



A YOLO-Based Approach for Small-Object Defect Detection in High-Voltage Transmission Towers

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ABSTRACT

Reliable transmission of electrical energy through high-voltage power towers requires continuous and accurate inspection of their components and potential defects. This research aims to facilitate the transition from traditional, labor-intensive inspection methods to automated inspection systems. Existing image datasets often fail to comprehensively cover all components and defects of power towers, and certain critical parts are overlooked. For example, due to their small size, essential elements such as split pins and bolts have not received sufficient attention. In this study, images captured by drones from a 400 kV transmission line were utilized. The goal was to move toward automated inspection by annotating key components in two classes—*intact* and *damaged*—and training object detection models from the YOLO family on the generated dataset. The performance of the trained models was evaluated. The best model achieved a precision of 0.754 for classification and a mean Intersection over Union (mIoU) of 0.740 for object localization.

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1. Introduction

High-voltage transmission networks are vital infrastructures, whose stability directly influences social, economic, and political security. Failures in components such as insulators, yokes, bolts, and pins can result in severe consequences like blackouts and costly damages (Hu et al., 2019). Timely identification of such defects is therefore essential to prevent network disruptions. Traditional inspection methods relying on human operators are not only expensive and hazardous but also prone to error (Thakallapelli et al., 2016).

In recent years, the adoption of modern technologies—particularly drones and machine vision systems—has significantly advanced the monitoring of high-voltage equipment. Drones allow for safe imaging of hard-to-access tower components, even under energized conditions, enabling automated analysis through machine learning and deep learning algorithms (Mo et al., 2021; Surantha et al., 2022; Z.-Q. Zhao et al., 2019).

In computer vision, Convolutional Neural Networks (CNNs) have emerged as the core of object and defect detection systems. Networks like YOLO (various versions), ResNet, Faster R-CNN, and VGG have been employed in numerous studies for detecting tower components and insulator defects (Shuang et al., 2023; Z. Zhao et al., 2019; Zormpas et al., 2018). Many works highlight YOLOv3 for its real-time performance in detecting small components (et al., 2019; Varghese et al., 2017), while others suggest optimized versions like YOLOv4 to improve accuracy (Shuang et al., 2023; Tomaszewski et al., 2019). Models such as Faster R-CNN and ResNet are preferred in certain scenarios due to higher precision (Hu et al., 2019; Z. Zhao et al., 2019), and lightweight architectures like MobileViT have also been explored to reduce computational costs in complex environments (Hu et al., 2019; Z. Zhao et al., 2019).

Despite advancements in deep learning, a key challenge remains the availability of diverse and comprehensive training data. Many studies rely on specific datasets such as the Power Line Assets Dataset (PLAD) (Siddiqui et al., 2018), Insulator Defect Image Dataset (P. Kulkarni, 2022), and InsPLAD (Vieira e Silva et al., 2023), which, though targeted, still suffer from limited environmental variability (e.g., lighting, pollution, and weather conditions) and incomplete coverage of all transmission tower components. The difficulty and danger of capturing images from live, high-voltage towers contribute to this data scarcity.

To address data limitations, some researchers have turned to simulated data or data augmentation techniques (Bianchi et al., 2024; Vieira-e-Silva et al., 2021). However, there remains a strong need for richer, real-world datasets that enable reliable algorithm performance under practical conditions. Object detection networks also tend to perform better on larger-scale objects in images (Mo et al., 2021; Z.-Q. Zhao et al., 2019), which may explain the lack of attention to small but critical components in previous works.

This research focuses on creating a novel image dataset from the 400 kV Yazd–Mehrehgan transmission line, targeting overlooked yet essential components like missing bolts, missing cotter pins, and intact cotter pins. As shown in Table 1, these specific defect classes are not addressed in comparable datasets such as InsPLAD (Vieira e Silva et al., 2023), PLT-AI (De Oliveira et al., 2022), TTPLA (Abdelfattah et al., 2020), CPLID (Tao et al., 2018), Tomaszewski et al. (Tomaszewski et al., 2018), Reinaldo et al. (Bianchi et al., 2024), and RSIn (Shuang et al., 2023). In this table, MP stands for Missing Pin, DI stands for Defect Insulator, HP stands for Healthy Pin, HI stands for Healthy Insulator, MB stands for Missing Bolt, and No.TN stands for the number of tested networks.

By annotating and training YOLO-family object detection models on this new dataset, we move closer to enabling fully automated inspection systems that reduce human dependence and improve defect localization, especially for small-scale components.

Table 1. Comparison of Classes in the Custom Dataset with Existing Image Datasets.

	MP	DI	HP	HI	MB	No. T.N
InsPLAD	×	✓	×	✓	×	7
PLT-AI	×	✓	×	✓	×	9
STN PLAD	×	×	×	✓	×	2
TTPLA	×	×	×	×	×	6
CPLID	×	✓	×	✓	×	No training
Tomaszewski et al	×	×	×	✓	×	No training
Reinaldo et al	×	✓	×	✓	×	7
RSIn	×	×	×	✓	×	9
Our Data	✓	✓	✓	✓	✓	9

2. Dataset and Methods

2.1. Section and sub-section headings

The dataset used in this study was derived from inspection images of high-voltage transmission lines, reviewed and annotated based on reports by human operators. A complete list of possible defects identified during inspections is provided in Table 2. Key criteria for defect selection included structural features, color differences between defective parts and adjacent components, and defect frequency in operator reports.

Unlike previous works where components and defects were treated separately (Vieira e Silva et al., 2023), our dataset integrates both tower components and their corresponding defects. Based on this, five classes were selected for training: missing cotter pin, intact cotter pin, missing bolt and nut, healthy insulator, and defective insulator (highlighted in Table 2).

Table 2. Defects of tower components of high-voltage power tower inspection

Missing bolt	Excess wire on guard	Missing anti-climbing clip	Armor rod malfunction
Missing nut	Broken angle bracket	Corona ring damage	disconnected angle bracket
Rusted bolt	Missing cotter pin	Armor rod defect	Intact cotter pin
Rusted ladder bolt	Broken snow guard	Paint/welding defect	Damaged damper
Loose bolt	Broken insulator	Worn-out aerial signboard	Bent angle bracket
jumper disconnected	Base cracking	Missing angle bracket	Healthy Insulator

A brief description of the selected components and their defects is presented below.

Insulator: The insulator is a vital component of transmission towers (Jia et al., 2023), frequently highlighted in related studies due to its importance (Z. Zhao et al., 2019). Prior research has focused on insulator detection, defect identification (Vieira e Silva et al., 2023), and type classification (Bianchi et al., 2024). Its relatively large size in images facilitates easier detection compared to smaller components. Beyond classification, defect analysis has also been addressed (Wang et al., 2023), with common issues including bird droppings, dust, fractures, and flashovers.



Figure 1 illustrates the difference between a clean and bird-contaminated insulator.

To avoid the need for providing a sufficiently large dataset with labelled fault types for detection and diagnosis, insulators have been classified into only two categories: healthy and faulty.

Bolts and Nuts: Bolts and nuts connect the components of the tower. Missing bolts can cause serious damage to the tower. Despite the critical importance of this component in technical inspections of high-voltage power towers, no training data has been provided in similar studies due to its small size in the images. An example of healthy bolts and nuts, as well as missing ones, is shown in Figure 2.

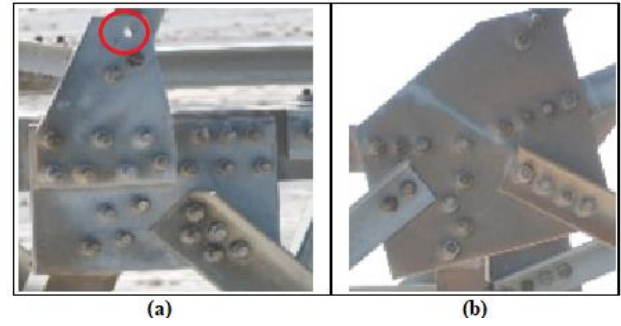


Figure 2. Healthy and missing bolts and nuts. (a) Missing bolts and nuts, (b) Healthy bolts and nuts.

Cotter Pins: Cotter pins prevent nuts from loosening on bolts, especially in critical tower components like insulators. However, they can occasionally dislodge due to various factors. Inspection images of high-voltage towers show that cotter pins are even smaller than nuts, and thus have not been considered in other studies. In Figure 1, you can see cotter pins and missing cotter pin.

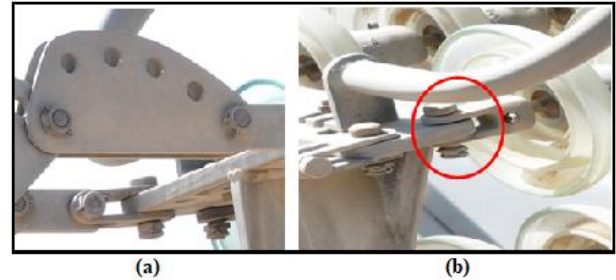


Figure 5 – Cotter pin: (a) Presence of cotter pin in the nut. (b) Absence (missing) cotter pin.

2.2. Labelling and Class Definition

The dataset includes images of 60 transmission towers captured from the ground by an operator and from various aerial angles using a drone. Since defect detection requires expertise and precision, an experienced operator assisted in the annotation process. Labelling was performed using the open-source tool LabelImg (D.Tzatalin, 2015). In densely structured regions, careful boundary identification between components was ensured to prevent inaccurate annotations. The imaging operator also captured scenes from optimal angles to maximize visual clarity and feature separability.

2.3. Dataset Characteristics

The dataset comprises both ground-based and drone-based images. Due to varying camera resolutions, all images were resized to uniform dimensions to build a consistent and specialized dataset. The number of images and annotated object dimensions are summarized in Table 3.

Table 3. Number of annotated objects and the average area of each class in the images of the custom dataset.

Class	No. of annotated objects	Average object area in pixels
Missing Bolt	3573	4342.16
Healthy Insulator	5509	1174292.55
Healthy Pin	12212	23284.01
Defect Insulator	3167	1483417.59
Missing Pin	372	26312.44

A total of 9,650 ground and drone images were collected across all inspected towers. Some images did not contain any of the five target classes and were therefore excluded from annotation. The final dataset includes 5,796 annotated images with 31,629 labeled objects.

For deep learning-based object detection, datasets are typically divided into training, validation, and test subsets. Training data are used to optimize model parameters, validation data to monitor intermediate performance and tune hyperparameters, and test data to evaluate the final model accuracy after training.

A common split ratio is 80% for training and 20% for testing (Matos et al., 2022); however, when three subsets are used, previous studies often recommend a 70%, 15%, and 15% division (Arafin et al., 2022). The present study adopts the latter ratio (70/15/15) for training, validation, and testing, respectively. During dataset partitioning, class distributions were balanced across subsets to prevent bias and ensure fair performance evaluation. Table 4 summarizes the number of annotated objects per class and subset, illustrating the balanced composition of the proposed dataset.

Table 4. Number of annotations broken down by training, validation, and test, and by class.

No.	HP	DI	MB	HI	MP	Images
Training Set	9186	2193	2369	3958	241	4057
Validation Set	1966	484	650	718	71	869
Test Set	2060	490	554	833	60	870

3. Experiments and Benchmarking

3.1. Models and Experimental Step

3.1.1. Model Selection

The You Only Look Once (YOLO) family represents one of the most widely used architectures for object detection, classification, and segmentation (Ramos & Sappa, 2025). Over the years, successive versions of YOLO have evolved (Terven et al., 2023) and have been effectively applied to

multi-class detection, autonomous driving, and inspection of high-voltage transmission towers. Researchers often use either pretrained YOLO models or adapt them by adding custom modules to enhance performance for specific tasks (Ge et al., 2021).

All YOLO variants are accessible through the Ultralytics library, which offers easy installation, extensive documentation, and multi-platform support. In this study, the following versions were evaluated: YOLOv3, YOLOv5x, YOLOv6x, YOLOv9e, YOLOv10x, YOLOv11x, YOLOv12x, YOLORt-DETR1, and YOLO RT-DETRx.

3.1.2. Hardware Configuration

Model training and evaluation were performed on a workstation equipped with an Intel Core i7-13700K CPU and an NVIDIA RTX 3090 GPU.

3.1.2. Hyperparameter Settings

Training hyperparameters were grouped into four categories:

Learning rate and scheduling: lr0 = 0.01, lrf = 0.01, momentum = 0.937, weight_decay = 0.0005

Batch and image parameters: batch_size = 16, image_size = 640, workers = 8

Optimization settings: optimizer = Auto, epochs = 500 warmup_epochs = 3

Loss weighting: box = 7.5, cls = 0.5, dfl = 1.5

3.2. Evaluation Metrics

Performance was assessed using standard object detection metrics, including Precision (Everingham et al., 2010; Lin et al., 2014; Powers, 2020), Recall (Everingham et al., 2010; Lin et al., 2014; Powers, 2020), F1-score (Sasaki, 2007), mIoU (Lin et al., 2014), Average Precision (AP), and mean Average Precision (mAP) at thresholds mAP@0.5 and mAP@0.5:0.95 (Everingham et al., 2010; Lin et al., 2014). Precision measures the proportion of correct predictions among all detections (Fawcett, 2006), while Recall quantifies correctly detected objects among all ground truths (Sokolova & Lapalme, 2009). The F1-score provides the harmonic mean of Precision and Recall (Sasaki, 2007). AP is the area under the Precision-Recall curve for a single class, and mAP is the mean across all classes (Everingham et al., 2010; Lin et al., 2014). The mean inference time per image was also computed to evaluate real-time applicability.

4. Results and Discussion

The custom five-class dataset (see Table 4) was used to train all YOLO models listed in Table 5 via the Ultralytics framework. Each trained model was then tested using the defined test set, and results for Precision, Recall, IoU,

mAP@0.5, mAP@0.5:0.95, and average inference time (s) are reported in Table 6.

According to Table 6, YOLOv6x achieved the highest Precision, while YOLOv9e yielded the best Recall. Since defect detection emphasizes minimizing missed faults rather than avoiding occasional false positives, Recall plays a crucial role. However, the task involves both defect identification and component detection; thus, a balanced trade-off between Precision and Recall is required for optimal performance in transmission tower analysis.

Table 6. Evaluation of the performance of various networks within the YOLO family for defect detection and designed classes across different metrics

Neural Network	Precision	F1-score	Recall	mAP@0.5	mAP@0.5:0.95	mIoU	average detection time (seconds)
YOLO 12x	0.689	0.659	0.632	0.630	0.510	0.724	0.192
YOLO 11x	0.684	0.648	0.616	0.631	0.508	0.731	0.192
YOLO v10x	0.707	0.655	0.611	0.632	0.512	0.740	0.190
YOLO v9e	0.694	0.675	0.652	0.635	0.511	0.723	0.192
YOLO v8x	0.724	0.668	0.619	0.634	0.511	0.723	0.192
YOLO RT_DETR x	0.686	0.634	0.589	0.582	0.435	0.578	0.192
0.558YOLO RT_D0.668ETR	0.625	0.595	0.568	0.547	0.407	0.558	0.197
YOLO v6x	0.754	0.661	0.588	0.603	0.473	0.668	0.184
YOLO v5x	0.715	0.682	0.651	0.650	0.520	0.714	0.194
YOLO v3	0.747	0.670	0.610	0.620	0.498	0.726	0.191

Given that the proposed dataset combines defect detection and object recognition, the optimal model must balance Precision and Recall. Therefore, the F1-score, representing their harmonic mean, was used to assess overall performance. Based on this metric, YOLOv5x achieved the best results. While a Recall-focused model is more sensitive to defects, it may produce more false detections; conversely, a Precision-oriented model may miss some true defects. Hence, F1-score provides a more reliable indicator for balanced evaluation.

For object detection tasks, both classification accuracy (Precision, Recall, F1-score) and localization quality (mIoU, mAP) are critical. Among models, YOLOv10x achieved the highest mIoU, indicating better overlap between predicted and ground-truth bounding boxes. However, since both correct classification and accurate localization are essential, mAP was considered the main combined metric.

The mAP@0.5 metric, representing the average Precision–Recall area at an IoU threshold of 0.5, was used to assess overall detection and localization performance. Under this criterion, YOLOv5x again delivered the best results. For stricter evaluation, mAP@0.5:0.95, averaging performance over IoU thresholds from 0.5 to 0.95, was also computed. YOLOv5x achieved the top performance for this metric as well, confirming its robustness across varying localization thresholds.

Inference time is another key factor for real-time applications. Average detection time per image was measured across all test samples. YOLOv6x achieved the best runtime, processing each image in 0.1835 seconds (~5.45 FPS), making it suitable for real-time inspection, such as drone-based tower monitoring.

Considering all evaluation criteria, YOLOv5x demonstrated the best overall balance between accuracy and efficiency. It achieved the highest F1-score and mAP values across both IoU thresholds, indicating strong capability for both defect detection and component identification. Although YOLOv5x was not the absolute best in all metrics or classes (see Table 7), it consistently ranked near the top, confirming its reliability.

Qualitative examples in Figures 5–7 illustrate both correct and missed detections of YOLOv5x. For instance, missing bolt defects were not identified in Figure 5, and some intact cotter pins were missed in Figures 6 and 7.

Finally, per-class mAP@0.5 results (Table 7) were analyzed to evaluate dataset quality and model behavior. For the missing bolt and nut class, YOLOv8x achieved the best performance. Although this class (2,369 annotations) is similar in sample size to the damaged insulator class (2,193 annotations), the mAP difference (0.422 vs. 0.926 in YOLOv8x) suggests that object size and annotation area significantly influence detection accuracy.

Table 7. Report of the mean average precision at an IoU threshold of 0.5, by class and network.

	MB	HI	HP	DI	MP
YOLO 12x	0.419	0.913	0.820	0.92	0.075
YOLO 11x	0.402	0.918	0.845	0.931	0.056
YOLO v10x	0.415	0.911	0.821	0.926	0.084
YOLO v9e	0.404	0.911	0.828	0.922	0.112
YOLO v8x	0.422	0.916	0.821	0.926	0.086
YOLO RT_DETR x	0.311	0.873	0.758	0.855	0.112
YOLO RT_DETR i	0.251	0.869	0.715	0.846	0.054
YOLO v6x	0.339	0.890	0.791	0.918	0.076
YOLO v5x	0.420	0.914	0.825	0.926	0.166
YOLO v3	0.407	0.899	0.819	0.919	0.056

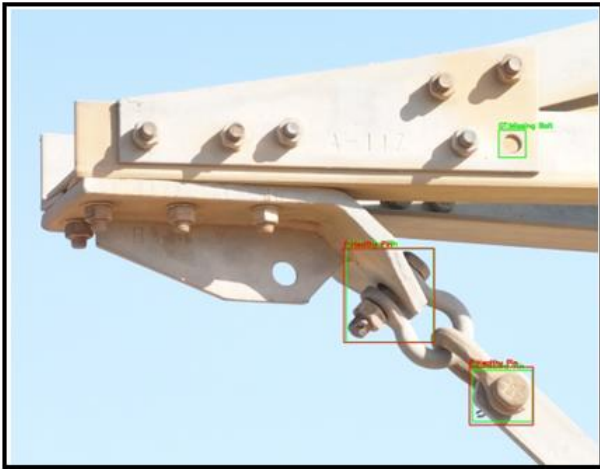


Figure 5. Example of non-detection of a fractional bolts and nuts class by the YOLO v5x network

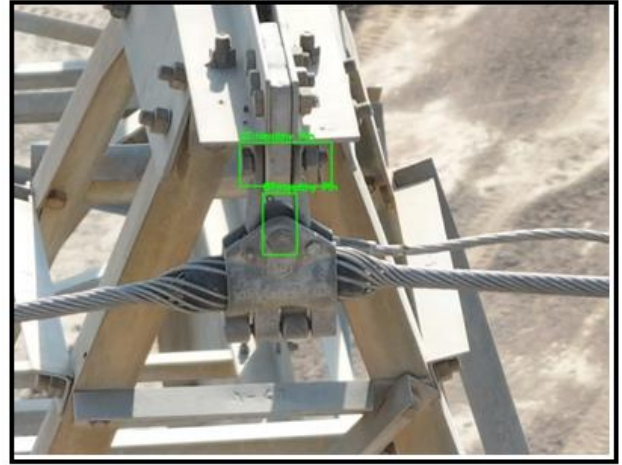


Figure 6. Example of non-detection of Healthy Pin by the YOLO v5x network

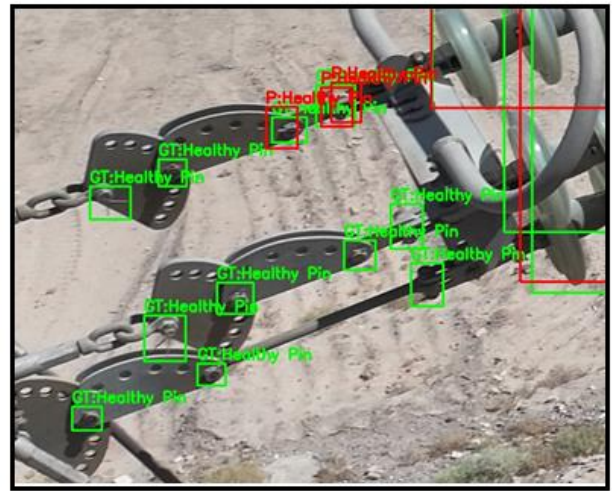


Figure 7. Another example of non-detection of Healthy Pin by the YOLO v5x network

According to Table 3, the average object areas for the damaged insulator and missing bolt & nut classes are 1,483,417.59 and 4,342.16 pixels², respectively—a 341× size difference. Prior studies (Hu et al., 2025; Saad et al., 2024; Tariq & Javed, 2025) have shown that larger objects generally improve detection accuracy, while smaller ones negatively affect object detection performance. Hence, the observed gap in mAP@0.5 between these classes, despite similar annotation counts, can be attributed to object size differences.

Comparing the missing bolt & nut and missing cotter pin classes, the latter has a mean area of 26,312.44 pixels²—about 6× larger than the former—yet achieves a lower mAP@0.5 (0.166 with YOLOv5x, Table 7). Based on dataset statistics (Table 4), this is due to severe class imbalance: the missing bolt & nut class includes 2,369 samples, while missing cotter pin has only 241. Similar to

findings in (Hu et al., 2025; Saad et al., 2024; Tariq & Javed, 2025), such data imbalance significantly limits model performance on underrepresented classes.

For the intact cotter pin and missing cotter pin classes, object sizes are comparable (23,284.01 vs. 26,312.44 pixels²), but the annotation counts differ greatly—9,186 vs. 241 ($\approx 38\times$). This imbalance explains the gap in mAP@0.5 (0.845 vs. 0.166). Among the intact insulator, intact cotter pin, and damaged insulator classes, YOLOv11x achieved the highest mAP values (0.918, 0.845, and 0.931, respectively). Despite smaller object sizes, the intact cotter pin class performed comparably due to its higher sample count, confirming the strong influence of dataset balance on detection results.

5. Conclusion

This study introduces a new dataset for detecting specific components and defects in high-voltage transmission towers, collected from real inspections of the Mehrgan–Yazd 1 line. The dataset combines defective and intact components into five classes: intact insulator, damaged insulator, intact cotter pin, missing cotter pin, and missing bolt & nut. Notably, three of these classes consist of small-scale objects, which are often neglected in prior studies.

As the key contribution, this work focuses on small-object defect detection, a challenging and underexplored domain in transmission tower inspection. Given the rarity and small size of such defects, detection remains difficult for current models. The presented dataset provides a foundation for further research toward improving detection of small and rare tower components.

All models from the YOLO family were trained on this dataset. Based on the evaluation metrics, YOLOv5x demonstrated the best overall performance across all classes. However, all networks showed reduced accuracy for small and underrepresented classes. Future work should focus on data augmentation and synthetic sample generation to balance class distributions and enhance detection of small objects, ultimately enabling more reliable automated power tower inspection systems.

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