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Enhancing Insulator-Defect Detection in Transmission Lines with the Latest YOLO Object Detection Models

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Abstract

This study investigates the application of the YOLOv8, YOLOv9, and YOLOv10 object detection models for detecting defects in transmission line insulators using the Insulator Defect Image Dataset (IDID). The dataset comprises high-quality images categorized into three classes: good insulator shell, broken insulator shell, and flashover damage insulator shell. The images were divided into training, validation, and testing sets, with performance metrics such as mAP@0.50 and mAP@0.50:0.95 used to evaluate the models. The study concludes that all three YOLO family members are highly accurate for insulator defect detection, with YOLOv8 and YOLOv9 showing superior performance.

Keywords: YOLOv8, YOLOv9, YOLOv10, Insulator defect detection, Transmission lines, Object detection, Mean Average Precision (mAP), Precision, Recall

Introduction

The integrity of electrical transmission insulators is critical for ensuring the reliable operation of power systems. Insulators are designed to prevent unwanted current flow from the high-voltage conductors to the ground, and any damage or breakage in these components can lead to power outages, equipment damage, and even catastrophic failures. Traditional methods for inspecting insulators, such as manual visual inspection or the use of helicopters, are often time-consuming, expensive, and prone to human error. In recent years, automated detection methods, particularly using deep learning-based object detection models like YOLO (You Only Look Once) [1], have gained significant traction in the industry. Here we provide an overview of the application of YOLO models for detecting broken insulators in electrical transmission systems.

YOLO is a state-of-the-art object detection model that is widely recognized for its ability to perform real-time detection with high accuracy. Unlike traditional object detection methods that involve a two-stage process of generating region proposals followed by classification, YOLO frames object detection as a single regression problem. The model divides the input image into a grid, predicts bounding boxes and class probabilities directly from the image, and performs detection in a single pass. This architecture enables YOLO to achieve high inference speeds, making it well-suited for real-time applications such as insulator inspection.

Since its inception, the YOLO family has evolved through multiple iterations, each improving upon the previous in terms of speed, accuracy, and robustness.

Application of YOLO to Insulator Broken Detection

The application of YOLO for insulator broken detection typically involves the following steps:

1. **Data Collection and Annotation:** A large dataset of images containing both intact and broken insulators is required for training the YOLO model. These images can be collected using drones, cameras mounted on towers, or even from historical inspection records. Each image must be carefully annotated with bounding boxes around the insulators, and labels indicating whether they are broken or intact.
2. **Model Training:** The annotated dataset is used to train the YOLO model. During training, the model learns to recognize the features that distinguish broken insulators from intact ones. Given the small size of insulators in images and the potential for varying lighting conditions, it is crucial to apply data augmentation techniques such as rotation, scaling, and contrast adjustment to improve the model's robustness.
3. **Detection and Evaluation:** Once trained, the YOLO model can be deployed to detect broken insulators in real-time. The model processes each input image, predicting the bounding boxes and classifying the insulators as either broken or intact. The performance of the model is typically evaluated using metrics such as mean Average Precision (mAP), Intersection over Union (IoU), and inference speed. The model's ability to detect small and partially occluded insulators is of particular interest in this application.

In the following, we summarize the YOLO and recent papers that apply various YOLO models to insulator broken detection.

- **Redmon et al. (2016)** introduced You Only Look Once (YOLO), a real-time object detection system. This groundbreaking work revolutionized the field by performing object detection in a single network evaluation, achieving high accuracy and speed [1].
- **Redmon and Farhadi (2018)** presented YOLOv3, an improvement over the original YOLO. It introduced new features like skip connections and feature map scaling, enhancing object detection accuracy for small objects [2].
- **Bochkovskiy et al. (2020)** built upon YOLOv3 with YOLOv4. YOLOv4 aimed for optimal performance for real-time applications. It incorporated techniques like path aggregate network (PAN) and spatial attention modules, further improving speed and accuracy [3].
- **Ultralytics (2020)** released YOLOv5, an open-source implementation known for its focus on ease of use, speed, and accuracy. YOLOv5 offers various pre-trained models and allows for customization for specific tasks [4].
- **Hong et al. (2022)** proposed an improved YOLOv7 model specifically for insulator surface defect detection. While there's no official YOLOv7 yet, their work suggests modifications to an existing YOLO version for insulator defect analysis [5].
- **Chen et al. (2023)** introduced Insu-YOLO, an insulator defect detection algorithm based on multiscale feature fusion. Insu-YOLO utilizes YOLO's framework and leverages multiscale feature fusion to effectively detect defects across various sizes [6].
- **Wang et al. (2023)** presented an improved YOLOv5s model for insulator defect detection. Their approach focuses on modifying the lightweight YOLOv5s version to achieve accurate defect detection for insulator inspection [7].

- **Liu et al. (2023)** proposed a novel deep learning method based on YOLOv5 for insulator defect detection. Their work explores modifications to YOLOv5 to improve its ability to identify and localize defects in insulators [8].
- **Han et al. (2023)** developed an improved algorithm based on YOLOv4 for insulator and defect detection. This work focuses on enhancing YOLOv4 to simultaneously detect both insulators and any defects present on their surface [9].
- **Weng et al. (2024)** presented a lightweight network based on improved YOLOv5 for insulator fault detection. They aimed to create a more efficient model by modifying YOLOv5 while maintaining its effectiveness in detecting insulator faults [10].
- **Kumar et al. (2024)** investigated insulator defect detection using a deep learning-based approach. Their work explores deep learning techniques beyond YOLO for analyzing and identifying defects in insulators [11].
- **Fahim and Hasan (2024)** proposed a YOLO-based approach for insulator defect detection to enhance the reliability of power grids. This work highlights the potential of YOLO in improving power grid maintenance by facilitating efficient insulator defect detection [12].

Challenges and Considerations

While the application of YOLO for insulator detection shows great promise, several challenges must be addressed to ensure its effectiveness:

- **Small Object Detection:** Insulators often occupy only a small portion of the image, making them difficult to detect accurately. Advanced YOLO models, such as YOLOv8 and YOLOv9, incorporate features like multi-scale detection and attention mechanisms to improve small object detection, but further optimization may be required for insulator-specific applications.
- **Class Imbalance:** In many datasets, the number of intact insulators far exceeds the number of broken ones, leading to class imbalance issues. Techniques such as data augmentation, focal loss, and oversampling of minority classes can be employed to mitigate this issue and improve detection accuracy.
- **Environmental Variability:** Insulators are often located in outdoor environments where lighting conditions, weather, and background clutter can vary significantly. The YOLO model must be trained on a diverse dataset that captures these variations to generalize well across different conditions.

The Latest YOLO (You Only Look Once) Family Members

Since the introduction of the first YOLO model, the YOLO family has evolved through various iterations, each improving upon its predecessor in terms of accuracy, speed, and efficiency. We provide an overview of the recent advancements in the YOLO family, specifically focusing on YOLOv8 [13], YOLOv9 [14], and the YOLOv10 [15] models.

YOLOv8: Bridging the Gap Between Speed and Accuracy

Ultralytics YOLOv8 [13] is a cutting-edge, state-of-the-art (SOTA) model that builds upon the success of previous YOLO versions and introduces new features and improvements to further boost performance and flexibility. YOLOv8 is designed to be fast, accurate, and easy to use, making it an excellent choice for a wide range of object detection and tracking, instance segmentation, image classification and pose estimation tasks., marked a significant milestone in the evolution of the YOLO family. The model was developed with a focus on deployment in resource-constrained environments such as mobile devices and embedded systems, without compromising on detection accuracy.

YOLOv9: Pushing the Boundaries of Real-Time Detection

YOLOv9 is a novel object detection model [14] that addresses the problem of information loss in deep neural networks. The authors propose a new method called Programmable Gradient Information (PGI) that allows the model to learn what information is important for the task at hand. This is done by training the model to predict the gradient information of the input data, which can then be used to update the model's weights. The authors also propose a new network architecture called GELAN that is designed to be more efficient and accurate than previous architectures. Experimental results show that YOLOv9 outperforms other state-of-the-art object detection models on a variety of benchmarks.

In addition to the above, YOLOv9 also introduces a new loss function that is designed to be more robust to noise and outliers. This loss function helps the model to learn more accurate representations of the data. Overall, YOLOv9 is a significant advance in the field of object detection and is likely to have a major impact on a variety of applications.

YOLOv10

YOLOv10 is a novel object detection model that addresses the limitations of previous YOLO models [15]. The authors propose two new methods to improve the performance and efficiency of YOLOv10: consistent dual assignments for NMS-free training and a holistic efficiency-accuracy driven model design strategy. Consistent dual assignments allow the model to be trained without the need for non-maximum suppression (NMS), which can improve performance and efficiency. The holistic efficiency-accuracy driven model design strategy takes into account both accuracy and efficiency when designing the model, leading to a more balanced and efficient model. Experimental results show that YOLOv10 achieves state-of-the-art performance and efficiency compared to other methods.

In addition to the above, YOLOv10 also introduces a new method for object detection called YOLOv10-GhostNet. This method is based on the GhostNet architecture, which is a lightweight and efficient convolutional neural network. YOLOv10-GhostNet can achieve similar performance to YOLOv10 while being significantly smaller and faster.

Overall, YOLOv10 is a significant advance in the field of object detection and is likely to have a major impact on a variety of applications.

Enhancing Insulator-Defect Detection in Transmission Lines with YOLOv8, YOLOv9 and YOLOv10

Data Set

The Insulator Defect Image Dataset (IDID) consists of labeled high quality images of transmission line insulators. The images have insulator string as the primary subject and parent class. These images contain 3 sub-classes: 1) Good insulator shell; 2) Broken insulator shell; and 3) Flashover damage insulator shell. Correspondingly, we have three classes: 'insulator', 'broken', 'pollution-flashover', corresponding to class 0, class 1 and class 2, respectively.

In our experiments, we randomly divide all images into training, validation, and testing dataset with 1296 images on training, 144 images on validation, and 160 images on testing. The best model is achieved by the best validation performance, and then applied to the testing dataset.

Performance Metric and Experimental Results

In object detection, **Mean Average Precision (mAP)** is a widely used metric to evaluate the performance of object detection models. It provides a comprehensive measure of how well a model can locate and classify objects within an image. Calculating mAP involves several steps:

1. **Generate predictions:** The object detection model predicts bounding boxes and class probabilities for each image.
2. **Calculate Intersection over Union (IoU):** Compare the predicted bounding boxes with the ground truth boxes using IoU. A threshold (e.g., 0.5) is often used to determine if a prediction is correct.
3. **Sort predictions:** Rank the predictions based on their confidence scores.
4. **Compute precision and recall:** Calculate precision and recall for different confidence thresholds.
5. **Plot precision-recall curve:** Plot the precision-recall curve for each class.
6. **Calculate Average Precision (AP):** Calculate the area under the precision-recall curve for each class.
7. **Calculate mAP:** Compute the mean of the AP values across all classes.

mAP is a robust metric because it considers both precision and recall, providing a balanced evaluation of the model's performance. It is widely used in object detection competitions and research to compare different models. In object detection, mAP@0.5, which means a predicted bounding box is considered a correct detection if it overlaps with the ground truth box by at least 50%. Instead of a single IoU threshold, mAP@0.5:0.95 metric considers a range of IoU thresholds from 0.5 to 0.95 with increments of 0.05, it provides a more robust evaluation of the object detector's localization accuracy by considering a wider range of overlap thresholds.

Table 1. The mAP@0.5:0.95 testing results on the nano-models

	Yolov8n	Yolov9t	Yolov10n
Class 0	0.969	0.977	0.971
Class 1	0.659	0.672	0.622
Class 2	0.457	0.453	0.439
Overall	0.695	0.701	0.677

Table 2. The mAP@0.5:0.95 testing results on the small models

	Yolov8s	Yolov9s	Yolov10s
Class 0	0.977	0.980	0.975
Class 1	0.713	0.710	0.690
Class 2	0.512	0.499	0.497
Overall	0.734	0.730	0.720

Table 3. The mAP@0.5:0.95 testing results on the medium models

	Yolov8m	Yolov9m	Yolov10m
Class 0	0.980	0.980	0.976
Class 1	0.731	0.732	0.714
Class 2	0.527	0.529	0.513
Overall	0.746	0.747	0.734

Table 4. The mAP@0.5:0.95 testing results on the large models

	Yolov8l	Yolov9c	Yolov10l
Class 0	0.980	0.980	0.976
Class 1	0.737	0.731	0.736
Class 2	0.542	0.535	0.529
Overall	0.753	0.748	0.747

Additionally, we compare the following metrics:

Precision measures the proportion of correctly predicted positive instances (true positives) out of all instances that were predicted as positive (true positives + false positives).

Recall (also known as sensitivity or true positive rate) measures the proportion of correctly predicted positive instances out of all actual positive instances (true positives + false negatives).

mAP@0.50 (Mean Average Precision at IoU threshold 0.50) is the mean of the average precision values for each class at an Intersection over Union (IoU) threshold of 0.50.

mAP@0.50:0.95 is the mean of average precision values across multiple IoU thresholds, typically from 0.50 to 0.95 in increments of 0.05. This is a stricter and more comprehensive measure than mAP@0.50 because it evaluates the model's performance at various levels of overlap.

The **fitness** metric is often a weighted combination of several key metrics (like precision, recall, and mAP) that is used to assess the overall performance of the model. The exact calculation may vary depending on the implementation, but it generally serves as a single score to evaluate the model's effectiveness.

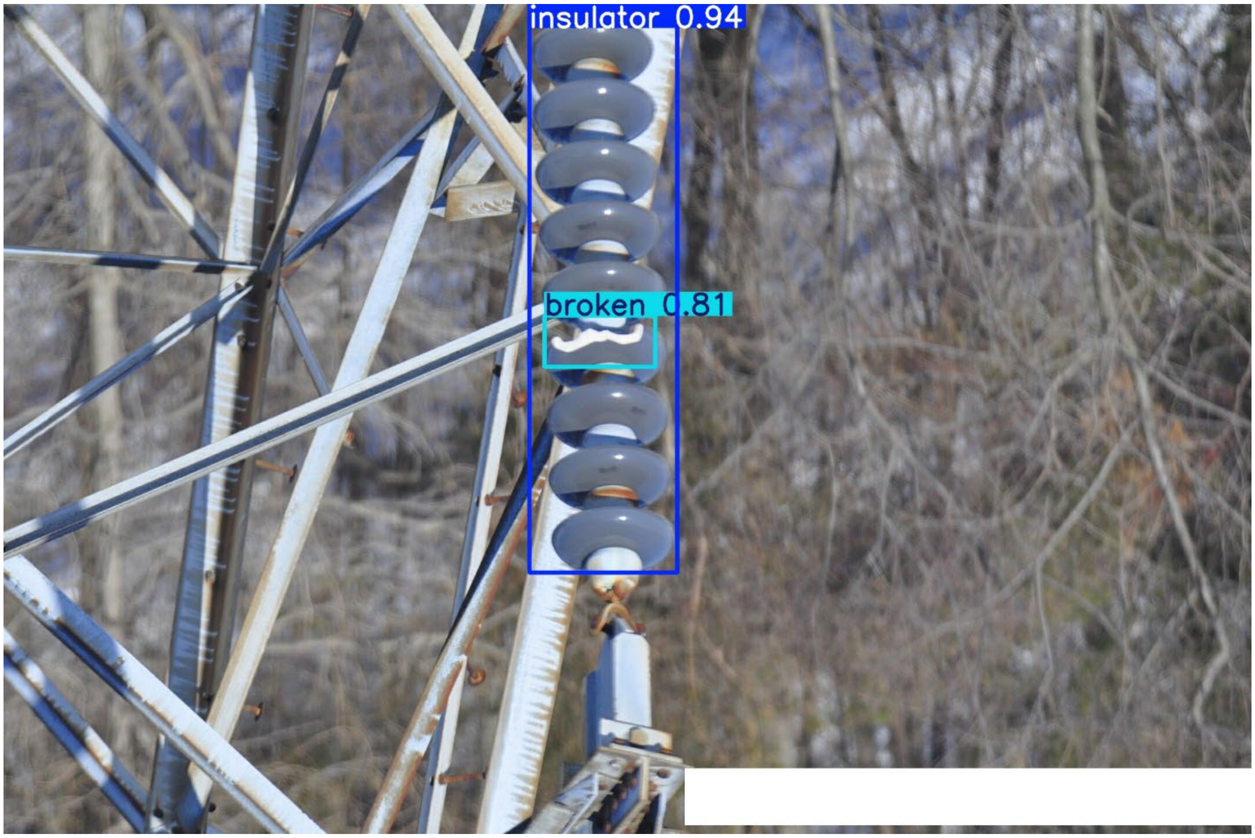
Table 5. The performance compared in different models

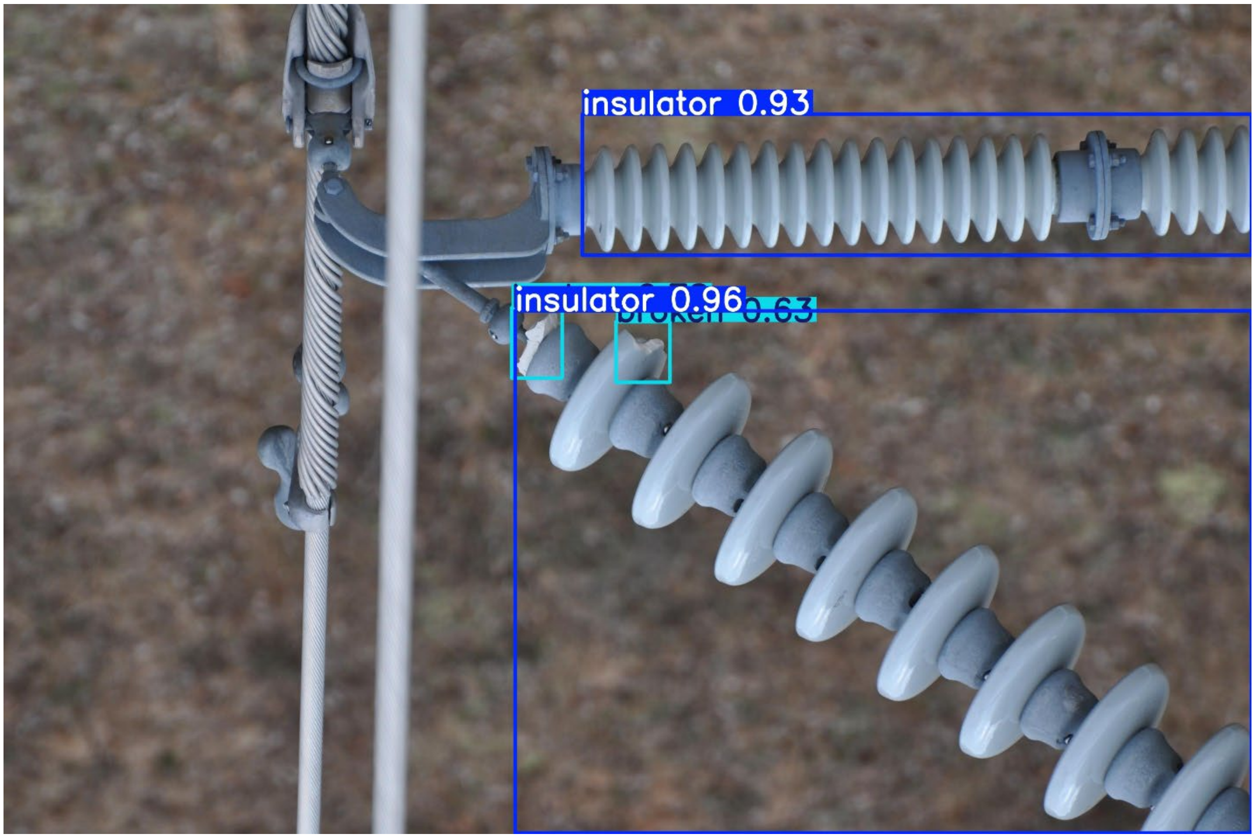
	Precision	Recall	mAP@0.50	mAP@0.50:0.95	fitness
Yolov8n	0.942	0.909	0.948	0.695	0.720
Yolov9t	0.942	0.910	0.945	0.701	0.725
Yolov10n	0.890	0.868	0.923	0.677	0.702
Yolov8s	0.949	0.944	0.968	0.734	0.757
Yolov9s	0.948	0.938	0.964	0.730	0.753
Yolov10s	0.929	0.918	0.956	0.720	0.744
Yolov8m	0.951	0.954	0.974	0.746	0.769
Yolov9m	0.955	0.954	0.974	0.747	0.770
Yolov10m	0.932	0.934	0.966	0.734	0.757
Yolov8l	0.949	0.956	0.974	0.753	0.775
Yolov9c	0.950	0.956	0.975	0.748	0.771
Yolov10l	0.922	0.944	0.969	0.747	0.769

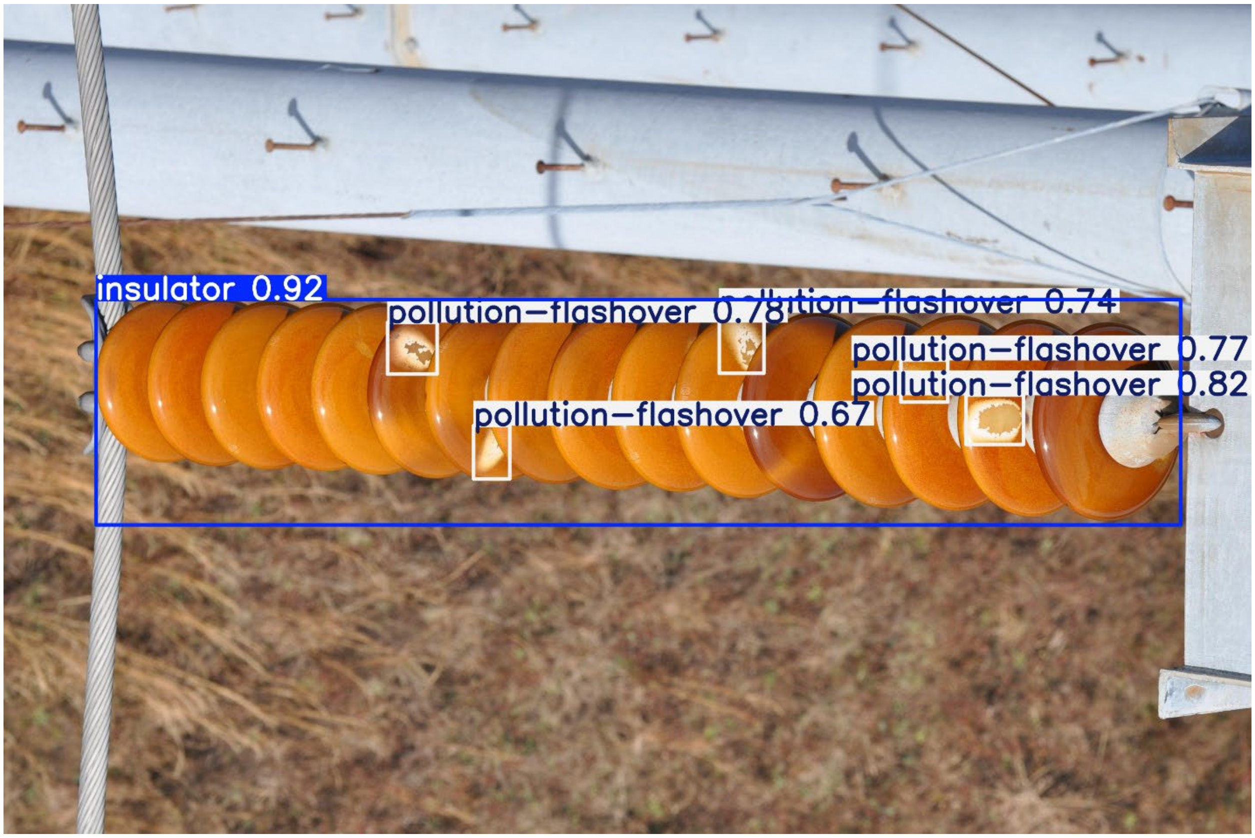
To explain the values in Table 5, for instance, on the first row with using Yolov8n model, a value of `0.942` indicates that approximately 94.2% of the predicted positive instances are indeed correct (true positives). This means the model is highly accurate when it predicts a positive detection. A value of `0.909` indicates that the model correctly identifies about 90.2% of all the actual positive instances. This shows that the model is effective at finding most of the positive instances. A value of `0.948` indicates that the model's average precision across all classes is approximately 94.8% when considering an IoU threshold of 0.50. This suggests the model is quite effective at detecting objects with moderate overlap between predicted and ground truth bounding boxes. A value of `0.695` indicates that when considering a range of IoU thresholds, the model's average precision drops to about 69.5%. This is expected since higher IoU thresholds are more stringent, requiring closer overlap between predicted and ground truth bounding boxes. A value of `0.720` suggests that, considering the chosen combination of metrics, the model has an overall fitness score of approximately 72.04%.

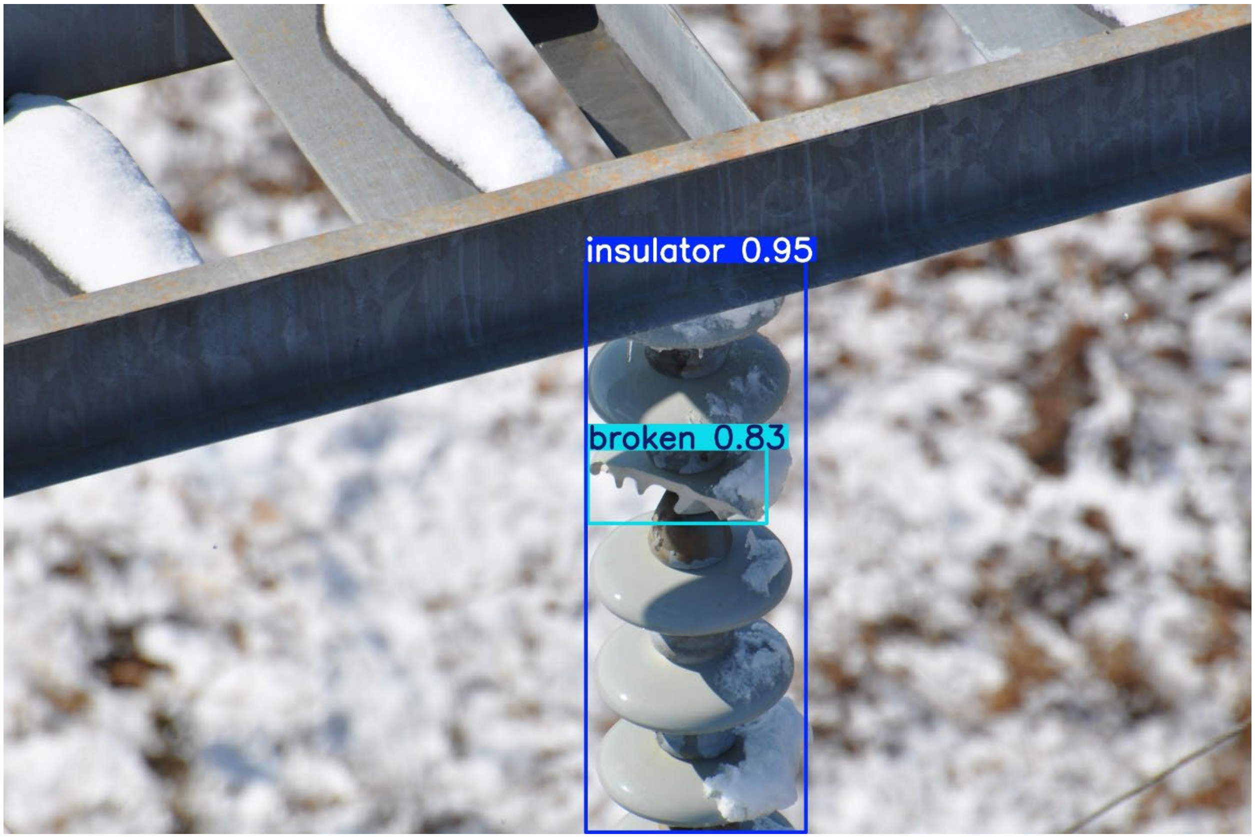
The results in Tables 1 to 5 show that all three YOLO versions are highly accurate. Overall, Yolov8 and Yolov9 are slightly better than Yolov10.

The following figure shows the detection results by applying trained Yolov8l model to some testing images. These results indicate that the trained model is highly accurate in detecting the three classes of objects: insulator, broken, and pollution-flashover.

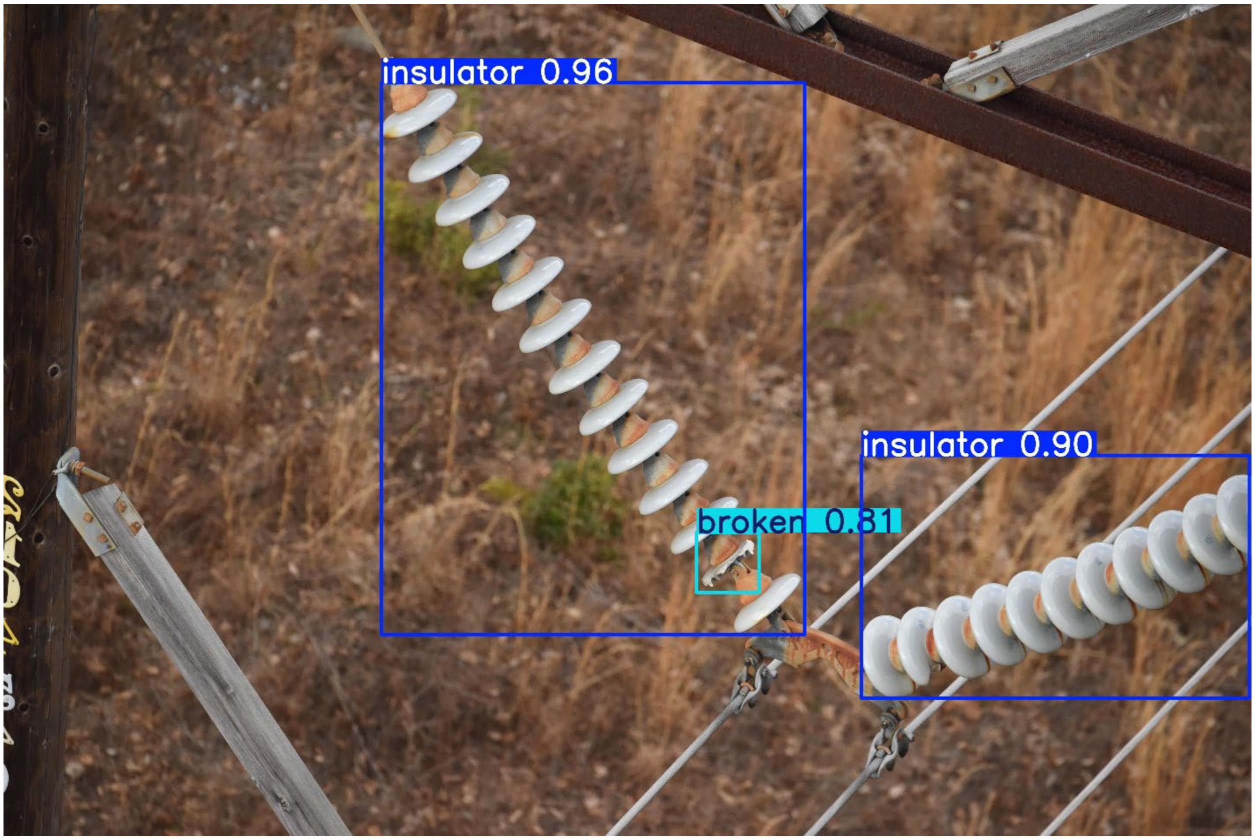

insulator 0.94
broken 0.81

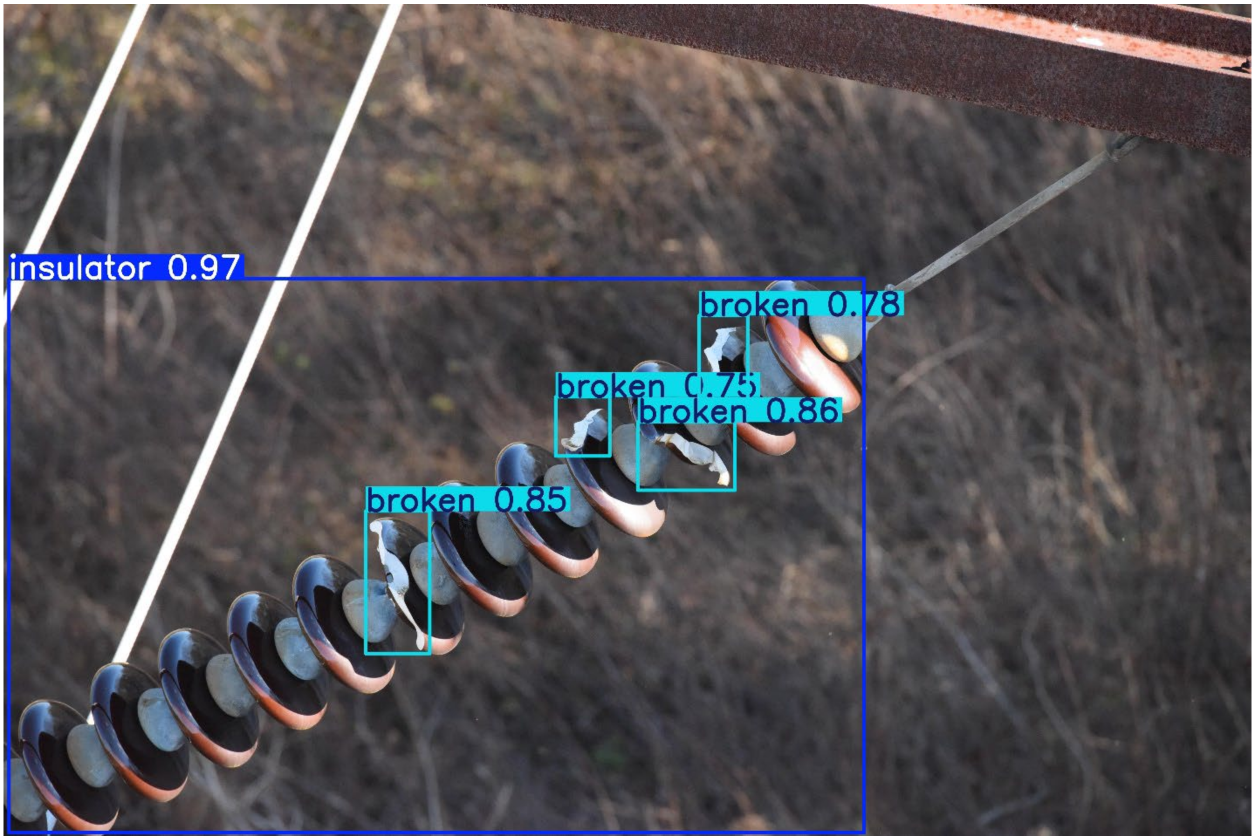

insulator 0.93
insulator 0.96
broken 0.63


insulator 0.92
pollution−flashover 0.78
pollution−flashover 0.74
pollution−flashover 0.77
pollution−flashover 0.82
pollution−flashover 0.67

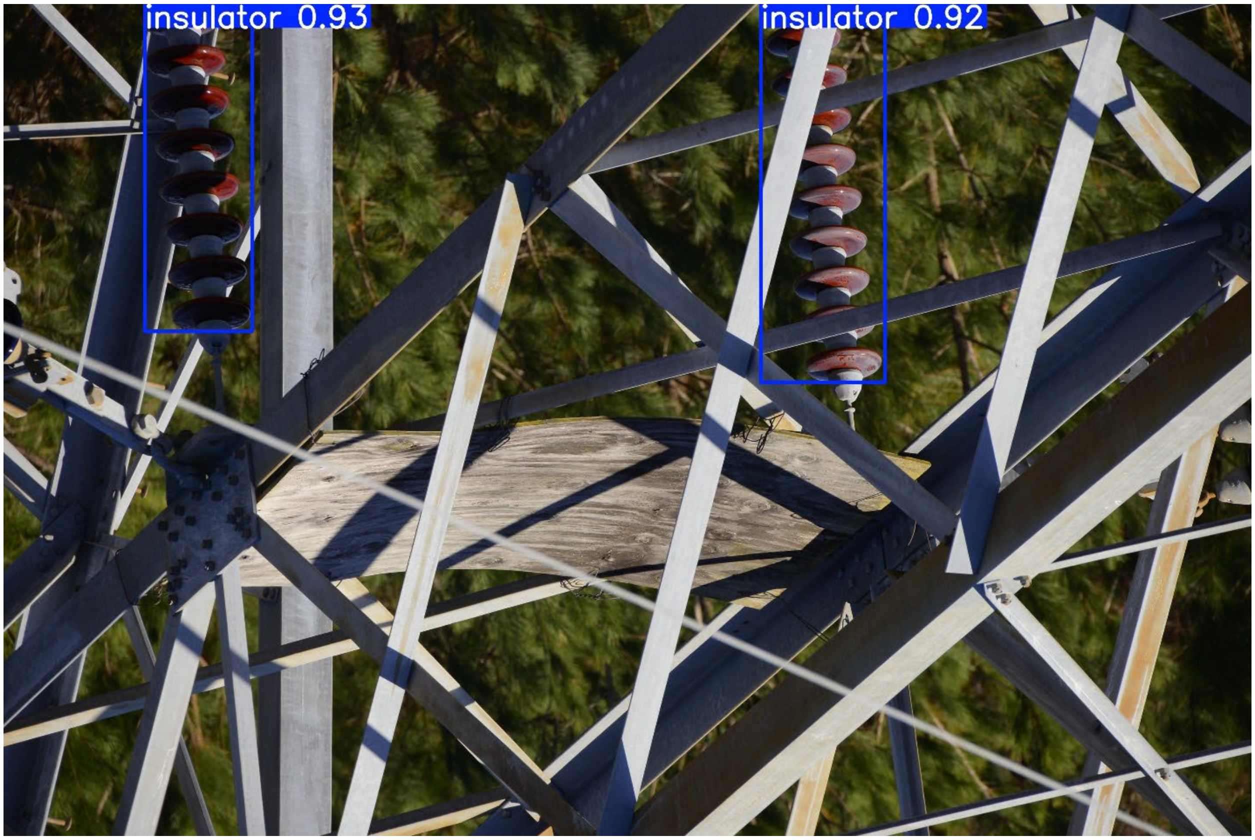

insulator 0.95
broken 0.83


insulator 0.97
pollution−flashover 0.69


insulator 0.96
insulator 0.90
broken 0.81


insulator 0.97
broken 0.78
broken 0.75
broken 0.86
broken 0.85


insulator 0.92
broken 0.68


insulator 0.93
insulator 0.92

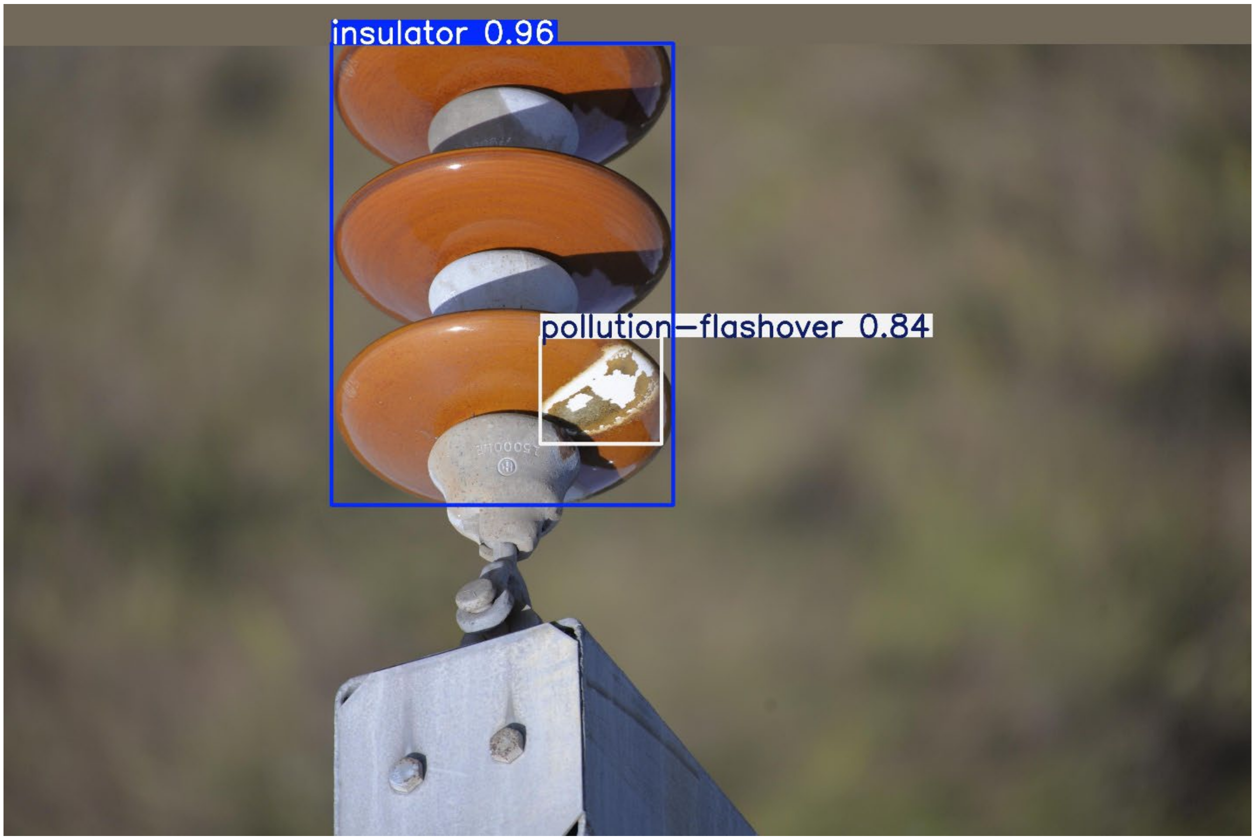

insulator 0.96
pollution—flashover 0.84

Fig 1. Prediction results on some testing image examples

Conclusion

In this study, we compare different models in Yolov8, Yolov9, and Yolov10 to insulator-defect detection in transmission lines. Our study shows that the latest YOLO family members are highly accurate in identifying the positive instances. In general, Yolov8 and Yolov9 are slightly better than Yolov10 in our experiments.

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