Assignment 3 Response Sheet

2025 Semester 2

Contents

Chapter 1

Instructions

Submission deadline: 30 September 2025, 23:00 (Tuesday) Please type your answers in the spaces provided. Do not repeat the questions in your answers. All tasks are compulsory.

Note that you must correctly cite and reference any sources you have consulted. You may use any internationally recognized referencing style such as APA or IEEE referencing.

Submit this document to the "Assignment 3 Main Submission" inbox by the published deadline.

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Chapter 2

Task 1: Literature Review

2.1 Introduction

With the rapid development of technology, the demand for electricity has been continuously increasing, leading to the expansion of power grids. However, power grids are vulnerable to damage caused by various factors such as human activities, animals, and natural conditions. While human-induced damages are relatively easy to detect since they are often reported directly, damages caused by animals or harsh weather conditions are more difficult to locate.

The consequences of power grid damage go beyond simple power outages. In severe cases, they may lead to wildfire[1]. For example, in California, it is estimated that around 10% of wildfires are caused by transmission line failures. Such incidents not only threaten public safety but also result in enormous economic losses, highlighting the necessity of regular transmission line inspection.

Traditionally, inspection methods include manual patrols and helicopter-based inspections. However, these methods heavily rely on human judgment, which make them costly and risky[2]. In recent years, Unmanned Aerial Vehicles (UAVs) have become increasingly popular for power line inspection. By integrating deep learning and computer vision techniques, UAV-based inspection achieves higher efficiency, greater safety, lower costs, and higher automation[3].

A typical UAV inspection framework can be divided into four main tasks: Power Component detection (PC), Power Line detection (PL), Power Tower detection (PT), and Defect detection (D). Specifically, PC aims to identify individual components such as insulators and fittings, PL focuses on extracting conductor lines, PT deals with detecting transmission towers as structural entities, and D involves locating and classifying faults on the detected components or lines.

The remainder of this paper is structured as follows. Sections 2.2–2.5 review the literature on the four major inspection tasks: power component, power line, power tower, and defect detection. Section 2.6 provides a gap analysis, highlighting the limitations of current approaches and potential research directions. Finally, Section 2.7 concludes the paper.

2.2 Detection of Power Components

Table 2.1: Summary of Power Components detection studies in power line inspection.[3]

Year	Ref	Component	Type of Detection	Imaging Platform	Dataset	Algorithm	Performance
2019	[4]	Porcelain, Composite insulator	Bounding box	UAV	7605 RGB images	SSD	Porcelain: 90.51–94.12%, Composite: 86.70–87.29%
2023	[5]	Insulator	Bounding box	UAV	1887 RGB images	YOLOv4++	mAP: 94.24%
2023	[6]	Damper	Semantic segmentation	UAV	240 RGB images	Improved GrabCut	F1 Score: 89.1–97.3%
2023	[7]	Bolts	Bounding box detection	UAV	1852 RGB images	UPOM (ResNet + Attention)	Recall 0.94–1.00

Power components mainly include insulators, power line fittings, dampers, bolts, and conductors. These components are highly susceptible to damage, such as rusting, breakage, or surface defects, which makes their accurate detection essential for reliable power line inspection.

Currently, the primary detection approaches for power components can be classified into three categories: bounding box detection, semantic segmentation, and instance segmentation. Bounding box–based methods are the most widely adopted due to their balance between accuracy and computational efficiency [3]. Specifically, they are well suited for real-time applications, achieving processing speeds of over 80 frames per second [8], while effectively localizing target objects within images. In contrast, semantic segmentation provides pixel-level class assignments, which enable detailed differentiation between component types, and instance segmentation further allows precise separation of closely positioned or overlapping objects, offering the highest granularity in detection tasks.

Early works focused on improving detection accuracy under limited data conditions. For example, in 2019, Miao et al. [4] proposed a two-stage fine-tuning approach for insulator detection in UAV images. The first stage initialized the model with COCO weights and fine-tuned on a general insulator dataset to capture diverse features, while the second stage fine-tuned the model on a region-specific dataset to learn local characteristics. This coarse-to-fine, generic-to-specific strategy not only enhanced detection accuracy but also allowed efficient adaptation to new inspection areas, highlighting the importance of transfer learning in UAV-based power component detection.

Building on the trend toward lightweight and efficient models, YoloV4++ [5], proposed in 2023, was designed for real-time insulator detection. It replaces the backbone with MobileNetv1 and standard convolutions with depthwise separable convolutions to reduce computational cost. The use of focal loss addresses class imbalance by emphasizing hard-to-detect objects and down-weighting easy negatives. By extracting multi-scale feature maps for simultaneous category prediction and bounding box regression, YoloV4++ balances detection speed and accuracy. However, its performance is limited in certain environments, and further optimization of parameters and expansion of the small dataset (1887 RGB images) could improve generalization.

At the same time, researchers began addressing structural defect detection beyond insulators. In 2023, a damper defect detection method [6] was proposed to identify multiple types of transmission line damper defects. This approach first enhances the main structure using Relative Total Variation (RTV) and then applies an improved GrabCut segmentation algorithm to automatically extract damper regions. Morphological operations and double bounding rectangles isolate damper components, which are then analyzed by a mathematical diagnosis model to classify the damper status. This method is lightweight and efficient, requiring only simple computations, yet it remains sensitive to complex backgrounds and extreme UAV angles, indicating that environmental robustness is an ongoing challenge.

For ultrasmall components, such as bolts, the 2023 UBDDM [7] addresses the challenge of detecting tiny defects while maintaining computational efficiency. It combines a ResNet backbone with hybrid attention and Feature Pyramid Network (FPN) for multiscale feature fusion, enhancing both shallow and deep representations. The Ultrasmall Object Perception Module (UOPM) identifies salient bolt regions without additional markers, and the Local Bolt Detection Module (LBDM) employs multiscale self-attention to capture contextual relationships among bolts. Final detection is achieved by fusing global and local results with non-maximum suppression. This method demonstrates that combining attention mechanisms with hierarchical feature extraction is effective for ultrasmall target detection, though performance can degrade in extremely dense or overlapping scenarios.

Taken together, these studies illustrate an evolution in UAV-based power component detection: from coarse-to-fine transfer learning for insulators, to lightweight networks for real-time processing, to specialized algorithms for structural and ultrasmall components. Across all methods, balancing accuracy, efficiency, and robustness to complex environmental conditions remains a central challenge, suggesting future research could integrate adaptive attention mechanisms, larger diverse datasets, and multi-component unified frameworks to improve generalization and inspection reliability. Table 2.1 summarizes the relevant literature on power component detection.

2.3 Detection of Power Lines

Power line detection is a crucial task for enabling UAVs to safely and autonomously follow transmission systems during inspection. However, existing research consistently highlights several challenges: (1) power lines occupy only a very small portion of the image, leading to severe foreground–background class imbalance; (2) their thin and elongated structures are easily lost during pooling or down-sampling; and (3) the natural environments surrounding power lines, such as trees, sky, and buildings, introduce complex background noise. To address these issues, semantic segmentation has emerged as the dominant approach, providing pixel-level detection capable of separating power lines from cluttered scenes.

Yang et al. [9] tackled these challenges by introducing an attention fusion network based

Table 2.2: Summary of Power Line detection studies in power line inspection.[3]

Year	Ref	Component	Type of Detection	Imaging Platform	Dataset	Algorithm	Performance
2022	[9]	Power Line	Semantic segmentation	UAV	366 RGB images	UNet with Attention blocks	Dice: 0.957
2022	[10]	Power Line	Semantic Segmentation	UAV, stereo camera	4102 RGB images	VGG16 backbone + MLFA + JA modules	MaxF: 0.7736–0.8418, MAE: 0.0129–0.0291, S-M: 0.8161–0.8589
2023	[11]	Power Line	Semantic segmentation	UAV	PLD dataset: 573 RGB images; OPL dataset: 571 RGB images	DRA-Net	mIOU: 93.19% (PLD dataset), mIOU: 96.04% (OPL dataset)

on a U-Net encoder–decoder structure. Their design incorporated two innovations: attention blocks, inspired by CBAM, to force the network to focus on the extremely thin line structures; and attention fusion blocks, which combined multi-scale decoder features to mitigate information loss from repeated pooling. To further handle the severe class imbalance, they proposed a hybrid loss function blending binary cross-entropy and Dice loss. Experimental results on the OPL dataset (366 UAV RGB images) showed that this model consistently outperformed U-Net variants in detecting fine power lines within complex natural backgrounds. Nonetheless, the relatively small dataset and the computational overhead introduced by the attention modules may restrict the model's generalizability and real-time usability.

While Yang et al. focused on enhancing segmentation precision through attention-based feature refinement, another line of research emphasized integrating detection with UAV navigation. A 2022 study [10] proposed an end-to-end CNN framework combined with a real-time motion planning strategy. Unlike pure segmentation models, this framework used multilevel feature aggregation (MLFA) and a JA module to suppress background noise and capture global context, before reconstructing the detected lines into 3D coordinates using binocular stereo vision. This allowed UAVs not only to detect but also to localize power lines in 3D space. The system further integrated YOLO-based tower detection to enable waypoint-based UAV navigation, significantly improving inspection robustness in cluttered environments. Compared with Yang et al., this work placed greater emphasis on operational deployment, demonstrating how detection results can directly support autonomous UAV flight.

More recently, Yang et al. [11] introduced the Dual-branch Residual Attention Network (DRA-Net), representing a further evolution of semantic segmentation for power line detection. DRA-Net employs a dual-branch encoder with RCNN and RRCNN modules to jointly model spatial and sequential dependencies, while multi-scale pooling enriches contextual features. It further integrates a Context Fusion Block (CFB) with shuffle attention, a U-shaped Noise Denoising (UND) block to reduce shallow-layer noise, and Edge Enhancement Blocks (EEB) to refine thin structures. Evaluated on the OPL and PLD datasets, DRA-Net achieved Dice scores of 96.41% and 93.26%, significantly outperforming U-Net, DeepLabV3, and PSPNet. Compared with Yang et al.'s attention fusion network, DRA-Net introduced more sophisticated recurrent and attention mechanisms, yielding superior segmentation accuracy. However, the added architectural complexity and reliance on dense pixel-level annotations raise concerns about computational cost and scalability for large-scale or real-time inspection.

Taken together, these studies highlight both the progress and limitations of current approaches. Attention-based U-Net variants improve fine-structure segmentation but are limited by small datasets; stereo CNN frameworks extend detection to 3D localization, making them more suitable for UAV navigation but at the cost of higher system complexity; and advanced architectures like DRA-Net achieve state-of-the-art accuracy but face challenges in efficiency and data requirements. Overall, semantic segmentation remains the dominant paradigm, yet future research must balance accuracy, efficiency, and scalability to enable practical large-scale deployment of UAV-based power line inspection. Table 2.2 summarizes the relevant literature on power line detection.

2.4 Detection of Power Towers

Table 2.3: Summary of Power Tower detection studies in power line inspection.

Year	Ref	Component	Type of Detection	Imaging Platform	Dataset	Algorithm	Performance
2020	[12]	Power Tower	Geolocation-based	UAV and GPS	Open Street Map (OSM)	OSM API and ElementTree parsing	NA
2014	[13]	Power Tower	Two-stage MLP	helicopter /UAV	3200 RGB image	HOG and MLP	Detection: 91.7–96%, Classification: 87–98%

Automatic detection of power towers has become a crucial task in UAV-based power line inspection, as towers serve as reliable anchors for navigation along transmission corridors. Unlike power lines, which are thin, sometimes occluded, and difficult to distinguish from complex backgrounds, power towers are more easily identifiable and provide reference points for maintaining the UAV's trajectory. Detecting towers accurately is challenging due to the heterogeneity of tower types, varying structures of high- and medium-voltage towers, background clutter, illumination changes, and variations in image quality caused by UAV motion, vibrations, and payload limitations. Despite these difficulties, robust tower detection is a key prerequisite for subsequent tasks such as fault analysis, line recognition, and automatic route planning.

In 2020, Schofield et al. [12] proposed a cloud-based geolocation approach that bypasses complex computer vision algorithms by utilizing publicly available geodata from OpenStreetMap (OSM). In this method, the UAV transmits its GPS position along with a bounding box to the OSM server, which returns a list of pylons. Using Python's ElementTree library, nodes tagged as $< tagk = "power"v = "tower"/ >$ are filtered to extract tower coordinates, and the nearest tower is automatically identified. Furthermore, the direction of the transmission corridor is inferred from three neighboring towers, and waypoints with a 25-meter safety radius are generated for safe UAV navigation. This approach significantly reduces computational load and allows real-time operation. However, its robustness is constrained by the completeness and accuracy of the OSM database, and missing or inconsistent geodata may lead to navigation errors.

On the other hand, Sampedro et al. [13] investigated a purely learning-based strategy for tower detection and classification using low-quality aerial images. Their approach employs a two-stage pipeline leveraging Histograms of Oriented Gradients (HOG) features and feed-forward multi-layer perceptron (MLP) neural networks. In the first stage, a binary MLP distinguishes tower regions from the background using a sliding window approach. In the second stage, a 4-class MLP classifies the detected towers into four types (Type 1–4). The dataset comprises 3200 cropped image regions from 11 aerial inspection videos, evenly distributed between tower and background regions, with equal representation of each tower type. Training, cross-validation, and test sets were carefully split to ensure generalization. Experimental results from Sampedro et al. demonstrated robust performance: the tower detection MLP achieved a total test error of 3.25%, with a false positive rate of 2.5% and a false negative rate of 4%. The tower classification MLP reached 92–98% accuracy depending on tower type, with high-voltage towers (Types 1 and 2) being easier to classify than medium-voltage towers (Types 3 and 4). When evaluated on new, uncropped images, the complete system detected towers correctly in 91.7% of cases, and classification accuracy ranged from 87% to 93%, showing robustness to cluttered backgrounds, varying illumination, and different tower structures.

Comparing the two approaches, the geolocation-based method [12] excels in reducing computational cost and enabling real-time UAV navigation, but it is limited by the quality and availability of geospatial data. In contrast, the learning-based approach [13] demonstrates strong generalization across multiple tower types and complex visual environments, but it relies on relatively small datasets, incurs computational overhead due to the sliding window technique, and suffers from error propagation from detection to classification stages. Both methods highlight complementary advantages: geolocation methods are efficient and less data-intensive, while vision-based learning methods are more adaptable to heterogeneous tower structures and environmental variations. Future research should explore hybrid strategies that combine the strengths of both approaches. For instance, using geolocation data as a coarse navigation guide while employing vision-based algorithms for fine-grained tower detection and fault analysis could enhance both accuracy and efficiency. Additional improvements could include expanding datasets to cover diverse tower types and backgrounds, integrating ensemble or alternative feature representations, incorporating visual tracking to improve detection continuity, and fusing data from multi-sensor inputs such as infrared cameras and LiDAR to support automatic fault detection and condition monitoring. Overall, electric tower detection remains a critical step toward fully autonomous power line inspection, providing both a foundation for advanced analysis and a practical solution for UAV navigation along transmission corridors. Table 2.3

summarizes the relevant literature on power line detection.

2.5 Detection of Defect

Table 2.4: Summary of Faults detection studies in power line inspection.[3]

Year & Ref	Component	Platform	Fault	Dataset	Algorithm	Performance
2022[14]	Insulators	UAV	Bunch drop defect	Synthetic CPLID dataset: 848 RGB images	Improved YOLOv4-ResNest	mAP: 95.63%
2022[15]	Insulators	UAV	Self-explosion defect	8500 RGB images	F-RCNN, RetinaNet, YOLOv3 Fusion	Precision: 99.04%, Recall: 93.69%
2023[16]	Glass insulators	UAV	Self-explosion defects	8463 RGB images	YOLOv3 & Improved ResNet-18	F1-Score: 86.25%
2023[17]	Insulators	UAV	Self-explosion defect	Synthetic CPLID dataset: 848 RGB images	GhostNet-YOLOv4	mAP: 99.50%
2024[18]	Insulator	UAV	Structural defects	5939 RGB images	YOLO-v5 and DETR	mAP: 98%
2023[19]	Bolts	UAV	4 types of bolt defects	VIBD dataset: 8972 bolt instances in RGB images	PA-DETR (Based on ResNet50, FPN and Attention)	mAP: 81.9%
2023[20]	Dampers	UAV	Structural defect	490 RGB images	DSA-Net	mAP@0.5: 0.935
2023[21]	Tower components	UAV	Structural defect	956 RGB images	PSTL-Net	mAP: 0.848

The detection of defects in power line systems is a critical task for ensuring the safe and reliable operation of electrical transmission infrastructure. Faults can occur in a wide range of components[3], including insulators, conductors, towers, and associated fittings, each of which presents unique challenges for automated inspection. Visual inspection, augmented by advanced computer vision and deep learning techniques, has emerged as a powerful tool for identifying both surface-level anomalies and structural defects. For instance, insulator faults may manifest as surface contamination, cracking, or missing caps, while conductor defects can include aging, corrosion, or internal damage, and tower structures can experience cracks, material degradation, or component loss. The application of UAVs, high-resolution cameras, and multi-sensor platforms has enabled the collection of detailed imagery, facilitating automated fault recognition even under complex environmental conditions such as varying illumination, cluttered backgrounds, and large-scale inspection areas.

This section reviews recent advances in defect detection across key power line components, highlighting state-of-the-art algorithms, including convolutional neural networks, instance segmentation models, attention-based frameworks, and multi-task learning architectures. Emphasis is placed on the strengths and limitations of these approaches, including their accuracy, computational efficiency, robustness to environmental factors, and applicability to small-scale or hard-to-detect components. The subsequent subsections provide a structured overview of defect detection for insulators, conductors, and tower structures, summarizing representative studies, key methodologies, and emerging trends in automated power line inspection. Table 2.4 summarizes the relevant literature on faults detection.

2.5.1 Insulator Defect

In recent years, UAV-based insulator fault detection has been largely dominated by bounding box detection approaches, with YOLO and its improved variants becoming the prevailing algorithms due to their high efficiency and accuracy. As summarized in 2.4, most of the latest studies build on YOLO frameworks by introducing enhancements such as lightweight feature extractors, attention mechanisms, and hybrid architectures to better address diverse fault types under complex aerial environments. A clear reliance on RGB images, often combined with synthetic datasets like CPLID, further illustrates a common direction in dataset design and evaluation. In the following analysis, I will highlight the shared characteristics of these methods, discuss how they tackle challenges specific to UAV-based inspection, and explore emerging trends that may shape future development in insulator defect detection.

Among these YOLO-based approaches, Hao et al. [14] proposed an improved YOLOv4-based detector (ID-YOLO) specifically tailored for insulator bunch-drop detection in UAV imagery. The method retains the one-stage, real-time detection paradigm of YOLOv4 but replaces and augments key components: a CSP-ResNeSt backbone (ResNeSt units with split-attention) for stronger feature extraction, an SPP module to enlarge the receptive field, and a novel Bi-SimAM-FPN neck that fuses multi-scale features with the lightweight SimAM attention and depthwise-separable convolutions to better preserve small-object and localization information. ID-YOLO uses K-means anchors and CIoU loss, plus training practices such as mosaic augmentation and label smoothing. Experiments were run on the authors' CPLMID benchmark (UAV images merged from CPLID and an inspection dataset and augmented to 3,536 images; split 8:1:1), and the model was also evaluated on VOC2007 and the DIOR aerial benchmark. Quantitatively, ID-YOLO achieved a mAP of 95.63% on CPLMID (insulator-defect AP 99.13%), ran at 63 frames/s with 227 MB memory footprint, and produced consistent gains over baseline YOLOv4 and popular detectors (e.g., YOLOv5, YOLOX, Faster R-CNN); mAP increases of 0.7% on VOC and 3.35% on DIOR were also reported. Ablation studies indicate that CSP-ResNeSt mainly improves insulator detection, while Bi-SimAM-FPN materially boosts small-object (bunch-drop) localization and overall fusion effectiveness; training loss curves corroborate faster convergence and lower final loss for the full model. The main drawbacks are modest increases in model complexity and inference cost relative to vanilla YOLOv4 (some variants trade off a small drop in throughput for higher accuracy) and continued dependence on relatively limited, domain-specific datasets. The authors therefore point to future work on further optimizing runtime and memory for onboard UAV deployment and extending dataset diversity and generalization for real-world, in-flight inspections.

Building on the focus of architectural improvement, Wei et al. [15] shifted attention toward practical deployment strategies, proposing an edge–cloud hybrid framework for online monitoring of insulator self-explosion. This framework couples a lightweight SSD deployed on edge devices with a cloud-side multi-model fusion detector. At the edge, a MobileNet-based, depthwise-separable convolution SSD (input resized to 512×512) performs fast insulator localization and preliminary filtering to reduce uplink traffic. In the cloud, detections from three advanced detectors (YOLOv3, RetinaNet, and an improved Faster R-CNN) are fused via a confidence-weighted bounding-box fusion scheme to produce the final diagnosis. The authors collected a large in-house dataset (8,500 raw insulator images, expanded via augmentation to 12,000 images with 6,000 fault instances) and used a train/val/test split that yielded 10,000 training images (5,000 faulty + 5,000 normal), 1,000 test images, and 1,000 validation images. On this dataset, the improved edge SSD achieved 89.0% accuracy, 87.4% recall, inference time of 30 ms, and a model size of 22 MB (compared with the baseline SSD: 88.2% acc, 75 ms, 94 MB), demonstrating strong suitability for edge deployment (NVIDIA TX2). The cloud multi-model fusion substantially outperformed single models (fusion AP 93.52%, R 93.69%, P 99.04%, VAL 94.68% versus YOLOv3 AP 89.8%, RetinaNet AP 89.1%, Faster-RCNN AP 87.8%), and the end-to-end edge+cloud pipeline reduced running time and transmitted data while raising cloud recognition accuracy (reported improvement from 90.7% to 95.8%). Key strengths of this work include its practical edge-first design that cuts bandwidth and latency, the demonstrated effectiveness of multi-model fusion for robust detection in complex aerial images, and careful evaluation on a large, augmented dataset with realistic edge/cloud hardware. Limitations include modest additional system energy consumption due to edge preprocessing (25.6 W in working state), added system complexity and dependency on cloud connectivity for final decisions, and reliance on a proprietary dataset, which may limit generalization. Future work includes optimizing energy savings, refining edge node deployment strategies, further reducing model size and latency for true onboard UAV operation, and continuously updating the cloud model library to improve generalization in real-world inspections.

While deployment strategies play a critical role, data augmentation and feature preservation remain equally important. Cao et al. [16] focused on aerial image augmentation to improve detection of self-detonation defects in insulators, emphasizing preservation of key insulator regions through edge feature integration and Grad-CAM-based saliency maps. Their pipeline first uses YOLOv3 to crop insulator regions from UAV images, followed by Sobel-based edge feature extraction and integration into an improved ResNet-18 model. For data augmentation, Cutout and GridMask are guided by saliency maps to avoid erasing critical regions. The dataset included 1,209 defect-free and 383 defect images (cropped to 224×224), augmented to balance class distribution. Experiments showed that the improved ResNet-18 with edge features and proposed augmentation achieved 95.1%

classification accuracy, outperforming baseline ResNet-18 and other CNN models (VGG-16, MobileNet-v2). Ablation studies highlighted the benefits of the edge feature branch, Grad-CAM-guided augmentation, and higher-resolution inputs. Limitations include increased training and inference time due to the edge extraction branch (though trainable parameters increased by less than 10%), reliance on a small, proprietary dataset, and limited evaluation under diverse environmental conditions. Future work aims to extend evaluation on larger, more varied datasets, incorporate richer prior feature knowledge, and improve robustness under diverse inspection scenarios such as adverse weather, further enhancing fine-grained defect detection.

Zhang et al. [17] proposed GhostNet-YOLOV4 to improve UAV-based detection of self-exploded insulator defects in power transmission systems, emphasizing lightweight deployment and real-time detection. The model replaces YOLOV4's backbone with GhostNet, incorporating depthwise separable convolutions and FPN+PANet feature fusion to reduce computational cost while enhancing small-defect detection under complex backgrounds. Experiments on a 1,000-image dataset (balanced between normal and defect classes) showed 99.50% AP overall, with 83.19% recall for normal insulators and 99.72% recall for self-exploded insulators, outperforming baseline YOLOv4 and lightweight YOLO variants. Strengths include efficient UAV deployment, accurate small-defect detection, and reduced manual inspection workload. Limitations involve slightly lower recall for normal insulators, dependency on well-annotated datasets, and potential sensitivity to diverse environmental conditions. Future work seeks to extend detection to multiple power components (e.g., wires, towers), enhance robustness under adverse weather, explore edge–cloud hybrid deployment for continuous monitoring, and further compress the model for faster UAV operation, ultimately supporting safer and more cost-effective power infrastructure maintenance.

Nikheel Jain et al. [18] proposed a transfer learning-based deep learning pipeline for automated detection of faulty porcelain insulators (pins and discs) on power distribution lines, addressing limitations of previous methods such as low generalization across component types and poor small-component detection. The multi-source dataset included UAV, camera, and mobile phone images labeled into four classes: normal pin, normal disc, defective pin, and defective disc. Dataset quality and quantity were enhanced using no-reference image quality assessment (BRISQUE), super-resolution (WDSR), and data augmentation (positional, color, mosaic, scene cropping), effectively tripling the training data. YOLOv5 (CSPDarknet backbone) and DETR (transformer-based) models were used for object detection. While DETR excelled at larger components, YOLOv5 performed better on small objects, achieving 73% MAP@50 on defective components. A transfer learning strategy—pre-training on existing environments and fine-tuning on 5% of new images—substantially improved generalization, raising MAP@50 for defective pins and discs to 98%, 25% higher than baseline YOLOv5. Strengths include comprehensive dataset treatment, effective integration of YOLOv5 and DETR, and practical transfer learning for adaptation to new environments. Limitations involve reliance on manual labeling and potential under-representation of extreme conditions. Future work will extend the approach to polymeric insulators and explore transformer-based architectures for enhanced performance across diverse environments.

Taken together, these studies highlight several shared trends and challenges in UAV-based insulator defect detection. Common strengths include high efficiency and accuracy of YOLO-based detectors, effective handling of small defects via multi-scale feature fusion and attention mechanisms, and improved generalization through data augmentation or transfer learning. Lightweight architectures and edge-cloud deployment strategies further enable practical, real-time UAV inspection. Common limitations remain: strong reliance on RGB images, relatively small or proprietary datasets, limited evaluation under diverse environmental conditions, and increased model complexity or computational cost in some methods. Future directions are likely to involve (1) continued optimization of lightweight architectures for real-time onboard UAV deployment, (2) more robust edge–cloud integration for efficient and adaptive monitoring, (3) development of larger, more diverse datasets incorporating multiple sensor modalities, and (4) exploration of transformer-based or hybrid architectures to enhance both small-defect detection and model generalization across varied operational scenarios. Collectively, these advancements are expected to push UAV-based insulator defect detection toward more accurate, reliable, and scalable solutions suitable for complex real-world power systems.

2.5.2 Conductor Defect

Due to the unique characteristics of transmission conductors, UAV-based detection methods are rarely employed. Conductors extend over long spans at high altitudes, making it difficult for UAVs to capture continuous and comprehensive coverage of the lines. Moreover, external surface defects, such as minor corrosion or cracks, are typically very subtle and require close-range, high-resolution imaging, which UAVs operating at a distance cannot easily provide. In addition, conductor faults are not limited to external visible damage but also include internal defects, such as core fractures in composite conductors. Detecting such internal anomalies often relies on advanced techniques such as X-ray imaging, infrared sensing, laser scanning, or current analysis, which are challenging to integrate into UAV platforms[3].

2.5.3 Power Line Fittings

Power line fittings, such as bolts and dampers, are critical for securing conductors, insulators, and lightning wires to transmission towers, ensuring both mechanical stability and electrical reliability. Despite their small size, defects such as cracks, corrosion, deformation, loosening, or missing parts can cause severe mechanical or electrical failures, including conductor slippage, line breakage, or increased contact resistance leading to overheating or arcing. Detecting these subtle defects is challenging due to their tiny dimensions and fine-grained features, requiring high-resolution imagery and advanced deep learning algorithms[3]. UAV-based inspection combined with computer vision offers a practical solution for automated detection, improving grid reliability, reducing maintenance costs, and enhancing operational efficiency.

Zhang et al. [19] introduced PA-DETR, a novel end-to-end transformer-based framework designed for automated detection of bolt defects on transmission towers, aiming to overcome the limitations of existing object detection approaches such as poor generalization, weak small-object detection, and dependence on handcrafted priors. The proposed architecture enhances conventional DETR through three tailored components: a dilated encoder that enlarges the receptive field without sacrificing spatial resolution, an implicit position knowledge module that compensates for DETR's slow convergence and limited spatial sensitivity, and an explicit attributes knowledge module that encodes prior information on bolt geometry and defect characteristics to guide the learning process. Extensive experiments conducted on a large-scale UAV bolt inspection dataset demonstrate that PA-DETR consistently outperforms baseline detectors, achieving superior precision and recall on small-scale defect categories while maintaining competitive inference efficiency. Key strengths of this study include the principled integration of domain-specific prior knowledge into a transformer pipeline, the tailored design for small-object detection, and the practical validation on real-world UAV inspection data. Nonetheless, limitations remain, particularly the increased architectural complexity and potential scalability issues when extended to multi-component detection scenarios. Future research is expected to explore more lightweight variants of PA-DETR and expand its applicability to other tower fittings and structural components under diverse environmental conditions.

In parallel, Zhang et al. [20] proposed DSA-Net, a one-stage, anchor-free, attention-guided network for real-time detection of damper structural defects from UAV RGB imagery. The architecture combines a GhostConv-based backbone enriched with a novel Damper Attention (DA) module (strip-convolutions tuned to damper aspect ratios), a Stile-PAN neck that aggregates more shallow features to improve small-object representation, and an ASFFs fusion applied at the P3 scale to resolve pyramid inconsistencies for tiny/distant dampers. Inputs are resized to 640×640 and the model was trained on the authors' TLD benchmark (490 UAV RGB images, train/test split 8:2) with standard augmentations; training used SGD (batch size 16) for 300 epochs. On TLD, DSA-Net achieved mAP@0.5 = 0.935 (mAP@0.5:0.95 = 0.789) while running at 7.2 ms per image, delivering state-of-the-art accuracy for small, dense dampers with real-time throughput and competitive Params/FLOPs versus leading detectors. Ablation studies show the DA block significantly improves focus on damper regions and that Stile-PAN + ASFFs materially boost small/dense object detection. Key strengths are its high accuracy on challenging UAV scenes, excellent small-object performance, and real-time speed suitable for onboard/edge deployment. Limitations include dependence on a relatively small, domain-specific dataset (TLD), reduced interpretability and additional hyperparameter tuning introduced by the attention/strip-conv design, and limited evaluation on fine-grained states (e.g., slip or corrosion). The authors suggest future work to enlarge and diversify datasets (more environments and weather), extend the model to detect slip/corrosion and severity levels, develop lighter/pruned variants for embedded UAV platforms, and improve interpretability of the DA attention.

Taken together, these studies underscore two converging research directions for UAV-based fitting inspection: (1) architectural innovations tailored to the challenges of small-object detection in complex aerial scenes, as exemplified by PA-DETR and DSA-Net, and (2) complementary dataset-driven strategies, reported in related studies, that leverage augmentation, quality enhancement, and transfer learning to improve model generalization across diverse environments. While both directions have demonstrated promising results, they also highlight open challenges, including the need for lightweight, scalable models that can run efficiently on UAV platforms, as well as the scarcity of large, standardized datasets covering multiple types of fittings and environmental conditions. Future work should therefore integrate architectural advances with robust dataset design, aiming to achieve accurate, real-time fitting defect detection that can generalize across diverse grid infrastructures.

2.5.4 Tower Structural Defect

Transmission towers are critical for supporting high-voltage conductors and maintaining the stability of power transmission systems. Structural defects, such as corrosion, cracks, or deformation, can compromise tower integrity and potentially cause line failures or cascading outages. Detecting these defects is challenging due to tower height, complex geometries, and environmental influences including weather and surrounding vegetation[3].

Recent studies have applied UAV-based inspection combined with computer vision and deep learning to automate the identification of tower structural anomalies. For instance, Yi et al. [21] proposed PSTL-Net, a single-stage CNN framework designed to address challenges such as weak texture representation, small-object detection, and occlusion. The framework incorporates a Self-Texture-Learning Module (STLM) for enhancing local and global feature representation, a Patch-Aware Spatial Attention Module (PSAM) to focus on semantically consistent patches, and a Probabilistic NMS Head (PNH) to alleviate category imbalance and improve detection alignment. Experiments on a UAV-collected dataset demonstrated that PSTL-Net outperforms state-of-the-art CNN and transformer-based models, particularly for small, occluded, or low-texture components.

Overall, PSTL-Net shows strengths in feature enhancement, occlusion handling, and practical detection performance. Limitations include reduced effectiveness under extreme occlusion and dependence on the dataset distribution. Future work aims to expand dataset coverage and improve detection performance in severely occluded and cross-domain scenarios.

2.6 Gap

Despite considerable progress in UAV-based power system inspection, several key gaps remain, particularly in **insulator defect detection**, which is critical for ensuring grid reliability. Across studies on power component, line, tower, and fitting detection, common challenges include small-object detection, occlusion, complex backgrounds, limited dataset diversity, and computational constraints for real-time UAV deployment. While recent works on power component and line detection have leveraged attention mechanisms, multi-scale feature fusion, and lightweight architectures to improve accuracy and efficiency, these approaches often rely on relatively small, proprietary datasets and are evaluated under limited environmental conditions.

Insulator defect detection, in particular, faces additional challenges. Although YOLO-based detectors and transfer learning strategies have improved small-defect detection and cross-environment generalization, current methods remain strongly dependent on RGB imagery and lack large-scale, standardized datasets that encompass diverse environmental scenarios, lighting conditions, and defect types. Lightweight architectures and edge-cloud deployment have facilitated real-time inspection, yet model performance still degrades under extreme occlusion or rare defect categories, limiting reliability for autonomous UAV operations. Furthermore, most approaches focus on surface-visible defects, neglecting the potential for multi-sensor integration (e.g., infrared, LiDAR) to detect subtle or hidden faults.

Future research must address these gaps by:

1. Developing larger, multi-modal, and diverse datasets that capture a wide range of insulator types, defect severities, and environmental conditions.
2. Enhancing model robustness to extreme occlusion and small, rare defects, potentially via transformer-based or hybrid architectures with adaptive attention mechanisms.
3. Integrating lightweight, real-time deployable models with edge-cloud frameworks to balance accuracy, efficiency, and scalability for practical UAV inspection.
4. Exploring multi-sensor fusion to enable detection of subtle or hidden defects, extending beyond conventional RGB imagery.

Collectively, addressing these gaps will improve the accuracy, reliability, and scalability of UAV-based insulator defect detection, enabling more comprehensive and autonomous monitoring of power transmission systems.

2.7 Conclusion

This literature review has examined the state-of-the-art in UAV-based inspection of power transmission systems, covering detection of power components, lines, towers, insulators, conductors, and line fittings. Across these domains, significant advancements have been achieved through the integration of deep learning, attention mechanisms, multi-scale feature fusion, and lightweight architectures, enabling higher detection accuracy, improved efficiency, and more practical deployment on UAV platforms.

However, several persistent challenges remain. Small-object detection, occlusion, complex environmental conditions, and limited dataset diversity continue to hinder robust performance, particularly in **insulator defect detection**, which is critical for ensuring grid reliability. While YOLO-based models and transfer learning approaches have improved defect localization and cross-domain generalization, reliance on RGB imagery, small or proprietary datasets, and sensitivity to extreme occlusion limit the effectiveness of current methods.

Future research is likely to focus on: (1) constructing large, multi-modal datasets covering diverse insulator types, defects, and environmental scenarios; (2) designing transformer-based or hybrid architectures with adaptive attention mechanisms to enhance robustness against occlusion and rare defects; (3) integrating lightweight models with edge-cloud frameworks to balance real-time deployment with high accuracy; and (4) exploring multi-sensor fusion techniques, such as infrared and LiDAR, for detecting subtle or hidden defects.

Overall, addressing these challenges will be crucial for advancing UAV-based inspection systems toward more accurate, reliable, and scalable solutions, ultimately supporting autonomous monitoring and maintenance of power transmission infrastructure.

Chapter 3

Task 2: Research Problem Identification Report

3.1 Research Problem

UAV-based inspection of power transmission systems has seen remarkable advancements in recent years, particularly in the detection of insulator defects. Methods leveraging YOLO-based architectures, lightweight backbones, attention mechanisms, and edge–cloud hybrid deployment have demonstrated high efficiency and promising accuracy in detecting small, surface-visible defects under complex aerial environments. However, several critical challenges persist, which limit the reliability, scalability, and generalization of current approaches.

First, most existing methods rely heavily on RGB imagery and relatively small, proprietary datasets, which restricts generalization to new environments, lighting conditions, or defect types. Second, extreme occlusion, adverse weather, and rare or subtle defect categories remain difficult to detect reliably, even with advanced multi-scale feature fusion and attention modules. Third, while edge–cloud frameworks facilitate real-time deployment, they introduce system complexity and energy consumption, and current methods still lack efficient strategies to balance accuracy, speed, and model size for practical UAV operations. Finally, most approaches focus exclusively on surface-visible defects, neglecting the potential of multi-sensor integration—such as infrared, LiDAR, or hyperspectral imaging—to detect subtle or internal anomalies that are otherwise invisible to RGB cameras.

Taken together, these limitations motivate a focused research problem: **how to develop a robust, generalizable, and efficient UAV-based insulator defect detection framework that can reliably identify both common and rare defects under diverse operational and environmental conditions, while supporting real-time deployment and multi-sensor data fusion.**

3.2 Proposed Contributions

To address the above research problem, the proposed research aims to make the following contributions:

1. **Enhancing existing dataset:** Due to limited resources, building a completely new dataset is challenging. However, I can merge existing open-source datasets, as mentioned in [3], and apply image enhancement techniques to create a more diverse and generalized dataset for model training.
2. **Discover a more robust model:** Based on the literature review, YOLO-based approaches have been increasingly recognized as effective for defect detection. I plan to explore and experiment with novel YOLO variants identified in recent studies, aiming to develop a more robust model with improved performance for insulator defect detection.

3.3 Dataset

Several free, open-source UAV-based insulator inspection datasets have been identified in [3], which provide a practical starting point for model development. I plan to leverage these existing datasets and enhance them through data augmentation techniques, such as rotation, scaling, color jittering, and mosaic augmentation, to improve diversity and generalization. Additionally, I will selectively refine or enhance images that contain rare or challenging defect types to better support the training of robust detection models.

3.4 Evaluation Plan

The effectiveness of the proposed research contributions will be evaluated through a combination of controlled experiments and realistic UAV deployment scenarios:

- **Quantitative evaluation:** Metrics such as AP, mAP, precision, recall, and F1-score will measure defect detection performance across different defect types, environmental conditions, and sensor modalities. Comparisons will be made against existing YOLO-based detectors and hybrid transformer architectures. Ablation studies will evaluate the impact of each component, such as attention modules, multi-sensor fusion, and edge–cloud deployment strategies.
- **Robustness testing:** The model will be evaluated on multiple datasets to simulate diverse real-world inspection scenarios.
- **Efficiency assessment:** Real-time deployment feasibility will be measured in terms of inference speed and memory usage (e.g., NVIDIA Jetson or similar edge devices). Trade-offs between model complexity and accuracy will be analyzed.

3.5 Time Schedule

This section outlines a conceptual timeline for executing the proposed research on UAV-based insulator defect detection. The schedule spans from December 2025 to May 2026 and details the key stages, expected outputs, potential contingencies, and mitigation strategies.

3.5.1 Stage 1: Dataset Preparation and Enhancement

Weeks 1-4 (Dec 2025 – Jan 2026)

- **Objectives:** Collect and merge existing open-source UAV-based insulator datasets ([3]), apply image enhancement and data augmentation to improve diversity and generalization, and curate subsets for rare defect types.
- **Methodology:**
  1. Identify and download all relevant datasets.
  2. Apply augmentation techniques such as rotation, scaling, color jittering, mosaic, Cutout, and GridMask.
  3. Perform selective enhancement for rare defect instances to ensure balanced representation.
- **Expected Outputs:** A unified, augmented dataset suitable for robust YOLO-based model training.
- **Risk Factors:**
  - Limited diversity of available datasets may lead to insufficient coverage.
  - Imbalanced representation of rare defects.
- **Mitigation:** Focus on targeted augmentation of rare defects and incorporate synthetic transformations to increase dataset variability.

3.5.2 Stage 2: Model Development and Optimization

Weeks 5-12 (Feb – Mar 2026)

- **Objectives:** Explore and implement YOLO-based variants with attention mechanisms, multi-scale feature fusion, and lightweight backbones to develop a more robust insulator defect detection model.
- **Methodology:**
  1. Benchmark existing YOLO variants (YOLOv4, YOLOv5, GhostNet-YOLO, ID-YOLO, etc.).
  2. Incorporate transformer-inspired attention modules or hybrid designs for enhanced small-defect detection.
  3. Conduct hyperparameter tuning and ablation studies to optimize detection accuracy, speed, and model size.
- **Expected Outputs:** A robust YOLO-based insulator defect detection model, validated on the enhanced dataset.
- **Risk Factors:**
  - Increased model complexity may hinder real-time deployment.
  - Performance may degrade for rare or occluded defects.
- **Mitigation:** Prioritize lightweight architecture optimizations and conduct progressive evaluations on subsets representing challenging conditions. If persistent difficulties arise, consult with the supervisor to ensure methodological soundness and efficiency.

3.5.3 Stage 3: Multi-Sensor Integration and Edge–Cloud Deployment

Weeks 13-16 (Apr 2026)

- **Objectives:** Integrate additional sensor data (e.g., infrared, LiDAR) with RGB images to improve detection of subtle or hidden defects, and design edge–cloud hybrid deployment strategies for real-time UAV operation.
- **Methodology:**
  1. Preprocess and align multi-modal sensor data with the RGB dataset.
  2. Experiment with feature fusion strategies (early fusion, late fusion, or attention-based fusion).
  3. Deploy lightweight models on edge hardware and benchmark inference speed, memory usage, and energy consumption.
- **Expected Outputs:** A prototype multi-sensor insulator defect detection system deployable on UAV edge devices with cloud support.
- **Risk Factors:**
  - Sensor misalignment or synchronization issues.
  - Increased computational load may impact real-time performance.
- **Mitigation:** Implement calibration procedures, optimize feature extraction pipelines, and experiment with selective sensor usage to reduce computational overhead. If computational resources remain a limitation, additional cloud or high-performance computing resources may be leveraged.

3.5.4 Stage 4: Evaluation and Validation

Weeks 17-20 (May 2026)

- **Objectives:** Rigorously evaluate the proposed framework on quantitative, robustness, and efficiency metrics.
- **Methodology:**
  1. Robustness testing: Evaluate performance under occlusion, low-light, adverse weather, and rare defect instances.
  2. Efficiency assessment: Measure inference speed and memory usage on UAV-compatible edge hardware.
- **Expected Outputs:** Comprehensive evaluation report demonstrating performance, generalization, and real-time feasibility of the proposed model.
- **Risk Factors:**
  - Edge hardware constraints may limit deployment experiments.
  - Simulated environmental conditions may not fully capture real-world variability.

- **Mitigation:** Combine simulation and field test scenarios to iteratively optimize the model for real-time performance. If real-time constraints cannot be fully met despite optimization, document the remaining limitations in the report for transparency and further discussion.

3.5.5 Stage 5: Report Writing and Submission

Weeks 21-22 (Late May 2026)

- **Objectives:** Compile all research outcomes, methodology, experimental results, and analysis into a coherent research report/thesis chapter.
- **Methodology:**
  1. Organize datasets, model development notes, and evaluation results.
  2. Write sections on Research Problem, Proposed Contributions, Dataset, Model Development, Multi-Sensor Integration, Evaluation, and Discussion.
  3. Include figures, tables, and charts summarizing results, and finalize references.
  4. Proofread, check formatting (e.g., LaTeX), and submit the report.
- **Expected Outputs:** Complete research report ready for submission.
- **Risk Factors:**
  - Last-minute issues in experiment results or missing data.
  - Formatting or reference errors delaying submission.
- **Mitigation:** Maintain up-to-date documentation throughout the project, and reserve at least one week solely for report writing and proofreading.

3.6 Expected Impact

By addressing dataset limitations, incorporating multi-modal sensing, and designing robust hybrid architectures with practical deployment strategies, this research is expected to improve the accuracy, generalization, and operational reliability of UAV-based insulator defect detection. The proposed framework will provide a foundation for more autonomous, scalable, and cost-effective monitoring of power transmission infrastructure, potentially reducing manual inspection workload, preventing unexpected outages, and enabling proactive maintenance strategies.

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