Predictive Maintenance of Insulator Caps and Guy Adjustors

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***Abstract*— Manual inspection of high-voltage transmission lines is a hazardous and labor-intensive task, yet it is crucial for preventing power outages and maintaining grid stability. Components such as insulator caps and guy adjusters are vital for structural integrity but are often overlooked in traditional defect detection frameworks. If these components fail, insulators can detach, leading to blackouts and significant safety risks. This paper presents an automated predictive maintenance solution utilizing the YOLOv3 object detection architecture to identify faults in these specific components. By leveraging computer vision, we eliminate the need for dangerous manual climbing and visual inspection. Through our model, we detect various faultsincluding rust and critical damageallowing for early health assessment of the grid infrastructure. Our proposed model operates without human intervention, offering a viable industrial solution to enhance the efficiency and safety of electricity transmission.**

I. INTRODUCTION

Governments worldwide are emphasizing the expansion of renewable energy sources to achieve net-zero targets by 2050. Countries are implementing measures to shift energy production from non-renewable sources, such as coal and natural gas, to renewables like solar farms, wind farms, and microgrids. However, transitioning to renewable production is insufficient; we must also enhance the efficiency and reliability of energy transmission.

Before transmission, step-up transformers increase electricity voltage to enhance efficiency. High voltage lowers the current, resulting in reduced resistance and energy loss. This electricity travels through aluminum or copper wires supported by electric towers. To prevent electricity from grounding through the steel towers, the system uses insulators made of glass, porcelain, or composite polymers. These insulators are fragile; therefore, an insulator cap (Fig. 1) protects them from impact damage. Another crucial component is the guy adjustor (Fig. 2), also known as a U-bolt, which secures the insulators to the electric towers.

Insulator caps and guy adjustors play a vital role in electricity transmission. If either component breaks, the insulator may fall, leading to earthing, power loss, and potential blackouts across cities or states. Furthermore, component failure poses a risk of serious injury and accidents.

Consequently, regular inspection is crucial. Currently, linemen perform this task, facing numerous challenges. The Bureau of Labor Statistics (BLS) classifies line installers and repairers as having one of the most hazardous occupations. In the United States, there are approximately 242,000 such positions, with a job growth rate of around 4%. Given the inherent hazards and the difficulty of manual health checks, there is a pressing need for predictive maintenance utilizing AI technology.

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Fig. 1: Insulator Cap

Fig. 2: Guy Adjustor

In this paper, we employ artificial intelligence and computer vision for the predictive maintenance of these objects. This allows us to assess component health in advance, enabling proactive repairs and preventing accidents. Our approach removes the need for human intervention in the prediction process.

In addition to detecting structural damage, we forecast the presence of rust. Rust directly impacts component integrity; as these parts undergo constant stress, rust weakens them, reducing their load-bearing capacity and leading to failure. The insulator cap is particularly prone to rust because it attaches to insulators via a ball-and-socket joint where water often accumulates due to lack of protection from rain.

We propose a novel method using AI and Machine Learning (ML) to determine which components are intact, damaged, or rusted. Our automated model streamlines the process, ensuring efficient maintenance and the safety of transmission towers.

II. LITERATURE REVIEW

Limited literature discusses the health of guy adjustors or insulator caps specifically; however, several studies focus on transmission line failures. Peixoto et al. [8] concluded that the failure rate of HVDC transmission line caps is significantly higher than in AC applications. Despite extensive research, the specific causes remain debated. Nevertheless, researchers observe that porcelain and glass insulators demonstrate a high failure rate under high DC stress. Increased pollution also contributes to failure rates.

Insulators are outdoor devices subjected to rigorous stress. Studies indicate that several years post-manufacturing, the load test threshold for failure increases by 14.7%, and life expectancy depends on the percentage of SiO_2, Fe_2O_3, and Al_2O_3 [11]. Strain rate significantly affects transmission towers, increasing maximum base shear forces and decreasing maximum top displacements; consequently, seismic analysis must account for strain rate [15]. While conventional methods can detect corrosion, modern techniques using computer vision and machine learning significantly enhance detection, improving cost-effectiveness and reliability [5].

Alahyari et al. [1] used CNNs to detect defects such as broken insulators or missing/burned insulator caps. We extend this approach by including guy adjustors and increasing the number of defect classes. Failures can also result from severe weather, such as wind and lightning [4]. Mili et al. [6] discuss the risks of power system failures, noting that current practices often neglect protection systems. While catastrophic failures cannot be entirely prevented, newer developments in power and computer engineering can reduce their frequency and impact [2].

Regarding detection algorithms, varying CNN-based models like Faster R-CNN, R-CNN, and YOLO are reviewed in [7]. We found YOLO to work best for our application due to its speed and ability to detect small objects like insulator caps [9] [12].

III. Methodology

A. Image Classification using CNN

As noted in [3], Convolutional Neural Networks (CNNs) offer high spatial feature extraction capacity and low processing costs. CNNs consist of multiple layers utilizing convolution kernels. While no perfect topology exists, the Inception network [14] yields robust results.

In a CNN, a kernel (filter) passes across the image, modifying it based on the filter's values. The feature map values are determined using the input picture f and the kernel h:

$$G[m,n] = (f \times h)[m,n] = \sum_j \sum_i h[j,k] f[m-j, n-k] \tag{1}$$

Since image size decreases with each layer, we add a border (padding) to increase the impact of edge pixels. Padding p is calculated using the filter dimension f:

$$P = (f-1)/2 \tag{2}$$

Stride length determines the step size of the kernel. The output matrix size is calculated as follows, where s denotes the stride:

$$n_{\text{out}} = \text{floor}\left(1 + \frac{n+2p-f}{s}\right) \tag{3}$$

When applying multiple filters, the convolution occurs independently, and results are stacked. The dimension of the received tensor is given by:

$$[n, n, n_c] \times [f, f, n_c] = \left[\text{floor}\left(1 + \frac{n+2p-f}{s}\right), \text{floor}\left(1 + \frac{n+2p-f}{s}\right), n_f\right] \tag{4}$$

During forward propagation, we calculate the intermediate value Z by convolving the input data from the previous layer with the weight tensor W and adding bias b. A non-linear activation function g is then applied:

$$Z^{[l]} = W^{[l]} \cdot A^{[l-1]} + b^{[l]}, \quad A^{[l]} = g^{[l]}(Z^{[l]}) \tag{5}$$

Derivatives during backpropagation are calculated as:

$$dA^{[l]} = \frac{\partial \mathcal{L}}{\partial A^{[l]}}, \quad dZ^{[l]} = \frac{\partial \mathcal{L}}{\partial Z^{[l]}}, \quad dW^{[l]} = \frac{\partial \mathcal{L}}{\partial W^{[l]}}, \quad db^{[l]} = \frac{\partial \mathcal{L}}{\partial b^{[l]}} \tag{6}$$

While architectures like ResNet or Inception work well for single objects, they may struggle with multiple objects in complex environments [13]. Therefore, we utilize object detection models.

B. Object Detection using CNN

Object localization involves drawing a bounding box around an item, while object detection combines localization with classification. We update the output labels to teach the model both the object's class and its position.

The output layer includes four additional values: the object's centroid location and the bounding box's width and height proportions. To detect multiple objects, we effectively crop the image into numerous sections and run the CNN on each. The YOLO algorithm optimizes this by using a grid approach to predict bounding boxes and classes simultaneously.

C. YOLOv3

The YOLOv3 architecture consists of 53 convolutional layers trained on ImageNet, with 53 additional detection layers, totaling 106 layers. It uses detection kernels on feature maps of three different sizes. The detection kernel shape is $1 \times 1 \times (B \times (5 + C))$, where C is the number of classes, 5 represents the bounding box attributes plus object confidence, and B is the number of bounding boxes a cell can predict. In YOLOv3, $B = 3$ and $C = 80$, resulting in a kernel size of $1 \times 1 \times 255$.

Detections occur at the 82nd, 94th, and 106th layers to handle different scales. The network down-samples the image until the 81st layer (stride 32). The feature map from layer 79 is upsampled and concatenated with the feature map from layer 61 for the second detection. Similarly, the feature map from layer 91 is concatenated with layer 36 for the final detection. This multi-scale detection addresses the difficulty of recognizing small objects, a limitation of YOLOv2. Figure 3 illustrates the complete architecture.

IV. Results

This section summarizes the results from our model. We detect two objects: the Guy Adjustor and the Insulator Cap. For each, we classify whether they are intact or critically damaged, and whether they are rusted or non-rusted.

Our model includes eight classes:

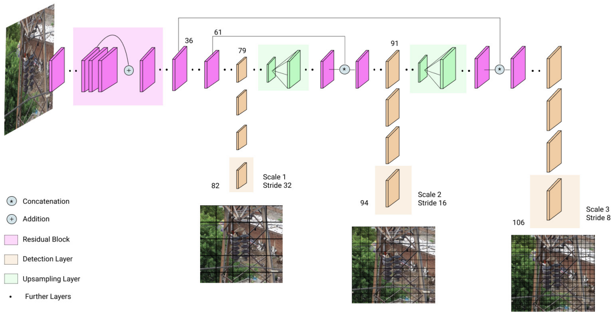

Fig. 3: The YOLOv3 Network Architecture.

Fig. 4

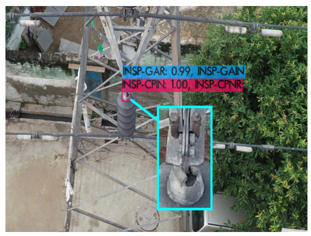

Fig. 5

Insulator Cap (CP)	Guy Adjustor (GA)
CPCD - Critically damaged	GACD - Critically damaged
CPIN - Intact	GAIN - Intact
CPNR - Non-Rusted	GANR - Non-Rusted
CPR - Rusted	GAR - Rusted

The results indicate that certain classes are interrelated. Specifically, the following pairs are inversely proportional: 1) Intact vs. Rusted, 2) Rusted vs. Non-Rusted, 3) Intact vs. Critically Damaged, and 4) Non-Rusted vs. Critically Damaged.

Figure 4 shows that the Guy Adjustor has a high probability of being intact (INSP-GAIN: 94%) and a correspondingly low probability of being rusted (INSP-GAR: 79%).

We observed that the "Intact" class is directly proportional to "Non-Rusted." This is evident in Figure 5, where the insulator cap has a high probability of being intact (INSP-CPIN: 100%) and a high probability of being Non-Rusted (INSP-CPNR: 99%). These interdependencies validate the correctness of our model. As noted by Saha et al. [10], severe rusting compromises component health, leading to reduced strength and deformation.

Object detection in complex environments is challenging due to background clutter and occlusion [14]. Our dataset contains towers surrounded by trees and buildings (Fig 6). Despite this, our model predicts with high accuracy. We accounted for varied angles and lighting conditions by using data augmentation and collecting images at different times of the day.

Figure 7 shows the training loss approaching zero within the first 250 epochs. However, further training was necessary to minimize the loss function. Figure 8 (500 to 2700 epochs) shows the loss graph damping, indicating convergence.

Fig. 6

Figures 4, 5, and 6 demonstrate how our algorithm outperforms challenges. It identifies components and isolates critical faults in complex backgrounds with varying lighting conditions.

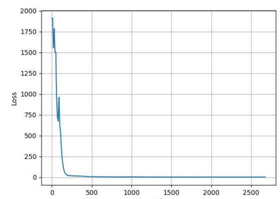

Fig. 7: Loss Graph

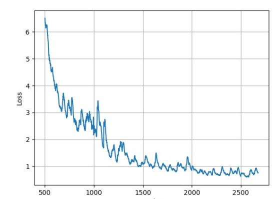

Fig. 8: Zoomed Loss Graph

Figure 9 confirms that accuracy fluctuates between 99% and 99.4% from 2000 to 2700 epochs. This high confidence allowed us to use the trained weights on the isolated test dataset. Our model achieved a final average accuracy of 99.2%.

Figure 10 plots the standard deviation of each predicted class. Error bars help visualize real-world accuracy fluctuations. For example, CPIN accuracy is observed at 85% but can fluctuate between 70% and 100%.

In Figure 11, we removed false positives by eliminating predictions with less than 50% confidence. This increased accuracy and reduced the error range, improving the worst-case accuracy from 70% to 80%.

We conclude that our model is sufficiently trained for the 8 classes, providing an average accuracy of 85%, reaching as high as 95% in some cases. Lower accuracy in some classes is attributed to the limited size of the training dataset.

V. Future Work

This paper proposed an AI/ML and computer vision-based method to determine the integrity and rust status of insulator caps and guy adjustors. The goal is to establish an industrial standard that eliminates human intervention for identifying faults. While the model achieves good accuracy, future work will focus on classifying specific corrosion types to enable targeted rectification. Expanding the dataset will improve class-specific accuracy, and applying post-processing image techniques may further enhance results.

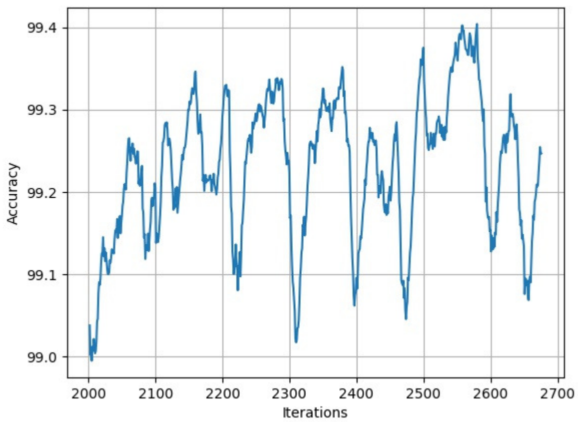

Fig. 9: Model Accuracy

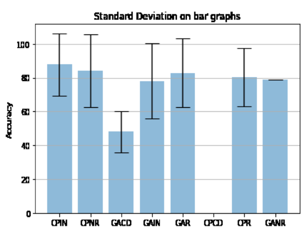

Fig. 10: Standard Deviation

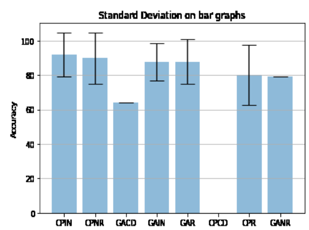

Fig. 11: Standard Deviation without false positives

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