SYFLo: augmenting yolo for real-time health monitoring of electric assets in power transmission lines

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Research Article

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Posted Date: July 4th, 2024

DOI: https://doi.org/10.21203/rs.3.rs-4584579/v1

Additional Declarations: No competing interests reported.

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Received: date / Accepted: date

Abstract Sustainable transmission of electrical energy to consumers across regions relies heavily on the integrity of power transmission lines and continuous monitoring of assets is crucial for maintaining system reliability. Unmanned Aerial Vehicles (UAVs) have revolutionized defect identification in real-time and accessibility, even in difficult-to-reach geographical landscapes, thereby improving image-based inspections. This work introduces SYFLo(Semisupervised Yolo with Focal Loss function), a novel method that augments YOLO for real-time health monitoring of electric assets in power transmission lines. SYFLo integrates the focal loss function with semi-supervised learning to effectively address the lack of abundant labeled data, data imbalances and enhance detection accuracy. Additionally, it improves data generalizability across a wide range of images, ensuring robust performance despite varied image backgrounds. By leveraging YOLOv8, SYFLo significantly improves fault identification, achieving a detection accuracy of 96.5% and an FPS of 283.2. Experimental results demonstrate the impact of the proposed approach, highlighting its potential to enhance the reliability of power transmission line monitoring. These findings underscore the importance of integrating advanced deep learning techniques with innovative loss functions to address common challenges in real-time health monitoring systems.

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1 Introduction

Transmission lines serve a vital role in the efficient conveyance of electricity from its source to major consumption centers, often operating in difficult outdoor environments [1]. Regular inspections are essential in these systems to detect issues before they become disruptive, such as the need to reduce current leakage between conductors and structures and guarantee insulator safety to maintain system efficiency [2]. Network failures can encompass various challenges, including pollution accumulation on insulators and the absence of adequate insulation, posing significant challenges to maintaining network integrity [3]. Deploying UAV inspection for transmission lines encounters numerous challenges, including the automated diagnosis of faults in expansive aerial images. This concern has garnered considerable global interest. Transmission lines serve a vital role in the efficient conveyance of electricity from its source to major consumption centers, often operating in difficult outdoor environments [1]. Regular inspections are essential in these systems to detect issues before they become disruptive, such as the need to reduce current leakage between conductors and structures and guarantee insulator safety to maintain system efficiency [2]. Network failures can encompass various challenges, including pollution accumulation on insulators and the

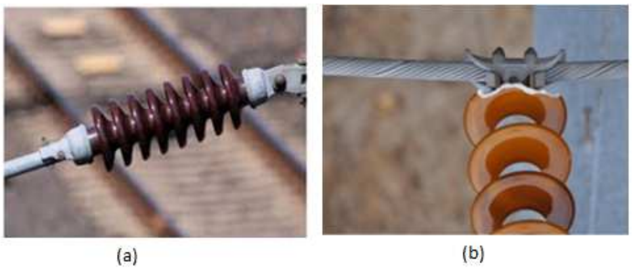

Fig. 1 The figure illustrates (a) the healthy insulator and (b) the defective insulator.

absence of adequate insulation, posing significant challenges to maintaining network integrity [3]. Deploying UAV inspection for transmission lines encounters numerous challenges, including the automated diagnosis of faults in expansive aerial images. This concern has garnered considerable global interest.

Crucial parts of the power transmission system that guarantee current safety include transmission towers, conductors, and insulators. The stability and efficiency of the system are improved by additional components such as Stockbridge dampers, tower plates, and spacers. Transmission towers resist external stresses and support conductor weight to give structural support. Insulators reduce current leakage between conductors and structures, preserving system efficiency and safety. Spacers increase transmission efficiency and reduce conductor interference in multi-circuit lines. Tower plates balance the weight of the tower and provide a stable anchorage, and Stockbridge dampers reduce conductor vibration to extend the life of transmission lines. When combined, these parts provide a reliable and effective power transfer system.

Specialized equipment like ultrasonic detectors [9], radio interference [10], and acoustic approaches [11] are used to detect defects during inspections. Skilled operators are essential for successful detection, and electrical machinery can introduce interference, making precise identification challenging [12]. Sound-based techniques also require proximity to the network, demanding inspection crews to traverse challenging terrain to obtain measurements.

Fig. 1 represents, the illustrative comparison of two scenarios, each representing the state of an insulator. While Fig. 1(a) shows an insulator that appears to be in good condition with no visible damage or faults, the other shows an insulator that has a defect[13]. This graphic assistance most likely acts as a guide for examining and differentiating between various situations in electrical power networks. The real-time monitoring and maintenance of electricity transmission lines' dependability and safety depend greatly on this kind of differentiation[17].

Fig. 2 Instances from all five classes of power line assets in STN PLAD are showcased in the table. Each column corresponds to one class, displaying examples sequentially: Transmission tower, Tower plate, Stockbridge damper, Spacer, and Insulator arranged from left to right.

The You Only Look Once (YOLO) real-time object identification system allows for quick and precise detection within UAV data, which improves the effectiveness of inspection and fault diagnostics when integrated with deep learning. Particularly in locating transmission components, identifying electrical lines, and controlling vegetation development, advanced algorithms and multi-layer networks—such as RNNs, CNNs, and reinforcement learning—perform better than traditional methods[15].

Prior studies on fault detection in power system components were conducted by Zhai et al. and Wang et al. Zha0 et al. employed UAVs in conjunction with a spatial morphological method to enhance the accuracy of insulator inspections, whilst Wang et al. utilized infrared photography to facilitate predictive maintenance[17].

Identifying insulator faults becomes more difficult when using UAV-captured overhead images since they frequently have complex backdrops and varied textures. Research has indicated that the constant edge properties of insulators can be used to facilitate efficient localization and analysis of these assets.

The salient features of the YOLO model is found in its capacity to perform exceptionally well in object recognition tasks, such as identifying defects in power system components. YOLO is a specialized tool for evaluating datasets gathered by UAVs during grid inspections because of its real-time capabilities. This research aims to assess the YOLO model's effectiveness in analyzing the dataset collected by UAVs and enhance power system inspection capabilities by using its advantages[10].

- This research unifies bleeding edge YOLO models and the Focal loss function to enhance power line inspections, ensuring accurate object detection and streamlined processes for better system reliability.
- The incorporation of semi-supervised learning and the Focal loss function improves data usage, significantly boosting the model's ability to detect and evaluate components, elevating overall performance.
- The integration of deployable detection methods, considering parameters and size for embedded systems in UAVs, with advanced detection techniques, enables remote inspections. This application facilitates predictive maintenance, reducing downtime, and strengthening power grid resilience for more reliable electrical networks.

2 Related works

The integration of deployable detection methods, tailored for parameters and size in embedded systems within UAVs, enables advanced remote inspection capabilities[10]. This application facilitates predictive maintenance, significantly reduces downtime, and strengthens power grid resilience, leading to more reliable and efficient electrical networks.

The Fig. 2 represents examples of all five classifications of power line assets. Every column represents a class, with the following examples shown successively from left to right: Transmission tower, Insulator, Spacer, Tower plate, and Stockbridge damper. The visual depiction of the many power line components in Fig. 2 enhances the overall complete understanding of each class in the dataset.

Furthermore, Liu et al. have proposed that refining specific algorithms tailored for object detection holds significant promise in the realm of transmission line inspections. This is particularly significant as conventional models often encounter difficulties when categorizing images with diverse background interferences[15]. To facilitate efficient inspections using Unmanned Aerial Vehicles (UAV's), which are increasingly popular, a thorough analysis and specialized model training are essential[16]. Techniques such as segmentation and feature extraction have emerged as valuable tools for handling images with varied backdrops, particularly in the context of transmission line analysis.

Deep learning frameworks have been introduced to efficiently analyze feature extraction techniques for insulator detection in aerial photographs. These frameworks not only identify insulators but also detect foreign objects that may disrupt the power grid[17]. The utilization of multiple methodologies has demonstrated precision in categorizing adverse circumstances in transmission lines. Models designed for both object identification and adverse situation classification have been integrated to enhance the identification of faults in transmission lines, including the detection of faulty insulators[18].

The restricted observer or camera location that obstructs view, particularly during ground-level inspections, insulator defect detection is difficult. Through the rotation of the bounding box during the Intersection over Union computation, Abbasi et al. proposed the R-YOLO model, which increases the detection accuracy of inclined objects. Capture angle fluctuations are addressed by including inspection images taken by UAVs during training[20].

Using UAV images, deep learning models make it easier to identify transmission line defects. Kim et al. point out that improved light spectrum cameras further enhance flaw identification. Using frequently larger information, research has concentrated on pinpointing fault locations and insulator positions. Li et al., for instance, used a big dataset to find problems such as insulator flaws. Square wave transformations, segment connection algorithms, scale histogram matching, and automatic visual shape grouping networks are some of the other methods used in inspections[24].

The amount and distribution of images within classes have a major impact on how machine learning is applied to computer vision problems. The popular YOLOv8 paradigm is being applied more and more in a variety of sectors. Sadykova et al. customized an improved version of YOLOv8 for use in UAV applications, while Zhu et al. integrated it for object recognition in UAV settings[29]. Zhang and colleagues utilized YOLOv8 for the examination of photovoltaic modules, while Souza et al. devised an enhanced method for UAV object recognition[30].

Liu et al. discovered that when a Res YOLOv8 variation was used for power electrical system inspection, the mean average precision increased[23]. By using the YOLOv8x, Feng et al. were able to acquire high precision scores for fault and anomaly detection. YOLOv8s were used by Gemn et al. to identify anomalies on power transmission lines brought on by pollution problems. Studies evaluating the performance of different YOLOv8 iterations are used for electrical system issue detection. The Prune-MobileNetv3-YOLOv8s model was presented by Zhang et al. for moving object identification in power grids[13].

The use of YOLOv8s for insulator detection by Wang et al. illustrates how fault classification and insulator

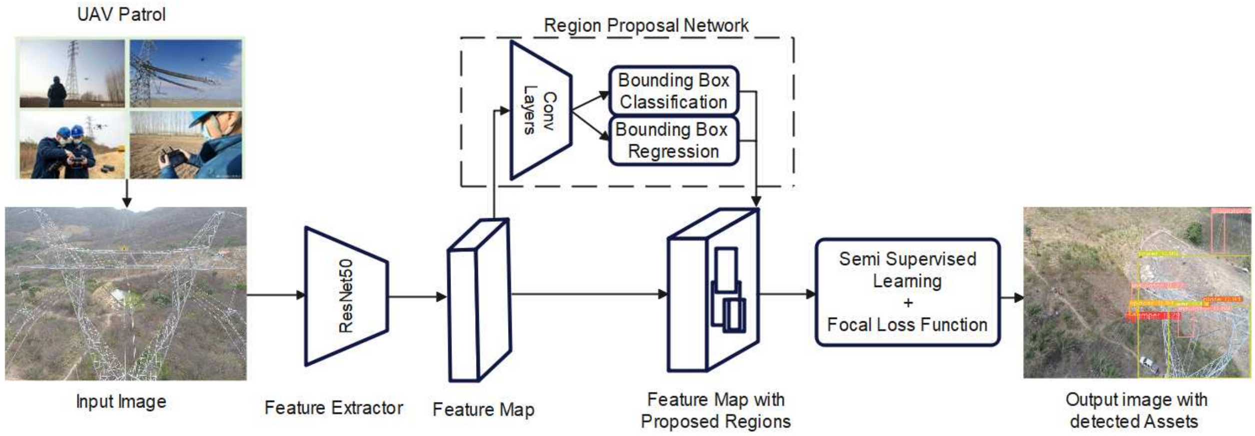

Fig. 3 Proposed methodological framework for transmission line asset detection

identification are not the same. Zhang et al. used the YOLOv8s model in distribution network development to improve worker safety. An enhanced YOLOv5s for protective gear identification in high-voltage equipment maintenance was assessed by Stefenon[30].

3 Semi-supervised object detection in imbalanced class environments

Semi-supervised learning for object detection in the context of finding the health condition of Electric assets in transmission lines using YOLOv8 involves a combination of labeled and unlabeled data to train a more robust model.

The object detection pipeline is shown in Fig. 3, which begins with the input image and uses the ResNet to extract features. The obtained feature map is used to determine proposed regions of interest. It is constituted with convolutional layers for both regression and classification. The focal loss function and semi-supervised learning enhance the model's resilience, resulting in output images that precisely identify and categorize power line assets with well-defined bounding boxes.

3.1 YOLOv8(You Only Look Once) structure:

Convolutional Neural Networks (CNNs) have proven to be highly efficient in the realm of object detection algorithms, resulting in the development of various models such as R-CNN, Fast R-CNN, Faster R-CNN, SSD, RetinaNet and YOLO over the years. Prior to YOLO, these models followed a two-stage detection approach, incorporating processes like selective search or regional proposal networks to identify regions of interest. These selected regions were subsequently fed into a classifier for further analysis. However, YOLO was innovatively designed to treat detection as a regression problem, enabling it to simultaneously handle both detection and classification tasks using a single neural network. This unique approach sets YOLO apart as the swiftest one-stage detector available.

The most recent version of YOLO model is YOLOv8 Fig. 4, which places a strong emphasis on achieving a balance between speed, compactness, and accuracy. It introduces a range of novel features including a new backbone network, an anchor-free split head, and improved loss functions, resulting in enhanced overall performance while maintaining a small model size and exceptional processing speed. YOLOv8 exhibits a remarkable versatility, catering to a wide array of computer vision tasks, including object detection, image segmentation, pose estimation, tracking, and classification. Its exceptional capabilities and accuracy render it a valuable and indispensable tool in the domains of object detection and image segmentation.

YOLOv8, a sophisticated object detection model, is a notable advancement above previous YOLO versions. Its tecture allows for better information flow between layers. It consists of a modified CSPDarknet53 backbone with 53 convolutional layers and improved cross-stage partial connections. Because of the flexibility of this architecture, it can handle a wide range of object sizes and aspect ratios, which makes YOLOv8 especially suitable for extensive object detection tasks in a variety of scenarios and environments.

Fig. 4 represents the distinct components of the YOLOv8 are head, neck, and backbone—are one of its main advantages. Convolutional layers are used to build the backbone, which diligently pulls complex information from input images that are essential for precise object detection. Serving as a link between the head and the backbone, the neck enhances and further processes

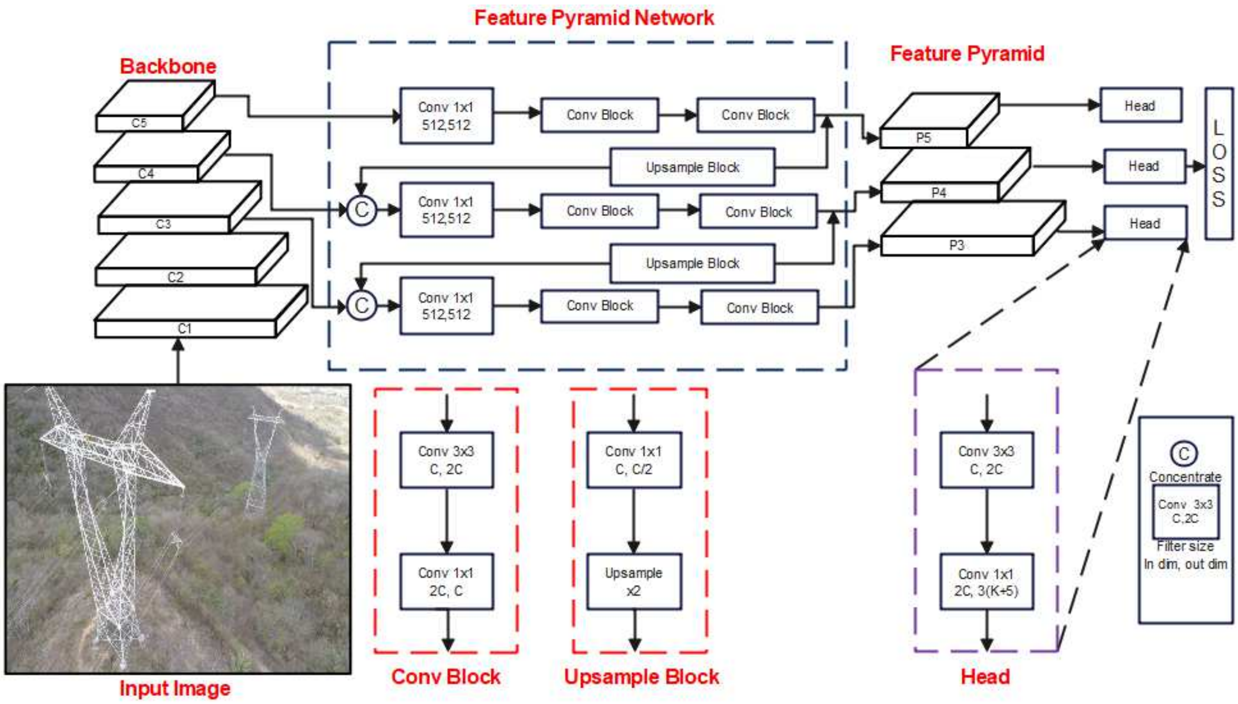

Fig. 4 YOLOv8 model architecture.

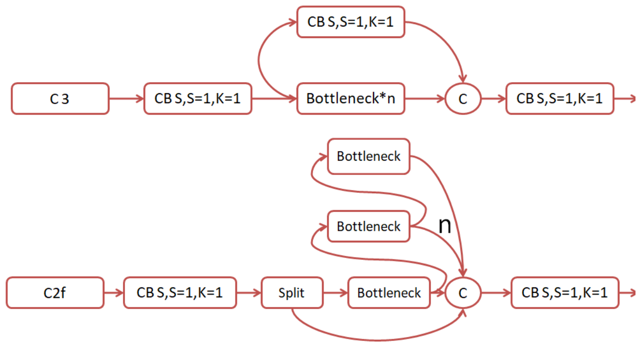

Fig. 5 C2f convolutional block module in YOLOv8 model.

these characteristics to maximize their usefulness for future examination. A key component, the head performs complex tasks like object detection, categorization, and instance segmentation, producing accurate predictions that are essential for a thorough comprehension and interpretation of visual input.

Furthermore, YOLOv8 encompasses more functionalities beyond its advanced design. It makes the process of transferring learning across different datasets and domains easier by presenting pre-trained models. Additionally, the use of adaptive training methods and sophisticated data augmentation techniques by YOLOv8 greatly enhances learning rates and efficiently balances loss functions, which in turn produces better model performance and flexibility in a variety of circumstances.

Fig. 5 is represents, the Conv block (Convolutional to Fused(C2f) convolutional block) module is utilized for visual feature extraction. In the YOLOv8, the CBS 1×1 convolution structure from the PAN-FPN upsampling stage present in YOLOv5, and additionally substitute the C3 module with the C2f module. The YOLOv8's Decoupled-head employs two separate convolutions for classification and regression tasks, incorporating the concept of DFL simultaneously.

By increasing the number of layers in neural network, the Depth Multiple parameters regulates model's depth. Nevertheless, the Width Multiple is in charge of adding more filters to the layers, which raises the total number of channels in the layer outputs and differentiations between YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x variants result from variations in these configurations.

Table 1 shows the performance metrics of many YOLOv8 models that vary in terms of size (pixels), inference speed, and mAPval (mean average precision value at 50-95) on the CPU ONNX and A100 TensorRT platforms. It also contains the number of FLOPs (B) and parameters (M). Although there is a speed trade-off, the transition from YOLOv8n to YOLOv8x demonstrates an upward trend in mAPval, indicating increased accuracy. In contrast to YOLOv8x, which achieves a higher mAPval of 53.9 but runs at a slower pace of 479.1 ms (CPU ONNX), YOLOv8n, with a lower mAPval of 37.3, operates faster at 80.4 ms (CPU

Table 1 YOLOv8 models setup information for 640−pixel images.

Model	parameters (M)	Speed CPU ONNX (ms)	mAPval 50-95	FLOPs (B)	Speed A100 TensorRT (ms)	size (pixels)
YOLOv8n	3.2	80.4	37.3	8.7	0.99	640
YOLOv8s	11.2	128.4	44.9	28.6	1.2	640
YOLOv8m	**25.9**	234.7	50.2	78.9	1.83	**640**
YOLOv8l	43.7	375.2	52.9	165.2	2.39	640
YOLOv8x	68.2	479.1	53.9	257.8	3.53	640

ONNX). This table highlights the trade-offs between speed and accuracy for several YOLOv8 models, which are crucial factors to take into account when choosing the best model for specific applications or platforms.

3.2 Semi-supervised learning:

The core of methodology lies in the innovative application of semi-supervised learning techniques. The dataset is segmented into three subsets: a smaller labeled dataset and two larger unlabeled subsets. In the unlabeled subsets, a semi-supervised approach is employed to extend the model's learning capacity[3]. First, supervised learning to pre-train the object detection model using the labeled dataset[16]. This initial training phase establishes a fundamental understanding of the objects and their characteristics, enabling the model to recognize them effectively. Subsequently, the knowledge gained from pre-training is leveraged to make predictions on the unlabeled data. These predictions are then used to generate pseudo-labels for objects in the unlabeled images[10].

The initial phase involves establishing a series of stochastic transformations for a given datapoint (such as an image) with the objective of minimally altering its semantics (e.g., class label). In the context of image classification, common augmentations include rotation and shearing.

$$\overline{y} = \frac{1}{K}\sum_{k=1}^{K} P_{Model}(\hat{u_k};\theta) \tag{1}$$

$$Sharpen(\bar{y},T)_i = \frac{\bar{y}_i^{\frac{1}{T}}}{\sum_{j=1}^{L}\bar{y}_j^{\frac{1}{T}}} \tag{2}$$

The equation 1 calculates the average $\bar{y}$ over K different model predictions ($P_{Model}(\hat{u_k};\theta)$). Here, $\hat{u_k}$ represents some input u with associated parameters θ, and $P_{Model}(\hat{u_k};\theta)$ is the model's prediction for this input.

In equation 2, T, referred to as temperature, regulates the smoothness of the output distribution (approaching a one-hot vector as T $\to$ 0). The sharpening operation inherently compels the model to generate low-entropy predictions for unlabeled data. To elaborate, when provided with a labeled (or unlabeled) data point along with its label (or predicted target), denoted as (x, y), augmentation generates a stochastic linear interpolation with another training example sampling λ, creating $\tilde{\lambda}$, $(x',\ y')$ either labeled or unlabeled, as follows.

$$\lambda \sim Beta(\eta,\eta) \tag{3}$$

$$\tilde{\lambda} = max(\lambda, 1-\lambda) \tag{4}$$

$$\hat{x} = \tilde{\lambda_x} + (1-\tilde{\lambda})x' \tag{5}$$

$$\hat{y} = \tilde{\lambda_y} + (1-\tilde{\lambda})y' \tag{6}$$

The aforementioned processes yield a set of augmented training examples that incorporate supervision signals from both labeled and unlabeled data. Subsequently utilized the supervised objectives to train the model parameters.

3.3 Focal Loss function:

Class imbalance:

In machine learning, balanced training datasets are common, but real-world scenarios often present imbalanced class distributions, such as in fraud detection, medical diagnosis, and software failure prediction. This class imbalance poses challenges, affecting model convergence and generalization. Addressing class imbalance involves two primary approaches: data-level and algorithmic-level methods. Data-level methods, like oversampling and undersampling, modify the training dataset but can lead to overfitting. Algorithmic-level methods, such as threshold moving, adjust learning algorithms to handle imbalanced data.

A hybrid sampling approach utilizing generative adversarial networks is proposed to address class imbalance. Additionally, the effectiveness of techniques like

Normal Loss, Focal Loss, Semi-Supervised Learning, and their combinations has been compared in various applications, including medical image segmentation, object detection, and anomaly detection. These comparisons provide insights into the advantages and limitations of each technique in different scenarios.

In power transmission line inspections, precise identification of objects, especially rare and defective components like insulators, is crucial. The focal loss function effectively mitigates class imbalance by focusing on intricate examples, which are often early indicators of potential issues. By assigning higher significance to these crucial yet less frequent instances, the focal loss function enhances the model's ability to distinguish between various object classes, making it particularly valuable for early fault detection in electrical power systems.

$$\begin{aligned} Loss_{fl} = -1/N \sum_{i=1}^{N} \alpha y_i (1 - (p(y_i))^{\gamma} log(p(y_i)) \\ + (1-\alpha)(1-y_i)((p(y_i))^{\gamma} log(1-(p(y_i)) \end{aligned} \tag{7}$$

The equation 7 Focal Loss Function, denoted as "$\mathrm{Loss_{fl}}$", operates under the influence of two essential weight factors: "α" which governs the balance between positive and negative samples, and "γ," which fine−tunes the equilibrium concerning challenging instances.

Here, "$p(y_i)$" signifies the predicted value generated by the network model, while "y_i" represents the true tag value. In this context, "1" denotes a positive sample, while all other values denote negative samples. The associated loss value also diminishes when the difference between the anticipated and true values shrinks, suggesting that the sample will be easier to classify. On the other hand, a bigger difference leads to a higher loss value, which indicates how hard it is to predict the sample with accuracy.

The focal loss function, originating from its basis in binary cross-entropy, offers a unique methodology for deep neural network training. Unlike traditional loss functions, it incorporates dynamic scaling to minimize the influence of easily distinguishable training samples. This mechanism encourages the network to prioritize more complex instances, whether positive or negative, thereby enhancing training effectiveness. The focal loss is mathematically represented by the provided equation.

This balanced approach allows the model to accurately detect even subtle anomalies in power line components, facilitating timely interventions when necessary. Given the diverse environments that power transmission lines traverse and the various forms of insulators used, the focal loss function's adaptability is crucial. It ensures sustained accuracy across different settings, making it a robust and reliable tool for maintaining the integrity of electrical power systems. Thus, the focal loss function is not merely significant but essential in developing a comprehensive and precise health real-time monitoring system tailored to the specific challenges of power transmission lines.

3.4 Model training and evaluation:

The subsequent phase involves fine-tuning the model using both labeled and pseudo-labeled data. This combination enhances the model's generalization by learning from expert-labeled examples and its predictions on unannotated images. Fine-tuning is iterative, allowing adaptation to real-world conditions, refining the model's understanding of insulators, electrical components, and fault detection.

Performance is assessed by using metrics such as mean Average Precision (mAP) and the F1-score. mAP evaluates the model's detection and classification abilities under diverse conditions, while the F1-score balances precision and recall, crucial for identifying faults in power transmission. Benchmarking the semi- supervised YOLOv8 model against traditional models provides insights into the advantages of this approach. This evaluation phase is essential for determining real-world effectiveness.

4 Experimental results

Selecting the best model for object detection is difficult because popular models have many different versions. Models with too many layers should be avoided in order to preserve efficacy; the dataset is the primary determinant of this choice. It is important to balance computation speed, resource availability, and model applicability. Performance is given priority above training time in this study, which uses the mAP metric to optimize structures and fine-tune them. Using YOLOv5, Fig. 6 illustrates insulator health issues; red boxes denote troubles. Plad [9] boundary boxes with SSD. To evaluate each electric asset's health, the suggested approach combines YOLOv8, semi-supervised learning, and the Focal Loss Function.

4.1 Dataset construction

The experiment utilized data from two primary sources: the Power Line Assets Detection (STN-PLAD) dataset

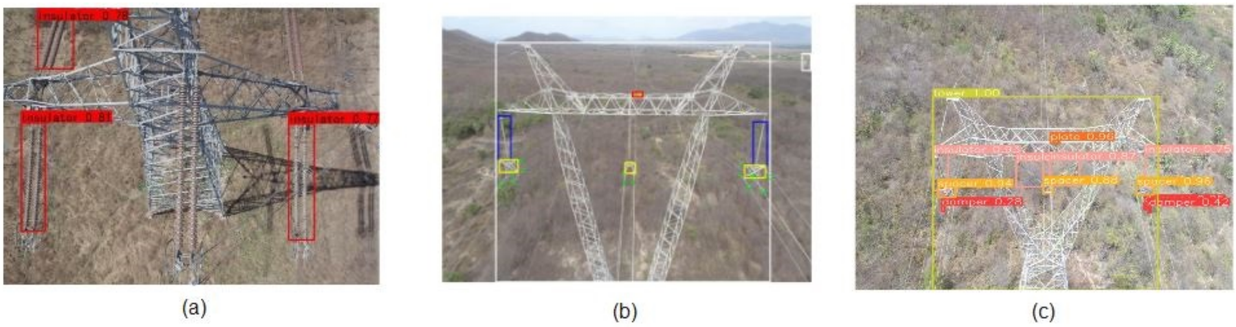

Fig. 6 Illustration of the detection outcomes for Electric Assets, presenting the qualitative results obtained by (a) YOLOv5 approach specifically for insulator health condition detection[9], (b) SSD technique for bounding boxes of electric assets[20], and (c) Proposed approach, which integrates YOLOv8, Semi-supervised Learning, and the Focal Loss Function for health monitoring of electric assets.

and the China Power Line Insulator Dataset (CPLD), along with images of insulator flaws from National Grid Power's inspection records.

There are 133 high-resolution (4048 × 3040 pixels) images of transmission towers with consistent dampers and insulators in the STN-PLAD dataset. There are 1181 images showing defects such as breakages and missing components thanks to the 848 aerial and synthetic defect photographs and the 333 glass insulator flaw images provided by the CPLD dataset. 2280 images were added to the dataset through data augmentation, and for YOLO framework compatibility, the images were rescaled to 640x640 pixels. To guarantee efficient model evaluation and training for insulator defect identification, the dataset was split into a test set (20%) and a training set (80%).

4.2 Deep learning environment configuration

Table 2 Experimental environment configuration

Component	Configuration	Quantity
Graphics	QUADRO RTX-A5000	4
CPU	Intel(R) Xeon Gold 6342	2
Hard Disk	4TB SATA HDD	2
Memory	960GB SATA SDD	2

Table 2 represents the experimental environment configuration used for conducting the research. It details the components utilized along with their respective configurations and quantities of Graphics, CPU, Hard Disk, and Memory.

4.3 Evaluation metrics

Precision (P), recall (R), mean average precision (mAP), and f1-score were used to assess the effectiveness of the experiment.

Precision: Precision is a metric used to measure the accuracy of positive predictions. It represents the percentage of correctly identified positives among all positive predictions.

$$P = \frac{TruePositives}{TruePositives + FalsePositives} \tag{8}$$

Recall: Recall, also known as sensitivity, evaluates the completeness of positive predictions by measuring how effectively the model can recognize all real positives.

$$R = \frac{TruePositives}{TruePositives + FalseNegatives} \tag{9}$$

mean Average Precision (mAP): mAP offers a comprehensive performance metric encompassing multiple categories, taking into account accuracy and recall.

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{10}$$

F1-Score: The F1-score is particularly helpful in situations when there is an imbalance in classes since it balances precision and recall into a single statistic.

$$F1 = 2 * \frac{P * R}{P + R} \tag{11}$$

[a] [b] [c] [d]

Fig. 7 Visualization of Electric Assets Health Status: (a) Detection of electric asset health status in two towers, with insulators shown in pink, dampers in red, and spacers in orange (b) Image capture from the top and detection of electric asset health status, with insulators shown in pink, dampers in red, and spacers in orange. (c) Image capture from the side angle and detection of electric asset health status, with insulators shown in pink, dampers in red, and spacers in orange. (d) Close-up Image Capture of Tower and Detection of Electric Asset Health Status, with insulators shown in pink, dampers in red, and spacers in orange.

4.4 Performance analysis and comparative evaluation

A comprehensive review of the various YOLOv8 models – YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x across a range of batch sizes is shown in the table. Table 3 lists their performance characteristics at various thresholds, such as mean average precision (mAP), recall, F1 score, and precision. While YOLOv8s has better accuracy (0.82 to 0.902) with consistent recall (0.768 to 0.8), YOLOv8n exhibits steady precision (0.82 to 0.879) and varied recall (0.752 to 0.77). While YOLOv8l maintains steady precision (0.837 to 0.91) and variable recall (0.772 to 0.802), YOLOv8m consistently demonstrates accuracy (0.862 to 0.874) and recall (0.78 to 0.806). Finally, YOLOv8x shows variable recall (0.759 to 0.817) and good precision (0.835 to 0.921). Model-to-model, mean average precision at various IoU thresholds varies from 0.528 to 0.837, indicating the higher object recognition performance of YOLOv8x.

Fig. 8 represents, how different visual and quantitative indicators are presented to assess the condition of electrical assets. According to the figure, the plate is at 0.97, the spacer is at 0.97, the damper is at 0.70, and the insulator is at 0.99 health. Using these findings each asset's health status can be efficiently tracked, and remedial action can be taken if the condition shows a noticeably lower value.

Table 3 Object evaluation of YOLOv8 models

MODEL	Batch Size	Precision	Recall	F1_Score	mAP [0.5]	mAP[0.5:0.95]
YOLOv8n	2	0.82	0.764	0.788	0.795	0.541
	4	0.847	0.760	0.803	0.799	0.551
	8	**0.879**	0.770	**0.821**	**0.805**	**0.555**
	16	0.822	0.752	0.785	0.784	0.528
YOLOv8s	2	0.820	0.791	0.791	0.817	0.575
	4	**0.902**	0.768	0.768	**0.826**	**0.596**
	8	0.837	**0.803**	**0.800**	0.822	0.582
	16	0.836	0.796	0.797	0.831	0.580
YOLOv8m	2	0.858	0.783	0.821	0.823	0.604
	4	**0.874**	**0.788**	0.829	0.827	0.609
	8	0.862	0.806	**0.834**	**0.842**	**0.613**
	16	0.842	0.780	0.810	0.808	0.574
YOLOv8l	2	0.837	0.777	0.806	0.807	0.587
	4	0.841	0.789	0.814	0.825	0.617
	8	**0.910**	0.772	**0.835**	**0.832**	**0.624**
	16	0.844	**0.802**	0.821	0.829	0.606
YOLOv8x	2	0.837	0.759	0.796	0.802	0.576
	4	0.835	0.795	0.815	0.809	0.58
	8	**0.921**	**0.817**	**0.866**	**0.812**	**0.637**
	16	0.897	0.802	0.848	0.796	0.606

Table 4 Comparative analysis of YOLOv8 Models with Vanilla and Focal Loss Across Varied Labeled Data Percentages

		10%		20%		30%		40%	
Model	**Approach**	**Precision**	**Recall**	**Precision**	**Recall**	**Precision**	**Recall**	**Precision**	**Recall**
YOLOv8n	YOLO+VL	0.829	0.768	0.841	0.777	0.890	0.821	0.921	0.902
	YOLO+FL	0.937	0.918	0.942	0.891	0.952	0.928	**0.962**	0.942
YOLOv8s	YOLO+VL	0.821	0.776	0.849	0.744	0.905	0.823	0.923	0.900
	YOLO+FL	0.956	0.930	0.957	0.919	0.948	0.922	0.956	0.931
YOLOv8m	YOLO+VL	0.827	0.773	0.839	0.732	0.829	0.808	0.887	0.859
	YOLO+FL	0.937	0.905	0.946	0.915	0.931	0.882	0.949	0.921
YOLOv8l	YOLO+VL	0.831	0.783	0.840	0.815	0.862	0.827	0.903	0.859
	YOLO+FL	0.960	0.926	0.936	0.921	0.962	0.911	0.954	**0.936**
YOLOv8x	YOLO+VL	0.874	0.833	0.859	0.831	0.890	0.863	0.937	0.907
	YOLO+FL	**0.963**	**0.939**	**0.959**	**0.929**	**0.965**	**0.936**	0.960	0.921

Table 5 Comparison of the proposed approach with different baselines to well-established models

Ref. No	Method	Detection of Assets	Accuracy	Recall	F1-Score
[7]	F-RCNN	Insulator	0.912	0.964	0.937
[8]	SSD		0.921	0.947	0.934
[9]	YOLOv3		0.935	0.948	0.941
[10]	YOLOv5		0.945	0.944	0.944
[11]	YOLOv8		0.952	0.952	0.952
Proposed approach		Insulator	**0.965**	**0.972**	**0.968**
		Spacer	0.955	0.948	0.951
		Stockbridge damper	0.921	0.941	0.932
		Transmission tower	0.961	0.951	0.956
		Tower Plate	0.964	0.951	0.957

Table 6 Performance analysis of various algorithms

Algorithms	mAP@0.5%	time/s
Faster R-CNN	64.8	0.087
SSD	73.1	0.062
YOLOv3	77.7	0.037
YOLOv5	85.8	0.058
Proposed approach	96.5	0.052

The Table 4 shows evaluation metrics for several YOLOv8 models (n, s, m, l, x) at different percentages of labeled data (10%, 20%, 30%, 40%) using two approaches: YOLO+Vanilla Loss(VL) and YOLO+FL. With 10% labeled data, YOLOv8n with YOLO+VL model achieves 82.9% Precision and 76.8% Recall. These values steadily rise with more labeled data, reaching 92.1% Precision and 90.2% Recall at 40%. Conversely, YOLOv8n with YOLO+FL exhibits a similar good trend with increasing labeled data, reaching 96.2% Precision and 94.2% Recall at 40%. It begins with a high Precision of 93.7% and Recall of 91.8% at 10% labeled data.

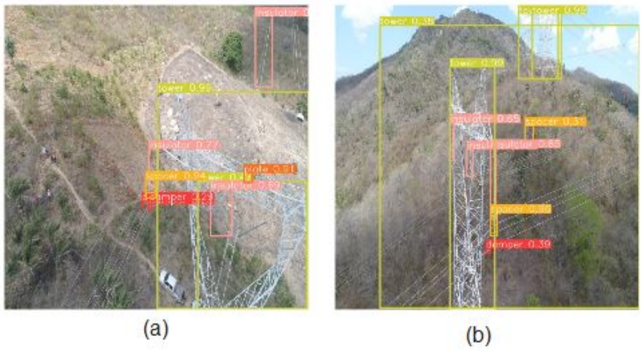

Fig. 8 The figure illustrates (a) Closeup Shot from the Side Angle: Health Conditions of Electric Assets - Insulator in Pink, Damper in Red, and Spacer in Orange and (b) Closeup Shot from the Top Angle: Health Conditions of Electric Assets - Insulator in Pink, Damper in Red, and Spacer in Orange.

Similar results can be seen in the other YOLOv8 models, with both Precision and Recall usually getting better for both the YOLO+VL and YOLO+FL approaches as the amount of labeled data grows. The results showed how different approaches and models perform differently when dealing various amounts of labeled data in object detection tasks.

Table 5 shows the comprehensive comparison of various object detection architectures, including F-RCNN, SSD, YOLOv3, YOLOv5, and YOLOv8, to a new approach. Metrics like accuracy, recall, and F1-score are used to evaluate each model's effectiveness in identifying different kinds of things. Notably, the proposed method produces outstanding results, especially when it comes to locating specific objects such as spacers, insulators, Stockbridge dampers, transmission towers, and tower plates. To give an example, the proposed method performs well across different entity categories and detects Insulators with an accuracy rate of 0.965 and a recall rate of 0.972. This investigation highlights how well the suggested methodology performs in entity detection assignments compared to well-known models such YOLOv8.

In comparison to other methods, the algorithm proposed for this study shows highest detection accuracy, as shown in Table 6, and still maintains excellent real-time performance.

Proposed model for detecting defects in transmission line assets effectively tackles numerous notable challenges faced during the inspection of transmission line images. The model excels in addressing issues such as the detection of minor defects, the identification of insulators of little significance in practical settings, the handling of substantial overlapping, and the eradication of slow detection, ultimately ensuring prompt and precise recognition of asset imperfections during transmission line inspections.

Abbreviations

SYFLo	Semisupervised Yolo with Focal Loss
DL	Deep Learning
UAV	Unmanned Aerial Vehicles
CNN	Convolutional Neural Network
YOLOv8	You Only Look Once version 8
SSD	SSD & Single Shot Multibox Detector
SWT	Stroke Width Transform
EXACT RCNN	Ensemble Cross Attention Transformer Region Convolutional Neural Network
FASTER RCNN	Faster Region-based Convolutional Neural Network
AVSC-Net	Atrous Vision Single Shot MultiBox
ResNest	Residual Neural Network
YOLOv8n	YOLOv8 Nano
YOLOv8s	YOLOv8 Small
YOLOv8m	YOLOv8 Medium
YOLOv8l	YOLOv8 Large
YOLOv8xl	YOLOv8 Extra Large
PAN	Path Aggregation Network
FPN	Feature Pyramid Network

5 Conclusion

The research enhances the effectiveness of a YOLOv8-based object detection method, semi-supervised learning and the focal loss function, for real-time monitoring electric asset health in power transmission lines. The achieved high accuracy in identifying crucial components, particularly insulators, showcases the potential for seamless power transmission and offers a cost-effective solution through the integration of semi- supervised learning with limited labeled samples.In future studies, refining and scaling the training dataset with diverse and extensive data related to transmission line components is paramount for further improving model accuracy. Real-time monitoring and predictive maintenance, when coupled with this approach, can revolutionize line management, providing actionable insights for timely maintenance and minimizing disruptions. Exploring advanced technologies like 3D computer vision, LiDAR, and multispectral imaging holds promise for comprehensive analysis of component health, while adapting this methodology to address challenges posed by renewable energy and smart grid technologies will contribute to advancing power transmission systems' monitoring and maintenance in this evolving energy landscape.

Author contributions All authors have equally contributed for this paper.

Funding This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
Data availability Not applicable.

Declarations

Conflict of interest The authors declare no competing interests.

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