Discover Applied Sciences

Review

Drone-based fault recognition in power systems: a systematic review of intelligent methods

Carlos A. F. Persiani[1] · Felipe M. Sallazar[2] · Roberto S. Inoue[2] · Valdir Grassi Jr.[1] · Marco H. Terra[1] · Mário Oleskovicz[1]

Received: 6 January 2025 / Accepted: 24 March 2025
Published online: 09 May 2025

Abstract

Electrical power systems are susceptible to several damaging effects, potentially leading to faults reaching safety limits and posing critical operational risks. Traditionally, manual inspection has been employed to detect such faults; however, this method is inefficient—being both time-consuming and lacking precision. Once a fault is observed, prompt recognition becomes paramount to ensure the safe resumption of system operations. Addressing this issue, Drone-based strategies have proven to be effective in recognizing these irregularities. In particular, intelligent inspection methods have gained much attention in the past few years, evidenced by a remarkable 1000% surge in the adoption of deep learning techniques and a 420% surge in the utilization of drones. In this survey, we explore the main strategies of evolving Drone-based intelligent inspection methods for fault recognition in electrical power systems. The application of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses methodology revealed a total of 36 papers in the literature on the subject. As primary results, a synthetic description of the works was provided, unveiling the most frequently used algorithms, fault types, and sensors, along with their relationships established through a heatmap diagram. The identification of literature gaps and future research directions reveals the path for further exploration, including the need for more robust algorithms to improve fault detection accuracy, techniques to mitigate the impact of blurred images, methods for detecting multiple faults simultaneously, advancements in real-time processing, increased automation for field deployment, and the development of more comprehensive and diverse datasets.

Article highlights

- A structured review of drone-based fault detection in electrical systems using artificial intelligence methods;
- A detailed comparison of fault types, detection sensors, and algorithms used in existing studies;
- Key research gaps and future trends identified to improve drone-based fault detection technologies.

Keywords Unmanned aerial vehicles · Drone · Fault recognition · Fault identification · Electrical power systems · Transmission lines · Power line inspection · Aerial images · Deep learning · Survey

✉ Carlos A. F. Persiani, carlospersiani@usp.br; Felipe M. Sallazar, felipe.sallazar@estudante.ufscar.br; Roberto S. Inoue, rsinoue@ufscar.br; Valdir Grassi Jr. , vgrassi@usp.br; Marco H. Terra, terra@sc.usp.br; Mário Oleskovicz, olesk@sc.usp.br | [1]Department of Electrical and Computer Engineering, Sao Carlos School of Engineering, University of Sao Paulo, Av. Trabalhador Sao-Carlense, 400, Sao Carlos, SP 13566-590, Brazil. [2]Computer Science Department, Federal University of Sao Carlos, Rod. Washington Luis, Km 235- Jardim Guanabara - Caixa Postal 676, Sao Carlos, SP 13565-905, Brazil.

1 Introduction

Historically, fault identification in electrical power systems has relied on manual processes, where trained teams navigate corridors to detect anomalies and subsequently report their findings, as illustrated in Fig. 1. This traditional, manual-style inspection remains present today. However, this method is inherently inefficient, being both time-consuming and lacking in precision. Ensuring the continuous functionality of components within electrical power systems necessitates the development of more effective inspection strategies.

This gap in automatic inspection methods has inspired efforts in data capturing and processing to identify faults and anomalies properly. In recent years, robotic-based solutions have garnered significantly, as evident in studies such as [2–4] and references therein. Within the realm of robotic-based inspection, Unmanned Aerial Vehicles (UAVs) are among the most prominent implementations.

Indeed, the collaborative use of drones and machine learning for pattern recognition has inspired a wide range of applications. The work presented in [5] provides a review of UAV swarms and machine learning for monitoring and disease identification in Brassica plants. By highlighting the most commonly used cameras, sensors, image processing techniques, and machine learning methods, the study underscores the growing importance of UAV-based technologies alongside vision-based approaches in modern applications.

In various contexts, such as electrical distribution and transmission systems, drones can significantly investigate potential system defects. Common fault types include storms, lightning, freezing rain, fog, corrosion [6], partial discharges, insulation breakdown, and short circuits caused by birds, external objects coming into contact with the lines, or tree branches striking the lines, as mentioned in [7]. Figure 4 presents an analysis of faults within distribution systems.

A broad spectrum of research has been developed to delve into UAV-based technologies for the commented purpose. Utilizing unmanned aircraft necessitates an embedded electronic platform for efficient algorithm computations [8–15], a dedicated path planning model to guide the aircraft with precision while ensuring operational safety (considered in both online and offline modes) [9, 16–21], and computational simulations to test propositions in a safe and controlled environment [17, 22–25]. Furthermore, fault recognition encompasses a unique and extensive domain of research endeavors.

To access elements related to the inspection and fault analysis as conducted today, a query was formulated in the Scopus database, searching within the title, abstract, and keywords. The following words express our intent to find works in this direction:

- "Electrical power Systems", "Transmission Line", "Distribution Power System" and
- "Inspection", "Fault Detection"

Fig. 1 A person manually inspecting elements of an electrical tower is a widely employed approach in electrical power systems inspection, as noted by [1]

With this search, 2433 documents were identified in the Scopus system. These works were then exported to the SciVal platform [26] for a more in-depth analysis. Our goal was to discern the prevailing trends in solutions for inspecting electrical power systems. Figure 2 illustrates the main keyphrases uncovered.

Within the SciVal software, it is possible to visualize the rate of growth of each term. Comparing the years 2022 with 2018, the following results were obtained.

- Deep Learning: + 1000.0%
- Drone: + 420.0%
- Object Detection: + 385.7%
- Intelligent: + 371.4%
- Aerial Image: + 212.5%
- Unmanned Aerial Vehicles: + 128.6%
- Power Line: + 54.5%

Therefore, among the various strategies for inspecting and detecting faults in electrical power systems, UAV-based methods, and artificial intelligence models, particularly those utilizing deep learning techniques that rely on learning from data to recognize patterns and make decisions, are becoming increasingly prominent. The rapid growth of deep learning and drone technologies in recent years highlights this most significant pathway towards automating the inspection process. It underscores the necessity for a comprehensive review in this area.

Following this need, surveys identified in the conducted literature review relate to similar yet distinct research endeavors. In Yang et al. [1], the authors review general state-of-the-art techniques for inspecting power lines without a specific focus on the use of drones. In the work of Foudeh et al. [7], the authors extensively explore the power line monitoring process, with a particular focus on control methods grounded in machine learning principles. Meanwhile, the study in Luo et al. [27]. explores intelligent transmission line inspection based on UAVs, primarily emphasizing the drone's use and mission establishment rather than intelligent fault identification methods. In Xu et al. [28], UAV-based visual inspection methods are surveyed in sight of power line detection. While their work does touch on intelligent methods, but they are not the main focus, and the primary purpose is not centered on general fault types such as insulators or pins.

Therefore, due to the absence of a complete survey addressing intelligent visual inspection methods for UAV-based fault recognition, the Reporting Items for Systematic Reviews (PRISMA methodology) [29] was chosen to conduct the methodological structure of this survey. As a well-established systematic method, this methodology has been employed in several reviews in related areas, including [30–34].

1.1 Contributions

With the growing appeal of utilizing UAVs for fault recognition in electrical power systems through intelligent methods, there is a need for a comprehensive literature review on this topic. This study addresses this gap by conducting a systematic PRISMA review of the issue. The major contributions can be outlined as follows:

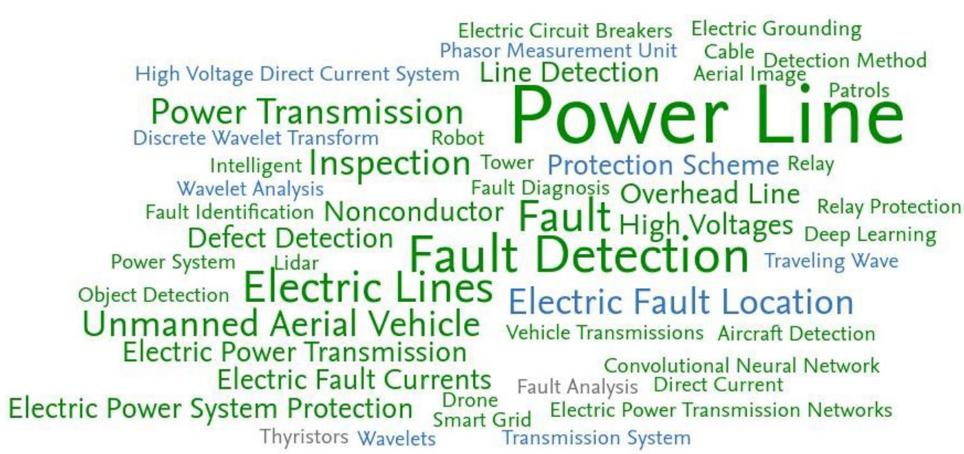


Fig. 2 A word cloud was generated using the SciVal tool, representing the 50 most recurrent keyphrases. The size of each word reflects its relevance, while the color indicates its growth rate: green for increasing, gray for stagnation, and blue for decreasing

Carlos A. Persiani F. contributed to conceptualization, methodology guidelines, screening and eligibility process, writing the original draft, and review and editing. Felipe M. Sallazar worked on conceptualization, figures composition, screening and eligibility process, methodology, and writing the original draft. Roberto S. Inoue provided supervision, contributed to screening and eligibility process, conceptualization, and writing review and editing. Valdir Grassi Jr. was involved in supervision, screening and eligibility process, conceptualization, and writing review and editing. Marco H. Terra contributed to supervision, conceptualization, and writing review and editing. Mário Oleskovicz participated in supervision, conceptualization, and writing review and editing. All authors read and approved the final manuscript.

1. A comprehensive PRISMA review of the state-of-the-art in intelligent methods for UAV-based fault recognition in electrical power systems;
2. Synthesis of the literature works revealed by the review, including neural networks descriptions and results score evaluations, when applicable;
3. An explicit mapping between different fault types and the sensors employed for each task;
4. An explicit mapping between different fault types and the algorithms employed for each task;
5. A table relating the different fault types, sensors, algorithms, scores, and frame per second for each work found in the literature review;
6. A compilation of literature gaps and future trends.

The remainder of this paper is structured as follows: Sect. 2 outlines the methodology used to select relevant papers, following the PRISMA framework. Section 3 presents the selected studies and extracts key features for comparison. Finally, Sect. 4 summarizes the main findings and highlights directions for future research.

2 Methods

The PRISMA framework [29] is a widely recognized guideline designed to enhance the transparency and quality of systematic reviews. It provides a structured approach to literature selection, data extraction, and result synthesis, ensuring reproducibility and reducing bias. PRISMA includes a 27-item checklist and a flow diagram that help researchers systematically identify, screen, and assess relevant studies while maintaining clarity in reporting. By promoting rigorous methodology and comprehensive reporting, PRISMA facilitates the synthesis of high-quality evidence, making it a crucial tool in evidence-based research across various disciplines.

Following the method's guidelines, a series of questions were formulated to capture the essence of the key aspects related to the review, as follows:

- Which faults are usually identified?
- What intelligent algorithms are used to identify these faults?
- What are the most used sensors?
- What is the most studied type of fault in the literature?
- Which sensor is the most used for a given fault type?
- Which intelligent algorithm is most employed for each fault type?

Further, the following search keywords were chosen to cover the main aspects related to the context of the application:

- The agent performing the task of interest: "RPA" (Remotely Piloted Aircraft), "UAS" (Unmanned Aerial System),"drones", "UAV";
- The task of interest: "inspection", "surveillance", "maintenance", "fault detection";
- The object of interest: "transmission lines", "electrical distribution systems", "distribution power systems", "smart grid", "power transmission", "electrical grid", "power grid";
- The methods associated with the task of interest: "detection", "recognition", and "deep learning".

The literature review on visual inspection methods for UAV-assisted operations aims to show the key algorithms used to automatically recognize components of the electrical power systems and detect faults in those components. Based on that, Fig. 3 shows the filtering stages applied to select the papers that should be included in the review.

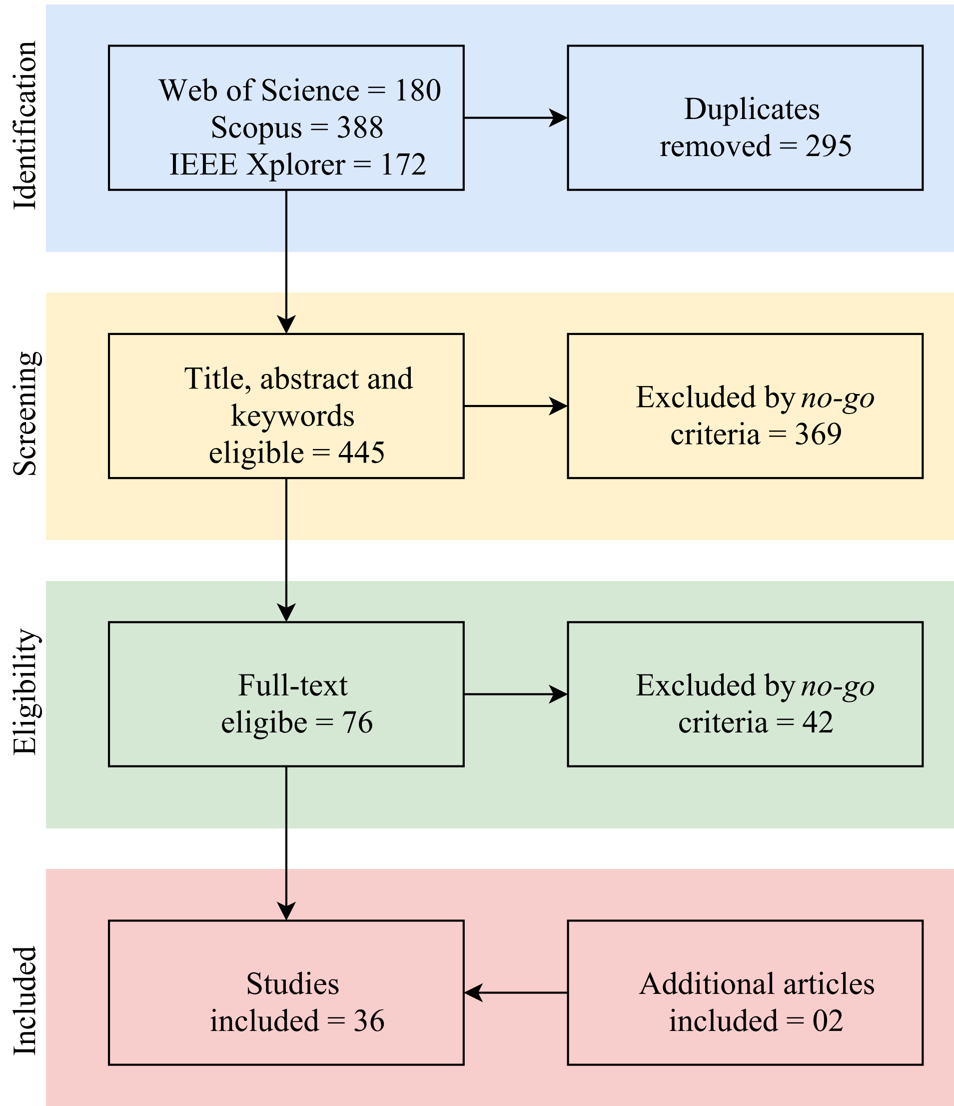


Fig. 3 Filtering states to select the papers related to UAV-assisted visual inspection of electrical power systems

These keywords were formally searched in three databases: Web of Science, Scopus, and IEEEXplore. The papers should have at least one keyword for each aspect previously listed. The search yielded 180 articles in Web of Science, 388 in Scopus, and 172 in IEEEXplore. Out of the 740 articles, 295 duplicates were eliminated, leaving 445 articles for analysis.

Only papers meeting all the following criteria were considered for inclusion in this review:

- The paper was available for download to the University of Sao Paulo;
- The paper was sufficiently clear;
- Real-life applications were demonstrated;
- The work employed intelligent algorithms to classify components and visually identify faults in electrical power systems;
- Unmanned aerial vehicles were used to acquire the necessary data.

After conducting the database search, the process of gathering and organizing the articles was carried out using an Excel sheet. Each entry included the article's title, abstract, keywords, and DOI. Based on the predefined criteria, one author initially assessed each article to determine its eligibility for inclusion. Whenever an article was selected, a second author independently reviewed the decision to ensure it met the stated criteria. If both authors agreed, the article proceeded to the next stage. In cases of disagreement, a third author was consulted to make the final decision.

Applying the aforementioned criteria, 34 articles were selected for the literature review on intelligent inspection methods for UAV-based inspections of electrical power systems. After that, two additional works were chosen to be added, completing 36 studies.

After selecting the relevant studies, the synthesis process involved summarizing their key characteristics, including the research context, the elements they aimed to recognize, and the methods and algorithms employed. Additionally, where applicable, specific metrics were extracted, such as fault types, sensor usage, algorithm performance, evaluation scores, and frame rates. This structured approach provided a comprehensive comparison of the selected works, facilitating a deeper understanding of their contributions and methodologies.

2.1 Bias analysis

This survey was evaluated using the Critical Appraisal Skills Programme, confirming all assessed points except for the bias analysis, which was only partially addressed. To ensure the completeness of this work, a detailed bias analysis is now provided.

Focusing on intelligent methods, particularly deep learning techniques, may have led to the overlooking of earlier studies that relied on traditional computer vision or statistical methods. These earlier approaches could still provide valuable insights into UAV-based fault recognition, although intelligent methods were the focus here.

Since the review was limited to works indexed in Web of Science, Scopus, and IEEEXplore, findings from unpublished studies, technical reports, and industry white papers may have been excluded. This introduces a risk of publication bias, potentially skewing the review towards studies with more favorable evaluations of UAV-based fault detection methods. However, it is important to note that the selected databases are widely recognized for their reliability and comprehensive coverage.

Furthermore, only studies available in English and accessible through institutional subscriptions were considered, which may have introduced language bias by overlooking research from non-English-speaking regions that may have made contributions to UAV and AI development. Additionally, some studies behind paywalls and inaccessible through institutional access could not be included, potentially limiting the breadth of the review. However, it is important to note that the University of Sao Paulo's institutional subscriptions provide extensive access to academic resources, ensuring coverage of a wide range of high-quality studies.

3 Results

The main results obtained from the systematic literature review on intelligent methods for fault recognition in drone-based electrical systems are presented and analyzed in the following sections. First, the identified research works are discussed, highlighting their approaches and contributions. Next, the most commonly used algorithms and sensors, along with their efficiencies, are explored. Finally, specific applications in fault detection are pointed out.

3.1 Surveys and reviews

As an initial step, the review revealed four surveys [1, 7, 27, 28] that emphasize the historical foundations and the growing interest in employing intelligent techniques in UAV operations.

In the survey paper published in 2020 by Yang et al. [1], the authors presented an overview of power line inspection techniques. The survey encompassed using Unmanned Aerial Vehicles (UAVs), image processing, and various deep-learning architectures. It emphasized the role of sensors, platforms, and methodologies in power line inspection.

A comprehensive literature review was conducted in 2023 by Foudeh et al. [7], with some of the most common faults illustrated in Fig. 4. The paper delved into learning-based control strategies in the context of overhead power line monitoring and the automation of UAV patrols in electrical power systems.

It described various learning approaches integrated with drone dynamics and presented recharging strategies to enhance mission autonomy.

In another survey published in 2023, Luo et al. [27] emphasized the increasing role of artificial intelligence, cloud computing, and big data in overhead line inspection and fault detection. The survey showed the development of intelligent inspection systems focusing on unmanned aerial vehicles. Besides covering the systems' development, it elaborated on aspects such as UAV path planning, trajectory tracking, and fault detection and diagnosis.

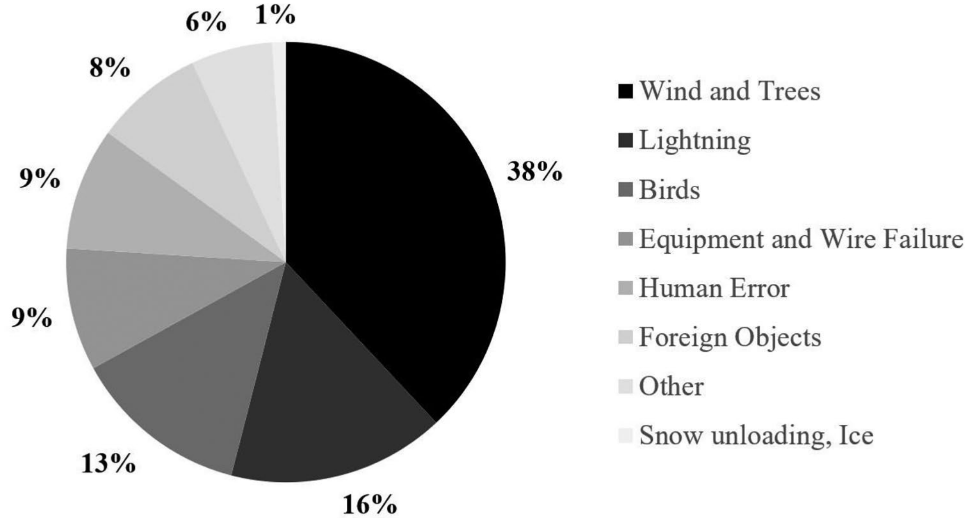


Fig. 4 The survey paper published by [7] compiled the most prevalent causes of faults in power networks. Particular attention should be paid to factors such as wind and trees, with lightning effects following closely

On the other hand, Xu et al. [28] focused on power line detection technology, discussing aspects such as aircraft features, internal systems of UAVs, and visual methods driven by collected data. The survey encompassed both traditional techniques such as image edge-detection and recent deep learning methods. The authors concluded that, despite being more complex, deep learning models exhibit greater resistance to interference from trees and roads, thereby capable of reducing detection errors.

3.2 General methods to identify faults types

As an initial model for automatic identification and detection, Huiying and Tingting [35] outlined a process for transmission line extraction, beginning with using the Sobel operator to detect edges in transmission line images after preprocessing. Traditional Hough transform was then applied to extract the lines. Additionally, the paper introduced two novel algorithms for line extraction: one based on the directional wavelet transform in conjunction with the Hough transform and the other based on morphology combined with the Hough transform. The paper compared the three methods regarding runtime and extraction results. Although they could identify the lines, a fault detection methodology was not presented.

From another view, to overcome poor lighting conditions and complex background, Azevedo et al. [36] proposed a novel approach called Power Line LiDAR-based Detection and Modeling (PL^{2}DM), which uses Light Detection and Ranging (LiDAR) technology for power line detection and modeling. The proposed method incorporates adaptive neighborhood comparison within a point cloud to identify power lines. The final model is constructed by matching and grouping line segments based on their collinearity properties. Validation of the algorithm with actual data showcased promising accuracy and processing time results, offering real-time object-based perception capabilities for subsequent processing layers.

The work of Wang et al. [37] proposed a framework for semantic segmentation of overhead lines and their accessories. An algorithm based on a line segment detector and matrix operations was proposed to segment the elements of interest in the image. Then, electrical towers, electrical lines, and line accessories are classified and identified on the images. Finally, after identifying the expected components, the framework detects broken strands and foreign bodies. The proposed method reduced the processing time compared to the loop-based algorithm for image processing. The achieved F1 score for detecting vibration damper, missing vibration damper, broken strand, and foreign body was 0.678, 0.383, 0.725, and 0.843. The framework has limitations on detecting missing vibration damper (low F1 score) and was designed to focus on a specific type of vibration damper. According to the authors, the obtained tower's detection performance was also insufficient.

In Odo et al [38], the authors established a deep learning-based approach to assess electrical tower conditions from aerial images. The proposed method uses supervised learning on a real-world industry dataset for which only the condition labels for the individual towers are available. There was no need to label the condition of each component of the towers. However, ultimately, the tower classification as healthy or unhealthy was based on the images of detected insulators and insulated U-bolts of the tower. The approach used a Mask R-CNN (Region-based Convolutional Neural

Network) or a RetinaNet to detect the components (insulators and insulated U-bolts). Then, cropped images of the tower's components were fed to another network trained for tower condition classification.

In the study conducted by Renwei et al. [39], the authors presented an improved deep learning model based on the network YOLOv3 (You Only Look Once) for critical parts inspection of transmission lines. The model aimed to overcome slow detection, low efficiency, and poor performance in low-light conditions. The improvements included reducing feature maps, optimizing anchor values using K-means++ clustering, and augmentation of the dataset with diverse lighting conditions and viewing angles. Experimental results demonstrated that this modified YOLOv3 model achieved a 6.0% increase in detection accuracy and a 6.0% improvement in detection speed.

A dataset comprising images sourced from the web and provided by Hohhot Northern Airlines in Inner Mongolia Inc. was employed to evaluate the proposed method.

The original dataset comprised 637 images, which were augmented using algorithms and subsequently divided into 2478 training samples, 276 validation samples, and 306 test samples, following an 8:1:1 ratio. In addition to the traditional and modified YOLOv4 tiny deep networks, the study also compared the performance of the Faster R-CNN model and the Efficient Detection Transformer (EDET) model. The results are presented in Table 1. In comparison with the traditional YOLOv4 tiny deep learning network, the proposed model exhibited advantages in recognition accuracy and processing speed. Furthermore, the feature extraction performance of the improved YOLOv4 tiny deep learning algorithm showed improvements of 0.94% in mean Average Precision (mAP), 1.19% in Average Precision (AP) for missing insulator defects, and 2.99% in AP for broken insulator defects. Despite the promising potential of the proposed algorithm for real-time applications, it is important to note that the dataset and network code are currently unavailable.

The power line corridor poses as a critical environment to be perceived. The safe operation of the electrical power system depends on the absence of vegetation encroachment within the corridor region. To address the vegetation inspection task, the study by Vemula and Frye [41] proposed a multi-head attention-based transformers neural network to detect vegetation encroachment using unmanned aerial vehicles. The dataset used in their work was obtained by drone, composed of photos of their power line corridor. Eight hundred images were selected and randomly distributed for network training, validation, and testing (75%, 15%, and 15%), respectively. The authors used a Convolutional Neural Network (CNN) with filters of sizes 64, 128, and 256 to extract the features from the original image. The resultant images were then fed into the transformer network. Further, the proposed model was compared with state-of-the-art Mask R-CNN. The resultant multi-head attention-based transformers proved to be faster and use fewer parameters than the Mask R-CNN. Although good results were obtained, the dataset was not made available.

The research and application of LiDAR technology on unmanned aerial vehicles (UAVs) for power line inspections are rapidly advancing. However, there is a need to explore automatic data fusion technology tailored to the characteristics of multi-source and heterogeneous power line data, particularly from UAV LiDAR in LAS (LASer) format. In this context, Su et al. [42] aimed to generate a three-dimensional model of the power line system and electrical equipment by leveraging LiDAR point cloud and visible light measurements. The point cloud underwent classification into distinct categories, such as surface points, vegetation points, building points, power line points, pylon points, etc., employing the PointNet++ deep learning algorithm. Utilizing vectorized lines, the point cloud data of trees, buildings, and intersections were systematically processed, facilitating the computation of the shortest distance from each point to the line, as well as the distance between individual lines. By comparing with the safe operation requirements, an alarm for dangerous objects can be given if needed. Experimental results demonstrated that the proposed method performed well regarding detection accuracy in the identification and classification of lines and towers in a complex environment.

Table 1 Comparison among faster R-CNN, EDET, Traditional Yolov4-Tiny Deep Learning Algorithm (TYTDLA) and Improved Yolov4-Tiny Deep Learning Algorithm (IYTDLA) for insulator identification deep learning networks showed by [40]. It is possible to notice that the proposed IYTDLA delivered excellent results

Models	Faster R-CNN	EDET	TYTDLA	IYTDLA
Insulator AP%	90.25	89.85	97.57	96.20
Defect AP%	79.05	92.03	97.54	98.73
Broken AP%	78.93	76.50	80.14	83.13
mAP%	82.74	86.13	91.75	92.69
Reasoning speed/FPS	21	20	130	112

Figure 5 illustrates a point cloud analysis in the context of an electrical distribution system. The classification accuracies for transmission and power lines were 97.26% and 95.29%, respectively. The average classification accuracies of both lines and towers were 80.88% and 82.25%, respectively.

In the work of Yu et al. [43], the authors presented an electrical component recognition algorithm based on an improved YOLOv5s model. It incorporated self calibrated convolutions to enhance feature extraction and utilized Gamma transform for image preprocessing to improve the algorithm's robustness in handling overexposed and underexposed scenarios. Experimental results demonstrated that the proposed algorithm achieved real-time recognition of electrical components at the UAV's front end, with recognition accuracy exceeding 98% for various typical parts.

In the same context, the study proposed by Madaujo et al. [44] investigated the capability of the Single Shot Multibox Detector (SSD), a one-stage object detection model, to localize, detect, and classify faults, specifically focusing on missing insulators, broken insulators, rusty clamps, and broken fittings. Their proposed system comprised a convolutional neural network based on a multiscale layer feature pyramid network (FPN). Moreover, all presented networks exhibited high precision rates, confirming their overall effectiveness. A comparison was developed among different models, such as SSD Rest101, SSD Rest50, and SSD MobNet, to assess their performance in detecting faults in electricity transmission components. Among the three, SSD Rest50 achieved the highest mAP of 89.61%, outperforming both SSD Rest101 (mAP of 88.7%) and SSD MobNet (mAP of 82.98%).

The work presented by Yu et al. [45] introduced a deep learning algorithm based on YOLOv7. Their approach combined genetic hyperparameter optimization with spaceto-depth (SPD) convolution, differing from the previously proposed approaches. Aerial images were utilized as the framework for employing this proposed method. Results included a comparison of the improved YOLOv7 with other YOLO series algorithms, revealing that the proposed model achieved the highest mAP of 92.20%. Furthermore, the study demonstrated that the applied hyperparameter optimization significantly accelerated the model's convergence.

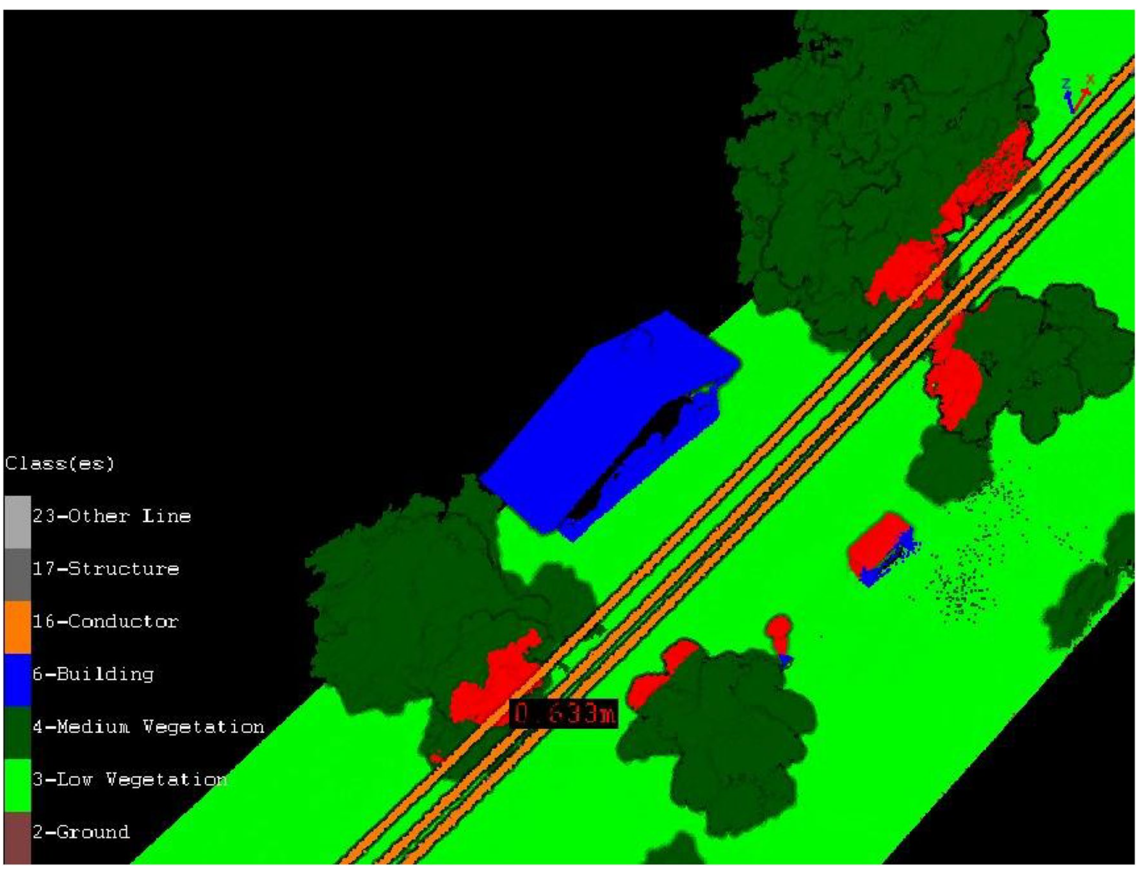


Fig. 5 The image depicts a point cloud classification within the context of an electrical distribution system. The classification identifies various elements, including low and medium vegetation, buildings, conductors, structures, and other lines. Additionally, a risk analysis has been performed, highlighting the areas closest to the system that pose potential risks. This classification and analysis were carried out using the LiPowerLine software

Another study that proposed a modified YOLO network, with particular emphasis on insulator detection, was presented by Souza et al. [46]. They incorporated a ResNet-18 classifier, which significantly enhanced network performance. For object detection, the modified model achieved an mAP of 99.26%, while in the context of multiclassification tasks, the network performed with an F1 score metric of 96.22%.

The work of Liu et al. [47] addressed the distinction between distant and close-up views by utilizing Mask R-CNN to detect various components of power transmission devices. It employed techniques such as edge processing, hole filling, and Hough Transform for wire identification at a distance. Major components such as poles, trusses, cross arms, and insulator strings were recognized with 100% accuracy. The proposed model exhibited high recognition speed and accuracy, making it a valuable tool to assist UAVs in conducting adequate inspections.

Finally, in Yu et al. [48], the authors employed three YOLO series target detection algorithms (YOLOv3, YOLOv5, and YOLOx) to identify pylons, insulator pollution, corrosion of insulator steel pin, and steel cap in images and text. Experimental results demonstrated that YOLOv5 outperforms the other algorithms, achieving a mAP50, which considers a detection to be correct if the IoU is equal to or greater than 50%, of 90.59%. These results validated the effectiveness and feasibility of the proposed fault detection method.

All reviews in this section were summarized and displayed in Table 2 for a broader view of the scenario explored in the general scope, elucidating up to this point the predominance of the use of RGB cameras, together with the preference for using the YOLOx algorithm for fault detection.

3.3 Insulator faults identification

Zhaohui et al. [49] automatized the identification of insulator faults using infrared images. The paper suggests that infrared images offer a more practical and effective framework for handling various issues. The proposed methodology comprises several modules, including surf feature points, K nearest neighbor matching, adaptive spatial clustering, and segmentation correction. The insulator temperatures are obtained through the proposed approach. The study demonstrated that the method can estimate fault diagnosis with good quality, though further improvements are needed.

In the work conducted by Han et al. [50], the authors presented a method to identify single and multiple insulator faults through aerial images captured by UAV. A complicating factor arises from background interference, which makes detection challenging. Additionally, the shapes of the insulators can vary considerably due to changes in filming angles and distances. To this end, the author comprehensively used deep neural networks for distinction. Aerial images of insulators are collected and manually labeled. Subsequently, they introduced a new convolutional network architecture designed to identify the positions of insulator chains in these images. Experimental results demonstrated that the method is more effective and efficient than other detection methods from time to time.

Table 2 Aspects of the reviewed literature on general methods to identify faults types in electrical power systems

References	Fault type	Sensors	Algorithm	Score (mAP/AP/F1/IoU)	Frame per seconds
[35]	–	RGB Camera	Hough Transform	–	–
[36]	Corridor	LiDAR	Novel	–	–
[37]	–	RGB Camera	–	–/–/38.3–84.3/–	–
[38]	Bolts, Insulators	RGB Camera	R-CNN, RetinaNet	–/96.7%, 97.9%/–/–	–
[39]	Insulator	RGB Camera	YOLOv3	–	–
[40]	Insulator	RGB Camera	YOLOv4	92.69%/–/–/–	112
[41]	Corridor	RGB Camera	Novel	–	–
[42]	Corridor	LiDAR	Novel	80.88–97.26%/–/–/79.66–80.09%	–
[43]	–	RGB Camera	YOLOv5	98%/–/–/–	–
[44]	–	RGB Camera	SSD	89.61%/–/–/–	–
[45]	Corridor	RGB Camera	YOLOv7	92.2%/–/–/–	–
[46]	Insulator	RGB Camera	YOLOv5	99.26%/–/96.21%/–	–
[47]	Corridor	RGB Camera	R-CNN	–/100%/–/–	–
[48]	Multiple components	RGB Camera	YOLO	90.59%/–/–/–	–

Another work addressing the insulator visual inspection issue was done by Yan et al. [51]. In their context, particular emphasis was placed on scenarios characterized by complex background pollution. The paper proposes a method based on convolutional neural networks (CNNs) for fault detection and recognition in transmission line insulators from images captured by drones equipped with high definition (HD) cameras. The system detects insulators in aerial images and identifies explosions using a CNN model trained for feature extraction, combined with a saliency map and a SOM (Self-Organizing Map) network for segmentation, in addition to using superpixel segmentation, contour detection, and other image techniques. The results show that the method reduces the error rate in insulator detection to 5.1% and achieves an accuracy of 82.5% in identifying explosions in complex scenarios, outperforming traditional approaches such as HOG (Histogram of Oriented Gradients) + SVM (Support Vector Machine) and DPM (Deformable Part Model). The study concludes that the use of CNNs significantly improves the efficiency of insulator inspection, allowing the automation of fault analysis and suggesting future improvements in system robustness and in the detection of other types of damage.

Hot spots are thermal faults usually caused by current leakage. Their occurrence in insulator-related problems is a topic of great attention.

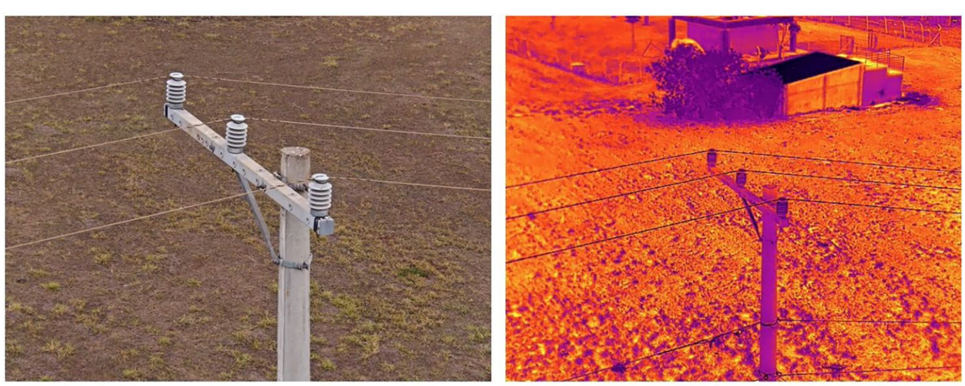
In Jalil et al. [52], the authors outlined a three-part method to detect hot spots in power overhead lines: sensor fusion, power line extraction, and fault detection. Initially, a fusion algorithm was presented to combine visible and infrared power line images, using manual control points as feature points and geometric transformations for image registration. Subsequently, power lines were extracted using Canny edge detection and Hough transform. The method effectively identifies edges with high accuracy from a series of frames. Finally, hot spots in power lines were identified using histogram-based thresholding after line detection.

The same research group proposed a fusion algorithm designed for infrared and visible power line images [53], which can maintain its effectiveness despite large-scale changes and variations in lighting conditions within real operational environments. To achieve this, they applied distinct image processing algorithms to visible and infrared thermal data, allowing them to track power lines and identify faults and anomalies. The method was highly proficient in accurately detecting edges and hot spots within a sequence of frames. Ultimately, the final step involved the identification of hot spots using thermal images.

An example of infrared image usage in the context of electrical distribution systems is shown in Fig. 6.

Another insulator defect detection is proposed in Liu et al. [54], addressing insulator detection in the presence of complex background interference. They present a deep learning model based on YOLO, explicitly using the YOLOv3-dense network to enhance feature reuse and propagation. A multiscale feature fusion structure is integrated into the model to accommodate different-sized insulators. Multilevel feature mapping captures semantic information from upper and lower layers. After training and comparing the improved YOLOv3 with several related networks, it achieved an average precision of 94.47%, surpassing YOLOv3 by 4.16% and YOLOv2 by 11.04%. Test results further validate the efficacy of the improvements.

In Yang et al. [55], on the other hand, the authors proposed a detection algorithm based on a deep cascade architecture to solve insulator defect detection problems due to shallow learning methods that rely on handcrafted image features targeting specific scenarios or prior knowledge. To this end, they proposed an insulator localization algorithm based on the improved YOLOV3 model to remove complex backgrounds. Then, they constructed a new semantic segmentation algorithm to perform defect segmentation for minor boundary fault defects. The results showed that the proposed algorithm meets the needs and is robust enough to inspect power lines.



a) b)

Fig. 6 An illustration of the main components of an electrical distribution system is presented. **a** On the left, the visible image provides a general view of the insulators, cross-arm, and overall tower top components. **b** On the right, an infrared image captures the same perspective, highlighting the thermal characteristics of each component within the structure

Insulators are essential components, and vibration dampers play a fundamental role in ensuring the proper functioning of the electrical network. In this context, Bao et al. [56] proposed an automated detection method for identifying component defects during UAV patrolling inspections. They compiled a dataset consisting of images captured by a UAV, specifically focusing on vibration dampers and insulators along overhead lines. The dataset comprised three types of insulators and four types of vibration dampers. To enhance detection, YOLOv5, equipped with a coordinate attention module, was employed to prioritize the features of vibration dampers and insulators while minimizing interference from complex backgrounds. In the feature fusion framework, a weighted Bidirectional Feature Pyramid Network (BiFPN) was utilized instead of the original Path Aggregation Network (PANet) to improve the network's capacity to detect small targets, such as vibration dampers. A comparative study was done to show the effectiveness of the proposed approach using the dataset obtained. An improvement of 2.7% higher than for YOLOv5 was obtained with the new method.

Figure 7 highlights an example of YOLO usage in the context of the identification of the electrical power system's main components.

In the work of Liu et al. [57], the issue of insulator defect detection was addressed using a deep learning approach based on image segmentation and object detection. The method combined the semantic segmentation network U-Segnet with the object detection model YOLOx. Notably, enhancements are made to the U-Segnet to account for complex backgrounds and larger image sizes. Furthermore, a residual network structure was added to the semantic segmentation network to address gradient dispersion issues that often lead to convergence problems. Through conducted tests, the accuracy was significantly improved to exceed 90%.

Zhang et al. [58] proposed a lightweight detection neural network for inspecting insulators in overhead transmission lines. In the proposed model, GhostNet-YOLOv4, a lightweight GhostNet with a complete convolution attention module (C-SE), replaced the original backbone of YOLOv4 for feature extraction. The obtained model met the computational requirements, detection accuracy, and processing speed for UAV inspection applications. The model achieved an average precision of 99.5% for detecting standard and defective insulators. The authors compared their results with the original YOLOv4 and other lightweight networks (different versions of MobileNet), confirming the proposed model's benefits and advantages.

The Table 3 lists the methods used and the results achieved in each work discussed in this section for better comparison. As can be seen, the dominance of the use of RGB cameras is still clear; however, the Novel algorithm now stands out over YOLOx and the others.

3.4 Small components faults identification

Chen [59] proposed an optimized method for diagnosing critical failures in small power transmission components using an enhanced YOLOv3 algorithm. The study aimed to address the low detection rate of small, hard-to-detect, and high-risk component failures during unmanned aerial vehicle (UAV) inspections. To achieve this, a Spatial Pyramid Pooling (SPP) network was integrated into the same convolutional layer, enabling multi-scale feature extraction without requiring image resizing, thereby preserving critical information. Furthermore, the original YOLOv3 scale prediction framework

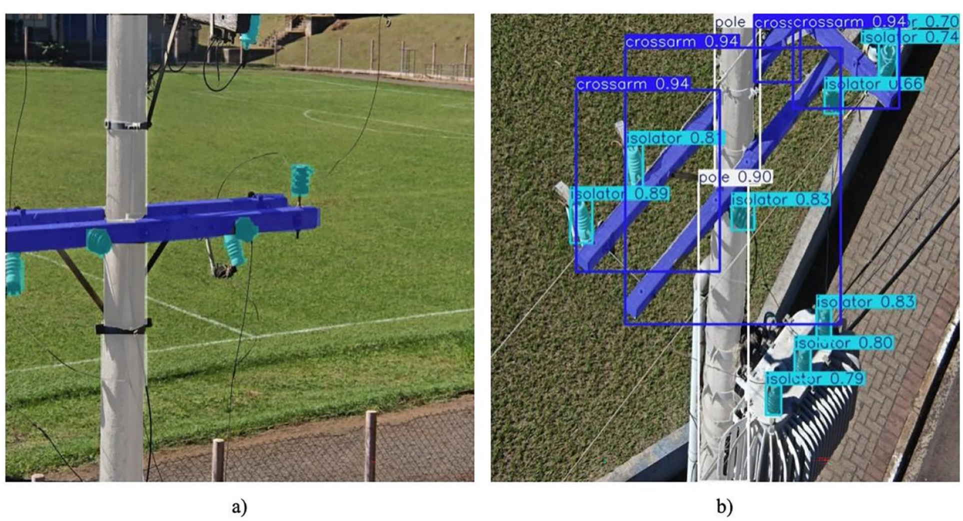


Fig. 7 A pre-trained YOLO algorithm is utilized to identify the main components of an electrical distribution system. **a** The first image demonstrates the segmentation of insulators, the main tower, and cross-bars, while **b** the second image both segments and detects these components, highlighting their positions and classifications within the system

Table 3 Aspects of the reviewed literature on insulator faults identification methods

References	Fault type	Sensors	Algorithm	Score (mAP/AP/F1/IoU)	Frame per seconds
[49]	Insulator	Thermal camera	Novel	–	–
[50]	Insulator	RGB camera	Novel	–	–
[51]	Insulator	RGB camera	Novel	–	–
[52]	Hot spots	RGB and thermal cameras	Novel	–	–
[53]	Hot spots, corridor	RGB and Thermal cameras	Novel	–/94.47%/–/–	–
[54]	Insulator	RGB camera	YOLOv3	94.47%/–/–/–	–
[55]	Insulator	RGB camera	YOLOv3	–/–/93.2%\–	–
[56]	Vibration dampers, insulators	RGB camera	YOLOv5	89.1%/–/–/–	–
[57]	Insulator	RGB camera	Novel	91.7%/–/–/92.3%	–
[58]	Insulator	RGB camera	YOLOv4	99.5%/–/–/–	–

was expanded from three to four scales, incorporating the concept of Feature Pyramid Networks (FPN). This enhancement ensured that both low-level image details and high-level semantic features were effectively retained, significantly improving the detection of small and otherwise undetectable faults. The effectiveness of the optimized algorithm was validated using a dataset comprising real-world images of electrical transmission components, specifically targeting small and difficult-to-detect faults. Experimental results demonstrated that the optimized YOLOv3 improved the average recognition rate of the selected categories by 3.98%. More notably, for smaller and less detectable defects, the recognition rate increased by 11.95%, highlighting the superior performance of the proposed approach compared to the original YOLOv3 algorithm.

Detecting defects on small cotter pins installed in electric power fittings is an essential part of the overhead line inspection task using Unmanned Aerial Vehicles.

In the work of Chaoyue et al. [60], the authors proposed a cascaded convolutional network to address the challenge posed by the small size of pins and the complex background of UAV images. The method was divided into two stages: positioning and diagnosis. Initially, an improved Faster R-CNN network, enhanced with a Feature Pyramid Network (FPN), was used to detect all fasteners, including cotter pins. The anchor box sizes were optimized using K-means clustering, improving small-object localization. In the second stage, a RetinaNet classifier was applied to diagnose pin defects, using Focal Loss to mitigate class imbalance and enhance detection accuracy. The method was validated on a UAV image dataset, where the Faster R-CNN achieved an AP of 0.889 for fastener localization, and RetinaNet reached an AP of 0.861 for defect detection. By combining multi-scale feature extraction, anchor box optimization, and a two-step detection approach, the proposed method significantly improved the accuracy of cotter pin defect identification in transmission line inspections.

Wu et al. [61] proposed a pin defect detection algorithm based on an improved Faster R-CNN model. Their approach began with transfer learning to pre-train weights with higher matching degrees. Additionally, a regional proposal network was employed to extract features from the model. Experimental results demonstrated the efficacy of the modified network, with a pin defect detection accuracy reaching up to 81.25%.

Jiao et al. [62] proposed a deep neural network called Camp-Net to detect defects in bolts. To this end, the Multi-scale feature merged deep and shallow characteristics to detect small-size bolts. A context information structure was used to mitigate the harmful effects of the complex background. A dataset was obtained by reuniting several UAV images from different sources. It is worth pointing out that more than one bolt was usually found in one image. The dataset contains 78,764 screw samples characterized as good and 19,356 screw samples as bad. Real-world tests were carried out, and the proposed method outperformed state-of-the-art methodologies. Some results showed that the Camp-Net network can be 11.4% larger than Faster R-CNN models.

In the study conducted by Gong et al. [63], they introduced an efficient and high-performance Defect Detection model named DDNet, designed to identify minor component defects in images captured by unmanned aerial vehicles. The improved detection model incorporated an attention mechanism to enhance the representation learning of images. Drawing inspiration from the human visual system, the Receptive Field Block (RFB) module was integrated into the Featured Pyramid Network (FPN) module, thereby expanding the receptive field of the entire detection network, which proved beneficial for detecting small objects. Subsequently, a dataset featuring cotter pins was introduced for model training and testing. The findings of the study revealed that the proposed DDNet significantly increased the average precision from 82.0 to 90.1% and concurrently reduced the defect detection miss rate from 14.5 to 7.4%. when compared to the baseline RetinaNet model, using the dataset presented in [63].

The authors also compared existing frameworks for object detection and discussed other common ways to improve precision. The optimized model from [63] enhanced detection performance, thereby substantiating the practicality and effectiveness of the proposed model.

Another commonly encountered fault concerns bird nests. Bird nests on electrical power towers have the potential to lead to bird flash accidents, posing a threat to the secure and dependable operation of the power grid. So, the objective of Ge et al. [64] was to develop an approach to detect bird's nest defects in transmission lines. The authors composed a dataset with 3695 aerial images of bird's nest defects. They also used YOLOv5 to identify and position the nests in real-time. The results indicated that the YOLOv5 model achieved a recognition rate of 83.4% for bird nests, with an accompanying frames per second (FPS) of 85.32%.

Wu and Wang [65] analyzed a corrosion detection method based on multiscale enhanced fusion. They introduced a novel approach named PWR-YOLOv5, built upon YOLOv5, and incorporated innovations such as the Pyramid Split Attention (PSA) mechanism, which enhanced the feature expression of corrosion targets, followed by the Weight Adaptive Path Aggregation Network (WA-PANet) and utilizing a Receptive Feature Enhancement Network (RFENet). These three components form the acronym PWR, which was incorporated into YOLOv5. Moreover, implementing the Efficient Intersection over Union (EIoU) Loss [66] optimized the cost function, improving positioning accuracy. PWR-YOLOv5 achieved an mAP of up to 95.37%, surpassing YOLOv5 by 5.22%. Overall, the proposed algorithm demonstrated strong performance.

Vieira et al. [67] highlighted that the scarcity of publicly available data related to power line assets hinders progress in this field. To address this gap, they introduced the STN (*Sistema de Transmissao Nordeste*) Power Line Assets Dataset, a comprehensive collection of high-resolution, real-world images featuring diverse high-voltage power line components. This dataset encompassed 2,409 annotated objects classified into five categories: electrical tower, insulator, spacer, tower plate, and Stockbridge damper.

These objects exhibited variations in size, orientation, illumination, angulation, and background. The study also conducted an evaluation of prevalent deep object detection methods alongside MS-PAD (Multi-Size Power line Asset Detection), a novel pipeline designed for detecting power line assets in high-resolution UAV images. MS-PAD demonstrated superior performance with an 89.2% mean average precision (mAP), indicating significant potential for enhancement. The STN PLAD dataset has been made publicly available to facilitate further research in this area.

Finally, the Table 4 shows the different solutions addressed by the papers for each specific component and compiles the results achieved by the authors.

Table 4 Aspects of the reviewed literature on small components faults identification methods

References	Fault type	Sensors	Algorithm	Score (mAP/AP/F1/IoU)	Frame per seconds
[59]	Small components	RGB camera	YOLOv3	89.6–96.5%/–/–/–	–
[60]	Pin	RGB camera	Novel	–	–
[61]	Insulator, pin, counterweight	RGB Camera	R-CNN	73.59%/81.25%/–/–	–
[62]	Bolts	RGB Camera	CampNet	80.5%/–/–/–	–
[63]	Pin	RGB camera	DDNet	90.1%/–/–/–	–
[64]	Nest	RGB camera	YOLOv5	83.4%/–/–/–	85.32
[65]	Corrosion	RGB camera	YOLOv5	95.37%/–/–/–	64.9
[67]	Multiple components	RGB camera	SSD and Faster R-CNN	89.2%/–/–/–	–

4 Conclusions

After summarizing several fundamental aspects related to the review, that were listed throughout Tables 2, 3 and 4, the examination has shed light on effectively detecting and identifying various fault types commonly found in power lines. These anomalies include faults in bolts and insulators, occurrences along the power line corridor, concerns with dampers, hot spots, and more.

The successful identification of these faults has been achieved by integrating cutting-edge technologies, including RGB and thermal cameras, LiDAR 3D, and applying deep learning and other computational vision methodologies. Notably, the remarkable performance achieved using the YOLO approach for fault detection is worth highlighting. Results showed good scores, around 90%.

The heatmap illustrated in Fig. 8 demonstrates the bias in research on fault detection on electrical power systems with UAVs. The illustration summarizes the different techniques used for the inspection of overhead lines. In essence, it points out the relationship between the types of faults to be detected with the sensors used by researchers and the algorithms to process them. Through this heatmap, it is possible to conclude in which areas there is a greater focus of research, where there is a more solid foundation to rely on, and where more innovation will be needed.

In Fig. 8, it is observed that most research focuses on using RGB Cameras in conjunction with the YOLO algorithm. The widespread use of visible cameras is strongly motivated by their low cost. Despite being cost-effective sensors, it is evident that they can be highly effective. Also, it can be observed from Fig. 8a that most works deal with failure detection in insulators using YOLO. However, other algorithms are also used significantly for the same purpose.

Figure 9 shows the relationship between the use of algorithms over the years. Firstly, it is essential to point out the increase in research in this area over the years, demonstrating the topicality of the theme. Secondly, it is worth highlighting that the sovereignty of using YOLO as the central failure identification algorithm is evident.

One of the most significant trends that can be observed is the recent exploration, dating back to 2017 according to our query. This indicates that considerable attention still needs to be devoted to this field of study, as it is in its early stages and requires further development.

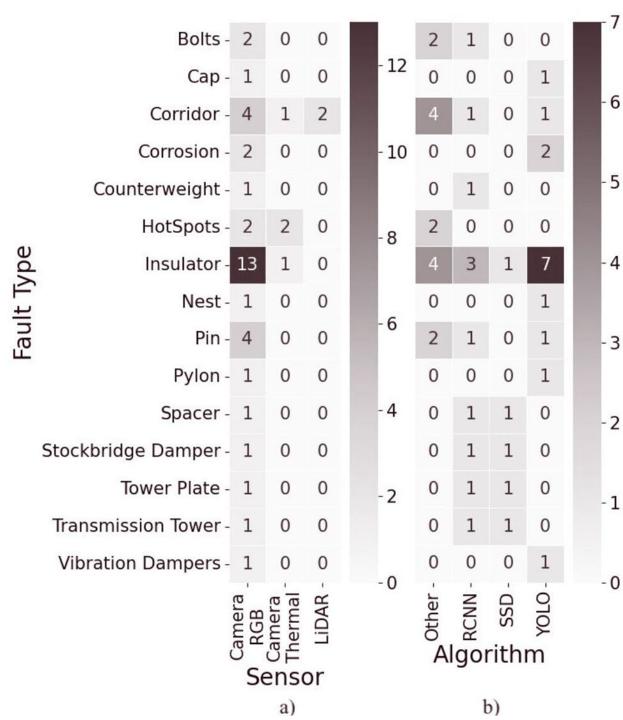


Fig. 8 A heatmap relating to fault type. **a** A heatmap relating the most commonly used sensors to their respective fault types shows that the visible camera is the prevailing sensor, and insulator faults are the most frequently detected. **b** A heatmap relating algorithms' usage to identify each fault type reveals that YOLO-based networks are the most commonly used. Furthermore, insulators are the most frequently identified objects

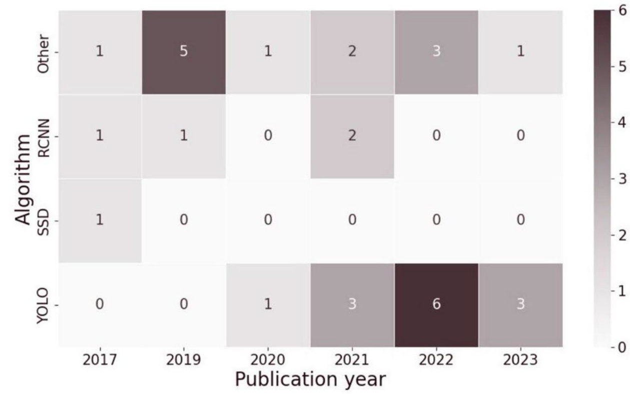


Fig. 9 A timely presentation on the usage of detection algorithms for fault identification, with recent prominence of YOLO bases networks

4.1 Literature gaps and future research

The works presented in this literature review underscore the identification of several areas for improvement. The authors' main findings and identified needs are compiled and reported accordingly based on a collection of themes, as expressed by Table 5.

The first identified area focuses on enhancing the accuracy of algorithms. This measure is crucial for accurately recognizing faults while ensuring a reliable operation. When hard real-time criteria are necessary, accuracy becomes paramount in the overall system recognition. Although more complex networks tend to deliver better results, they often come at the expense of high computational time costs. Exploring the use of a multi-sensor framework and filtering strategies may be a promising direction for further investigation.

One performance aspect that requires improvement is the recognition of faults in blurred images. Such blurring can be attributed to various factors, such as inadequate drone stabilization during image capture or adverse environmental conditions like fog. In addition to investigating suitable neural network architectures to tackle this issue, formulating a more precise and robust path-planning methodology emerges as a viable resolution.

Another consideration shown in the review is the necessity of establishing a more reliable framework to recognize multiple faults simultaneously. While some works have explored this issue, many networks were trained in the context of specific faults, such as insulator faults, and therefore need updating to recognize other components. Given that different components may vary in size and color, addressing a multitude of challenges is essential for providing a reliable operation to identify multiple faults. Once again, one potential solution may involve exploring a multi-sensor platform capable of offering a more comprehensive and detailed description of the environment.

The most frequently mentioned concern for future discussion was the real-time implementation of the proposed algorithms. Achieving precision in running the developed models requires substantial computational effort, posing a significant challenge for hard real-time operations. This effort may even suggest drone trajectory adjustments based on real-time data. Many of the reviewed works are currently addressing this common problem. Exploring both embedded solutions and algorithmic improvements are possible solutions.

Process automation also requires significant contributions. Currently, a standardized mission, starting with the UAV taking-off, proceeding to recognize one or multiple faults, and reporting back to the electrical system's operators,

Table 5 The identified literature gaps and future research directions are organized into six principal themes, each elucidated based on the analysis conducted by the works studied in this review

Theme	References
Algorithm accuracy	[36, 37, 40, 53, 59, 63]
Blurred objects	[50, 62, 63]
Multiple defects	[27, 44, 51, 56]
Real-time performance	[39, 42–46, 50, 51, 54]
Automation	[27, 38, 51]
Dataset	[44, 50, 52]

is only formulated in specific cases. An issue of interest could be to reconsider the pipeline used for helicopters, for example, and adapt it to the context of UAVs.

Lastly, enhancing the dataset with a greater variety of images is fundamental to ensure the qualified training of the developed neural networks. Similarly, developing techniques for data augmentation and automating the labeling of thousands of images is paramount for the further advancement of intelligent algorithms.

Author contributions Carlos A. Persiani F. contributed to conceptualization, methodology guidelines, screening and eligibility process, writing the original draft, and review and editing.Felipe M. Sallazar worked on conceptualization, figures composition, screening and eligibility process, methodology, and writing the original draft. Roberto S. Inoue provided supervision, contributed to screening and eligibility process, conceptualization, and writing review and editing. Valdir Grassi Jr. was involved in supervision, screening and eligibility process, conceptualization, and writing review and editing. Marco H. Terra contributed to supervision, conceptualization, and writing review and editing. Mário Oleskovicz participated in supervision, conceptualization, and writing review and editing. All authors read and approved the final manuscript.

Funding We gratefully acknowledge the support of the RCGI—Research Centre for Greenhouse Gas Innovation (23.1.8493.1.9), hosted by the University of Sao Paulo (USP), sponsored by FAPESP—São Paulo Research Foundation (2020/15230-5), and sponsored by Total Energies, and the strategic importance of the support given by ANP (Brazil's National Oil, Natural Gas and Biofuels Agency) through the R&DI levy regulation.

Availability of data and material No datasets were generated or analysed during the current study.

Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

References

1. Yang L, Fan J, Liu Y, Li E, Peng J, Liang Z. A review on state-of-the-art power line inspection techniques. IEEE Trans Instrum Meas. 2020;69(12):9350–65. https://doi.org/10.1109/TIM.2020.3031194.
2. Toussaint K, Pouliot N, Montambault S. Transmission line maintenance robots capable of crossing obstacles: state-of-the-art review and challenges ahead. J Field Robot. 2009;26(5):477–99. https://doi.org/10.1002/rob.20295.
3. Zengin AT, Erdemir G, Akinci TC, Seker S. Measurement of power line sagging using sensor data of a power line inspection robot. IEEE Access. 2020;8:99198–204. https://doi.org/10.1109/ACCESS.2020.2998154.
4. Alhassan AB, Zhang X, Shen H, Xu H. Power transmission line inspection robots: a review, trends and challenges for future research. Int J Electr Power Energy Syst. 2020;118:105862. https://doi.org/10.1016/j.ijepes.2020.105862.
5. Ali ZA, Deng D, Shaikh MK, Hasan R, Khan MA. AI-based UAV swarms for monitoring and disease identification of brassica plants using machine learning: a review. Comput Syst Sci Eng. 2024;48(1):1–34.
6. Martin L. Transmission structure risk management. IEEE Power Energ Mag. 2016;14(5 Supplement):28–33. https://doi.org/10.1109/MPAE.0.7564228.
7. Foudeh HA, Luk PC-K, Whidborne JF. An advanced unmanned aerial vehicle (UAV) approach via learning-based control for overhead power line monitoring: a comprehensive review. IEEE Access. 2021;9:130410–33. https://doi.org/10.1109/ACCESS.2021.3110159.
8. Hui X, Bian J, Yu Y, Zhao X, Tan M. A novel autonomous navigation approach for UAV power line inspection. In: 2017 IEEE international conference on robotics and biomimetics (ROBIO); 2017. pp. 634–9. https://doi.org/10.1109/ROBIO.2017.8324488.

9. Xie X, Liu Z, Xu C, Zhang Y. A multiple sensors platform method for power line inspection based on a large unmanned helicopter. Sensors. 2017;17(6):1222.
10. Ma Y, Li Q, Chu L, Zhou Y, Xu C. Real-time detection and spatial localization of insulators for UAV inspection based on binocular stereo vision. Remote Sens. 2021;13(2):230.
11. Jeong S, Kim D, Kim S, Ham J-W, Lee J-K, Oh K-Y. Real-time environmental cognition and sag estimation of transmission lines using UAV equipped with 3-D lidar system. IEEE Trans Power Deliv. 2021;36(5):2658–67. https://doi.org/10.1109/TPWRD.2020.3024965.
12. Kim S, Jeong S, Kim D, Jeon M, Moon J, Kim J-H, Oh K-Y. GPU-oriented environmental cognition of power transmission lines through LiDAR equipped UAVs. IEEE Syst J. 2022;16(3):4541–51. https://doi.org/10.1109/JSYST.2021.3100278.
13. Zhou Y, Xu C, Dai Y, Feng X, Ma Y, Li Q. Dual-view stereovision-guided automatic inspection system for overhead transmission line corridor. Remote Sens. 2022;14(16):4095.
14. Yakkati RR, Pardhasaradhi B, Yeduri SR, Pandey OJ, Cenkeramaddi LR. Power transmission line classification from images using pre-trained deep learning models. In: 2022 IEEE international symposium on smart electronic systems (iSES) (2022), pp. 394–397. https://doi.org/10.1109/iSES54909.2022.00086
15. Li Z, Wang Q, Zhang T, Ju C, Suzuki S, Namiki A. UAV high-voltage power transmission line autonomous correction inspection system based on object detection. IEEE Sens J. 2023;23:10215–30.
16. Gugan G, Haque A. Path planning for autonomous drones: challenges and future directions. Drones. 2023;7(3):169. https://doi.org/10.3390/drones7030169.
17. Liu C-A, Dong R, Wu H, Yang G-T, Lin W. A 3-D laboratory test-platform for overhead power line inspection. Int J Adv Rob Syst. 2016;13(2):72.
18. Schofield, O., Lorenzen, K., Ebeid, E.S.M.: Cloud to cable: a drone framework for autonomous power line inspection, pp. 503–509 (2020). https://doi.org/10.1109/DSD51259.2020.00085.
19. Xu C, Li Q, Zhou Q, Zhang S, Yu D, Ma Y. Power line-guided automatic electric transmission line inspection system. IEEE Trans Instrum Meas. 2022;71:1–18.
20. Ahmed MF, Mohanta J, Sanyal A. Inspection and identification of transmission line insulator breakdown based on deep learning using aerial images. Electric Power Syst Res. 2022;211: 108199.
21. Ahmed MF, Mohanta J, Sanyal A, Yadav PS. Path planning of unmanned aerial systems for visual inspection of power transmission lines and towers. IETE J Res 1–21 (2023)
22. Shuai C, Wang H, Zhang W, Yao P, Qin Y. Binocular vision perception and obstacle avoidance of visual simulation system for power lines inspection with UAV. In: 2017 36th Chinese control conference (CCC); 2017. pp. 10480–5. https://doi.org/10.23919/ChiCC.2017.8029026.
23. Cakır A, Akpancar S. ROS-based control of the DJI matrice 100 robot with qr images obtained from DJI guidance. Int J Eng Trends Technol. 2020.
24. Silano G, Baca T, Penicka R, Liuzza D, Saska M. Power line inspection tasks with multi-aerial robot systems via signal temporal logic specifications. IEEE Robot Autom Lett. 2021;6(2):4169–76. https://doi.org/10.1109/LRA.2021.3068114.
25. Fu J, Nunez A, De Schutter B. Real-time UAV routing strategy for monitoring and inspection for postdisaster restoration of distribution networks. IEEE Trans Ind Inf. 2022;18(4):2582–92. https://doi.org/10.1109/TII.2021.3098506.
26. SciVal Platform. https://www.scival.com.
27. Luo Y, Yu X, Yang D, Zhou B. A survey of intelligent transmission line inspection based on unmanned aerial vehicle. Artif Intell Rev. 2023;56(1):173–201.
28. Xu B, Zhao Y, Wang T, Chen Q. Development of power transmission line detection technology based on unmanned aerial vehicle image vision. SN Appl Sci. 2023. https://doi.org/10.1007/s42452-023-05299-7.
29. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, Shamseer L, Tetzlaff JM, Akl EA, Brennan SE, et al. The prisma 2020 statement: an updated guideline for reporting systematic reviews. Int J Surg. 2021;88:105906.
30. Benos L, Tagarakis AC, Dolias G, Berruto R, Kateris D, Bochtis D. Machine learning in agriculture: a comprehensive updated review. Sensors. 2021;21(11):3758. https://doi.org/10.3390/s21113758.
31. Montalvo-Romero N, Montiel-Rosales A, Purroy-Vasquez R, Quechulpa P. Agro-technological systems in traditional agriculture assistance: a systematic review. IEEE Access. 2023;11:123047–69.
32. Alharbi S, Alrazgan M, Alrashed A, Alnomasi T, Almojel R, Alharbi R, Alharbi S, Alturki S, Alshehri F, Almojil M. Automatic speech recognition: systematic literature review. IEEE Access. 2021;9:131858–76.
33. Chukwu E, Garg L. A systematic review of blockchain in healthcare: frameworks, prototypes, and implementations. IEEE Access. 2020;8:21196–214.
34. Gohari A, Ahmad AB, Rahim RBA, Supaat A, Abd Razak S, Gismalla MSM. Involvement of surveillance drones in smart cities: a systematic review. IEEE Access. 2022;10:56611–28.
35. Huiying D, Tingting H. Transmission line extraction method based on hough transform. In: The 27th Chinese control and decision conference (2015 CCDC) (IEEE, 2015), pp. 4892–4895
36. Azevedo F, Dias A, Almeida J, Oliveira A, Ferreira A, Santos T, Martins A, Silva E. Real-time LiDAR-based power lines detection for unmanned aerial vehicles. In: 2019 IEEE international conference on autonomous robot systems and competitions (ICARSC); 2019. pp. 1–8.
37. Wang L, Chen Z, Hua D, Zheng Z. Semantic segmentation of transmission lines and their accessories based on UAV-taken images. IEEE Access. 2019;7:80829–39.
38. Odo A, McKenna S, Flynn D, Vorstius JB. Aerial image analysis using deep learning for electrical overhead line network asset management. IEEE Access. 2021;9:146281–95. https://doi.org/10.1109/ACCESS.2021.3123158.
39. Renwei T, Zhongjie Z, Yongqiang B, Ming G, Zhifeng G. Key parts of transmission line detection using improved YOLOv3. Int Arab J Inf Technol. 2021;18(6):747–54.
40. Zan W, Dong C, Zhao J, Hao F, Lei D, Zhang, Z.: Defect identification of power line insulator based on an improved YOLOv4-tiny algorithm. In: 2022 5th International conference on renewable energy and power engineering (REPE); 2022. pp. 35–9.
41. Vemula S, Frye M. Multi-head attention based transformers for vegetation encroachment over powerline corriders using UAV. In: 2021 IEEE/AIAA 40th digital avionics systems conference (DASC); 2021. pp. 1–5. https://doi.org/10.1109/DASC52595.2021.9594293.

42. Su C, Wu X, Guo Y, Lai CS, Xu L, Zhao X. Automatic multi-source data fusion technique of powerline corridor using UAV LiDAR. In: 2022 IEEE international smart cities conference (ISC2); 2022. pp. 1–5. https://doi.org/10.1109/ISC255366.2022.9922293.
43. Yu X, Liu T, Zhang F, Liu L, Liu Y, Yuan Y, Yang R, Jiang K, Wang T, Zhang L. Research on front-end electrical component recognition algorithm based on improved YOLOv5s. In: 2022 4th international academic exchange conference on science and technology innovation (IAECST); 2022. pp. 35–40.
44. Maduako I, Igwe CF, Abah JE, Onwuasaanya OE, Chukwu GA, Ezeji F, Okeke FI. Deep learning for component fault detection in electricity transmission lines. J Big Data. 2022;9(1):1–34.
45. Yu C, Liu Y, Zhang W, Zhang X, Zhang Y, Jiang X. Foreign objects identification of transmission line based on improved YOLOv7. IEEE Access; 2023.
46. Souza BJ, Stefenon SF, Singh G, Freire RZ. Hybrid-YOLO for classification of insulators defects in transmission lines based on UAV. Int J Electr Power Energy Syst. 2023;148:108982.
47. Liu Y, Huo H, Fang J, Mai J, Zhang S. UAV transmission line inspection object recognition based on mask R-CNN. J Phys Conf Ser. 2019;1345(6):062043. https://doi.org/10.1088/1742-6596/1345/6/062043.
48. Yu C, Shi J, Yang X, Liu M, Zhang D, Shi L, Zhang C, Gao M, Ma H. Power transmission fault detection method based on UAV and YOLOs algorithms. In: 2022 IEEE 8th international conference on computer and communications (ICCC); 2022. pp. 2144–50.
49. Zhaohui L, Weiping F, Zihui Y, Yunpeng L, Jiangwei W, Shaotong P. Insulator identification method based on infrared image. In: 2017 IEEE international conference on smart grid and smart cities (ICSGSC) (IEEE, 2017), pp. 137–141
50. Han, J., Yang, Z., Zhang, Q., Chen, C., Li, H., Lai, S., Hu, G., Xu, C., Xu, H., Wang, D., Chen, R.: A method of insulator faults detection in aerial images for high-voltage transmission lines inspection. Applied Sciences **9**(10) (2019) https: //doi.org/https://doi.org/10.3390/app9102009
51. Yan B, Chen Q, Ye R, Zhou X. Insulator detection and recognition of explosion based on convolutional neural networks. Int J Wavelets Multiresolut Inf Process. 2019;17(02):1940008.
52. Jalil B, Pascali MA, Leone GR, Martinelli M, Moroni D, Salvetti O. To identify hot spots in power lines using infrared and visible sensors. In: Multimedia and network information systems: proceedings of the 11th international conference MISSI 2018 11 (Springer, 2019), pp. 313–321
53. Jalil B, Pascali M, Leone G, Martinelli M, Moroni D, Salvetti O, Berton A. Visible and infrared imaging based inspection of power installation. Pattern Recognit Image Anal. 2019;29:35–41.
54. Liu C, Wu Y, Liu J, Sun Z. Improved YOLOv3 network for insulator detection in aerial images with diverse background interference. Electronics. 2021;10(7):771.
55. Yang L, Gu Y, Wu M, Liu Y. An intelligent fault location algorithm of high voltage lines using cascading deep network. In: Proceedings of the 7th international conference on robotics and artificial intelligence (2021), pp. 99–105
56. Bao W, Du X, Wang N, Yuan M, Yang X. A defect detection method based on BC-YOLO for transmission line components in UAV remote sensing images. Remote Sens. 2022. https://doi.org/10.3390/rs14205176.
57. Liu S, Xiao J, Hu X, Pan L, Liu L, Long F. Defect insulator detection method based on deep learning. In: 2022 IEEE 17th conference on industrial electronics and applications (ICIEA) (IEEE, 2022), pp. 1622–1627
58. Zhang S, Qu C, Ru C, Wang X, Li Z. Multi-objects recognition and self-explosion defect detection method for insulators based on lightweight GhostNet-YOLOv4 model deployed onboard UAV. IEEE Access. 2023;11:39713–25. https://doi.org/10.1109/ACCESS.2023.3268708.
59. Chen JC. Critical fault diagnosis method of small components of power transmission based on optimizational YOLOv3 algorithm. J Phys Conf Ser. 2020;1619:012001.
60. Chaoyue G, Zhe L, Jintao S, Gehao S, Xiuchen J. Pin defect detection method of UAV patrol overhead line based on cascaded convolution network. J Phys Conf Ser. 2020;1659:012021.
61. Wu J, Cheng S, Pan S, Xin W, Bai L, Fan L, Dong X. Detection method based on improved faster R-CNN for pin defect in transmission lines. In: E3S web of conferences, vol. 300 (EDP Sciences, 2021), p. 01011.
62. Jiao R, Liu Y, He H, Ma X, Li Z. A deep learning model for small-size defective components detection in power transmission tower. IEEE Trans Power Deliv. 2022;37(4):2551–61. https://doi.org/10.1109/TPWRD.2021.3112285.
63. Gong Y, Zhou W, Wang K, Wang J, Wang R, Deng H, Liu G. Defect detection of small cotter pins in electric power transmission system from UAV images using deep learning techniques. Electr Eng. 2023;105(2):1251–66.
64. Ge Z, Li H, Yang R, Liu H, Pei S, Jia Z, Ma Z. Bird's nest detection algorithm for transmission lines based on deep learning. In: 2022 3rd international conference on computer vision, image and deep learning and international conference on computer engineering and applications (CVIDL and ICCEA) (2022), pp. 417–420. https://doi.org/10.1109/CVIDLICCEA56201.2022.9824057
65. Wu J, Sun Y, Wang X, et al. Corrosion detection method of transmission line components in mining area based on multiscale enhanced fusion. Mobile Inf Syst. 2022;2022:1–12.
66. Zhang YF, Ren W, Zhang Z, Zhen J, Liang W, Tieniu, T. Focal and efficient iou loss for accurate bounding box regression (2021). arXiv:2101.08158
67. Silva ALB, Castro Felix H, Menezes Chaves T, Simões FPM, Teichrieb V, Santos MM, Cunha Santiago H, Sgotti VAC, Neto HBDTL. Stn plad: a dataset for multi-size power line assets detection in high-resolution UAV images. In: 2021 34th SIBGRAPI conference on graphics, patterns and images (SIBGRAPI) (2021), pp. 215–222. https://doi.org/10.1109/SIBGRAPI54419.2021.00037