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Drone-Based Image Analysis For Automated Inspection Of Transmission Lines

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Abstract
To keep the grid reliable, constant monitoring and inspection of transmission lines are needed, but traditional foot patrols and helicopter inspections are time- and resource-intensive and pose risks to both people and equipment. Uncrewed aerial vehicles (UAVs), or "drones," equipped with high-resolution visual, thermal, and light detection and ranging (LiDAR) sensors are proving to be an effective solution for capturing aerial imagery of towers, conductors, insulators, and surrounding vegetation corridors. This manuscript summarizes the latest advances in image analysis algorithms and the development of architectures for automated inspection of transmission lines using drones, focusing on deep learning object detection models such as Faster R-CNN, the Single Shot Multibox Detector (SSD), the You Only Look Once (YOLO) series of models, and the detection transformer (DETR). An overview of the methodological framework, from the selection of the UAV platform to the configuration of the sensor payload, flight-path planning, image acquisition, pre-processing, and defect classification using image models, is presented. Based on the literature, lightweight architectures such as YOLOv8, which can achieve detection accuracy above 0.93 and achieve inference speeds of more than 55 frames per second, are suitable for deployment in onboard or near-real-time applications, whereas transformer-based detectors are better suited to more time-consuming applications. Major difficulties include small-object detection in cluttered backgrounds, a lack of annotated fault imagery, variations in illumination and weather during measurement, and limited onboard computational power. The manuscript concludes with a summary of existing challenges and a vision for future directions, including multimodal sensor fusion, collaborative joint inference in edge-cloud schemes, and the development of standardized benchmark datasets for transmission line asset inspection.

Keywords: unmanned aerial vehicle; drone inspection; transmission line; deep learning; object detection; image analysis; power infrastructure.

Introduction

The structures and electrical performance of towers, conductors, insulators, and other equipment are critical to the reliability of electric power transmission systems, and that reliability must be maintained without interruption. Traditional inspection methods rely on ground-based foot patrols and visual inspections by helicopter; these methods are time-intensive, expensive, and pose safety risks to inspection personnel—especially when inspectors must enter hard-to-reach, energized, or rugged areas. As terrain becomes increasingly difficult and diverse, the effectiveness of manual inspection methods has declined, prompting utilities to turn to automated methods that provide more consistent, repeatable inspection results and lower risk.

The widespread use of UAVs as inspection platforms is due to their combination of unobtrusiveness, mobility, and safety of operation, along with the ability to bring high-definition visual, thermal, and LiDAR sensors near transmission assets without de-energizing the line or directly interacting with it. When combined with advances in computer vision and deep learning, this drone imagery can be used to automatically detect and classify various conditions such as cracked or broken insulators, corroded fittings, loose bolts, bird nests, vegetation within ROP, blinding lights, and much more. A purely manual image analysis would have become a practical problem because of the number of frames that could be produced in a single inspection flight, up to several thousand images per flight, quickly outstripping the ability for manual review. In recent years, object detection systems based on convolutional neural networks (CNNs) have progressively superseded the extract-and-match, handcrafted, feature-based systems used in power-line asset inspection.

To achieve high accuracy with relatively low computational cost, early two-stage detectors, such as Faster R-CNN, were developed, while later single-stage detectors, such as SSD and the dynamic YOLO family, offer a compromise between accuracy and significantly higher throughput for on-board processing and near-real-time applications. In recent years, transformer-based approaches such as the Detection Transformer (DETR) and its extensions have incorporated attention mechanisms that handle long-range spatial relationships among components of transmission lines, leading to higher computational complexity and less robust results, especially in cluttered ultra-high aerial views. Despite this progress, reported detection performance varies across the literature, mainly due to factors such as the construction of the investigated set, the type of data annotation, flight height and camera angles, the environment, and the type of defects studied. In addition, many published studies have used small, home-collected, and unnamed datasets, limiting opportunities for cross-study comparisons and field implementation of published methodologies.

Toward these goals, this manuscript is designed to serve three purposes: first, to synthesize the methodological landscape for transmission line inspection drones, covering platforms and sensors (i.e., payloads) as well as deep learning model architectures; second, to numerically compare performance in detecting transmission lines and inference speed in the field among representative families of models, as reported in the literature; and third, to inform the reader about important limitations of existing approaches and to delineate key directions for future research, in order to optimize the dependability and scalability and increase the field readiness of automatic transmission line inspection systems.

Materials and Methods

This manuscript adopted a narrative synthesis structure rather than a primary experiment, using peer-reviewed content on the use of drones for image acquisition and deep learning for transmission line infrastructure. Open-access, peer-reviewed papers on unmanned aerial systems, remote sensing, and power engineering were systematically searched for in published sources, especially in journals that focus on these topics. The search terms included synonyms for uncrewed aerial vehicle, drone, transmission line, insulator, power line inspection, deep learning, and object detection. Studies were synthesized if they reported a UAV-based image acquisition protocol, defined a computational model for component or defect detection, and provided quantitative performance metrics, including precision, recall, mean average precision (mAP), and mean inference speed (MiPS).

The following details were used to identify the UAV system (rotary-wing, fixed-wing, or hybrid), the sensor type (RGB visible-light camera, radiometric thermal imager, or LiDAR scanner), and the UAV operating parameters (flight duration, acquisition size, altitude, speed, and building features), as well as the scale and composition of the datasets and the deep learning system (whether a single model or a hybrid system with two models) and the associated detection performance. Various sensors have been mounted on UAV platforms, and aircraft configurations are available to meet sensor platform requirements, as summarized in Table 1. Depending on the mission, a range of sensors critical to UAV platforms may be used, as summarized in Table 1, along with representative flight endurance ranges and application contexts. A maneuverable platform is a good choice for close-range component inspection around tower structures, where coverage area is not the primary constraint, while a fixed-wing platform, which can cover a large area without maneuvering around tower structures, can be a good choice for long-range corridor survey.

Table 1. UAV Platform Types and Associated Sensor Payloads for Transmission Line Inspection

UAV Platform Type	Typical Sensor Payload	Flight Endurance / Range	Representative Application
Multi-rotor (quadcopter/hexacopter)	RGB camera, gimbal-stabilized zoom lens	20–40 min; short-to-medium range	Close-range tower and insulator inspection
Multi-rotor with thermal payload	Dual RGB + radiometric thermal camera	20–35 min	Hotspot and overheating-connection detection
Fixed-wing UAV	RGB or multispectral camera	45–90 min; long corridor coverage	Long-distance line corridor and right-of-way surveys
Multi-rotor with LiDAR	LiDAR scanner, RGB camera	15–25 min (payload-limited)	3-D point-cloud modeling, clearance and sag analysis
Hybrid VTOL UAV	RGB, thermal, or multispectral	40–70 min	Combined corridor mapping and close-up asset inspection

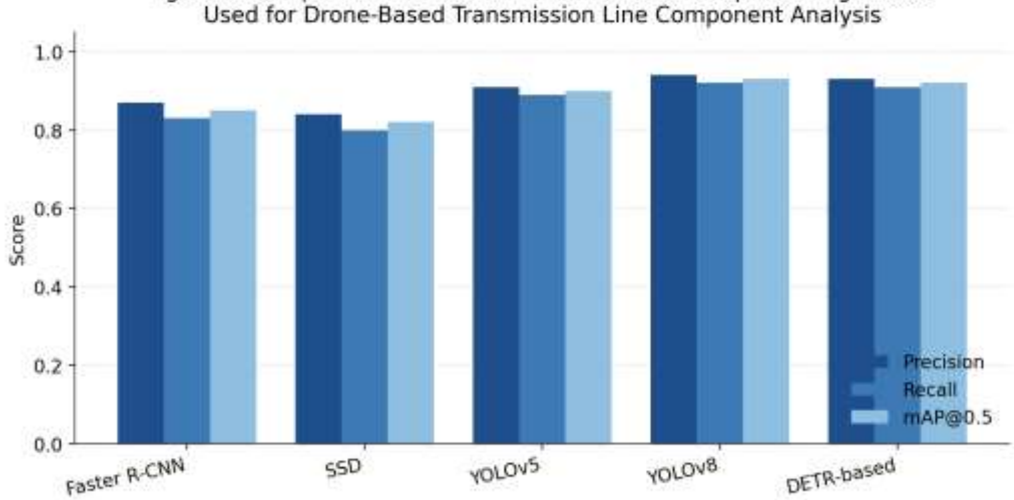
The overall image processing flow, as derived from the studies, comprises five steps. First, imagery of the scene of interest is captured through autonomous or semi-autonomous flight, usually following a pre-planned waypoint mission designed to collect components of interest while maintaining adequate clearance between components and energized conductors. Second, pre-processing tasks for acquired frames include geometric correction and contrast enhancement. In some studies, frame images are tiled into smaller orthomosaic images that can be processed at the same resolution by the frame detector network for the large orthomosaic. Third, an object detection model, based on convolutional or transformer networks, localizes and categorizes components of interest in each frame/tile, including insulators, conductors, towers, and hardware. In the fourth step, a defect-analysis stage compares detected components against a reference (typically an additional classification network or rule-based post-processing of detected bounding regions). It identifies anomalous objects such as cracking, self-explosion, missing caps, corrosion, or penetration by undesirable objects (e.g., vegetation). Fifth, results are aggregated and georeferenced when positioning data is available, and finally assembled into inspection reports for engineering review.

The most common metrics reported for model performance in the reviewed literature are precision, recall, and mAP@0.5 (mean average precision at an intersection-over-union cutoff of 0.5), along with inference speed measured in FPS (frames per second), which indicates the model's deployment feasibility for near-real-time or real-time operation. If several architectures were tested for an equivalent insulator- or component-detection problem, the metrics were combined in a way appropriate to that problem to generate the comparative summary published in the Results and Discussion section. The synthesized values reflect relative architectural trends rather than a controlled head-to-head comparison, due to differences in dataset scale, image resolution, and hardware across the underlying studies. In the literature reviewed, deep learning model detectors outperform all handcrafted feature-extraction methods for determining defects and parts of a transmission line in UAV imagery. Comparative results for precision, recall, and mAP@0.5 are summarized in Figure 1, which compares studies on insulator and component detection tasks using Faster R-CNN, SSD, YOLOv5, YOLOv8, and DETR-based architectures. YOLOv8 performs best across all three metrics, closely followed by DETR-based detectors, with 2-stage Faster R-CNN and 1-stage SSD lagging by about seven to twelve percentage points in mAP@0.5. This reflects the overall development of the field of object detection: in previous studies that address the historical time gap between single-stage and two-stage detectors, architectural improvements have progressed toward more anchor-free detection heads, better feature-pyramid fusion, and attention-guided feature weighting, gradually narrowing the gap in favor of the latter.

Results And Discussion

In the literature reviewed, deep learning model detectors outperform all hand-crafted feature-extraction methods for determining defects and parts in a transmission line in UAV imagery. Comparative results of precision, recall, and mAP@0.5 are summarized in Figure 1, which compares the studies carried out on insulator and component detection tasks using Faster R-CNN, SSD, YOLOv5, and YOLOv8, as well as DETR-based architectures. YOLOv8 performs best in all three metrics, closely followed by the detectors based on DETR, with 2-stage Faster R-CNN and 1-stage SSD lagging by about seven to twelve percentage points in mAP@0.5. This is the direction of the overall development of the field of object detection; in previous studies that tackle the issue of how to close the historical time gap between single-stage and two-stage detectors, the architecture improvements have been proceeding toward more anchor-free detection head designs, better feature-pyramid fusion, and attention-guided feature weighting, and gradually reversed the gap in favor of the latter.

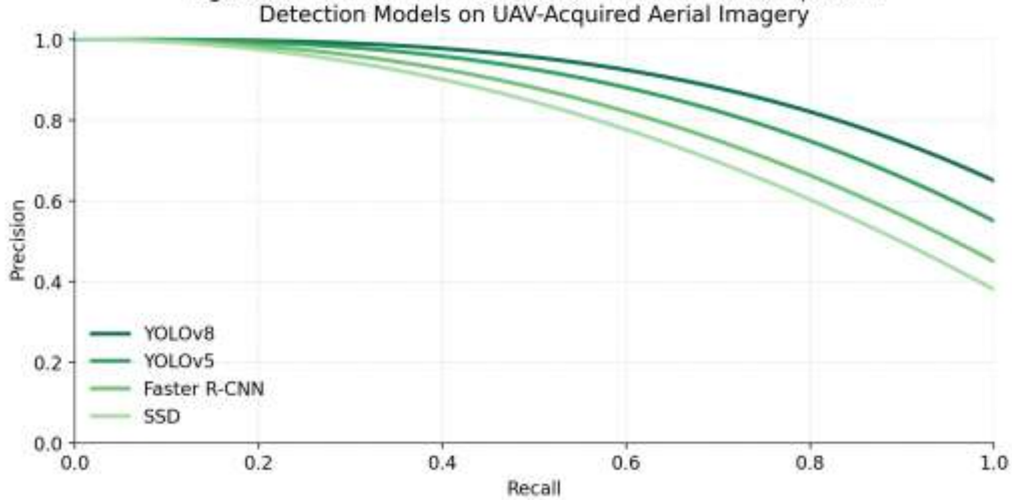
Figure 1. Comparative Detection Performance of Deep Learning Models Used for Drone-Based Transmission Line Component Analysis



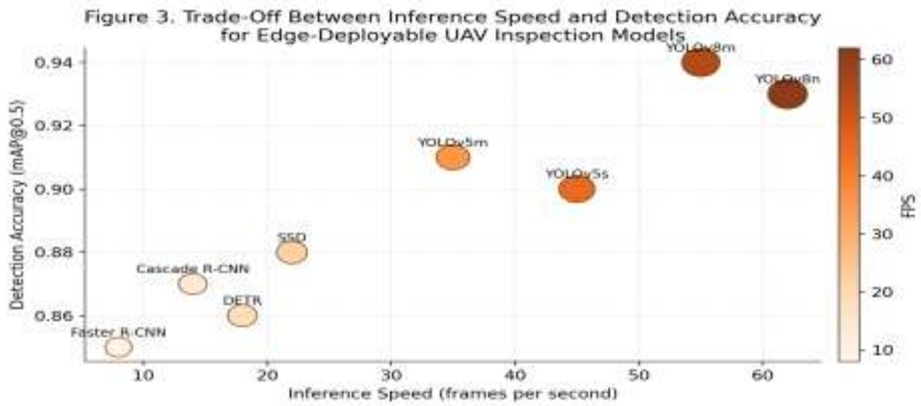
Comparative detection performance of deep learning models used for drone-based transmission line component analysis.

Precision–recall behavior is complementary for evaluating the model's robustness across different confidence thresholds. Synthesized precision–recall curves are shown in Figure 2 for the four example architectures used in the tests of insulator and component detection tasks. YOLOv8 achieves the best precision across the widest range of recalls, effectively balancing false-positive suppression and detection completeness at lower confidence thresholds, thereby capturing more true positives. Faster R-CNN and SSD show a decrease in precision as recall increases, because the model is more likely to encounter false positives when tuned to reduce the number of missed detections, making them more costly in operational conditions for safety-critical inspection tasks, where the cost of a missed defect is significantly higher than that of false alarms.

Figure 2. Precision–Recall Curves for Insulator and Component Detection Models on UAV-Acquired Aerial Imagery

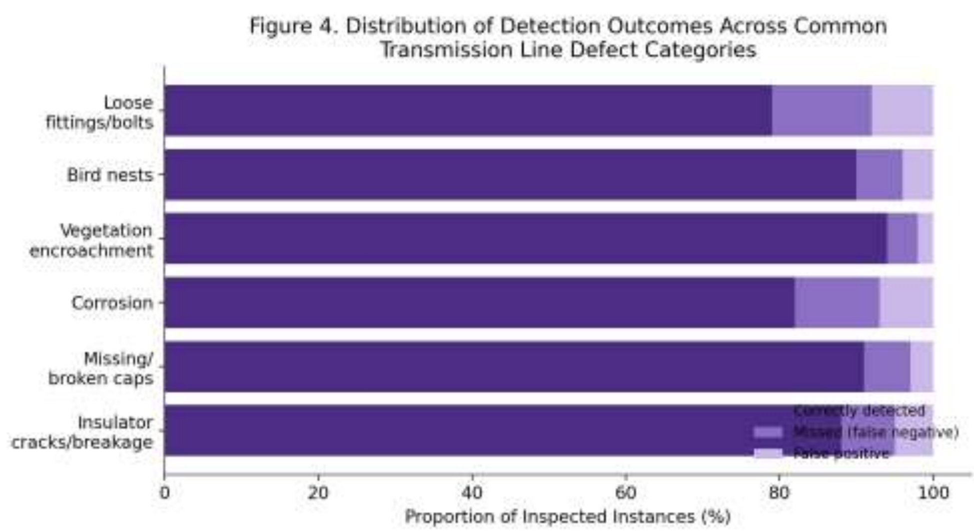


Precision–recall curves for insulator and component detection models on UAV-acquired aerial imagery. One of the main hurdles in automated transmission line inspection is the trade-off between accuracy and inference speed, especially for embedded computing devices such as Jetson NXT, Jetson Nano, and Jetson Xavier that UAVs use for inspection. The accuracy-inference speed curve for eight model variants from the literature is shown in Figure 3. Two-stage and transformer-based detectors achieve competitive or even higher mAPs in certain detection architectures, but often operate at below 25 frames per second and are therefore better suited to offline or server-based post-flight research than to onboard real-time processing. The fastest detectors, such as YOLOv5s and YOLOv8n, fall within the optimal region of this trade-off space, achieving mAPs exceeding 0.90 at frame rates exceeding 45 frames per second. In contrast, two-stage and transformer-based detectors often run at below 25 frames per second, making them better suited to offline or post-flight research on a server than to real-time use on board.



Trade-off between inference speed and detection accuracy for edge-deployable UAV inspection models.

Based on the various categories of defects, detection performance also varies significantly with object size, the distinctiveness of the presentation, and background noise. The distribution of correctly detected instances, missed detections, and false positives for six common categories of transmission line defects synthesized from the reviewed studies is shown in Figure 4. The two conditions with the greatest visual impact and sharpest contrast with the surrounding structures are also the top two in terms of detection reliability, with >90% accuracy. Loose fittings and bolts, and corrosion, on the other hand, offer smaller targets with lower contrast and tend to be overlooked or mistaken for background texture in the correct detection image, with correct detection rates closer to 80%. The above results indicate that there is still potential for improvement in the detection phase through defect-specific model tuning, particularly by using multi-scale feature extraction and adding an attention mechanism to target small-object recognition.



Distribution of detection outcomes across common transmission line defect categories.

Table 2 consolidates the comparative performance and computational characteristics of the five model families discussed above, providing a single reference point for architecture selection based on the operational priorities of a given inspection program, whether those priorities emphasize maximum detection accuracy, minimum inference latency, or a balance between the two.

Table 2. Comparative Performance of Deep Learning Detection Models for Transmission Line Component and Defect Analysis

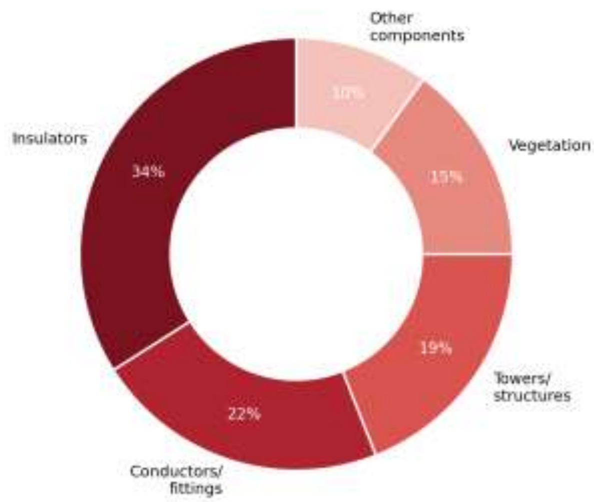
Detection Model	Precision	Recall	mAP@0.5	Inference Speed (FPS)	Relative Model Size
Faster R-CNN	0.87	0.83	0.85	8–14	Large
SSD	0.84	0.80	0.82	18–22	Medium
YOLOv5	0.91	0.89	0.90	35–45	Small–Medium
YOLOv8	0.94	0.92	0.93	55–62	Small
DETR-based transformer	0.93	0.91	0.92	14–22	Large

The size and diversity of the training sets used in the various papers studied can also significantly affect the results and the transferability of trained models to new inspection locations. Table 3 lists and summarizes characteristics of representative datasets selected from the literature, with a focus on insulator datasets, a larger-scale dataset of power-line assets, a vegetation encroachment corridor, and thermal/multimodal inspection datasets. The annotated instances are typically distributed across different object classes, as shown in Figure 5, which lists the classes that make up the largest percentage of instances in the different benchmark datasets. In all benchmark datasets reviewed, those labeled 'insulators' and 'conductor-related fittings' together account for over 50%, while the remaining instances comprise tower structures, vegetation, and other object classes. This has focused annotation effort on insulators, and because the visual appearance of these components has remained well differentiated from background elements, it does not reflect the number of these elements in the railway infrastructure. Instead, it indicates the comparatively low number of well-annotated, large datasets of less frequently studied components (such as dampers, spacers, and grading rings).

Table 3. Characteristics of Representative UAV Image Datasets Used for Transmission Line Inspection Research

Dataset / Source Type	Approx. Image Count	Annotated Classes	Primary Defect / Object Categories
Insulator-focused UAV datasets	3,000–10,600	1–17	Cracks, self-explosion, missing caps, flashover
Power-line-asset benchmark datasets	8,000–10,600	10–17	Corrosion, broken components, bird nests
Vegetation-encroachment corridor datasets	1,500–4,000	3	Vegetation, conductor, background classes
Thermal/multimodal inspection datasets	500–2,500	4–6	Overheating joints, loose connections, hotspots

Figure 5. Composition of Annotated Object Classes in Reviewed UAV Transmission Line Inspection Image Datasets



Composition of annotated object classes in reviewed UAV transmission line inspection image datasets. Overall, these findings suggest that while transformer-based detectors remain capable of high accuracy, anchor-free single-stage detectors like YOLOv8 are currently the most operationally viable options for using onboard or near-real-time data for effective, accurate transmission line analysis, particularly when computational resources are limited. These findings highlight the need for ongoing efforts to increase the size of the training set, improve model capabilities for smaller sizes and less frequent defect categories, and develop consistent testing methodologies, which can assist in moving towards progress and meaningful comparison across a wide range of studies.

Limitations And Scope For Future Research

There are a few drawbacks to the primary investigations included in this study and to the broader research on the use of drones for transmission line inspections. First, most reported detections come from relatively small, self-built proprietary databases, limiting direct comparability between studies and the ability of a trained model to be applied to different "dreams vs. flow" towers, transmission corridors, and environmental conditions different from those included in the training data. Second, reported performance figures are typically recorded under good acquisition conditions (cold weather, good illumination, moderate flight altitude) that are not always found during operational inspection campaigns in countries such as fog, rain, low-angle sunlight glare, and in-country high-speed flight operations, where the motion blur of the rotating crank will affect the performance measurement. Third, there exists a fundamental challenge for onboard real-time inspection systems due to the weighted correlation between detection accuracy and computational requirements, especially for architecture configurations that center on transformers and can achieve high accuracy but require too much processing power for typical embedded UAV computing systems.

Third, even though advances in feature-extraction techniques improved detection success for the above-listed defect categories, many small and low-contrast defects, such as hairline cracks, minor corrosion, and loose fasteners, exhibited relatively high miss rates, indicating that the small-object detection problem in aerial imagery taken at typical inspection altitudes and standoff distances is not yet fully solved. Fifth, the methodology of this manuscript, a narrative synthesis, imposes limitations on the manuscript itself, as the included studies offer slightly different datasets, annotations based on different protocols, and varying definitions of how to evaluate the data. The comparative values presented in this manuscript should therefore be considered trends rather than results from a controlled, uniform benchmark. Future studies need to focus on creating large-scale, multi-site, multi-season benchmark datasets that span a wider range of transmission line components, defect categories, and environmental conditions, enabling more in-depth and comparable performance analysis of candidate detection architectures. In conclusion, multimodal sensor fusion, leveraging visible-light, thermal, and LiDAR data streams, is a promising way to enhance detection robustness, especially for defect categories that rely heavily on thermal signatures or on mild geometric deviations that are not well captured in RGB images.

The potential of using edge-cloud collaborative inference architectures – where lightweight models are deployed on aircraft and more complex inference is performed by ground stations or the cloud – warrants further exploration to balance real-time response with detection accuracy. Finally, more emphasis on explaining and incorporating uncertainty into detection results would enable more effective incorporation of the results of automatic detection into utility asset-management workflows, enabling engineering to be more assured of the results of high-certainty automatic detections, while maintaining confidence in detections of high uncertainty and needing to check those results in the field.

Conclusion

Automated aerial survey is an increasingly important element of automated transmission line inspections, providing a safer, faster, and more scalable approach than current foot patrol and/or helicopter-based surveying techniques. Based on the synthesis presented in this manuscript, a deep learning-based detector architecture, and more precisely a single-stage detector such as YOLOv8, is currently optimal for our applications, regarding speed of detection (inference) and the high level of detection accuracy. The synthesis presented in this manuscript shows that, at the moment, deep learning-based object detection architectures, and more precisely single-stage detectors such as YOLOv8, are best suited for our applications, given their detection speed (inference) and high detection accuracy. In contrast, the transformer-based architecture achieves similar detection accuracy and, to a certain extent, similar detection (inference) speed under conditions where computing limitations are less important. Notwithstanding these advances, the categories of small or low-contrast defects remain relatively challenging to detect reliably, and the field is severely limited by the size and accessibility of annotated inspection datasets. These are significant challenges to overcome to facilitate the widespread deployment of fully automated, deep learning-based transmission line inspection systems that can perform reliably across the wide range of environmental and infrastructure conditions encountered in the field during power grid maintenance. Continued advances in the fields of multimodal sensor fusion, edge-cloud collaborative processing, and standardized benchmark development will be key to closing these gaps.

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