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Anomaly Detection System for Solar Power Distribution Panels utilizing Thermal Images

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Abstract

This study aimed to develop an advanced anomaly-detection system tailored for solar power distribution panels using thermal imaging cameras to ensure operational stability. It addresses the imperative shift toward digitalized safety management in electrical facilities, transcending the limitations of conventional empirical methodologies. Our proposed system leverages a faster R-CNN-based artificial intelligence model optimized through meticulous hyperparameter tuning to efficiently detect anomalies in distribution panels. Through comprehensive experimentation, we validated the efficacy of the system in accurately identifying anomalies, thereby propelling safety protocols forward during the fourth industrial revolution. This study signifies a significant stride toward fortifying the integrity and resilience of solar power distribution systems, which is pivotal for adapting to emerging technological paradigms and evolving safety standards in the energy sector. These findings offer valuable insights for enhancing the reliability and efficiency of safety management practices and fostering a safer and more sustainable energy landscape.

Index Terms: Anomaly Detection, Digitalization of Power Facilities, Faster R-CNN, Object Detection, Thermal Image

I. INTRODUCTION

Solar power distribution panels play a pivotal role in modern energy systems by ensuring the reliability and safety of power supply. These panels are responsible for converting high- or extra-high-voltage electricity from power plants or substations into usable voltages for consumers, and for distributing power safely throughout the grid. However, maintaining the safety and integrity of these electrical facilities requires effective anomaly detection and response measures. Traditional approaches to safety management often rely on experience and subjectivity, which can be inefficient and may not adequately address the potential risks.

Previous safety management methods have been predominantly reactive and manual, addressing issues only after they occur. This reactive approach makes it challenging to respond to anomalies before escalation, and preventive measures may be limited. As the scale and complexity of power facilities continue to increase, the limitations of traditional methods have become more apparent.

Recent technological advancements have offered new possibilities for the safety management of power facilities. Digital technologies and artificial intelligence (AI) enable real-time data collection and analysis, allowing faster and more accurate anomaly detection. Systems utilizing sensors, such as thermal imaging cameras, to monitor temperature variations within distribution panels, coupled with AI algorithms for anomaly detection, are gaining prominence as innovative

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solutions for safety management.

In this context, this paper proposes a novel anomaly-detection system to enhance the stability of solar power distribution panels. By utilizing thermal imaging cameras and a faster R-CNN-based AI model, we aim to effectively identify and address anomalies within distribution panels. In this study, we sought to improve the safety and efficiency of safety management practices in power facilities.

Based on these motivations and objectives, this paper discusses the design, implementation, and experimental results of the proposed anomaly-detection system. This study is anticipated to contribute to the advancement of safety management in power facilities, thereby enhancing safety and reliability.

II. RELATED WORKS

Panthi et al. investigated methods for detecting anomalies in power distribution systems using machine-learning techniques and proposed effective methods for detecting anomalies in power systems by applying various machine-learning algorithms and data mining techniques [1-4].

Furthermore, Imenes et al. combined thermal imaging with deep learning to detect faults in power systems. They used thermal cameras to automatically detect faults in power systems by analyzing images using deep-learning algorithms [5-8].

Syu et al. identified anomalies in power networks using AI algorithms and immediate actions to enhance the safety of power networks [9-11].

Additionally, studies have focused on developing data-driven predictive models to detect equipment faults in power systems in advance and optimize maintenance schedules to enhance system reliability [13,14]. Moreover, notable research involves the utilization of the Internet of things and machine learning for real-time monitoring and anomaly detection in power systems [15].

These related studies have proposed innovative approaches for the safety management and reliability enhancement of power facilities, contributing to strengthening the safety of power systems alongside this study.

In this study, we utilized YOLOv5, which evolved from YOLOv1 to YOLOv8 [16-18]. The YOLOv5 model consists of two main components, the backbone and the head, with the following details:

The backbone extracts feature maps from images; in our case, we employed CSP-Darknet.

YOLOv5 offers four backbone variations ranging from the smallest and lightest YOLOv5s to m, l, and x.

The head is responsible for locating objects based on the extracted feature maps.

Initially, the anchor boxes were set and then utilized to generate the final bounding boxes.

Similar to YOLOv3, the bounding boxes were generated at three scales: small objects with 8-pixel information, medium objects with 16-pixel information, and large objects with 32-pixel information. Each scale employs three anchor boxes, resulting in nine anchor boxes.

In this study, which focused on detecting anomalies in solar power distribution boards using thermal images, we trained the YOLOv5 model to differentiate various parts of the thermal image corresponding to different components of the system. Our study aimed at enhancing object detection rates through hyperparameter tuning using YOLOv5.

The following is a summary of the architecture used in our study:

- Backbone: CSP-Darknet53
- Neck: SPPF
- Head: YOLOv3 Head

This study focused on detecting anomalies in solar power distribution boards by training with thermal images. We aimed to classify the different parts of the thermal images corresponding to various components of the system. Accordingly, we utilized YOLOv5 and aimed to enhance the object detection rates through hyperparameter tuning.

III. SYSTEM MODEL AND METHODS

Anomaly-detection systems for solar power distribution panels integrate cutting-edge technologies with thermal imaging, AI, and real-time monitoring to enhance the stability, safety, and reliability of solar power distribution panels. The key components and design considerations of the proposed system are outlined below:

1) Thermal Imaging Sensors

High-resolution thermal imaging cameras are strategically positioned to capture thermal data from solar power distribution panels. These sensors continuously monitor temperature variations within the distribution panels, providing valuable thermal images for anomaly detection.

2) Data Acquisition and Preprocessing

Raw thermal images captured by the sensors were transmitted to a central processing unit for data acquisition.

Preprocessing techniques, such as noise reduction, image enhancement, and normalization, were applied to ensure the quality and consistency of the input data.

3) Artificial Intelligence Model Selection

The system utilizes YOLOv5, which was selected for its superior performance in object detection tasks and ability to handle various types of anomalies effectively.

4) Training Data Preparation

To achieve the best learning outcomes, the dataset included a minimum of 1,500 images per class and a minimum of 10,000 instances (labeled objects) per class.

The dataset encompasses diverse thermal images representing different times, angles, and camera configurations to accurately represent real-world scenarios.

5) Model Training and Optimization

The YOLOv5 model was trained on the prepared dataset, starting with pretrained weights to accelerate convergence.

The training settings, including epochs, image size, batch size, and hyperparameters, were carefully selected and optimized to achieve the best performance without overfitting.

6) Real-time Anomaly Detection

Upon completion of training, the trained AI model was deployed for real-time anomaly detection on the incoming thermal images.

The model analyzed each image to identify the regions of interest (ROIs) that exhibited abnormal temperature patterns, indicating potential faults or anomalies within the distribution panels.

7) Alerting and Response Mechanism

The detected anomalies trigger immediate alerts to designated personnel through visual displays or notification systems.

Predefined response protocols, ranging from remote diagnostics to onsite inspection and maintenance, are initiated based on the severity and nature of the anomaly.

8) Continuous Monitoring and Feedback Loop

The system operates in a continuous monitoring mode, regularly updating its anomaly-detection capabilities based on new data and feedback. Feedback mechanisms enable the system to learn from past detections and improve its accuracy over time, enhancing the overall reliability of anomaly detection.

By encompassing these components and design principles, the proposed anomaly-detection system offers a comprehensive solution for enhancing the stability, safety, and reliability of solar power distribution panels.

Fig. 1 illustrates the process used in this study. The system receives thermal images as the input, utilizes the YOLOv5 model to detect objects, displays bounding boxes around the detected objects, and performs pixel mapping. Subsequently, the components where the temperature increased are highlighted.

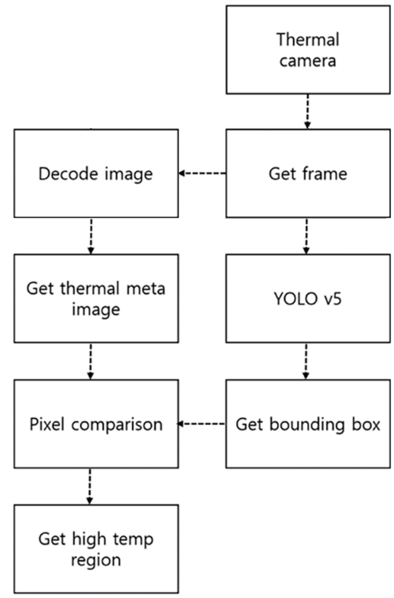

Fig. 1. Flowchart of object detection system for anomaly detection in solar power distribution panels.

IV. RESULTS AND DISCUSSIONS

A. Optimization

In this study, optimization was performed to improve the performance and computational efficiency, prevent overfitting, and reduce the model size. The initial hyperparameters in machine learning control various aspects of training, and determining their optimal values can be challenging. Traditional methods, such as grid search, face issues, such as increased computation, owing to the high-dimensional search space, unknown correlations between dimensions, and the cost associated with evaluating fitness at each point. Therefore, genetic algorithms are utilized as suitable candidates for initial hyperparameter searches because of their ability to efficiently navigate complex search spaces.

Table 1 lists the hyperparameters and their respective optimization ranges. Table 2 displays the evolution results of the hyperparameters obtained over five iterations.

Fig. 2 shows the results of the training and validation processes using the YOLOv5 model for various loss and performance metrics. The graphs display the results over the epochs, with the horizontal axis representing the epochs and the vertical axis representing the values of the respective metric. These graphs are useful for diagnosing the performance of a machine-learning model and detecting overfitting

Table 1. Hyperparameter evolution list

No.	Hyperparameters	Optimization domain
1	lr: initial learning rate (SGD=1e-2, Adam=1e-3)	[1e-5, 1e-1]
2	lrf: final OneCycleLR learning rate (lr*lrf)	[0.01, 1.0]
3	momentum: SGD momentum/Adam beat1	[0.6, 0.98]
4	weight_decay: optimizer weight decay 5e-4	[0.0, 0.001]
5	warmup_epochs: warmup epochs (fraction ok)	[0.0, 5.0]
6	warmup_momentum: warmup initial momentum	[0.0, 0.95]
7	warmup_bias_lr: warmup initial bias lr	[0.0, 0.2]
8	box: box loss gain	[0.02, 0.2]
9	cls: cls loss gain	[0.02, 4.0]
10	cls_pw: cls BSELoss positive_weight	[0.5, 2.0]

Table 2. Result of hyperparameter evolution

Epochs			100		
Optimization algorithm			Genetic algorithm		
Number of evolutions			300		
Fitness			mAP		
Hyperparameters	T1	T2	T3	T4	T5
learning rate (lr)	0.01	0.0098	0.0092	0.0109	0.0086
lrf	0.01	0.0103	0.0107	0.0112	0.0108
momentum	0.937	0.9364	0.9359	0.98	0.9422
weight_decay	0.0005	0.0005	0.0004	0.0003	0.0004
warmup_epochs	3	3.4024	3.0464	3.4194	3.0996
warmup_momentum	0.8	0.8641	0.8951	0.95	0.8457
warmup_bias_lr	0.1	0.1001	0.1034	0.1058	0.1206
box	0.05	0.0578	0.0442	0.0478	0.0496
cls	0.5	0.4426	0.5006	0.6177	0.4831
cls_pw	1	1.044	0.9766	0.8184	0.9627
mAP	0.8572	0.869	0.8719	0.8774	0.8797

or other issues.

- train/box_loss and val/box_loss: These losses measure the accuracy of the bounding box location. Both the training and validation losses tended to decrease as the epochs progressed, indicating that the model was better at predicting the locations of the objects.
- train/obj_loss and val/obj_loss: The object presence loss indicates how well the model predicts the presence of an object in a certain location. This value also decreased as the number of epochs increased.
- Train/cls _loss and val/cls_loss: The classification loss shows how accurately the model classifies the class of the object within the bounding box. This loss also exhibited a decreasing trend.

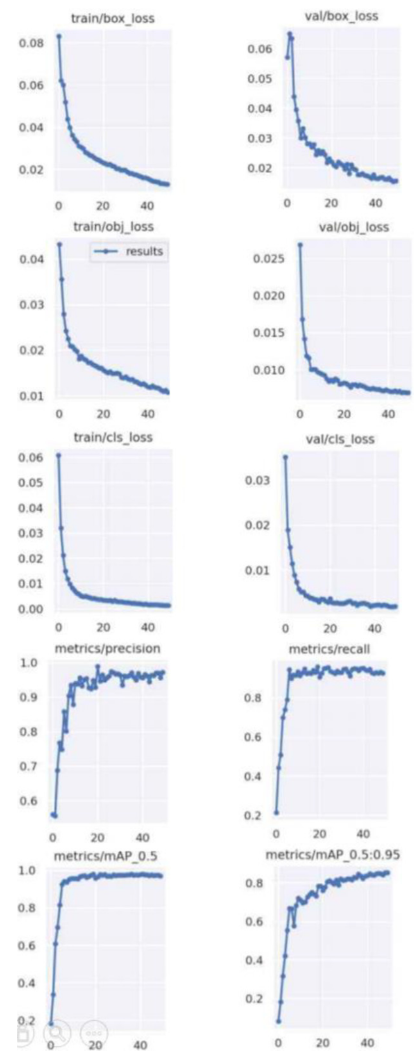

Fig. 2. Results of training and validation

- Metrics/precision and metrics/recall: Precision is the ratio of correctly included actual objects in the predicted bounding boxes, and recall is the ratio of actual objects that the model correctly detects. Both these metrics maintain high values, indicating that the model performs well in detecting and classifying objects.
- metrics/mAP_0.5 and metrics/mAP_0.5:0.95: The mean average precision (mAP) is an important indicator that reflects the average precision over several thresholds, evaluating the overall performance of an object detection model. mAP_0.5 refers to the mAP when the intersection over union (IoU) threshold is 0.5, and mAP_0.5:0.95 is the average mAP when the IoU increases from 0.5 to 0.95 in increments of 0.05. Both indicators initially increase sharply and then maintain a stable level, indicating that the model performs at a high level.

Overall, these graphs show that the performance of the

YOLOv5 model improved as it progressed through the epochs, particularly through a decrease in loss functions and an increase in mAP, demonstrating good training results. Additionally, the similar values of losses and metrics between the training and validation data suggest minimal signs of overfitting.

V. CONCLUSIONS

Based on the experimental results, it is evident that the proposed anomaly-detection system operates effectively within solar power distribution panels. Object detection using the YOLOv5 model demonstrated high accuracy and rapid processing speed, enabling the identification of various components within distribution panels. Furthermore, the observation of decreasing loss functions and increasing mean accuracy throughout the model training process validated the stability and reliability of the system. An evaluation of the performance of the anomaly-detection system confirmed its applicability and potential benefits in real-world power facilities, indicating significant advancements in safety and reliability enhancement. Therefore, the findings of this study open new horizons for safety management in solar power distribution panels and suggest promising opportunities for future applications in both the business and research domains.

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