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Research Article

Deep learning-based fault detection for power transmission ınsulators using a custom-developed UAV platform

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ABSTRACT

The efficient transmission of electrical power is essential for the stability and reliability of modern grids. Insulators play a critical role in isolating high-voltage conductors, yet they are highly susceptible to defects such as cracks, contamination, and mechanical damage, which can cause power losses, equipment failure, and outages. This study presents an Unmanned Aerial Vehicle (UAV) based inspection framework integrated with the You Only Look Once version 8 (YOLOv8) deep learning model for automated detection of insulator faults. A custom UAV platform was developed to ensure stable flight, adaptability, and reliable data acquisition under diverse operational and environmental conditions. Using this platform, a dedicated dataset of 8,300 high-resolution annotated images of transmission insulators was collected across varying weather and lighting scenarios. To improve generalization and mitigate overfitting, advanced data augmentation strategies were employed. The proposed system achieved a detection accuracy of 92% and a mean Average Precision (mAP@[0.5:0.95]) of 50.1%, outperforming benchmark methods such as R-FCN, Faster R-CNN, YOLOv5, and YOLOv7. These results confirm the novelty and effectiveness of combining UAV-based aerial imaging with advanced deep learning for reliable, real-time insulator monitoring. The approach reduces dependence on manual inspections and enables predictive maintenance, thereby contributing to improved grid reliability, operational efficiency, and cost-effective infrastructure management.

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INTRODUCTION

The continuous rise in global electricity demand has made efficient utilization of energy resources a key focus to minimize transmission losses and ensure stable grid operations. The power line industry faces persistent challenges in the form of losses during transmission and distribution, caused by conductor resistance, insulator degradation, transformer inefficiencies, and inherent grid

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limitations [1,2]. These losses not only undermine economic efficiency but also contribute to environmental degradation. Insulators are critical components of transmission systems because they provide both mechanical support and electrical isolation of conductors. Defects in insulators such as cracks, surface contamination, or missing fittings pose significant risks to system stability, potentially leading to blackouts, equipment damage, and safety hazards. Hence, timely monitoring and defect detection are essential to ensure reliable grid operation and minimize economic losses [2–5].

Traditional inspection techniques, such as foot patrolling and helicopter-based surveys, have long been employed. However, these approaches are slow, labour-intensive, costly, and often expose workers to hazards in difficult terrains, adverse weather, or near live lines. Helicopter inspections, although faster, are highly expensive and depend on subjective human judgment, which can lead to inconsistent results. The key limitations of these methods are summarized in Table 1, along with representative examples [6].

To overcome these drawbacks, researchers have explored automated inspection methods, such as mobile robots, wavelet analysis, neural networks, and support vector machines (SVMs). While these approaches improve efficiency, they often suffer from scalability issues and require complex configurations. In recent years, unmanned aerial vehicles (UAVs) have emerged as a promising alternative due to their compact size, flexibility, and ability to access difficult environments at reduced cost [7-9].

UAVs equipped with cameras and sensors can capture high-resolution imagery of transmission components, enabling automated inspections and reducing reliance on human operators. Figure 1 illustrates a typical UAV-assisted inspection route for a transmission tower, where the UAV follows predefined waypoints to capture images of Conductors, insulators, and fittings for fault analysis. Despite their advantages, UAVs face challenges such as limited endurance, payload constraints, and sensitivity to weather. At the same time, recent advances in deep learning-based computer vision have enabled robust fault detection in real time. In particular, the You Only Look Once (YOLO) family of models has gained prominence for its ability to deliver high-quality object detection at high inference speeds [9–12].

Compared to traditional machine learning methods such as support vector machines, wavelet analysis, or handcrafted feature-based neural networks, deep learning offers significant advantages for insulator defect detection. Classical methods rely heavily on manual feature engineering and are often sensitive to noise, illumination changes, and background complexity, which limit their scalability in real-world environments. In contrast, deep learning models, particularly convolutional neural networks and advanced detectors like YOLOv8, automatically learn hierarchical features directly from raw imagery. This enables greater robustness to environmental variations, reduces false detections, and allows end-to-end processing at real-time speeds. These advantages make deep learning a more practical and industry-ready solution for UAV-assisted power transmission inspection tasks.

This study focuses on the design and implementation of a UAV-based inspection system integrated with YOLOv8 for automatic detection of faults in power transmission insulators. The methodology encompasses UAV platform development, dataset acquisition, image pre-processing, model training, and evaluation under real-world conditions. A new Power Line System (PLS) dataset was developed to train and validate the detection model. Experimental results demonstrate that YOLOv8 outperforms existing approaches in both accuracy and inference speed, highlighting its suitability for real-time UAV inspections.

Table 1. Limitations of traditional inspection methods for power transmission system (with representative images)

Inspection method	Key limitations	Representative image
Foot-patrolling	• Slow and labour-intensive. • Safety risks to technicians. • Limited by terrain, weather, and disaster aftermath.	
Helicopter-based	• High cost and low precision at high speeds. • Dependent on human visual skills. • Risk of contact with live lines.	

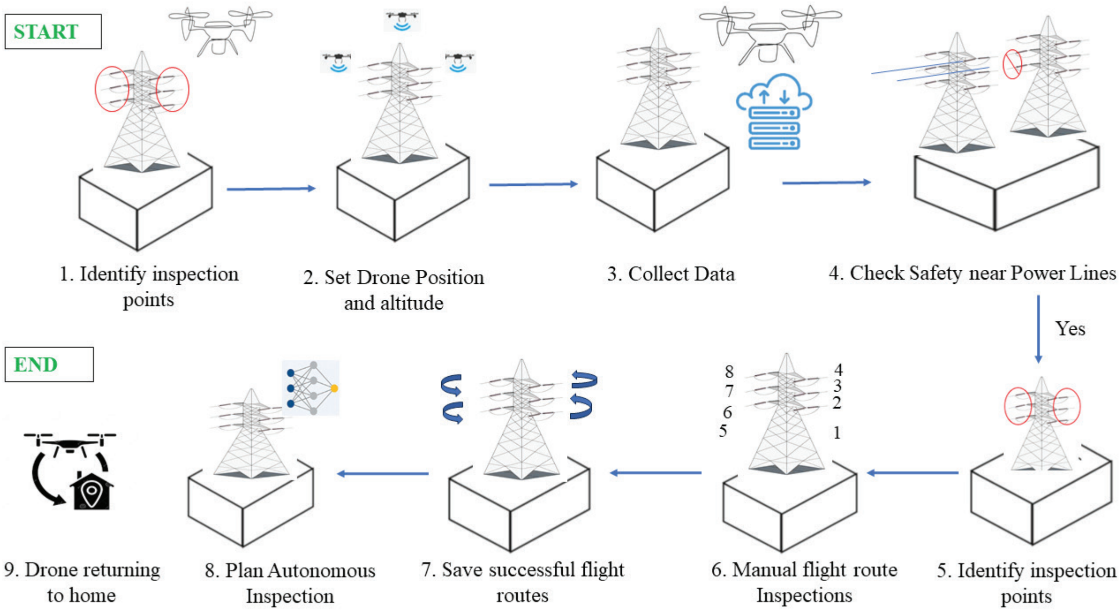


Figure 1. Path planning inspection of power transmission system with UAV.

The primary obstacle to widespread use of UAVs in power transmission systems is their limited endurance period. The You Only Look Once model (YOLO) has attracted significant interest for its capacity to deliver high-quality object detection in real time. This paper delves into the design and implementation of a UAV that utilizes deep learning approaches, which include data collection, pre-processing, training, and assessment processes. This work has produced the PLS dataset for model training. Additionally, the performance metric employed to evaluate the system's efficacy is elucidated. The authors identified pragmatic considerations and challenges encountered throughout the development and execution of the defects detection system in a real-world context. The authors showed test results that show using YOLOv8 is better for finding faults in power transmission insulators more accurately.

Related Works

Researchers in the field of power transmission structure maintenance have conducted several relevant studies in recent years. Author employed a single wireless camera on transmission poles to transmit data to a base station via inter-camera communication [13]. Authors detected encroached vegetation using image-processing-based tracking, while utilized UAVs to monitor high-voltage structures and identify malfunctions through classification and refinement of suspected regions. Researchers prepared datasets comprising multiple categories of defects, employing Faster R-CNN to achieve high recognition accuracy [14-18]. Authors proposed information aggregation methods to enhance detection of insulators, conductors, bird nests, suspended foreign objects, and smog, thereby improving YOLO's performance and introduced a bird's nest detection technique integrating visual saliency with deep learning, achieving high precision and recall. Similarly, employed UAVs with YOLOv5-s for bird nest detection on transmission systems, reporting superior accuracy compared to traditional models [19-25].

Researchers enhanced YOLOv4 with anchor-free strategies, attention mechanisms, and Swin Transformer blocks, reaching 88% accuracy in bird nest identification and proposed small-sample learning techniques for nest detection, achieving a 95.5% recognition rate. Authors developed a risk assessment framework for bird pecking on composite insulators, integrating deep learning with electric field studies and applied a YOLOv3-based method for detecting foreign objects, reporting improvements in precision (+3.7%), mAP (+6.8%), and efficiency [26-35]. In summary, prior studies demonstrate significant progress in UAV-assisted inspection and deep learning–based detection of transmission system faults. However, limitations remain in terms of dataset scale, diversity of environmental conditions, and robustness of real-time inference for insulator-specific defects. To address these gaps, this study makes the following contributions:

- Development of a lightweight UAV platform with integrated propulsion, navigation, and imaging units for high-resolution inspection of transmission insulators.
- Creation of a large-scale dataset of 8,300 annotated images collected under varied weather and lighting conditions.
- Implementation of an optimized YOLOv8-based detection framework achieving high accuracy and real-time performance.

- Benchmarking against R-FCN, Faster R-CNN, YOLOv5, and YOLOv7, demonstrating superior detection accuracy and efficiency.

The structure of the paper is as follows: Section 2 presents the development process of the UAV and its procedure for collecting a dataset from the power transmission system for fault detection in insulators. Section 3 describes the experiments and analyses, whereas Sections 5 and 6 provide the results summary and conclusions.

DESIGN AND DEVELOPMENT OF UAV PLATFORM

The unmanned aerial vehicle (UAV) platform for power transmission insulators inspection was developed through a systematic design and validation process. Both structural robustness and functional integration were considered to ensure reliable operation under varying environmental and operational conditions. The design process was divided into three phases: structural design and validation, hardware integration, and system assembly.

Structural Design and Validation

The UAV frame provides the foundation for mounting payload, propulsion, and navigation systems [36]. An S500 carbon fiber X-shaped frame was chosen due to its lightweight construction, high stiffness-to-weight ratio, and modular design, which simplifies integration of inspection payloads and maintenance. The X-configuration also ensures stable thrust distribution and improved manoeuvrability during flights. To verify its structural integrity, a Finite Element Analysis (FEA) was performed in SolidWorks as shown in Figure 2. The model was subjected to fixed constraints at the motor mounts and distributed loads representing thrust and payload weight. The von Mises stress distribution indicated a maximum of ~6002 psi concentrated at the central hub, while stresses along the arms and landing gear remained much lower. These values are well within the strength limits of carbon fiber composites, confirming that the frame can withstand operational loads [37–39]. The analysis further showed minimal deformation at the arm ends, ensuring propeller alignment and flight stability. Thus, the selected S500 frame was validated as mechanically reliable for UAV-based power transmission insulators inspection tasks.

Hardware Integration and Components

Following structural validation, the UAV platform was systematically equipped with essential subsystems to achieve autonomous inspection of power transmission insulators. The design focused on ensuring stable flight performance, long-range communication, and high-quality data acquisition under challenging outdoor conditions. The propulsion unit consisted of four Emax MT 3506 (650 kV) brushless DC motors, each driven by a Hobbywing XRotor 40 A electronic speed controller (ESC) and paired with 13 × 5.5 in nylon propellers. This configuration provided a balanced combination of thrust, efficiency, and manoeuvrability, enabling the UAV to maintain steady hover as well as agile motion during inspection flights.

For navigation and flight control, the Pixhawk Cube Orange controller served as the core processing unit, coordinating all onboard subsystems. It was coupled with the HERE2 GNSS module to deliver precise global positioning, while the HereFlow optical flow sensor ensured stable local navigation in environments where GPS signals are weak or unavailable, such as under dense vegetation or near tall structures. Communication between the UAV and the ground control station was enabled through a dual-link system. The HereLink receiver with dual

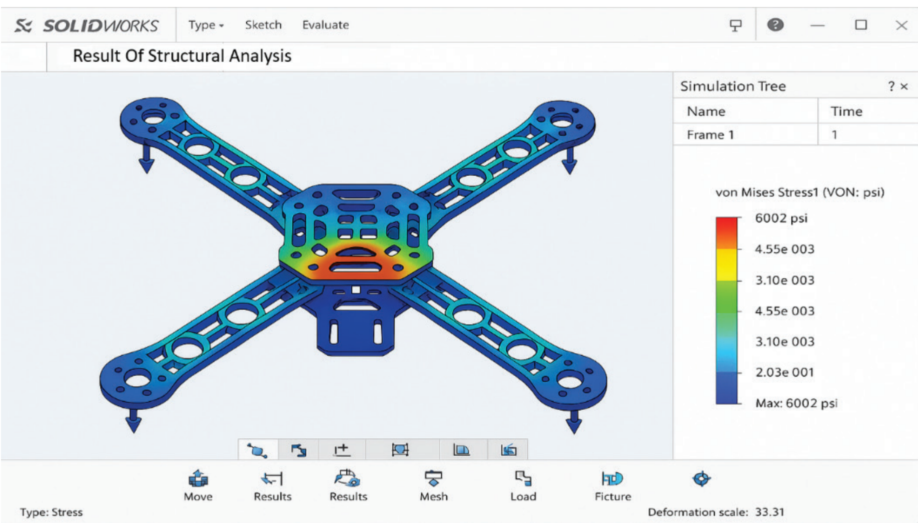


Figure 2. SolidWorks structural analysis of the UAV frame showing von Mises stress distribution concentrated at the hub region.

antennas-maintained command and telemetry exchange, while the RFD900X telemetry module provided extended communication range, ensuring uninterrupted monitoring and control throughout inspection missions. The power supply was delivered by a Bonka 5200 mAh 35 C-4S Li-Po battery, which offered sufficient energy density to support extended flight durations without compromising payload capacity. Its discharge rating ensured reliable current delivery during rapid thrust demands. For imaging and data acquisition, a GoPro Hero7 Black camera was mounted on a custom-modified Tarot T-3D gimbal. This setup provided stabilized, high-resolution video and photographs of transmission components, minimizing image distortion caused by vibrations or sudden UAV movements [40].

Real-time onboard processing was achieved using the NVIDIA Jetson Nano, a compact GPU-enabled computing platform. It handled defect detection tasks directly during flight, reducing dependence on ground-based post-processing and enabling faster decision-making in inspection workflows. A consolidated summary of all hardware specifications and their functional roles is presented in Table 2, while the physical appearance of key modules and the developed frame are shown in Figure 3. The subsequent step was to assemble and integrate these components into a unified UAV platform, which is detailed in Section 2.3.

UAV Assembly and Integration

Once the individual subsystems were validated, they were integrated into a unified UAV platform optimized for power transmission insulators inspection. The assembly process emphasized mechanical balance, vibration isolation, and efficient use of space to ensure reliable flight

Table 2. Summary of UAV hardware components and their functional roles

Component	Specification	Role in UAV platform
Frame	S500 (11.42*7.09*2.36 inches)	Structural support and payload integration
BLDC motors Equation [41]	Emax MT 3506 650 kV	Provides thrust for lift and maneuvering
ESC Equation	Hobby wing XRotor 40 A	Controls motor speed and stability
Flight controller	Pixhawk cube orange	Core unit for autonomous navigation and control
Receiver	HereLink with dual antennas	Ensures long-range communication
GNSS	HERE2	Provides positioning and navigation data
Propellers Equation	1355 inches (nylon)	Converts motor torque into thrust
LiPo battery [42]	Bonka 5200mAh 35 C-4S	Power supply for extended flight duration
Camera and Gimbal	GoPro Hero7 black and Tarot T-3D	Captures stabilized high-resolution inspection images

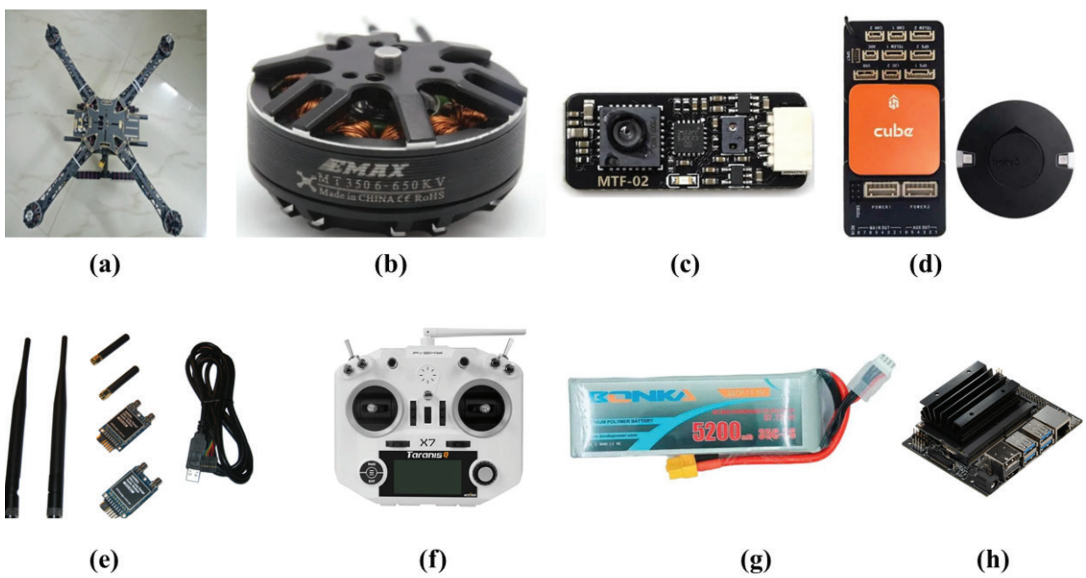


Figure 3. Key UAV components and developed frame: (a) S-500 X-shaped frame, (b) BLDC motor (650 kV), (c) HereFlow optical flow sensor, (d) Pixhawk Cube Orange controller, (e) RFD900X telemetry, (f) Taranis Q X7 transmitter, (g) Bonka 5200 mAh Li-Po battery, (h) NVIDIA Jetson Nano.

and high-quality data acquisition. The structural S500 X-shaped frame served as the base for component installation. The Pixhawk Cube Orange flight controller was centrally mounted on the main hub to minimize vibration effects and maintain stable control dynamics.

The Bonka Li-Po battery was positioned close to the centre of gravity, improving flight stability and reducing pitch/roll imbalance during manoeuvres. For reliable communication, the HereLink receiver antennas were extended outward from the frame to minimize interference, while the RFD900X telemetry module was mounted away from high-power electronics to reduce electromagnetic noise. The HERE2 GNSS module was fixed at the top of the UAV to maintain clear satellite visibility, and the HereFlow optical flow sensor was mounted at the bottom to support local navigation in GPS-challenged environments.

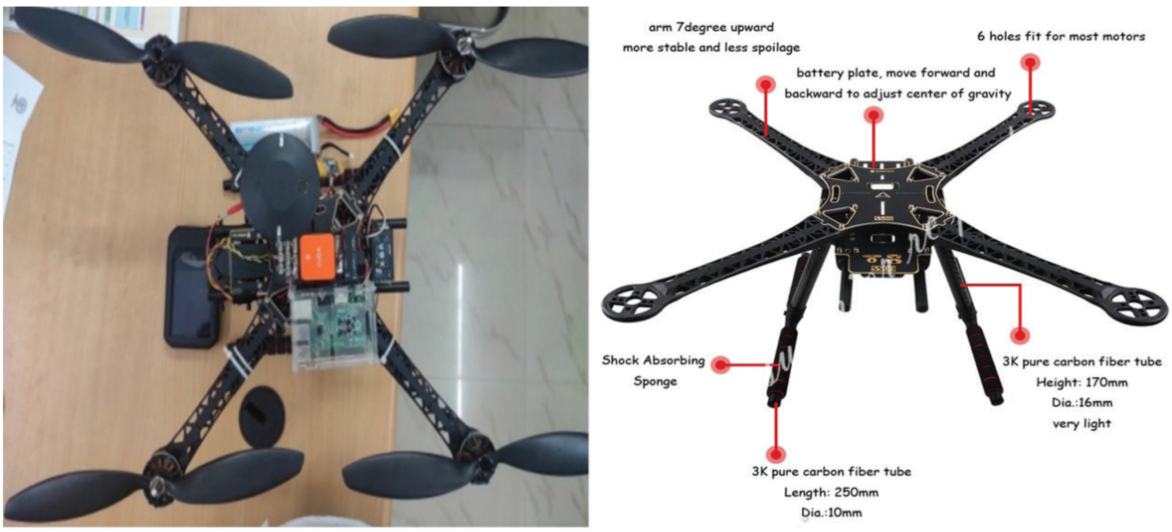
The NVIDIA Jetson Nano was installed on a vibration-damped mount to safeguard real-time processing performance during flight. The GoPro Hero7 camera, coupled with the Tarot T-3D gimbal, was mounted at the front underside of the frame, providing an unobstructed field of view of insulators and conductors during inspection. This placement reduced motion blur and ensured that image framing remained consistent throughout the mission.

The complete integration of these subsystems resulted in a compact, balanced, and mission-ready UAV platform optimized for reliable inspection of transmission infrastructure. Careful positioning of each module ensured stable flight dynamics, minimal interference, and high-quality data capture during operations. The final integrated system, together with the structural layout of the frame, is illustrated in Figure 4.

UAV based Power Transmission System Inspection process

To complement the UAV design and integration, a structured inspection workflow was developed for monitoring power transmission lines and insulators. The process is based on autonomous waypoint navigation, aerial imaging, and real-time defect detection. After take-off, the UAV follows a pre-programmed flight path consisting of sequential waypoints positioned around the transmission line towers. At each waypoint, the UAV hovers briefly to capture high-resolution images and video of conductors, insulators, and associated components.

During flight, the onboard vision system records potential anomalies such as broken or contaminated insulators, conductor wear, or structural defects. A thermal sensor assists in identifying hotspots that could indicate partial discharges, power losses, or potential failure points. All data, including images, sensor readings, and GPS coordinates, are transmitted in real time to the Ground Control Station (GCS), where operators can monitor mission progress and receive alerts of detected anomalies [43-46]. The integration of communication and computing modules allows real-time execution of deep learning algorithms, reducing reliance on post-flight analysis and enabling prompt decision-making. This automated inspection process not only improves coverage consistency and accuracy but also reduces the risks and operational costs associated with traditional manual inspections [47-49]. Figure 5 presents the overall UAV inspection workflow, illustrating the sequential steps from path planning and image acquisition to defect detection and reporting.



(a) **(b)**

Figure 4. UAV assembly and integration: (a) fully assembled quadcopter platform with installed subsystems (flight controller, battery, GNSS, telemetry, onboard computer, and gimbal) and (b) structural S500 frame layout highlighting key mounting features and design specifications.

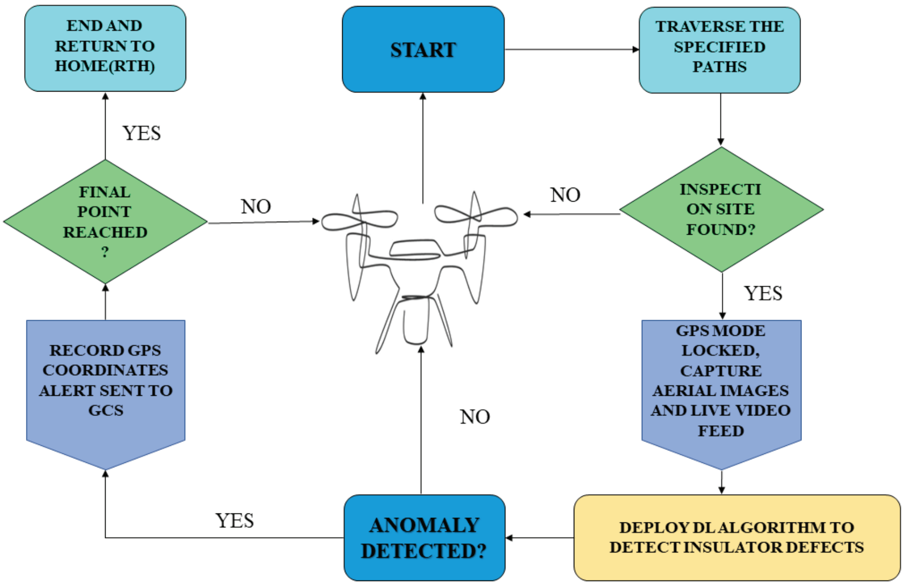


Figure 5. Workflow of the UAV-based inspection process for power transmission systems.

METHODOLOGY

This section describes the methodology adopted for detecting and identifying defective insulators using the dataset collected with the developed UAV platform. Figure 6 illustrates the overall workflow, detailing each stage from image acquisition to defect detection and analysis. The process begins with large-scale collection of high-resolution images of power transmission insulators under diverse environmental conditions. Next, a deep learning-based defect identification model is employed to distinguish defective insulators from normal ones. The methodology also outlines the effectiveness metrics used in this study, the preparation of datasets for training and testing, and the architecture of the YOLOv8 detection network. Upon completion, the proposed framework enables real-time detection of defective insulators in power transmission systems. The novelty of this work lies in the integration of a custom-built UAV platform, a dedicated large-scale insulator dataset, and a two-stage fine-tuning strategy applied to YOLOv8, which together provide a comprehensive and robust solution for automated inspection.

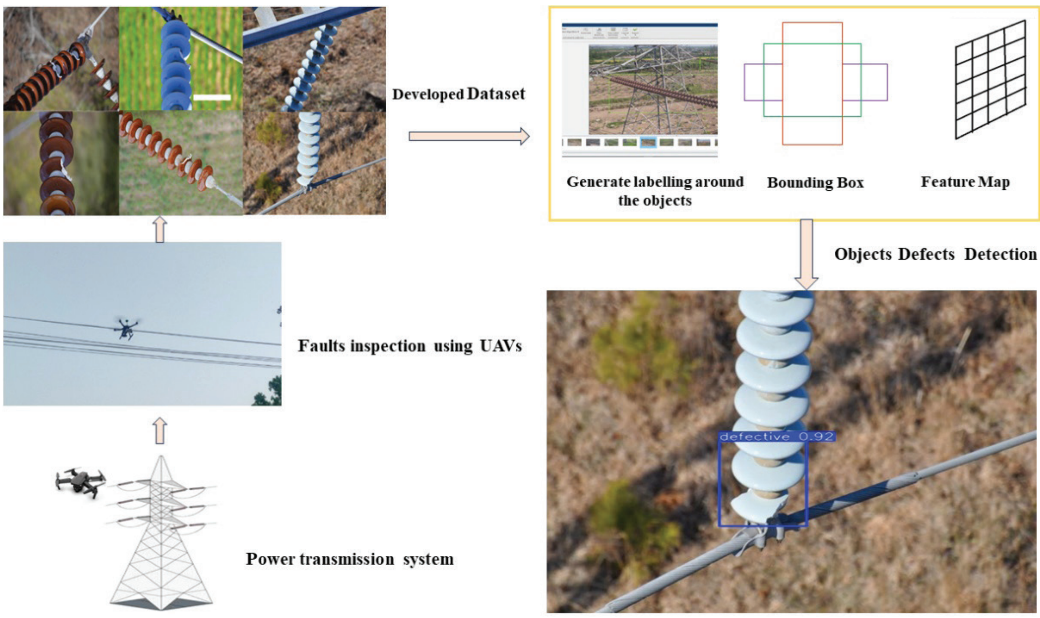


Figure 6. Overview of the UAV-based fault inspection and defect detection process for power transmission insulators.

Descriptions of Power Transmission Insulators Datasets

The development of a robust dataset on power transmission insulators is essential for advancing research that aims to enhance the safety, reliability, and efficiency of power systems. Existing publicly available datasets contain only a limited number of defective insulator samples, which restricts the effectiveness of training deep learning models for fault detection. To address this gap, a large-scale dataset was created in this study to support vision-based inspection and classification of transmission insulators, as illustrated in Figure 7.

The dataset was collected using a custom UAV platform equipped with a 4K GoPro Hero7 Black camera, capable of capturing images at resolutions of 1080p (1920×1080) and 7360×4912, with a frame rate of 60 FPS. UAV-based aerial inspections enabled the collection of diverse images from different perspectives and altitudes across real-world transmission environments. Careful attention was given to capturing data under varying lighting conditions, weather scenarios, and geographical terrains to ensure diversity and robustness of the dataset [50–52].

In total, 8,300 images were collected and categorized into two groups: normal and defective insulators. The dataset was further split into training and testing subsets, with 3,135 images used for training and 195 images reserved for testing. Table 3 summarizes the specifications of the developed dataset, including image resolution, category distribution, and acquisition equipment. By integrating high-resolution UAV imagery with real-world variability, the dataset provides a reliable foundation for developing, training, and evaluating deep learning models for automated insulator defect detection.

Labelling and Resizing images

Image resizing is essential for preparing image data to detect faulty insulators in power transmission systems and ensure consistency throughout the processing stages. Author employ interpolation techniques like nearest neighbour, bilinear, and bicubic to modify pixel values, maintain the aspect ratio, and incorporate padding as needed also used scaled images for subsequent analysis. Which includes identification and feature extraction, to ensure consistent input for the proposed algorithm and improved the dataset by putting together different pictures of power transmission systems taken by drones and vision cameras.

This made a full set with resolutions of 1080p (1920x1080) and 7360x4912 at 60 frames per second. The first step in the identification process is to collect and pre-process image data. Next, the data is manually annotated using tools like "Roboflow" to set bounding box

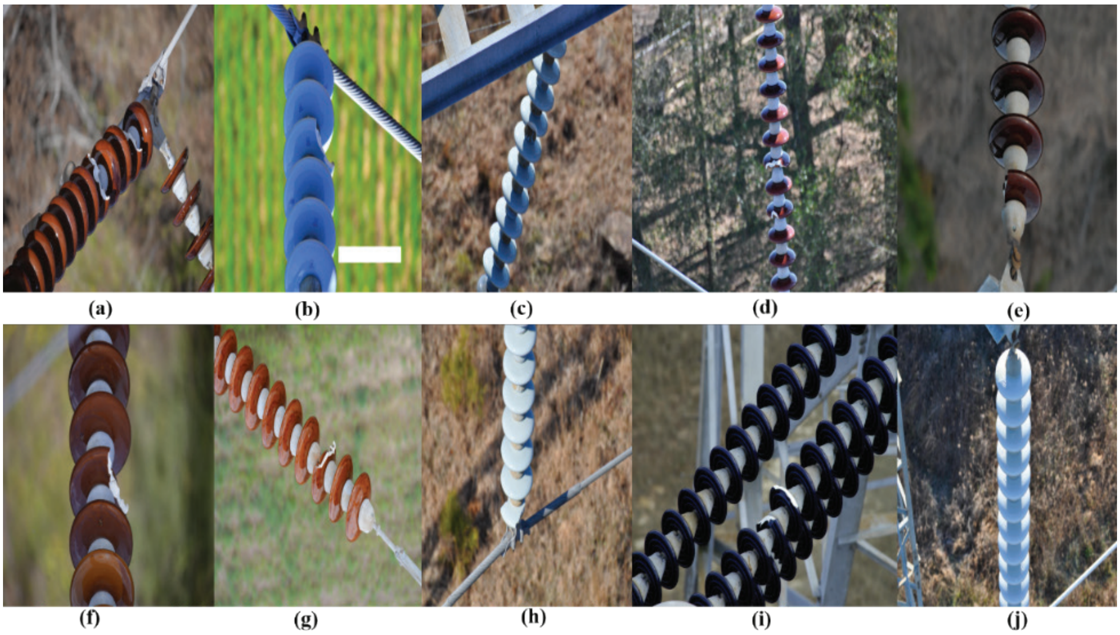


Figure 7. Collection of Insulators datasets, in various backgrounds (a-j).

Table 3. Specifications of Power Transmission insulators Datasets

Dataset	Category Identification	Images	Avg. Size of images	Equipment used
Insulators	Normal and Damage Insulators	8,300	1920×1080	UAV

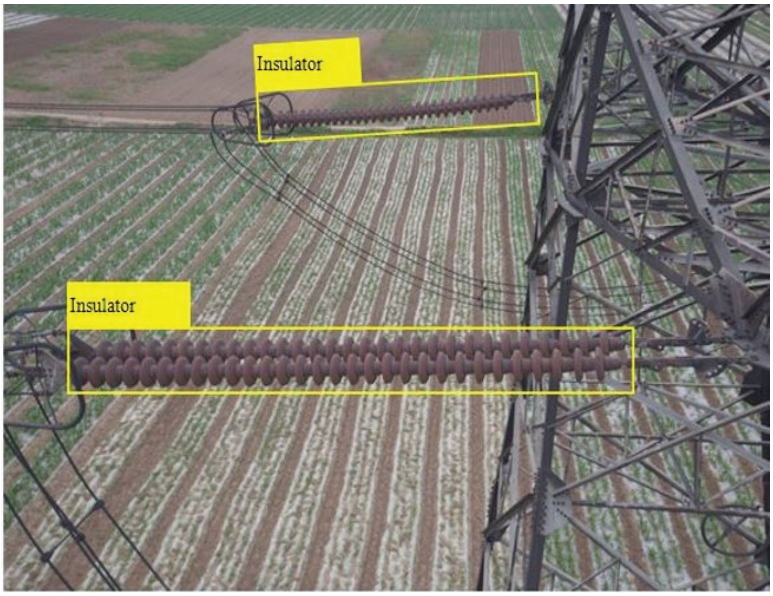


Figure 8. Labelling process on Power Transmission Insulators Dataset.

delineates the defect region of the insulator. This creates the "ground truth" for training, as shown in above Figure 8. To prevent overfitting and enhance real-world applicability, techniques such as transfer learning and online data augmentation, including mirror flipping and random scaling, are employed. This systematic method improves the model progressively, increasing its accuracy in detecting insulator defects within power transmission systems.

Data augmentation and fine-tuning methods

The proposed method detects defective insulators in two stages is employed to tackle the challenge of detection procedures an effective data augmentation technique designed to generate additional training data through transformations in the data space as shown in Figure 9. The dataset of original images is randomly flipped in multiple directions (right, left, top, and bottom) to produce four additional images then utilized the fine-tuning technique on the collected images, as shown in Figure 10.

This process consists of two steps, utilizing a crucial dataset that includes more than 8000 images. In the early stages of fine-tuning, an essential dataset comprising images is employed to train the model. In the second

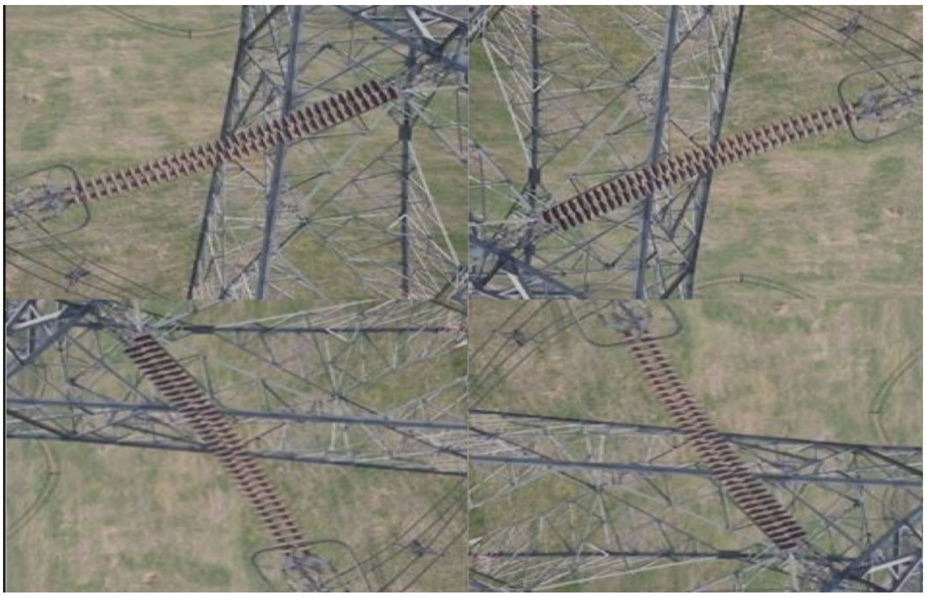


Figure 9. Power Transmission Insulators Dataset Augmentation process.

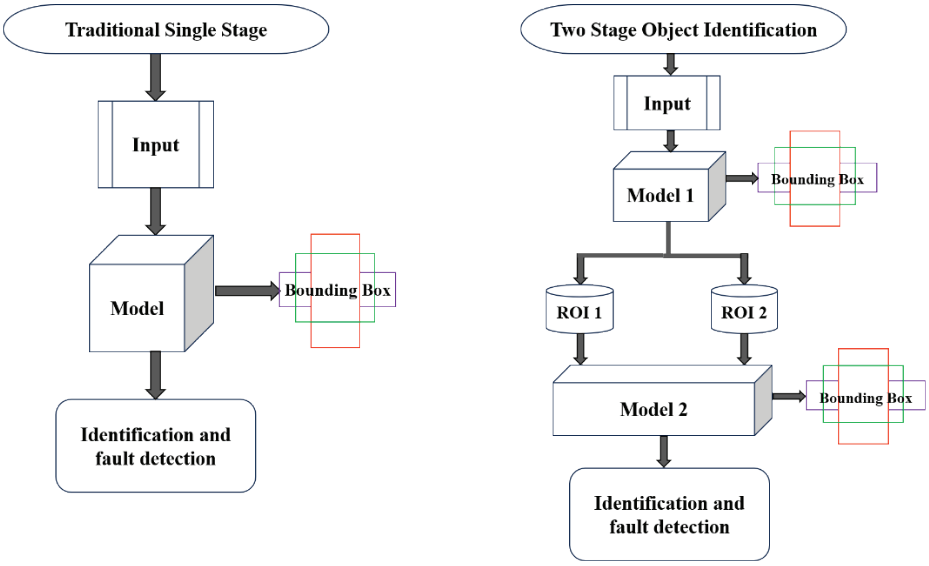


Figure 10. Traditional Fine-tuning methods and proposed Two-stage objects detection method.

stage, a designated dataset is generated, encompassing both defective and normal categories. Which surpasses earlier single-stage fine-tuning methods in sophistication [53]. The proposed approach entails the integration of a greater volume of data into the training and detection frameworks, resulting in optimal outcomes.

RESULTS AND DISCUSSION

To validate the proposed method, the defective insulator detection model was trained and tested using the UAV-acquired dataset comprising 8,300 annotated images. The experiments were conducted in Python 3.8 with OpenCV 4.5.5 on a GPU-enabled workstation. Training lasted 400 epochs with a batch size of 16, a learning rate of 0.01, momentum of 0.937, and weight decay of 0.005. A total of 20,000 iterations were performed, with convergence observed around the 10,000th iteration. Each trial required approximately 0.6 seconds, and the proposed system achieved an inference speed of 142 frames per second in real time. Model evaluation was carried out on an independent test set of 195 images. Standard COCO metrics were

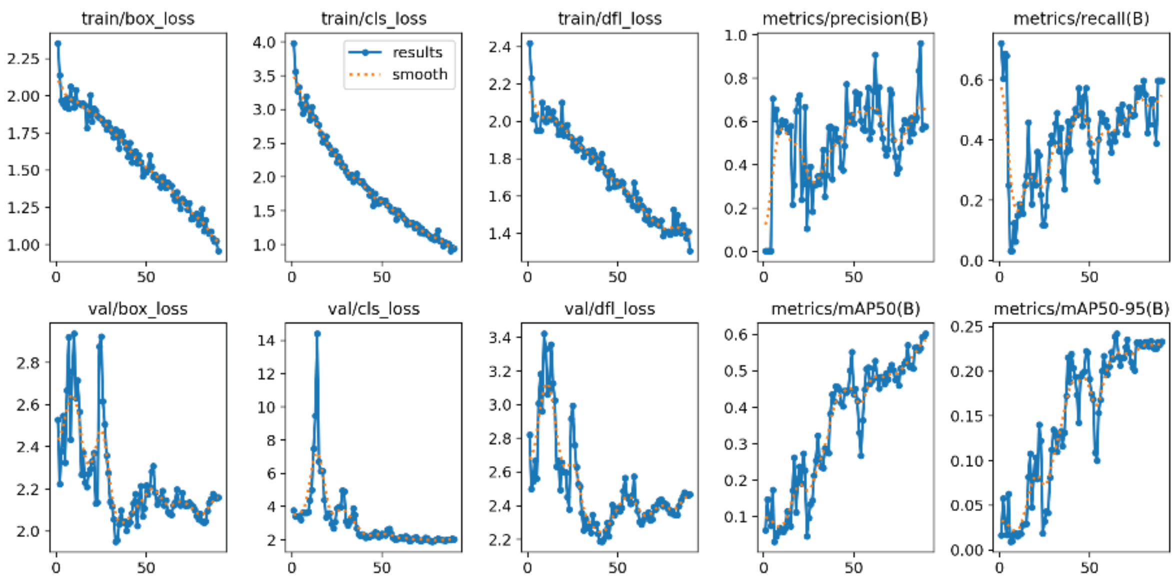


Figure 11. Training and validation performance curves of the proposed YOLOv8 model for insulator fault detection, illustrating loss functions (box, classification, distribution focal loss), precision, recall, and mean Average Precision (mAP).

adopted, including Average Precision (AP) at IoU = 0.5 and mean Average Precision (mAP@[0.5:0.95]).

The YOLOv8-based model achieved an AP of 92% for detecting defective insulators and a mAP@[0.5:0.95] of 50.1%. Here, the AP reflects class-specific detection performance, while the mAP offers a stricter measure across IoU thresholds. The corresponding training and validation curves are shown in Figure 11, highlighting precision, recall, loss functions, and mAP progression. Representative detection outputs for defective and normal insulators are illustrated in Figure 12.

When compared with baseline detectors, YOLOv8 demonstrated clear advantages in both accuracy and speed. As summarized in Table 4, the proposed framework outperformed R-FCN, Faster R-CNN, YOLOv5, and YOLOv7 in terms of accuracy, sensitivity, balanced accuracy, and mean precision–recall. For example, Faster R-CNN provided competitive accuracy but suffered from low inference speed (12.8 fps), which limits real-time UAV inspections. YOLOv7 exceeded YOLOv5 in accuracy but still underperformed relative to YOLOv8 in stricter mAP@[0.5:0.95] evaluation. The YOLOv8-based approach yielded more reliable bounding box localization, fewer false positives/negatives, and strong robustness across varied weather and lighting conditions.

The proposed YOLOv8 algorithm achieved an accuracy of 92%, sensitivity of 89.9%, specificity of 89.5%, balanced accuracy of 91.8%, a precision–recall mean of 0.95, and a detection speed of 63.6 frames per second.

Beyond achieving high detection accuracy, the novelty of this study lies in the integration of multiple innovations into a single inspection framework. Unlike prior works that rely solely on existing datasets or off-the-shelf UAVs, the present work introduces a custom-built UAV platform

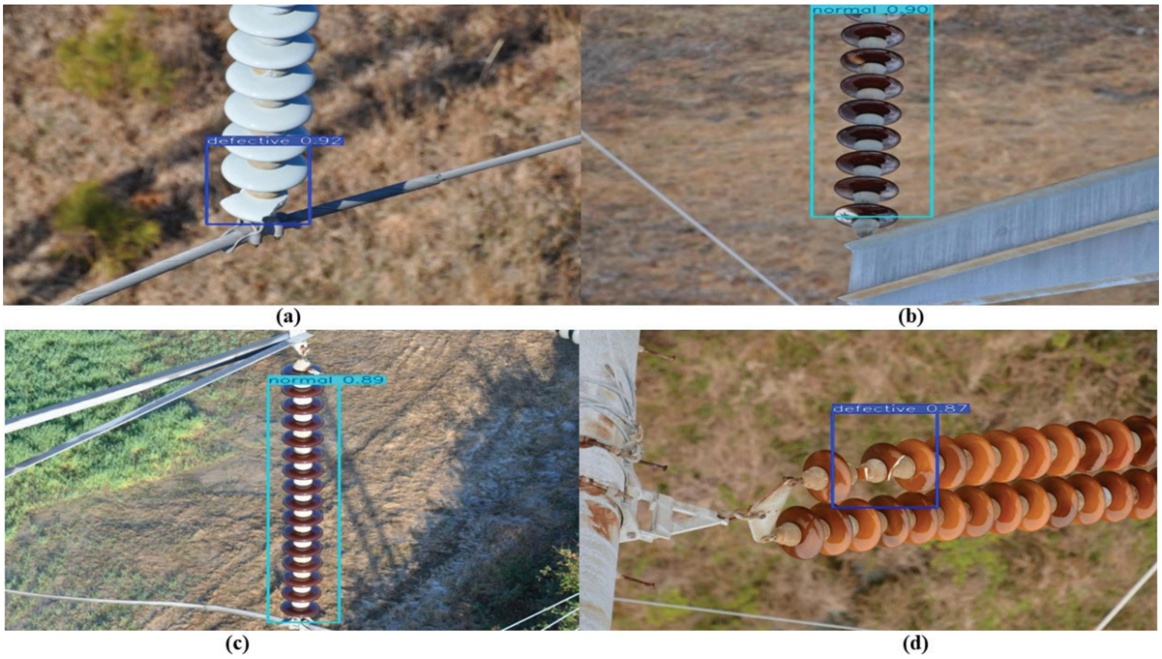


Figure 12. Detection results of the proposed YOLOv8 model on transmission insulators: (a, d) defective insulators with cracks; (b, c) normal insulators.

Table 4. Comparison results of proposed algorithm with multiple parameters

Algorithm	Accuracy	Sensitivity	Specificity	Balanced Accuracy	Precision-recall mean	Detection speed/ second
R-FCN [54]	83.1%	84.6	83	84.8	0.80	16.9
Faster R-CNN [55]	87.6	89	86.2	87.6	0.90	12.8
YOLO v5	89.8	88.1	88.2	88.65	0.91	46.3
YOLOv7 [56]	90.5	87.0	88.4	85.4	0.90	58.2
Proposed algorithm YOLOv8	92	89.9	89.5	91.8	0.95	63.6

designed for stable flight in inspection environments, coupled with a dedicated large-scale insulator dataset collected under real transmission conditions. Furthermore, the use of a two-stage fine-tuning strategy with YOLOv8 significantly improved generalization across varying lighting and weather scenarios, enabling both high accuracy and real-time performance (63.6 fps). These combined elements establish a unified and scalable methodology for UAV-based power transmission insulators monitoring, representing a step beyond conventional single-focus approaches.

Although the YOLOv8-based UAV inspection system demonstrates strong performance, several limitations should be acknowledged. First, the dataset, while diverse, was limited to 8,300 images collected from specific transmission environments in India; larger and more geographically varied datasets are required to further enhance generalization. Second, the experiments were primarily performed on still images, and real-time video detection has yet to be validated under continuous flight conditions. Third, certain fault categories such as subtle surface erosion, contamination, or vegetation-induced faults were underrepresented, which may affect robustness in those scenarios. Finally, the UAV was tested under controlled flight paths, and its performance under highly dynamic or adverse weather conditions (e.g., heavy rain or fog) remains untested. Addressing these limitations will be the focus of future work to ensure broader scalability and practical deployment in utility operations.

The following section presents the overall conclusions and future directions of this study.

CONCLUSION

The efficient transmission of electrical power is essential to maintaining the stability, safety, and reliability of modern power grids. Insulators, which serve as critical components in isolating high-voltage conductors, are highly susceptible to faults such as cracks, contamination, and mechanical damage. These defects not only reduce system efficiency but can also lead to costly equipment failures and large-scale outages if left undetected. To address these challenges, this study developed an Unmanned Aerial Vehicle (UAV)–based inspection framework integrated with the You Only Look Once version 8 (YOLOv8) deep learning model for automated, real-time detection of insulator defects.

A custom UAV platform was designed and structurally validated to ensure flight stability, payload flexibility, and reliable image acquisition under diverse operating conditions. Using this platform, a dedicated dataset of 8,300 high-resolution annotated insulator images was compiled under varied weather and illumination scenarios. To further enhance generalization, advanced augmentation strategies were employed, effectively mitigating class imbalance and overfitting. The experimental evaluation demonstrated that the proposed framework achieved a detection accuracy of 92% and a mean Average Precision (mAP@[0.5:0.95]) of 50.1%, while maintaining real-time inference capability. When benchmarked against state-of-the-art methods such as R-FCN, Faster R-CNN, YOLOv5, and YOLOv7, the YOLOv8-based approach outperformed these detectors in both accuracy and detection speed, thereby validating its practical utility for UAV-assisted inspections.

The novelty of this research lies in its holistic integration of a purpose-built UAV platform, a large-scale real-world dataset, and a two-stage augmentation fine-tuning strategy to deliver superior performance in aerial defect detection tasks. Unlike prior studies that rely on either synthetic data or limited environmental conditions, this work demonstrates robustness across diverse real-world scenarios, ensuring both technical advancement and field-level applicability. These findings confirm that UAV-enabled deep learning provides a reliable, scalable, and cost-effective solution for predictive maintenance in modern power transmission systems, reducing reliance on hazardous manual inspections and enabling proactive grid management.

Future research will focus on the following directions:

- Expansion of defect categories: Extending the detection capability to cover additional fault types such as conductor wear, vegetation encroachment, and foreign object interference.
- Real-time video analysis: Developing and validating continuous detection from UAV video streams to support dynamic inspections.
- Large-scale deployment: Scaling the framework across extensive transmission corridors and varied geographic regions to improve generalization.
- Adverse weather adaptation: Enhancing resilience under challenging environmental conditions, including fog, heavy rain, and high winds.
- Industry readiness: Strengthening scalability, robustness, and integration mechanisms to facilitate adoption in utility operations.

By addressing these avenues, the proposed system has strong potential to evolve into a comprehensive, industry-ready solution for intelligent monitoring of power transmission infrastructure, ultimately improving grid reliability, operational efficiency, and cost-effectiveness.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports thefindings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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