Point Cloud-based Computer Vision Framework for Detecting Proximity of Trees to Power Distribution Lines

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Abstract –

The maintenance of power lines is challenged by the encroachment of vegetation, posing significant risks to the reliability and safety of power utilities. Traditional methods, based on manual inspection, are not only resource-intensive but also lack the necessary precision for effective and proactive maintenance. This paper aims to develop an automated, accurate, and efficient approach to vegetation management in the vicinity of power lines. It leverages advancements in data collection using LiDAR scanning technology, which despite its potential, faces computational challenges in processing large-scale 3D point clouds to accurately identify power lines and surrounding vegetation. To overcome this challenge, the proposed method deploys the RandLA-Net model for the semantic segmentation of power lines and nearby vegetation in point cloud datasets. Furthermore, the post-processing analysis of the segmented data uses clustering and rule-based thresholding to refine the identification of vegetation. Then, proximity detection is applied using spatial queries based on a KDTree structure. The results of the case study demonstrate the computational efficiency and accuracy of the proposed method, presenting a promising solution for power utilities.

Keywords –

Computer Vision; 3D Point Cloud; Power Lines; Proximity Detection

1 Introduction

Vegetation management is critical for ensuring the safety and reliability of power distribution systems. The encroachment of overgrown vegetation near power lines poses significant risks, potentially leading to power outages, fires, and other hazards. The primary problem in this sector has been the reliance on manual inspection, which is labor-intensive, time-consuming, and often limited in accuracy and frequency. This traditional approach struggles to keep pace with the growing demand for stable energy and the urgent need to mitigate risks associated with overgrown vegetation. Consequently, there is a need for more efficient, automated solutions in vegetation management. Advances in sensing technologies, particularly Light Detection and Ranging (LiDAR) scanning, combined with Machine Learning (ML) algorithms, have led to the development of Automated Vegetation Management (AVM) systems. These systems promise more frequent monitoring, potentially revolutionizing vegetation management [1]. However, a significant challenge lies in processing the vast volumes of 3D point cloud data generated by LiDAR [2], particularly in accurately segmenting and classifying each point to identify vegetation-related risks effectively. Unlike conventional methods relying on visual inspection or 2D imaging, point cloud data provides comprehensive spatial representation, allowing accurate distance measurements and identification of fine details of power lines and surrounding vegetation. This advancement offers a systematic and reliable approach to power line monitoring, supported by recent studies demonstrating its efficacy in automated vegetation management systems and power line inspection [3].

The objectives of this paper are: (1) to accurately detect vegetation and power lines from LiDAR data using Deep Learning (DL), and (2) (2) to conduct detailed post-processing analysis to detect the proximity of trees and power lines. This approach is expected to enhance the reliability of power distribution systems and potentially lead to significant cost savings for utility companies. The results demonstrate the practical application of the proposed method in a real-world urban setting.

2 Literature Review

LiDAR technology has emerged as a powerful AVM tool for power distribution lines. Its ability to provide high-resolution 3D data has made it crucial for detecting and analyzing vegetation in the context of power line management. Gollob et al. [4] investigated the accuracy of estimates for individual trees and forest stand variables using a mobile laser scanning system. Their study highlights the impact of scan variation on tree parameter measurements. Voelsen et al. [5] segmented point cloud data from a Mobile Mapping LiDAR dataset. They used a method combining region growing and random forest classification to distinguish between static and dynamic objects, such as poles and vegetation. Wen et al. [6] emphasized the significance of high-accuracy and high-efficiency 3D sensing and associated data processing techniques for various applications, including detecting trees and poles. Lu et al. [7] introduced a localization system for autonomous vehicles using cluster-based methods to extract pole-like objects, including trees and street lights, from 3D LiDAR point clouds. Kutz et al. [8] discussed the application of high-resolution imagery and LiDAR-derived canopy height models in land cover mapping, crucial for resource management and planning. Gaha et al. introduced a new LiDAR-based clustering method for detecting poles and distribution lines, offering improvements in accuracy and efficiency [9]. However, the scope of their study was primarily focused on single-phase lines and had limited effectiveness in occluded environments.

ML has significantly changed AVM around power lines, allowing for rapid data processing and previously unattainable insights. Kyuroson et al. developed an unsupervised ML framework to detect and analyze power lines and surrounding vegetation in Power Line Corridors (PLCs) using various remote data acquisition techniques such as airborne, mobile, and terrestrial laser scanning [10]. Torres de Almeida et al. combined satellite imagery, airborne LiDAR data, and ML algorithms, including Linear Regression, Classification and Regression Trees (CART), and Random Forest (RF) to map vegetation height in PLCs, aiding in management planning [11]. Li et al. employed drone data, airborne LiDAR, and ML algorithms, including RF, and Support Vector Machine (SVM) for classifying tree species in transmission line corridors [12].

Abongo et al. introduced a novel framework for detecting power lines using LiDAR data, utilizing a combination of ML (XGBoost) and geometric methods [13]. However, their approach was primarily limited to the detection aspect, without exploring subsequent data processing and analysis for vegetation management. Haroun et al. reviewed vegetation encroachment detection techniques using satellite images, emphasizing the potential of ML and DL algorithms to enhance detection accuracy and flexibility [14]. Park et al. used feature-enhanced convolutional neural networks (CNNs) including AlexNet, ResNet18, and VGG11 for classifying images from Google Street View into categories related to utility systems and vegetation overgrowth, aiding in vegetation management prioritization [15]. Mohd Rapheal et al. assessed a ML-based geospatial method for classifying electricity assets using high-density mobile laser scanning data, achieving detection accuracies of 65% for overhead power lines and 63% for electricity poles [16]. Although focused on river management, Rabanaque et al. presented a ML approach (SVM and RF) for analyzing geomorphological characteristics and vegetation density using LiDAR and multispectral satellite images [17]. Horning et al. discussed the challenges and advances in mapping land cover using ultra-high-resolution aerial imagery, including ML algorithms for image processing [18]. Oehmcke et al. utilized DL systems (MSENet14, KPConv, PointNet) to predict wood volume and above-ground biomass directly from airborne LiDAR point clouds [19]. Their method showed significant improvements in accuracy compared to traditional approaches. Gribov and Duri proposed a solution for constructing line features modeling each catenary curve present within a series of points representing multiple catenary curves [20]. This solution can be applied to extract power lines from LiDAR point clouds.

Mahoney et al. utilized a combination of various ML algorithms, including RF, Gradient Boosting Machine, and Artificial Neural Network (ANN), to integrate remote sensing of structural and optical properties of vegetation cover for classifying and mapping shrubland habitats [21]. Furthermore, studies like that of Amani et al., which utilized bathymetric LiDAR data for marine habitat mapping, showcase the versatility of LiDAR and RF algorithms in vegetation classification [22]. Amado et al. presented a method for extracting power lines from LiDAR point cloud data, demonstrating accurate and automatic extraction capabilities [23]. Awrangjeb introduced a power line extracting and modeling approach using LiDAR data, which significantly aids in the detection and modeling of power lines, offering a reliable solution to the challenges faced in power line extraction [24]. Li and Guo discussed the application of LiDAR technology for power line inspection, highlighting its advantages in obtaining high precision 3D spatial information and entire power line corridor data, which is critical for effective inspection and maintenance [25]. Table 1 shows a comparative overview of most related works, outlining key aspects such as methodology, utilized dataset, main research focus, and critical performance metrics across different studies.

3 Proposed Framework

This paper proposes using Random Sampling in Large-scale Point Cloud Analysis Network (RandLA-Net) model [28], designed for the semantic segmentation of large 3D point clouds, for AVM. This model was selected due to its highest overall accuracy level in semantic segmentation of the Toronto-3D dataset [29].

However, the trained model was not available; thus, we retrained the model with our specific data considering the intensity of the points and focusing on the three classes of interest: vegetation, poles, and power lines. This approach addresses the challenge of handling extensive volumes of 3D point cloud data to accurately segment and classify each point to efficiently pinpoint vegetation-related risks in AVM. However, the segmentation process is only the first step. The subsequent challenge, and a critical aspect of this paper is the post-processing analysis of semantic segmentation. This involves employing Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [30] and rule-based thresholding to isolate objects that meet specific criteria, crucial for separating distinct urban elements and reducing noise. Additionally, we implement a proximity detection using KDTree method to evaluate potential risks based on spatial relationships between trees and power lines in urban environments. Figure 1 provides an overview of the proposed framework.

Table 1. Comparative overview of most related works

Reference	Year	Methodology	Used Dataset	Main Focus	IoU for classes	Comparative Highlights
Wang et al. [26]	2023	CA-PointNet++ with Coordinate Attention module	Utilized a self-constructed UAV Lidar dataset	Transmission corridor segmentation	Power lines: 67.4%	Lacks proximity focus, lower IoU
Cano-Solis et al. [27]	2023	VEPL-Net focusing on ensemble methods	UAV imagery may lack LiDAR's depth resolution	Vegetation and power line segmentation without proximity focus	Vegetation: 77%, Power lines: 64%, showing room for improvement	Good in vegetation detection, less so in detailed context, lacks proximity analysis
Abongo et al. [13]	2023	XGBoost with basic geometric analysis	Standard LiDAR dataset without specified complexity	Sole focus on power line detection	Power lines: 82.49%	Effective in basic detection, lacks complexity
Our study	2024	Advanced RandLA-Net with specific post-processing optimizations	Toronto-3D, providing diverse urban landscape challenges	Dual focus on both power line and vegetation with proximity analysis	Trees: 96.81%, Power lines: 87.83%, Poles: 79.36%	KDTree for proximity analysis, detailed class-specific IoU scores, and enhancing detection accuracy

3.1 Semantic Segmentation

The RandLA-Net model [28], efficient in processing high-density point clouds, was used for semantic segmentation, focusing on trees, power distribution lines, and poles. RandLA-Net stands out due to its unique approach, employing random point sampling for downsampling. This significantly reduces computational complexity while maintaining the integrity of the point cloud geometric details. It incorporates a local feature aggregation module, which includes Local Spatial Encoding and Attentive Pooling, to capture intricate local

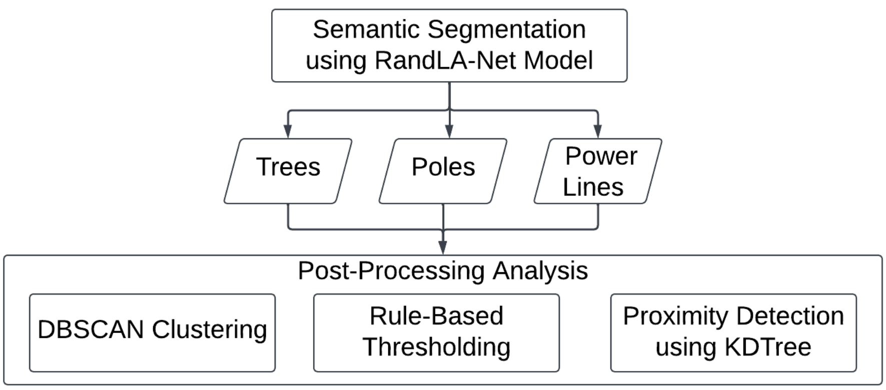


Figure 1. Overview of the proposed framework

structures effectively [28]. The network's architecture, featuring shared Multilayer Perceptrons (MLPs) and dilated residual blocks, enhances its processing speed, allowing it to handle up to one million points in a single pass with notable accuracy. This efficient and innovative approach makes RandLA-Net particularly suitable for large-scale point cloud analyses, demonstrating superior performance in both speed and accuracy compared to other methods, such as PointNet++.

To assess the performance of the RandLA-Net model in this context, we used the Intersection over Union (IoU) metric. This is a standard metric in evaluating segmentation models, as it quantifies the accuracy of the model in classifying each point. It works by measuring the overlap between the model's predicted classifications and the actual, ground truth classifications. The IoU provides a comprehensive overview of the model's performance across all classes, offering insights into its precision and effectiveness in segmenting different urban elements. A higher IoU value indicates better model performance and a more accurate representation of the real-world scenario.

3.2 Clustering and Rule-Based Thresholding

In order to refine the segmented point cloud data in the initial stage of post-processing, partial clustering algorithm, DBSCAN, was selected for its ability to identify clusters of various shapes and densities within the data without the need for predefined number of clusters. This feature made DBSCAN particularly suitable for handling the complex and varied structure of the urban dataset. Key parameters like the epsilon values and minimum samples were carefully adjusted to align with the dataset's unique features, ensuring sensitivity to the varied densities and distributions of urban elements. In addition to DBSCAN, rule-based thresholding was implemented, setting specific height and point count thresholds for each urban feature class, such as trees and poles. This approach effectively isolated significant urban objects within each category while reducing noise and irrelevant data, thereby enhancing the clustering results' overall quality and accuracy.

3.3 Proximity Detection between Trees and Power Lines

To assess the risk associated with trees near power lines, a K-Dimensional Tree (KDTree) structure was adopted for streamlined spatial querying, aiming to effectively evaluate potential risks. The KDTree, known for its ability to rapidly query points in a multi-dimensional space, proved ideal for analyzing spatial relationships within the point cloud data. The process involved utilizing the KDTree structure to efficiently identify the nearest power line to each tree. Once these proximities are calculated, they are compared against a safety threshold. Tree areas falling within this threshold are identified as potential hazards. Considering the dataset's large scale, ensuring computational efficiency was a critical concern. This approach optimizes performance and resource utilization in large-scale, complex data operations.

4 Implementation and Case Study

In the implementation phase, post-processing techniques including clustering, rule-based thresholding, and proximity detection were deployed using Python.

4.1 Data Acquisition and Preparation

Toronto-3D dataset, developed by Tan et al. [2] was used in the case study. This dataset was collected along a 1-kilometer section of Avenue Road in Toronto, Canada. It is a large dataset containing about 78.3 million data points. The dataset is notable for its high point density, with an average of 1000 points per square meter on the ground. This high density is crucial for capturing detailed features of the urban environment, which is vital for this study. The data was collected using a LiDAR sensor on a Mobile Laser Scanning (MLS) system. The LiDAR sensor captured up to 700,000 points per second, with a vertical field of view from -10 to +30 degrees, and an accuracy of better than 3 cm. Each point in the dataset has several attributes including the position in meters (XYZ coordinates), the color reflectance (RGB), LiDAR intensity, GPS time of collection, scan angle, and the object class label. The object class labels cover a range of urban features, making the dataset useful for semantic segmentation. These labels include roads, road markings, natural elements (trees, shrubs), building parts, power distribution lines, poles (utility poles, traffic signs), vehicles, and vertical barriers (fences, walls).

Data preparation involved loading the point cloud data and performing grid subsampling with a grid size of 0.06 meters to reduce data volume while preserving key features. For validation datasets, projection indexes were created to map model results back to the original dataset, ensuring a structured and efficient dataset ready for semantic segmentation and analysis. A projection index is a reference that maps each point in a subsampled point cloud back to its original location in the full dense point cloud, ensuring that any analysis or modifications applied to the reduced dataset can be accurately reflected in the original, larger dataset. The raw data from the dataset underwent preprocessing to convert the .ply files into a suitable text format for the semantic segmentation process. Figure 2 shows a sample area of point cloud data.

Figure 2. A sample area of point cloud data

4.2 Semantic Segmentation

The Toronto-3D dataset was divided into four sections, each covering about 250 meters of the road. Sections 1, 3, and 4 were used for training and Section 2 was used for testing. The dataset underwent two separate training processes. Initially, it was trained without considering RGB and intensity data to focus on the geometric features (X, Y, Z). Then, it was trained again, this time incorporating the RGB and intensity information (X, Y, Z, R, G, B, intensity) to assess the impact of these attributes on model performance.

Using this dataset, the RandLA-Net model underwent 100 epochs of training to enhance its accuracy in segmenting point cloud data. The Adam optimizer, known for its efficiency with large-scale data, was utilized. An initial learning rate of 0.01 was set, gradually reduced by 5% per epoch to refine model adjustments and convergence. A batch size of 4 was maintained to balance computational resources and effective learning during training sessions. Throughout this segmentation process, the model accurately assigned a class label to each point, enabling the differentiation of various urban elements. The training time for the model was 124 hours and 33 minutes on a LAMBDA workstation with one NVIDIA RTX A6000 GPU, 48 GB RAM/GPU, and an AMD Ryzer Threadripper 3960×48-core CPU. The model without considering RGB and intensity achieved an overall accuracy of 93.08%, representing the ratio of correctly labeled points to the total number of points across all classes. The model considering RGB and intensity achieved an overall accuracy of 95.42%.

During the testing phase, each epoch was composed of 25 steps, with every step processing a batch of test data. In the testing, a step is a single iteration over a batch of data and an epoch represents a single pass through the entire test dataset. For individual classes, the model without considering RGB and intensity showed very good performance with the classes of trees, power distribution lines, and poles achieving IoU of 95.76%, 87.61%, and 76.37%, respectively. The model considering RGB and Intensity showed improved performance with the classes of trees, power distribution lines, and poles achieving IoU of 96.81%, 87.83%, and 79.36%, respectively. The observed improvement of over 3% in the poles class in the model considering RGB and intensity may be due to the distinctive and unique colors of the poles. However, the lower accuracy in pole detection in both models could be attributed to the inherent complexity of urban environments where poles are located. Factors such as occlusion by other objects, varying lighting conditions, and the poles' similarity to other vertical structures might make them harder to distinguish accurately. Compared to the work of Abongo et al. [13] focusing only on power distribution line detection, which achieved an IoU of 82.49%, our method notably surpasses this performance, achieving an IoU of 87.83% for power distribution lines.

4.3 Clustering and Rule-Based Thresholding

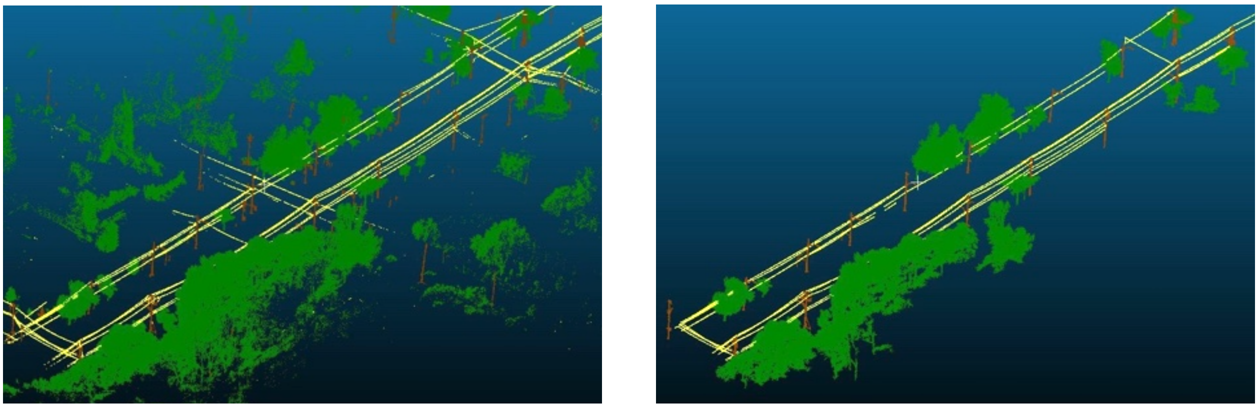
In the subsequent stage of our analysis, we used a combination of DBSCAN, height, and point count thresholding techniques to identify and isolate objects meeting our predefined criteria. This method involved adjustments of DBSCAN parameters, such as epsilon (i.e. maximum distance between samples) and the minimum number of samples, to match the unique attributes of the Toronto-3D dataset. Following the clustering process, we retained clusters that surpassed the designated height threshold (e.g., 8 meters for poles) and fulfilled the minimum point count threshold (e.g., 500 points for poles). This step resulted in a refined dataset, distinctly differentiating and emphasizing significant urban features from less relevant objects. Table 2 presents the clustering values and thresholds for each class. Figure 3 shows segmentation results before and after clustering and rule-based thresholding.

Table 2. Clustering values and thresholds for each class

Class	Clustering values		Defined thresholds	
	Epsilon (m)	Minimum samples	Minimum point count	Minimum height (m)
Trees	0.5	20	12000	6.5
Poles	0.5	10	500	8
Power lines	0.3	3	-	-

RGB and intensity data analysis for precise urban vegetation management. This is further complemented by novel post-processing techniques, including DBSCAN clustering and rule-based thresholding, which collectively refine risk assessment and provide a detailed understanding of vegetation's proximity to power lines. This paper presents a comprehensive approach for urban vegetation management in proximity to power lines using point cloud data in conjunction with the RandLA-Net model. The approach is further enhanced by post-processing techniques such as clustering and rule-based thresholding considering the specific needs of the application. Moreover, the incorporation of proximity detection for risk assessment added a practical dimension to the proposed framework. The RandLA-Net model considering RGB and intensity showed improved performance with various classes, including trees, power distribution lines, and poles, achieving IoU of 96.81%, 87.83%, and 79.36%, respectively. The effectiveness of DBSCAN clustering and rule-based thresholding was apparent in the clarity and distinction of the isolated objects. Additionally, the proximity detection analysis efficiently pinpointed significant tree areas where trees can pose threats to power lines.

The study's findings rely on the Toronto-3D dataset, which might not fully represent all urban, and/or suburban landscapes. While the results of RandLA-Net exhibited high accuracy, its performance in different or more complex environments requires further exploration. Moreover, the computational demands of these methods could limit their feasibility in resource-constrained settings. Future research should prioritize testing the proposed framework across diverse environments, refining the algorithms for broader applicability, and integrating additional data sources for a more comprehensive approach.



(a) Before (b) After

Figure 3. Comparing segmentation results before and after clustering and rule-based thresholding

4.4 Proximity Detection between Trees and Power Lines

The next step aims to compare the spatial data of trees and power lines to enable proximity detection for risk assessment. Leveraging KDTree's queries, we efficiently determined the closest power line point to each tree point in a multidimensional space. Assessing this against a predetermined safety threshold of 1 meter allowed us to identify parts of trees posing risks due to their proximity to power lines, which were flagged as potential hazards. Figure 4 shows the post-processed semantic segmentation result, highlighting hazardous tree areas (red points) within the safety perimeter of power distribution lines.

5 Conclusions and Future Work

The contribution of this paper lies in its integrated approach, utilizing the RandLA-Net model enhanced by

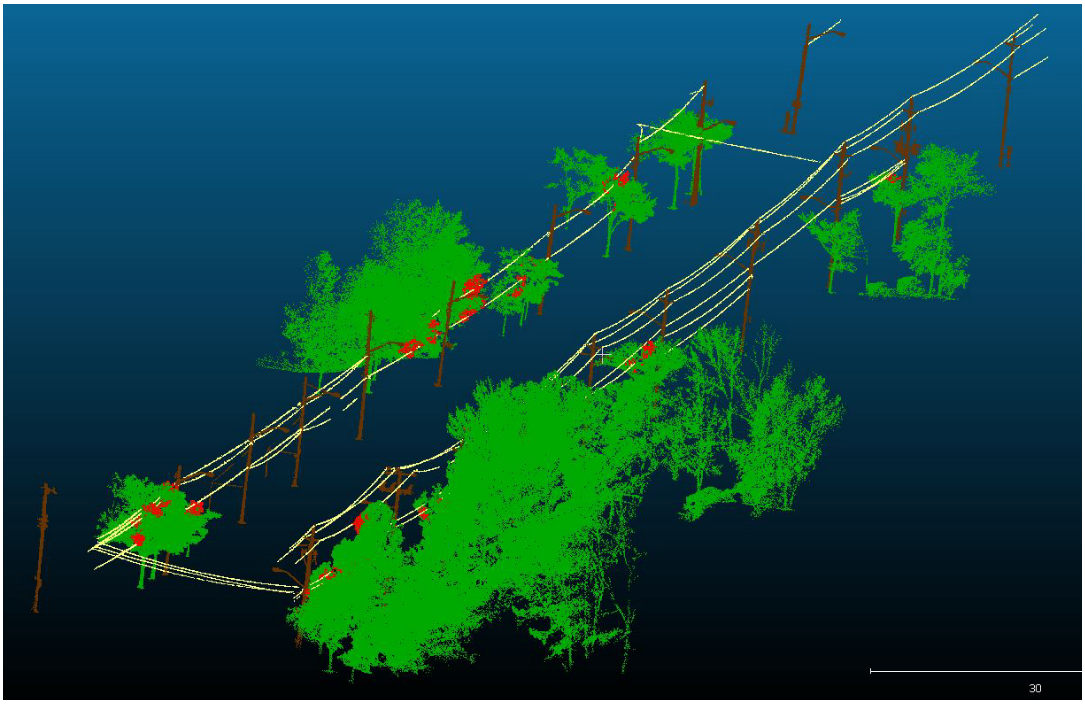


Figure 4. Post-processed result of semantic segmentation, highlighting hazardous tree areas

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