

Isolator Detection in Power Transmission Lines using Lightweight Dept-wise Convolution with BottleneckCSP YOLOv5

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Abstract:

The detection of insulators is of great importance in power transmission lines. This is because accurate detection ensures reliability and continuity of energy transmission, preventing line interruptions. The proposed method in this study utilizes the DWB-YOLOv5 (Dept-wise convolution with BottleneckCSP YOLOv5) model to effectively detect insulators, contributing to the safe and uninterrupted operation of power lines. In the suggested approach, the DWB-YOLOv5 model is employed to detect insulators. The bottleneckCSP module enhances the accuracy of targets at various scales, while the depth-wise convolution module assists in reducing the model's complexity. Images undergo preprocessing steps such as automatic orientation and resizing. The preprocessed images are fed into the DWB-YOLOv5 model to extract deep features, perform object detection, and conduct classification. The insulator detection model obtained through this method exhibits a minimum of 8.53% better mean average precision (mAP) performance compared to existing methods. This study represents a significant step towards ensuring the safe and uninterrupted operation of power transmission lines. Accurate detection of insulators facilitates the smooth functioning of lines, ensuring reliability and continuity in energy transmission. The proposed method offers important advantages such as high accuracy, lightweight design, and efficiency.

1. Introduction

Electric power transmission lines are fundamental components of power systems, facilitating the effective transmission of electric energy over long distances. Given that these lines carry electric energy at high voltage levels, the safety and efficiency of their operation are of paramount importance. Insulators serve as critical elements in ensuring the healthy and safe operation of these transmission lines. They provide insulation between the transmission line structure on the line and the voltage, preventing the loads on the line from being grounded and transferring to other equipment by isolating them from the ground [1,2]. Due to the extensive distances covered by transmission lines, the condition and integrity of insulators should be continuously monitored. Faults in insulators can lead to negative impacts on the safety and ongoing functionality of the lines. Breakage, cracking, corrosion, or other damages in insulators can reduce the reliability of transmission lines and cause power

outages in case of failure. Thus, regular detection and maintenance of insulators are of great importance. Most studies on insulator detection have employed the following methods [3-5];

- Acoustic and Vibration-Based Approaches: These methods detect faults using acoustic or vibration properties of insulators. Microphones or vibration sensors are used in these approaches. They detect abnormalities by analyzing the sound or vibration patterns emitted by insulators under normal operating conditions.
- This approach is typically used for real-time monitoring and rapid fault detection [3–5].
- Remote Sensing and Sensor Networks: Sensor networks or remote sensing systems are used to monitor the condition of insulators. These systems consist of sensors measuring the electrical properties of insulators, as well as environmental parameters such as temperature, humidity, or vibration. These data are used to monitor the operating status of insulators, detect faults, and optimize maintenance planning [6,7].

- Image Processing-Based Approaches: Image processing algorithms are used to analyse the visual features of insulators. This approach captures and analyses images of insulators using imaging technologies such as thermal cameras or high-resolution cameras. It evaluates the colour, shape, and textures of insulators to detect issues like breakage, cracks, or surface damage [8].
- The common goal of these studies is to ensure the proper functioning of insulators and to increase the reliability of energy systems by early detection of faults. With the development of new technologies and ongoing research, further advancements in the field of insulator detection are expected.
- This study undertakes object detection based on image processing.

The significance and contributions of this study are as follows:

- This study aims to accelerate the detection and classification of insulators on transmission lines using YOLOv5's (You Only Look Once-YOLO) fast inference speed and high detection accuracy while intending to lighten the model and increase its accuracy. Thus, it aims to reduce the margin of error in insulator detection.
- Toward the task of insulator detection, improvements and innovations have been made to the YOLOv5 structure in this article. Firstly, the detection accuracy has been increased by using the bottleneckCSP module to obtain the semantic depth information of insulator images. Moreover, the Focus layer used in the YOLOv5 structure is specially designed to increase the detection accuracy of particularly smaller objects.
- In the proposed model, a depth-wise convolution structure is used, applying a separate kernel to each channel of the input data for computation, hence performing the operation in parallel. This method allows models to be lighter and operate efficiently in resource-constrained environments.
- This study has improved the mAP value of the proposed insulator detection approach by at least 8.53%. While reducing the computational cost of YOLOv5s, a lightweight and efficient structure is presented. Moreover, this method achieves better results compared to the latest technical methods.

2. Materials and Methods

The task of insulator detection possesses two fundamental characteristics: first, the location of the object is determined, and then the class of the insulator is detected. Models in the YOLOv5 series

are quite successful in location detection, and YOLOv5s has a lighter structure. Compared with other deep learning techniques, YOLOv5s is a good option for this purpose, providing a balance between detection accuracy and speed [8,9].

In this research, the YOLOv5s network structure has been developed and applied. The network consists of four sections: head, backbone, neck, and prediction [10]. The head section represents the input and aims to resolve the imbalance in the distribution of the small target dataset using different frame settings for adaptive frame setting. The backbone network is implemented using focus, SPPF, and bottleneckCSP. The insulator detection model is designed using the focus structure and the depth-wise convolution layer to reduce the number of network layers and parameters, increase the forward and backward computation speed, and prevent information loss in sampling [11]. The architecture of the proposed model is provided in Figure 1. In this study, the task of insulator detection was conducted with a model obtained through the enhancement of the YOLOv5 network structure. The network consists of four sections: head, backbone, neck, and prediction. This structure maintains a balance between detection accuracy and speed, ensuring the accurate detection of various defects.

2.1 Dataset

The study used an open-access dataset containing 1547 insulator images [12]. Insulators can be classified into different types based on voltage type and usage purpose. The two main types of insulators commonly used in transmission lines are tension type and suspension type insulators. Tension type insulators are typically insulators that hang below or beside the transmission lines. These types of insulators isolate the loads on the line from the ground while carrying the voltage on the line. Suspension type insulators consist of a series of insulator rings and are used to support the transmission line [13]. These types of insulators carry the voltage on the line, protecting the line and the support structure. The images in the dataset labelled as tension and suspension types have been divided into 1083 for training, 233 for validation, and 232 for testing. Example images used in the study are given in Figure 2.

2.2 Performance Metric Measures

In this study, confusion matrix was used as an evaluation metric for supervised learning. Precision (P), Recall (R), and Mean Average Precision (mAP) values were the evaluation criteria obtained [14],

[15]. The equations for these metrics are given in Equation (1)-(3);

$$P = \frac{TP}{TP+FP} \times 100\% \quad (1)$$

$$R = \frac{TP}{TP+FN} \times 100\% \quad (2)$$

$$mAP = \frac{\sum_{k=1}^N P(k)\Delta R(k)}{C} \quad (3)$$

In the equations above, TP represents the number of true positives, FN represents the number of false negatives, FP represents the number of false positives, N represents the number of samples in the validation set, P(k) represents the magnitude of Precision when k targets are detected at the same time, and $\Delta R(k)$ represents the change in Recall when the number of detected samples changes from k-1 to k. C represents the number of classes in the model [11,16].

3. Results

The trained model was evaluated using mAP, precision, and recall evaluation metrics. A Tesla T4 with a 15110MiB memory NVIDIA GPU was used in this study. The proposed model was optimized using stochastic gradient descent. Table 1 shows the mAP, precision, and recall values. The dataset was randomly divided into 70% training, 15% validation, and 15% testing data. All analyses in the study used the same training, validation, and testing images, ensuring that the models were compared under equal conditions. Values for the 500 epochs used to track performance metrics were plotted and are given in Figure 3 and Figure 4 shows the isolators predicted by the model using randomly selected test images. As the loss curves show a downward trend while the performance metric values show an upward trend, this indicates the improvement during the training process. Another performance metric, the precision-recall curve, was plotted and is given in Figure 5. In the analysis carried out with four different models for insulator detection, the performance of each component has been analysed and the effect of each component is presented in Table 1. Also, the number of layers and parameters for each model is given in the table.

Effect of Dept-wise Convolution: Unlike traditional convolutions, dept-wise convolution performs separate operations along the depth (number of channels) of the input data. By applying separate filters along the depth of the input data, it reduces the computation cost and allows for model lightening.

Effect of BottleneckCSP: While reducing the depth and computational intensity of the model, it maintains the ability to learn more complex features. In this way, it is possible to obtain lighter and faster

operating models. Bottleneck structures enhance the generalization ability of the model and reduce the risk of overfitting. It allows obtaining more generally valid models with fewer parameters and more learnable features.

Effect of Model Merging: In the proposed model, a lighter model with high accuracy was obtained by replacing bottleneckCSP and normal convolutions with dept-wise convolution modules. Table 2 presents the layer count, parameter values, and average image processing time for the models. As indicated by the table, DWB-YOLOv5 has a lower layer count than YOLOv5s, leading to a reduced image processing time. This suggests that the model is both lighter and faster in performance. As can be seen from the figure, the curve shows a trend towards the top right corner, indicating that most values are close to one.

4. Conclusion

In this study, DWB-YOLOv5, an approach integrating dept-wise convolution and BottleneckCSP to the YOLOv5 model, is proposed for insulator detection. Bottleneck structures used in the model reduce the depth and computational intensity of the model, enhancing its ability to learn complex features. Additionally, the generalization ability of the model has been improved to reduce the risk of overfitting. DWB-YOLOv5 is a modified version of the YOLOv5 model, lightened and reduced computational cost with depth-wise convolution modules. Two modules and a focus module were added to improve the performance of the model. The proposed insulator detection network has provided at least 8.53% improvement in mAP (mean precision) performance compared to the YOLOv5s model. Future works may focus on improving the real-time performance of lighter network structures. Additionally, the use of this approach for the detection of other objects on transmission lines can be considered.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge

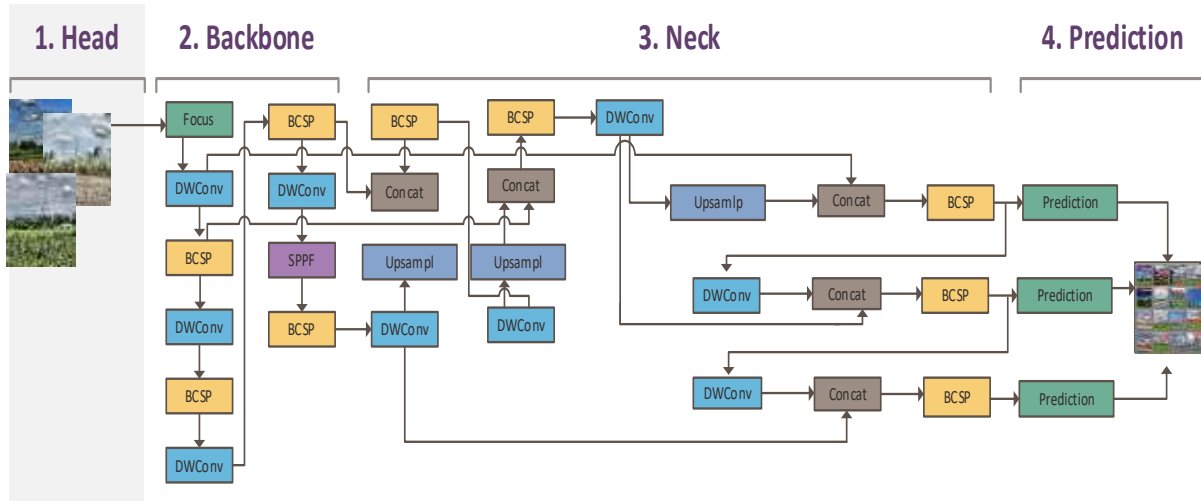


Figure 1. Architecture of the proposed model

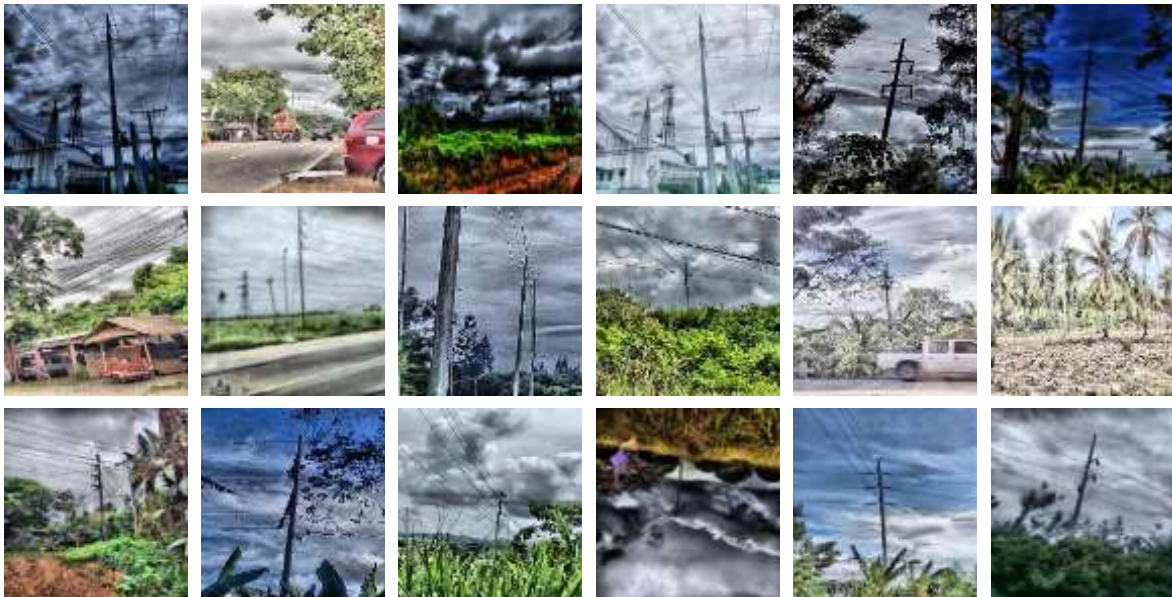


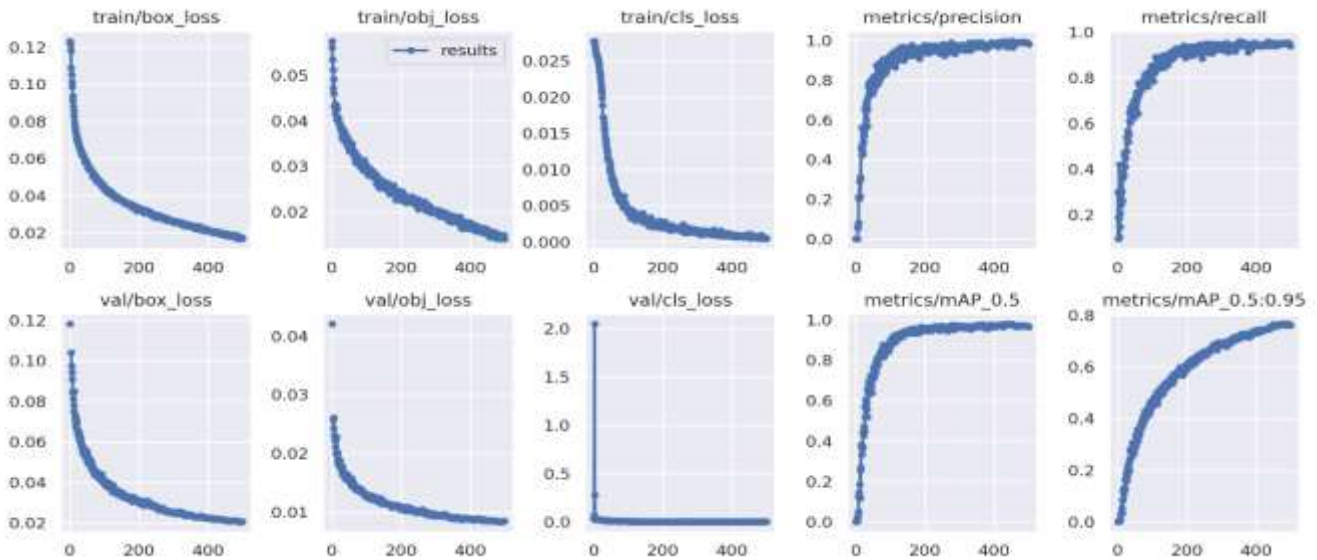
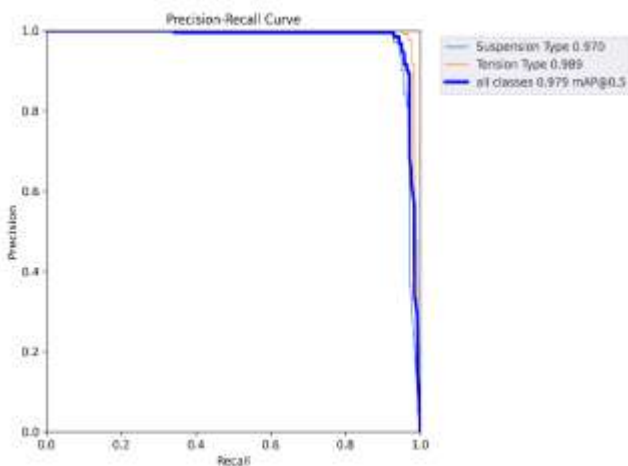
Figure 2. Sample images from the dataset

Table 1. Performance metrics values of the models.

| Methods | Description | mAP (%) | Precision (%) | Recall (%) |
|------------|------------------------------|-----------|---------------|------------|
| YOLOv5s | YOLOv5s | 90.2±0.03 | 91.6±0.02 | 84.2±0.04 |
| YOLOv5-2 | YOLOv5s+DWConv | 92.5±0.02 | 94.7±0.03 | 94.3±0.03 |
| YOLOv5-1 | YOLOv5s+BottleneckCSP | 95.6±0.04 | 97.5±0.05 | 90.5±0.02 |
| DWB-YOLOv5 | YOLOv5s+BottleneckCSP+DWConv | 97.9±0.03 | 97.1±0.04 | 95.7±0.04 |

Table 2. The summary of the different models and the average elapsed time on the test set.

| Methods | Model Layers | Number of parameters (10^4) | Average Time Consuming (s) |
|------------|--------------|---------------------------------|----------------------------|
| YOLOv5s | 224 | 7.03 | 0.645 |
| YOLOv5-2 | 226 | 7.02 | 0.842 |
| YOLOv5-1 | 202 | 7.04 | 0.763 |
| DWB-YOLOv5 | 208 | 7.01 | 0.563 |

**Figure 3.** Overall summary of training.**Figure 5.** Precision-recall curve

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- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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Figure 4. Isolators detected in test images

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