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Real-Time Insulator Defect Detection in Overhead Transmission Lines Using YOLOv8

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Insulator defects significantly affect the reliability and safety of overhead transmission lines; hence, their early detection is critical for the stability of the power system. Existing inspection techniques are time-consuming, expensive, and risky, as they involve manual line inspections or helicopter-based systems. This paper presents a real-time insulator defect detection system using the YOLOv8m deep learning model to detect two prominent types of insulator defects: broken insulators and pollution flashovers. A new dataset was created and labeled using Roboflow, and the model was trained and optimized using Google Colab with GPU support. The experimental results indicate that the YOLOv8m model yielded a mean Average Precision (mAP@0.5) of 94.0% and mAP@0.5:0.95 of 68.0%, which is better than the lighter models YOLOv8n and YOLOv8s in terms of detection precision while maintaining real-time performance. The proposed system is a reliable and efficient solution for intelligent inspection and helps in the development of fully automated UAV-based monitoring systems for overhead transmission lines.

Keywords: Insulator Defect Detection; YOLOv8m; Deep Learning; Overhead Transmission Lines; Computer Vision; Real-Time Monitoring

Introduction:

Overhead transmission lines, an essential part of the modern power system, enable large-scale electricity transmission from generating stations to consumers. The dependability and operational safety of these transmission lines depend heavily on the insulators, which provide mechanical support and ensure electrical insulation between grounded structures and energized conductors. Degradation of insulator performance can lead to decreased transmission network reliability and power system instability [1].

Because they are constantly exposed to environmental factors like dust, moisture, wind, and temperature changes, insulators are extremely prone to defects. These defects include things like mechanical damage, surface contamination, cracks, and pollution flashovers. Such flaws can lead to power outages, unstable grids, and higher maintenance expenses if they are not identified promptly [2].

Visual inspections and aerial surveys have previously been used to identify insulator flaws. However, these techniques are time-consuming, labor-intensive, and may jeopardize the security of maintenance personnel. As transmission networks grow in size and complexity, there is an increasing need for more automated and efficient inspection methods [3].

Recent advances in deep learning-based computer vision have produced promising alternatives to infrastructure monitoring. Specifically, real-time processing capabilities and high detection accuracy have been demonstrated by object detection models like Faster R-CNN, SSD, and the YOLO family. Improved YOLO variants have been successfully used in a number of studies for the detection of insulator defects, and recent surveys have demonstrated the efficacy of deep learning in this field [4].

Nevertheless, only a small amount of research has assessed the most recent YOLOv8 architecture for automated maintenance reporting mechanisms and real-time insulator defect detection. This paper suggests a real-time insulator defect detection system based on the YOLOv8m model in order to close this gap. Roboflow was used to create and annotate a new dataset, and Google Colab with GPU acceleration was used to train the model. To further improve its practical applicability in the power industry.

Convolutional Neural Networks (CNNs) and transformer-based models achieve state-of-the-art performance in visual recognition tasks when trained on large labeled datasets. One-stage object detection models, such as the YOLO family, are particularly suitable for real-time applications due to their high accuracy and end-to-end detection pipeline [5].

Driven by such progress, this paper utilizes YOLOv8m as the primary detection model to identify defects in insulators on overhead transmission lines. A well-defined dataset, annotated using Roboflow, consists of several defect types, including broken insulators and pollution flashovers, as well as defect-free samples to enhance reliability. Training and fine-tuning of the model are conducted on Google Colab with GPU acceleration, which facilitates efficient optimization and faster convergence. The proposed system can also process video sequences, which may be useful for more dynamic inspection scenarios [6].

In this work, real-time drone inspection is not explored, as the focus is on the analysis of static images and video sequences; however, the presented approach lays the groundwork for future integration into autonomous aerial monitoring platforms based on computer vision systems. By addressing insulator breakage as a key challenge in overhead transmission line maintenance, this study contributes to both academic research and the development of practical applications for enhancing power grid reliability.

Background and Motivation:

Though power system monitoring has improved, overcoming the potential failure of overhead transmission lines is difficult, especially with respect to damage to insulators caused by age, weather, or pollution. Manual inspection and traditional survey techniques take time, are expensive, prone to inaccuracies, and cannot be used in many cases on a large scale or frequently. There is a burgeoning demand for the development of an automated, precise, and cost-effective method of inspection. Computer vision provides a great solution as it enables continuous, accurate detection of defects without the need for direct human attention, providing higher safety and reduced downtime.

Literature Review Section:

Historically, the process of checking overhead transmission line insulators has been based on manual fieldwork. This is time-consuming and exposes workers to the risks of high-voltage working environments. To address these limitations, some early work has used classical image processing techniques, e.g., thresholding, edge detection, morphological operations, local binary patterns (LBP), and histogram of oriented gradients (HOG). These methods were employed in locating cracks, contamination, and other surface anomalies. Although they demonstrated certain potential, they showed poor results when applied to real-life conditions, as they were sensitive to light, shadows, and complicated backgrounds, and, as a result, decreased accuracy and reliability.

Due to the development of machine learning methods, support vector machines (SVMs), random forests (RFs), and k-nearest neighbors (KNNs) began to be used. These models outperformed rule-based approaches, especially in detecting clean/polluted insulators or cracks. Nevertheless, they still depended on manually designed features, which limited their flexibility to new situations and unobserved defects.

When the use of Convolutional Neural Networks (CNNs) was introduced, a huge leap in the inspection of insulators was achieved. Models such as Faster R-CNN, SSD, and Mask R-CNN proved to be more accurate in detecting faults like broken caps, flashovers, cracks, among others [7][8]. In contrast to classical methods, CNNs did not require any manually constructed features, and they learned directly from image data, thus being more adaptable to complicated situations [9]. CNN-based models, however, require significant computational resources, making them less accessible for embedded architectures or UAVs. Moreover, they require relatively large, well-annotated datasets to conduct insulator defect detection [10].

Scholars have analyzed real-time object detectors, such as those in the YOLO (You Only Look Once) series. YOLOv3 was among the first to be used in UAV-based inspection and proved to be effective at identifying broken insulators in real time [11]. In addition, YOLOv4 showed increased accuracy in recognizing insulator contamination and physical damage on different backgrounds [12]. YOLOv4 was used by [6] in high-voltage transmission lines, and their optimization techniques improved detection speed by an order of magnitude without affecting detection precision. Analogously, [13] indicated that, regardless of noisy environmental conditions, the YOLOv4 model was reliable for identifying insulators. One more study by [14] emphasized the stability of YOLOv4 when targeting large-scale inspections with UAVs. [15], modifying the YOLO frameworks through anchor box clustering and transfer learning, also contributed to detecting insulator defects in complicated backgrounds. [16] introduced data augmentation techniques, which enhanced the cross-data generalization of YOLO-based detectors.

Comparative analyses conducted by scholars [17] supported the assertion that YOLO is more effective than traditional CNN-based detectors for real-life inspection. Later benchmarking studies [18] validated the usefulness of YOLO frameworks by subjecting them to challenging insulator defect datasets, revealing their applicability in field operations. With the introduction of YOLOv5, a lighter and faster architecture was developed, making deployment on UAVs possible [19]. [20] showed that YOLOv5 could perform real-time detection of cracked or contaminated insulators with great precision. Another study [21] indicated the scalability of YOLOv5 to large-scale transmission system monitoring.

Other studies have integrated UAVs with optimal flight strategies or UAVs with multispectral and thermal imaging to enhance coverage and inspection precision. Additionally, hybrid models combining traditional image processing with deep learning networks have been proposed, which can be more flexible under changing environmental conditions. A further example of UAVs combined with deep learning is presented in **[X]**, who proposed a hybrid approach using UAV techniques. Lightweight models such as MobileNet have also been applied to enable on-board defect detection without cloud connectivity using embedded devices. Similarly, YOLOv5s has been applied to edge devices to monitor insulators, demonstrating strong inference speed and accuracy.

In addition, semi-supervised learning has been employed to utilize both labeled and unlabeled data. Parallel techniques of domain adaptation were used to enhance cross-setting and cross-illumination generalization of detection models. Despite these developments, most current research relies on earlier YOLO versions, i.e., YOLOv3, YOLOv4, and YOLOv5, which are commonly used in UAV-based inspection. YOLOv7 has also been applied in some insulator detection applications, expanding the utility of one-stage detectors before YOLOv8.

Along with this, other algorithms such as the ViBe algorithm have been investigated for defect detection due to their ability to model backgrounds and operate in noisy environments. The performance of YOLOv8, which introduces architectural innovations to achieve better accuracy and efficiency in real-time tasks, has been analyzed in such studies. Additionally, the majority of the works focus solely on defect detection and do not address automated reporting system integration, which can help utilities in scheduling and maintenance decision-making.

Objectives:

The main aim of the paper is the development and testing of a computer vision model capable of automatically detecting defects in insulators on overhead transmission lines using the YOLOv8 algorithm. The purpose of the system is to precisely identify and categorize defects, in particular Broken Insulators and Pollution Flashovers, in real time, thereby enabling timely physical intervention and improving the safety and reliability of power transmission networks. The details of the specific objectives are as follows.

Realization of a Real-Time Defect Detection System: The development of a high-accuracy real-time system using the optimized YOLOv8 architecture to achieve a balance between detection quality and inference speed.

Manufacture of a Bespoke-Labeled Dataset: To improve the quality of embedded details concerning defect types, such as Broken Insulators and Pollution Flashovers, this dataset was developed to collect and annotate information under diverse environmental and operational conditions of insulators.

Integration with Aerial Inspection Processes: To utilize the trained YOLOv8 model for inspection using UAVs or high-resolution imaging platforms, reducing the need for manual inspection processes.

Performance Evaluation: To assess the system's performance with respect to mean Average Precision at IoU 0.5 (mAP@0.5), detection speed, and resilience under real-world field inspection conditions.

Novelty:

This study proposes a novel application of the YOLOv8 object detection model for overhead transmission lines to detect insulator defects. The proposed system is distinguished by its advantages over conventional defect inspection methods based on manual observation or simple image processing techniques, as it combines state-of-the-art, high-speed deep learning models to both detect and classify insulator defects. The novelty lies in the integration of a custom-labeled, defect-specific dataset with the effectiveness and efficiency of YOLOv8, enabling deployment in UAV-based or stationary camera inspection workflows. The system is designed to operate under varied environmental conditions, accurately and quickly localize defects, and significantly reduce the time and cost associated with manual inspections, thereby enhancing the reliability of transmission line maintenance decision-making.

Materials and Methods:

This section presents the proposed methodology for developing an insulator defect detection system, specifically targeting Broken Insulators and Pollution Flashover defects. The system is highly structured, following stages that include data collection, data labeling, model training, testing, and output generation Figure 1. A diverse set of data is collected across varied environmental and operational conditions to ensure the model's robustness. Images are annotated during pre-processing using the Robo flow tool to mark defect areas corresponding to the target classes. The annotated data are then used to train a high-accuracy, real-time object detection model, YOLOv8, which has demonstrated the desired capability. The trained model is subsequently tested with images not used during training to evaluate its detection ability and reliability. Once validated, the system operates in real time, processing inspection images or video streams to identify defects. Upon detection, the system generates alerts or graphical displays that can be used to initiate maintenance actions promptly.

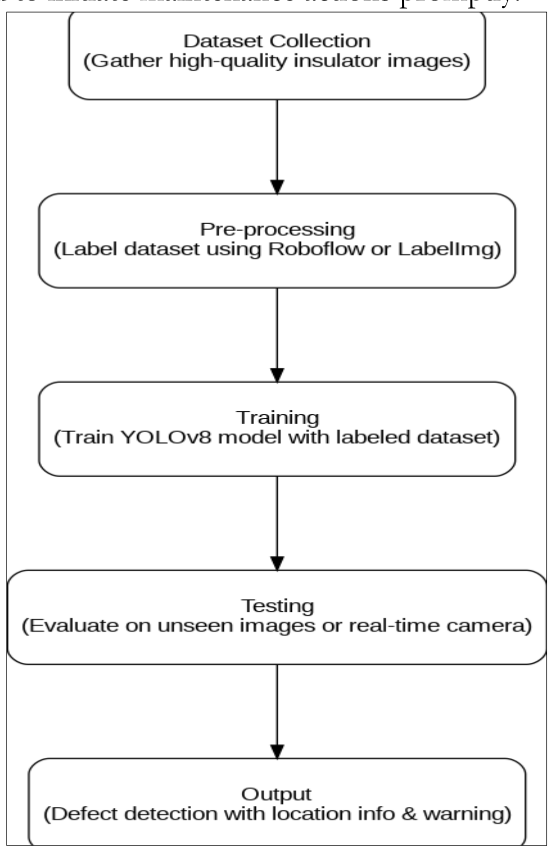

Figure 1. Flow diagram of the proposed insulator defect detection methodology.

System Design:

The proposed insulator defect detection system can continuously record visual data using inspection sources, such as UAV-mounted or ground-based cameras, and analyze images or video streams using advanced computer vision algorithms. These algorithms process each frame to identify insulators and detect the presence of defects, specifically Broken Insulators and Pollution Flashover types. The framework is thus capable of monitoring visual data from multiple sources and analyzing images or video streams with sophisticated computer vision techniques. Within this process, each frame is examined to locate insulators and determine the occurrence of defects, namely Broken Insulators and Pollution Flashovers.

When defects are detected, the system generates alerts and provides visual annotations on the defective insulators. The resulting display may appear on a monitor, within a maintenance management application, or via remote over-the-air transmission to field technicians. Through these forms of real-time reporting, preventative maintenance can be carried out promptly, the risk of equipment failures is reduced, and the stability of overhead transmission line operations is enhanced.

Dataset:

The dataset used in this study consists of 1,600 images of overhead transmission line insulators captured from various sources, as shown in Figure 2, and were augmented multiple times to enhance model performance and generalization. To ensure robustness, images representing the target defect classes, Broken Insulators and Pollution Flashovers, were collected under diverse environmental and operational conditions. To improve annotation quality, images and selected video frames were manually labeled using the Rob flow labeling tool, with defect areas precisely marked for training. The dataset was divided into three parts: 80% for training, 15% for validation, and 5% for testing, as illustrated in Figure 2, to ensure balanced model learning, reliable performance evaluation, and effective generalization to new data. Before training, the images were resized to 640 x 640 pixels. To enhance generalization performance, data augmentation methods such as mosaic augmentation, random rotation, brightness adjustment, and horizontal flipping were used.

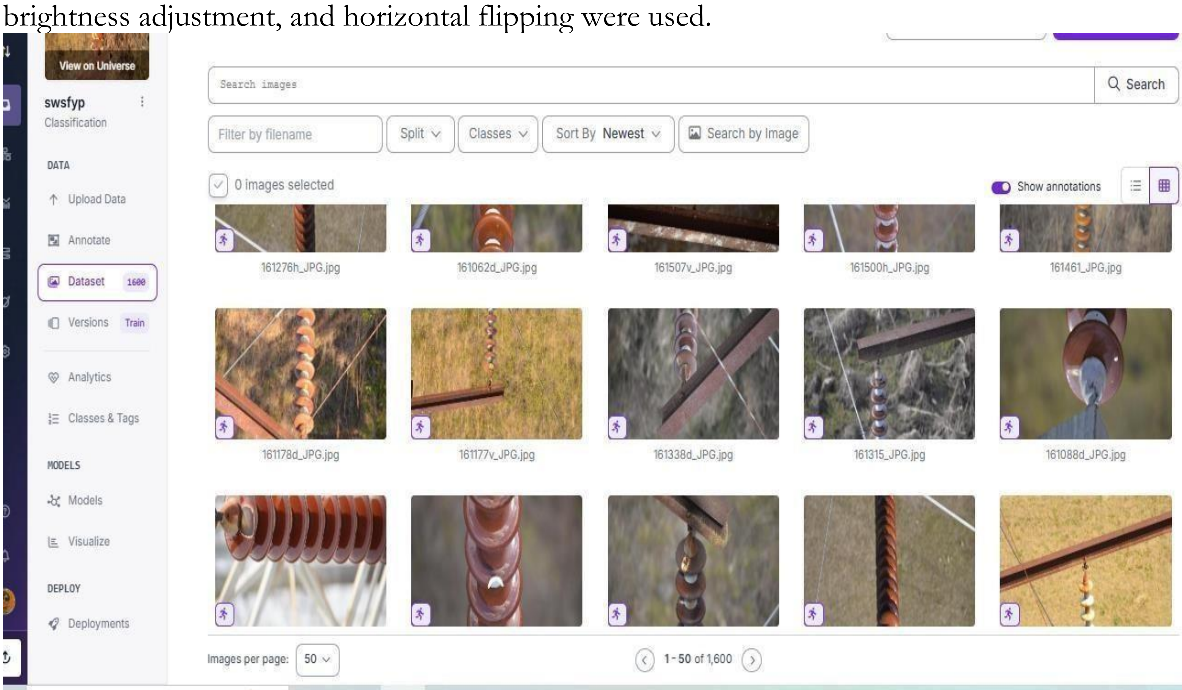

Figure 2. Roboflow dataset interface showing the manual annotation of broken insulators and pollution flashover defects, along with dataset partitioning for training, validation, and testing.

Proposed Algorithms:

One of the most popular and efficient methods for handling large and complex datasets is deep learning, which has been widely used as the primary tool for defect detection in industrial inspections. Algorithms for object detection in this domain are typically classified into two groups. The first group comprises two-stage object detection approaches, such as R-CNN (Region-based Convolutional Neural Network), Fast R-CNN, and Faster R-CNN. These methods generally achieve high accuracy but are less suitable for real-time applications, as they tend to have slower processing speeds.

The second group corresponds to single-stage object detectors, including the YOLO family. These techniques enable much higher detection speeds while maintaining competitive accuracy, making them suitable for real-time defect monitoring. The YOLOv8 algorithm is used in this study because it features an improved architectural design, a powerful backbone, and high performance in detecting the target defects, namely Broken and Pollution Flashover, in insulators of overhead electrical transmission lines.

Object Detection Algorithm:

This study employs the latest YOLOv8 object detection model, which operates as a single-stage detector. As a member of the YOLO family, YOLOv8 utilizes a regression-based approach that accelerates the detection pipeline while maintaining high precision. Its efficient design and low power consumption make it highly suitable for real-time defect detection in overhead transmission line inspections. The proposed system architecture, illustrated in Figure 3, consists of three main components: Backbone, Neck, and Head. The Adam optimizer was used to train the YOLOv8 model with a starting learning rate of 0.001. With a batch size of 16, training was carried out over 20 epochs. To guarantee effective model convergence, Google Colab with NVIDIA Tesla T4 GPU acceleration was used for the experiments.

Additionally, YOLOv8 includes the SPPF (Spatial Pyramid Pooling - Fast) module, which captures spatial contextual information to enhance detection consistency under varying lighting and environmental conditions. This architecture demonstrates high performance in real-time insulator fault detection, effectively balancing speed and accuracy, making it particularly suitable for automated monitoring of overhead transmission lines.

Experimental Results:

The experimental findings of the proposed real-time insulator defect detection system are shown in this section. The model was assessed in various scenarios involving overhead transmission lines with both normal and faulty insulators.

Scenario 1: Identification of Broken Insulators:

A damaged insulator in the transmission line is depicted in Figure 4. The model's ability to detect structural damage is demonstrated by its successful identification of the insulator string and accurate localization of the faulty unit.

Scenario 2: Detection of Pollution Flashover:

The identification of a pollution flashover defect is shown in Figure 5. The system accurately detects the affected region and distinguishes it from normal insulator units, confirming its effectiveness in identifying surface contamination defects.

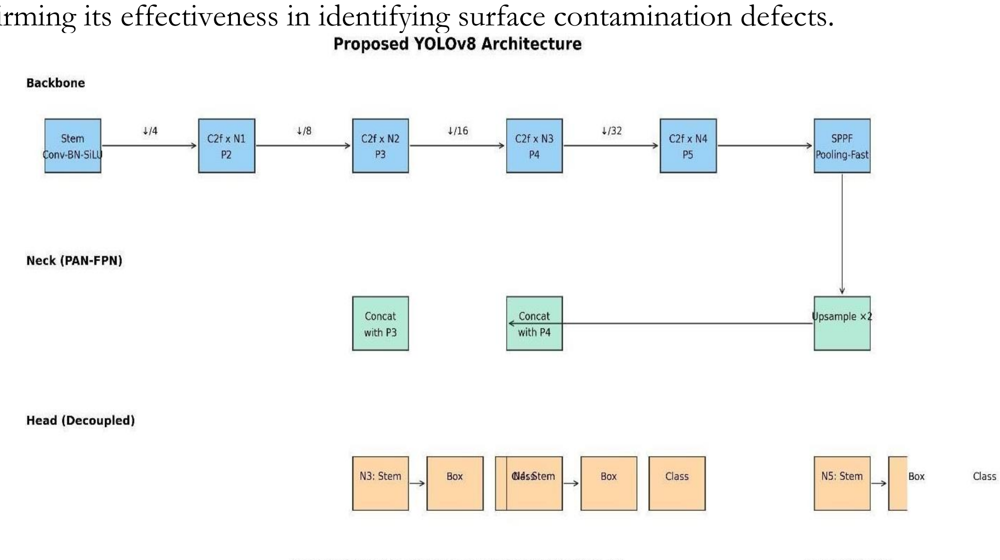

Figure 3. YOLOv8 architecture illustrating backbone, neck, and detection head components.

Figure 4. Detection of a Broken insulator using YOLOv8m with accurate localization.

Figure 5. Detection of a Pollution Flashover defect using YOLOv8m.

Results and Discussion:

Tables 1 and 2 present the comparative performance of the YOLOv8 variants, mean average precision at IoU 0.5 (mAP50) and across the range 0.5–0.95 (mAP50–95). These metrics evaluate how accurately the models identify insulators, broken insulators, and pollution flashovers under different IoU thresholds.

According to Table 1 (mAP50)**,** YOLOv8m demonstrates the strongest overall performance, achieving 94.0%**.** The model excels in detecting insulators (99.3%), with high precision in identifying broken insulators (95.1%) and pollution flashovers (87.5%). While the lighter YOLOv8n and YOLOv8s variants provide slightly lower results, with overall scores of 88.6% and 90.0%, respectively, they remain competitive. These findings indicate that YOLOv8m offers the optimal balance between accuracy and consistency for defect detection.

The YOLOv8m **model** achieved a precision of 91%**, a** recall of 90%**, an** mAP50 of 92%**,** and an mAP50–95 of 64%**.** These results confirm the model's robustness and its ability to reliably locate and classify multiple defect types under diverse conditions. The high mAP50 score reflects accurate object localization at the standard IoU threshold, while the mAP50–95 score indicates the model's stability and reliability across stricter detection criteria.

Overall, these performance metrics justify the adoption of YOLOv8m for real-time monitoring of overhead transmission systems. The model is not only accurate but also computationally efficient, making it highly suitable for practical deployment in automated defect inspection workflows.

As shown in Table 1 (mAP50)**,** YOLOv8m demonstrates the best overall performance, achieving 94.0%**.** The model performs nearly perfectly in detecting insulators (99.3%), with high accuracy in identifying broken insulators (95.1%) and pollution flashovers

(87.5%). The smaller variants, YOLOv8n and YOLOv8s, also perform well, providing competitive results, though slightly lower, with overall scores of 88.6% and 90.0%, respectively.

Table 1. Simulation Results (mAP50)

YOLOv8 Version	Overall	Insulator	Broken Insulator	Pollution Flashover	Other Defect
YOLOv8n	88.60%	98.00%	79.50%	85.00%	73.30%
YOLOv8s	90.00%	98.60%	87.00%	86.50%	71.70%
YOLOv8m	94.00%	99.30%	95.10%	87.50%	80.40%

Besides this overall comparison, if we delve deeper into the class-wise results, some interesting performance patterns can be noted. For instance, the consistently higher detection rate for insulators across all model variants indicates **their effectiveness** in learning the prominent structural characteristics of intact components. On the other hand, the lower scores for broken insulators and other defect types, especially for YOLOv8n and YOLOv8s, suggest that learning the finer characteristics of **these defects** is necessary for effective defect detection.

The improved performance of YOLOv8m for **these defect classes** can be explained by its higher depth and parameter size, which allow for finer visual feature learning. This again points to the trade-off between model deployment size and detection accuracy, reinforcing the reliability of the YOLOv8m model for such inspection tasks.

Table 2. Simulation Results (mAP50–95)

YOLOv8 Version	Overall	Insulator	Broken Insulator	Pollution Flashover
YOLOv8n	63.00%	92.00%	58.00%	40.00%
YOLOv8s	65.50%	93.50%	60.00%	42.50%
YOLOv8m	68.00%	95.40%	63.10%	45.60%

The findings shown in Table 2 (mAP50–95) evaluate the models under more stringent criteria with higher IoU thresholds. While the lighter models exhibited lower mAP50–95 scores due to these stricter conditions, YOLOv8m outperformed the others, achieving an overall score of 68.0%. It performed particularly well on insulators (95.4%) and broken insulators (63.1%), but showed lower accuracy for pollution flashovers (45.6%). The smaller variants scored slightly lower, with YOLOv8s at 65.5% and YOLOv8n at 63.0%.

A more detailed analysis of the mAP50-95 results shows that detection accuracy is reduced under more stringent IoU conditions, as expected, since a more accurate overlap is necessary for a prediction to be considered correct. Lower scores for pollution flashovers in all models suggest that this type of defect is more challenging in terms of localization accuracy, possibly due to irregular patterns of contamination. On the other hand, insulators have high scores for mAP50-95, reflecting regular geometry and clear visual features. Enhanced performance by the YOLOv8m model in such stringent conditions further supports its superior generalization capability and improved bounding box regression, which is critical for accurate real-time inspection in actual conditions.

The confusion matrix in Figure 6 offers a detailed analysis of the classification results for the YOLOv8m model. The high number of correctly classified images for broken insulators (138), insulators (268), and pollution flashovers (327) is depicted in the diagonal of the confusion matrix. The misclassification is low, and some confusion is seen between pollution flashover and background classes, and a few images of broken insulators are misclassified as background. This could be due to subtle defect features and low contrast between defective and other areas of images caused by environmental factors. The confusion matrix shows a high degree of separability between classes and robust detection ability of the model, validating the quantitative results in Tables 1 and 2.

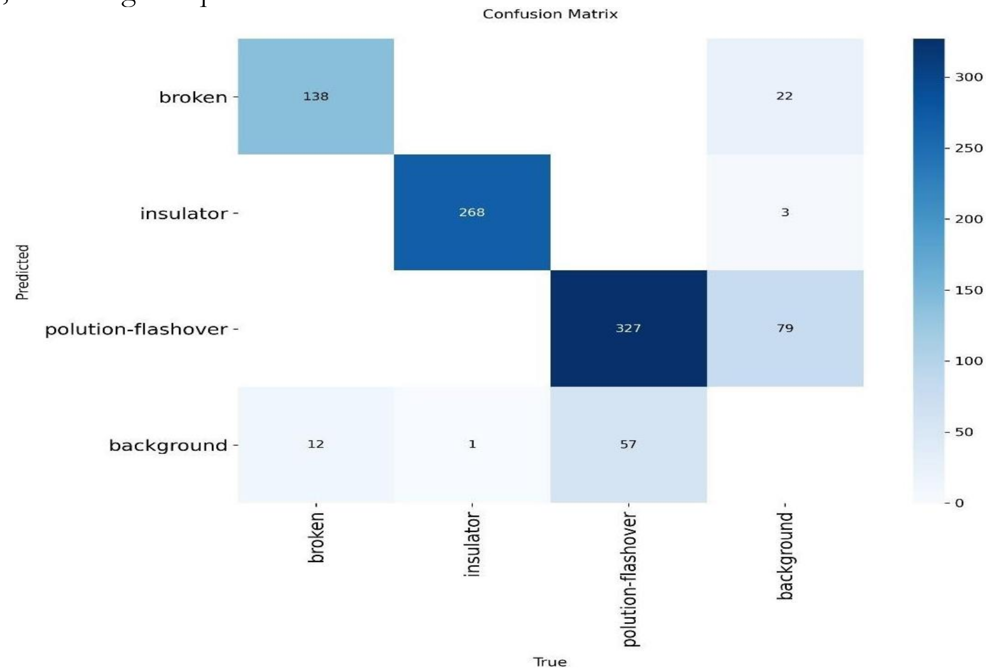

Figure 6. Confusion matrix showing the classification performance of YOLOv8m.

The confusion matrix in Figure 6 offers a detailed analysis of the classification results for the YOLOv8m model. The high number of correctly classified images for broken insulators (138), insulators (268), and pollution flashovers (327) is depicted on the diagonal of the confusion matrix. The misclassification is low, and some confusion is seen between pollution flashover and background classes, and a few images of broken insulators are misclassified as background. This could be due to subtle defect features and low contrast between defective and other areas of the images due to environmental factors. The confusion matrix shows a high degree of separability between classes and robust detection ability of the model, validating the quantitative results in Tables 1 and 2.

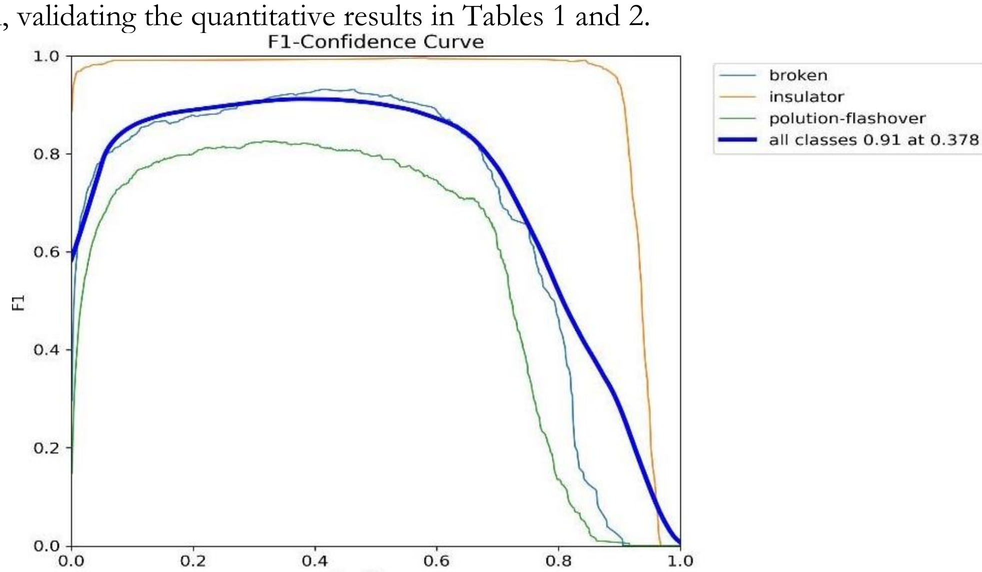

Figure 7. F1–Confidence Curve indicating optimal threshold selection**.**

The F1–Confidence Curve Figure 7 indicates that the optimal operating threshold is **0.414**, corresponding to the maximum F1 score of **0.87**. This finding is further supported by the accompanying visual performance metrics.

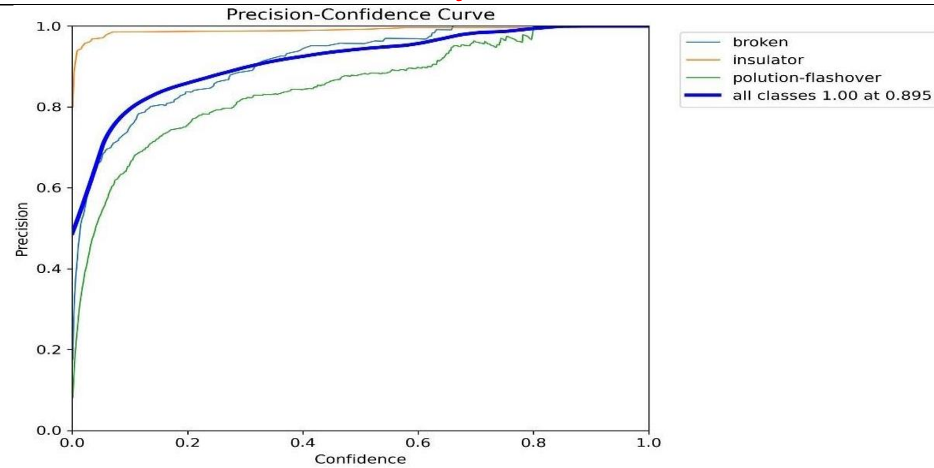

Figure 8. Precision–Confidence Curve demonstrating prediction reliability.

The Precision–Confidence curve Figure 8 demonstrates that the model maintains high precision at elevated confidence scores, further confirming its reliability.

A careful analysis of the curve shows that the precision increases steadily with the rise in confidence threshold, approaching near-perfect levels at higher thresholds. This shows that the chances of false positives are minimized at higher confidence levels. Among the classes, the precision for the detection of insulators remains at high levels for all confidence levels, while the detection of pollution flashovers shows lower levels of precision at lower confidence levels, which might be due to the visual similarity with the background. However, the combined curve for all classes shows stable levels of precision, which indicates that the model can perform at high levels of reliability, provided the confidence threshold is chosen at the appropriate level.

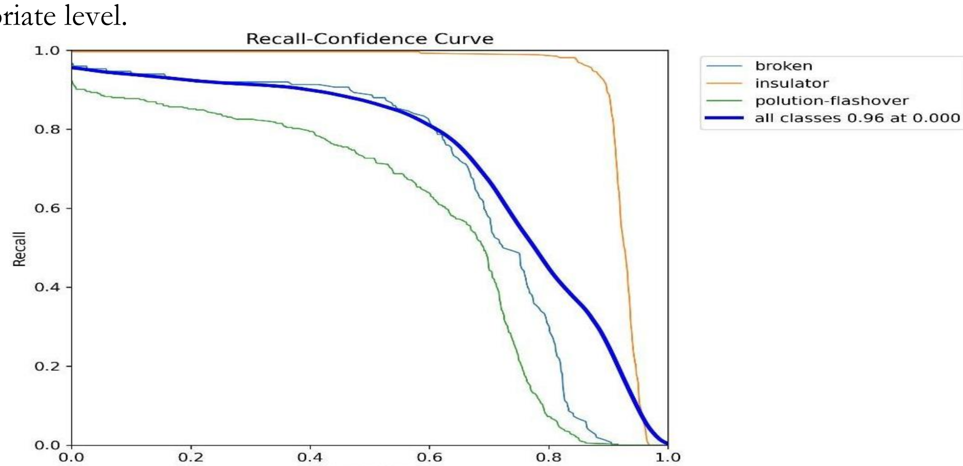

Figure 9. Recall–Confidence Curve showing detection sensitivity across thresholds.

The Recall–Confidence curve (Figure 9) illustrates the stability of recall at lower confidence thresholds, indicating the consistent detection of true positives by YOLOv8m.

As the confidence threshold increases, the recall value gradually decreases, which is expected because more stringent thresholds eliminate lower-confidence predictions, including some true positives. The graph indicates that the detection of insulators has a high recall for a broad range of confidence scores, which indicates the strong capability of the model to detect this class of objects. On the other hand, pollution flashover has a sharper drop in the recall value for higher confidence thresholds, which indicates that some pollution flashover instances are predicted with moderate confidence scores. The overall recall graph for all classes indicates a good trade-off between sensitivity and prediction confidence, which supports the need for choosing an optimal confidence threshold to ensure high detection coverage in real-time transmission line inspection.

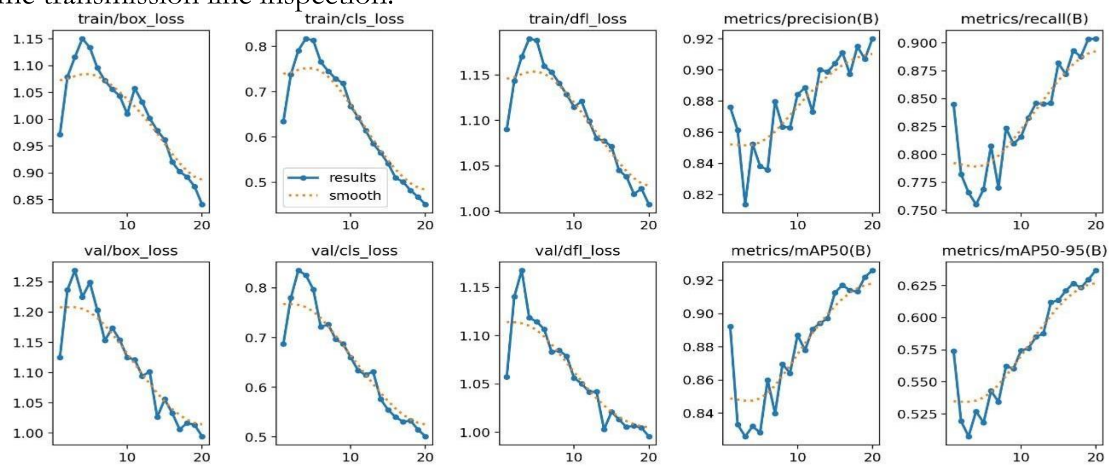

Figure 10. Training Curves showing loss reduction and performance improvement.

The training curves (Figure 10) highlight the stability of YOLOv8m. Both classification and localization losses consistently decreased throughout the training process, while recall, precision, and mAP values steadily increased. Upon completion of training, YOLOv8m achieved a precision of 91.2%, a recall of 89.8%, an mAP50 of 94.0%, and an **mAP50–95** of 68.0%, demonstrating robust performance across various defect types and environmental conditions.

Discussion:

The effectiveness of the YOLOv8m model in real-time detection of insulator defects in overhead transmission lines is established in our study, which provides high accuracy and fast inference for practical applications. Table 3 presents a comparison of the performance of our method with other recent methods of insulator defect detection reported in the literature, which shows improvements in accuracy and real-time detection.

Table 3. Comparison of Detection Accuracy and Real-Time Performance in Existing Studies

Literature	Detection Target	Accuracy (%)	Model Used	Real-Time Performance (fps)	Remarks
Current Study	Broken & Pollution Flashover	94	YOLOv8m	120 fps	High accuracy with real-time capability
[5]	Insulator damage identification	90.2	Improved YOLOv4-Tiny	35 fps	Enhanced detection accuracy but limited generalization
[7]	Insulator string defects	91.5	Improved YOLOv5	50 fps	High accuracy with real-time performance
[8]	Insulator defect detection	89.8	ML-YOLOv5	48 fps	Improved feature extraction using modified YOLOv5
[9]	Insulator self-blast detection	88.5	YOLOv4	40 fps	Effective for aerial images, but moderate precision
[10]	Insulator defect detection	91.0	Improved YOLOv5s	55 fps	Good balance between speed and accuracy

[11]	Insulator defect detection	91.8	Improved YOLOv5s	55 fps	Enhanced robustness in complex backgrounds
[6]	Insulator defect detection	90.5	YOLOv7-based model	50 fps	Improved attention mechanism for better localization
[18]	Transmission line insulator fault detection	92.5	Lightweight YOLOv8	60 fps	Improved lightweight architecture for real-time deployment
[21]	UAV-based insulator inspection	91.0	Hybrid CNN–Transformer	45 fps	Robust inspection using a hybrid architecture

Limitations and Future Work:

A major limitation of the proposed method is the decrease in the overall accuracy of the detection process in extreme weather conditions like heavy rainfall, fog, or low-light conditions. The visibility of insulator defects may be reduced under such conditions. However, it should be noted that this is not a limitation specific to the proposed method alone, as other studies in the field have also reported similar problems in the detection of insulator defects [16]. Furthermore, we aim to extend the dataset with a variety of conditions in the transmission lines.

Contribution to Power Transmission Monitoring:

The main contribution of this research is the advancement of automated transmission line inspection through the integration of advanced computer vision algorithms into monitoring systems. Unlike the traditional methods used for inspecting transmission lines, the proposed system uses the YOLOv8 algorithm for real-time defect detection with high accuracy. The ability to detect critical insulator defects in real-time is a major advancement over traditional methods, which either lacked real-time capability or relied on simple algorithms for defect identification.

Conclusion:

The present work proposes a YOLOv8-based framework for the real-time detection of critical insulator defects on overhead transmission lines, which is indeed a significant step forward in the field of automated power system monitoring. The proposed framework is highly effective in the detection of broken insulators as well as pollution flashovers, which are critical issues in the operation of power transmission lines.

The quantitative analysis of the proposed framework using various parameters such as mAP50 and mAP50–95 indicates that YOLOv8-based detection is highly accurate compared to existing detection techniques. Additionally, the real-time detection ability of YOLOv8-based detection, along with the low computational overhead, makes it highly feasible for the detection of defects in the overhead transmission lines.

Future work may focus on improving detection accuracy under diverse environmental conditions, increasing the framework's scalability, and exploring hybrid or next-generation YOLO-based techniques to further enhance performance. However, the proposed framework is indeed a comprehensive solution for the effective maintenance of the stability of the power transmission infrastructure.

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