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Review: the application of artificial intelligence in distribution network engineering field

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Abstract. The use of deep detection networks can help to enhance the management, reduce workload, and improve the efficiency and quality of dynamic defect detection in distribution network engineering. This involves classifying defects, researching and analyzing advanced deep detection networks and their applications in dynamic defect detection, reviewing existing research, and identifying key issues and their solutions. The paper also explores future research directions to provide useful references for future studies. Overall, the aim is to address potential safety and quality issues and mitigate hazards in the operation of distribution networks.

Keywords: artificial intelligence, application of deep learning, target detection, computer vision.

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INTRODUCTION

Key technology of dynamic defect detection in distribution network engineering

While there has been some initial research conducted in the field of dynamic defect detection [1] in distribution network engineering [2], the use of deep detection networks to achieve this goal presents various challenges. These challenges include the optimization design of deep detection network architecture and the complex nature of the construction site in distribution network engineering. Research in this area is still in its early stages.

Sample library establishment

When constructing a sample library for distribution network project defects, it is important to consider the specific type or types of defects to be detected, as there are many different types with distinct characteristics. However, there are three main challenges that may be encountered during this process. First, the number and quality of available samples may be insufficient. Second, the samples may not be balanced, meaning that there may be an unequal distribution of samples across different defect types [3]. Finally, the labeling work may not be detailed enough, which can hinder the accuracy and effectiveness of the deep detection network.

Equal emphasis on sample quality and quantity

To enhance the accuracy of defect identification, it is important to establish high-quality standards for image capture, including shooting angle, lighting, size, and clarity [4]. Additionally, it is necessary to gather as many effective samples of different defect types as possible while eliminating unqualified and invalid samples through data cleaning. Unqualified samples refer to those that do not meet the required shooting quality, while invalid samples include wrong or redundant pictures. As an example, unqualified samples of the insulation sheath added to the tension clamp may have poor angles, insufficient lighting, and severe detection target obstructions [5].

The limited number of samples or insufficient annotation information can be a challenge when implementing deep detection networks in the electrical industry. To overcome the problem of small samples, various methods are available, including data augmentation, transfer learning, and meta-learning. For example, literature proposes a detection technology for on-site foreign object detection in distribution network engineering based on sample expansion Faster R-CNN [6]. By synthesizing samples through Gaussian filtering, the training set is expanded, leading to an improvement in the accuracy of the detection model. Data augmentation, which involves simulating human vision, can help increase the training data and improve the robustness of the algorithm model. Common methods of data augmentation include scale transformation, translation, rotation, and cropping.

Balanced sample size

When building a sample set for dynamic defect detection in distribution network engineering, there may be an imbalance in the number of positive and negative samples for a certain type of defect. This can greatly reduce the accuracy of defect detection and affect the generalization ability of the model. To solve this problem, one solution is to expand the sample set through data augmentation [7]. There are various methods to address sample imbalance, including hard sampling, soft sampling, no sampling, and generating methods. Mosaic data enhancement integrated in the YOLOv4 [8] algorithm has been proven to be effective in improving the robustness of the model. Overall, data augmentation is considered an effective method to solve the problems of small sample sizes and sample imbalance.

In distribution network engineering, the sample set may have an imbalance in the number of positive and negative samples for a certain type of defect. This can greatly reduce the generalization ability of the model and affect the accuracy of defect detection. To solve this problem, data augmentation can be used to expand the sample library. Literature divides the solutions to class imbalance into four categories, including hard sampling method, soft sampling method, no sampling method, and generating method. The mosaic data enhancement integrated in the current YOLOv4 [9] algorithm has been proved to be an effective means to improve the robustness of the algorithm model through geometric, illumination, and image distortion. Data augmentation is considered an effective method to solve the problem of small samples and sample imbalance.

Differentiated sample labeling

In dynamic defect detection of distribution network projects, each type or subtype of defect has unique characteristics. Therefore, it is necessary to use differential labeling and analyze specific problems during the labeling process to help the algorithmic models understand the features accurately. For instance, when labeling whether a wire clamp is equipped with an insulating sheath, positive and negative samples are marked differently based on their characteristics. Since there are various types of wire clamps used in the distribution network construction project, positive and negative sample labeling is done using boxes and labels 1 and 0 to distinguish them accurately and improve defect identification accuracy [10]. Illustrates the labeling method for positive and negative samples of cross-arm flip-up. Since the orientation of the bolt positioning hole is the basis for distinguishing the flip-mounting of the cross-arm, the labeling includes the single bolt positioning hole as well as the position of the pair of bolt positioning holes. It is important to note that the label frame should be as small as possible while still encompassing all the information of the detection target to eliminate background interference information, and irregular label frames can also be used depending on the target's appearance. Prior to large-scale labeling work [11], intelligent labeling can be used to establish preliminary labeling schemes. However, some defect detection may not have clear positive and negative samples, such as cable without insulators. In such cases, literature proposes an end-to-end model with a biased objective function that jointly extracts entities and their relationships without separately identifying entity relationships, providing a reference for addressing these labeling challenges.

MODEL CONSTRUCTION

Building a dynamic defect detection model for distribution networks comes with its own set of challenges, apart from designing the deep detection network model as discussed in Section 3.1. These challenges include dealing with unbalanced target sizes, detecting and classifying compound targets, and developing algorithm models that cannot be applied to transfer learning in the specific scene of the distribution network engineering site [12].

Adapting to the unbalanced target size

The distance and viewing angle between the monitoring equipment on the distribution network construction site and the detection target are not always the same, which leads to inconsistencies in the size of the detection target in the sample image. This is known as the problem of detecting spatial imbalance in target domains. In such cases, the algorithm and model should have the ability to detect targets of the same type but with different sizes [13]. For instance, a positive sample of the grounding of transformers on pole in different scenarios is depicted in Figure 8, where the ground ring appears small in proportion to the sample image due to the long shooting distance.

To address the issue of unbalanced target size, various strategies have been proposed in literature. For instance, some studies have discussed the use of image pyramid series and anchor points to optimize the scale problem in target detection. Other researchers have developed multi-view neural networks that extract features from merged isomers and use multi-view classifiers to analyze the correlation between images, leading to better efficiency and generalization performance. Several methods have been proposed to address spatial imbalance, such as cascaded R-CNN [14], hierarchical shot detector, and IoU uniform R-CNN. Weight factors can also be added to balance the loss term. However, small-sized target detection remains a challenging issue, as most deep neural network models only use the last layer for prediction, resulting in poor performance in small target detection.

Small objects are difficult to detect in deep feature maps due to the loss of spatial and detailed feature information. Shallow layers of a deep neural network have smaller receptive fields, weaker semantic information, and less contextual information but can provide more spatial and detailed feature information. To enhance the detection accuracy of small objects, the feature pyramid technique has been proposed in literature [15], which down samples the image multiple times and improves the model's applicability in object detection of different sizes. However, this method may require a significant amount of memory and computation. Models like YOLOv4 and above have been successful in detecting objects of different sizes due to the feature pyramid integrated into the backbone network.

Model Selection and Deployment

Selecting an appropriate deep detection network model and deployment strategy is crucial when building a distribution network dynamic defect detection model. The selection process can be based on factors such as the size of the sample library, the size of the detection target, the accuracy of detection, the real-time performance, and the shooting scene. To tackle the issue of unbalanced target sizes, researchers have proposed several strategies such as image pyramid series [16], anchor points, intersection ratio threshold, dynamic convolution, and bounding box loss function. The feature pyramid method has shown promising results in detecting small objects by down sampling the image multiple times.

Object detection can be performed using single-stage detectors or two-stage detectors. Single-stage detectors [17] are faster in training and recognition, while two-stage detectors have higher accuracy. Anchor-free object detection, introduced by CornerNet [18], has simplified the network structure and reduced the difficulty of adjusting hyperparameters.

For scenarios with high real-time requirements but low detection accuracy, lightweight algorithms can be deployed on mobile devices such as drones, mobile phones, and tablets. For scenarios with high detection accuracy but low real-time requirements, complex multi-target defect detection scenarios in station building projects and distribution transformer projects can be equipped with video surveillance and deployed on servers [19].

Model pre-training

While some deep detection network models have achieved high accuracy in image classification and target detection on open-source datasets like ImageNet or COCO [20], the specialized task of dynamic defect detection in distribution network engineering lacks directly relevant image collections. Therefore, when training a deep detection network model for this field, it's not recommended to rely solely on transfer learning, as the knowledge and features learned from other fields may not be directly applicable. Due to the specialized nature of dynamic defect detection in distribution network engineering, it is not recommended to use transfer learning from other fields directly. Instead, pre-training the algorithm and model using weight sets from mainstream algorithms as initialization parameters is recommended. Model pre-training involves feature extraction and fine-tuning, which can reduce the amount of model training required. Combining pre-training with knowledge distillation can also be used for model compression, which is beneficial for online deployment on mobile devices. In addition to technical means, interpretability of the introduced model is necessary for significantly improving detector performance.

DISCUSSION

In specific application scenarios of distribution network engineering, geometric and color interpretability can be introduced to the algorithm model to accurately judge the position and presence of different objects. By incorporating various interpretability relations as prior knowledge of the network, constraints can be introduced to achieve relationship modeling between targets, which can effectively improve the performance of the algorithm model for defect detection in distribution network engineering.

CONCLUSION

In deep detection network design, a non-hierarchical architecture and visual Transformer based on the attention mechanism can be introduced to optimize the backbone network and reduce the inductive bias for detecting common features. Machine learning can be used to construct a network architecture suitable for the technical requirements of distribution network engineering defect detection.

Through preset neural network structure search algorithms, the model can learn to detect parameters and network configurations without human intervention.

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