INSULATOR FAULT DETECTION FROM UAV IMAGES WITH YOLOv5 FAMILY

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ABSTRACT

One of the crucial objectives for an intelligent inspection of high-voltage transmission lines is insulator defect identification. Insulators are crucial to the safe and dependable operation of power networks because they offer electrical insulation and mechanical support for electric transmission lines. First, aerial photos with one or more flaws are gathered in a variety of scenes, and then a new dataset is created. The CSPD-YOLO model uses a feature pyramid network and an improved loss function to improve the accuracy of insulator fault detection. The proposed method utilizes the Insulator Defective data set containing two classes (Insulator, Defect) to train and test the model through YOLOv5 Object Detection algorithm. We compare the performance of YOLOv3, YOLOv5 Family while training them on a Insulator Defective dataset. This information will be helpful for practitioners to select the best technique based for the Insulator Defective dataset.

Keywords: YOLOv5l, YOLOv5, YOLOv3, object detection, YOLOv5l6, YOLOv5x6

1. INTRODUCTION

High-voltage transmission [1] is essential because of the rising demand for electricity, particularly in the context of smart power grids. However, a defect will inevitably happen because the insulator is exposed to the outside environment for a long time. Unmanned aerial vehicle (UAV) patrols have gradually replaced traditional manual patrol, which is ineffective and wasteful of human resources. As a result, employees no longer need to use telescopes to find insulator defects along transmission lines. The automatic diagnosis of insulator failures has, however, been extremely difficult because to the complexity and diversity of application settings.

To discover insulators and their flaws, many researchers employed aerial photographs and conventional image processing techniques . The majority of the time, fault detection was carried out using matching algorithms after segmenting insulators using specified criteria (such as colour, gradient, texture, form, etc.). The accuracy of conventional image processing algorithms is lowered because the correlation properties of insulators in aerial photos are unknown. These techniques have various advantages over more conventional image processing techniques. With the widespread use of CNN [2], deep learning techniques are able to surpass the constraints of conventional image processing methods, displaying outstanding performance and significantly enhancing object detection accuracy.

2.RELATED WORK

In [3] the authors presented paper, the setting of anchor in traditional quicker R-CNN models only satisfy the requirements for general object detection. After fine-tuning a quicker R-CNN, some cases of subpar insulator identification produce power transmission and transformation inspection images. There are two horizontal insulators with colours that resemble the background. One insulator can only be detected in small portions, and the output box's dimensions are inadequate for the insulator. Infrared images were taken on-site, which are what actual applications require. The selection of the photographs took into account a variety of settings. The country's 110–500 kV indoor high-voltage laboratories of various grades, four substations, one converter station, and about 33 transmission lines were selected. In terms of materials, glass, porcelain, and composite insulators were all taken into consideration. The quicker R-CNN in the VGG-16 Net had an average precision (AP) value of 0.640. We concentrated on how to further increase the detection accuracy based on this. It can successfully accomplish the distinct detection of the insulators in the image, laying the groundwork for further insulator defect diagnostics and status detection.

Rahman.et.al, [4] developed the electric supply businesses concentrate mostly on inspecting damaged and faulty insulators to guarantee consumers receive safe and dependable power transmission. In both classes, YOLOv4 has an average precision (AP) of 82.9%, with APs of 78.2% on pin insulators and 87.7% on suspension disc insulators. YOLOv4 Tiny has a lower AP than the regular YoloV4 model since it is a lightweight model with a fast rate of inference. The complicated dataset is made up of pictures of several complex electric poles that are located outside a 132 kV grid substation that were captured with a cell phone camera. To avoid overfitting and noisy estimations, cross iteration batch normalisation (CmBN) is utilised.

Liao.et.al, [5] developed the identification of regional feature points or regional patches is referred to as "feature detection." We want to find as many feature points of the insulator as we can in order to simplify the subsequent processing (to increase recall, we allow noise to exist but restrict the insulator point from being missed). There are numerous ways to find local feature points, including the Lowe's difference-of-Gaussians detector and the Harris affine area detector. By employing a z-score normalisation, our improved Harris corner selection technique only looks for corners that are close to enhanced edges. The exact same quantity of training data is used by all methods.

Wang, S..et.al, [6] developed model they contrast the proposed algorithm with the BOW and SIFT-based method. The exact same quantity of training data is used by all methods.Features may be mapped between several feature mapping groups using blocks. The dimensions of the matching floor space are connected. Conv3, Conv4, and Conv5's comparable anchor scales are 32^2, 62^2, and 128^2. Three ratios—1:2, 1:3, and 2:1—are employed in this essay. In the training, samples are categorised as positive or negative according on their Intersection over Union (IoU) value, which ranges from 0.7 to 0.3. All tiers of feature pyramid networks provide comparable semantic information because of parameter sharing. Faster RCNN using the suggested technique as the backbone had higher ACC, mAP with ResNeSt101-RPN, at 0.0067, 2.5% respectively. RetinaNet's ACC, mAP, and AUC were 0.0099, 0.8%, and 0.0164 higher with the suggested technique as the backbone than they were with ResNeSt101-RPN. The accuracy is increased, but the FPS drops by 1.18 when the proposed technique serves as the foundation of our proposed network.

In [7] the author presented paper the insulator parts are spaced equally apart from one another. The breadth of the surrounding insulator pieces will considerably increase following a bunch-drop. Human visual observation reveals a distinct gap in the insulator area. Once the insulators have been located, the morphological method is used to highlight the missing piece's location so that the fault site can be found using the spatial properties of the data. Insulators are exposed to extremely high voltage and huge mechanical tension for an extended period of time outside. Insulator flaws or imperfections can cause significant power losses and potentially widespread power outages or blackouts. Ceramic and glass are the two most common materials used as insulators in transmission lines. As polycrystalline heterogeneous materials, ceramic insulators are susceptible to cracking from environmental, electrical, and mechanical stresses. Although toughening increases tensile strength, overloading can cause a bunch-drop. Unmanned aerial vehicle (UVA) inspection has become a more popular method of line inspection in recent years. The defects in the insulators can be effectively found and located by processing and analysing the aerial photos taken by the UAV.

3 METHODOLOGY

We use YOLOv5 [8] model to detect Insulator and defective areas because YOLOv5 model has a focus layer witch cable to detect low level features accurately. The Workflow of YOLOv5 for the Insulator and Defective dataset is as shown in Figure 1.

YOLOv5

Figure 1 : Workflow of YOLOv5

YOLOv5 which uses the MS COCO AP50.95 and AP50 is a cutting-edge detector that is both more accurate and faster (FPS) than any other detector in the market. They adopted substantial network enhancements to speed up the network's performance in terms of mean average precision (mAP). In FPN[9] top-down augmentation path is used and in PAN[10] bottom-up data augmentation path is used. YOLOv5 comes with 30 unique training hyper parameters . It is possible to think of the learning rate as a step size that keeps the expense of each repetition to a bare minimum. To prevent overfitting, the learning rate needs to be carefully chosen. How many pictures will be transmitted to the network in a single transmission depends on the batch size. Thus, using a bigger batch size will speed up training. The different versions of YOLOv5 based on p5 and p6 models as shown in Table 1. The YOLOv5 architecture is as shown in Figure 2 and different networks of YOLOv5p5 models are shown in figure 3.

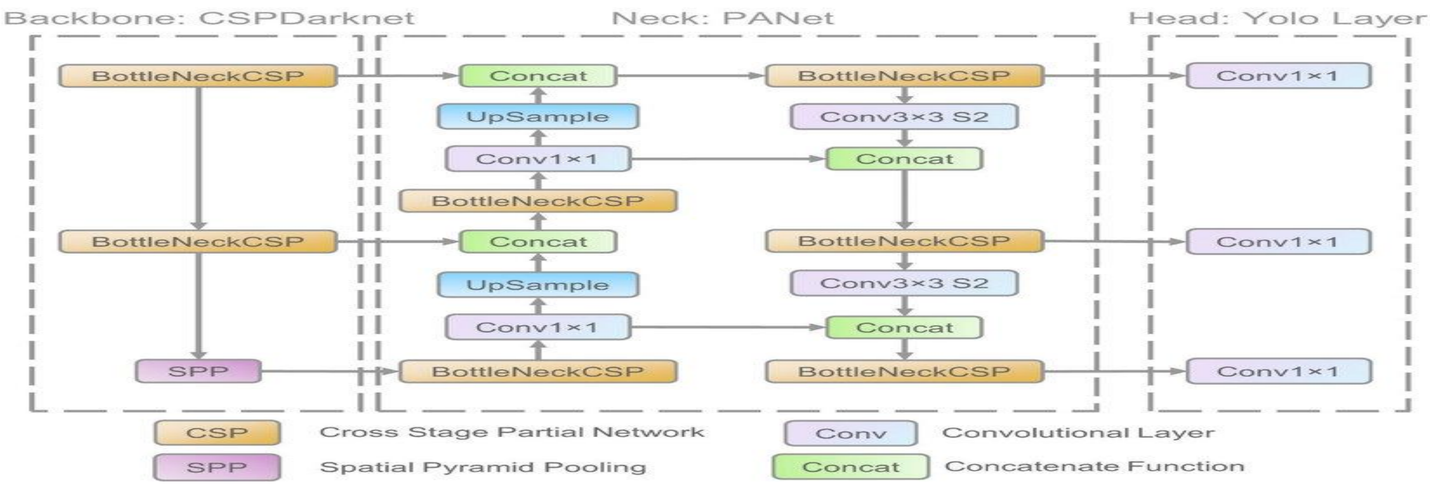


Figure 2 : YOLOv5 Architecture

Table 1 : Various types of YOLOv5 models

S.no	**YOLOv5p5 Models**	**YOLOv5p6 Models**
1	YOLOv5n	YOLOv5n6
2	YOLOv5s	YOLOv5s6
3	YOLOv5m	YOLOv5m6
4	YOLOv5l	YOLOv5l6
5	YOLOv5x	YOLOv5x6

Figure 3 : Different versions of YOLOv5 p5 models

RESULTS:

Experimental Setup

To Implement YOLOv5 model we require the following Hardware and Software support.

Hardware requirements: Processor: i3 or better,RAM: 8GB or More,Storage: 120GB or More,Nvidia GPU Recommended are used.

Software requirements:,OS: Windows,Python3.7 or later,Pytorch,OpenCV Other necessary Python Modules are used.

Precision, Recall, F1 score, map 0.5, map 0.725 are used to evaluate the performance of the model.

DATASET:(Insulator and Defective)

The Insulator and Defective dataset contain images from Electrical areas collected using UAV's.The Insulator and Defective detection dataset contains 701 images across two classes namely Insulator and Defect. The whole dataset is divided into train/test sets by ratio 70% and 30% within each event class so 501 used for training and 200 images used for testing. The dataset collected from https://github.com/InsulatorData/InsulatorDataSet [11] website.

Sample output of Insulator and Defective for YOLOv5x shown in Figure 4 with probability values.

Figure 4 : sample output of crop and weed for YOLOv5x

The performance of YOLOv3 and YOLOv5 family for the given image dataset is listed in the Table 2, Table 3 and Table 4. We also compared the accuracy of all models in the form of bar chart as shown in Figure 5. Figure 6, 7 , 8, 9, 10 and 11 shows the confusion matrix, Recall, Precision, Precision vs Recall, F1 score and graph of all losses for YOLOv5x model.

Table 2 : Precision,Recall,F1 score,map 0.5 and map 0.5 to 0.95 values for Insulator

YOLOv3 and YOLOv5 models	Insulator				
	map 0.5	map 0.5:0.95	Precision	Recall	F1 score
YOLOv3-tiny	98.4	74.9	0.935	0.959	0.946
YOLOv3	99.5	98.2	1	1	1
YOLOv3-spp	99.5	99.4	1	1	1
Yolov5n	99.5	94	0.985	0.996	0.990
Yolov5s	99.5	98	1	1	1
Yolov5m	99.5	99.2	1	1	1
Yolov5l	99.5	99.4	1	1	1
Yolov5x	99.5	99.5	1	1	1
Yolov5n6	99.5	95.3	0.997	0.998	0.997
Yolov5s6	99.5	99	1	1	1
Yolov5m6	99.5	96.9	0.999	1	0.999
Yolov5l6	99.5	94.8	0.998	1	0.998
Yolov5x6	99.4	92.1	0.989	0.998	0.993

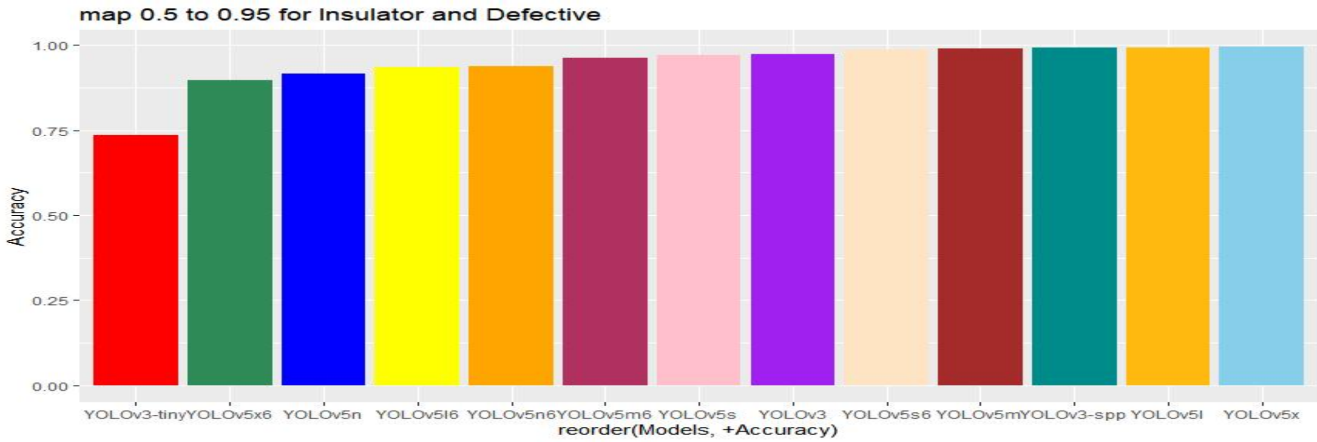
Table 3 : Precision,Recall,F1 score,map 0.5 and map 0.5 to 0.95 values for Defective

YOLOv3 and YOLOv5 models	Defective				
	map 0.5	map 0.5:0.95	Precision	Recall	F1 score
YOLOv3-tiny	99.5	88.5	0.998	1	0.998
YOLOv3	99.5	96.3	1	1	1
YOLOv3-spp	99.5	99.3	1	1	1
Yolov5n	99.5	89.5	0.998	1	0.998
Yolov5s	99.5	96.1	0.999	1	0.999
Yolov5m	99.5	98.8	0.999	1	0.999
Yolov5l	99.5	99.5	0.999	1	0.999
Yolov5x	99.5	99.5	1	1	1
Yolov5n6	99.5	92.5	0.999	1	0.999
Yolov5s6	99.5	98.7	0.999	1	0.999
Yolov5m6	99.5	95.5	0.999	1	0.999
Yolov5l6	99.5	92.2	0.999	1	0.999
Yolov5x6	99.5	87.2	0.999	1	0.999

Table 4 : Precision,Recall,F1 score,map 0.5 and map 0.5 to 0.95 values for all(Insulator and Defective)

YOLOv3 and YOLOv5 models	All				
	map 0.5	**map 0.5:0.95**	**Precision**	**Recall**	**F1 score**
YOLOv3-tiny	99	77.7	0.966	0.98	0.9729
YOLOv3	99.5	97.3	1	1	1
YOLOv3-spp	99.5	99.3	1	1	1
Yolov5n	99.5	91.7	0.992	0.998	0.994
Yolov5s	99.5	97.1	1	1	1
Yolov5m	99.5	99	0.999	1	0.999
Yolov5l	99.5	99.4	1	1	1
Yolov5x	99.5	99.5	1	1	1
Yolov5n6	99.5	93.9	0.998	0.998	0.998
Yolov5s6	99.5	98.8	0.999	1	0.999
Yolov5m6	99.5	96.2	0.999	1	0.999
Yolov5l6	99.5	93.5	0.999	1	0.999
Yolov5x6	99.4	89.7	0.994	0.999	0.996

Figure 5 : Accuracy comparisons of all models for All(Insulator and Defective) category



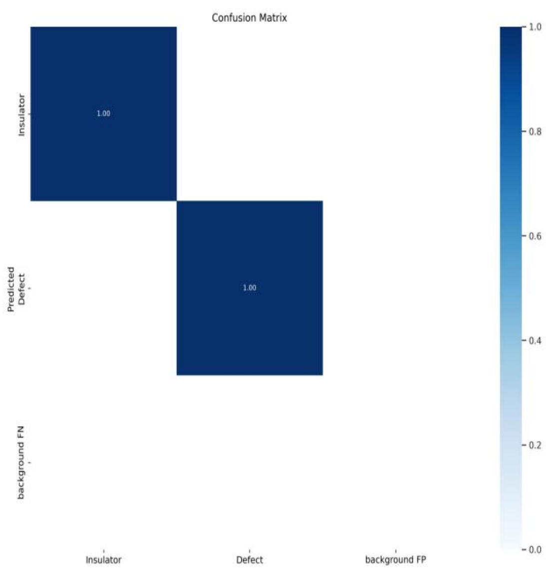


Figure 6 : Confusion matrix for YOLOv5x model

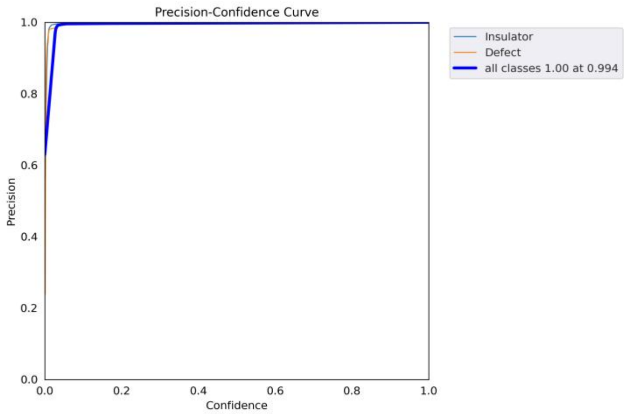


Figure 7 : Recall graph for YOLOv5x model

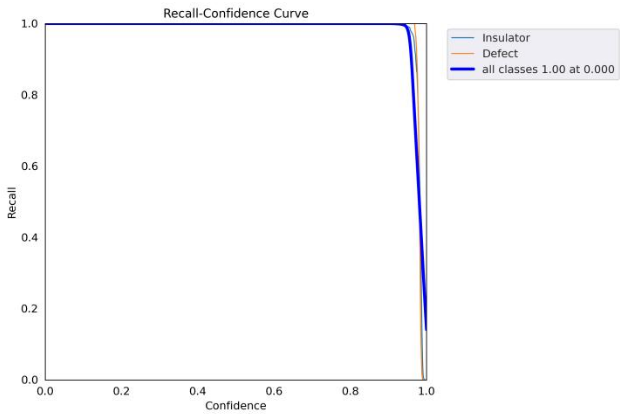


Figure 8 : Precision graph for YOLOv5x model

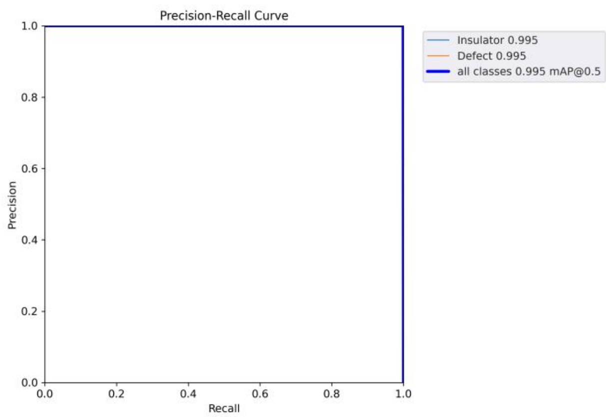


Figure 9 : Precision vs Recall graph for YOLOv5x model

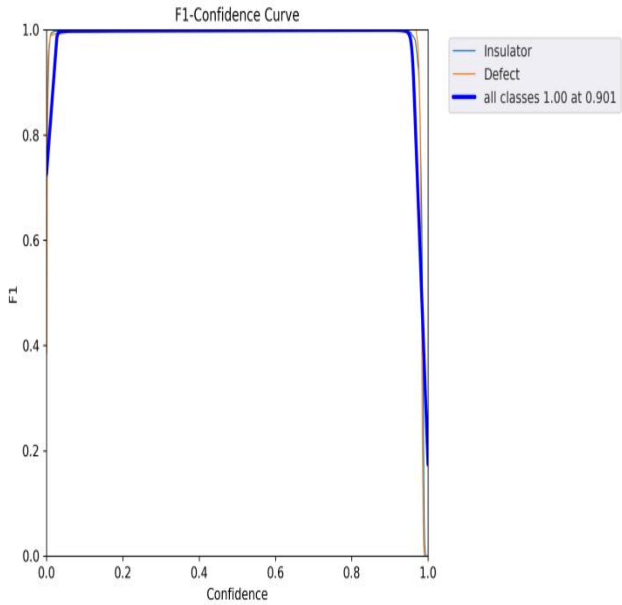


Figure 10 : F1 score graph for YOLOv5x model

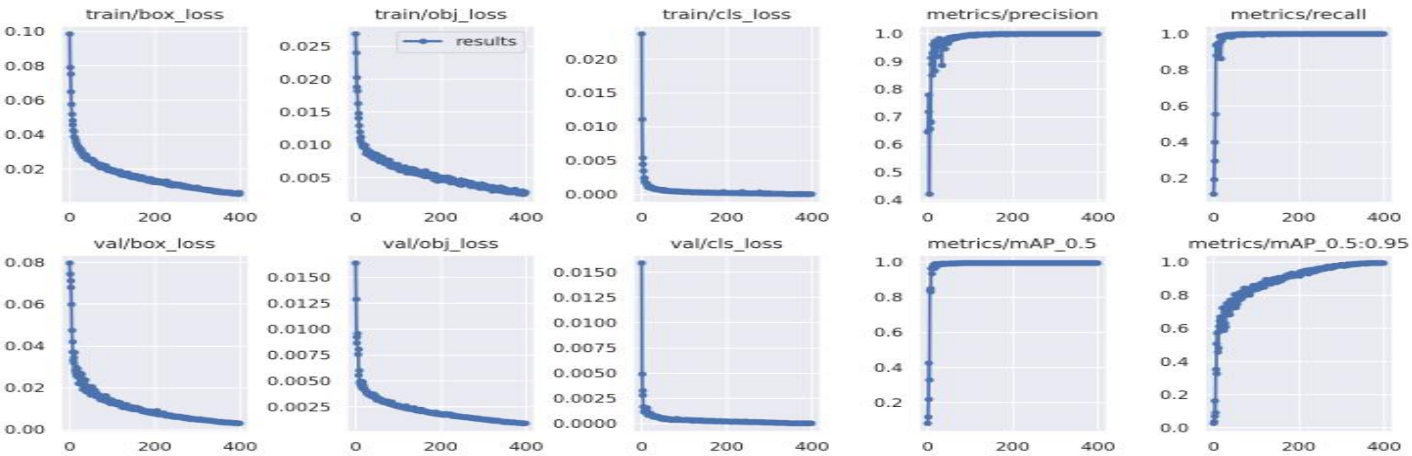


Figure 11 : Graph of all losses of training YOLOv5x

Conclusion

In most computer and robot vision systems, object detection is crucial. Despite recent improvements and the implementation of some current approaches into various consumer devices or assistance driving systems. Accuracy (map 0.5), Accuracy (map 0..5 to 0.95), Precision, Recall and F1 score for YOLOv5l model are 99.5, 99.5, 1, 1, 1 respectively. Accuracy (map 0.5), Accuracy (map 0..5 to 0.95), Precision, Recall and F1 score for YOLOv5l model are 99.5, 99.5 1, 1, 1 respectively. Therefore, we can affirm that YOLOv5x can be preferred than YOLOv3 family and other models of YOLOv5 family like YOLOv5x for the Insulator Defect dataset with appropriate speed and accuracy.

Summary

On Comparing the YOLOv3 family and YOLOv5 family on the Insulator and Defective dataset, YOLOv5x can able to predict Insulator and Defective accurately than the other models.

Future Enhancement

YOLOv7 [12] improves speed and accuracy by introducing several architectural reforms like E-ELAN (Extended Efficient Layer Aggregation Network), Model Scaling for Concatenation based Models and several Trainable BoF(Bag of Freebies) like Planned re-parameterized convolution, Coarse for auxiliary and Fine for lead loss.

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