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Review

Detection of Vegetation Proximity to Power Lines: Critical Review and Research Roadmap

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Abstract

The resilience of power distribution systems is crucial for maintaining the stability and functionality of modern societies. The proximity of natural vegetation to power lines poses significant risks, particularly when combined with adverse weather events. This review paper examines state-of-the-art methods for detecting and managing tree proximity to power distribution lines using advanced machine learning (ML) techniques, including deep learning (DL) applied to remote sensing data. The complex interactions between adverse weather conditions and power outages caused by tree encroachment are explored. The potential of AI-driven monitoring systems to enhance vegetation management strategies, thereby mitigating the risks associated with tree-related power outages, is underlined. A significant gap in the literature is identified, with few studies specifically addressing the application of ML/DL for dynamic monitoring of tree proximity to power lines. A detailed comparative analysis of existing methodologies is provided, emphasizing the unique contributions and limitations of current approaches. Future research directions, including the development of more sophisticated ML/DL models and the integration of multi-sensor data, are outlined. This review serves as a critical resource for researchers, utility managers, and policymakers aiming to improve the resilience and reliability of power infrastructure management.

Keywords: machine learning (ML); deep learning (DL); computer vision; vegetation management; power lines; predictive maintenance

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1. Introduction

The resilience of power distribution systems is crucial for the smooth operation of modern societies and economies. The presence of natural vegetation near these infrastructures poses significant risks, especially when combined with adverse weather events. Weather events such as windstorms, heavy snowfall, and extreme conditions not only directly damage power infrastructures but also increase the likelihood of power outages through interactions with trees. Trees encroaching on power lines are a well-known cause of service disruptions, particularly during severe weather conditions that can destabilize trees and cause failures. Recent work has also shown that modifying vegetation structure within transmission corridors can reduce fire hazards and enhance resilience of power infrastructure [1]. This paper explores advanced methods for detecting and managing the proximity of trees to power distribution lines, focusing on machine learning (ML), including deep learning (DL) techniques. Deep learning, a specialized branch of ML, employs neural networks with a large number of layers for automatic feature extraction and complex pattern recognition. These technologies have the potential to significantly enhance the accuracy and efficiency of monitoring and intervention strategies, thereby mitigating the risks associated with tree-related power outages. Current research on the interactions between adverse weather conditions and power outages is reviewed, assessing the application of ML/DL in monitoring tree–power line interactions, and investigating the dynamic behaviors of trees that influence their risk levels.

Despite the extensive application of ML/DL across various domains of power system management, the literature specifically addressing the detection of tree proximity to power distribution lines using these technologies is notably sparse. This thorough literature review reveals a limited number of review papers focused directly on this topic, highlighting a significant gap. However, several closely related review papers discuss broader applications of ML/DL within power systems, providing foundational knowledge potentially applicable to the specific challenge of vegetation management. This review paper addresses a critical gap by focusing specifically on the application of ML/DL technologies for dynamic monitoring of tree proximity to power lines. A comparative analysis of existing literature is provided, emphasizing the unique contributions and existing gaps addressed by this review. Unlike the broader applications discussed in other review papers, this review uniquely contributes to the field by: (1) Focused Review of Methodologies: Integrating advanced ML/DL techniques with technologies such as LiDAR and cutting-edge imaging methods specifically for proximity detection, a topic not comprehensively covered in existing reviews. (2) Operational and Environmental Benefits: Highlighting the significant operational and environmental benefits of these technologies, such as reducing power outages, which is crucial for utility managers and policymakers. (3) Future Research Directions: Proposing future research directions that encompass both the development of more sophisticated ML/DL models and broader power line resilience strategies, including predictive maintenance, multi-sensor data integration, and advanced outage prediction models.

Through these perspectives, this review aims to guide utility managers and policymakers in integrating cutting-edge technologies into traditional power system operations, facilitating the transition towards more resilient and efficient power infrastructure management. This review serves as a critical resource for researchers, utility managers, and policymakers, guiding the integration of advanced computational methods in the pursuit of enhanced power system resilience. Table 1 provides a comparative analysis of existing literature, emphasizing the unique contributions, and existing gaps addressed by this paper review. The order of the table is arranged based on the publication year, highlighting the evolution and focus shifts on related research. Existing review papers predominantly concentrate on power line inspection and extraction using deep learning and LiDAR technologies but often overlook the specific issue of vegetation proximity detection around power lines. Figure 1 provides an overview of the key themes covered in this review, including outage causes, vegetation dynamics, detection methods, resilience strategies, and the proposed research roadmap.

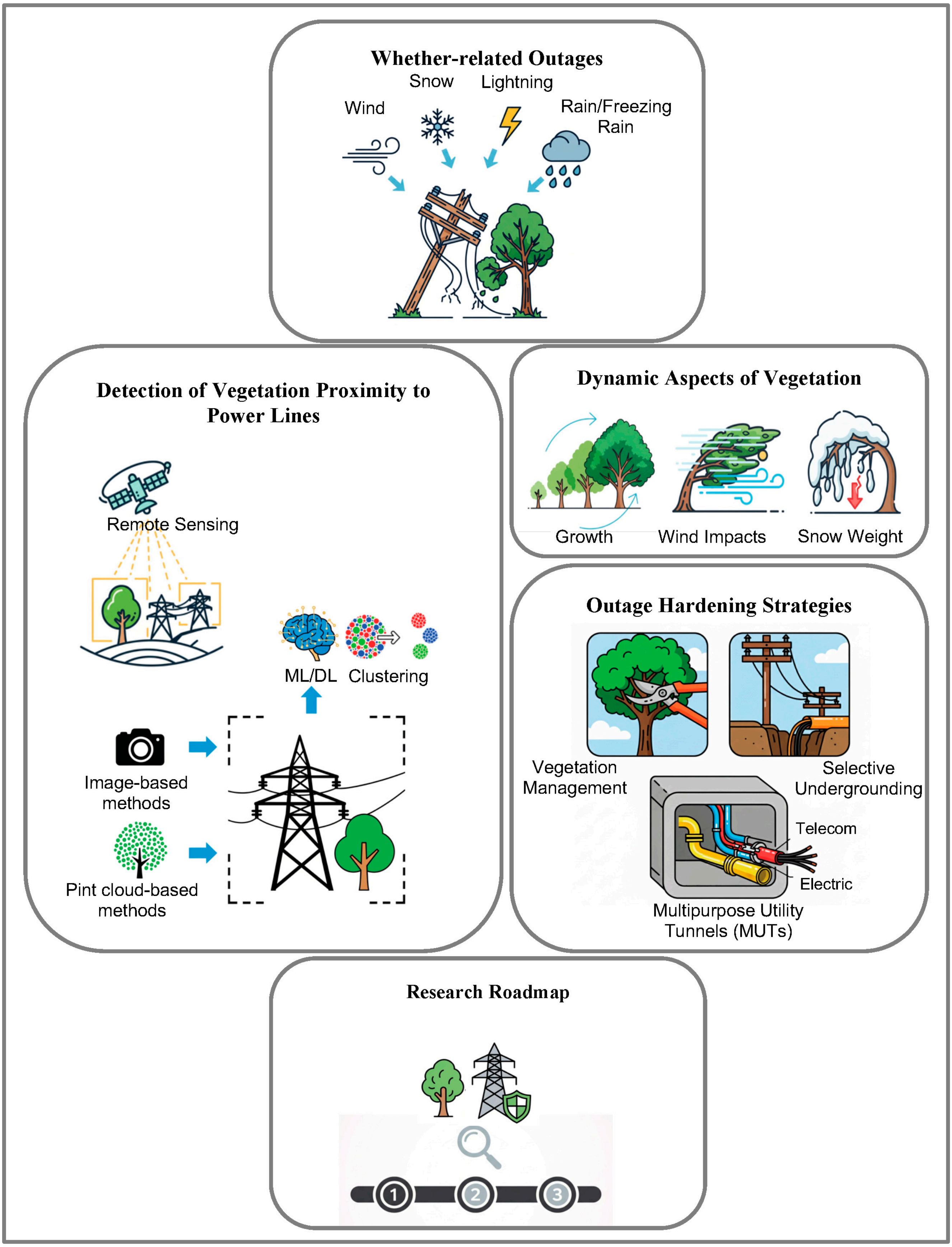

Figure 1. Conceptual overview of the review.

Table 1. Existing review paper contributions and comparison (2020–2025).

No.	Authors	Year	Key Contributions	Relevance and Gaps
1	Faisal et al. [2]	2025	Reviews deep learning approaches for automated power line inspection, covering component detection, fault diagnosis, imaging modalities, and datasets.	Focuses broadly on inspection tasks where vegetation is treated as a secondary item and does not provide a framework for vegetation proximity detection and resilience in distribution lines.
2	Shen et al. [3]	2024	Reviews LiDAR-based methods using ML/DL for power line and pylon extraction	Focuses on power line extraction with limited discussion on vegetation proximity detection.
3	Mantach et al. [4]	2022	Explores the application of deep learning in high voltage engineering, focusing on power line inspection.	Offers valuable insights into DL applications but does not address tree proximity issues.
4	Singh et al. [5]	2022	Discusses AI techniques for tree detection using UAV and remote sensing, with a focus on deep learning models for object detection.	Emphasizes aerial image analysis without addressing proximity detection in the context of power lines.
5	Ibitoye et al. [6]	2022	Reviews ML techniques for fault detection in power grids, focusing on ensuring reliable power supply.	Focuses on ensuring reliable power supply. Limited discussion on vegetation management strategies using ML/DL.
6	Khodayar et al. [7]	2021	Comprehensive review of deep learning methodologies applied in power systems.	Provides foundational knowledge on DL in power systems without focusing on vegetation proximity detection.
7	Haroun et al. [8]	2020	Reviews satellite image techniques for vegetation encroachment detection, focusing on cost-effectiveness and extensive coverage.	Primarily focuses on satellite imagery techniques without analyzing ML/DL applications for dynamic environments.
8	Alimi et al. [9]	2020	Reviews ML techniques for power system security and stability.	Focuses on event classification in power systems. Does not address specific vegetation management.

2. Review Method

This section outlines the methodology used to systematically review the existing literature. The content analysis framework from Chen et al. [10] was adopted, as shown in Figure 2, which encompasses four main stages: collecting relevant papers, conducting an initial review, performing an in-depth analysis, and formulating a roadmap for future research.

2.1. Paper Selection Method

To initiate, A comprehensive search was performed using multiple academic databases, including Google Scholar, Web of Science, and Scopus, focusing on publications from 2020 to 2025. The search employed keyword terms related to vegetation or power lines, and ML/DL, such as "vegetation detection," "power line detection," "proximity detection," "power outage," and "ML/DL application". After aggregating the results and removing duplicates, a substantial collection of 772 relevant papers was collected. In the subsequent step, the titles and abstracts of these papers were screened to eliminate those that were not relevant to this review. Works that concentrated on vegetation management, power line monitoring, or vegetation proximity detection were prioritized. A thorough review of the full content of each paper was also conducted to further refine the selection. This rigorous process narrowed the pool down to 116 journal and conference papers considered suitable for an in-depth review. Following this, a detailed examination of these 116 selected papers was conducted. In the final stage of the methodology, findings from the 116 core papers, along with insights from snowballing, were synthesized to identify research gaps and formulate a roadmap for future studies in vegetation management using ML/DL.

Additionally, several influential studies published before 2020, which were frequently cited in the literature, were also incorporated. To ensure comprehensive coverage of influential studies and recent advancements, a secondary snowballing step was incorporated, comprising: (1) Backward snowballing: The reference lists of the 116 selected papers were examined and identified 28 additional studies that were frequently cited and provided foundational insights; and (2) Forward snowballing: Using citation tracking, 22 papers that cited the 116 selected studies were identified, ensuring that the latest advancements in the field were captured. These 50 additional papers were not included in the quantitative analysis of this section, but were used to enrich the discussion, highlight research gaps, and support contextual insights. Figure 3 shows the integration of snowballing in systematic review process.

2.2. Paper Distribution and Bibliometric Analysis

To achieve a comprehensive understanding and identify emerging trends from previous publications, a bibliometric analysis was performed based on 116 core papers using VOSviewer (V1.6.20) [11] and Bibliometrix (V5.1.1) [12] tools. These software applications were utilized to conduct the analysis and visualize the results.

Based on a bibliometric analysis, key journals and conferences that serve as leading venues in this domain were identified. Table 2 shows the frequency distribution of articles by type and publication title. Among the journal articles, certain publications emerged as leading platforms for disseminating research in this area. The journal Forests accounted for the highest number of publications with 8 articles, indicating its significant role in vegetation-related studies involving advanced technological applications. Remote Sensing followed with 5 articles, emphasizing the crucial role of remote sensing technologies in monitoring vegetation and power lines. Several journals contributed three articles each, including IEEE Access, Sustainable Cities and Society, Energies, IET Generation Transmission and Distribution, and the International Journal of Applied Earth Observation and Geoinformation. These journals represent a mix of engineering, energy, and geospatial disciplines, emphasizing the interdisciplinary nature of the research. A diverse array of other journals contributed 1 or 2 articles each, such as Utilities Policy, Electronics Switzerland, Urban Forestry and Urban Greening, and Applied Sciences Switzerland, among others. This diversity reflects the wide-ranging interest and applicability of the research across different fields, from urban planning and environmental sciences to technological forecasting and social change.

The conference papers were similarly distributed across various reputable proceedings. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS) Archives contributed 3 papers, making it the most prominent conference source in the analysis. The Proceedings of the International Symposium on Automation and Robotics in Construction (ISARC) contributed 2 papers, indicating active research intersections between automation and infrastructure monitoring. Other conferences, each contributing 1 paper, included prominent events such as the International

Geoscience and Remote Sensing Symposium (IGARSS), IEEE Power and Energy Society General Meeting, and the IEEE International Conference on Autonomous Robot Systems and Competitions. The presence of these conferences highlights the engagement of the engineering and geoscience communities in addressing challenges related to vegetation and power line interactions.

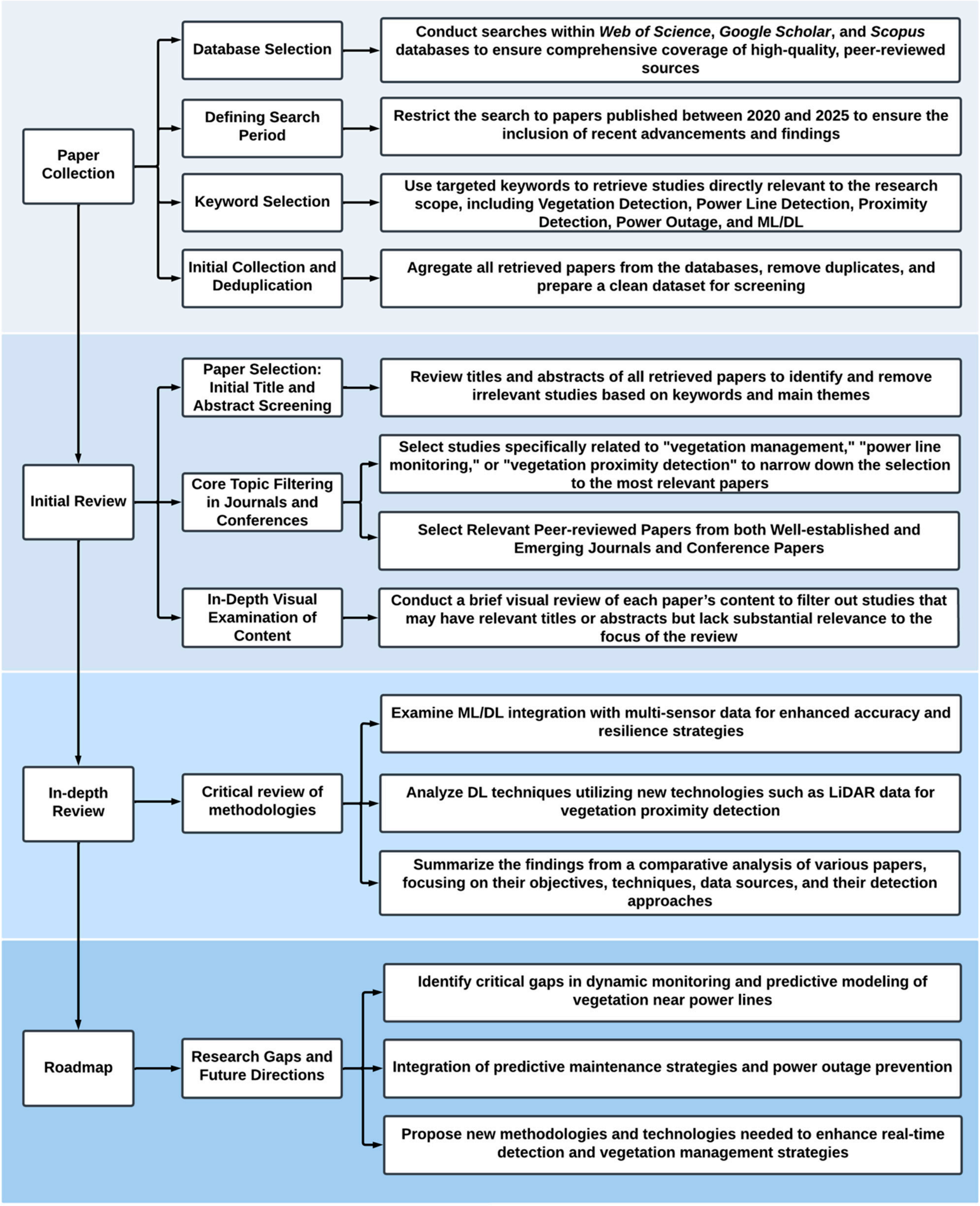

Figure 2. Systematic review methodology.

Table 2. Frequency distribution of articles by type and publication title.

Article Type	Publication Title	Frequency Count
Journal papers (92 papers)	Forests	8
	Remote Sensing	5
	IEEE Access, Sustainable Cities and Society, Energies, IET Generation Transmission and Distribution, International Journal of Applied Earth Observation and Geoinformation	3
	Applied Energy, Utilities Policy, Electronics Switzerland, Urban Forestry and Urban Greening, Bulletin of Glaciological Research, Canadian Journal of Forest Research, Applied Sciences Switzerland, Tunnelling and Underground Space Technology, Ecology Letters, ASCE ASME Journal of Risk and Uncertainty in Engineering Systems Part A Civil Engineering, Giscience and Remote Sensing, Water Resources Management, Cryosphere, IEEE Sensors Journal, IEEE Transactions on Geoscience and Remote Sensing, Automation in Construction, International Journal of Agricultural and Biological Engineering, International Journal Of Information Security, Forecasting, Sustainability Switzerland, Frontiers In Plant Science, Nature Communications, Molecular Ecology, Arboriculture And Urban Forestry, Croatian Journal Of Forest Engineering, Frontiers In Applied Mathematics And Statistics, Science, Science of The Total Environment, Scientific Reports, Sensors, Journal of Geophysical Research Biogeosciences, Journal Of Ecology, Climatic Change, Journal Of Cloud Computing, ISPRS International Journal Of Geo Information, Forestry, Annals of Botany, Technological Forecasting and Social Change, Spatial Information Research, High Voltage, Remote Sensing in Ecology and Conservation, ISPRS Journal of Photogrammetry and Remote Sensing, Emerging Science Journal, CSEE Journal of Power and Energy Systems, IEEE Systems Journal, IEEE Transactions on Power Delivery, Environmental Research Letters, Recent Advances in Computer Science and Communications, Forest Ecology and Management, Renewable and Sustainable Energy Reviews, International Journal of Energy Research, Ain Shams Engineering Journal, Wood Science and Technology, Journal of the Indian Society of Remote Sensing	1
Conference Paper (24 papers)	International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS) Archives	3
	Proceedings of the International Symposium on Automation and Robotics in Construction (ISARC)	2
	International Geoscience and Remote Sensing Symposium (IGARSS), Lecture Notes in Mechanical Engineering, Lecture Notes in Networks and Systems, Proceedings IEEE Symposium on Computers and Communications, Lecture Notes in Computer Science Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, AIAA IEEE Digital Avionics Systems Conference Proceedings, IFAC-PapersOnLine, IEEE Power and Energy Society General Meeting, GIS: Proceedings of the ACM International Symposium on Advances in Geographic Information Systems, Proceedings of the TEPEN International Workshop on Fault Diagnostic and Prognostic, Southern African Universities Power Engineering Conference/Robotics and Mechatronics/Pattern Recognition Association of South Africa, SAUPEC/RobMech/PRASA, IEEE 13th International Conference on Computer Research and Development, Proceedings—6th Asia Conference on Power and Electrical Engineering, ACPEE, IEEE International Conference on Autonomous Robot Systems and Competitions, Proceedings of the International Conference on Electrical Engineering and Informatic (ICLP)—36th International Conference on Lightning Protection, Proceedings of the 11th International Conference on System Modeling and Advancement in Research Trends (SMART), Proceedings IEEE International Symposium on Circuits and Systems, Proceedings of 3rd International Conference on Intelligent Systems Advanced Computing and Communication (ISACC)	1

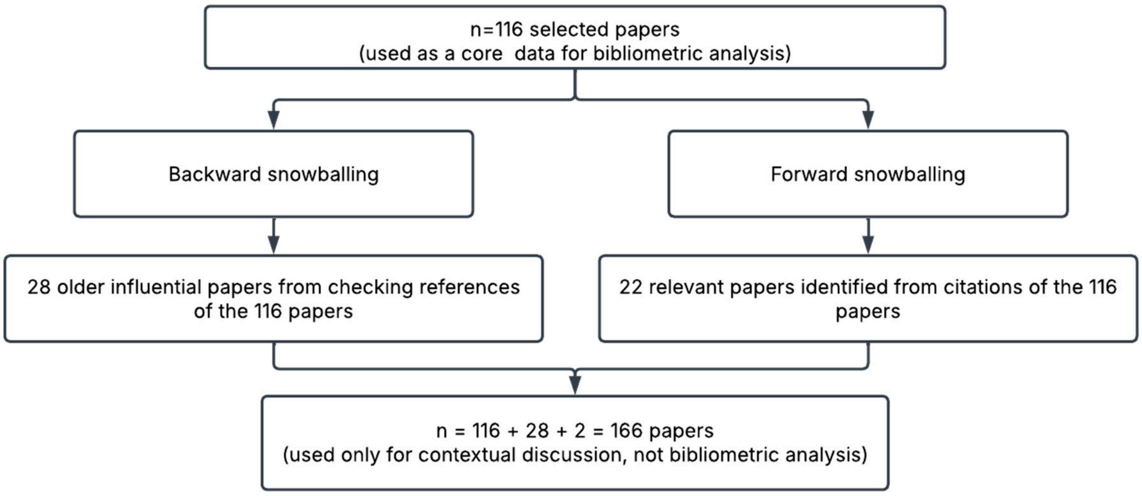

Figure 3. Integration of snowballing step in systematic review process.

The bibliometric analysis highlights a wide geographical distribution of research outputs, illustrating the global interest in vegetation management and power line interactions. As depicted in Figure 4, the United States leads with 34 affiliations, reflecting its prominent role in this field through extensive collaboration and contribution. China follows with 19, underscoring strong engagement from its academic and technological sectors. Canada ranks third with 18, underlining its focus on both research and practical applications, likely driven by infrastructure and resource management needs. European countries such as France and Germany (8 each), Italy and Spain (5 each) also make notable contributions. This global distribution extends to a range of emerging economies across Asia, Africa, the Middle East, and Latin America, including Malaysia, India, South Africa, and Colombia, which emphasizes the universal relevance of this topic across environmental and industrial challenges.

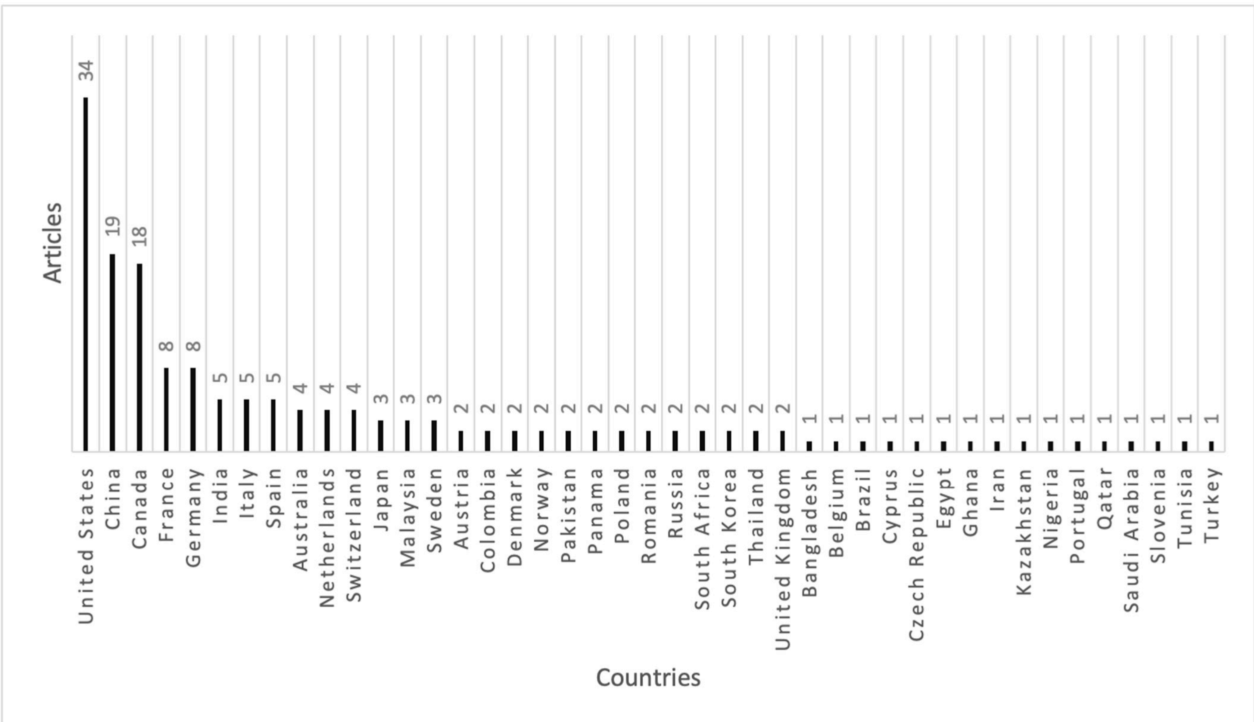

Figure 4. Distribution of corresponding author affiliations across countries (multiple affiliations possible per paper).

Figure 5 displays the publication trends from 2020 to 2025 for the top five contributing countries based on collective authorship data from all papers, considering all listed authors affiliations in each paper. The United States demonstrates steady growth, reaching more than 150 contributions by 2025, affirming its leadership in research outputs and technological investments. Similarly, China exhibits a rising trend, reflecting its focus on environmental monitoring technologies as part of ecological initiatives. Canada's trajectory also reflects consistent growth, showcasing its commitment to integrating vegetation management into its power infrastructure. While Germany and Switzerland contribute fewer total affiliations, their steady trends align with Europe's focus on sustainability and innovation in resource management.

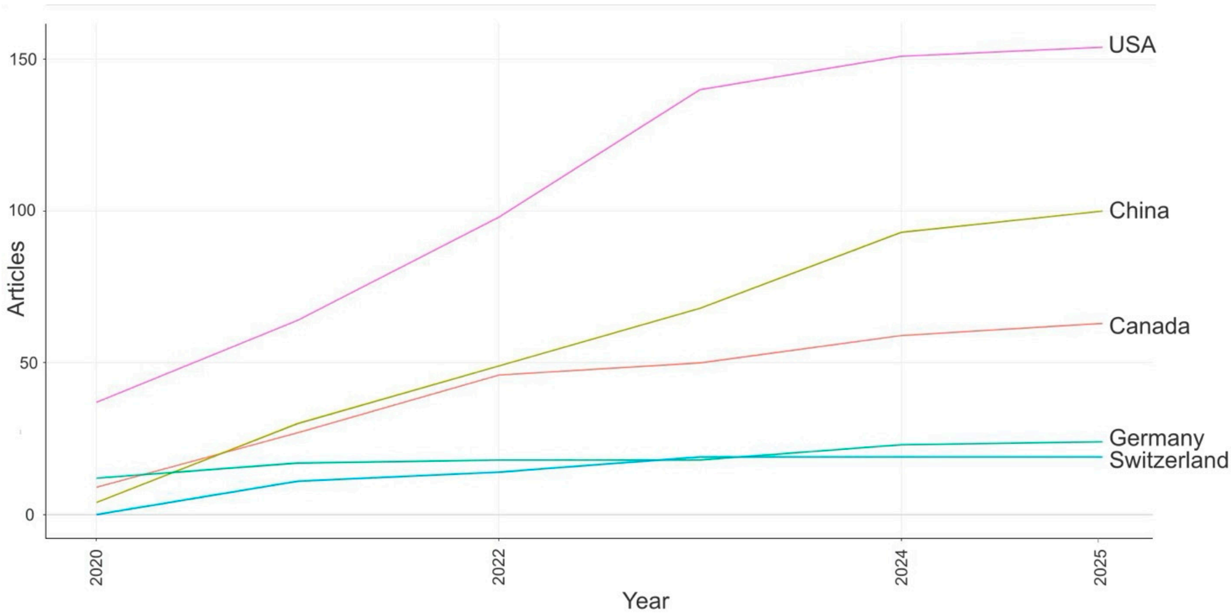

Figure 5. Publication trends (2020–2025) by country based on collective data from all listed author affiliations.

To categorize the thematic focus within the selected literature, the selected 116 papers were analyzed to identify the primary areas of their research topics. Figure 6 shows the distribution of research topics across the 116 selected articles. Among these, 35% of the papers were focused on vegetation and environmental interactions. A total of 25% of papers explored applications of computer vision; 22% addressed power line infrastructure and resilience; 13% concentrated on data analysis and modeling techniques; and 5% examined socioeconomic and safety considerations.

To further understand the thematic focus and interconnectedness of research topics in selected papers, a co-occurrence network analysis was performed using all keywords, including both author-assigned and automatically extracted terms. Figure 7 shows the keywords co-occurrence network derived from the analysis. Prior to constructing this network, keywords with similar meanings were consolidated to streamline the data and set a minimum occurrence threshold of 10 times for a keyword to be included. This refinement reduced the original list from 1423 keywords to 15 significant ones. Each node represents a keyword identified in the relevant studies, with the size of the node indicating how frequently the keyword appears. The connections between nodes demonstrate the instances where two keywords co-occurred in the literature, and the thickness of these links reflects the strength of their association based on the number of co-occurrences. From the initial 1423 keywords, 6 appeared as the most frequent, with a minimum occurrence threshold of

16 times. These frequently occurring keywords are machine learning, vegetation, power lines, outages, remote sensing, and climate change.

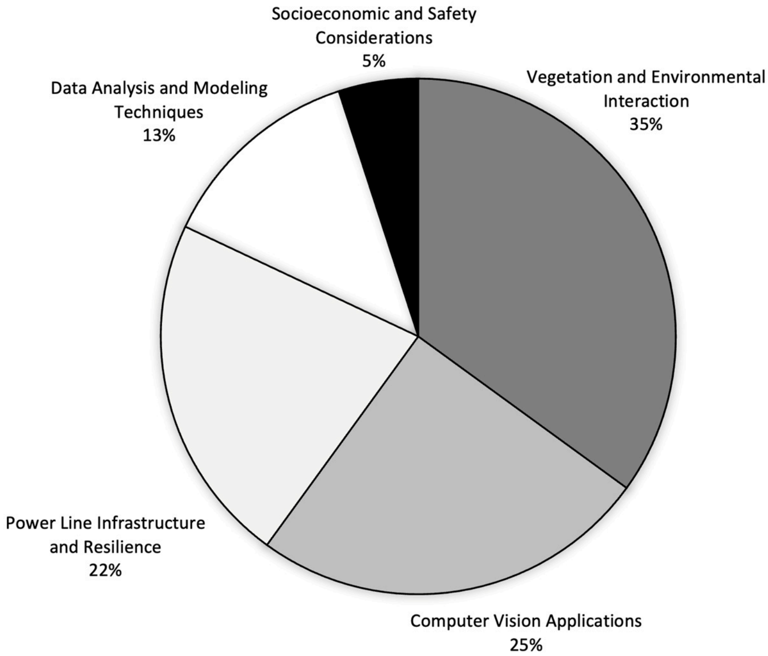

Figure 6. Distribution of research topics.

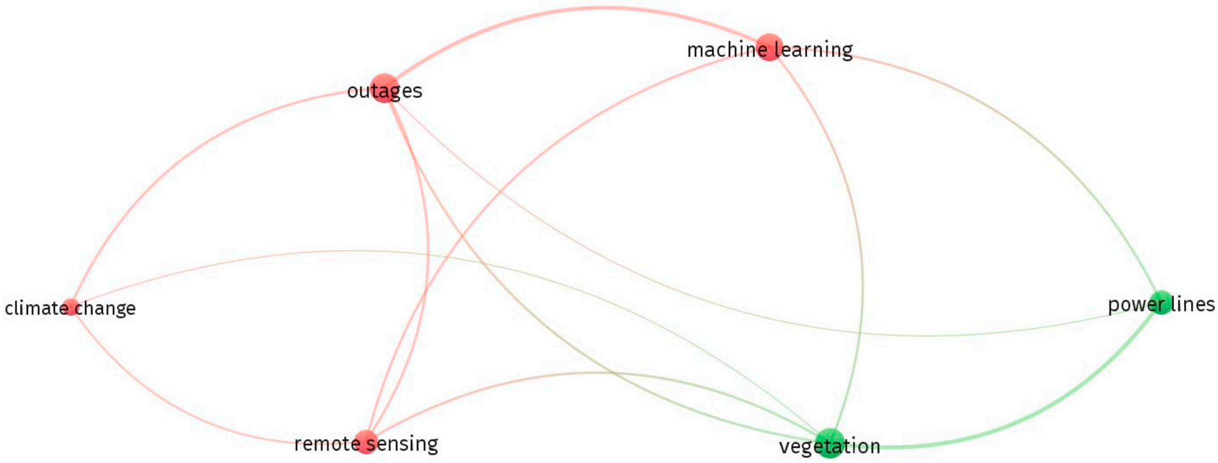

Figure 7. Keywords co-occurrence network of the most frequent terms in selected publications.

3. Outages Caused by Weather Events

3.1. Overview

Weather conditions such as windstorms, heavy snow, and rain significantly impact vegetated areas ecosystems, often leading to tree failures and subsequent power outages. This review synthesizes the findings from recent literature to understand the mechanisms through which these weather events contribute to tree failures and the implications for power system reliability.

3.2. Wind-Related Outages

Wind is a main factor causing extensive damage to vegetation, leading to both immediate and long-term impacts on power infrastructure. Research has shown that wind affects tree stability and integrity, leading to mechanical failures such as uprooting and stem breakage. The aerodynamic interactions between wind and trees play a critical role, where factors such as tree height, crown size, and wood density determine a tree's resistance to wind [13]. Wind-related outages are a significant concern for power distribution systems due to the direct and indirect effects of wind on vegetation and infrastructure. Several studies have documented the direct correlation between severe weather events and increased rates of power outages. For instance, Pretzsch [14] discussed the urban context where windstorms have led to significant tree fall incidents, disrupting urban infrastructure and power lines. Abd-Elaad et al. [15] studied transmission line failures due to high-intensity winds from downbursts, highlighting the need for improved modeling and structural analysis to prevent catastrophic failures. Haes Ahelou et al. [16] discussed the cascading failures in power systems due to severe weather events, including wind, and emphasize the challenges in protecting systems against such unpredictable events. Kumar et al. [17] assessed the integration of wind energy into power systems and its effects on reliability, including the challenges of managing the intermittent nature of wind. Zhang et al. [18] studied methods for assessing the risk of power outages due to typhoon-induced winds, suggesting improvements in data processing and risk evaluation. Omogoye et al. [19] discussed proactive operational planning measures to enhance the resilience of power distribution systems against hurricane events, using statistical models. Ahmed et al. [20] explored the operational and control challenges presented by the large-scale integration of wind energy into existing power grids. Nelson and Ebakumo Thomas [21] examined the impacts of wind on high voltage transmission lines, emphasizing the need for accurate analysis and solutions to mitigate wind-related damages. Suttle et al. [22] studied how wind-induced tree damage could exacerbate power outages near utility corridors. Their findings emphasize the importance of adaptive vegetation management practices in mitigating these outages by proactively assessing tree stability and structural integrity.

3.3. Rain, Snow and Freezing Rain Outages

Rain, snow, and freezing rain are critical weather factors that influence the reliability of power distribution systems. Recent research has focused on understanding how these conditions contribute to power outages, particularly through their impact on trees and infrastructure. Heavy snow and ice accumulation can exert additional mechanical loads on trees, particularly affecting branches and crowns. Research indicates that similar mechanical stresses caused by wind loads also apply to snow and ice, leading to branch breakage and potential tree collapse in areas where these weather conditions are prevalent [23]. The severity of damage is often correlated with tree species, age, and health, as well as the density and water content of the snow [23]. In regions with severe winter conditions, such as North America, snow and freezing rain have been shown to significantly contribute to power outages due to the physical stress they place on trees and power infrastructure [24].

Prolonged rainfall can saturate the soil, reducing its ability to anchor roots and increasing the likelihood of uprooting during windstorms. The destabilization of soil can be exacerbated in areas with poor drainage, leading to higher susceptibility to windthrow [24]. Additionally, heavy rains can lead to increased incidence of landslides and soil erosion, further destabilizing tree stands and increasing the risk of failure [24]. Daeli and Mohagheghi [25] discussed the resilience of power systems against extreme weather, including strategies to enhance grid stability during adverse weather conditions. They emphasize the need for innovative grid design to withstand extreme weather impacts. Bindu [26] studied methodologies to optimize power systems for resilience against extreme weather events, highlighting the role of distributed energy resources and advanced control strategies. Jufri et al. [27] provided a detailed review of power grid resilience to extreme weather, covering definitions, frameworks, and quantitative assessment methodologies. They discuss the challenges and future directions for enhancing grid resilience. Powluk et al. [28] examined the impact of snow accumulations on photovoltaic systems, quantifying generation losses and discussing mitigation strategies to manage snow effects. Mohamed et al. [29] explored proactive strategies for enhancing the resilience of power systems against extreme weather-related events, with a focus on microgrids and resilience planning. Mahzarnia et al. [30] studied the current measures for managing power system resilience against high-impact, low-probability events like heavy snow and floods, outlining future trends for improvement. Paul et al. [31] provided a comprehensive analysis of resilience evaluation and planning in power distribution systems, highlighting the importance of understanding interdependencies among critical infrastructures to enhance overall resilience.

3.4. Lightning

Lightning is a natural phenomenon with significant implications for power distribution systems, particularly when it leads to fires that exacerbate the risk of power outages. This section reviews the literature on the impacts of lightning on power systems, the conditions under which lightning induces fires, and the preventative strategies that have been developed to mitigate these risks. Lightning strikes can cause direct damage to power infrastructure or induce fires that lead to further damage. Research has shown that lightning strikes are a significant cause of power outages and can result in severe economic impacts due to downtime and damage repair costs. For instance, a study on nuclear power plants highlighted that lightning strikes to transmission lines are unlikely to result in a total loss of offsite power but can cause significant protective relaying operations due to ground faults induced by the strikes [32].

Moreover, lightning strikes can ignite fires, particularly in vegetated areas or where dry conditions prevail. These fires pose a risk to nearby power lines and can lead to widespread outages. Preventative measures are crucial in regions prone to lightning to mitigate the initiation and spread of fires. Studies have documented the dynamics of lightning-induced fires and the effectiveness of early warning systems and lightning rods in preventing these fires [33]. The implementation of advanced detection and protection systems can significantly reduce the risk of lightning-induced outages. For example, the installation of surge protectors, the proper grounding of electrical systems, and the use of automated switching and fault detection technologies can help prevent outages. Research has also focused on improving the resilience of power systems to withstand the impacts of lightning by enhancing grid design and maintenance practices [34].

Analyzing historical data on outages caused by lightning offers insights into patterns and trends that can inform better risk management strategies. Such analyses help utilities prepare for and quickly respond to potential disruptions caused by lightning [16]. Case studies from various regions have shown the effectiveness of integrated approaches that combine physical protections with predictive analytics to minimize the impact of lightning on power systems. These studies emphasize the need for a proactive approach to infrastructure protection, involving both physical hardware and sophisticated modeling techniques to predict and react to lightning events efficiently. Doostan and Chowdhury [35] present a data-driven approach for predicting lightning-related outages in power distribution systems, using machine learning algorithms and actual outage data. Three case studies demonstrate the effectiveness of the proposed approach. Rawi et al. [36] provide statistical information on transmission line outages and lightning stroke data, highlighting the impact of lightning on power system performance in Malaysia. Volpov and Katz [37] characterize local environmental data and analyses lightning-caused outages in Israel's power grid, providing long-term monitoring data and statistical patterns. Andreotti et al. [38] discuss the effects of lightning-induced voltages on power distribution lines and employs a probabilistic procedure to analyze these effects, providing valuable statistical insights. Ravaglio et al. [39] integrate experimental data and digital simulations to evaluate lightning-related faults in distribution feeders, offering insights into the conditions leading to sustained outages.

4. Proximity Detection

4.1. Object Detection

While deep learning, a subfield of machine learning (ML), has significantly enhanced capabilities in this area, traditional machine learning methods still play a crucial role, especially where computational resources are limited or in hybrid systems.

4.1.1. Conventional ML Approaches

This section of the review highlights traditional machine learning methods employed in object detection, especially the proximity of vegetation to electrical distribution lines. ML has revolutionized the automated vegetation management (AVM) by enabling fast processing of data and insights that were previously unachievable. Kyuroson et al. [40] developed an autonomous point cloud segmentation system for power lines inspection in the smart grid. Li et al. [41] used machine learning methods to classify tree species along transmission line corridors, aiding in management planning. Mohd Rapheal et al. [42] evaluated a machine learning-based geospatial technique to classify electrical infrastructure using dense mobile laser scanning data, achieving detection accuracies of 65% for overhead power lines and 63% for utility poles. Mahoney et al. [43] conducted classification and mapping of low-statured shrubland cover types in post-agricultural landscapes of the US Northeast. Abongo et al. [44] proposed a new framework for identifying power lines, employing a mix of machine learning (XGBoost) and geometric techniques. Wang et al. [45] studied machine vision techniques for vegetation detection. Liakos et al. [46] provided insights into machine learning application in crop vegetation.

4.1.2. Deep Learning Approaches

Deep learning has revolutionized the field of object detection, including the detection of trees near power lines, which is critical for maintaining the reliability and safety of power distribution systems. Haroun et al. [8] assessed techniques for detecting vegetation encroachment, highlighting the potential of ML/DL algorithms to improve accuracy and flexibility in detection methods. Park et al. [47] implemented enhanced-feature convolutional neural networks (CNNs) such as AlexNet, ResNet18, and VGG11 to sort images from Google Street View into classes pertaining to utility systems and vegetation overgrowth, which support prioritization in vegetation management. Oehmcke et al. [48] applied deep learning models (MSENet14, KPConv, PointNet) to estimate wood volume and above-ground biomass, demonstrating substantial enhancements in precision over traditional methods. Bahreini et al. [49] proposed an integrated approach, utilizing the RandLA-Net model for deep learning-based semantic segmentation of LiDAR data and post-processing techniques for urban vegetation management. Their methodology enhances detection accuracy and computational efficiency, providing a robust framework for proximity detection of trees to power distribution lines. Subsequently, the approach was advanced to a digital twin tailored to power distribution networks, integrating the earlier segmentation workflow to support ongoing monitoring and decision-making [50].

These datasets include high-resolution point clouds and corresponding imagery, offering a representative sample of urban utility corridors under varying vegetation densities. Ozcanli et al. [51] discussed the broad applications of deep learning in electrical power systems, including the detection of proximity between trees and power lines, emphasizing the role of deep neural networks in enhancing system reliability and operational efficiency.

Singh et al. [5] reviewed the use of AI, especially deep learning models, in detecting trees from UAV and remotely sensed imagery, a methodology that can be directly applied to managing tree proximity to power lines. Khodayar et al. [7] discussed the impact of deep learning on various aspects of power systems, including vegetation management and the detection of obstacles near power lines, showcasing how these methods can lead to better predictive and operational tools. Nguyen et al. [52] emphasized the advances in using autonomous vision-based systems for power line inspections, discussing how deep learning can enhance the detection and analysis of proximity risks. Rahman et al. [53] explored the progress in 3D object detection, which can potentially be applied to various contexts, including the detection of objects in three-dimensional space. Wang et al. [54] provided an overview of deep learning applications in vegetation, including detection and classification of tree species, relevant for managing vegetation near power infrastructure. Koirala et al. [55] reviewed deep learning models for agricultural applications, focusing on fruit detection and yield estimation. Pu et al. [56] explored power line corridor inspection and vegetation risk detection using deep learning, semantic classification and UAV-based LiDAR point clouds. Mantach et al. [4] presented the application of deep learning in high voltage engineering, including aspects related to power line monitoring. Diez et al. [57] focused on reviewing methods using UAV-acquired RGB data for vegetation applications through deep learning, useful for monitoring and managing vegetation around power lines. Kattenborn et al. [58] focused on the effectiveness of CNNs in representing spatial patterns to extract vegetation properties from remote sensing imagery, which is beneficial for monitoring tree proximity to power lines. Alimi et al. [9] reviewed machine learning approaches to power system security and stability, mentioning some deep learning techniques but not specifically addressing tree proximity to power lines. Datta et al. [59] analyzed the potential of deep learning algorithms in urban remote sensing using UAVs, but their work does not specifically focus on vegetation management around power lines.

4.1.3. Image-Based vs. Point Cloud Methods

LiDAR technology has become a prominent tool in Automated Vegetation Management (AVM) for power distribution lines, offering high-resolution 3D data essential for detecting and analyzing vegetation in power line management. This section provides a comparative analysis of image-based and point cloud technologies for detecting the proximity of trees to power lines. Both methods are essential for environmental sensing, especially in the context of utility management. Advancements in technology, such as LiDAR scanners and sensors, have substantially enhanced the safety and efficiency of power distribution systems by improving the accuracy and reliability of detection methods. While there has been considerable progress in image processing through computer vision, the development of machine learning techniques for semantic segmentation of point cloud data is still in its early stages. LiDAR technology has established itself as a significant tool in Automated Vegetation Management (AVM) for power distribution lines. It provides high-resolution 3D data that is crucial for the effective detection and analysis of vegetation, facilitating better management of power line corridors. Additionally, recent UAV-focused research has highlighted the rapid adoption of drones integrated with LiDAR and image sensors for power line inspections, emphasizing their ability to replace hazardous inspection with safer and more cost-effective alternatives [60]. Gollob et al. [61] explored the accuracy of tree variable estimates using mobile laser scanning, noting the influence of scan variability on tree measurements. Gaha et al. [62] presented a new LiDAR-based clustering technique for detecting poles and distribution lines, showing improved accuracy and efficiency, though primarily effective for single-phase lines and less so in occluded settings. Hernández-López et al. [63] demonstrated how high-resolution drone LiDAR data enhances the detection of vegetation encroachment risks, enabling more proactive vegetation management around critical infrastructure. Gribov and Duri [64] proposed a technique to construct line features modeling each catenary curve from a set of points representing multiple catenary curves, which can be applied to extract power lines from LiDAR data. Amado et al. [65] offered a method for extracting power lines from LiDAR point clouds, proving accurate and automatic extraction capabilities. Awrangjeb [66] introduced a power line extraction and modeling approach using LiDAR, significantly aiding in the detection and modeling of power lines, and providing a reliable solution to the challenges of power line extraction. Li and Guo [67] discussed the use of LiDAR for power line inspection, emphasizing its benefits in capturing high precision 3D spatial information and comprehensive corridor data, crucial for effective inspection and maintenance. Horning [68] addressed the challenges and advancements in mapping land cover using ultra-high-resolution aerial imagery, incorporating ML algorithms for image processing.

Publicly available datasets form the foundation for high-performance DL models in vegetation proximity detection. Notable examples include Toronto-3D [69], which provides labeled urban LiDAR point clouds for semantic segmentation of power lines and vegetation; TTPLA (Transmission Tower/Power Line Aerial-Image) [70] for aerial imagery-based object detection and encroachment assessment; VEPL Dataset [71] for UAV RGB orthomosaics in vegetation and power line segmentation; and DALES [72] for diverse airborne LiDAR scenes including power infrastructure. Datasets for LiDAR and image-based methods in vegetation proximity detection present several technical challenges. LiDAR data often suffers from issues such as point density variations, occlusions in dense vegetation, and high computational demands for processing large-scale point clouds, which can lead to inaccuracies in semantic segmentation and proximity measurements [62]. Image-based datasets, including RGB and hyperspectral imagery, face challenges like lighting inconsistencies, atmospheric distortions, and limited resolution in adverse weather, complicating feature extraction and object detection [57]. Moreover, data is frequently collected for different purposes (e.g., general environmental mapping vs. targeted utility inspections), resulting in mismatches in scale, labeling standards, or geographic coverage, which hinder model generalization and require extensive preprocessing for integration [73]. Addressing these challenges requires standardized datasets and hybrid fusion techniques to improve robustness. Table 3 provides a comprehensive comparison of recent research focused on vegetation and power line detection. The order of the table is arranged based on the publication year. It highlights the diverse objectives, networks, and techniques explained across various studies, alongside their data sources and main application areas.

4.1.4. Transmission Network vs. Distribution Network

The electrical power grid comprises two fundamental segments: the Transmission Network and the Distribution Network, each distinct in function, operating voltage, and management strategies. The transmission network acts as the power system's high-voltage backbone, efficiently transporting substantial electricity volumes over long distances from generation plants to substations at high voltages. In contrast, the distribution network functions at lower voltages, managing the delivery of electricity from substations to end users, including residential, commercial, and industrial customers. Vegetation management is crucial in both segments but differs in execution; the transmission network, due to higher voltages, employs stringent safety measures and advanced technologies like LiDAR and aerial surveillance to detect vegetation encroachment. Meanwhile, the distribution network, often embedded within residential and urban environments, requires more frequent vegetation management and utilizes simpler technologies such as image processing for effective monitoring. Each network's management strategies are personalized to their operational needs, with transmission networks employing broad-scale data models suitable for remote sensing data, and distribution networks using more localized, detailed data analysis models to address the dense, varied data landscapes of urban areas.

Pascucci et al. [73] discussed relevant remote sensing technologies that can be adapted for vegetation management in both network types. Usman et al. [74] reviewed strategies for managing losses in active distribution networks, which indirectly relate to broader system reliability. Mohseni-Bonab et al. [75] explored integrated transmission and distribution system simulations, which are crucial for optimizing overall system operations. Lind et al. [76] emphasized the need for coordination between transmission and distribution networks to manage distributed energy resources effectively. Meskin et al. [77] analyzed how distributed generation impacts distribution network protection systems. Rajora et al. [78] investigated various ML models for improving asset management in power distribution networks.

4.2. Post-Processing Techniques for Proximity Detection

In the context of detecting the proximity of trees to power lines using machine learning and deep learning technologies, clustering algorithms play a crucial role in analyzing the spatial distribution of vegetation. Clustering helps in segmenting tree clusters that pose potential risks to power lines, improving maintenance strategies and preventing outages. Sankaran et al. [79] discussed how clustering algorithms can help understand spatial patterns and their implications for ecosystem resilience. Ahmad and Khan [80] discussed the latest clustering algorithms for mixed data types, incorporating various types of sensors and data formats. Tchórzewski and Kania [81] applied cluster analysis to the operation data of the National Power System, demonstrating how similar techniques can be used for spatial analysis of vegetation around power lines. Gao [82] explored spatial clustering techniques in agriculture, which can be adapted for analyzing spatial distributions of trees relative to power lines.

Table 3. Comparison of research papers focusing on vegetation and power line detection in last six years (2020–2025).

Reference	Year	Objective	Investigated Network/Technique	Data Source	Main Focus	ML/DL	Power Line Detection	Vegetation Detection	Vegetation Proximity Detection to Power Lines
Ni et al. [83]	2025	Detect and predict tree-related risks and vegetation encroachment on transmission lines	Random Forest, 3D catenary reconstruction, distance-based risk detection	UAV LiDAR (DJI Matrice 350 + Zenmuse L1)	Dynamic risk detection and five-year prediction of vegetation proximity in a 110 kV corridor	✓	✓	✓	✓
Harini et al. [84]	2025	Monitor vegetation encroachment and fire risk around power lines	YOLOv5, LiDAR-derived CHM, distance- and height-based risk assessment	Satellite and aerial images, LiDAR point clouds	Power line and vegetation detection with proximity risk and wildfire-mitigation context	✓	✓	✓	✓
Al-Najjar et al. [85]	2025	Automated detection and reporting of vegetation encroachment on power lines	DBSCAN clustering, PCA alignment and rotation, sliding window traversal, voxel downsampling, proximity-based severity classification	Airborne and mobile LiDAR point clouds from ECLAIR, DALES, and Toronto 3D	Generalized LiDAR pipeline with scalable proximity analysis and severity reporting across diverse datasets	✓	✓	✓	✓
Rong et al. [86]	2025	Real-time detection of power lines and quantitative assessment of vegetation encroachment	PL-YOLOv8 with directional filters, OBB detection, encroachment metric (GI + TGDI)	TTPLA aerial images (tiling + OBB annotations)	Power line OBB detection and metric-based encroachment scoring suitable for on-board/near-real-time alerts	✓	✓	✓	✓
Bahreini et al. [49]	2024	Detect proximity of trees and power lines	RandLA-Net with DBSCAN and KDTree for post-processing optimizations	Toronto-3D—Point Cloud	Dual focus on power line and vegetation detection with proximity analysis	✓	✓	✓	✓

Table 3. *Cont.*

Reference	Year	Objective	Investigated Network/Technique	Data Source	Main Focus	ML/DL	Power Line Detection	Vegetation Detection	Vegetation Proximity Detection to Power Lines
Al-Najjar et al. [87]	2024	Detect vegetation encroachment on power lines	PointCNN, RandLA-Net, P-BED Algorithm	Mobile and airborne LiDAR Point Clouds	Vegetation and power line classification and proximity analysis	✓	✓	✓	✓
Zhou et al. [88]	2024	Segment power line corridor to detect vegetation hazards	Bilinear Distance Feature Network (BDF-Net)	Power line Corridor Point Cloud (PPCD)	Semantic segmentation of power line corridor, including vegetation risks	✓	✓	✓	✓
Sun et al. [89]	2024	Monitor safety in Power line corridors and detect hazards	YOLOX with ConvNeXt backbone, EPNP for 3D ranging	UAV LiDAR, surveillance camera images	Safety distance and hazard detection in power line corridors	✓	✓	-	-
Li et al. [90]	2024	Improve accuracy and speed of transmission line detection	Res2Net-YOLACT, Feature Pyramid Network, DIoU-NMS	Transmission Tower/Power Line Aerial-Image (TTPLA)	Transmission line detection for UAV-based inspections	✓	✓	-	-
Sey et al. [91]	2023	Monitor vegetation encroachment near power lines	Pix2Pix GAN for NDVI estimation, YoLov5 for power line detection	UAV RGB and multispectral imagery	Vegetation health monitoring, power line detection, proximity assessment	✓	✓	✓	✓
Shi and Kissling [92]	2023	Evaluate power line removal methods to improve vegetation metrics	PointCNN, eigenvalue decomposition, hybrid method	Airborne LiDAR	Vegetation height, cover, and vertical variability metrics	✓	✓	✓	✓
Kyuroson et al. [40]	2023	Autonomous segmentation and analysis of power lines and vegetation	Unsupervised ML (DBSCAN, Kd-tree, PCA)	LiDAR—Unlabeled Point Cloud	Power line corridor monitoring for hazard detection and inspection of both vegetation and lines	✓	✓	✓	✓

Table 3. *Cont.*

Reference	Year	Objective	Investigated Network/Technique	Data Source	Main Focus	ML/DL	Power Line Detection	Vegetation Detection	Vegetation Proximity Detection to Power Lines
ElGharbawi et al. [93]	2023	Estimate canopy heights along power lines for vegetation hazard monitoring	Seg-Net, Res-Net	S2 satellite data, airborne LiDAR	Vegetation height estimation for encroachment monitoring	✓	-	✓	✓
Abongo et al. [44]	2023	Efficient detection of distribution power lines	XGBoost with geometric analysis	LiDAR Dataset—Point Cloud	Power line detection in dense vegetation areas	✓	✓	-	-
Gollob et al. [61]	2023	Tree detection in forested areas	SLAM algorithm with density-based clustering	Mobile LiDAR—Point Clouds	Detection of individual trees and structural analysis	-	-	✓	-
Wang et al. [94]	2023	Semantic segmentation of transmission corridor	CA-PointNet++ with Coordinate Attention module	UAV LiDAR dataset—Point Cloud	Transmission corridor vegetation and power line segmentation	✓	✓	-	-
Cano-Solis et al. [71]	2023	Vegetation encroachment detection in power line corridors	VEPL-Net (DeepLab, U-Net, and VGG-16)	VEPL Dataset (UAV RGB Orthomosaics)	Vegetation and power line segmentation without proximity focus	✓	✓	✓	✓
Oehmcke et al. [48]	2022	Predict vegetated area biomass and wood volume	Minkowski-CNN, KPConv, PointNet	Airborne LiDAR—Point Cloud	Vegetated area biomass estimation	✓	-	✓	-
Mahoney et al. [43]	2022	Classify and map vegetation types	Stacked ensemble (Random Forest, GBM, ANN)	LiDAR and Landsat satellite imagery	Classification of vegetation types in post-agricultural landscapes	✓	-	✓	-
Almeida et al. [95]	2022	Canopy height mapping	Random Forest, CART, Linear Regression	S1 and S2 satellite, airborne LiDAR	Vegetation height estimation in transmission corridors	✓	✓	✓	✓

Table 3. *Cont.*

Reference	Year	Objective	Investigated Network/Technique	Data Source	Main Focus	ML/DL	Power Line Detection	Vegetation Detection	Vegetation Proximity Detection to Power Lines
Mohd Rapheal et al. [42]	2022	Detect and classify power lines and poles	Random Forest, LiDAR360	Mobile Laser Scanning (MLS) data	Power line and electricity pole inventory in suburban areas	✓	✓	-	-
Li et al. [41]	2022	Classify tree species in transmission corridors	Random forest, SVM	LiDAR, Aerial imagery	Vegetation species classification in transmission corridors	✓	-	✓	✓
Chen et al. [96]	2022	Detection of tree encroachment using and growth models in high voltage power line corridor	Richards's growth model, two-phase tree encroachment detection algorithm	UAV-borne LiDAR (Fujian, China)	Vegetation encroachment detection and growth prediction	✓	✓	✓	✓
Gazzea et al. [97]	2021	Develop a method to monitor vegetation encroachment near powerlines	Semi-supervised segmentation, supervised classification (NDVI, FCN)	WorldView-2, Pleiades-1 satellite images, LiDAR	Monitoring vegetation risks in powerline corridors	✓	-	✓	✓
Qayyum et al. [98]	2021	Estimate vegetation threat near power lines	CNN and sparse representation for disparity map estimation	UAV and satellite stereo imagery	Vegetation height and proximity estimation for threat detection	✓	✓	✓	✓
Kandanaarachchi et al. [99]	2021	Detect vegetation ignition risks caused by high impedance faults near power lines	Fourier and Wavelet transforms, decision tree classifiers	Power line Bushfire Safety Program (PBSP) dataset	Early detection of vegetation ignition risk	✓	✓	✓	✓
Vemula et al. [100]	2021	Detect vegetation encroachment near power lines	VE-DETR, Multi-head Attention Transformer, ResNet	UAV-acquired imagery	Vegetation encroachment detection and segmentation	✓	✓	✓	✓

Table 3. *Cont.*

Reference	Year	Objective	Investigated Network/Technique	Data Source	Main Focus	ML/DL	Power Line Detection	Vegetation Detection	Vegetation Proximity Detection to Power Lines
Park et al. [47]	2021	Detect power lines and classify vegetation overgrowth for wildfire prevention.	Feature-enhanced CNNs (AlexNet, ResNet18, VGG11), HOG, Hough Transforms	Google Street View images	Classification of vegetation encroachment for fire risk	✓	✓	✓	✓
Gaha et al. [62]	2021	Detect poles and power lines	RANSAC, 3D Parabola Modeling, Cylinder Detection	Mobile LiDAR Point Cloud	Power line and pole detection for distribution networks	-	✓	✓	✓
Kattenborn et al. [58]	2021	Identify and classify vegetation traits (species, structure)	CNN architectures (VGG, ResNet), multi-modal approaches	High-resolution satellite imagery, UAV, LiDAR	Species classification, segmentation, and structure detection in vegetation	✓	-	✓	-
Diez et al. [57]	2021	Review of DL applications for tree detection, species classification, and forest health	CNN (VGG, ResNet, U-Net), transfer learning	UAV-acquired RGB data	Tree detection, species classification, forest health monitoring	✓	-	✓	-
Ma et al. [101]	2020	Detect vegetation-related wildfire risks caused by power line faults	Hybrid Step XGBoost (HSXG)	188 ignition field tests	Vegetation fault detection and ignition risk prediction	✓	✓	✓	✓
Nardinocchi et al. [102]	2020	Detect power lines and classify obstacles in power line corridors	3-D Power Line Obstacle Detection (3-D-PowLOD) algorithm	UAV LiDAR point clouds and airborne surveys	Power line detection and obstacle classification, including vegetation	-	✓	✓	✓

5. Considering Dynamic Aspects of Vegetation

This section discusses the dynamic aspects of trees, such as growth rates, seasonal changes, and environmental impacts, which are crucial for understanding their behavior and management near power lines. Further detailed information concerning the dynamic nature of trees will be explained in the following sections.

5.1. Growth Dynamics of Trees

Trees exhibit dynamic growth patterns that are influenced by various environmental factors. Understanding these dynamics is crucial for effective vegetation management near power lines. Growth dynamics can be understood through tree rings, which provide a record of past growth conditions and climate variables [103]. Schmitt et al. [104] investigated tree growth dynamics in tropical forests, showing that tree species in French Guiana have genetically determined growth strategies that are adapted to local light and competition environments influenced by treefall gaps. This adaptation highlights the dynamic growth nature of trees as they respond to ecological niches shaped by vegetation dynamics. Studies have shown that the growth rates of trees are closely tied to climatic conditions, particularly temperature and rainfall, which affect the physiological processes within trees. Etzold et al. [105] studied radial stem growth dynamics in temperate trees across Switzerland. They highlighted that the number of growth days, rather than the length of the growth period, significantly influences annual radial stem growth, underlining the non-static growth behaviors of trees in temperate climates. Research on trees in urban settings has found that growth is also impacted by soil quality, water availability, and human management practices, which can either inhibit or enhance growth depending on the context. Pretzsch [14] explored the overall tree growth course, discussing how different environmental conditions and vegetation management practices influence the growth and competitive dynamics of various tree species in temperate forests. The findings stress that tree growth is a complex process affected by numerous factors over time, which challenges the static view of tree development. Wilmking et al. [106] studied the non-stationary nature of tree growth responses to environmental changes, challenging the assumption that these relationships are linear and unchanging over time. They emphasized the need for revised methodologies to accurately assess tree growth in the context of global change. Maes et al. [107] demonstrated that multiple environmental drivers, including temperature, precipitation, and nitrogen deposition, interactively influence tree growth. Their study emphasized the complexity of growth dynamics across different species and environments, highlighting how these factors do not act in isolation but rather in conjunction to affect tree growth. Teets et al. [108] used advanced statistical models to link climate variability with stand-level growth metrics, offering valuable insights into the responses of mixed-species vegetated areas to climatic changes. Trotsiuk et al. [109] evaluated the impact of rising temperatures and evaporative demand on tree growth, particularly in Switzerland. Their study emphasized the significant constraints imposed by climatic stressors on forest ecosystems. McDowell et al. [110] explored global trends in vegetation dynamics, noting the increasing prevalence of younger stands and faster turnover rates due to climate change and anthropogenic disturbances. This study emphasized the worldwide changes in vegetation growth patterns. Ren et al. [111] analyzed the differential responses of trees at various life stages to environmental factors such as soil fertility and spatial competition. Their study highlighted the importance of these factors in understanding growth variations within vegetation stands. Sanmiguel-Vallelado et al. [112] demonstrated that snow cover dynamics significantly influence tree growth by modulating soil temperature and moisture conditions. Their study emphasized the crucial role of winter conditions in determining annual growth cycles. Jochner et al. [113] focused on the intricate links between tree growth at the treeline and fine-scale temperature gradients. Their study provides detailed insights into how microclimatic conditions drive growth patterns at high elevations. Kijowska-Oberc et al. [114] reviewed various adaptations of tree species to changing climate conditions, such as modifications in seed resistance and germination strategies, crucial for their survival and growth under new environmental stresses. Ciceu et al. [115] analyzed the influence of climate change on tree growth using long-term data, highlighting how different climatic variables affect the growth rates of major boreal tree species. Their findings emphasize the sensitivity of certain species to drought and temperature changes. Anderson-Teixeira et al. [116] provided a global assessment on how climate, tree size, and annual variations interactively influence tree growth. They explored the complex interactions between environmental factors and tree growth at a global scale, emphasizing the importance of these interactions in understanding vegetation dynamics.

Studies About Growth of Trees in Quebec

In Quebec, the diversity of tree species significantly influences the urban landscape and infrastructure, including power distribution systems. Different species exhibit varied growth patterns, responses to environmental conditions, and implications for proximity to power lines. This section of review focuses on the major tree types in Montreal city of Quebec. Table 4 provides an overview of some key tree species found in Montreal and their specific characteristics.

Table 4. Some major tree species in Montreal, along with their specific characteristics.

Tree Species	Characteristics
Norway Maple	Dense canopy, tolerant to pollution and soil compaction, can become invasive if not managed [117,118].
Silver Maple	Withstands waterlogged soils, suitable for areas near water bodies [119].
Green/Red Ash	Adaptable to urban conditions, susceptible to emerald ash borer [118,120].
Littleleaf Linden	Compact shape, ideal for limited space urban settings [118].
Skyline Honey-Locust	Tolerant to urban pollutants, provides light shade, resistant to pests [121].
Hackberry	Durable, adaptable, resistant to air pollution, provides substantial shade [118].
Thornless Honey-Locust	Tolerant to urban conditions, frequently chosen for street planting [122].
Colorado Spruce	Aesthetic appeal, suitable for parks and larger spaces [123].
Siberian Elm	Highly tolerant to adverse conditions, drought and poor soil, robust but requires management [118].
Columnar Norway Maple	Upright narrow form, suitable for streets with limited space, tolerant to urban conditions [124].

Limoges et al. [125] explored factors influencing the growth of street trees in Montreal, indicating that species and planting conditions significantly affect growth rates. This is relevant for understanding how different tree types respond in urban settings. Martin et al. [126] examined radial growth patterns of trees in old-growth forests in eastern Canada, including several species common in Quebec. The study identifies different growth patterns linked to vegetation types or successional stages, which can inform how tree species near power lines might behave. Chavardès et al. [127] studied how diversity and competition affect tree growth in response to environmental stressors in forests of western Quebec, which is crucial for managing tree health near power lines. Boakye et al. [128] investigated how different tree species respond to climate change in Quebec, which can affect their growth patterns near power infrastructure. Moreau et al. [129] provided insights into the growth and survival of sugar maple in Quebec, a common species in Montreal, under vegetation management practices. Duchesne and Prévost [130] explore how disturbances and competition affect tree growth, focusing on species like yellow birch and conifer which are prevalent in Quebec. Rossi et al. [131] examined how growth characteristics of black spruce vary across different altitudes and latitudes within Quebec, offering insights into how environmental factors influence tree physiology across a geographic gradient.

Jutras et al. [132] discussed the growth patterns of various tree species in Montreal, including species like Norway Maple, Silver Maple, Hackberry, Green Ash, Honeylocust, Littleleaf Linden, and Siberian Elm. The research highlights how differential growth between commercial and residential zones is influenced by ecological tolerance and local environmental conditions. Additionally, another study by Jutras et al. [133] conducted research on the significant inventory parameters for street trees in Montreal. This work provides a detailed examination of the growth models for these trees, which can aid in understanding their performance in urban settings.

5.2. Dynamic Impact of Environment

5.2.1. Impact of Wind on Trees

Wind plays a significant role in shaping the growth, structure, and stability of trees [134], influencing ecological dynamics and vegetation management strategies. Lee and Ham [135] investigated the critical wind speeds that heighten the risk of wildfires by assessing the distance between trees and power lines under wind loads. Using airborne LiDAR data, the research provides valuable insights for utility companies to manage tree pruning and cutting to prevent contact with high-voltage lines during windy conditions, thus mitigating wildfire risks.

The impact of wind on trees is significant in determining their shape and structure, often leading to formative pruning which is a common phenomenon in areas with consistent wind patterns. Kang et al. [136] utilized computational fluid dynamics (CFD) to investigate how trees enhance pedestrian wind comfort in urban environments. By incorporating a tree drag parameterization scheme in the model, the researchers found that trees significantly improve wind comfort when air flows horizontally through the tree lines. Computational models have been developed to simulate tree dynamics under wind loads, aiding in understanding how trees withstand and react to wind forces over time. Xu et al. [23] described a physics-based algorithm designed to simulate tree dynamics under wind load. The model, using a bending cantilever beam for stem deformation, provides a realistic simulation of tree swaying in the wind, which is crucial for understanding tree stability and designing effective vegetation management practices.

Trees respond dynamically to wind stresses through structural adaptations such as the thickening of trunks and alteration of root systems, which enhance stability and resilience. Yang et al. [137] introduced a comprehensive model that simulates the dynamic responses of a tree's aerial structure and root–soil system to turbulent winds. The model is significant for assessing tree anchorage under various soil and root conditions, exploring how gust patterns impact tree stability, which is essential for understanding windthrow vulnerability in vegetation management.

Tomczak et al. [138] explored how wind exposure influences the mechanical properties of wood, showing that trees at the stand edge adapt by increasing the modulus of elasticity to compensate for greater wind loads. This study highlights the intricate balance between tree form and function in response to wind exposure. Wang et al. [139] demonstrated how trees exhibit considerable phenotypic plasticity in response to wind speeds, with higher wind speeds resulting in reduced tree height and increased trunk diameter. This study uses a functional–structural plant model to simulate these effects. Moore et al. [140] provided an overview of how trees respond to wind loads, from minor movements to catastrophic failures like stem breakage and uprooting. It discusses advancements in understanding tree mechanics under wind stress, crucial for managing vegetated areas and urban trees. Jackson et al. [141] evaluated critical wind speeds in different tree species and suggests that trees with lower critical wind speeds adjust their leaf shedding earlier to minimize damage from winter storms. This study emphasizes the role of tree architecture in determining wind resistance. Camarero et al. [142] investigated the aftermath of windthrows on forest ecosystems, noting enhanced tree growth in windthrow gaps due to increased resource availability. This study is essential for understanding the ecological consequences of wind disturbances. Krišāns et al. [143] highlighted how diseases like root rot can exacerbate the susceptibility of trees to wind damage, stressing the importance of vegetation health in managing wind risk. Défossez et al. [144] discussed the dual effects of wind exposure and resource availability on tree growth, showing that trees acclimate to increased wind exposure by adjusting growth patterns, which has implications for vegetation management under changing climatic conditions.

5.2.2. Impact of Snow Weight on Trees

Research into the effects of snow loads has led to improved vegetation management practices that aim to mitigate risks associated with heavy snowfalls and maintain vegetation health and stability. The weight of snow on trees significantly influences their physical structure, health, and overall stability, particularly in vegetated areas and urban environments where proximity to power lines is a concern. Hojatimalekshah et al. [145] explored the relationships between tree canopy and snow depth using terrestrial laser scanning. It highlighted how tree structure, along with wind and topography, significantly influences snow depth variations, particularly under tree canopies in Grand Mesa, Colorado. This research is critical for understanding snow accumulation and its hydrological implications in vegetated landscapes. Snow accumulation on trees can significantly impact their physical structure and overall health. Heavy snowfall can lead to branch breakage and increased mechanical load, especially on evergreen species. Duperat et al. [146] examined the wind and snow loading on balsam fir during Canadian winters. The study continuously monitored the turning moments on trees caused by snow accumulation, providing insights into how trees mechanically respond to heavy snow loads. The findings help inform vegetation management practices aimed at minimizing risk during harsh winter conditions. Li et al. [147] assessed the compensation effects of winter snow on larch growth in Northeast China, demonstrating that snow cover during winter can positively affect tree growth during the growing season, especially in regions facing seasonal drought stresses. The dynamics of snow on trees not only affect individual trees but also have broader implications for forest ecosystems, influencing aspects such as water runoff and habitat structure. Miyashita et al. [148] monitored the bending stress in tree trunks during the snowy season in Japan using strain gauges. The study provided valuable data on how different types of trees, particularly beech trees and Japanese cedars, handle the mechanical stresses induced by snow accumulation. This has implications for understanding tree stability and growth in snowy environments. Wu et al. [149] discussed how winter snow depth variably affects tree growth across different regions, highlighting that in areas with significant snow accumulation, snow cover has a positive influence on tree growth during the growing season. Reinmann et al. [150] provided evidence that reduced snowpack and increased soil freezing adversely affect tree physiology and growth, particularly in *Acer saccharum* (sugar maple), leading to significant reductions in biomass increment. Sanmiguel-Vallelado et al. [112]

detailed how snow cover affects soil temperature and moisture, impacting tree growth patterns in pine trees, emphasizing the importance of snow dynamics in early growing season conditions. Qin et al. [151] analyzed how snow impacts the radial growth of trees, revealing spatial variations and the significant role of snow in supporting tree growth in water-limited regions.

6. Outage Hardening Strategies

Electric power supply grids are vital to social and economic activities, as well as to public safety and well-being. There are substantial adverse impacts on society when power grids fail. The distribution network in urban and rural areas remains the most vulnerable part because most of the distribution cables are aboveground and are in proximity to trees. Outages caused by extreme weather events are becoming more frequent and longer because of climate change [152], resulting in lower quality of service and reduced customer satisfaction [153]. The impacts of these outages are usually longer for suburban and rural communities where restoration efforts may take weeks [154]. The current state of power distribution is not compatible with the high quality-of-service requirements of future smart grids and the increased demands of the electrification of society [155]. As shown in Figure 8, three main hardening strategies have been proposed for Overhead Power Distribution Lines (OPDLs):

(**a**) (**b**) (**c**)

Figure 8. Hardening strategies. (**a**) Vegetation management [156]. (**b**) Conduit duct bank [157]. (**c**) MUT [158].

(a) **Vegetation management** (i.e., pruning the trees). Trees are the cause of more than 40% of the weather-related outages in Quebec [159]. The current manual method to identify the lines that require vegetation interventions is time-consuming. Perrette et al. [160] emphasized the significance of evaluating tree vitality before undertaking pruning activities. The study found that trees with diminished vitality tend to develop fewer, shorter, and less voluminous epicormic branches after pruning, which consequently affects the frequency of required maintenance and enhances the safety and efficacy of power distribution systems. Additionally, they employed reduction pruning on principal tree stems as a strategic approach to redirect the growth of scaffold limbs away from power lines, thereby maintaining safe clearance distances and promoting healthy tree growth. Intriguingly, trees with higher vitality exhibited a greater extent of wood discoloration at pruning sites, indicating that although these trees might necessitate less frequent pruning, their management strategies need to account for potential risks associated with their rapid growth and the possibility of more severe wood damage. Dupras et al. [161] emphasized the superiority of pruning over other vegetation management techniques for both urban and rural settings, highlighting its negligible impact on ecosystem services when compared to the more disruptive practice of complete tree removal. The study defined two main strategies for vegetation management in urban areas: (1) total removal of obstructive trees and (2) pruning. These approaches are crucial in reducing the risk of power disruptions and improving the reliability of power distribution networks. Notably, pruning is recognized for its minimal effect on a wide array of ecosystem services provided by trees, woodlands, and forests, establishing it as the optimal choice for preserving ecological balance while managing vegetation near power infrastructure.

(b) **Selective undergrounding, (i.e., burying** electrical wires underground within a conduit duct bank) is preferable in neighborhoods of high population density because this solution is better from an aesthetic point of view, immune to most weather events, and much safer for the public [162]. The percentages of underground distribution cables in Montreal and the Province of Quebec are 50% and 11%, respectively [163]. Current regulations in most cities in North America do not require undergrounding, and the decisions are taken based on specific urban development projects. This ad hoc mechanism results in social inequity. European countries (e.g., Netherlands and Germany) have made significant commitments to undergrounding. The major concern with undergrounding is its high capital cost and for accessing damaged cables for repair purposes, as well as its vulnerability to floods. This cost should be weighed against the benefits, considering the impact on the economy and society; and suitable regulations and cost-sharing models should be developed to pave the way for undergrounding according to a long-term plan.

(c) **Multipurpose Utility Tunnels (MUTs)**. A MUT can be built under the road right-of-way to host power cables in addition to telecommunication cables, gas pipes, municipal water pipes, heating ducts, etc. MUTs have all the advantages of undergrounding in addition to providing better protection and continuous access to all hosted private and public utilities for inspection, maintenance, and repair [164]. Therefore, MUTs greatly reduce the need for repetitive excavations and road closures to access different types of utilities; and will consequently reduce the related social and environmental costs (e.g., traffic congestion). MUTs are a long-term solution for sustainable and resilient underground utility management [165]. However, like undergrounding, their initial cost is high, which requires good coordination between utility owners for MUT initial and operation cost sharing. Moreover, MUTs are more difficult to build in established cities with open-cut methods. Therefore, innovative construction methods should be used to build them (e.g., micro-tunneling) [166]. MUTs have been built in Europe since the 19th century, and are more common in Japan, Singapore, and China [164].

Previous research areas and related gaps are as follows:

(a) **Outage Prediction Models (OPMs) and Climate Change**: Researchers used machine learning (ML) to create OPMs that can forecast power outages caused by weather events [167–171] using a variety of data such as system disturbances reports [172]. The frequency, intensity, and duration of weather-related outages are affected by climate change. Several studies [173,174] associated the failure of electrical poles to climate-driven disasters. A weather-based OPM aiming at increasing resilience was developed by Ahmad et al. [175]. Despite the importance of these studies, none of them fully integrated climate change models with ML-based OPMs.

(b) **Automated Vegetation Management**: Several studies have considered vegetation management as an approach for reducing the effect of storm-related outages. An ML-based model was developed by Gdanitz et al. [176] for predicting power outages during snow and ice storms to evaluate the effectiveness of Enhanced Tree Trimming (ETT), which is costly because it requires frequent monitoring of tree encroachments [173]. The use of Light Detection and Ranging (LiDAR) data has been popular in automatically detecting vegetation along power line corridors [177]. The common limitation of most of these studies is the dependency on one source of data for object detection.

(c) **Cost–Benefit Analysis (CBA)**: A CBA considering several power distribution resilience measures was proposed by Zamuda et al. [178]. Furthermore, a framework was introduced by Larsen [179] to predict and monetize the societal costs and benefits of undergrounding both transmission and distribution power cables. The CBA should consider both internal and external costs [180] and the customers' willingness to pay for undergrounding. Previous studies tried to quantify the social cost based on outage size. Different methods were used to estimate the cost of outages: the production function approach, customer surveys, and case studies. These social costs were estimated for different sectors. The study of Rylander [181] leveraged data spanning a decade, capturing instances of both prolonged and short unforeseen outages to determine the effect of several economic factors. Several studies showed significant social and spatial inequalities in power outage recovery [182–188]. However, none of the previous studies provided a comprehensive model for comparing hardening solutions.

7. Research Roadmap for Enhancing Power Line Resilience Through Vegetation Proximity Detection Using ML/DL Approaches

Enhancing the resilience of power distribution lines against vegetation encroachment necessitates a comprehensive approach that leverages advanced ML and DL techniques. This roadmap outlines a structured research plan aimed at developing effective methodologies and tools to mitigate the risk of power outages caused by trees growing close to power lines. Figure 9 shows the overview of the proposed research roadmap. The solid lines indicate direct, sequential dependencies between stages. In contrast, the dotted lines represent iterative or bidirectional relationships, emphasizing feedback loops and repeated interactions between stages, particularly during validation, testing, and optimization processes.

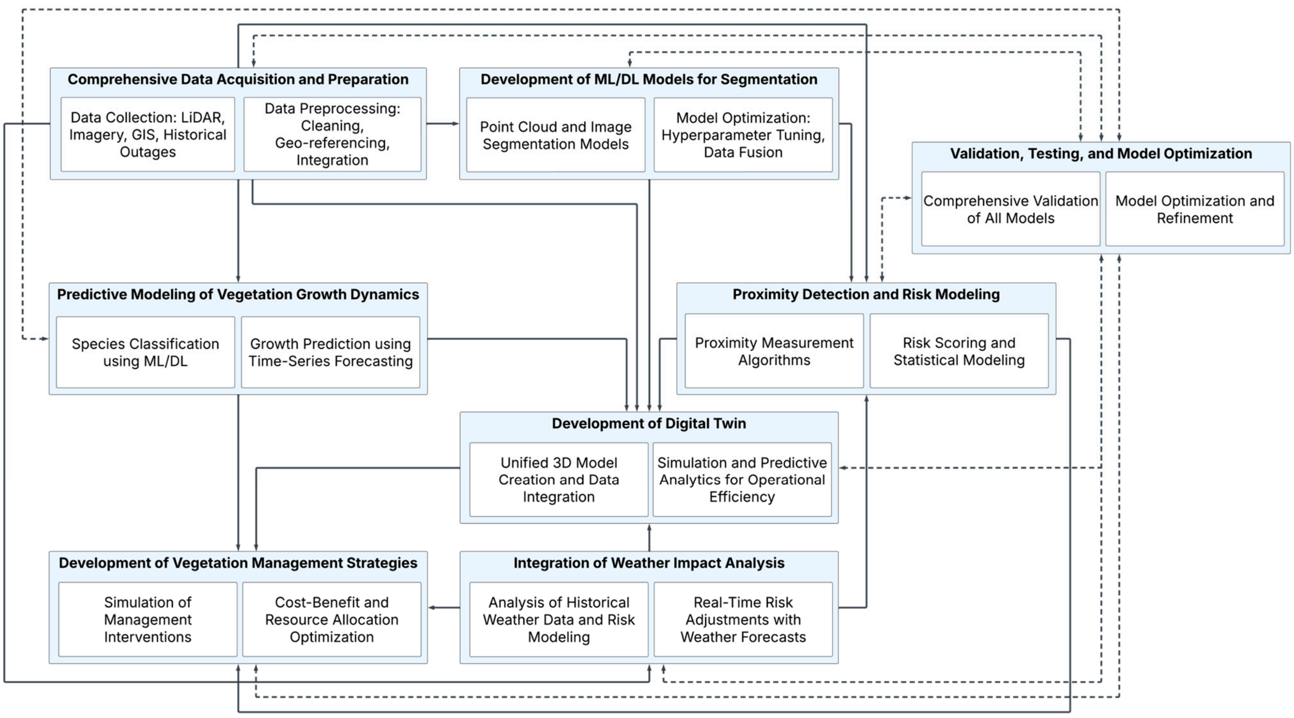

Figure 9. Overview of the proposed research roadmap for vegetation proximity detection to power lines.

(1) **Comprehensive Data Acquisition and Preparation:** A critical foundation for this research is the collection and preparation of high-quality data. Therefore, the following specific steps should be considered: (a) Collect high-resolution LiDAR point cloud data to capture detailed three-dimensional spatial information of vegetation and power lines, which is essential for accurate spatial analysis and modeling; (b) Acquire high-resolution hyperspectral and RGB imagery from drones, satellites, or ground-based cameras to provide detailed visual information necessary for identifying vegetation types and assessing their conditions; (c) Compile existing Geographic Information System (GIS) data to map power line locations, infrastructure details, and environmental features, facilitating spatial correlation analyses; (d) Obtain historical data on power outages related to vegetation to identify patterns, critical factors, and high-risk areas; (e) Apply techniques for data cleaning and noise reduction to remove irrelevant data points and artifacts; and (f) Perform geo-referencing, alignment, and integration of different data sources to create a coherent and comprehensive dataset suitable for analysis. This integrated dataset forms the basis for developing advanced ML/DL models.

(2) **Development of Advanced ML/DL Models for Vegetation and Infrastructure Segmentation:** Developing sophisticated ML/DL models for vegetation and infrastructure segmentation is a critical component of the research. Therefore, the following specific steps should be considered: (a) Implement and train advanced DL models such as RandLA-Net [49] and Kernel Point Convolution (KPConv) networks [189] for semantic segmentation of LiDAR point clouds or hyperspectral and RGB images, enabling the distinction between vegetation, power lines, poles, and other objects with high precision; (b) Apply model optimization techniques to enhance accuracy while ensuring computational efficiency, making the models practical for large-scale applications; and (c) Use data fusion techniques to combine insights from LiDAR data and imagery, improving segmentation outcomes by capitalizing on the strengths of each data type.

(3) **Predictive Modeling of Vegetation Growth Dynamics:** Understanding and predicting vegetation growth is essential for proactive management. Therefore, the following specific steps should be considered: (a) Develop ML/DL models to classify tree species based on spectral signatures and morphological features extracted from the data; (b) Ensure accurate species identification, as different species have varying growth rates and patterns [103], and build a comprehensive database of local tree species, including their growth characteristics and environmental preferences, to support growth predictions; (c) Integrate environmental factors such as climate data (temperature, precipitation), soil conditions, and seasonal variations into the growth models to enhance prediction accuracy; and (d) Prioritize integration of publicly available regional datasets, such as those from weather stations or soil surveys, to ensure model generalizability across different geographic areas, and employ time-series forecasting methods, potentially incorporating recurrent neural networks (RNNs) or long short-term memory (LSTM) networks, to predict future vegetation growth and potential encroachment on power lines [190].

(4) **Integration of Weather Impact Analysis:** Adverse weather conditions can intensify the risks posed by vegetation proximity. Therefore, the following specific steps should be considered: (a) Analyze historical weather data to understand how events such as storms, high winds, and heavy snowfall affect vegetation-related outage risks, identifying patterns and correlations critical for risk assessment; (b) Enhance risk assessment models to account for the combined effects of vegetation proximity and adverse weather conditions, providing a more comprehensive risk profile;

and (c) Develop models capable of adjusting risk assessments in real time based on weather forecasts, which involves continuously updating risk levels as weather conditions change using live data to assess the likelihood and impact of outages dynamically [191], enabling proactive measures such as preventive pruning in high-risk scenarios to prevent outages.

(5) **Proximity Detection and Risk Modeling:** Detecting the proximity of vegetation to power lines and developing models to assess the associated risks is the next vital task. Therefore, the following specific steps should be considered: (a) Develop algorithms to automatically measure the distances between vegetation and power lines using the segmented data, incorporating 3D Euclidean distance calculations to provide precise, quantifiable metrics for risk thresholds; (b) Define critical clearance distances based on industry safety standards to ensure that the analysis aligns with regulatory requirements; and (c) Create a risk scoring model to evaluate the likelihood of vegetation-related outages based on proximity measurements, vegetation characteristics, and historical outage data [192,193], using statistical methods including regression analysis and machine learning classification techniques to identify significant predictors of outage risks and enhance the robustness of the risk assessment model.

(6) **Digital Twin Development:** Unlike segmentation models, which provide valuable but static insights, a digital twin offers a dynamic and continuously updated virtual model of the physical network. Therefore, the following specific steps should be considered: (a) Integrate multiple data sources, including point clouds, satellite imagery, GIS data, and real-time weather information, to reflect current conditions with high fidelity [194,195]; (b) Leverage the digital twin's ability to simulate various scenarios that impact the power grid, addressing limitations of real-time proximity detection (which identifies immediate risks but lacks foresight into risk evolution); (c) Incorporate prediction of vegetation growth patterns using advanced machine learning and deep learning algorithms, including forecasts of how environmental factors (such as seasonal changes and weather events) influence vegetation dynamics and proximity to power lines; (d) Enhance risk management by integrating predictive analytics with environmental modeling, including assessments of how adverse weather conditions (like storms or high winds) could exacerbate outage risks due to vegetation interference; (e) Simulate the impact of different vegetation management strategies (such as varying pruning schedules or growth inhibitors) to provide data-driven recommendations for preventive actions, enabling maintenance teams to prioritize high-risk areas, optimize resource allocation, and reduce costs by minimizing unnecessary inspections; (f) Foster improved collaboration across departments by using the digital twin as a centralized platform for up-to-date network status, ensuring consistent information for teams in outage management, vegetation management, and maintenance planning to enhance communication and decision-making; and (g) Design the digital twin with a modular architecture to support incremental updates and integration with existing utility systems, justifying the additional effort over static tools (like Google Earth) by emphasizing its interactive, predictive capabilities for strategic planning and risk mitigation beyond basic detection methods.

(7) **Development of Vegetation Management Strategies:** Based on the risk assessments and growth predictions, effective vegetation management strategies need to be formulated. Therefore, the following specific steps should be considered: (a) Simulate different vegetation management interventions, such as varying pruning schedules, selective removals, and the use of growth inhibitors, to assess their effectiveness in reducing risks [196]; (b) Conduct economic analyses to evaluate the trade-offs between the costs of interventions and the potential reduction in outage risks, aiding in

decision-making for resource allocation; and (c) Develop optimization models, possibly using operations research techniques, to allocate maintenance resources efficiently based on risk levels and priorities, and create scheduling algorithms to plan vegetation management activities at optimal times, considering factors like growth rates, accessibility, and weather conditions, to maximize effectiveness and minimize costs.

(8) **Validation, Testing, and Model Optimization:** Ensuring the reliability and accuracy of the developed models requires accurate validation and testing procedures. Therefore, the following specific steps should be considered: (a) Conduct field studies to validate the accuracy of the ML/DL models and proximity measurements, involving comparisons of model outputs with actual observations gathered through ground surveys, and perform systematic comparisons against ground truth data to assess performance metrics such as accuracy, precision, recall, F1-score, and Intersection over Union (IoU) for segmentation tasks, as well as mean average precision (mAP) for object detection. Additionally, apply hyperparameter tuning methods to statistically evaluate interactions between parameters like batch size and learning rate, ensuring robust model performance [197]; (b) Perform sensitivity analyses to understand how variations in model parameters affect outputs, helping identify the most influential factors and ensuring model robustness under different conditions, and quantify uncertainties in predictions using statistical methods to enhance model reliability and inform confidence levels in decision-making processes; (c) Apply cross-validation techniques, such as k-fold validation, during testing to assess model performance across diverse subsets of the dataset; (d) Implement pilot deployments of the optimized models and digital twin in selected real-world power line segments to evaluate practical performance and gather user feedback from utility operators; (e) Conduct scalability assessments to identify challenges in expanding to larger networks, such as data volume management and integration with existing monitoring systems; and (f) Explore future extensions like incorporation of emerging sensor technologies to ensure the research evolves with technological advancements, and emphasize knowledge transfer through workshops or reports to stakeholders, promoting adoption in the power sector.

8. Summary and Conclusions

The resilience of power distribution systems is essential for ensuring the continuous and reliable delivery of electricity, especially in the face of increasing adverse weather events and the presence of natural vegetation near these infrastructures. This review has underscored the significant risks posed by trees encroaching on power lines, which are exacerbated by extreme weather conditions such as windstorms, heavy snowfall, and freezing rain. The dynamic interaction between these environmental factors and the power distribution infrastructure necessitates advanced monitoring and management strategies. The integration of ML/DL techniques offers promising advancements in the detection and management of tree proximity to power lines. These technologies have the potential to significantly enhance the accuracy and efficiency of monitoring systems, thereby reducing the risk of tree-related power outages. Despite the extensive application of ML/DL across various domains, there remains a notable gap in the literature specifically addressing their use for dynamic monitoring of vegetation encroachment in power distribution systems.

This comprehensive review provides a detailed analysis of current methodologies, emphasizing the unique contributions and limitations of existing approaches. Key findings include the operational and environmental benefits of integrating advanced ML/DL techniques with technologies such as LiDAR and high-resolution imaging. The review also underscores the need for developing more sophisticated models and integrating multi-sensor data to improve the predictive capabilities of these systems. In particular, the development of digital twins emerges as a crucial innovation, offering a dynamic and continuously updated virtual model of the power distribution network that can simulate and predict vegetation growth and its impact on the infrastructure.

The proposed roadmap outlined in this review offers a strategic direction for future research and implementation. It focuses on enhancing power line resilience through vegetation proximity detection using ML/DL approaches. The roadmap emphasizes critical steps such as comprehensive data acquisition and preparation; development of advanced ML/DL models for vegetation and infrastructure segmentation; predictive modeling of vegetation growth dynamics; integration of weather impact analysis; proximity detection and risk modeling; development of digital twins; formulation of vegetation management strategies; and rigorous validation and testing of models.

By systematically addressing these areas, including the advancement of digital twin technology, the roadmap aims to contribute significantly to enhancing the resilience of power distribution systems. The implementation of digital twins represents a transformative step, providing dynamic, real-time virtual models that integrate various data sources and predictive analytics to simulate and manage the power network more effectively. Implementing this roadmap has the potential to reduce the incidence of vegetation-related power outages and provides valuable insights for utility companies, policymakers, and researchers. The approach emphasizes the importance of combining advanced technological solutions with practical considerations in vegetation management, ultimately contributing to the development of smarter and more resilient power infrastructure.

Future research should focus on refining the proposed methodologies, exploring the integration of additional data sources, and advancing the predictive capabilities of ML/DL models. The development and refinement of digital twin technology for power distribution networks should be a key area of focus, as it holds significant potential for improving monitoring and predictive maintenance. Collaboration between researchers, utility companies, and policymakers will be crucial in translating these technological advancements into practical solutions that enhance the safety and reliability of power distribution networks.

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