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Review on an Insulator Fault Detection Using Improved Yolo V5

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Abstract - Insulators are critical components of high-voltage power systems, guaranteeing efficient electrical transmission by reducing leakage currents and energy loss. However, a variety of environmental and operational variables can cause insulator deterioration, resulting in cracks, punctures, or contamination. These flaws can have a substantial influence on power transmission dependability, potentially resulting in disruptive outages, safety risks, and higher maintenance costs. Traditional problem detection technologies, such as physical inspection and infrared imaging, are sometimes time-consuming, labor-intensive, and subject to human error.

In this research, we provide a deep learning-based automated fault detection system that uses the You Only Look Once (YOLO) method for real-time object identification and classification of insulator flaws. YOLO is a cutting-edge convolution neural network (CNN) model built for quick and efficient detection, capable of simultaneous localization.

YOLO is a cutting-edge convolution neural network (CNN) model that can detect and localize many types of insulator flaws in a single picture. Using a large-scale dataset of insulator photos tagged with defect categories, the YOLO-based model is trained to identify between healthy and defective insulators with high precision.

***Key Words*:** Insulator, Detection, Modified, Yolo V5

1. INTRODUCTION

Insulators serve an important function in electrical transmission by providing strong support and efficiently separating conducting portions. Transmission lines, on the other hand, are frequently operated for extended periods of time in a variety of natural conditions, making them vulnerable to flashover damage and spontaneous explosions. This makes insulator fault identification an essential step in ensuring the safe functioning of transmission lines.

In recent years, drone inspection technology has been widely used in the electric power industry to obtain a large number of electric power inspection images or videos by installing a high-resolution camera on a drone, which can accurately detect insulator defects, significantly improve the efficiency and quality of electric power inspection, and relieve inspectors' workload.

But conventional methods for detecting insulator faults, such the Hough transform, canny edge extraction, ant colony clustering, and others, seldom work unless the picture backdrop is straightforward and the insulator flaws are clearly visible1. In reality, aerial photographs are frequently influenced by many sorts of noise, and their backgrounds are complicated and varied. Furthermore, inconsistent insulator defect characteristics present hurdles for standard methods in insulator defect detection. There are three major issues in the existing UAV inspection technology for gearbox line insulators:

(1) Detection speed and accuracy cannot be available at the same time: when inspecting transmission lines with UAVs, the UAV's carrying equipment is limited by volume and weight, so a lightweight model is required to reduce computational demand, increase real-time performance, and improve UAV efficiency. However, lowering model complexity typically means sacrificing some detection accuracy, which might have major ramifications in electric utility inspection. The main difficulty in identifying defects and detecting insulator targets is thus striking a balance between average detection accuracy and network lightweight.

(2) Difficulty in defect identification and classification: During circuit inspection, the unique characteristics of many defects, such as cracks, pollution, ageing, and so on, combined with the diversity of shapes, colors, and textures of the insulators themselves, as well as the influence of the field environment, such as light, weather, and background, cause the defects to manifest themselves in a variety of ways, making it more difficult to identify. Furthermore, the unequal distribution of positive and negative samples in the insulator defect detection dataset creates a gap in the model's capacity to distinguish between normal and faulty

insulators. There is also the issue of how difficult it is to correctly fuse the shallow network's positional detail information with the deep network's semantic information, which affects the model's insulator defect detection accuracy. Figure 1 depicts numerous typical insulator faults.

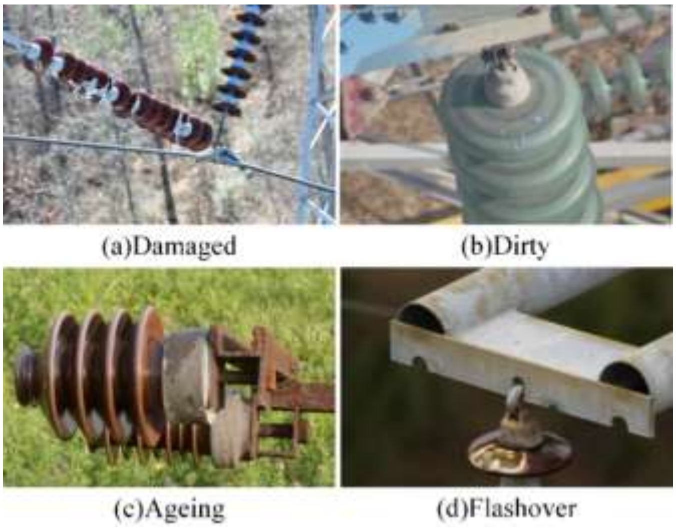

Fig.1: Several common insulator defects.

(3) Insufficient information for small-sized targets: Insulator flaws are often shown as small targets with limited semantic information. Because of the image's limited visual representation of small-sized insulator flaws, the model struggles to extract effective and adequate feature information for successful detection in practice. At the same time, because the fraction of small-sized targets in the picture is often low, feature fusion in multiple dimensions yields relatively low weights for tiny targets6, thus limiting reliable identification of insulator flaws.

2. Related Work

An insulator is a type of insulating control used in power systems. It is responsible for fastening the current-carrying conductor in the overhead transmission line to prevent the current from returning to the ground, and it is a crucial component of the power system [1]. The collapse of the insulator will immediately affect the line's safety and stability. According to limited statistics, insulator failure is responsible for more than half of power equipment failures [2]. To protect the safety of the power grid, insulator defect detection has become the key function of power system maintenance. With the advancement of deep learning, a variety of object identification algorithms have emerged. The research on insulator target detection offers a significant contribution to the detection of aerial insulators during power inspection. On this basis, insulators must be further classified and identified. Scholars at home and abroad are now conducting research on the identification of defects in insulators. Traditional defect identification approaches continue to rely on graph segmentation and machine learning, among other things. Literature [3] preprocessed insulators, transformed RGB data to brightness space, and eliminated the effects of lighting on photographs. The OTSU algorithm was then used to segment, and the faults were analyzed using the morphological technique. Finally, the number of pixels on the insulator string is calculated to assess if there are any self-explosion or other damage faults. Traditional approaches mostly rely on picture segmentation, and the algorithms are sophisticated. The implementation of an insulator segmentation algorithm in different scenarios varies, and it is difficult to spot defects in a large number of aerial photography insulators with complicated backgrounds. The convolution neural network does not require extensive data preparation; instead, it extracts the characteristics of the input picture as a whole and learns the image's features autonomously to identify defects. In the literature [4], the SSD model was used to detect the state of insulators, Dense Net was introduced as a feature extraction network to improve the model's classification ability, and data enhancement was used to solve the sparse data problem and improve the model's accuracy. In the literature [5], the random forest technique is used to segment insulators for target identification, followed by a convolution neural network to determine whether there are any flaws on the insulators. Finally, a faster R-CNN network is employed to pinpoint the location of flaws on insulators. In the literature [6], the Faster R CNN method was applied in the identification of UAV power line inspection image parts, and while the detection impact of power parts was improved, it did not match the real-time requirements. The literature [7] provides an aerial insulator detection approach based on the U-net deep network, which is a highly successful method. However, because the backdrop of an insulator picture is rather basic, it cannot be effectively identified against a complex background. The missing insulator detection algorithm in literature [8] was designed using the Random Sample Consensus (RANSAC) algorithm and combined with the Single Shot MultiBox Detector (SSD) algorithm to locate the missing insulators in the image, but the method of fitting the line to detect defects had poor anti-interference ability. Many studies have been conducted on deep learning in the subject of insulator detection, which has resulted in new concepts for power inspection. Furthermore, insulator defect detection has emerged as the primary trend in deep

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learning in power inspection research, offering benefits over previous detection approaches in terms of detection accuracy, speed, and model generalization ability. However, there is still a lot of opportunity for advancement in the field of insulator fault identification in power inspection. There are few public data sets, and the majority of the data sets utilized in research studies are insufficient to fulfill current requirements. The amount of layers in the feature extraction network is insufficient, and the features retrieved from the insulator picture with complicated backdrop are hazy. The defect size is smaller than the insulator size target, and there is only one approach for boosting the accuracy of defect detection on tiny targets. This study proposes an enhanced YOLOv5 algorithm for detecting insulator defects in transmission lines, taking into account the tiny target scale, complicated backdrop, difficulty of detection, false detection, and leakage detection. First, a CBAM attention module is introduced to the YOLOv5 backbone network to increase the feature extraction capabilities of the images. Second, in the feature extraction section, the PANet structure is replaced with the BiFPN structure to fully use the underlying feature information. Finally, the modified K-means method is utilized to identify the prior frame, which improves the stability of the produced prior frame as well as the accuracy of insulator defect identification.

3. Methodology

YOLOv5 contains four network models of varying sizes: s, m, l, and x. YOLOv5s is the smallest, and the other models are the result of expanding network depth and width on its base. Although its detection performance is always improving, the model's size is increasing while its detection speed is decreasing. The YOLOv5s was chosen as the base model to make it lightweight and portable to embedded devices. There are several YOLOv5 variants; this article utilizes version 5.0, and the activation function has changed from the LeakyReLU and Hard swish unity of the early days to the SiLU function. In addition, the C3 module is used to replace the original Bottleneck CSP module.

When compared to the Bottleneck CSP module, the C3 module cuts one convolution layer, resulting in a smaller overall model and faster reasoning. Although the accuracy has fallen by 0.8% compared to the 3.0 version, it is still acceptable given the speed gain. This experiment is an enhancement to the 5.0 version model. YOLOv5's model consists mostly of a backbone and a head. The Backbone module, which extracts features, is primarily made up of Focus, C3, and SPP modules, whereas the Head module is made up of Neck and Detect modules for extracting fusion features. The network model is depicted in Figure 1. The Backbone consists of three components.

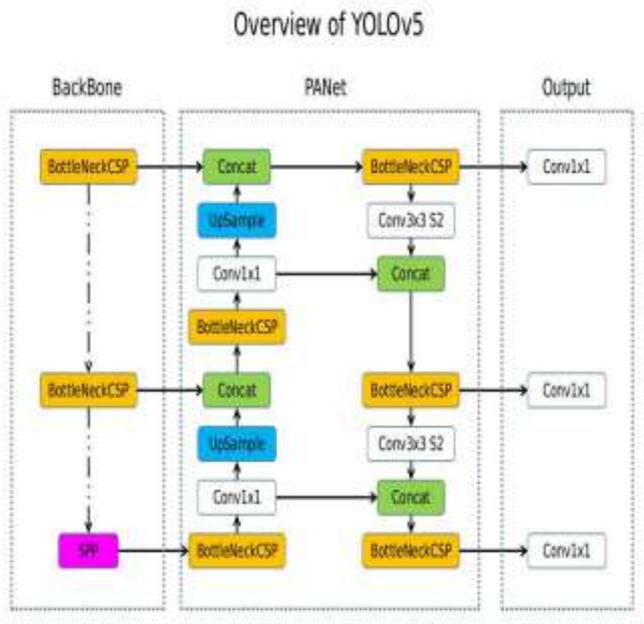

Fig.2: Yolov5 network structure diagram

1) Focus module. This is the distinctive structure of YOLOv5. Its fundamental concept is to slice the input image, remove pixels from the high resolution image at regular intervals, and rebuild them into the low resolution image, stacking the four neighboring image locations. Gathering w and h dimension information into c channel space improves each point's receptive field while reducing computation, avoiding the loss of original information.

2) Cross Stage Partial Network (CSP) Module. The base layer's feature map is separated into two portions and coupled with the cross-stage hierarchical structure to provide a richer gradient combination. The creator of YOLOv5 also cites this structure as a reference. However, unlike YOLOv4, which only employs a CSP structure in the backbone, the inventor of v5 creates two CSP structures, one for the backbone and one for the neck. Later, the author enhances this structure by deleting a convolution layer from the bottleneck structure and converting it to C3 mode Block.

3) The spatial pyramid pooling network (SPP) module. This module is based on The Keming's 2014 proposal for the SPPNet, commonly known as the spatial pyramid

pooling network. Feature maps of multiple scales are spliced using maximum pooling k=(1x1, 5x5, 9x9, 13x13), resulting in the fusing of features of different scales and enhancing the sensitivity field.

In the Head section, Y0LOv5 employs the feature pyramid FPN+PAN. The FPN layer transmits and integrates feature information from the upper and lower layers via up-sampling, whereas the PAN layer splices the lower layer's feature with the upper layer's feature, resulting in the transmission of the lower layer's high-resolution feature to the upper layer. Using the structure of FPN+PAN, feature aggregation of distinct detection layers from different trunk layers may successfully handle the multi-scale problem.

3.1 YOLO's Working Principle:

1. Grid-Based Detection: The input picture is split into S × S grids, with each cell predicting bounding box, item class likelihood, and confidence score.

2. Deep CNN extracts features, classifies objects, and refines bounding box predictions.

3. YOLO reduces computing costs by detecting, classifying, and localising defects in a single forward pass.

4. Anchor Boxes and Non-Maximum Suppression (NMS): These approaches improve bounding boxes and prevent repeated detections.

5. Fast and Efficient Processing: The model balances speed and accuracy, making it suitable for automated insulator fault detection in high-voltage electrical transmission networks.

3.2. The Dataset Collection and Annotation Process

The success of YOLO models is strongly reliant on the quality and amount of training data. Commonly utilized datasets include MS COCO and PASCAL VOC, which provide a wide variety of pictures with annotated bounding boxes and class labels. For bespoke applications, datasets must be manually chosen and tagged. Tools like CVAT (Computer Vision Annotation Tool) are used to make the annotation process easier, allowing for efficient labeling of pictures with bounding boxes and related class names.

The annotation format generally comprises the class label and the bounding box's normalized coordinates (center_x, center_y, width, height), which are required for training YOLO models. Proper annotation ensures that the model learns the correct object localization and categorization.

3.3 Dataset Collection and Annotation Process.

A high-quality dataset is required to train the YOLO model for insulator defect detection. The dataset contains:

• Healthy Insulators serve as baseline benchmarks for categorization.

• Insulators with defects are classified into many categories.

• Cracks and fractures.

• Punctures and burns.

• Surface contamination from dust, pollutants, moisture, and chemical deposits.

3.4 Dataset Collection Process:

• Images are gathered from transmission lines, substations, and industrial sites utilizing high-resolution cameras and drone systems.

• UV and thermal imaging techniques improve flaw visibility compared to traditional image capturing methods.

• Image annotation with technologies like Labeling involves manually drawing bounding boxes around problems to ensure proper categorization.

• Augmentation methods like rotation, brightness modifications, and noise addition enhance dataset variety and minimize model over fitting.

4. CONCLUSIONS

This study proposes an enhanced YOLOv5 insulator defect detection method to address the issues of small target size, complicated background, difficult detection, false detection, and leakage detection of aerial insulators in transmission lines. First, a CBAM attention module is introduced to the YOLOv5 backbone network to increase the feature extraction capabilities of the images. Second, in the feature extraction section, the PANet structure is replaced with the BiFPN structure to fully use the underlying feature information. Finally, the modified K-means method is utilized to identify the prior frame, which improves the stability of the produced prior frame as well as the accuracy of insulator defect identification. A significant number of experiments have demonstrated the usefulness of the proposed strategy.

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