [4]which are highly effective at capturing spatial hierarchies in picture input. Large-scale annotated datasets have been the source of major success for methods like U-Net, SegNet, and DeepLab when it comes to extracting road networks. When there is enough training data available, the main benefit of supervised techniques is their high accuracy and good generalization to various image types. Still, the performance

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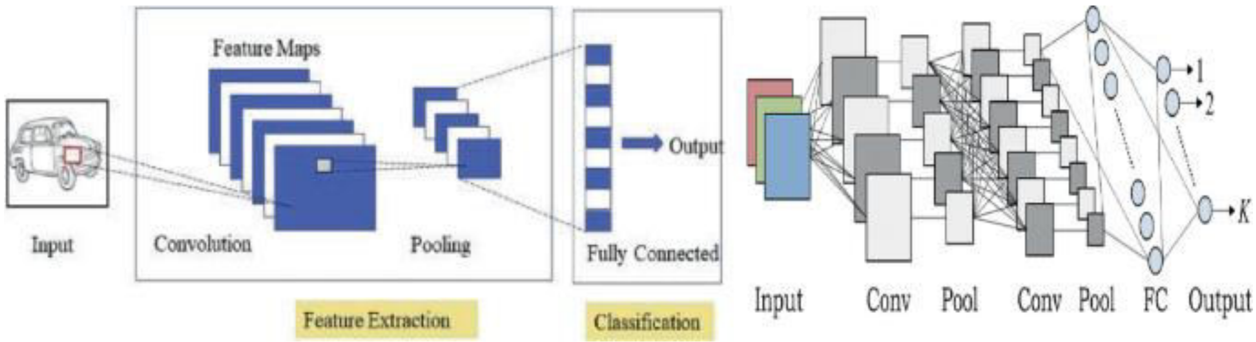

Figure 4. The general architecture of a patch-based CNN model

Table: Approaches, Advantages, and Limitations of Fully Supervised Models for Road Extraction-

Approach	Advantages	Limitations
CNN-Based Methods	High accuracy and precision .Effective in capturing spatial hierarchies in image data.	Requires large, annotated datasets High computational cost
U-Net	Excellent performance in segmentation tasks.Efficient architecture for learning from limited data.	Sensitive to variations in image quality and lighting
SegNet	Efficient memory usage.Good performance in pixel-wise classification.	Struggles with complex scenes and occlusions
DeepLab	Robust to scale variations and capable of capturing fine details.Employs atrous convolution for better segmentation	Computationally intensive Requires extensive tuning for optimal performance
Fully Connected Networks	Can handle high-dimensional data.Good for feature extraction and integration with other models	Less effective for pixel-wise classification Requires significant computational resources
ResNet	Deep architecture with residual connections that improve training.	High memory and computational demands.
FCN (Fully Convolution Network)	Suitable for end-to-end pixel-wise classification Can be adapted to different types of remote sensing data.	Limited by the quality of the input data Computationally expensive for very high-resolution images
Transfer Learning	Reduces the need for large annotated datasets by leveraging pre-trained models Faster convergence.	Limited by the domain gap between pre-trained data and target data May not fully capture specific road features

IV. UNSUPERVISED METHODS FOR ROAD EXTRACTION

Unsupervised methods for road extraction do not rely on annotated datasets for training. Instead, they utilize algorithms that can learn the inherent structure and patterns of road networks from high-resolution remote sensing images without manual labeling[2]. These methods often leverage clustering techniques, feature learning, and self-organizing maps to identify road features. One common approach involves using generative models, such as Generative Adversarial Networks (GANs), which can generate realistic road structures by learning from raw image data.

The primary advantage of unsupervised methods is their ability to operate without the need for extensive and labor-intensive labeled datasets, making them more scalable and cost-effective. They are particularly useful in scenarios where annotated data is scarce or unavailable. Additionally,[2] these methods can adapt to new and varied datasets without the need for retraining on labeled data, enhancing their generalization capabilities.

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However, unsupervised methods also face significant challenges. They typically achieve lower accuracy compared to supervised methods due to the lack of explicit guidance during training. The complexity of road networks and the presence of occlusions, [3]varying lighting conditions, and diverse urban environments can further complicate the extraction process. Additionally, the performance of unsupervised methods heavily depends on the effectiveness of the underlying algorithms in capturing relevant features and structures from the data.

Despite these challenges, ongoing research aims to improve the robustness and accuracy of unsupervised methods through advancements in algorithm design,[5] the incorporation of multi-modal data, and the development of hybrid approaches that combine the strengths of both supervised and unsupervised learning.

A Review of Deep Learning-Based Methods for Road Extraction

V. ROAD EXTRACTION DATASETS

Massachusetts Dataset- A diverse set of remote sensing images covering urban, suburban, and rural areas, suitable for training medium-scale models. It includes various terrains but poses challenges with occlusions and varying conditions.

DeepGlobe Dataset: Over 10,000 satellite images from countries like Thailand, Indonesia, and India. It features diverse environments, aiding robust algorithm development, but roads [4]can be mistaken for other linear features like rivers and railways.

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SpaceNet Dataset: Includes eight versions, with v3 and v5 focused on road extraction. Covers cities like Las Vegas, Paris, and Shanghai, and offers detailed information on road attributes. Challenges include narrow roads and varying urban complexities.

CHN6-CUG Dataset: Provided by China University of Geosciences, this dataset focuses on urban road extraction in six Chinese cities. It includes detailed annotations of various road types and conditions.

Comparison of fully supervised, semi-supervised, and unsupervised learning approaches-

Approach	Description	Advantages	Limitations
Fully Supervised Learning	Relies on annotated datasets where each pixel is labeled as "road" or "non-road".	High accuracy with sufficient annotated data. Well-suited for structured environments	Requires large, annotated datasets Costly and time-consuming to create and label data
Semi-Supervised Learning	Uses a combination of labeled and unlabeled data for training.	Reduces dependency on large annotated datasets .Cost-effective and scalable	Performance highly depends on the quality of labeled data
Unsupervised Learning	Learns from unlabeled data without explicit supervision.	Does not require labeled data. More scalable and adaptable to diverse datasets	Typically lower accuracy compared to supervised methods. Challenges in feature learning and validation

VI. CONCLUSION

This research analyzes techniques from relevant articles to construct deep learning algorithms used for road extraction from remote sensing photos. Based on annotated data requirements, we divide these methods into three categories: fully supervised, semi-supervised, and unsupervised learning. The review highlights the superiority of fully supervised learning and then breaks it down into five subcategories for in-depth analysis. Present-day road extraction methods suffer in complex circumstances, bad weather, and occlusions, but they function effectively in clear settings. Complexity of the images, high annotation costs, and generalization and resilience of the models are major obstacles. Given these problems, we propose that future studies concentrate on:-

Multi-modal Data Fusion: Bringing together information from several sensors (e.g., videos, LiDAR, and remote sensing photos) to capture detailed road details and enhance model resilience.

Semi-supervised and Unsupervised Networks: Investigating strategies that comprehend data structures or employ adaptive training devoid of human annotations, like GAN-based approaches, can help reduce dependency on annotated data.

Adaptive Modeling in Complex Scenarios: Using methods like as data augmentation and adversarial training, models are improved to extract road information in a variety of situations.

Lightweight Networks: Creating models that transfer important features from large, inefficient models to smaller, more efficient ones using methods like knowledge distillation, hence reducing processing requirements without sacrificing accuracy.

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