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Insulator Fault Detection Using Improved Yolo V5

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Abstract - A power supply system's stability is inextricably linked to the job of identifying problems in transmission lines. However, the insulator defect detection model based on deep learning is frequently employed in wire inspection. As a result, this study offers an enhanced YOLOv5s insulator defect detection model to address the issues of insufficient training data and low identification accuracy in the real-time detection of tiny target insulator flaws. To increase and improve the training data, tests were carried out using noise and random black blocks. The spatial and channel weight coefficients were generated by including an attention mechanism (Convolution Block Attention Module, CBAM), and the input feature map dimensions were altered to improve the model's capacity to extract and fuse tiny target defect features. Experiments show that with Faster RCNN, YOLOv3, SSD, and YOLOv4 comparison experiments, the algorithm achieves 97.38% detection accuracy for insulators and 93.32% detection accuracy for small target insulator defects with a fast detection speed, which is a better solution to the problem of detecting insulator defects with an insufficient proportion in the image.

Key Words: Insulator defect detection, Transmission lines, Object detection, Mean Average Precision (mAP), Precision, Recall

1. INTRODUCTION

When examining high-voltage transmission lines, a variety of sensors are used, with one critical approach being the status detection of electrical equipment. Vision sensor-based systems have evolved dramatically in recent decades, with research focusing on insulator identification, power line detection, and power tower detection. According to preliminary study, one of the most important pieces of equipment on a high-voltage gearbox line is the insulator string, which may provide both mechanical support and electrical insulation. However, insulator defects usually appear after some period of operating time due to variables such as lightning strikes, material ageing, and overloading. As a result, detecting insulator failures accurately is an important part of high-voltage transmission line inspection.

In a routine manual inspection, personnel must travel along high-voltage gearbox lines to inspect each insulator using a range of instruments including as cameras, ultraviolet imagers, infrared imagers, and audition sensors. However, because high-voltage transmission line. When examining high-voltage transmission lines, a variety of sensors are used, with one critical approach being the status detection of electrical equipment. Vision sensor-based systems have evolved dramatically in recent decades, with research focusing on insulator identification, power line detection, and power tower detection. According to preliminary study, one of the most important pieces of equipment on a high-voltage gearbox line is the insulator string, which may provide both mechanical support and electrical insulation. However, insulator defects usually appear after some period of operating time due to variables such as lightning strikes, material ageing, and overloading. As a result, detecting insulator failures accurately is an important part of high-voltage transmission line inspection. and lakes, the old manual technique is ineffectual and unworkable in real-world situations. Because of developments in UAV handling and image processing techniques, the analysis of aerial images produced by unmanned aerial vehicles (UAVs) has lately grown in popularity for insulator status check.

Multiple characteristics, including color, shape, edge, gradient, texture, key-points, and their fusions, have been studied in man-made feature-based techniques. In the interim, certain mathematical models such as the snake model, Hough transform, Active Contour

Model, Fuzzy c-means, and Receptive Field Model were applied. Machine learning-based techniques to insulator placement and issue detection include AdaBoost, Sparse representation-based classifier, SVM, Cascade classifier, and KNN. The insulators in aerial images, however, are frequently overlapped since the shooting angle and distance change rapidly during UAV inspection, making it impossible to capture spatial information for each insulator.

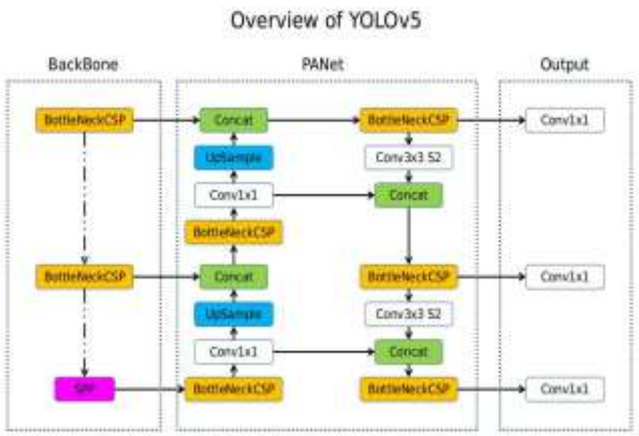

Fig.1: Yolov5 network structure diagram

3. Methodology and Results

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

1. Data collection and annotation: Training the YOLO model requires a large dataset of photos with unbroken and broken insulators. Images can be gathered utilizing drones, tower cameras, or previous inspection data. Annotate each picture with boundary boxes and labels to indicate broken or unbroken insulators.

2. Model Training: The annotated data is utilized to train the YOLO model. During training, the model learns to discriminate between damaged and unbroken insulators. To increase the model's resilience in photos with tiny insulators and shifting lighting conditions, data augmentation techniques including rotation, scaling, and contrast correction should be used.

3. Detection and Evaluation: Once trained, the YOLO model can identify damaged insulators in real-time. The model analyses input images to anticipate bounding boundaries and categorise insulators as broken or whole. Metrics like mean average precision (mAP), intersection over union (IoU), and inference speed are commonly used to evaluate model performance. The model's ability to detect tiny and partly occluded insulators is very useful in this application.

Fig.2: Several common insulator defects.

Challenges and Considerations:

Although YOLO has significant potential for insulator detection, it has numerous problems that need to be solved to achieve success.

- Small Object Detection: Insulators might be difficult to spot due to their small size in the picture. Advanced YOLO models like YOLOv8 and YOLOv9 use multi-scale detection and attention techniques to increase tiny item recognition. However, more optimization may be needed for insulator-specific applications.
- Class Imbalance: In many datasets, unbroken insulators outnumber damaged ones, resulting in class imbalance difficulties. To boost detection accuracy, consider techniques including data augmentation, focus loss, and oversampling of minority classes.
- Environmental Variability: Insulators are commonly found in outdoor settings with unpredictable lighting, weather, and background clutter. To effectively generalize across situations, the YOLO model requires training on a varied dataset that includes these variances.

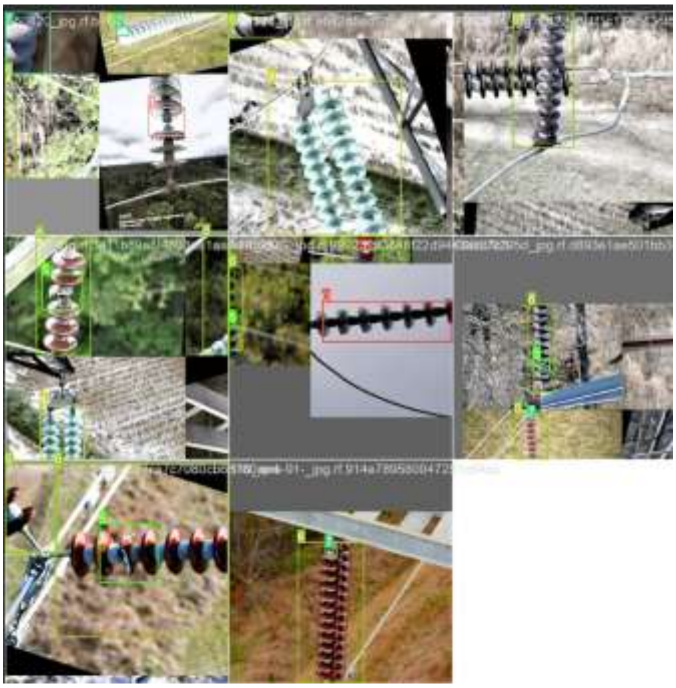

Fig.3: Comparison of image data before and after super-resolution reconstruction and enhancement.

Data Set:

The Insulator Defect Image Dataset (IDID) contains labeled high-quality photos of transmission line insulators. The photos have insulating strings as the main topic and parent class. These photos include three sub-classes: There are three types of insulator shells: good, broken, and damaged after a flashover. We have three classes: 'insulator', 'broken', and 'pollution-flashover'. These correspond to classes 0, 1, and 2, respectively.

In our research, we randomly partition all photos into three datasets: training (1296), validation (144), and testing (160). The optimal model is determined by its validation performance and then applied to the testing dataset.

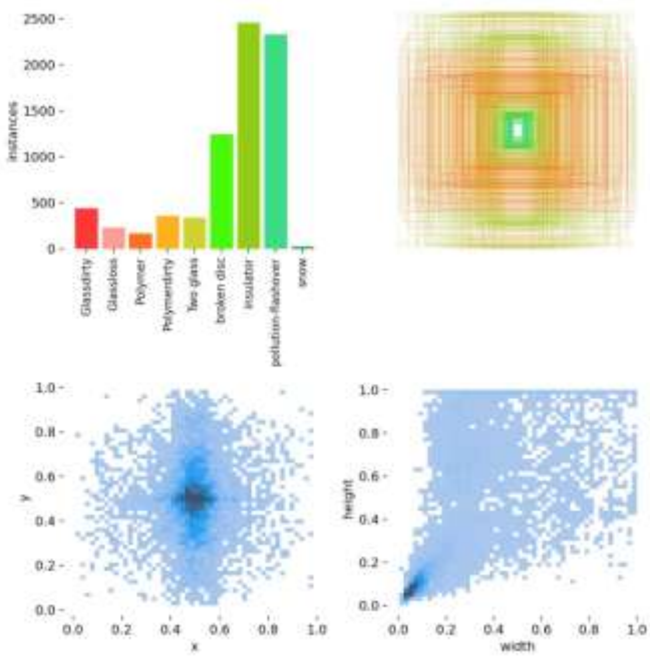

Fig.4: Histogram of label distribution in the dataset.

Performance Metrics and Experimental Results:

Fig.5: Train For labeling

Mean Average Precision (mAP) is a popular statistic for evaluating the performance of object identification algorithms. It assesses a model's ability to find and categories things in images. Calculating mAP entails multiple steps:

1. Object detection model predicts bounding boxes and class probabilities for images.

2. Use Intersection over Union (IoU) to compare

anticipated and actual bounding boxes. A threshold (e.g., 0.5) is commonly used to assess prediction accuracy.

3. Rank the forecasts according to their confidence scores.

4. Calculate precision and recall for varying confidence criteria.

5. Plot the precision-recall curves for each class.

6. Calculate Average Precision (AP): Determine the area under the precision-recall curve for each class.

7. Calculate mAP: Take the average of the AP values from all classes.

Fig.6: Streamlit for Framework

mAP is a reliable statistic that evaluates model performance by taking into account both accuracy and recall. It is commonly used in object detecting contests and research to evaluate various models. In object detection, a predicted bounding box is deemed accurate if it overlaps with the ground truth box by 50% or more (mAP@0.5). The mAP@0.5:0.95 measure takes into account a range of IoU thresholds from 0.5 to 0.95 with 0.05 increments, providing a more comprehensive analysis.

3. CONCLUSIONS

This work proposes an enhanced YOLOv5s model to address the issue of low accuracy in current target identification techniques for minor target insulator flaws. Experiments were carried out to compare its performance to that of Faster RCNN, YOLOv3, and YOLOv4. The findings indicate that by including the CBAM attention mechanism into the last layer of the YOLOv5s improved feature fusion network, more effective insulator features can be retrieved by raising the feature weights of space and channels. The identification of tiny target insulator defects may be improved by modifying the size of the input feature map, resulting in a final mAP of 93.32% for insulator defect detection and 97.38% for insulator detection. The findings demonstrate the revised model's efficiency in enhancing detection accuracy. While the detection speed decreased slightly when compared to the original YOLOv5s model, this did not influence the detection effectiveness in real time. The primary focus of further research will be on network model miniaturization in order to increase detection speed while maintaining detection accuracy. Taken together, these findings emphasize the significance of this study, which will aid in the advancement of related research and applications.

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