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Machine learning based power insulation fault detection using unmanned aerial vehicle images: A systematic review

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ABSTRACT

Insulators are critical components in power transmission systems, ensuring electrical stability and preventing current leakage to supporting structures. Faults in these components can cause power outages, equipment failures, and safety hazards. Traditional fault detection methods, such as manual visual inspection, are time-consuming, error-prone, and inefficient for large-scale grid monitoring. This systematic review explores recent advancements in power insulator fault detection using unmanned aerial vehicles (UAVs) integrated with advanced imaging systems and machine learning (ML) techniques. UAVs equipped with binocular vision and high-resolution cameras enable multi-angle, high-fidelity imaging of insulators in remote and hazardous environments. The review examines various ML and deep learning approaches, particularly convolutional neural networks (CNNs), for detecting cracks, contamination, and surface anomalies in aerial imagery. It also addresses key limitations, such as the lack of annotated datasets, weak model generalization under variable conditions, and challenges in real-time deployment due to computational constraints. A comparative analysis of existing techniques is presented, highlighting accuracy, scalability, and application readiness. Finally, the study identifies future research opportunities, including lightweight model design, multi-sensor data fusion, and explainable AI integration. The goal is to enhance fault detection reliability, reduce operational costs, and promote the intelligent maintenance of power transmission infrastructure.

Contribution/ Originality: This study is one of the few investigations that have examined UAV-based power insulator fault detection through a systematic review, highlighting the role of binocular vision systems, lightweight deep learning models, and dataset limitations. The paper provides the first consolidated analysis of hybrid machine learning approaches tailored for real-time aerial inspection.

1. INTRODUCTION

Power grid infrastructure plays a crucial role in ensuring uninterrupted electricity supply, supporting critical sectors such as industry, healthcare, and residential areas. Power transmission systems consist of various components, and insulators are essential elements that prevent the flow of electrical current to supporting structures. However, these insulators are susceptible to faults that can compromise the reliability and safety of the grid [1]. Insulator faults can lead to electrical breakdowns, power outages, and pose risks to personnel and equipment. Timely and accurate detection of insulator faults is essential for effective maintenance and prevention of electrical faults.

Traditional drone detection and recognition methods mainly rely on manual feature extraction [2], which requires a significant amount of time and effort and cannot handle all complex situations. However, in recent years, with the rapid development of deep learning [3], drone detection and recognition technology based on deep learning has made significant progress. The key feature of deep learning is that its algorithm models can autonomously learn features without relying on manual extraction. Deep learning-based methods have greatly improved the accuracy and efficiency of drone detection and recognition and can handle various complex situations. From the perspective of different types of drone data, drone detection and recognition can be divided into methods based on audio, vision, radar, and radio frequency [4]. Drone audio detection and recognition utilize environmental audio signals for perception and employ neural network classifiers to automatically identify drone audio signals [5]. However, various noises and interference signals in real environments can impair the performance of drone audio detection and recognition. To address this, the literature [5] proposed a result-level fusion convolutional neural network for drone audio detection. Image data contains rich visual information and can capture the appearance features of drones. Therefore, researchers have constructed neural networks to train drone visual datasets, enabling the detection and identification of drones [6]. However, in certain scenarios, the high-speed movement of drones presents significant challenges to image detection, because even if the drone is very close, timely countermeasures may not be possible due to delayed responses. To address these issues, the literature [7] proposed a detection method based on heat maps. The metal structure and body shape of drones typically cause reflection of radar waves, creating a unique echo signal that can be used to distinguish drones from other non-target objects. Consequently, some researchers have attempted to utilize radar signals for drone detection and identification [8]. However, due to the small size of the target drone, this results in the radar signal being unable to effectively cover the drone. Unlike the above methods, drone RF detection and identification have good stability in propagation, are not easily affected by the environment, and have high real-time performance. For example, the literature [9] proposed a method for classifying UAV radio frequency signals based on deep learning, and achieved a recognition rate of 95% on a real UAV dataset. It can be seen that the deep learning method has good adaptability in detection and recognition in different scenarios, especially the method based on radio frequency data has better performance and stronger robustness in UAV detection and recognition. In summary, the research on UAV detection and recognition based on deep learning has important theoretical significance and application value. This paper first clarifies the definition of UAV detection and recognition, as well as the research status of traditional methods in this field. Then, the research significance and importance of deep learning in UAV detection and recognition are analyzed. Subsequently, UAV detection and recognition are classified and reviewed according to different data types, and the principles, advantages, and disadvantages of various technologies are discussed. Finally, the current problems are analyzed, and future research directions and development trends are prospected.

The integration of acquisition systems with machine learning techniques has shown great potential in improving the reliability and efficiency of power insulator fault detection [10]. However, several research challenges remain to be addressed. These challenges include limited annotated datasets for training and evaluation [11], ensuring the generalization and robustness of fault detection models to different environmental conditions and insulator types [12], real-time processing and analysis of acquired images [8], and interoperability with existing power grid systems [13].

Power insulators are critical components in power transmission systems that serve the important function of maintaining electrical insulation and providing support for the conductors [14]. These insulators are strategically placed along the power lines and are designed to prevent the flow of electrical current to the supporting structures, thus ensuring safe and efficient electricity transmission. Power insulators are constructed from materials with high dielectric strength, which is the ability to withstand high voltage without allowing electrical current to pass through [15]. The choice of power insulator material depends on factors such as operating voltage, environmental conditions, and mechanical requirements. Common materials used for power insulators include porcelain, glass, and composite materials.

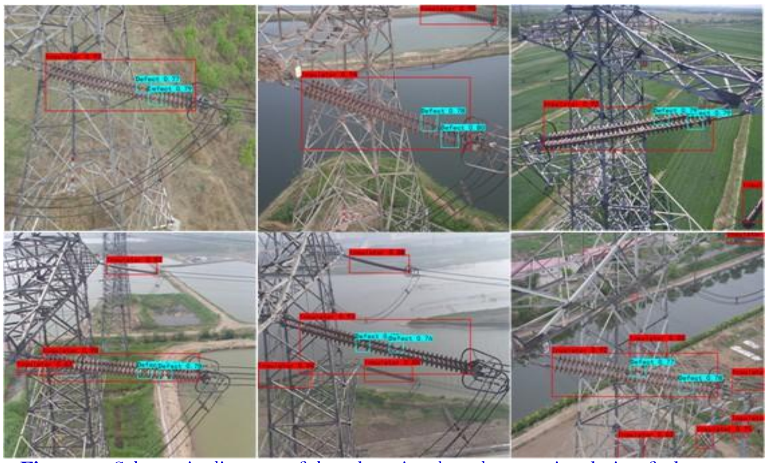

Figure 1. Schematic diagram of deep learning-based power insulation fault target detection using UAV images.

Power insulation faults refer to any anomalies or defects in the insulator's structure or performance that compromise its ability to insulate electrical current effectively [16]. These faults can occur due to various reasons, including mechanical stress, aging, contamination, or manufacturing defects. Common types of power insulation faults include cracks, flashovers, contamination, leakage, and perforations. As shown in Figure 1, timely detection and resolution of these faults are critical to preventing electrical failures, power outages, and ensuring the safe operation of power transmission systems. Fault detection in power insulators is essential to maintaining the reliability and safety of power transmission systems. Timely detection of insulation faults allows for timely maintenance interventions, preventing potential electrical failures and minimizing the risk of power outages [17]. By identifying and resolving faults as early as possible, power companies can ensure uninterrupted power supply, reduce downtime, and improve the overall efficiency of the power grid [18]. Fault detection also helps prevent safety hazards and protect personnel, equipment, and the surrounding environment [19]. To address these challenges and create opportunities for future developments in power insulator fault detection, this review aims to provide a comprehensive analysis of acquisition systems and deep learning methods in this field. By exploring the significance of using UAV binocular vision methods to acquire fault images and investigating various machine learning techniques for fault detection, this research article sheds light on the current state of the field and identifies areas for further exploration and innovation. The outcomes of this study are expected to optimize power grid maintenance procedures, increase the precision of fault detection, and finally enhance the dependability and security of power transmission systems.

To address these challenges and create opportunities for future developments in power insulator fault detection, this review aims to provide a comprehensive analysis of acquisition systems and deep learning methods in this field. By exploring the significance of using UAV binocular vision methods to acquire fault images and investigating various machine learning techniques for fault detection, this research article sheds light on the current state of the field and identifies areas for further exploration and innovation. The outcomes of this study are expected to optimize power grid maintenance procedures, increase the precision of fault detection, and finally enhance the dependability and security of power transmission systems.

Based on the above aims, this review seeks to answer the following research questions:

(1) What are the current technologies and methodologies used in UAV-based power insulator fault detection?

(2) How effective are machine learning and deep learning approaches in identifying and classifying faults from aerial images?

(3) What are the major limitations and open research challenges in this domain?

To address these questions, the remainder of the paper is structured as follows: Section 2 presents a comprehensive literature review covering UAV imaging, machine learning techniques, and deep learning-based detection methods. Section 3 outlines the review methodology. Section 4 introduces public datasets relevant to power insulator fault detection. Section 5 presents a comparative analysis of existing detection methods, while Section 6 highlights current technological and deployment challenges. Section 7 discusses open research challenges in drone-based object detection. Section 8 proposes future research directions. Section 9 presents an in-depth discussion of findings, and Section 10 concludes the study with key takeaways, limitations, and implications for future research.

2. LITERATURE REVIEW

2.1. Manual Inspection Methods and Their Limitations

The application of unmanned aerial vehicles (UAVs) in the domain of power infrastructure inspection has gained significant momentum due to the increasing need for efficient, safe, and scalable solutions for monitoring high-voltage transmission lines and associated components. Among the most critical elements in these systems are power insulators, which provide essential electrical insulation and mechanical support. Faults in these insulators can lead to power outages, system failures, and severe safety risks. Consequently, timely and accurate fault detection has become a central focus of academic and industrial research.

Initial approaches to fault detection were primarily based on manual inspection techniques, such as ground patrols and aerial surveillance using binoculars or infrared cameras mounted on helicopters. Although these methods were widely adopted, they were time-consuming, labor-intensive, and posed safety risks to field personnel. Additionally, manual inspections were limited in their ability to access remote or hazardous locations and were prone to human error and inconsistency. These limitations underscored the need for more automated, accurate, and scalable inspection solutions, ultimately paving the way for UAV-based monitoring.

2.2. UAV-Based Imaging and the Rise of Automated Inspection

The advent of UAV technology introduced a transformative shift in power insulator inspection, enabling high-resolution imaging and flexible data acquisition across a variety of terrains and altitudes. Drones equipped with advanced cameras, including binocular vision systems, have demonstrated the ability to capture detailed images of insulator surfaces from multiple perspectives. This advancement facilitates comprehensive visual analysis and supports automated detection workflows.

With the proliferation of UAV-based inspections, large-scale aerial image datasets have become available, allowing researchers to apply computer vision and machine learning techniques for automated fault identification. Early studies focused on collecting and annotating such datasets, laying the groundwork for developing intelligent models capable of distinguishing between normal and defective insulators. These datasets played a crucial role in training both traditional and deep learning models and are now seen as indispensable assets for model development and validation.

2.3. Traditional Machine Learning Approaches

Before the widespread adoption of deep learning, traditional machine learning methods were extensively employed for automated fault detection using UAV-captured images. These approaches relied on manual feature engineering, where experts extracted specific image characteristics such as texture patterns, shape descriptors, and color histograms. These handcrafted features were then fed into classifiers such as support vector machines (SVM), decision trees, k-nearest neighbors (KNN), and random forests to distinguish between normal and faulty insulator conditions. While these models offered moderate accuracy and were relatively easier to train with limited data, they often lacked robustness in complex environments. Factors such as changing lighting conditions, occlusions, image noise, and varying backgrounds significantly impacted the reliability of these models. Moreover, manual feature extraction was time-consuming and lacked adaptability, especially when dealing with diverse fault types or image distortions. These shortcomings highlighted the need for more flexible and scalable solutions.

2.4. Deep Learning for Power Insulator Fault Detection

Deep learning has emerged as a powerful alternative to traditional approaches by enabling models to automatically learn hierarchical features directly from raw image data. Convolutional Neural Networks (CNNs) have been widely used to classify, segment, and localize faults in power insulators with higher accuracy. Architectures such as VGGNet, ResNet, U-Net, and YOLO have demonstrated strong performance in detecting various fault types, including cracks, contamination, flashovers, and surface erosion.

To enhance model effectiveness, these architectures are often combined with image preprocessing techniques like contrast adjustment, noise filtering, and sharpening. Furthermore, recent studies have integrated attention mechanisms to focus on relevant fault regions and improve localization. Transfer learning strategies have also been adopted to address the challenge of limited training data by leveraging pre-trained models on large image datasets. In addition, lightweight model designs are being developed to support real-time deployment on UAV platforms with limited computational resources.

2.5. Challenges in Dataset Quality and Generalization

A major barrier to advancing power insulator fault detection using UAV imagery is the lack of large, diverse, and annotated datasets. Many existing datasets are either too small or limited to specific fault types, insulator materials, or environmental conditions. This restricts the ability of models to generalize across real-world variations, such as lighting differences, background clutter, or diverse geographic regions. Moreover, imbalanced datasets, where certain fault types are significantly underrepresented, hinder the training process and skew model predictions toward the majority classes.

Several efforts have attempted to address these issues through techniques such as data augmentation, synthetic dataset generation, and simulation-based image creation. Although these strategies help expand dataset diversity and volume, synthetic data often lacks the complexity and randomness present in real-world scenarios. As a result, models trained on such data may not perform consistently when deployed in practical environments. Therefore, building comprehensive, domain-specific datasets that reflect real operational conditions remains a critical need in this field.

2.6. Real-Time Deployment and System Integration

Integrating deep learning models into UAV-based inspection systems introduces additional challenges related to real-time processing, computational efficiency, and system interoperability. UAVs have constraints on onboard processing power and battery life, which limit the feasibility of deploying large and complex models in real-time scenarios. To address this, lightweight neural architectures and optimized inference frameworks are being developed to balance accuracy with processing efficiency.

Furthermore, for UAV-based fault detection systems to be practically adopted by utility providers, seamless integration with existing monitoring and maintenance workflows is essential. This includes ensuring data interoperability with SCADA systems, supporting geo-tagged fault reporting, and adhering to operational safety and regulatory requirements. Research is ongoing to enhance model interpretability, reduce false positives, and streamline decision-making processes, thereby facilitating smarter grid maintenance through UAV-based automation.

2.7. Future Directions and Research Opportunities

While substantial advancements have been made in UAV-based power insulator fault detection, several research directions remain open. One key area is the development of more robust and generalizable deep learning models capable of maintaining high performance across diverse environmental conditions, insulator types, and fault categories. Leveraging transfer learning, ensemble methods, and domain adaptation can further improve the adaptability of models to unseen scenarios.

Another important direction is the design of explainable AI (XAI) frameworks that provide transparent insights into model decisions. As these systems become part of critical infrastructure, interpretability is crucial for gaining trust and ensuring operational safety. In addition, the use of multi-modal data such as combining visual imagery with infrared, thermal, or LiDAR inputs could enhance detection accuracy and fault classification capabilities.

Moreover, the application of edge computing and federated learning may offer solutions for processing constraints and data privacy. These techniques allow for real-time inference directly on the UAV or in decentralized systems without the need for continuous data transmission. Finally, the creation of standardized benchmarks and evaluation protocols for UAV-based power inspection tasks will help unify future research efforts and accelerate progress toward practical, scalable solutions.

3. METHODOLOGY

This review systematically investigates the use of unmanned aerial vehicles (UAVs) and machine learning-based estimation methods for power insulator fault detection. Most of the reviewed studies collect data using UAVs equipped with high-resolution monocular or binocular cameras, which enable the capture of aerial images of power infrastructure from various angles and altitudes. These visual datasets are designed to capture subtle faults such as cracks, flashovers, and contamination under different environmental conditions.

The collected images are typically preprocessed using techniques such as denoising, contrast enhancement, segmentation, and resizing to optimize them for learning models. Image annotation is performed either manually or using automated tools to ensure reliable ground-truth labeling for supervised learning.

For estimation, a variety of techniques are employed across the reviewed literature. These include traditional machine learning algorithms (e.g., support vector machines, decision trees, random forests) and deep learning architectures such as convolutional neural networks (CNNs), You Only Look Once (YOLOv5), Fast R-CNN, and autoencoders. Hybrid approaches that integrate handcrafted features with deep learning frameworks are also explored to enhance accuracy, efficiency, and interpretability.

Unlike earlier reviews that primarily focused on algorithmic performance, the present study adopts a broader perspective. It highlights the entire fault detection pipeline from UAV image acquisition and preprocessing to fault estimation and considers critical deployment challenges. Emphasis is placed on binocular vision systems, dataset limitations, lightweight model architectures for real-time UAV processing, and hybrid learning frameworks. This holistic review offers valuable insights for developing robust, scalable, and real-world deployable inspection systems.

4. DATA ACQUISITION APPROACH FOR POWER INSULATOR FAULT SAMPLE

The purpose of obtaining samples of power insulator faults is to detect and fix potential problems early to maintain the safe and reliable operation of the power system. Since this review paper centers on machine learning approaches for effective insulator fault detection using aerial images, this section will provide a review of the data acquisition approach for aerial images. The data acquisition approach involves eight stages: aerial image capturing, image pre-processing, dataset construction, data labeling, data partitioning, simulation-based power insulator fault dataset, laboratory testing, and data augmentation.

4.1. Aerial Image Capturing

There are several advantages to using drones with binocular vision for aerial inspection of power insulators. Drones equipped with binocular cameras can capture images from all angles, providing a three-dimensional view of the insulators [20], allowing for precise detection of surface conditions and faults. Drones offer remote and efficient inspection capabilities, reducing the risks and costs associated with manual inspections [21] and can operate in challenging terrains and hard-to-reach locations, ensuring comprehensive coverage of grid infrastructure. However, drone-based inspection systems also face certain challenges. Variable weather conditions can lead to unstable lighting, which affects image quality [22]. Limited flight time due to battery limitations can reduce coverage efficiency [23]. In addition, image distortion caused by drone movement can affect data accuracy and make fault identification more difficult [24]. Deploying and maintaining drone systems also requires skilled operators and compliance with regulatory guidelines to ensure safe and reliable operation [25]. For image acquisition, it is critical to optimize the flight altitude, camera settings, and flight path to achieve the desired resolution and coverage [26]. Image georeferencing techniques can also be used to accurately map images to specific geographic coordinates, helping to pinpoint faults on power grid infrastructure [27].

4.2. Image Preprocessing

Aerial inspection systems use airborne visual sensors to capture image data of operating objects, and preprocessing is crucial to improve image quality for effective fault detection in power insulators. Various techniques such as contrast adjustment, noise reduction, and sharpening are used to improve the visibility of fault features [28]. Contrast adjustment makes faults easier to distinguish by enhancing the visual difference between the fault and the background [29]. Noise reduction methods such as median filtering and wavelet denoising can remove artifacts caused by sensors or environmental factors [30]. Sharpening techniques further enhance image edges and details, making the fault area clearer [31].

Segmentation techniques are also vital in preprocessing, helping to isolate fault regions from the background. Algorithms such as thresholding [32], region growing [33], and edge-based methods [34] are used to separate fault areas from surrounding elements. This accurate delineation allows subsequent fault detection algorithms [35] to focus on relevant areas, thereby improving detection accuracy.

4.3. Dataset Construction

Building a well-annotated dataset is vital for training and validating machine learning models in power insulator fault detection [36]. This involves either manual or semi-automated annotation methods. In manual annotation, experts inspect images to mark fault regions, requiring specific domain knowledge [37]. Semi-automated approaches [38] utilize computer vision algorithms to detect potential fault areas, which human experts then verify and refine. Dataset size and diversity are also essential for developing robust, generalizable models [39]. The dataset should encompass a range of insulator faults, including cracks, contamination, and flashover, to facilitate the model's ability to discern disparate failure modes [40]. Furthermore, the utilization of random data partitioning and stratified sampling can assist in achieving a more balanced distribution of normal and fault samples, thereby enhancing the model's generalization capacity [41]. The combination of aerial inspection, image preprocessing, and comprehensive data set construction ensures the acquisition of high-quality data, which in turn allows for the development of accurate and reliable fault detection models.

4.4. Data Labeling

When training machine learning models for power insulator fault detection, data labeling is critical to distinguish between normal and fault conditions [42]. This process typically involves domain experts reviewing images and assigning labels based on their expertise [43]. Accurate labeling ensures that the model can effectively distinguish between these conditions, supporting precise detection and classification. Maintaining labeling accuracy is critical to avoid bias that can harm model performance. Consistency and reliability of labeling are crucial, as incorrect or inconsistent labels can adversely affect model accuracy [44]. Regular quality checks and validation help maintain the integrity of the dataset. Given the subjective nature of labeling, it is recommended to work with domain experts to develop clear labeling standards. This approach can minimize uncertainty and improve the quality and reliability of the dataset.

4.5. Data Partitioning

Partitioning data into training, validation, and test sets is critical for developing and evaluating machine learning models. The training set is used for model learning, the validation set is used for hyperparameter tuning, and the test set is used to evaluate the performance of the model on unseen data [45]. To ensure that the model encounters a representative sample of normal and faulty cases, data partitioning should be done randomly. This randomness reduces potential bias introduced by the order of the data. In addition, using stratified sampling can maintain a balanced representation of normal and faulty samples in each partition, which helps the model generalize across a variety of scenarios [46]. In the case of imbalanced data, traditional evaluation metrics may not accurately reflect model performance, as they may overestimate the accuracy of the majority class [47]. Imbalanced data can cause the model to favor common classes and ignore less common classes, complicating model tuning and evaluation.

4.6. Simulation-Based Power Insulator Fault Dataset

Simulation-based approaches offer an effective alternative for generating power insulator fault samples. Using computer models, synthetic data can simulate a variety of fault scenarios, creating a controlled and cost-effective environment for training and testing machine learning models [48]. During simulation, parameters such as insulator material properties, fault type, environmental conditions, and sensor characteristics can be adjusted to create realistic scenarios. This can generate large datasets that enhance the robustness of the model by covering a wide range of fault conditions [49]. However, simulated data can lack some of the complexity of the real world, so it is recommended to combine it with real data to improve the model's adaptability to unpredictable situations. In addition, simulation-based approaches allow for controlled experiments, enabling researchers to test the model's sensitivity to specific parameters and evaluate performance under specific conditions. This flexibility makes simulated data a valuable complement to real datasets for developing reliable power insulator fault detection models.

4.7. Laboratory Testing

Laboratory testing collects data from power insulators under controlled conditions, allowing for rapid data collection by replicating specific fault scenarios or applying controlled environmental conditions [50]. This approach enables the simulation of faults efficiently within a stable setting.

However, data from laboratory testing may not fully capture real-world complexities, such as insulation material aging and environmental variations [51]. Consequently, machine learning models trained on laboratory data should be further validated and fine-tuned with real-world data to ensure practical effectiveness.

4.8. Data Augmentation

Data augmentation enhances dataset size and diversity by applying various transformations to existing samples, improving the generalization capability of machine learning models and reducing overfitting risks, especially valuable in power insulator fault detection [52]. Common techniques include rotation, scaling, flipping, and noise addition. For example, rotation helps models recognize faults from different angles, scaling simulates varied object distances, flipping aids in identifying symmetrical patterns, and noise addition prepares models for environmental distortions [53]. Beyond these, advanced methods like Generative Adversarial Networks (GANs) and image morphing further expand dataset diversity by generating realistic synthetic samples and creating transitional images, allowing models to detect subtle fault variations [54]. Strategic data augmentation increases model robustness and adaptability to real-world challenges. Regular validation with augmented data ensures models can handle diverse scenarios, enhancing the effectiveness of fault detection systems. By following a comprehensive approach including aerial inspection, image preprocessing, thorough dataset construction, precise labeling, balanced data partitioning, simulation, lab testing, and data augmentation the dataset becomes more representative and suitable for training accurate, robust models. These steps collectively strengthen fault detection systems, supporting the reliability and safety of power transmission networks.

5. DEEP LEARNING-BASED POWER INSULATOR FAULT DETECTION APPROACHES

Deep learning techniques have shown great promise in automating power insulator fault detection. This section explores various machine learning-based approaches used for fault detection, including deep learning methods and hybrid approaches.

5.1. Deep Learning Based Power Insulation Fault Detection Approaches

The application of deep learning techniques in power insulator fault detection leverages their robust ability to handle complex data and extract intricate features, which traditional machine learning methods often struggle to accomplish effectively. Convolutional Neural Networks (CNNs), for example, are widely employed for analyzing image data of insulators, enabling the detection of visual anomalies associated with faults [55]. These networks excel in identifying specific fault patterns in image data, yet they are heavily reliant on large, well-labeled datasets to perform optimally, which can be a limitation in contexts where such datasets are difficult to obtain. Furthermore, recurrent neural networks (RNNs) and autoencoders offer a significant advantage in processing time series data, such as voltage and current signals, due to their capacity to capture temporal dependencies that may indicate a failure in a power insulator. The capacity of RNNs to analyze patterns that evolve over time renders them particularly efficacious for the detection of faults. However, this approach also encounters challenges in terms of scalability and typically necessitates the availability of extensive training data to ensure the reliability of the results [55].

5.2. Hybrid ML-Based Power Insulator Fault Detection Approaches

Deep learning technology is applied to power insulator fault detection, taking advantage of its powerful ability to process data and extract features, which is difficult to achieve through traditional machine learning methods. For example, convolutional neural networks (CNNs) are widely used to analyze image data of insulators and are able to detect faults. Figure 2 illustrates the development history of object detection algorithms from 2013 to 2023, including key models such as R-CNN, YOLO, RetinaNet, and EfficientDet, which are widely used in aerial image-based fault detection.

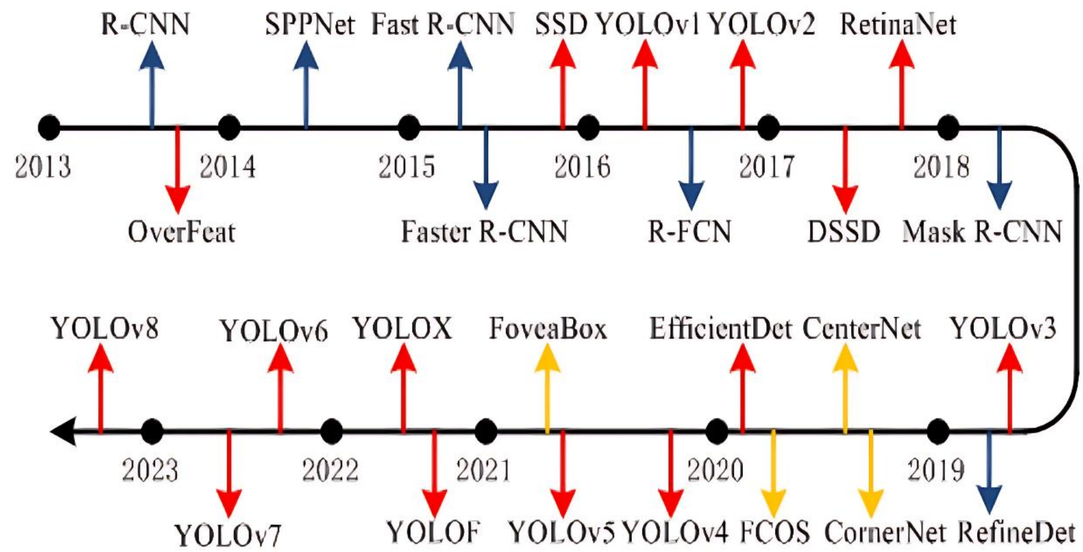

Figure 2. Development history of object detection algorithms.

These networks are effective at identifying specific fault patterns in image data, but their capabilities heavily depend on large, well-labeled datasets. Additionally, recurrent neural networks (RNNs) and autoencoders are more advantageous for processing time series data, such as voltage and current signals, because they can capture the time dependencies that indicate power insulator failures. The ability of RNNs to analyze patterns that change over time is particularly useful for fault detection; however, this approach has limitations in scalability and requires a substantial amount of training data [56].

Deep learning models are particularly capable of learning complex fault patterns from large amounts of historical data, thereby improving the prediction accuracy and reliability of insulator fault detection. For example, transfer learning has been adopted in the field to compensate for the scarcity of large labeled datasets dedicated to power insulators by fine-tuning pre-trained deep learning models on existing image datasets. This approach is especially beneficial for settings where creating expansive fault-specific datasets may not be feasible [57]. In parallel, autoencoders facilitate efficient dimensionality reduction and anomaly detection by learning the normal operational patterns of insulators, which allows them to identify deviations that signal potential faults [58]. However, while autoencoders streamline feature extraction, they can also struggle to handle highly variable environmental data, sometimes reducing their robustness in diverse operational settings.

Further advancements in object detection and localization techniques, such as Faster R-CNN and YOLO (You Only Look Once), offer powerful methods for identifying and pinpointing specific fault regions within insulator images. For instance, Liu, et al. [59] focused on using the YOLOv5 architecture to enhance real-time fault detection in electrical insulators, addressing the need for speed and accuracy in operational environments. The YOLOv5 model showed impressive detection accuracy and efficiency, offering an essential improvement over traditional image processing methods. However, Liu, et al. [59] also highlighted significant limitations, notably the dependency on large, well-labeled datasets and the high computational power required to implement these models. Figure 3 illustrates a lightweight object detection framework integrating convolution, self-attention, and feature fusion to improve UAV-based insulator fault detection under limited computational environments. Such limitations may hinder practical implementation, especially in resource-constrained environments, making it challenging to deploy these models where computational resources are scarce or datasets are insufficient.

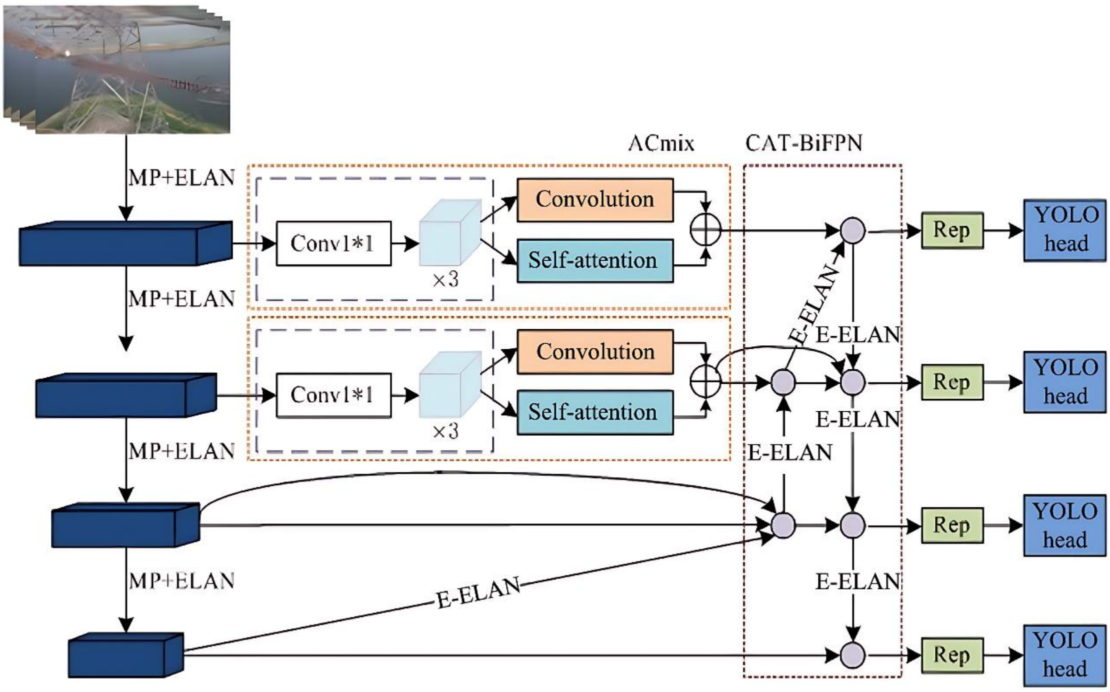

Figure 3. Lightweight strategy for target detection algorithm.

Liang, et al. [60] similarly applied Fast R-CNN techniques to improve fault detection efficiency and accuracy by automating the identification of complex features in insulator images. Their approach yielded high classification rates and efficient training times, which are critical in scenarios requiring quick, accurate fault analysis. Despite these benefits, Fast R-CNN is resource-intensive and requires significant computational support and extensive data, creating barriers to adoption in less technologically advanced or data-limited environments. These constraints underscore the challenges that accompany the adoption of deep learning methods, as their reliance on computational resources can limit accessibility and practical implementation in broader applications.

Another notable study by Li, et al. [61] introduced a two-phase aerial image detection approach using a Region-based CNN, fine-tuned on the Cifar10 dataset, to identify faults in insulators from aerial imagery. This method achieved high accuracy and highlighted its potential to reduce labor costs typically associated with manual inspection. However, the training phase required extensive epochs to achieve optimal accuracy, posing challenges in practical deployment. Furthermore, the risk of model overfitting to training data, potentially limiting generalization to different environments, presents a challenge for the widespread application of this method in real-world scenarios where environmental conditions vary.

In an effort to enhance traditional defect detection, Liu, et al. [59] utilized a suite of deep learning models, including R-CNN, Faster R-CNN, and YOLO, for real-time insulator defect detection in complex environmental conditions. Among these models, YOLOv5 stood out for achieving detection rates as high as 41 frames per second, demonstrating the potential for real-time application. This performance underscores the advantage of integrating deep learning in operational environments, allowing for more effective monitoring of power transmission systems and heightened safety. Nevertheless, such implementations often come at the cost of high computational demand and extensive training times, which may challenge resource-constrained facilities and create obstacles for large-scale deployment.

In resource-limited environments, Maduako, et al. [62] explored the use of high-resolution UAV imagery combined with CNN architectures to develop an automated inspection system capable of identifying faulty components in electricity transmission networks. The Single Shot Multibox Detector (SSD), integrated with a Feature Pyramid Network (FPN), achieved high precision and a balanced performance in fault localization and classification, reaching a mean Average Precision (mAP) of 89.61%. Although this method is effective in developing regions with limited resources, it remains dependent on specialized hardware and trained personnel, which may limit its accessibility for smaller utilities.

Lastly, Shang, et al. [63] at the State Grid Xinjiang Electric Power Research Institute demonstrated that Fast R-CNN combined with multi-fault target detection algorithms can significantly improve fault detection rates for insulator defects, achieving an accuracy of 82.4% with a brief training period. While this system presents a valuable improvement, it also remains reliant on computational resources and extensive labeled datasets, which are often not available in all regions, limiting the practical scalability of this approach.

As summarized in Table 1, recent advancements in fault detection for power insulators have seen a significant application of sophisticated deep learning techniques, as evidenced by a series of studies each aiming to improve the reliability and efficiency of current methodologies. Liu, et al. [59] embraced a variety of algorithms, including R-CNN and YOLOv5, achieving real-time detection with high accuracy, though their methods require substantial computational resources, which may not be feasible in less developed regions. Similarly, Maduako, et al. [62] utilized high-resolution UAV imagery and sophisticated neural networks to automate fault detection, yielding high precision but facing challenges when applied to diverse and complex real-world conditions outside of their training data. Meanwhile, Shang, et al. [63] at the State Grid Xinjiang Electric Power Research Institute implemented Fast R-CNN to achieve rapid and accurate classification, with the caveat that extensive computational and data resources limit its broader application. Zheng, et al. [64] also developed a novel image detection method that, while reducing manual labor costs and increasing accuracy, requires long training periods and risks overfitting to specific datasets, potentially compromising effectiveness in varied operational scenarios. Collectively, these studies highlight the dual edge of current deep learning approaches in insulator fault detection. While they push the boundaries of what's possible in terms of speed and accuracy, they also underscore the critical need for solutions that accommodate the limitations of computational intensity and data availability in diverse environmental settings.

5.3. Hybrid ML-Based Power Insulator Fault Detection Approaches

The field of power insulator fault detection is experiencing significant advancements due to the integration of both traditional and modern deep learning techniques. The hybrid approaches described combine the interpretability of traditional machine learning algorithms with the complex pattern recognition capabilities of deep neural networks, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Deep learning models, especially CNNs, excel in feature extraction from images, identifying patterns associated with wear, damage, or potential faults. For example, as seen in work by Tao, et al. [55] CNNs can automatically detect visual indicators of damage in insulators, improving the accuracy and speed of fault detection over traditional manual inspections.

In addition to CNNs, RNNs are useful for analyzing time series data, such as voltage or current readings, which can indicate faults when analyzed over time. Autoencoders further enhance detection by compressing data to identify anomalies that deviate from the norm, which may signify a developing fault [65]. Such advanced methods significantly enhance fault detection accuracy, reducing the need for labor-intensive manual inspection and improving maintenance practices.

Transfer learning is also a powerful tool in fault detection, as shown in recent studies. It allows models pre-trained on large, generic datasets to be adapted for power insulator tasks with smaller, more specific datasets. This is especially beneficial in scenarios where large labeled datasets are difficult to obtain. Faster R-CNN and YOLO are other deep learning frameworks that support object detection, allowing the precise localization of faults, which Liu, et al. [59] demonstrated effectively by enhancing real-time defect detection accuracy. Another promising method is ensemble learning, which aggregates predictions from multiple models to improve accuracy. For instance, a hybrid system may combine CNNs for feature extraction with algorithms like decision trees for interpretation [66]. This approach provides the benefits of both complex feature extraction and efficient decision-making, ensuring fault detection systems can handle the diverse nature of power insulator data.

Table 1. Summary of DL based power insulator fault detection approaches.

Article	Citation	Used Method	Detected Fault	Accuracy	Drawbacks
Omar, et al. [67]	Wavelet analysis and SVM	Partial discharges	92-96%	High complexity and need for expert knowledge	High accuracy and reliable fault prevention
Sarwar, et al. [68]	PCA and SVM	High impedance faults	98%	High computational demand	Fast and reliable fault detection.
Gustavo, et al. [69]	Wavelet transform and SVM	Series arcs	90%	Complex signal processing, not suitable for real-time	High detection accuracy and sensitivity
Zhou, et al. [70]	Binary tree SVM and image feature analysis	Winding faults	83.17%	Complexity and high computational effort	High detection accuracy
Zhang, et al. [71]	Genetic algorithms, GAP - SVM, and RFA	Boundary conditions	83.60%	High complexity and need for high computing power	Improved decision accuracy and robustness
Ding, et al. [72]	Improved sparrow search algorithm and SVM	Transformer faults	90%	Iterative nature leading to efficiency problems	Improved accuracy of fault diagnosis
Yin, et al. [73]	Multi-scale feature extraction and	Series arcs	Not specified	Scalability issues with large datasets	Robustness and fast processing capability

Article	Citation	Used Method	Detected Fault	Accuracy	Drawbacks
	random forest				
Wang and Zhang [74]	SVM with Gabor features and background subtraction	No accuracy, but can reduce time	50%	Challenges in accuracy in varied scenarios	Efficient identification in complex backgrounds.
Salem, et al. [75]	Leakage current analysis and new assessment metrics	Polluted polymer insulators	80.40%	Need for high quality and varied data	Innovative assessment approach
Liu, et al. [76]	YOLOv5 and various CNNs	More than 50% insulators faults	Not specified	Dependency on large datasets and high computational demands	Efficiency in real-time detection
Huang, et al. [77]	Fast R - CNN and deep learning	Complex insulators faults	Not specified	High computational resources and large datasets required	High classification rates and quick training times
Zheng, et al. [64]	Region-based CNN and Faster R-CNN	Faulty insulators	93.33%	Extensive training periods and risk of over-fitting	Cost-effective and reduces labor costs
Madakur, et al. [78]	SSD with FPN	Components in UAV imagery	89.61%	Faulty accuracy may be compromised under varied real-world conditions	Efficient for resource-limited environments.
Huang, et al. [77]	Multi-fault target detection and Fast R-CNN	Insulator faults	82.4%	Dependency on computational resources and large datasets	Allows for simultaneous multiple fault detection.

Moreover, innovative studies extend beyond basic fault detection to pre-fault analysis and protection schemes, such as Lin, et al. [79] who employed Support Vector Data Description (SVDD) to address faults in Distributed Energy Resources (DERs). They used a hyperspherical data generation model that enhances training speed, demonstrating that advanced machine learning can effectively manage complex distribution system challenges.

As research advances, hybrid approaches integrating both traditional and deep learning techniques promise enhanced detection performance, more accurate classification, and robust solutions for real-world operational challenges. Such integration allows for the practical, scalable application of these models in diverse environments, which can lead to more resilient and cost-effective power system management strategies.

As mentioned in Table 2, the research articles collectively advance various aspects of engineering and technology through innovative approaches and methodologies. Despite their significant contributions, each study has its limitations. Lin, et al. [79] improved robustness in distribution systems with DERs but faced real-world applicability issues. Sambyal and Sarwar [80] enhanced HIF detection accuracy but struggled with scalability and computational demands. Ali and Zhang [81] provided a reliable fruit maturity monitoring method, yet their lab-based approach limited real-world applicability. Qi and Tang [82] advanced slope stability prediction, though their high model complexity and limited dataset raised concerns. Shi, et al. [83] improved recommendation systems in HINs but at a high computational cost. Kumar, et al. [84] increased islanding detection accuracy, yet their method's generalizability was limited. Ren, et al. [85] effectively predicted cable insulation health but relied on simulated data. Pijarski and Belowski [86] and Teimourzadeh, et al. [87] streamlined dynamic security assessments in power systems but required further validation for fault generalization. Lastly, Ndung'u [88] improved fault detection in transmission lines, facing challenges with model complexity and training data needs.

These studies collectively highlight the advancements and ongoing challenges in applying machine learning and innovative techniques to practical engineering problems. The combination of these qualities ease of use and interpretation, effectiveness with categorical data, compatibility with other techniques, and intelligent variable selection makes decision trees (DTs) and CART powerful tools in the machine learning arsenal, particularly suitable for applications where transparency and understandability are as crucial as predictive accuracy.

By utilizing machine learning approaches, power insulator fault detection systems can automatically analyze and classify acquired data, enabling early detection of faults and facilitating prompt maintenance actions. These approaches offer the potential for real-time monitoring and can assist in preventing costly power outages and ensuring the reliability of the power grid.

Table 2. Summary of hybrid-based power insulator fault detection approaches.

Article	Problem Solved	Objective	Methods	Results	Advantages	Limitations
Lin, et al. [79]	Complexity and bi-directional power flow in distribution systems due to DERs.	Propose a data-driven protection framework.	SWI/SVM, incremental learning, artificial neural network, hyperbolic tangent data generation model	Validated effectiveness on 123-node test feeder, enhanced speed, improved robustness under DER integration levels.	Enhanced speed, improved robustness under DER integration levels.	Relies on simulation; environment-wide results may be inaccurate.
Sambyal and Sarwar [80]	High Impedance Fault (HIF) detection and location	Enhance HIF detection and location accuracy.	PCA, FDA, binary, and multi-class SVM	Outperformed existing methods in accuracy, stability, and speed of detection and location of HIF.	Increased reliability, security, and stability of the distribution network.	Small test network scalability; large-scale application needs more research.
Chen, et al. [89]	Non-destructive prediction of fruit maturity	Use E-Nose technology to predict fruit maturity.	PCA, DA	Successfully predicted fruit maturity stages with high accuracy.	Successfully predicted fruit maturity stages with high accuracy.	Reliance on specific environmental conditions; limited dataset size
Qi and Tang [82]	Slope stability prediction using dataset collection	Evaluate advanced AI approaches in slope stability prediction.	Logistic regression, decision tree, random forest, boosting, gradient boosting machine, SVM, MLP neural network.	SVM optimized with SMOTE outperformed others, achieving accuracy between 0.822 and 0.967.	SVM optimized with SMOTE outperformed, achieving an accuracy of 0.822–0.967.	Data may not represent all geographical conditions; high-quality data is required.
Zhao, et al. [90]	High-level semantic representation and improvement in recommendation systems	Improve recommendation accuracy in heterogeneous networks (HIN).	Meta-graph, factorization techniques	Proposed method outperformed state-of-the-art algorithms.	Proposed method outperformed state-of-the-art algorithms.	High computational complexity; challenges in handling heterogeneous data.
Kumar, et al. [84]	Passive islanding detection in distributed generation systems	Enhance the accuracy and speed of islanding detection.	Wavelet transforms and machine learning-based islanding detection system	Combined wavelet design and machine learning effectively detected islanding events.	Increased detection accuracy and system reliability.	Relies on specific test systems; generalizability may be limited and requires more real-world validation.
Ren, et al. [85]	Aging and partial discharge detection in cable insulation	Predict insulation health condition	SVM, ANN, ANFIS, Naïve Bayes	SVM achieved 98% accuracy in prediction	Assessed multiple-fault scenarios with reduced training needs.	Generalization to different fault types requires further research.
Pijarski and Belowski [86]	Multi-fault dynamic security assessment in power systems	Propose an efficient DSA (Dynamic Security Assessment) method.	Single model, transfer learning	Assessed multiple-fault scenarios with reduced training needs.	Assessed multiple-fault scenarios with reduced training needs.	Generalization to different fault types requires further research.
Teimourzadeh, et al. [87]	Multi-fault dynamic security assessment in power systems	Improve accuracy and efficiency of dynamic security assessment (DSA).	Single model, transfer learning, adapted to various fault scenarios.	Assessed multiple fault scenarios with high accuracy.	Assessed multiple-fault scenarios with high accuracy.	Adaptation to different scenarios requires more research.
Ndung'u [88]	Fault detection in transmission lines	Improve fault detection accuracy and speed.	TF method, CNN, DNNL	Outperformed existing methods in early fault detection.	Outperformed existing methods in early fault detection.	High-level accuracy requires large-scale training data.

6. UAV AERIAL IMAGE DATASET

There are many classic datasets in the field of machine vision based on deep learning. When training models, datasets are often divided into training sets, validation sets, and test sets. In recent years, datasets related to target detection and semantic segmentation based on UAV aerial images have also been rapidly updated. The following is a collection of datasets recently established based on UAV aerial images:

- Roundabout UAV Image Dataset: Produced by Puertas, et al. [91]. It contains 61,896 color images, captured at a flight altitude of 100-120m, annotated in Pascal VOC format, divided into 6 target categories, with an image resolution of 1920×1080 pixels.
- UAV floating objects (AFO) dataset: Established by Gąsienica-Józkowy, et al. [92]. It is used for maritime rescue and other applications. The dataset contains 3,647 images and 39,991 annotated objects, spanning a total of 6 categories. Image resolutions range from 1280×720 to 3840×2160 pixels. The UAV flight altitude during image capture was between 30 and 80 meters.
- NITRDrone dataset: Created by Behera, et al. [93] for road segmentation tasks. It consists of 16 video sequences of 8GB in size and 1,000 images, divided into 6 target categories. The drone's flight altitude ranged from 5 to 80 meters during shooting, and the image resolution ranged from 1280×720 to 3000×4000 pixels.
- UAV Detection and Tracking (UAVDT) dataset: Created by Du [94] for target detection, single target tracking, and multi-target tracking tasks. It consists of 100 video sequences, including a variety of common scenes and different target categories.
- HERIDAL dataset: Created by Božić-Štulić, et al. [95] for search and rescue work. It contains 68,750 images of 4000×3000 pixels in size, shot at an altitude of 30 to 40 meters, covering a variety of real scenes.
- AeroScapes semantic segmentation dataset: Established by Nigam, et al. [96] it includes 3,269 images extracted from 141 outdoor scene sequences captured by drones. The dataset is categorized into 12 different classes. The drones operated at altitudes ranging from 5 to 50 meters during image acquisition. The images have a resolution of 1280×720 pixels.
- Campus dataset: Established by Robicquet, et al. [97] used for target detection, multi-target tracking, and large-scale trajectory prediction. Shot by drones in outdoor environments, it contains more than 100 different bird's eye views and 20,000 targets participating in various types of interactions. The targets are divided into 6 categories. The flight altitude during shooting is about 80m, and the image resolution is 1400×1904 pixels.
- Large-Scale Parking Lot (CARPK) dataset: Established by Hsieh, et al. [98] used for target detection and counting. It contains drone images taken from 4 different parking lots, all targets are marked with the upper left and lower right corner coordinates, a total of 89,777 cars, the drones were flying at an altitude of about 40m during shooting, and the image size was 1000×600 pixels.
- Human action detection dataset Okutama Action: Created by Barekatain, et al. [99] it consists of 43-minute video sequences with comprehensive annotations, including 12 typical outdoor action categories. The drone was flying at an altitude of 10-45 meters during filming, with the camera tilted at angles of 45° or 90°, and the image resolution was 3840×2160 pixels.
- SARD dataset: Created by Sambolek and Ivašić-Kos [100] it is used for search and rescue missions in complex environments in drone images. It consists of 1981 images, including typical motion types, simulating behavioral differences caused by different age groups and physical fitness. The drone was flying at an altitude of 5-50m, and the shooting angle was 45°-90°.
- UAV123 dataset: Created by Mueller, et al. [101] it is used for target detection and tracking in drone images. It contains 123 video sequences, divided into 3 subsets, covering a variety of outdoor scenes and target categories, with common visual tracking task challenges. The drone was flying at an altitude of 5-25m when shooting, and the image size was 1280×720 pixels.

- VisDrone DET dataset: Du et al. [94] released a target detection challenge based on drone images, with a total of 8,599 images and 10 different target categories, with rich annotations, occlusions, and real scenes. Some very similar categories make the target detection task more challenging. These datasets have their own characteristics in terms of target category, image resolution, shooting height, etc., providing rich data support for the research on target detection and semantic segmentation of drone aerial images.

7. OPEN RESEARCH CHALLENGES

With the rapid development of drone technology and deep learning, the fusion of the two has shown great promise in drone-based object detection. However, there are still some key challenges in research and practical applications. The following are the main problems and future research directions for object detection in drone images:

- Model lightweight: Current model improvements usually focus on improving detection accuracy by extending the backbone network output, adding additional modules, and enhancing feature fusion structures. However, these adjustments typically increase model complexity and the number of parameters, making the training process more resource-intensive and slowing down detection. It is crucial to design lightweight models optimized for real-time performance on drones with limited processing power.
- Small object: Due to the high-altitude flight of drones, the objects captured in the images are usually very small, occupying only a few pixels. Multiple downsampling operations within the model can cause the loss of small object features, which significantly reduces the detection accuracy of these targets.
- Complex background interference: Drones capture images in various environments with diverse backgrounds, which introduces a lot of noise and interference compared to standard images. Complex backgrounds make accurate object detection challenging, especially in natural or cluttered environments.
- Large field of view (FOV): Drone images typically have a wide FOV and high resolution, which pose challenges for real-time processing. A wide FOV increases image processing time, while high resolution raises computational requirements. Efficient algorithms capable of handling wide FOV and high-resolution images are necessary for effective real-time detection.
- Uneven distribution of objects: Objects in drone images are often distributed at different densities, with some areas being sparsely populated and others densely populated. For example, animals in a pasture may be spread out, while vehicles in a parking lot may be tightly clustered. Such distribution extremes may reduce recall because the detection algorithm may erroneously suppress true positives in densely populated areas.
- Object rotation: Objects in drone images are often randomly oriented rather than horizontally aligned, complicating detection. Tilted objects are more susceptible to background interference during detection, resulting in bounding boxes that may include too much background, making feature extraction more difficult. Developing robust methods to handle object rotation is a priority.
- Unbalanced dataset classes: In drone datasets containing multiple object types, some classes often have far fewer samples than others, resulting in data imbalance. This imbalance can negatively impact model training, making it more difficult for the model to learn discriminative features for the minority class, thereby reducing the mean average precision (mAP) for object classes. Ensuring that the dataset is balanced or implementing strategies to address imbalance is critical to improving detection accuracy.

8. RESEARCH DIRECTIONS

In view of the above problems, the research trends of target detection methods for drone aerial images in the future are as follows:

1) In the optimization and upgrading of the model, more attention should be paid to factors such as computational complexity and detection speed. A high-performance model needs to achieve a good balance between detection

accuracy and operational speed. How to improve detection accuracy while maintaining or even reducing model complexity is a challenging area of research.

2) In the feature extraction part of the model, most of them use multi-layer stacked residual networks. Residual networks help alleviate gradient problems and can improve the detection performance of the model by increasing depth. How to optimize the traditional residual structure to enhance its feature extraction ability for small targets requires further research.

3) In image processing, attention modules are often used to eliminate the interference of complex backgrounds and improve the detection performance of the model. Through previous research, the attention mechanism has a variety of implementation forms, mainly divided into channel attention and spatial attention modules. How to design a more effective and lightweight attention module is very meaningful.

4) For the problem of processing multi-scale targets in large field of view images, the use of feature pyramid structures is a common solution. Pyramid structures such as FPN, PANet, NAS-FPN, and BiFPN have been proposed. How to strengthen the fusion of features of different scales, enhance feature reuse, and improve feature extraction still requires further research.

5) In the target detection algorithm, bounding box regression (BBR) is used to locate the target, which is a key step in determining the target positioning performance. A good loss function is crucial for bounding box regression. A variety of loss functions based on intersection-over-union have been proposed, such as IOU loss, GIOU loss, DIOU loss, CIOU loss, and EIOU loss. A well-designed loss function is conducive to better measuring the difference between the predicted value and the true value, and guiding the next step of training in the right direction.

6) There is still room for further improvement in the selection of model optimizers. In previous studies, the optimizer selection was too limited, primarily using only the SGD optimizer or Adam optimizer for momentum. In the future, combining adaptive and non-adaptive methods to optimize network model parameters could enable the model to better approach or reach the optimal value.

7) In terms of data set production, comprehensive data from multiple different sources should be used to verify the model, avoiding images collected from a single category and a single background. In addition, the number of pictures included is also an important indicator for measuring the dataset. In the subsequent data set production, we need to pay attention to issues such as multiple categories, multiple backgrounds, and the number of pictures.

9. DISCUSSION

The reviewed literature highlights significant advancements in using deep learning and hybrid machine learning models for power insulator fault detection through UAV-acquired imagery. Several recent studies support the efficacy of modern deep learning architectures such as CNNs, YOLOv5, and Faster R-CNN. For instance, Shi, et al. [102] demonstrated that YOLOv5 achieved superior accuracy and speed in detecting surface damage in composite insulators, outperforming traditional detectors like SSD and RetinaNet.

However, recent studies have also highlighted challenges and limitations in deep learning-based fault detection systems. For instance, Buda, et al. [103] demonstrated that YOLOv5 models, even when enhanced for UAV-based remote sensing, exhibited poor generalization when tested under real-world conditions such as occlusion, variable lighting, and dense scenes. This underscores the need for domain adaptation and environmental robustness in practical deployments. Similarly, Wang, et al. [104] found that traditional SVM classifiers using handcrafted features like HOG and Gabor filters sometimes outperformed CNN-based models in scenarios involving small or highly imbalanced datasets. This was attributed to the increased risk of overfitting in deep networks when trained on limited or skewed data distributions.

In the case of hybrid approaches, Zhao, et al. [90] proposed an ensemble-based Mixture-of-Experts (MoE) framework that combined multiple classifiers to enhance fault detection robustness in UAV systems. Their model demonstrated improved performance under noisy backgrounds and occluded imagery, which aligns with this review's conclusion that hybrid methods can improve detection stability. Nevertheless, Huang, et al. [105] highlighted that such hybrid and ensemble models often result in increased inference time and computational overhead, making them less practical for real-time UAV applications with limited onboard processing capabilities.

Dataset imbalance and lack of diversity continue to be critical challenges. While public datasets such as UAVDT and Okutama Action provide multi-environment and multi-object data, specialized datasets for insulator fault detection often suffer from limited class variety, weather variability, and resolution inconsistencies. Liu et al. [76] emphasized that the scarcity and imbalance of training samples in insulator datasets hinder effective training and evaluation of deep learning models. Additionally, Liu, et al. [106] reported that inconsistent image resolutions and limited scene diversity significantly reduce the generalization capability of models when deployed in real-world operational environments.

In summary, while recent studies largely support the benefits of deep learning and UAV-based approaches for power insulator fault detection, emerging evidence also reveals important limitations. These include weak generalization to novel environments, high computational costs, and dataset biases. Addressing these issues through model compression, domain adaptation, transfer learning, and improved dataset design will be essential for developing reliable, scalable solutions suitable for real-world deployment in power grid inspection systems.

10. CONCLUSION

10.1. Key Findings and Implications

This review systematically examined the integration of binocular vision systems with unmanned aerial vehicles (UAVs) and machine learning techniques for power insulator fault detection. The findings highlight how advanced imaging methods, such as binocular vision and optical correction, combined with deep learning models like YOLOv5 and Faster R-CNN, have significantly improved detection accuracy, inspection efficiency, and operational safety in power transmission systems. The integration of UAV platforms with AI-driven analysis presents a scalable and cost-effective solution for modernizing power grid maintenance.

10.2. Limitations

Despite promising advancements, several challenges persist. These include limited availability of diverse, annotated UAV datasets, generalization issues in deep learning models across varying environmental conditions, and the computational complexity of deploying real-time solutions on UAVs with constrained resources. Additionally, many existing studies lack benchmarking standards, making cross-comparison difficult.

10.3. Future Research Directions

Future research should prioritize the development of lightweight and generalizable models for real-time UAV deployment, address dataset imbalance through augmentation and simulation, and incorporate multi-sensor fusion approaches such as thermal imaging or LiDAR. Emphasis should also be placed on standardized evaluation protocols, explainable AI, and deployment-aware architectures to enhance practical adoption and reliability in diverse field conditions.

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