The Exploration of Small Sample-Oriented Object Detection Technology in the Field of Electric Power

Yanjun Dong[1], Shigeng Wang[2], Xiaoyu Yin[1], Xi Chen[1] and Jiao Peng[1]
[1]State Grid Hebei Electric Power Company Co., Ltd Information & Telecommunication Branch, Shijiazhuang, China
[2]Beijing University of Posts and Telecommunications, Beijing, China

Keywords: Power Technology, Small Sample, Target Detection.

Abstract: In view of the difficulties, low efficiency and large amount of data in current grid patrol inspection, this project plans to study a small sample patrol inspection method based on dual-core. Firstly, based on the object recognition method of FASTERRCNN, a two-person network model of image and query image is constructed. Then, the improved regional proposal network (RPN) module is used to generate a higher quality proposal; finally, the regional boundary of the supporting image and the query image is matched to a new regional boundary. The experiments show that the method can detect the“Bird's nest” and“Insulator” in the power network with only 10 support maps in the EPD database established by ourselves, its detection index mAP value can reach 18.92% . Compared with other algorithms, the detection model of small sample based on binary star network proposed in this project has better performance and greater lightweight advantage under the condition of small sample, it can provide reference for the research of new power detection methods.

1 INTRODUCTION

Power Transmission Equipment in outdoor operation, the long-term operation of the stability of higher requirements, its outdoor operation will be affected by many uncertain factors, or even damage it. The failure of power grid, such as insulator damage, voltage balance ring damage and fall off, bird invasion and shock hammer damage, has brought huge security hidden trouble to power grid operation and security operation of power grid. With the rapid development of UAV technology, UAV detection is gradually replacing manual detection. The unmanned aerial vehicle (UAV) has the advantages of convenient carrying, quick response, easy operation and large amount of image data collection. With the development of electric power industry to smart grid, the traditional mathematical model has been difficult to adapt to the new requirements of grid operation and maintenance. The introduction of deep learning technology in power industry can effectively solve this problem. In-depth learning extracts Galway's failure features from low-level data layer by layer, which can effectively circumvent the artificial features' selective preference for data information (Shenzhen., 2021). Aiming at the fault diagnosis of synchronous motor, a ReLU-DBN oil sample analysis method based on the volatile gas in transformer oil sample is proposed in this paper (Wen Haorapido, 2022), and the method is improved. For transmission line fault, double Softmax classifier is used in reference (Xu Weili, 2022), and a method of fault identification and phase selection for transmission line is proposed based on CNN, thus the problem of non-independent classification of internal and external fault judgement and phase selection is solved.

2 TWINNED NETWORK MODEL ALGORITHM FLOW

The entire process of the model is shown in Figure 1. The image input is from the support image and the query image input at the same time, they enter a binary network with the same weight. The RPN algorithm sifts for possible objects in the retrieval image based on the relevant information of the supporting image contained in the image (Yang Xuejie, 2022), and then classifies and regresses the position by the final detection head. Due to the simplicity of the image, only 1 branch of the binary network supporting the image is drawn. In practical

Dong, Y., Wang, S., Yin, X., Chen, X. and Peng, J.
The Exploration of Small Sample-Oriented Object Detection Technology in the Field of Electric Power.
DOI: 10.5220/0012278100003807

In *Proceedings of the 2nd International Seminar on Artificial Intelligence, Networking and Information Technology (ANIT 2023)*, pages 220-223
ISBN: 978-989-758-677-4

application, for N categories, each category has its own branch, and the RPN in this branch is used to screen the potential priority of the corresponding classification.

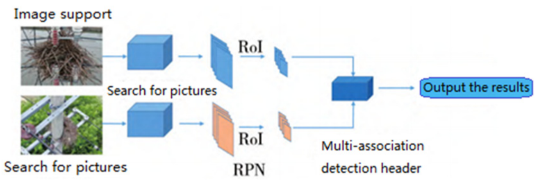

Figure 1: Overall structure of twinned network model.

The input of the improved proposal generation policy RPN is the output of the background, and the output of the background is a set of predicted values, each set of predicted values represents a set of predicted values. Figure 2 shows the overall structure of an RPN.

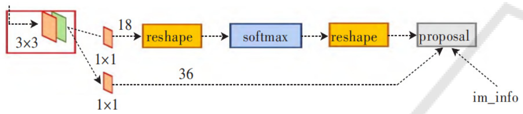

Figure 2: The Overall Structure of The RPN.

In theory, the function of RPN in object detection is to generate a potential precursor for subsequent classification and regression work. Ideally, when an RPN generates a candidate object, it will be measured by its support for the object contained in the image, rather than simply pre-and post-binary classification (that is, binary classification). However, the current RPN used by FASTERRCNN can only search blindly on the image and the feature layer of the image, resulting in the image containing objects that do not belong to the supporting set image, which leads to the existence of a large number of redundant objects in the image, thus, more work is added to the following classification and regression calculation. At the same time, because the number of target classes in the support set is much smaller than that in the actual scene, the effective prefix takes up a smaller proportion in the prefix generated by RPN, and the quality of the result is poor, may have a greater impact on the subsequent classification work. This is mainly due to the RPN algorithm in the process of proposal generation, did not make full use of the characteristics of supporting the centralized image, resulting in the generation of a large number of unrelated proposals. On this basis, an RPN model based on adaptive target classification is proposed. In the pre-processing, the model focuses on the target classification related to the support set, and eliminates the irrelevant classes, thus, the number of pre-processing is reduced and the workload of subsequent processing is reduced. Figure 3 illustrates the principle of adaptive improvement.

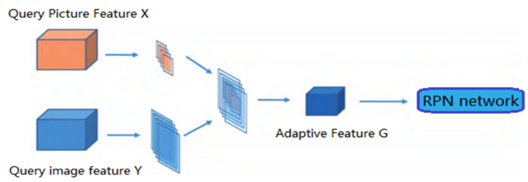

Figure 3: Principle of adaptive improvement in RPN.

Detection head classification and localization after RPN generation of a proposal, the probe is generally required to perform a target class score on the proposal and then classify it. This is the most important step in a dual-core network. A good model requires a single detector to distinguish between different types of data in a small sample (Zhang Ziqian, 2022). In the binocular network, the supporting image and the queried image are input into the feature extraction network. After generating the image, the feature association and matching are completed on the probe head. The multiple correlation probes used are shown in Figure 4.

The algorithm includes three modules: global correlation, local correlation and cross correlation. Among them, the global association represents the global feature matching of the support set and the query set on the scene scale, and the local association represents the one-to-one feature matching of the support set and the query set on the pixel level and the channel The cross-correlation represents a one-to-many pixel-level matching between the support and query scenarios, and is used to solve the spatial mismatch between the support and query scenarios.

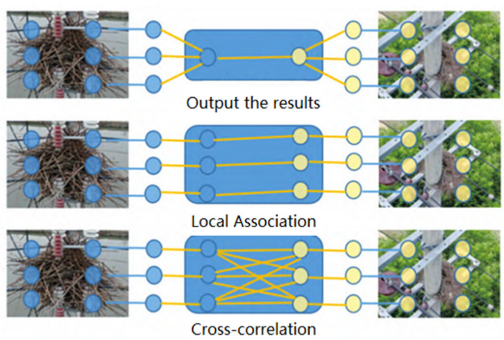

Figure 4: Multi-association detection header.

Loss function and model training process this paper uses a dual-card NVIDIAGEFORCERTX3060TIGPU hardware environment, using Python 3.7, Pytorch1.9.0, Torchvision0.10.0, CUDA11.1, Cudnn8.0.5.

The loss function differs from the image classification of machine vision in that object detection requires not only the classification of objects, but also the regression of coordinates of objects in rectangular position boxes. On this basis, two parallel output layers are used to implement the corresponding output variables. The output of the first output layer is a discrete category possibility confidence, where p=(p0,p1,…, pK) , corresponding to the K categories, there are （K+1） outputs, which include the confidence of the K categories and the confidence that the proposal belongs to the background. In this case, confidence p is the （K+1) FC layer output of the （K+1) FC layer obtained by the software maximum, which is the offset of the destination position boundary box. For class K targets, the deviation is $t^k = t_x^k, t_y^k, t_w^k, t_h^k$, where t^k does not refer to the absolute position coordinates of the regression target boundary box, but to the corresponding position coordinates generated by RPN.

Each trained RoI (area boundary) has a true classification marker u and a true locator box regression vector g. For the object detection task described above, we use the multi-task loss function, with RoI as the unit, to train the classification marks and the border regression:

$$L = L_{matching} + L_{box} \tag{1}$$

$$L(m,u,p^u,g) = L_{cls}(m,u) + \lambda[u \geq 1]L_{loc}(p^u, g) \tag{2}$$

$L_{cls}(m,u) = -\log m_u$ is the log loss for the category label u.

For the regression loss of the boundary box, it was defined as: the truth variable $g=(g_x, g_y, g_w, g_h)$ defining the target category U boundary box and the predicted boundary box location variable $p^u = (p_x^u, p_y^u, p_w^u, p_h^u)$

$$[u \geq 1] = \begin{cases} 1, u \geq 1 \\ 0, otherise \end{cases} \tag{3}$$

Where u is the result of the goal category prediction, and U = 0 is the goal framed by the proposal in the training sample that does not support the goal category in the set, but rather the background, that is, a deviation has occurred in the first classification task, so the regression error here is meaningless.

2.2 in the process of model training, the commonly used indexes to measure the training effect include Precision, Recall, AP and mAP. TP was defined as a positive sample for correct prediction, FN as a negative sample for false prediction, FP as a positive sample for false prediction, and the above assessment measures were defined as:

$$\text{Prcesion} = \frac{TP}{TP+FP} \# \tag{4}$$

$$\text{Recall} = \frac{TP}{TP+FN} \# \tag{5}$$

$$\text{AP} = \frac{\sum_i^n pi}{n} \tag{6}$$

$$\text{mAP} = \frac{\sum_{i=1}^k AP_i}{k} \tag{7}$$

3 CONCLUSION

The learning process of twin networks is divided into two stages. In the pre-training phase, we will improve the model's ability of multi-class image recognition by repeated training based on the existing standard large sample. In this paper, it is evaluated by using the existing mAP evaluation criteria, and it is pre-trained to reach 24.0 in the COCO data set. In the second step, the parameters of neural network are adjusted according to EDP data. The basic structure of ResNet is composed of four layers. In the retraining stage, the weights of the first two layers of ResNet are frozen, and the information of EDP data set is utilized, the latter two layers and the full-connection classification layer are adjusted to migrate the dataset.

The improved RPN algorithm is used to recognize the small sample of twin networks. In this method, the features of the supporting image set are extracted by dual-core network, and the object-related features are generated. There is still a big gap between the twin-sub-network small sample model proposed in this project and the existing large data object detection technology. In the future, we will further explore how to eliminate the interference of complex environment, explore new model evaluation methods, and how to make up the difference between training samples and test samples.

ACKNOWLEDGEMENTS

This work was supported by the National Key Research and Development Program of China under Grant 2020AAA0107500.

REFERENCES

Shenzhen. Research on power inspection based on small sample machine learning [J]. *Microcontroller and embedded system applications*, 2021, 21(8) : 4.

Wen Hao, Zhang Guozhi, Xiao Li, etc. Study on transformer PD planar localization based on small sample UHF signal [J]. *Transformers*, 2022, 59(4) : 6.

Xu Weili, Yuan Hegang and Kai Dong Yue, Mai Xiaoqing. Small sample generation based on antagonism neural network [J]. *Electronic testing*, 2022, 36(18) : 64-65.

Yang Xuejie, Song Kai, Cao Fuyong, etc. . Research on the application of front-end target detection technology in electric power patrol inspection [J]. *Shandong Electric Power Technology*, 2022, 49(1) : 6.

Zhang Ziqian, Xiong Zaili, Zhang Biao, etc. Small target detection in remote sensing image based on super-resolution reconstruction technology[J]. *Journal of Northeast Electric Power University*, 2022(002): 042.

Qinzhen Hu, Hongtao Su, Shenghua Zhou, Ziwei Liu, Yang Yang, Jun Liu. Two-stage constant false alarm rate detection for distributed multiple-input–multiple-output radar[J]. *IET Radar, Sonar & Navigation*. 2016, 10(2), pp 264-271

Bing Wang,Guolong Cui,Wei Yi, Lingjiang Kong,Xiaobo Yang. Constant false alarm rate performance prediction for non-independent and non-identically distributed gamma fluctuating targets[J]. *IET Radar, Sonar & Navigation*. 2016, 10(5), pp 992-1000

Wenjing Zhao,Deyue Zou,Wenlong Liu, Minglu Jin. New matrix constant false alarm rate detectors for radar target detection[J]. *The Journal of Engineering*. 2019, 2019(19), pp 5597-5601