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Insulator Detection in Intelligent Monitoring Based on Yolo Family and Customizing Hyperparameters

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ABSTRACT

Monitoring of power transmission lines plays an important task in high voltage transmission systems. The problem of damaged insulator causes bad effects on an electrical power grid. To make sure the power grid worked properly, electrical personnel usually need to be climbed on the electric post to inspect them which consists of risk latent in occupational safety. Therefore, constructing smart monitoring systems plays an important task to monitor and inspect insulator conditions without manual monitoring. Nowadays, UAV (unmanned aerial vehicles) systems have been become popular, which combines with computer vision supporting to implement an autonomous system for detecting and monitoring bad insulators. In this study, we present an approach which apply deep learning based well-known models to automatic detect insulators with hyperparameter optimization. In this experiment, some models are investigated to select the best one for the insulator detection task in the intelligent monitoring system. Image insulator data was collected by using drone system. The experimental image data consists of 972 samples taken under a variety condition such as clutter backgrounds, high contrast… This study has surveyed and experimented some well-known models such as the Yolov5 family and the newer Yolov7. The hyperparameter optimization and augmentation were applied for improving detected performance. Yolov5x with optimal hyperparameters achieves higher performance with the ratio of recall, precision, mAP:0.5, and mAP:0.5:0.95 are 98.5%, 99.3%, 99.0% and 68.6%, respectively. Meanwhile, the default hyperparameters Yolov5 achieved results with the ratio of recall, precision, mAP_0.5 and mAP_0.5:0.95 are 97.3%, 97.1%, 99.2%, 65.7% and Yolov7 are 95.7%, 97.6%, 98.6% and 63.3%.

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1. Introduction

Nowadays, artificial intelligent, IOT and UAVs have been used widely in many industries and fields, from office buildings, administrative agencies, small retail stores to intelligent surveillance in agricultural, natural disaster or in electrical power line. With these technologies we can acknowledge information and quickly response to each circumstance.

A power transmission line is an energy transmission system that connects the power generation source to the power consuming devices. Power transmission lines is usually carries out manually either the electrical personnel inspect from the ground or from the lines which can endanger the inspector since the lines have high voltage. This method is also time consuming, and the inspector needs to have rich professional experience to avoid misjudgment. Instead of manual inspection, drone or UAVs can be used to patrol the transmission lines and detect the insulator. They can capture image of the insulator and mark down their location so that professionals are able to know if each insulator are in good condition or they need maintenance. Insulator is a type of equipment used a lot in the power transmission network for the purpose of fixing the transmission line, creating a distance between the line and the pole body or between the transmission lines, to ensure safety in the transmission power grid system, avoiding the risk of electric shock causing line fire. There are many types of insulators such as ceramic insulator, polymer insulator, glass insulator, …

This study investigates on both glass and polymer insulator which have a repetitive structure and distinctive circular shape. The yolo family is selected for insulator detection problem due to fast speed, high accuracy, easy to customize for application. Some models of Yolo are analyzed and experimented for insulator detection, such as Yolov5n (nano) Yolov5m (medium), Yolov5x (extra-large) and the newer Yolov7. In this paper, we demonstrated some compared results among Yolov5n, Yolov5m, Yolov5x, Yolov7 and the customized Yolov5x.

2. Literature review

This section briefly reviews some existing methods for object detection, which include deep learning and shallow learning-based approaches in downstream tasks related to our method. There are some different approaches in the application in detecting and locating objects in the overall image. That is from an input image to detect and locate the position of objects in the image. They can be divided into the following main approaches: object detection method based on extracting feature map, object locating using instance segmentation. Amount of that some well-known contributions such as SSD [1], FCOS[2], ATSS[3]. These methods use CNN backbone combining with pre-defined bounding-boxes technique (also known as anchor boxes processing). That estimate probabilities of densely containing objects and positions. Then, machine learning techniques predict the probability and coordinates of objects from the locations of the anchor boxes. The method in [2] treats anchor boxes as anchor-points to avoid of the use anchor structures. Therefore, the method reaches high flexibility and computational speed. In the topic of feature extraction based deep learning for object detection, there are some well-known approaches for pattern recognition in high accuracy and fast computing, especially the CNN approaches such as GoogleNet[4], Microsoft ResNet[5], Faster R-CNN[6]. Instead of directly predicting the probability and position of objects in the anchor box, Faster R-CNN method processes on two steps: the first step generates region proposals and discards non-object anchors, and the second step solves the region proposal using the RoI pooling/RoI Align operator, and then it predicts the probabilities and refines the coordinates of the region proposal. Another approach, Yolo model has become a famous object recognition model along with R-CNN, SSD. Yolo model first introduced in [7] achieves fast processing speed along with high accuracy. The accuracy is quite high thanks to the advantage of using a rather compact, but efficient Darknet feature extraction network. The DC-SPP-YOLO [8] was constructed by YOLO based on combination of dense connection and spatial pyramid pooling . That paper is expected for ameliorating the accuracy of object detection in YOLOv2[9]. MTI-Yolo network combines some multi-scale feature maps and spatial pyramid pooling model. Another group of authors presented the method for utilizing high-level discriminative CNNs [10] for feature extraction and using deformation invariant nature of the locally vector aggregated descriptors .

In the topic of deep segmentation based object detection, the most well-known methods Mask R-CNN [11]. This method is based on the idea of the segment-by-detection that attaches one classification stage into the R-CNN module of the Faster R-CNN model [6] predicting masks of objects with the existing branch for bounding box recognition. A new method embarrassingly to instance segmentation SOLO [12] was presented. The input image separated into cell grids, then they are assigned object instances with each cell to each object. In order to generate masks, each grid cell is predicted the semantic category and their instance masks. A simple and fast method for real time instance segmentation, YOLACT method was presented in [13]. That method predicts region coefficients along with position of bounding box and prototype masks. The final mask is generated by a linear combination of coefficients and prototype masks. Beside of that, the method improved of YOLACT for instance segmentation on the edge was presented in [14]. That approach by using TensorRT optimization and similarity learning of temporal information while carefully trading off speed and accuracy.

In the topic of insulator detection, authors in [15] presented R-FCN approach for cracked insulator detection The authors applied some augmented data techniques, such as image correction and cropping images to make different sample sizes and directions. Images are also transformed by some image enhancement technologies to augment samples. The experimental results show that the model reaches

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accuracy rate of 90.5% and shows strong robustness and environmental adaptability. In the computational time, the detection system reaches less than 1fps.

3. Proposed approach for insulator detection

The overview architecture of the insulator detection system is shown in Figure 1. The method includes collecting the raw data which we use a DJI drones to capture images of the insulators. In data preparing task, we use Roboflow to preprocessing those images, processed data will be used to train using models such as Yolov5n, Yolov5m, Yolov5x[16] and Yolov7[17], insulator detection results will be used to embedded to drone and they will mark down the GPS coordinates for electrical technician to inspect whether that insulator needs repair or not.

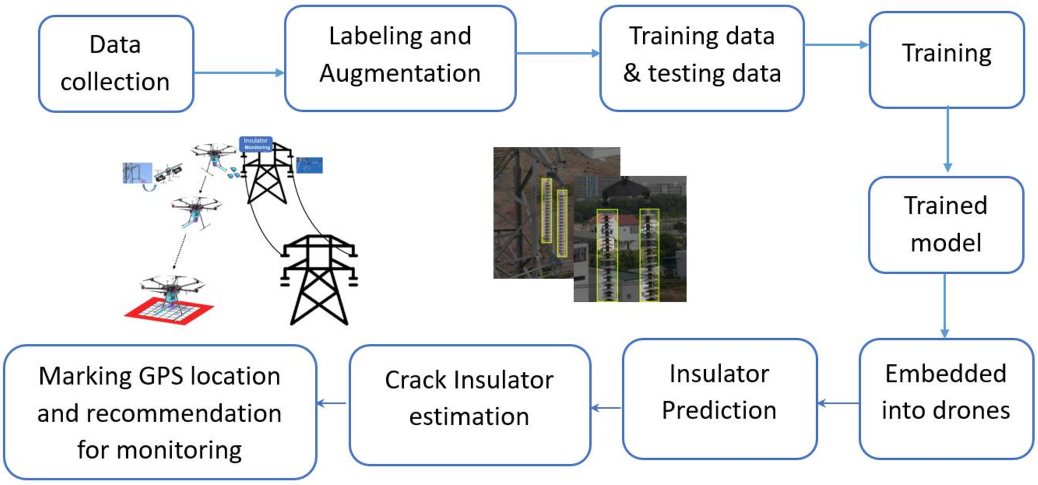

Figure 1. *General flowchart of the system*

Raw data are collected by using drones to capture insulator images along the overhead power lines. After that they are used in Roboflow to label, resize to 416x416 and add some augmentations such as changing the rotation, brightness and exposure of the images.

There are some types of object detectors based on deep learning such as Yolo, DETR as single stage detector and two-stage detectors such as CenterNet, an anchor-based detector like Yolov4, Yolov5 or anchor-free like Yolov7. Object detectors usually consist of two parts backbone using DCNN for feature extraction from input image and detection head for predicting the class of objects and their bounding box positions. In Yolov5, there are three parts the detection model, first input backbone for feature extraction based on to CSPDarknet, the results are fed to feature fusion (PANet neck). The head stage of Yolo outputs detection results, which consists of class, score, location, size of detected objects.

In this study, some hyperparameters are defaulted for training such as weighted metrics: mAP:0.5 with contributing 10% of the weight and mAP:0.5:0.95 remaining of 90%. Instead of default hyperparameters to Yolov5n, Yolov5m, Yolov5x and Yolov7 training, we also customized some hyperparameters with expected to improve the insulator detection performance.

There are different types of parameters that control the model learning. The task of hyperparameter evolution, genetic algorithm for optimization is the most popular method for hyperparameter optimization. In Yolov5 detection model, there are about 30 hyperparameters can be directory customized for data augmentation to improve performance rate. Some of the hyperparameters have more effect on the final results. For example, lr0 is used to initial learning rate for starting to determine step size at each iteration during training a model, the default value is 0.1, then its means at every iteration; The momentum parameter supports for controlling the gradient descent algorithm to update intrinsic weighting parameters of CNN model. In this processing, its work usual an aggregate of gradient. The mosaic is used for creating a new image based on a combination of some images. The image results are used as newly created images which supports for augmentation data to training with expected increase accuracy of the detected model. Beside of that many other parameters are customized, such as warmup

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epochs, warmup momentum, and so on. Although hyperparameters have a certain impact on the model's performance, they are usually unpredictable. You only know your augmented hyperparameters model is good or not after the model has already trained. Therefore, when optimizing hyperparameters usually rely on empirical search, e.g., tried and error approach to estimate the model performance on the training and validation task. We only presented some notable hyperparameters which have effects to the overall performance for insulator detection and not adjust all hyperparameters. In this paper, we proposed a way to optimize your model by adjusting the hyperparameters for a specific object, in this case is insulator. In tried and error method for selecting the best hyperparameters, as presented in Table 2. The set a random value for evaluating the model after each training result and finally, the optimal values are used hyperparameters settings. The experimental results illustrated how well the adjusted hyperparameters model compare to the default ones, e.g., precision, recall rate, mAP:0.5, and mAP:0.5:0.95.

4. Material and Data processing

One of the important tasks of the paper is to collect and process experimental data. Insulator images are captured by power line maintenance personnel in many locations. This task is collaborated with the EVN branch of Quang Tri with more than 2000 images divided into 2 kinds of insulator: polymer insulator which has grey and dark color and glass insulator which has light cyan transparent color. Image set was captured using the DJI drone camera and was taken in different time and places. After removing images which are too blurry or out of focus, we have selected 972 images, some examples of the insulators are demonstrated in Figure 2.

Figure 2. *Example of insulators*

The collected image dataset is rescaled, normalized and converted to a uniform format in Roboflow. In Roboflow images are also randomly adjusted brightness, exposure, and rotation to enrich the dataset. The dataset is separated to 78% for training, 11% for validation and 11% for testing.

Table 1. *Creating experimental dataset for training and testing*

	Number of images
Training set	752
Validation set	110

Test set	110
Total	**972**

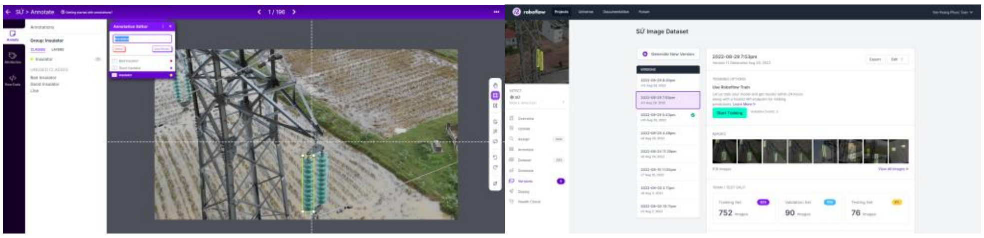

Figure 3. *Example of the use Roboflow to label and create experimental dataset*

5. Experiment and Analysis

In this study, some metrics are used for evaluating and performance comparing of some models as Yolov5 and Yolov7. The proposed deep learning-based methods used our dataset for performance evaluation, are evaluated using mean Average Precision (mAP) metric, specifically mAP:0.5 and mAP:0.5:0.95.

Precision measures how accurate is your predictions, the percentage of your predictions are correct. It measures how many of the predictions that your model made were correct, as equation (1).

$$Precision = TP/(TP + FP) \tag{1}$$

where TP is the number of true positive samples that predicted as positive samples as were correct values and FP is the number of false positive samples that predicted as positive samples, but they are true negative samples.

Recall ratio is used to measure how good of the prediction results all the positives, which related the percentage of recognized positive samples, as equation (2).

$$Recall = TP/(TP + FN) \tag{2}$$

where FN is the number of false negative samples, that means it predicts as a negative, but it is a true positive sample.

IoU ratio is used for the overlap measurement between ground true and predicted result, In the detection task, this metric is used to measure how predicted and the groundtruth regions are overlapped, as equation (3).

$$IoU = \ Area\ of\ Overlap/Area\ of\ Union \tag{3}$$

Average precision (AP) value is the value below the line representing the precision - recall relationship. To simplify the calculation of this zigzag pattern, we approximate them as follows: At each level of recall rate, the precision value is replaced with the largest precision rate at that level of recall rate.

The measurement metric of AP@:0.5 is AP value when IoU = 0.5. In this, mAP is mean average precision. The mean average precision score is used to calculate the mean AP over all classes and IoU meets the 0.5 threshold. In this paper, the insulator has only one class, so mAP is also AP. In object detection models, mAP is often used as a good metric to evaluate.

Because precision – recall changes when the IoU threshold changes, therefore at a specified IoU value, it is possible to measure the goodness of the models. For example, mAP_0.5 = 0.85 means that at IoU = 0.5, the AP value of the model is 85%. The results of the insulator detection model quality during the training process are shown below. The results show that the model achieves convergence after about 80 epoches for all measurements Precision, Recall, mAP_0.5 and mAP_0.5:0.95 with the IoU threshold = 0.6.

In this paper, we have tested the Yolov5 with the default hyperparameter and the augmented hyperparameter by changing them which we have shown below Table 2. Like we have said above, about 23 hyperparameters used for various training settings. Adjusting hyperparameters in machine learning model can affect its predictive performance, usually performed by trial-and-error process.

Some of the hyperparameters we use are the default ones such as: learning rate lr0, momentum, weight_decay, warmup parameters or the IoU threshold, focal loss gamma, … Hyperparameters which we adjusted are: In this study, the final learning rate adjusted to 0.2 and we keep the initial learning rate by 0.01. Cls loss gain adjusted to 0.25; Obj loss gain adjusted to 0.6: the confidence of object presence is the objectness loss (Binary Cross Entropy). Objectness determines whether an object exists at an anchor. Scale adjusted to 0.9: when capturing insulators using drones, they may have various distance between the drone and the insulators. Scale may use to make the insulator perspective bigger or smaller. We also adjusted the mixup to 0.15 and copy_paste to 0.1. Other hyperparameters such as shearing, or degrees is not so necessary because the dataset have already been rotated between 20° and -20° in Roboflow app.

Table 2. *The set of hyperparameters for data augmentation and tranining*

Parameters for augmentation	**Variable**	**Setting**
Initial learning rate	lr0	0.01
Final OneCycleLR learning rate	**lrf**	**0.2**
SGD momentum/Adam beta1	momentum	0.937
Optimizer weight decay 5e-4	weight_decay	0.0005
Warmup epochs	warmup_epochs	3.0
Warmup initial momentum	warmup_momentum	0.8
Warmup initial bias lr	warmup_bias_lr	0.1
Box loss gain	box	0.05
cls loss gain	**cls**	**0.25**
cls BCELoss positive_weight	cls_pw	1.0
obj loss gain (scale with pixels)	**obj**	**0.6**
obj BCELoss positive_weight	obj_pw	1.0

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IoU training threshold	iou_t	0.20
Anchor-multiple threshold	anchor_t	4.0
Image translation	translate	±0.1
Image scale	**scale**	**±0.9**
Image flip left-right	fliplr	0.5
Image mosaic	mosaic	1.0
Image mixup	**mixup**	**0.15**
Segment copy-paste	**copy_paste**	**0.1**

In this experiment, some models of Yolov5n, Yolov5m, Yolov5x and Yolov7 were executed on the Google Colab with Tesla T4 GPU 16GB RAM, disk 78GB. While the Yolov5n and Yolov5m have a smaller architecture and faster training time, the Yolov5x is a larger architecture, has more parameters and longer training time. However, Yolov5x accuracy based on many different criteria is not too superior to Yolov5n and Yolov5m due to the problem of detection with just one class is quite simple so smaller architecture model can also handle it well. On the other hand, while having the same 150 epoch like the Yolov5, the Yolov7 model has a longer training time, but the accuracy is likely the Yolov5x.

Figure 4. *Some progress results of training and evaluation on our dataset*

Table 3 presents some insulator detection results on the testing data using the trained Yolov5s, Yolov5m, Yolov5x, and Yolov7 model.

Table 3. *Experimental results of some trained models on the testing data*

	Yolov5n	Yolov5m	Yolov5x	Customized Yolov5x	Yolov7

Number of layers	157	212	322	322	314
Number of parameters	1.760.518	20.852.934	86.173.414	86.173.414	36.481.772
Training time	22m30s	29m55s	1h12m52s	1h15m17s	1h45m53s
Number of validation images	110 images with 640x640 resolutions				
Number of test images	110 images with 640x640 resolutions				
Number of insulators	295 insulators in 110 images				
Detection threshold	conf-thres=0.001, iou_thres=0.6				
Precision	0.963	0.953	**0.971**	0.933	0.957
Recall	0.963	0.976	0.973	0.**985**	0.976
mAP_0.5	0.989	0.989	**0.992**	0.990	0.986
mAP_0.5:0.95	0.623	**0.695**	0.657	0.686	0.633

(a) Ground true of labelled insulators *(b) Detected insulators by Yolov5x*

Figure 5. *Some examples of ground true samples and detection results*

(a) Correct results of insulator detection

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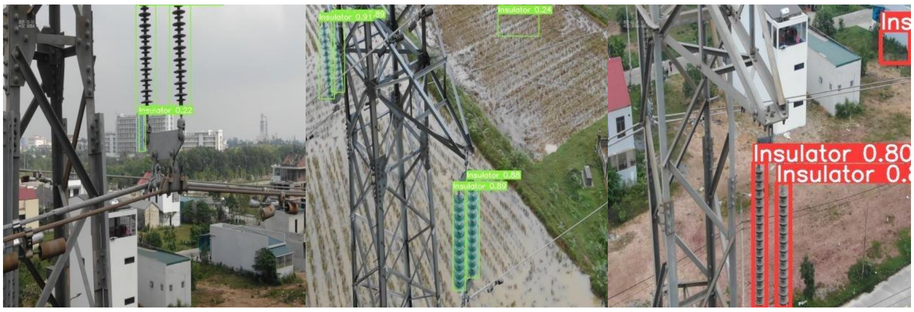

(b) False results of insulator detection

Figure 6. *Some detected results based on retrained Yolov5 and Yolov7*

Figure 6 shows some comparison results of insulator detection. This manual inspection illustrated that Yolov7 is more the false positive detected than Yolov5 family. On the other hand, the results also indicate that in some circumstances one model get a false positive detection, but other ones get a true positive detection. This problem is interesting for future work to investigate and combine both of advantages of Yolov5 and Yolov7 for improving detection performance.

6. Conclusions

In this paper, we have proposed an approach for insulator detection based on optimized Yolov5 model by customizing the hyperparameters. Firstly, Roboflow was used to labelling the image dataset and add some augmented method s such as rotation, brightness, and exposure. Then some hyperparameters for model training were customized that suit to the problem of insulator detection. Once the final detection model was trained. In next stage of applications, the detection system is embedded to drones and used to detect insulators on the power transmission lines and then crack insulators are classified and send to intelligent monitoring systems. The experimental results show that the customized Yolov5x for insulator detection reaches outperformer with the mAP_0.5 of 99.0% and mAP_0.5:0.95 of 68.6%. Details of comparison results: the mAP_0.5 is lower than the default Yolov5x which is 99.2% and higher than the Yolov7 which is 98.6%, the mAP_0.5:0.95 is higher than the default Yolov5x which is 65.7% and the Yolov7 which is 63.3%. Surprisingly, the mAP_0.5:0.95 of the optimized Yolov5x is lower than the Yolov5m which is 69.5%. The proposed approach for application has potential for real-time insulator detection which is embedded to drones. Improving performance of insulator detection as well as and crack recognition such as distinguish between healthy insulator and damaged insulator are future works.

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