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Fine-Tuning YOLOv8 for Insulator Defect Detection in High-Speed Railway Systems

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Abstract- Insulators are essential components in overhead catenary railway systems, providing electrical insulation and mechanical support. But lightning, physical damage, negative weather, and some other external factors that affect their performance, which in turn could interrupt the electricity supply. However, conventional inspection methods are both time consuming and labor-intensive and sensitive to environmental conditions. In order to address these challenges and improve detection performance on small defects, this work presents a deep learning-based approach to automatically detect insulator defects using the fine-tuned YOLOv8n model. The original YOLOv8n model is integrated with the custom loss function, the SGD optimizer, and some other parameters. The proposed model is trained on an unbalanced catenary defect detection dataset that contains seven categories of insulator images: missing, shelter, breakage, contamination, dirt, and the good class. Due to the class imbalance, a variety of data augmentation techniques are applied. We trained our same dataset with other existing methods, comparative results demonstrate that our model performs better than conventional methods, with achieving overall precision 95.3% and recall 93.4%. Experimental results also show excellent performance on contamination, shelter and good categories insulators, and produce promising results on more challenging defects like dirt, breakage, or cracks. In addition, the study also highlights that YOLOv8n can be used to automatically detect and classify insulator defects, which is more efficient and reliable in terms of maintenance and safety of the overhead contact lines.

Keywords- Yolov8; defect detection; insulator detection; deep learning; catenary insulator

I. INTRODUCTION

Insulators play an essential role in high-voltage power transmission lines, offering both mechanical support and electrical insulation between conductive components and their corresponding structural supports. According to the survey of 2022, mainland China's urban rail transit network consisted of 290 lines, 9,584 km across 53 cities, with subways constituting 78.3% of the total [1]. To maintain the grid stability and ensure the reliable operation of transmission lines, these insulators are essential. Nonetheless, extreme meteorological phenomena, bird nests, lightning variations, high winds, and some other external environmental factors are potentially leading to power interruptions [2]. A variety of defects can precipitate insulator malfunctions, including cracks, breakage, missing components, dirt accumulation, shelter flaws, and contamination. Cracks typically arise from thermal fluctuations, particularly mechanical stress, thermal cycling, alongside material degradation, and other external factors that may contribute to their deterioration. Breakage happens when insulators are physically damaged, which can be from poor maintenance, vandalism, and accidental incidents, which could influence both the insulator's mechanical strength and their insulation capabilities. The absence of critical components, like caps or hardware, typically results from improper maintenance or acts of vandalism, which affect the structural and functional integrity of the insulator. Industrial emissions and agricultural activities produce a lot of dust, pollutants, salt substances, and some other biological materials to cause insulator contamination. These are present on the insulator’s surface, resulting in flashovers, leakage currents, tracking phenomena, and enhanced surface conductivity [3]. Dirt occurs when moisture is present in the environment, especially during arid and windy conditions, potentially creating conductive pathways, leading to tracking and arcing. Finally, shelter can happen when the protective shields of the insulator are either damaged or inadequately installed, rendering the insulator susceptible to environmental exposure.

Different kinds of materials are used to make insulators, including ceramics, glasses, and composites [4]. Manually insulator defect detection is very challenging and time-consuming because of the diversity of their types and shapes, different environmental conditions, as well as their backgrounds [5]. Several researchers have proposed their techniques for insulator defect detection in the past few years. Most of their techniques are traditional image processing techniques, such as morphological filtering, threshold-based segmentation, and spatial transformation. These techniques are highly dependent on algorithms like adaptive thresholds, support vector machines (SVM), and template matching. However, these algorithms essentially concentrate on image segmentation tasks and are susceptible to making mistakes from environmental factors such as fog, light variations, and the complexity of image processing tasks, leading to computationally challenging [6][7]. labor-intensive, and time-intensive tasks. As the alternative option for automatically detecting the defects in insulators and overcoming the limitations of traditional visual inspection methods, deep learning offers a very powerful technique. They proved that insulator defects can be detected in complex environments with variable light conditions, shadows, and other environmental noise [8] [9]. These methods have also shown significant improvements in detection accuracy, particularly for minor and difficult-to-detect defects. Detection accuracy for minor and difficult-to-detect defects has been improved significantly by these methods. In deep learning, there are usually two stages: a single-stage and a two-stage target detection model [10]. YOLO, and even more, SSD, are single-stage families of models that predict both classification and bounding boxes after feature extraction with fast detection speed. Taken into consideration are these models like YOLOv1 [10], YOLOv2 [11], YOLOv3 [12], YOLOv4 [13], YOLOv5 [7], YOLOv7 [14], YOLOv8[15], due to their efficiency. There are two stage models, including RCNN, Fast RCNN [16], and Faster RCNN [17], which first generate areas of interest and then classify and refine bounding boxes in order to achieve increased accuracy but at much slower processing speeds and higher levels of computing complexity [18] [19].

For the detection of insulator defects in over speed railway systems, this work presents a fine-tuned YOLOv8n model. Firstly, various data augmentation methods, both linear and nonlinear, have been applied to reduce class imbalance, then the model has been modified by using a custom loss function and the SGD optimizer, as well as picking out specific model parameters such as a learning rate, weight decay, and batch size. Performance improvements occur on minority defect classes (dirt, breakage, and crack), and the model performs well with 50 epochs of training. The model performed well on the majority class but still needs more tuning to do better on certain defect categories. This study's major contributions include: (1) using targeted data augmentation techniques like flipping, rotation, and adding noise; these can help improve the model's generalization; (2) fine-tuning the YOLOv8 model to get the highest accuracy on that dataset; and

(3) a detailed evaluation of the results, such as bounding boxes, class names, and scores, which strengthen the results.

II. RELATED WORK

Insulator defect detection has received a lot of attention in recent years since it plays such an important role in maintaining power transmission networks especially in high speed railway systems. Several techniques have been presented, based on developments on deep learning and computer vision. Several research has used the YOLO architecture to develop improved models for detecting insulator defects. For instance, a Foggy Insulator Network (FINet) based on YOLOv5 uses a synthetic fog technique to improve defect identification in complex environments, resulting in the Synthetic Foggy Insulator Dataset (SFID) [20]. Similarly, a modified YOLOv8n model incorporates a Triplet Attention Module and SC-Detect lightweight architecture to handle complex backgrounds and size variations in defect detection [15]. Additional improvements to YOLOv8n, such as GSConv and CARAFE, increase feature retention and fusion, allowing for more precise identification of minor and complex defects [21]. Another major innovation, ID-YOLO, is based on YOLOv4 and uses a CSP-ResNeSt backbone and a Bi-SimAM-FPN to improve small-scale fault identification in aerial images [13].

Unsupervised approaches have also been investigated. A Siamese Defect Detection Network (SDDN) combines R-YOLOv5s for insulator localization with a real-time unsupervised defect detection network trained only on normal data [22]. Another unsupervised method employs Mask R-CNN for segmentation, together with Reconstruction and Classification Convolutional Auto Encoder Network (RCCAEN) for defect removal and identification [23]. The integration of newly developed modules into deep learning frameworks has greatly improved the subject. A CBAM-based YOLOv5 model, for example, concentrates on key image characteristics while using BiFPN for feature fusion across layers, which improves detection accuracy for small-scale defects [7]. Attention methods, such the SE module in SE-YOLOv5, improve performance by dynamically weighting feature channels [20]. The MobileNet_CenterNet model solves real-time detection difficulties by combining a lightweight backbone with CBAM for small-target detection [24].

Transformer-based models have also shown their potential. DETR (Detection Transformer) uses an encoder-decoder architecture for insulator defect detection, using bipartite matching loss to align predictions with ground truth [25]. Another hybrid model uses the Swin Transformer and CNN features to increase multiscale feature extraction and defect detection performance [26].

Two-stage detection methods remain popular. For example, a Faster R-CNN combined with Feature Pyramid Networks (FPN) increases detection in complicated backgrounds, whereas ResNet-152 as a backbone improves feature extraction [27]. Similarly, a Cascaded Split Detection Network (CSDN) combines two networks for sequential defect detection and classification, therefore improving accuracy and efficiency [28]. End-to-end techniques, such as the Box-Point Detector, combine localization and classification tasks into a single network, solving issues caused by small-scale faults and complicated settings [29]. Similarly, the Center Mask technique [30] combines instance segmentation with anchor-free detection to efficiently identify faults in high- resolution aerial images. These achievements reflect the fast growth of insulator defect detection methods, which has been fueled by advances in neural network designs and the incorporation of specific modules to meet distinct issues in power line inspection.

III. METHODOLOGY

1. The Network Structure of YOLOv8n

YOLOv8n is a lightweight and efficient object detection architecture designed for real-time applications, also known for their acceptable balance between accuracy and speed. There are different types of configurations in this model, such as YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x. They meet different computing requirements based on dataset length, and it offers deeper or wider as needed. It has four principal parts: backbone, input, head, and neck. For computational purposes, the model takes input images of 640x640x3 dimensions. The backbone serves an important role in feature extraction, which involves multiple convolutional neural network (CNN) layers and C2f modules. It is capable of retrieving hierarchical information efficiently. The SPPF (Spatial Pyramid Pooling-Fast) layer is integrated at the end of the backbone and improves the model's ability to process with a multiscale input image and enhances the model structure to recognize different size and shape objects.

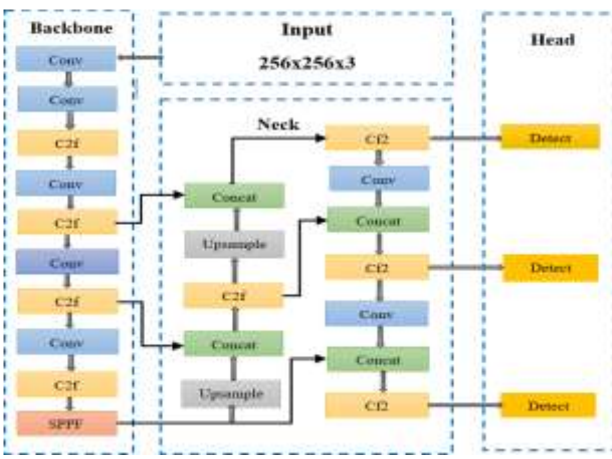

Figure 1. The network architecture of yolov8n

In Yolov8n architecture, the neck merges and refines the features in different backbone layers, thus improving the performance of detection. To ensure successful integration of high-level contextual data with fine-grained details, it incorporates upsampling, concatenation layers, and extra C2F modules. The ability of the model to detect objects in multiple shapes and sizes is provided by this multiscale feature fusion. Finally, the head leverages the refined features that are extracted from the neck to execute detection predictions. It helps the model find out the accurate object localization and classification using class probabilities, bounding boxes, and confidence scores across multiple scales. The design of this architecture is demonstrates reliable performance on real-time object detection tasks and well-suited for deployment on resource-limited devices.

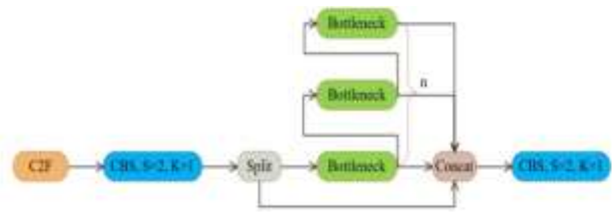

Figure 2. The schematic representation of C2f module [31]

To overcome the dataset imbalance problem for catenary insulator defect detection, a fine- tuned YOLOv8n architecture is proposed in this study. We made some adjustments here by customizing the loss function, using the SGD optimizer, and modifying some other parameters in this model. To increase the dataset length, especially for minority classes, we have separately applied some linear and non-linear data augmentation techniques and resized our input image by 256 x 256 with 32 batch sizes and 50 epochs for faster training. Our experimental results show that these adjustments improve the model's performance and achieved excellent detection accuracy in the unseen test images with the overall accuracy of 95.3%, recall 93.4%, and mAP50- 95 64%. It is also highlighted that this model outperformed in identifying minor defect classes such as contamination, shelter, and missing components. This supplement is to illustrate how the model is likely to reveal instant and exact defects of catenary insulators, serving as a means to automate the inspection in high-speed railway systems.

2. Evaluation Indicators

In this work explores the custom YOLOv8-based defect detection algorithm research for transmission line. Evaluation often takes place with the use of metrics such as precision, recall, mAP50 and mAP50–95, sometimes referred to as insulators. Measures of the performance of the model's detection for these indicators are closely associated.

Precision
A precision metric is used to evaluate classification and object detection tasks. how accurate positive predictions made by a model were. This is the proportion of correctly predicted all instances predicted as positive except for the positive instances. It is calculated using the following formula:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

where, TP presents the number of instances that the model is successfully predicted as positive, where FP presents the number of instances that the model is incorrectly predicted as positive.

Recall
Another performance metric for a model is to measure how well it can recall (i.e., all the relevant positive instances in a dataset). It shows the ratio of actual positive instances whose model returns on the right track. The formula for recall is:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

Where, TP denotes the number of instances that the model finds to be positive, and the number of instances that the model incorrectly classifies as negative where FN represents.

MAP50
A commonly used performance metric for object detection tasks, mAP50 (mean average precision at the IoU threshold of 0.5) measures with what precision a model is able to learn the objects at a specific IoU threshold. With IoU threshold 0.5, it calculates the average precision (AP); in other words, when the threshold of an IoU overlaps at least 50% with the ground truth value, we say the predicted box is correct. The mAP is calculated using this formula:

$$\text{mAP} = \sum \frac{(AP_i)}{N} \quad (3)$$

At an IoU threshold of 0.5, this is simply the average across all classes, N, where APi is the average precision metric for class i.

MAP50-95
Mean Average Precision at IoU thresholds between 0.5 and 0.95 (mAP50-95) is a generalization of the performance metric in object detection to multiple Intersection over Union (IoU) thresholds. mAP50-95 differs from mAP50, which only calculates the average precision (AP) at an IoU threshold of 0.5, at which increasing precision causes decreasing recall. It measures AP in steps of 0.05 at IoU values from 0.5 to 0.95.

By evaluating this metric, we are able to detect objects that have varying overlaps with the predicted and ground truth bounding box. In particular, we find it particularly useful for evaluating how well the model detects objects with fewer precise, smaller bounding box overlaps.

IV. DATASET PREPARATION AND EXPERIMENTS

1. Experimental Setting
A comprehensive experimental setup was set up to train and evaluate the proposed YOLOv8n-based model for insulator defect detection. We used Google Colab as the integrated development environment and used a Tesla T4 GPU for fast training. We implemented the model in Python 3.10.12, Torch 2.4.0 framework, and Ultralytics YOLOv8 version 8.0.20.

To have high- quality labeled datasets, Roboflow was used to data annotate. Resizing the input images to 256×256 improved processing speed, and the model was trained using an SGD optimizer with a learning rate of 0.01, weight decay of 0.0005, and momentum of 0.937. We trained over 50 epochs with a batch size of 32 for efficiency and accuracy, respectively. Table 1 presents detailed experimental configurations.

Table 1. Experimental Configuration Table

Parameter	value
IDE	Google Colab
GPU	Tesla T4, 15102MiB
Python	3.10.12
Framework	Torch 2.4.0
Ultralytics Yolov	8.0.20
Data annotation	Roboflow
Image sizes	256x256
Optimizer	SGD
Epoch	50
Batch size	32
Initial learning rate	0.01
Final learning rate	0.1
Weight decay	0.0005
Momentum	0.937

2. Dataset Preparation

For application in over speed railway systems, this work uses the publicly available Catenary Insulator Defect Detection (CID) dataset to detect and classify insulator defects. The dataset is categorized into seven categories: crack, dart, good, contamination, shelter, missing, and breakage. Individual characteristic requirements for successful detection of defects are represented by each category. The dataset had a substantial difficulty in class imbalance, with 3,900 "good" images and only 60 number of images for every defect class.

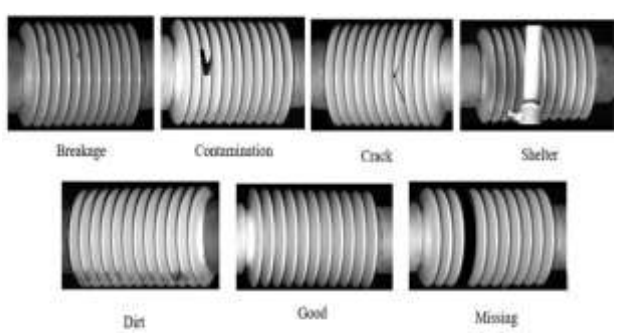

Figure 3. Our dataset samples

Therefore, only data augmentation was applied to the defective classes in order to address the class imbalance. Geometric variations were performed via random rotations, flips, and zooms for linear augmentation methods, and real-world conditions were simulated via non-linear techniques of changing brightness, contrast, and color. These augmentations significantly increased the amount of images in the defective categories, resulting in the following distributions: The "bad" class was contaminated (515), breakage (792), dirt (810), shelter (475), missing (531), crack (789), and the 'good' class was unchanged. The dataset was labeled online using the Roboflow online annotation tool after augmentation, so each image is correctly labeled. Finally, the dataset was divided into training, validation, and test sets for maximal performance evaluation through complete evaluation. To make sure the model can properly identify normal from defective images, the training set is also made of defective as well as "good" images

Table-2 Dataset details for our model

Before Augmentation		After augmentation	
Data type	Training data	Data type	Training data
Good	3900	Good	3900 (Keep)
Contamination	60	Contamination	515
Breakage	60	Breakage	792
dirt	60	dirt	810
Shelter	60	Shelter	475
Missing	60	Missing	531
Crack	60	Crack	789

In addition, to simplify data integration into the model training pipeline and easily handle dataset paths such as Train, Test, and Val, a YAML configuration file was created.

3. Non maximum suppression(NMS)

An important step in improving the results of object detection models is post processing. Non-Maximum Suppression (NMS) was applied in the improvement of the detection results of our YOLOv8n-based insulator defect detection system. This technique cuts out those unnecessary bounding boxes and keeps only the most confident predictions for each defect class. Specifically, the NMS technique filters low-confidence predictions using a confidence threshold and reduces potential false positives. We set an Intersection over Union

(IoU) threshold to avoid multiple bounding boxes of the same objects. If the IoU of two bounding boxes overlaps and exceeds a threshold, then we keep only the one with a higher confidence score, otherwise using the bounding box with the highest confidence score. All the detections present in the final output contain accurate and reliable outputs. Stepping down this pipeline and integrating it with NMS has greatly amplified the precision of the model by reversing low-confidence bounding boxes. Furthermore, recall levels were high at the same time, allowing all major defect areas to be identified. This led to better model outputs of mean average precision (mAP) such that even different categories with a significant loss in precision, such as 'contamination' (with 94.3% precision and mAP50 of 99.3%), were achieved. NMS resolved prediction overlaps and inconsistencies to produce stable and interpretable results when our YOLOv8n-based model was used in inspecting insulator defects in a high-speed railway system.

4. Visual Analysis of Our Model Performance

As shown in Figure 4, the fine-tuned YOLOv8n model can precisely and accurately detect defects in railway system insulators.

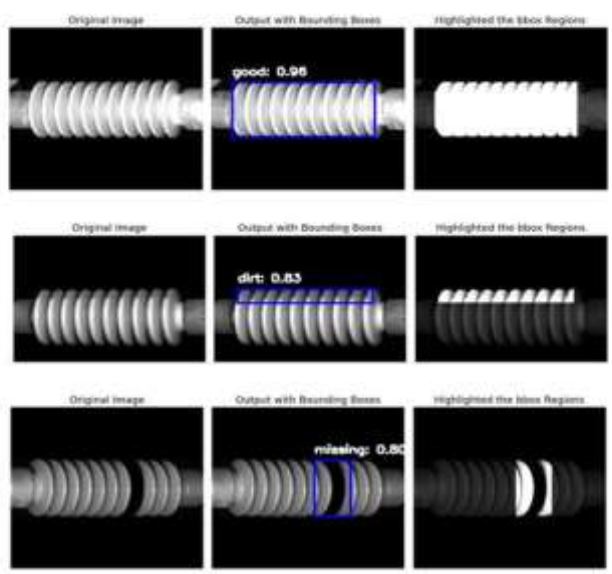

Figure.4: Our proposed model results.

Each output image uses a three-layered visualization to demonstrate the model's capacity to analyze and locate defect regions: bounding box predictions overlaid on corresponding defect regions, as well as defect highlighting with respect to the original input image. In addition to improving interpretability, it also guarantees that correct defects such as cracks, contamination, and breakages are detected even in situations such as small defects. This visual clarity demonstrates the durability of our method to providing effective defect detection in real- world applications.

Figure 5 shows our model’s precision-recall curve, which shows our model's ability to balance recall and precision across all defect classes. A close to perfect trade-off is observed in the curve, with all defect categories having high average accuracy values, implying that the model is relatively unlikely to generate false positives. While the Good, Shelter, and Contamination classes remain high and consistent on the slope, the model consistently identifies each of these classes. On the other hand, the breakdown class does not exhibit many variations, possibly due to the inherent class imbalance in the data along with the difficulty of this defect type.

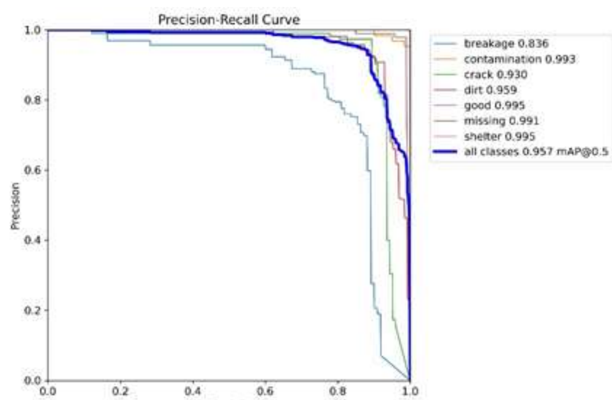

Figure 5. Precision-Recall Curve

As Figure 6 shows, the confusion matrix is a good overview of the classification accuracy for each defect class.

The fact that the model perfectly performs with a very small amount of misclassifications and has high overall accuracy indicates the matrix’s diagonal dominance. For example, good and missing types were almost perfectly classified, and minor confusions were found among breakage and crack types due to their similarity in visual appearance.

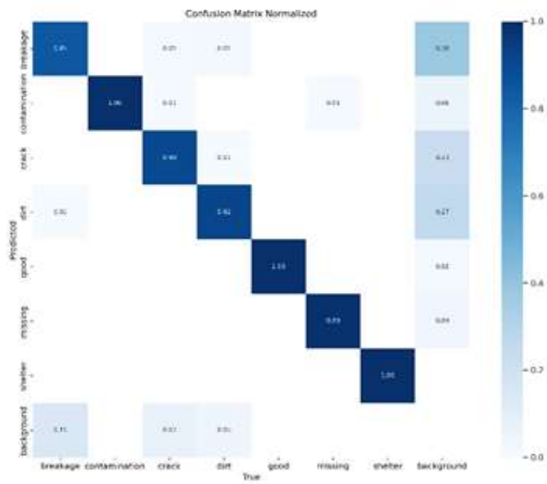

Figure 6. Confusion matrix

5. Performance Evaluation

In Table 3, we list a comprehensive overview of our experimental results and the class-wise performance metric of the fine-tuned YOLOv8n model. Thus the model was able to detect defect-free insulators with precision of 99.4%, recall of 100%, and mAP50-95 of 93.2%, and the model proved to be the best performing to detect this class. The shelter and missing types performed very well, but with mAP50-95 scores of 78.9% and 74.3%, respectively, while the breakdown suffers a lot, with mAP50-95 scores of 31.4%.

Table 3. Experimental Results

Class	Precision (%)	Recall (%)	mAP50 (%)	mAP50-95 (%)
all	0.953	0.934	0.957	0.64
breakage	0.874	0.757	0.836	0.314
contamination	0.943	1	0.993	0.636
Crack	0.973	0.891	0.93	0.454
Dirt	0.92	0.899	0.959	0.616
Good	0.994	1	0.995	0.932
Missing	0.974	0.989	0.991	0.738
shelter	0.994	1	0.995	0.789

In Table 4, we present a comparative analysis of the performance of our model against three YOLO variations trained on the same dataset and settings. We clearly demonstrate that our fine-tuned YOLOv8n outperforms YOLOv5, YOLOv6, and YOLOv7 on all the evaluation metrics. For instance, many may say that a well-developed model such as YOLOv5 got impressive results of 87.6% accuracy, 85.2% recall, and mAP50 of 87.4; the values from our model are 95.3%, 93.4%, and 95.7%, respectively.

Our fine-tuning procedure of using SGD optimizer, batch size 32 and data augmentation adapted for unbalanced for dataset is able to accomplish this constant outperformance, which indicates that it works.

Table 4. Comparison result of different yolo mode on our dataset

Model Name	Precision(%)	Recall(%)	mAP50(%)	mAP50-95(%)
Yolov5	87.6	85.2	87.4	55.2
Yolov6	66.8	67.5	88.1	59.1
Yolov7	83.6	85.1	84.6	57.7
Yolov8n	91.7	86	89.9	57.9
Yolov8n(ps2)	87	80.5	86.1	54
Yolov8n(ps6)	86.8	81.6	83.8	53.8
Our model	95.3	93.4	95.7	65.7

6. Comparative Analysis with Existing Methods

Table 5 compares the results of our fine-tuned YOLOv8n model with all other methods in the literature to evaluate the more general applicability and efficiency of our method.

Table 5 compiles performance measures given by other authors on similar insulator defect detection tasks, but unlike Tables 3 and 4, which focus on performance within our dataset.

Compared to previous techniques, our model achieved 95.3% accuracy, 95.7% mAP50 and set a new standard for the task. Moreover, such robustness is shown by our model when extended to a more complete metric, which additionally includes mAP50-95, where it reaches a value of 64% as opposed to other methods.

Table 5. Comparison table of the different existing methods with our prosed method

Method	Defect Type	Precision(%)	Recall(%)	MAP(%)	F1 score(%)	Ref.
CNNs(Vgg19), MTL	Defect and non-defect	80	-	85	75	[32]
Improved ResNet-18	Defect and non-defect	94	79	-	86	[33]
Improved YOLOv4	Defect and non-defect	94.53	93	93.09	94	[34]
AC-YOLO	Breakage and flashover	93.8	89	93.4	91	[35]
YOLOv7-C3C2-GAM	Bird Nest, cracked, blast and normal	89.1	84.7	87.9	-	[36]
Improved YOLOv7	Self-explosion, normal and partial damage	93.3	92	94.9	-	[14]
Improved YOLOv7	Flashover and damage	94	93.4	93.8	94	[37]
Improved YOLOv7-tiny	Defect and non-defect	94.51	94	98.31	96	[38]
ID-YOLOv7	Defect	92.6	80	85.7	-	[39]
YOLO-S	Defect and non-defect	88.5	85	57.2	-	[40]
LiteYOLO-ID	Broken, flashover	83	59	65.1	-	[41]
Cascaded CNN	Defect	94.10	92	93.46	90	[28]
GC-YOLO	Pollution, breakage, flashover	93.1	89	94.2	-	[42]
Ours method	Good, missing, crack, breakage, shelter, dirt, contamination	95.3	93.4	95.7	94	

Leveraging this comparative analysis, we demonstrate the validation of our approach over other advancements focused on adaptability to imbalanced datasets and to detect subtle defect types. We leverage a combination of data augmentation, fine-tuned hyperparameters and advanced visualization to address key challenges left out by previous methods, including the handling of varying defect categories with minimal class overlap.

V. CONCLUSION

A fine-tuned YOLOv8n model is proposed in this study to automatically detect catenary insulator defects in high-speed railway systems. By tackling the issues of unbalanced datasets and environmental unpredictability. Our methodology dramatically improves defect detection and classification accuracy over existing methods. Targeted data augmentation techniques and optimization of the YOLOv8n model with a custom loss function and SGD optimizer significantly improved the defect type identification of both common and rare defect types.

Our experimental results show that the model achieved very high accuracy, in particular for defects such as contamination, shelter, missing, and good-type insulators, and promising results for tiny, hard-to- detect problems like dirt, cracks, and breakage. However, the performance of some minority defect classes, particularly dirt and crack, should be improved.

The results also highlight that deep learning models require continual tuning for improving detection skills, especially under adverse conditions. We present a more efficient, reliable, and scalable solution for insulator fault detection using deep learning, which is highlighted by this study as having the capacity to change critical infrastructure inspection and maintenance in real time.

We will explore future work to increase the model's resilience through alternative training procedures for multi-modal data and carefully tend to extreme unbalanced datasets. In total, this paper serves as a solid base to continue the development of automatic inspection technologies within the railway sector, promoting the safety, reliability, and long life of catenary insulators.

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