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Comparative Analysis of Multi-Resolution Remote Sensing Data for Accurate Road Segmentation in Urban Environments

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Abstract

Road networks are crucial to urban infrastructure and significantly affect transportation, traffic management, and emergency response. Besides, accurate mapping is essential for detecting road networks effectively, but traditional methods like manual digitization and field surveys often struggle in fast-changing urban environments. Remote sensing and deep learning techniques have emerged as effective alternatives, although initial road segmentation faced challenges such as limited image resolution. Recent advances in satellite technology have alleviated these issues by providing ultra-high-resolution (sub-meter) imagery, which is vital for accurately representing road networks. Deep learning models like U-Net have enhanced road segmentation by accurately capturing complex features. This research examines the effectiveness of multi-resolution satellite imagery for road segmentation. This study aims to analyze the accuracy assessment of road segmentation using Sentinel-2 imagery (10 m resolution) and ultra-high-resolution Pléiades Neo imagery (sub-meter resolution). Ground truth data from the Google Maps API were used for validation. Among the tested resolutions, Pléiades Neo at 30 cm achieved the highest accuracy, with an F-score of 0.87. Pléiades Neo at 15 cm resolution followed closely with an F-score of about 0.85. Pléiades Neo at 1 m resolution (upscaled data) showed a moderate decline (F-score of 0.82), while Sentinel-2 had the lowest performance (F-score of 0.78). Overall, Pléiades Neo at 30 cm resolution offers the best balance of accuracy and data efficiency for road segmentation.

1. Introduction

Road networks are vital components of urban infrastructure, significantly impacting transportation systems, traffic management, urban planning, disaster preparedness, and emergency response. Accurate and up-to-date mapping of these networks is crucial for effective decision-making in these areas. Traditional methods of road mapping, such as manual digitization from aerial imagery or field surveys, are both time-consuming and laborintensive, especially in large or rapidly growing urban areas. In response to these challenges, remote sensing and deep learningbased image analysis techniques have become promising alternatives, providing scalable and efficient solutions. However, early efforts in road segmentation using remote sensing data encountered several obstacles. These included limitations in image resolution, pixel complexity, interference from environmental factors like buildings, vegetation, and shadows, and reduced segmentation accuracy, particularly in dense urban areas.

Advancements in satellite technology have mitigated some of these issues by offering ultra-high-resolution (sub-meters) commercial satellite imagery. These images provide more detailed and precise visual data, facilitating better illustration of road networks. With the use of high-resolution imagery satellites, starting with IKONOS and QuickBird, data extraction from satellite imagery has become a new way to obtain detailed geographic information, motivating the development of different data extraction techniques used to derive new data from satellite imagery (Christophe and Inglada, 2007), (Miao et al., 2015), (Maboudi et al., 2017), (Ghandorh et al., 2022), (Brkić et al., 2023). Nevertheless, access to such data can be costly and is often restricted, especially in developing countries. Alongside these technological advancements, deep learning techniques have emerged as powerful tools for analyzing remote sensing data. Deep learning models like U-Net, LinkNet, SegNet, and Generative Adversarial Networks (GANs) have been widely adopted to enhance road segmentation accuracy. U-Net, in particular, with its encoder-decoder architecture, is adept at capturing both high- and low-level features, making it well-suited for segmenting complex structures such as road networks.

U-Net is a sophisticated convolutional neural network (CNN) specifically designed for segmentation tasks, particularly excelling in the extraction of roads from satellite imagery. By utilizing a significant number of parameters during the training phase, U-Net effectively reduces noise and minimizes false positive pixels in road masks. This capability enables it to produce highly accurate masks that capture essential road features. Although the algorithm requires extensive datasets and fully labeled images, it is widely acknowledged in the literature as the leading solution for road segmentation.

Abderrahim et al. utilized the U-net algorithm on the Massachusetts City dataset to effectively extract the road network by cropping large images into 512×512 pixel tiles. The resulting road extraction demonstrated an impressive accuracy of 97.7% and an F-score of 87.5% (Abderrahim et al., 2020). Öztürk et al. applied two distinct neural network architectures, U-Net and Fully Convolutional Networks (FCN), for road segmentation on high-resolution images with a dimension of 512 x 512 pixels. They achieved approximately 96% segmentation accuracy using U-Net (Öztürk et al., 2020). Öztürk et al. conducted a study using Google Maps API, where they implemented the deep residual U-Net algorithm. At zoom level 17, they achieved F-score and Intersection over Union (IoU) values of 86% and 78%, respectively (Öztürk et al., 2022). Brkic et al.´ compared three machine learning algorithms for road extraction from Pléiades Neo satellite imagery and found that U-net significantly outperformed Random Forest and Extreme Gradient Boosting (Brkic et al., 2023). To investigate the impact of vary-´ ing resolution levels on the effectiveness of U-Net for object segmentation, Graf et al. employed Sentinel-2 satellite imagery to identify irrigation center pivot systems (Graf et al., 2020). They discovered that their accuracy aligned with that of Saraiva et al. (Saraiva et al., 2020), who conducted a comparable study using high-resolution images.

In order to investigate the potential of using multi-resolution satellite imagery for road segmentation in urban environments, we employ two primary sources of satellite images, each with varying spatial resolution levels, to compare road segmentation performance across different image qualities. The study utilizes Sentinel-2 imagery, which provides moderate resolution suitable for identifying prominent features, and very highresolution 15 cm optical satellite imagery derived from Pléiades Neo data for precise delineation of road networks in complex urban environments. Ground truth data is also sourced from Google Map API to validate the road networks extracted from satellite images. This ground truth data serves as the benchmark for evaluating the performance of our outputs from the deep learning model.

2. Materials and Methodology

2.1 Study Area

The research focuses on the area around the ˙Istanbul Technical University Campus in ˙Istanbul, Türkiye, characterized by extensive urbanization and a heterogeneous road network. This region presents significant challenges for road segmentation due to its intricate infrastructure, characterized by a combination of highways, arterial roads, and narrow urban streets alongside a high density of buildings and varied terrain features.

2.2 Dataset

To effectively analyze the road network, the study leverages multi-resolution satellite data from two prominent missions: Pléiades Neo and Sentinel-2. The Pléiades Neo constellation represents a cutting-edge optical satellite system characterized by its high-resolution capabilities and consists of two identical satellites positioned 180° apart. This configuration ensures continuity for the Pléiades mission while significantly enhancing operational performance regarding accuracy and data collection frequency. Key advantages of this mission include expedited tasking capabilities, high degrees of agility, and a substantial capacity for data handling. Airbus Defense and Space designed, owned, and operated the constellation. Pléiades Neo 3, the inaugural satellite in this constellation, was successfully launched on April 28, 2021, followed by the launch of Pléiades Neo 4 on August 16, 2021 (The European Space Agency, n.d.). The constellation continues to operate effectively, fulfilling its intended objectives. Nevertheless, acquiring this high-resolution imagery can incur significant costs, mainly when there is a need to cover extensive geographic areas.

Pléiades Neo stands out for its ultra-high-resolution imagery, boasting a spatial resolution of 30 centimeters. Images with a resolution of 15 centimeters are produced from 30-centimeter images utilizing a proprietary algorithm that integrates techniques from Artificial Intelligence and Machine Learning (Airbus, n.d.). As a result, this new offering features more vibrant colors and sharper details, facilitating easier interpretation. This level of detail is crucial for accurately detecting narrow roads and identifying complex urban features, such as small alleys and intricate intersections. The frequent revisit times of the Pléiades Neo satellite allow for near-real-time updates, making it particularly suitable for monitoring dynamic urban landscapes where infrastructure and conditions can change rapidly.

In contrast, Sentinel-2 represents a European Space Agency initiative characterized by a dual-satellite configuration operating in a shared orbit with an angular phase difference of 180 degrees. This arrangement facilitates a high revisit frequency, enabling observations every 5 days at the Equator. The Sentinel-2 mission offers medium-resolution imagery with different spatial resolutions for its various spectral bands. It has a resolution of 10 meters for the blue, green, red, and near-infrared bands. The red edge, near-infrared, and shortwave infrared bands have a resolution of 20 meters, while the coastal aerosol and cirrus bands have a resolution of 60 meters. Furthermore, the mission's orbital swath width extends to 290 kilometers, enhancing its capacity for comprehensive Earth observation. While the Sentinel-2 data is available at no cost through the Open Data Catalogue of the Joint Research Centre of the European Commission, and its smaller image files facilitate faster processing times, there are notable limitations for tasks like road segmentation. The resolution of 10 meters constrains the ability to capture detailed road networks effectively, resulting in primarily wide road features, such as highways, being detectable. In contrast, narrower roads and finer details within the road network often remain indistinguishable. The satellite imagery utilized in this study was acquired on 11 June 2024 for the Pléiades Neo satellite and 10 June 2024 for the Sentinel-2 satellite.

2.3 Ground Truth

Ground truth data is obtained from the Google Maps API, which serves as a crucial reference point for validating the road networks extracted from satellite imagery. This API is renowned for its accuracy and provides detailed road geometries that enable precise mapping of urban landscapes. One of its key features is the snap-to-road functionality, allowing for the alignment of extracted road data with actual road locations, significantly reducing discrepancies. Furthermore, the Google Maps API is continuously updated, ensuring that the road network information reflects real-time changes and developments in urban infrastructure.

To gather images from the Google Maps platform, it is essential to determine the appropriate zoom level in advance. Zoom level 0 presents the entire world in a single frame, whereas the maximum zoom level, 20, achieves a resolution of up to 0.15 meters. For in-depth studies, zoom level is generally recommended. However, the resolutions of the satellite images used in the study vary, and different zoom levels at the relevant resolution were utilized. The corresponding image resolutions for zoom levels 17, 19, and 20 are approximately 1.19 m/pixel, 0.30 m/pixel, and 0.15 m/pixel, respectively.

2.4 Preprocessing

Both Pléiades Neo and Sentinel-2 images were clipped into 512×512 pixel size sub-images. Road masks were generated at zoom levels that corresponded to the images' resolutions, utilizing the Google Maps API, taking into account consistency in both resolution and corner coordinates. The 30 cm resolution Pléiades Neo satellite images have also been upscaled to 1 m. Finally, 5000 image mask files were created for all data sets, covering all zoom levels of Google Maps roads. The mask images were subsequently converted into binary images as input to the U-Net model (Figure 1).

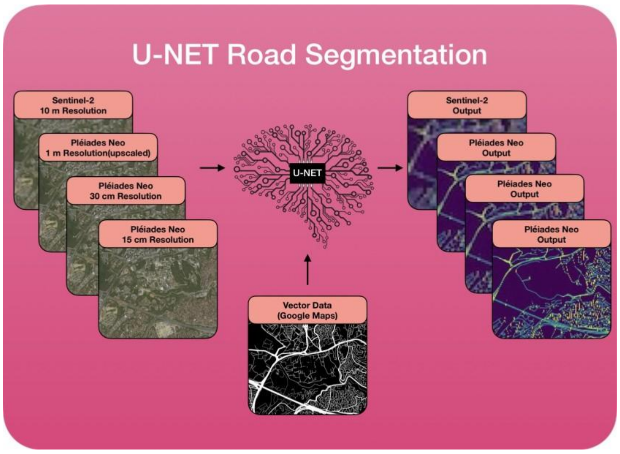

Figure 1. General flow chart of the study.

2.5 Methodology

The U-Net model is the primary architecture utilized in this study. U-Net is one of the most commonly utilized CNNs for image segmentation. This architecture was specifically designed to improve the segmentation of biomedical images (Ronneberger et al., 2015). In addition, many recent studies have shown outstanding results of using U-Net in road segmentation over remote sensing images. U-Net architecture comprises two components: the first, referred to as the contracting path, corresponds to the encoder, while the second, known as the expansive path, serves as the decoder. The encoder block within the architecture comprises two successive 3×3 convolution layers, implemented with a rectified linear unit (ReLU) serving as the activation function, and is accompanied by a 2×2 maxpooling operation. The decoder block incorporates a 2×2 upconvolution combined with the associated feature map from the encoder. It is subsequently followed by two 3×3 convolution layers and a ReLU activation layer. Because of the symmetrical U-shaped pattern formed by combining these two components, this model is called U-Net (Figure 2).

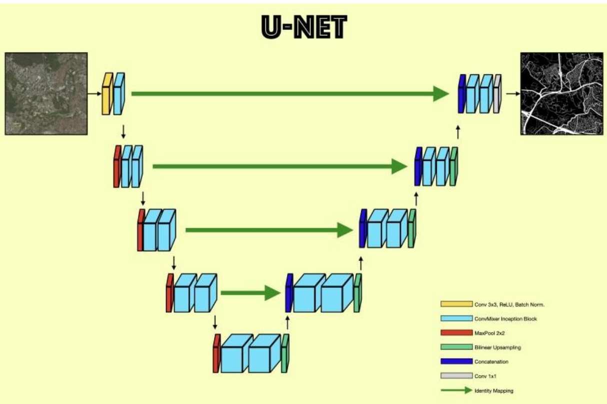

Figure 2. U-Net architecture used in the study.

The U-Net architecture, as provided by (Yakubovskiy, 2019), was implemented using the ResNet50 backbone for enhanced performance. U-net was implemented utilizing the Keras library, which facilitates GPU processing through the Google Colab platform. The model was trained, validated, and tested on image datasets in respective proportions of 70%, 15%, and 15% to ensure model generalization and prevent overfitting.

The training and evaluation processes were conducted on an NVIDIA Tensor Core GPU featuring 40 GB of RAM. The parameters for the study are established with an initial learning rate of 0.001, a batch size of 16, and a predetermined number of epochs set at 300. It is trained on satellite images from Sentinel2 and Pléiades Neo, with ground truth data serving as target labels. Cross-validation is employed to assess the model's robustness on unseen data. All trained models' performances were evaluated using standard metrics, including the IoU score, loss value, and F-score for performance assessment.

3. Results and Discussion

The road segmentation performance was evaluated using Fscore, IoU, and Loss value metrics across different spatial resolutions of Pléiades Neo (15 cm, 30 cm, and 1 m) and Sentinel-2 (10 m) imagery, as shown in Figure 3. Among the tested resolutions, the Pléiades Neo - 30 cm achieved the best performance with an F-score of 0.87, indicating the highest segmentation accuracy. The Pléiades Neo - 15 cm resolution closely followed, with an F-score of approximately 0.85 and a slightly lower IoU value (0.75), though it maintained a low loss value (0.12), highlighting its ability to capture fine-grained details effectively. At Pléiades Neo - 1 m, performance moderately declined, with an F-score of 0.82, IoU value of 0.68, and a loss value of 0.18, reflecting reduced segmentation accuracy at coarser resolution. The Sentinel-2 - 10 m imagery produced the lowest performance, with an F-score of 0.78, an IoU value of 0.65, and a loss value of 0.22, demonstrating the limitations of coarser spatial resolution for road segmentation. These results emphasize that while the Pléiades Neo - 15 cm and 30 cm resolutions perform exceptionally well, the 30 cm resolution provides the optimal balance between accuracy and data efficiency, achieving the highest segmentation performance overall.

The ultra-high-resolution Pléiades Neo data was particularly effective in capturing finer textures and well-defined edges of roads, which are critical for accurately delineating road boundaries. In contrast, Sentinel-2 imagery offered valuable contextual information. This contextual backdrop proved essential for distinguishing roads from their surrounding environments, aiding identification. This result underscores the limitations of coarse spatial resolution for road segmentation tasks. While extracting large features such as highways using Sentinel-2 data may be possible, the accuracy would likely be significantly lower, and finer road networks cannot be effectively identified. Overall, the results demonstrate that high-resolution imagery, particularly Pléiades Neo at 30 cm, provides the optimal balance of segmentation accuracy and data efficiency for road extraction.

Figure 4, 5, 6, and 7 present sample images from our dataset, illustrating the performance of the proposed road segmentation model. The input satellite images (left column), ground truth masks (middle column), and predicted masks (right column). The high-resolution imagery enables precise delineation of road networks, including fine details such as narrow road segments and intersections. The predicted masks demonstrate strong alignment with the ground truth, effectively capturing road geometries in both urban and vegetated areas. For coarser resolution, the predicted masks successfully capture the overall road structures, including major road segments and intersections. Discrepancies, such as variations in road width and occasional breaks, are observed.

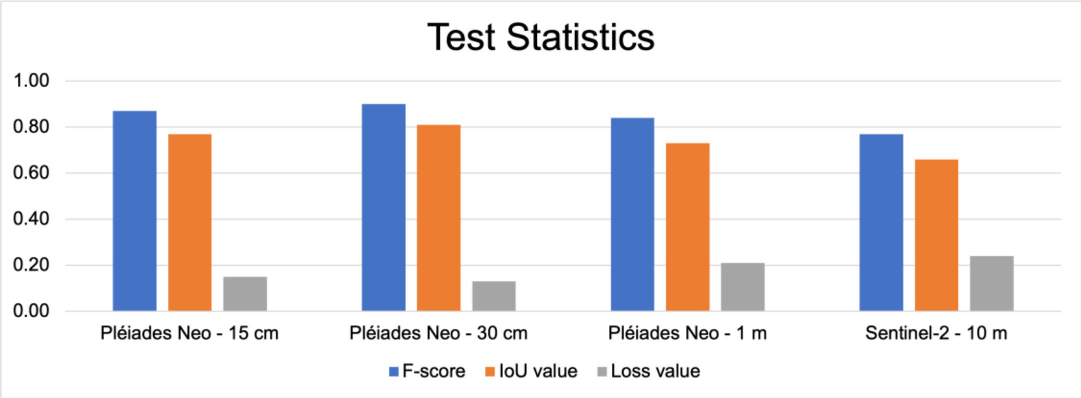

Figure 3. F-score, loss, and IoU values achieved by U-net algorithm.

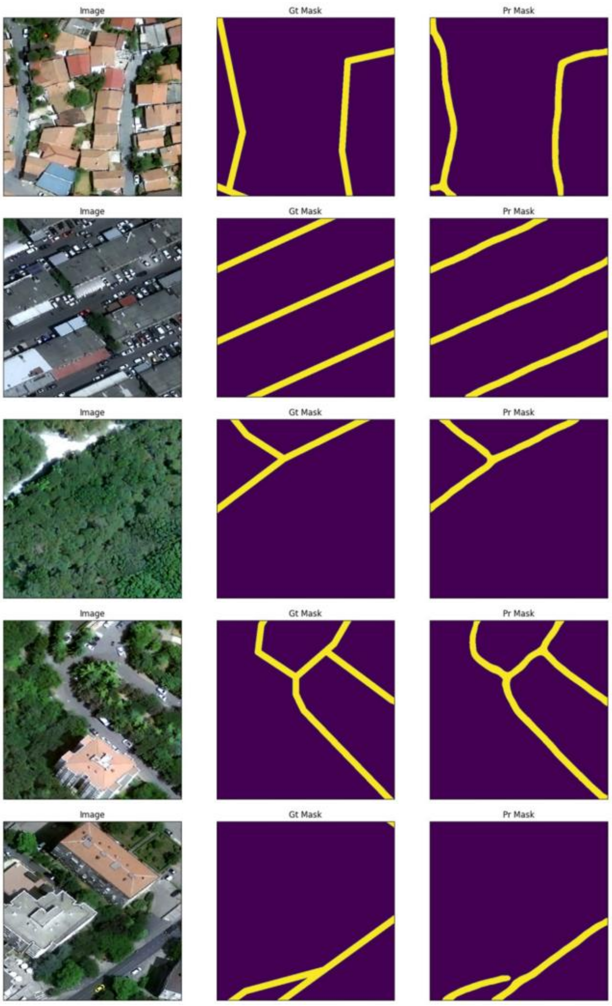

Figure 4. Sample images of Pléiades Neo (15cm spatial resolution).

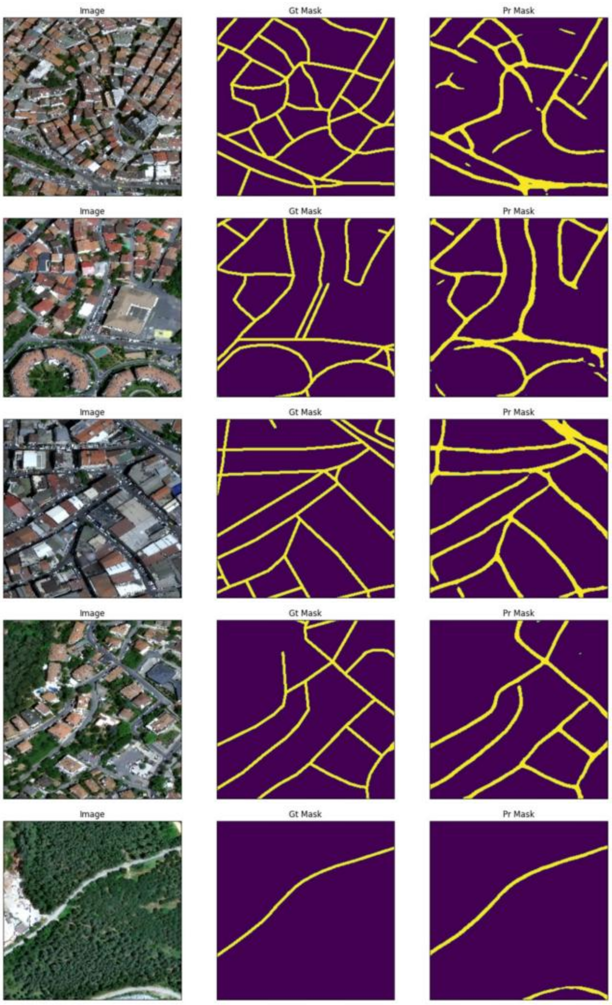

Figure 5. Sample images of Pléiades Neo (30cm spatial resolution).

Despite advancements in remote sensing and image processing techniques, road segmentation still faces several limitations, particularly with varying spatial resolutions of satellite imagery. Ultra-high-resolution imagery provides detailed information that enables accurate extraction of road networks. Still, it comes with higher data acquisition and processing costs, which can constrain large-scale applications. Coarser resolutions, such as Sentinel-2 - 10 m, pose significant challenges for road segmentation, as they lack the spatial detail necessary to capture narrow roads and complex urban networks. While highways and wider roads may still be detectable with moderate success, finer road networks, intersections, and intricate urban infrastructure cannot be effectively delineated, resulting in lower F-scores and higher segmentation loss. Additionally, the presence of shadows, obstructions from vegetation or buildings, and varying lighting conditions further complicate the segmentation process, regardless of resolution. These limitations highlight the need for a balance between resolution, cost, and computational efficiency, as well as the integration of advanced algorithms, such as deep learning, to improve segmentation accuracy under challenging conditions.

Figure 6. Sample images of Pléiades Neo (1m spatial resolution).

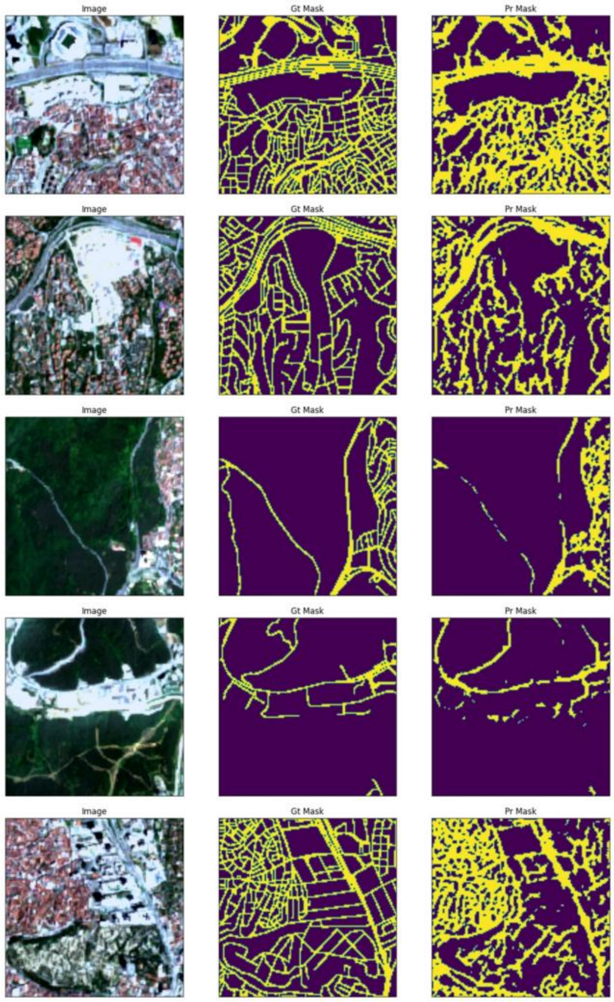

Figure 7. Sample images of sentinel-2.

4. Conclusion

In conclusion, this research highlights the effectiveness of multi-resolution satellite imagery and deep learning techniques for road segmentation in urban environments. By comparing the performance of Sentinel-2 and Pléiades Neo imagery at various resolutions, we demonstrate that the ultrahigh-resolution Pléiades Neo imagery, particularly at 30 cm, provides the best results for accurately identifying road networks. The integration of ground truth data from the Google Maps API further validates these findings, reinforcing the ability of deep learning models such as U-Net to capture complex road features. While Sentinel-2 imagery offers useful contextual information at a moderate resolution, its performance falls short compared to the Pléiades Neo images, confirming that higher-resolution imagery significantly improves road segmentation accuracy. When evaluating Pléiades Neo imagery at resolutions of 15 cm and 30 cm, it is observed that images with a resolution of 15 cm exhibit higher noise levels. In contrast, the 30 cm resolution images encompass a broader field of interest, resulting in a reduced data size concurrently. Additionally, utilizing 15 cm resolution images may produce improved results in a dataset from a different city with no unplanned urbanization and fewer side roads.

This study emphasizes the advantages of multi-resolution satellite imagery for road segmentation in urban environments, especially the benefits of ultra-high-resolution Pléiades Neo imagery. We observe significant improvements in segmentation accuracy at finer resolutions by utilizing deep learning models and validating the results with ground truth data from the Google Maps API. Although this research primarily focuses on urban areas, future work could expand this methodology to dynamic monitoring by incorporating temporal satellite data, enabling the detection of changes in road networks over time. Additionally, broadening the geographic scope to include diverse terrains, such as rural or mountainous regions, could further validate the robustness of this approach. Exploring advanced feature fusion techniques, such as deep feature fusion or decision-level fusion, may also enhance segmentation performance in more complex or challenging environments, providing a comprehensive tool for urban infrastructure management and planning.

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References

Abderrahim, N.Y.Q., Abderrahim, S., Rida, A., 2020. Road segmentation using u-net architecture. *2020 IEEE International conference of Moroccan Geomatics (Morgeo)*, 1–4.

Airbus, n.d. Pléiades Neo HD15. https://space-solutions.airbus.com/imagery/our-optical-and-radar-satellite-imagery/pleiades-neo/pleiades-neo-hd15/. Accessed on 25.12.2024.

Brkic, I., Miler, M., Sevrović, M., Medak, D., 2023. Analysis of machine learning algorithms performances for road segmentation on very high-resolution satellite imagery as support of road infrastructure assessment.

Christophe, E., Inglada, J., 2007. Robust road extraction for high resolution satellite images. *2007 IEEE International Conference on Image Processing*, 5, V – 437–V – 440.

Ghandorh, H., Boulila, W., Masood, S., Koubaa, A., Ahmed, F., Ahmad, J., 2022. Semantic Segmentation and Edge Detection—Approach to Road Detection in Very High Resolution Satellite Images. *Remote Sensing*, 14(3). doi.org/10.3390/rs14030613.

Graf, L., Bach, H., Tiede, D., 2020. Semantic Segmentation of Sentinel-2 Imagery for Mapping Irrigation Center Pivots. *Remote Sensing*, 12(23). doi.org/10.3390/rs12233937.

Maboudi, M., Amini, J., Hahn, M., Saati, M., 2017. Object-based road extraction from satellite images using ant colony optimization. *International Journal of Remote Sensing*, 38(1), 179–198. doi.org/10.1080/01431161.2016.1264026.

Miao, Z., Shi, W., Gamba, P., Li, Z., 2015. An Object-Based Method for Road Network Extraction in VHR Satellite Images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 8(10), 4853-4862.

Ronneberger, O., Fischer, P., Brox, T., 2015. U-net: Convolutional networks for biomedical image segmentation. N. Navab, J. Hornegger, W. M. Wells, A. F. Frangi (eds), *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, Springer International Publishing, Cham, 234–241.

Saraiva, M., Protas, E., Salgado, M., Souza, C., 2020. Automatic Mapping of Center Pivot Irrigation Systems from Satellite Images Using Deep Learning. *Remote Sensing*, 12(3). doi.org/10.3390/rs12030558.

The European Space Agency, n.d. Pléiades Neo. https://earth.esa.int/eogateway/missions/pleiades-neo. Accessed on 25.12.2024.

Yakubovskiy, P., 2019. Segmentation models. https://github.com/qubvel/segmentation_models.

Öztürk, O., Isik, M.S., Sariturk, B., Seker, D.Z., 2022. Generation of Istanbul road data set using Google Map API for deep learning-based segmentation. *International Journal of Remote Sensing*, 43(8), 2793–2812. doi.org/10.1080/01431161.2022.2068989.

Öztürk, O., Sarıtürk, B., Seker, D.Z., 2020. Comparison of Fully Convolutional Networks (FCN) and U-Net for Road Segmentation from High Resolution Imageries. *International Journal of Environment and Geoinformatics*, 7(3), 272–279. doi.org/10.30897/ijegeo.737993.